



jmetrics v0.1.1: a Python package for metrics and algorithms used to identify or characterise atmospheric jet-streams.

Tom Keel¹, Chris Brierley¹, and Tamsin Edwards²

¹Department of Geography, University College London, Gower Street, London, WC1E 6BT

²Department of Geography, King's College London, 40 Bush House, London, WC2B 4BG

Correspondence: Tom Keel (thomas.keel.18@ucl.ac.uk)

Abstract. The underlying dynamics controlling this planet's jet streams are complex, but it is expected that they will have an observable response to changes in the larger climatic system. A growing divergence in regional surface warming trends across the planet, which has been both observed and projected since the start of the 20th century, has likely altered the thermodynamic relationships responsible for jet stream formation and control. Despite this, the exact movements and trends in the changes to the jet streams generally remain unclear and without consensus in the literature. The latest IPCC report highlighted that trends both within and between a variety of observational and modelling studies were inconsistent (Gulev et al., 2021; Lee et al., 2021). Trends in the jet streams were associated with *low* to *medium confidence*, especially in the Northern Hemisphere.

However, what is often overlooked in evaluating these trends is the confused message in the literature around how to first identify, and then characterise, the jet streams themselves. For characterisation, approaches have included isolating the latitude of the maximum wind speed, using sinuosity metrics to distinguish jet 'waviness', and using algorithms to identify jet cores or jet centres. Each of these highlights or reduces certain aspects of jet streams, exist within given time windows, and characterise the jet within a given (Eulerian or Lagrangian) context. While each approach can capture particular characteristics and changes, they are subject to the spatial and temporal specifications of their definition. There is therefore value in using them in combination, to assess parametric and structural uncertainty, and to carry out sensitivity analysis.

Here, we describe *jmetrics* version 0.1.1, a new open-source Python 3 module with standardised versions of 16 metrics that have been used for jet stream characterisation. We demonstrate the application of this library with two case studies derived from ERA-5 climate reanalysis data.

1 Introduction

Jet streams are instantaneous features of the Earth's general atmospheric circulation. They manifest as fast-flowing ribbons of air, usually found near the thermodynamic boundary between the troposphere and stratosphere — the tropopause (Vallis, 2019). As their features are chaotic and loosely defined at any given scale, there is no universal process to capture jet streams in data (see recent reviews in Maher et al., 2020; Bösigler et al., 2022). As such, many strategies have been adopted to capture aspects of the jet stream. The most popular is to develop algorithms, indices, and statistics (here known as metrics) which



isolate and characterise regions in the atmosphere expected to be synonymous with jet streams within a given spatio-temporal
25 scale. Among the most popular approaches currently used, we identify 3 broad types:

1. *Jet statistics* — Statistics for isolating various quantities synonymous with the jet stream from upper-level wind speed within a given time window (Section 2.1);
2. *Waviness metrics* — Statistics and indices for determining the sinuosity or ‘waviness’ of upper-level mean flow within a given time window (Section 2.2);
- 30 3. *Jet core algorithms* — Two-step process for isolating and then characterising cores (also known as centres) of fast wind speeds in the upper-level wind (Section 2.3):
 - (a) *Identification* — based on wind speed thresholds and/or locality/neighbours.
 - (b) *Characterisation* — computing statistics (e.g. counts or standard deviation) of the cores identified.

The differences between these types of approaches have given rise to a confusing message about the various trends shown in
35 the planet’s jet streams across a range of modelling and observational studies (e.g. Cohen et al., 2020; Harvey et al., 2020; Overland et al., 2021; Stendel et al., 2021). While the variety of metrics developed can be used to improve understanding of the interactions of the jet stream with other components of the climate system, we argue that any understanding is inherently methodology-dependent. As such, this has made it difficult to understand the past and future behaviours of jet streams.

Here, we aim to address the need for a method of combining and/or comparing the various methods for jet stream identi-
40 fication. The tool we introduce, *jsmetrics*, is an open-source Python 3 package built from *xarray* that implements 16 existing metrics used for jet stream identification or characterisation. We first review the different metrics included with the package (Section 2), before discussing the design of the package (Section 3) and demonstrating an application (Section 4). We conclude by discussing further potential uses of the package and future directions for work on jet stream identification (Section 5).

1.1 Background

45 Although the identification of jet streams is dependent on the definition used, in general they can be characterised as strong localised winds within regions of the maximal thermal wind shear occurring where there is an extreme temperature and vertical pressure gradients (Vallis, 2019). The Earth’s atmospheric circulation gives rise to two processes that develop strong thermal wind shear and therefore jet streams: *eddy-driven processes* (relating to the behaviour of transient eddies in the mid-latitudes; Held, 1975) and *thermally-driven processes* (relating to conservation of angular momentum at the poleward edge of
50 the thermally-driven Hadley Cell; Held and Hou, 1980).

While eddy-driven processes tend to produce jet features that are deeper and more variable in their location and strength, thermally-driven processes produce jet features that are more shallow and narrow and closely tied to the poleward edges of the Hadley Cell (Madonna et al., 2017; Stendel et al., 2021). However, jet streams are often driven by a combination of both processes, so it is perhaps better to consider entirely eddy-driven or entirely thermally-driven jets as two ends of a spectrum



55 (Spensberger and Spengler, 2020). Jet streams in observations often exist in "merged states", especially across the mid-latitudes
(Stendel et al., 2021). As thermally-driven components of the jet streams may dominate wind speeds in the upper reaches of
the troposphere, using metrics that isolate lower-level winds magnifies the relative presence of eddy-driven components, and
this has been a common strategy for identifying these processes (see Section 2; Hallam et al., 2022). Deeper, eddy-driven jets
might stretch from the top of the troposphere to the atmospheric boundary layer, and tend to be more barotropic (Held, 1975;
60 Held and Hou, 1980; Madonna et al., 2017).

Jet streams play an influential role in the climate system. They help control, modify, and drive pressure systems across the planet, and their features are often directly synonymous with cold waves, heat waves, weather bombs and weather persistence. So it is of great interest to know how jets are responding to climate change (Gulev et al., 2021; Lee et al., 2019).

2 Strategies for characterising jet streams

65 Understanding how jet streams are operating between seasons, phases in climate oscillations and with greater changes in the climate system could be a key predictor for making projections about the future regimes of (extreme) surface weather (Harnik et al., 2016; Manney and Hegglin, 2018; Cohen et al., 2021). Despite this, features of jet streams are generally quite difficult to detect, and then characterise in data-space because they act in chaotic ways in the atmosphere (Barnes and Polvani, 2015; Peings et al., 2017). Any given metric, used in isolation, roots the understanding of the jet stream to a given context and within
70 a given spatial and temporal frame (Manney et al., 2011; Woollings et al., 2018). In general, the metrics included within the *jsmetrics* package have been developed in relative isolation from each other to answer a specific question about the jet stream's form, position, or trends over time and space. In Section 1, we made a distinction between metrics of three broad categories, discussed in further detail in this section.

2.1 Jet statistics

75 Jet statistics is a group that broadly encompasses all statistics and indices that extract a single value from upper-air wind/flow synonymous with features of jet streams and within a given time window and spatial reference. Most commonly, this includes metrics which extract a jet latitude (e.g. the latitude of maximum wind speed in a given spatial reference) and jet speed (maximum wind speed in a given spatial reference), but there are also methods for other characterisations such as jet width and jet depth. These metrics are generally not designed to capture individual events or general form in the jet such as troughs or
80 ridges, but instead to capture the general climatological characteristics of the jet (position, speed, operational range, etc.) in the atmospheric column (Koch et al., 2006; Barton and Ellis, 2009; Rikus, 2018). As such, they are most useful for approaching understanding the general regimes of jet streams and so have been adopted to evaluate latitudinal shifts, slowing or speeding up of the jet as well as narrowing or widening of the jet stream's operating range (Martin, 2021; Hallam et al., 2022). In Table 1, we review the 9 jet latitude metrics from the literature that feature in the *jsmetrics* package.

85 Jet statistics (Table 1) have typically been developed for pressure levels relatively close to the surface (700-925 hPa) and primarily with one variable: the zonal component of wind (u). As thermally-driven components of the jet streams may domi-



Table 1. Jet statistics from the literature included in the *jsmetrics* package (*u*- and *v*- refer to the zonal and vertical wind components)

Study	Variable(s)	Pressure (hPa)	Temporal	Method
Archer and Caldeira (2008)	<i>u, v</i>	100-400	Monthly	Mass-flux weighted mean latitude
Woollings et al. (2010)	<i>u</i>	700-925	Daily	Low-pass then Fourier filter over max wind speed
Barnes and Polvani (2013)	<i>u</i>	700-850	Daily	Low-pass filter then quadratic interpolation
Barnes and Polvani (2015) ¹	<i>u</i>	700-925	Daily	Fit a parabola around wind speed profile
Barnes and Simpson (2017)	<i>u</i>	700	10-day average	Maximum wind speed
Grise and Polvani (2017)	<i>u</i>	850	Daily	Quadratic interpolation of max wind speed
Bracegirdle et al. (2018)	<i>u</i>	850	Annual & Seasonal	Cubic-spline interpolation of max wind speed
Ceppi et al. (2018)	<i>u</i>	850	Monthly	Centroid of wind speed profile
Kerr et al. (2020) ²	<i>u</i>	500	Daily	Smoothed max wind speed by longitude

¹ adapted from Barnes and Polvani (2013); ² adapted from Barnes and Fiore (2013).

nate wind speeds in the upper reaches of the troposphere, using lower level winds, as these methods do, is mostly motivated by magnifying the relative presence of eddy-driven components (Hallam et al., 2022). Jets dominated by eddy-driven components tend to be more barotropic, so extend further down towards the surface than the shallower thermally-driven and, more latitudinally fixed, subtropical jets (Held, 1975; Held and Hou, 1980; Madonna et al., 2017). Despite this, in isolating lower-level winds, these methods suffer if the eddy-driven components do not extend throughout the atmospheric column towards the surface within the method’s given time window.

In each case, the jet statistics available in *jsmetrics* all centre around extracting the latitude of the jet stream as the point of fastest zonal wind, but how they achieve this and how they then establish a signal/trend from the outputs varies. The one exception is Kerr et al. (2020) who select a value of jet latitude and jet speed for each longitude. Metrics from Grise and Polvani (2017), Barnes and Simpson (2017), Bracegirdle et al. (2018) and Ceppi et al. (2018) use various smoothing functions (quadratic, cubic spline and centroid) to downscale the resolution for jet speed and latitude estimate (commonly to a resolution of 0.01 degrees). Woollings et al. (2010), Barnes and Fiore (2013) and Barnes and Simpson (2017) express jet latitude estimate as an anomaly from the seasonal cycle to distinguish seasonal modes of the jet latitude and their preferred positions over a study area.

Each of the methodologies is relatively adjustable and fast to compute (compared to the other metrics in the package), so can be used to produce quick diagnostics of fast-flowing wind over a given time period and region. Notably, these types of metrics have been employed mainly to evaluate shifts in position and speed of the jet streams at relatively longer time scales (intra-seasonal and interannual) to evaluate their response to changes in polar-tropical temperature gradients in a warming world (e.g. Barnes and Simpson, 2017; Zappa et al., 2018; Spensberger and Spengler, 2020).

Approaching any day-to-day spatial variation shown in the jet stream with this form of metric is generally regarded to be limited (Koch et al., 2006; Rikus, 2018). And when considering that the jet streams are inherently 3-dimensional and multifaceted



Table 2. Jet waviness metrics from the literature included in the *jsmetrics* package (*u*- and *v*- refer to the zonal and vertical wind components; *zg* refers to the gravity-adjusted geopotential height)

Study	Variable(s)	Pressure-level (hPa)	Temporal	Method
Francis and Vavrus (2015)	<i>u, v</i>	500	Daily	Meridional circulation index
Cattiaux et al. (2016)	<i>zg</i>	500	Daily	Sinuosity metric

structures, it is restrictive to view wind speed at one isolated slice of the atmosphere (Strong and Davis, 2005, 2006). As such, jet latitude metrics are typically less useful for diagnosing trends in synoptic-scale events such as cold-air outbreaks (Manney and Hegglin, 2018). Further, these metrics are developed to find a single-jet structure (one stream), so are less appropriate for studying splitting and merging in the jet (Hallam et al., 2022).

2.2 Waviness metrics

Waviness metrics can be considered to be more derived methods that describe the general nature of the winds in the upper parts of the troposphere. They look to quantify sinuosity within the structure of a single global jet stream. They broadly describe propagations of Rossby waves in the structure of the upper-level mean flow, and they do not necessarily isolate which parts of the mean flow are ‘jet streams’, such as driven by eddy- or thermal processes (Martin, 2021). Two jet waviness metrics feature in the *jsmetrics* package (Table 2).

These metrics consider the jet stream as a continuous pan-global feature, as opposed to a regional, split or emergent structure (Molnos et al., 2017; Martin, 2021). This conceptualisation is more observable in upper-air mean flow at seasonal and longer time aggregations (Koch et al., 2006; Spensberger et al., 2017). By framing the identification of jet streams as being about their propagation in Rossby waves, these metrics move towards diagnosing the propensity for peaks and troughs and thus can be used as a proxy to describe the poleward/equatorward transport of the underlying surface air masses (Hanna et al., 2017; Vavrus et al., 2017). Waviness metrics have been used to evaluate trends of jet stream flow in response to the warming world and whether this has encouraged extreme weather (Francis and Vavrus, 2015; Hanna et al., 2017; Vavrus et al., 2017; Cohen et al., 2020). The notion of a ‘wavier’ jet stream leading to more extreme (winter) weather in response to the warming world is a highly contested topic (Cohen et al., 2020, 2021), but it is suggested that the slower progression of the jet stream in a ‘wavier’ regime encourages surface weather systems to take a longer path and broader across the planet’s latitudes and as such encourage the transport of colder air to be pushed further equatorward and vice versa.

2.3 Jet core algorithms

Jet core algorithms are rule-based methods which isolate the jet stream in the upper-air wind as a collection of points in the atmosphere called ‘jet cores’, ‘jet occurrences’ or ‘jet centres’ (here we refer to them all as jet cores). They achieve this by



Table 3. Jet core algorithms from the literature included in the *jsmetrics* package

Study	Variable(s)	Pressure-level (hPa)	Temporal	Method
Koch et al. (2006)	u, v	100-400	Daily	Event-based jet stream climatology and typology
Archer and Caldeira (2008)	u, v	100-400	Monthly	Mass-flux weighted wind-speed
Schiemann et al. (2009)	u, v	100-500	6-hourly	Local maxima and above 30 m s^{-1}
Pena-Ortiz et al. (2013)	u, v	700-850	Month-Yearly	Local wind maxima
Kuang et al. (2014)	u, v	200-250	any	Jet occurrence and jet occurrence centres
Manney et al. (2014) ¹	u, v	100-400	Daily	Wind speed maxima and jet core separation

¹ adapted from Manney et al. (2011);

using a given wind-speed threshold before using further rule-based algorithms to classify a location (e.g. into a type of jet occurrence, a local maxima, etc). 5 jet core algorithms feature in the *jsmetrics* package (Table 3).

Typically, these algorithms have been employed at the finest temporal scales available in a given data product, so they are more computationally expensive. However, they provide a relatively more comprehensive detail about the features in the jet streams at a synoptic scale (Molnos et al., 2017; Kern et al., 2018).

The determination of jet cores varies between the algorithms, and they have been selected on: (i) predefined maximum speeds expected for jet streams (varying over $27\text{-}40 \text{ m s}^{-1}$; Koch et al., 2006; Strong and Davis, 2007; Schiemann et al., 2009; Pena-Ortiz et al., 2013; Kuang et al., 2014; Manney et al., 2014), (ii) in relation to wind-speeds of neighbouring data points (local wind-speed maxima; Schiemann et al., 2009; Pena-Ortiz et al., 2013; Kuang et al., 2014), or (iii) retaining continuity of a core across longitudes and/or pressure-levels (e.g. Molnos et al., 2017). By relying on defined wind-speed thresholds and local maxima, these methods can suffer from discounting the influence of multiple streams of jets, i.e. if they are only selecting the ‘maximum’ jet speeds (Spensberger et al., 2017; Rikus, 2018). Furthermore, they may also underestimate positions of the jet cores in different seasons and within different phases of the given climate oscillations (e.g. Woollings et al., 2010; Madonna et al., 2017; Manney and Hegglin, 2018). We expect jets to be faster and the eddy-driven and thermally-driven components to be more latitudinally separated in the winter versus summer (Maher et al., 2020).

Different processes are known to drive the jet streams that form over the planet (Ahrens and Henson, 2021), but, in the Northern Hemisphere especially, these processes are known to exist in combination and interact (Li and Wettstein, 2012; Madonna et al., 2017; Maher et al., 2020). Broadly, this has made it difficult to isolate the relationship between changes to the different processes driving jet streams and the patterns shown in upper-level wind conditions (Molnos et al., 2017; Manney and Hegglin, 2018; Hallam et al., 2022).

While there is no clear-cut method to separate eddy- and thermally-driven components of the jet stream (or the subtropical jet from the polar jet), some jet core algorithms make a consideration that the jet streams are driven by two mechanisms and attempt to separate them. Pena-Ortiz et al. (2013) develop a method to distinguish between merged and separate states of the polar and subtropical jets after the initial detection of jet cores. Manney et al. (2014) adopt a more *emergent* form of



distinguishing between different jet streams as their jet core algorithm separates the cores into groups, thus ignoring the reliance on two categories (i.e. polar and subtropical jets). Koch et al. (2006) subdivide jet events by depth.

3 Description of *jsmetrics*

jsmetrics is a package containing implementations of various metrics and algorithms for identifying and/or characterising jet streams, written in Python 3. The package can be installed from the Python Package Index (PyPI) repository using `pip` and is also available on GitHub. *jsmetrics* is published under the GNU v3.0 licence.

The main focus of the package is to standardise the methods used to either characterise or identify jet streams in atmospheric data such that they can be compared with each other. The hope is that a tool allowing for this inter-compatibility would help the research community to both help quantify what different metrics show about jets as features of atmospheric circulation, but also to provide a platform for researchers to edit existing, and develop new, metrics and algorithms in a standardised framework. The design of this framework is discussed in this section, and there are more details about how to add new metrics to the package in section 5.1.

3.1 Design

The package is built using *xarray* — an open-source Python package for working with labelled multidimensional arrays that has become a popular package for Earth Science research (Hoyer et al., 2022). As the package is built from *xarray*, each individual metric and algorithm in the package is stubborn about its inputs — only accepting an *xarray Dataset* or *DataArray* object as an input. Further, the inputs are expected to contain dimensions and variables with standardised names conforming to the ‘controlled vocabulary’ of Taylor et al. (2011) (e.g. `ua`, `va`, `zg`, `plev`, `lat`, `lon`) The use of the standard inputs in this way allows the package to have a logical output, i.e. *xarray dataset* containing additional variables computed by the given jet stream metric.

The design philosophy of this package was to decompose and de-couple each metric and algorithm into a collection of base functions that each perform one specific part of the methodology, e.g. to calculate a climatology, calculate a zonal mean or extract cells with wind-speed matching given criteria. This design decision was taken to allow metrics to share components, potentially making subsequent metrics easier to verify and implement, and also to improve bug detection and traceability. The package is built such that existing metrics can be modified by replacing the statistical filtering method used, the wind speed threshold limit, or by tweaking the steps of an algorithm, for example.

3.1.1 Flexibility

jsmetrics was designed in a way that does not predefine any sub-setting of input data or to be stubborn about receiving data of a given resolution, i.e. it can meet specifications defined by the various definitions of the methodologies of the metrics provided in the literature. Instead, the package passes the handling of sub-setting of the data onto the user. As such, each metric can be run on the same data without requiring sub-setting. In cases where not sub-setting is nonsensical (i.e. methods that can only



run on one pressure level or require specific temporal or spatial resolution), then the user is notified. Because of this, each metric is flexible, so it is possible to change the resolution of the input data, the spatial region or the number of pressure levels used. The motivation was to open up the possibility of sensitivity analysis with the metrics and the quantification of parametric uncertainty of the metrics. A full description of adjustments and difference between the literature's implementation and the (Python) implementation provided by *jsmetrics* is described in the documentation (see Keel, 2023).

3.1.2 Package organisation

An aim in designing the layout of the *jsmetrics* package was to keep it well-organised, hierarchical, and easy to navigate. Also, to hide all the implementation-level detail of each metric within a function sharing the given metrics name. To achieve this, we break the package down into 3 main folders: *core* — containing all the main functions for the package, *metrics* — containing the implementations of the jet stream metrics, *utils* — containing scripts with utility functions for general data, spatial and wind related operations. We break down the *metrics* folder further in Table 4. Notably, during the process of designing this package, it became important to distinguish between three distinct types of methods described earlier; here stored in three files: *jet_statistics.py*, *waviness_metrics.py* and *jet_core_algorithms.py*. These files contain the instructions (functions) to calculate a given metric or algorithm at a high-level of abstraction. In each case, they call sub-functions in three component files, and these component files can call upon various utility functions available within the *utils* folder. The implementation details of each metric are kept intentionally hidden (and de-coupled from the metric itself) in sub-functions to allow for readability and also to allow for the construction of new metrics and/or edit the existing ones. Finally, the package also provides a specification file, *details_for_all_metrics.py*, which details all the data sub-setting needed to replicate the specification from which the method was built on, i.e. Woollings et al. 2010 was built from zonal wind speed (*ua*) data at 700-925 hPa between 15-75 degrees N and 120-180 degrees W. This file also provides a description of the metric including citation details.

3.2 Development

The process by which metrics have been added to the *jsmetrics* package is diagrammatically represented in Figure 1. This process applies to metrics already added to the package, but also serves as a guide for adding metrics in the future, with a code review on GitHub being an essential part of the development of this project. As shown, we break down the process into 4 successive stages (which we organise in GitHub as a kanban board under 'projects').

As shown in figure 1, after the identification of a relevant metric (*Not started*), we first produce a pseudocode implementation on paper using the description of the method from the respective paper (*In progress*). After this, we translate the pseudocode to Python in Jupyter-Notebooks, where we rework and refactor the code so that it runs as fast and independently as possible (with an emphasis on minimising third-party packages/libraries, i.e. using only NumPy, xarray and base Python). In this stage, we start to write documentation (docstrings) for each function and class, and plan unit tests for when the metric is moved over to *jsmetrics*. After writing the implementation, we validate its accuracy by reproducing the results from the given study where possible in stage 3 (*Undergoing validation*). After which we either refactor the method further, if it fails the validation or write unit tests, finish the documentation and integrate the metric into the *jsmetrics* package if it succeeds. As of version 0.1.1, nine



Table 4. File layout of the *metrics* folder in the *jsmetrics* package.

File	Purpose
<i>higher-level of abstraction</i>	
jet_core_algorithms.py	Stores all the instructions to run the jet core algorithms.
jet_statistics.py	Stores all the instructions to run the jet statistics.
waviness_metrics.py	Stores all the instructions to run the waviness metrics.
<i>lower-level of abstraction</i>	
jet_core_algorithms_components.py	Sub-functions for the jet core algorithms.
jet_statistics_components.py	Sub-functions for the jet statistics.
waviness_metrics_components.py	Sub-functions for the waviness metrics.
<i>specification file</i>	
details_for_all_metrics.py	Stores all the data sub-setting specifications and descriptions for each algorithm and metric

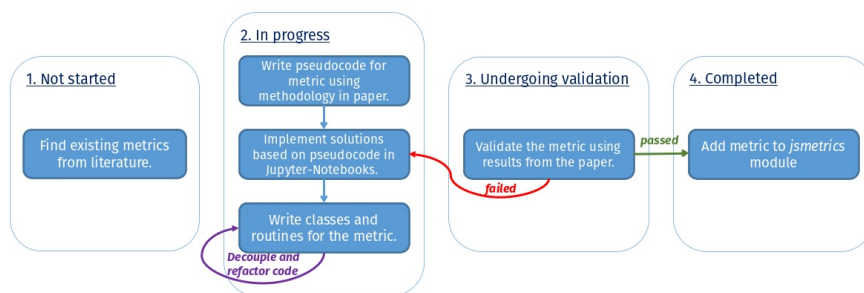


Figure 1. Stages involved with developing the *jsmetrics* package.

220 jet statistic metrics, two jet waviness metrics and five jet core algorithms have been added to the package. We have detailed the progress status of each metric included, and this is available via ReadTheDocs (see Keel, 2023).

4 Application of *jsmetrics* to ERA5 reanalysis data

Having covered some key features of *jsmetrics*, the aim of this section is to introduce how to install the package and to demonstrate its application on a climate data set — here chosen to be the European Centre for Medium-Range Weather Forecast’s
 225 ERA-5 (Hersbach et al., 2020). For the demonstration here, a limited amount of knowledge about Python is needed to replicate



our results, as the *jsmetrics* package is built to be simple and user-friendly (achieving this by hiding all most implementation-level detail). For more advanced use of this package, we recommend some working knowledge of Python and *xarray*.

4.0.1 Experiment setup, installation, and input data

jsmetrics is compatible with Python version 3.7 or later and can be installed via PyPI using the command `pip install`
230 `jsmetrics`. Installing via `pip` automatically collects and installs all the dependencies required for the package, but the
source code is also accessible via GitHub. More detail about installing *jsmetrics* is provided in its documentation (<https://jsmetrics.readthedocs.io/en/latest/>, last access 29th December 2022). To introduce the features of the package, we look at
two case studies using data from ERA-5 climate reanalysis (Hersbach et al., 2020), which we have accessed via the Climate
Data Store API. We have provided a link to the scripts we used for extracting data from the Climate Data Store API in *data*
235 *availability* at the end of this document.

4.1 Case study 1: Comparison of winter jet latitude and jet speed estimations

In this first case study, we use *u*-component wind data (in m/s) from the ERA-5 climate reanalysis to compare the monthly
averaged latitudinal position and speed of the jet stream over the North Atlantic, North Pacific and Southern Hemisphere as
determined by 7 metrics available in *jsmetrics* (Figure 2 & 3). The data is in NetCDF version 4.0 and details 2.5° by 2.5° global
240 *u*-component wind speed for each winter month (DJF or JJA) between January 1959 and December 2021 (189 months) at the
pressure levels: 700, 775, 850 and 925 hPa. In these figures, each violin plot is produced from 189 data points representing
the monthly averages of 3 winter months during this 63-year period. The latitude-longitude bounds of each region are not
consistently defined in the literature, and so we vary these according to each metric's respective study. We exclude two metrics
capable of calculating jet latitude and speed from this section: Archer and Caldeira (2008), as this method uses *v*-component
245 wind speed, and Kerr et al. (2020), as the methodology does not specifically look at any of these three regions. As the Ceppi
et al. (2018) metric is based on the centroid of the zonal velocity (Table 1), it does not produce an associated wind speed.

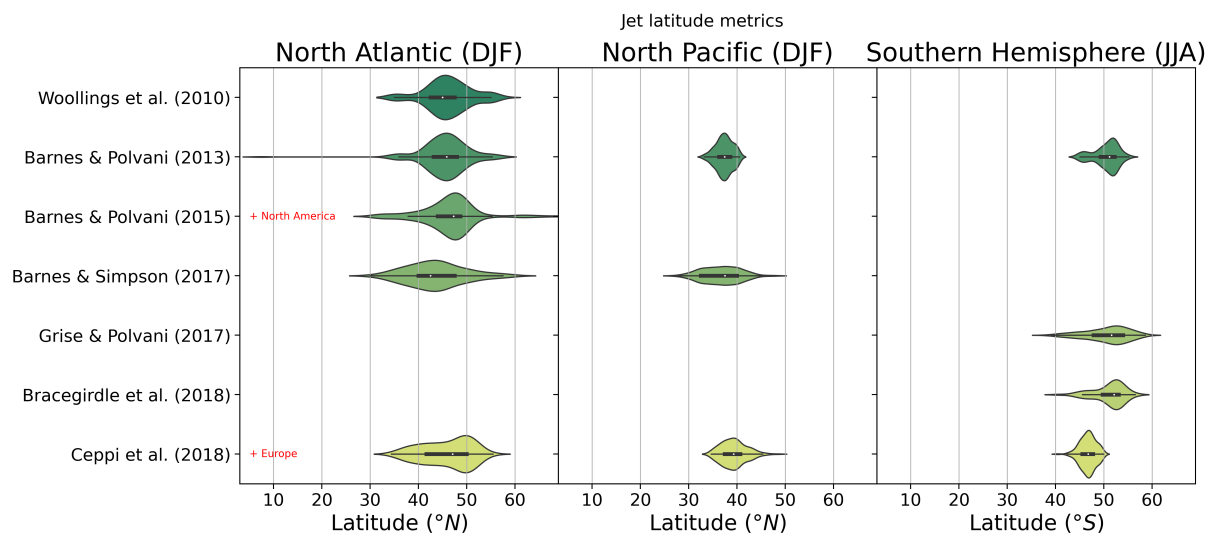


Figure 2. A comparison of the monthly averaged position of the jet stream during the winter months between January 1959 and December 2021 in three study regions as specified by 7 jet latitude metrics available in the *jsmetrics* package. The region of the North Atlantic is combined with North America in Barnes and Polvani (2015), and with Europe in Ceppi et al. (2018) (Data: ERA-5 climate reanalysis product; Hersbach et al., 2020).

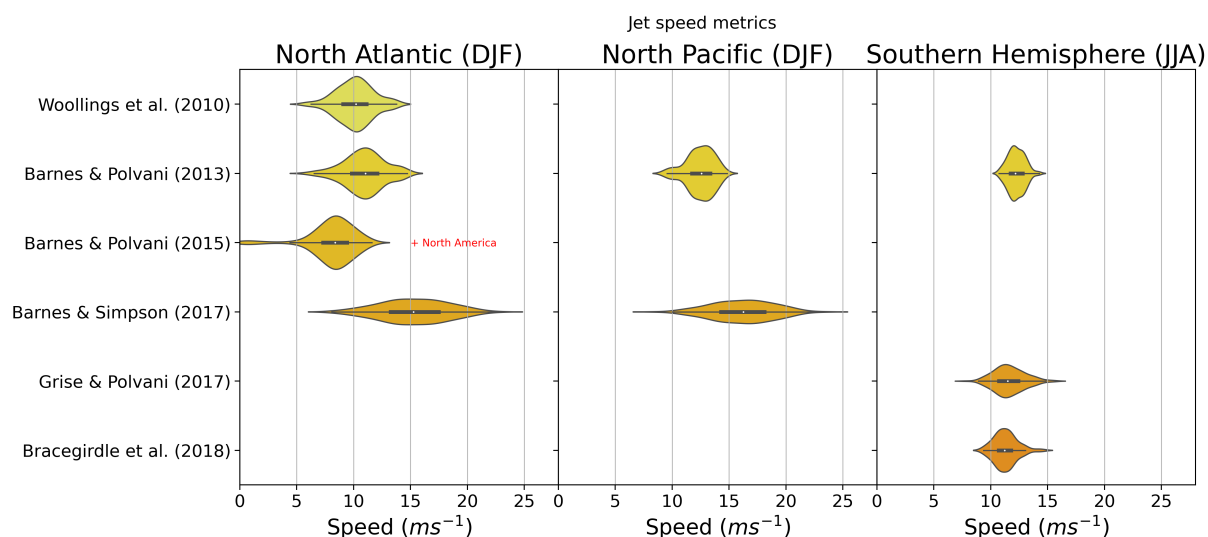


Figure 3. As for Figure 2, but for 6 jet speed metrics available in the *jsmetrics* package (Data: ERA-5 climate reanalysis product; Hersbach et al., 2020).

As shown in these figures, the distribution of monthly averaged latitude and speed of the jet stream in the winter is shown to be relatively wider in the North Atlantic region than in the North Pacific and Southern Hemisphere across all the metrics.



There is some degree of agreement between the position of the jet stream across 1959-2021 i.e. each metric estimates a similar
250 value of the mean jet latitude (Figure 2).

Nonetheless, there are differences between the variance of winter latitude and the mean and variance of speed of the jet
stream across the metrics (except in the Southern Hemisphere, where the mean speed estimate is relatively constrained i.e.
11.3, 11.6 and 12.3 $m s^{-1}$ for Bracegirdle et al. (2018), Grise and Polvani (2017), and Barnes and Polvani (2013) respectively).
The metrics from Barnes and Simpson (2017) are shown to be generally less aligned with the other metrics calculated for this
255 purpose. However, it is worth noting that these metric makes use of a single parabola which is fit to the profile of the wind
speed, so it is generally less effective at capturing the jet stream if there is more than one peak in the wind speed profile.

This difference expressed between the other metrics may be a result of the specification by which each metric is defined.
While Woollings et al. (2010), Barnes and Polvani (2013) and Barnes and Polvani (2015) adopt a similar methodology and look
at data from pressure levels between 700-925 hPa. Barnes and Simpson (2017), Grise and Polvani (2017), Ceppi et al. (2018)
260 and Bracegirdle et al. (2018) use one pressure level (either 700 hPa or 850 hPa). The motivation for using relatively low-level
pressure levels (between 700-925 hPa) is to remove the signal of thermally-driven parts of the jet stream and isolate the eddy-
driven parts (which act as an important control on various aspects of the mid-latitude climate; Hallam et al., 2022). Eddy-driven
jet streams tend to be deeper and thus are more likely to extend down towards the surface than thermally-driven jets, which
tend to be shallower and generally higher up in the troposphere (Held, 1975; Held and Hou, 1980; Madonna et al., 2017). As
265 such, the monthly averaged speeds of the jet stream are shown to be relatively lower than expected for an instantaneous jet
stream (whose cores can frequently reach upwards of 90-120 $m s^{-1}$ at an instantaneous scale; Riehl and Hinkelman, 1962).

We hope to express that when viewing jet latitude and speed estimations in this manner, researchers may be able to eval-
uate structural uncertainties arising from metric definitions within the estimation of jet streams. These figures highlight the
divergence in structural uncertainty when quantifying the jet stream in different regions of the globe using various existing
270 metrics.

4.2 Case study 2: Identifying the jet stream across North America during the February 2021 North American Cold Wave

For the second case study, we examine the representation of the jet stream across North America during the 2021 *North
American Cold Wave* event, which occurred between 6th to 21st February 2021. This event was associated with an anomalous
275 cold air outbreak over North America associated with a sudden stratospheric warming event occurring in late January 2021
(Cohen et al., 2020, 2021; Rao et al., 2021) and has been linked with a (strong) negative phase of the Pacific–North American
pattern (Hsu et al., 2022). For this section, we have used 6-hourly averaged u - and v -component wind-speed data from the
ERA-5 climate reanalysis (Hersbach et al., 2020) at a 1° by 1° grid for the pressure levels: 100, 250, 300, 400, 500 hPa accessed
via the Climate Data Store API. We isolate just one 6-hour period from the cold wave: 00:00 15th February 2021 and compare
280 wind speed at 250 hPa to 5 jet core algorithms from the *jsmetrics* package in Figure 4.

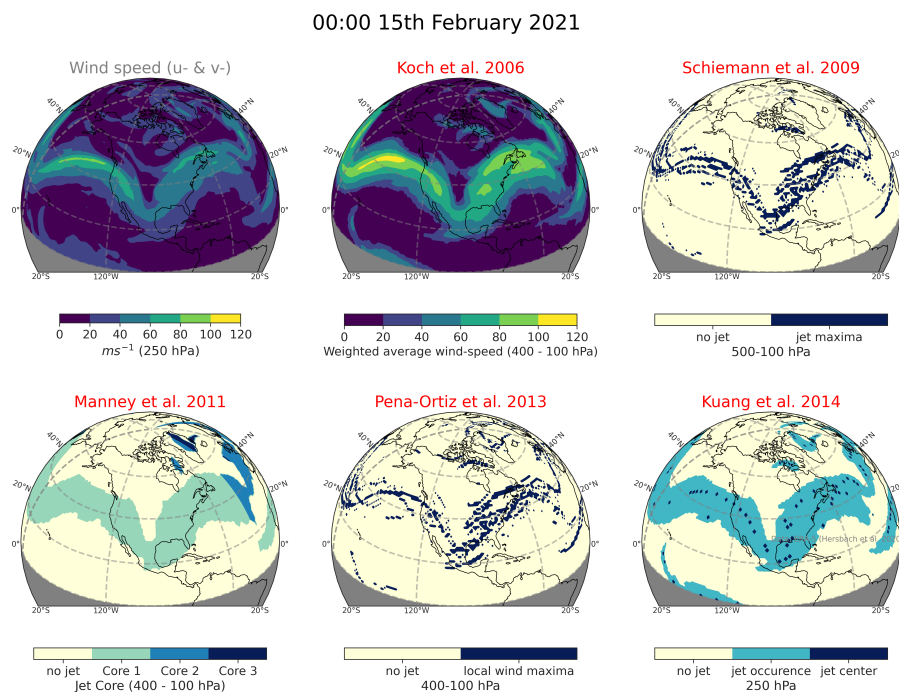


Figure 4. Comparison of the estimation of the jet stream position during the *North American Cold Wave* event at 00:00 on the 15th February 2021 as estimated by 5 jet-core algorithms available in the *jsmetrics* package. The top left panel shows the 250 hPa resultant wind speed as calculated from *u*- and *v*- component winds (Data: ERA-5 climate reanalysis product; Hersbach et al., 2020).

When viewing the upper-level jet stream over North America at this given instance of the *North American Cold Wave* event and between 5 unique *jet-core algorithm* metrics, it is clear that each metric is identifying the same broad pattern — a well-defined singular band across North America and a trough which extends down towards Texas. Notably, the metrics from Schiemann et al. (2009); Manney et al. (2011); Pena-Ortiz et al. (2013); Kuang et al. (2014) all use a 30 ms^{-1} threshold, but not in the same way, and both Schiemann et al. (2009) and Pena-Ortiz et al. (2013) set stricter conditions for jet-cores to be identified and hence isolate a thinner band. Schiemann et al. (2009) use the wind-speed threshold of 30 ms^{-1} but isolate *jet-cores* to be only those where the *u*-component wind is also shown to be above 0 ms^{-1} . The algorithm from Manney et al. (2011) includes a routine to split individual *jet-cores* into unique entities. Here they identify 3 unique cores over this reference frame — notably the jet over much of North America is shown to belong to the same core, i.e. *Core 1*. This method is not as successful at isolating the continuity of jet cores across the globe because the algorithm produces jet cores per longitude and as such, it works from lower to higher latitudes to produce different cores. A post-hoc algorithm may be needed to improve the combination of the cores. The algorithm by Kuang et al. (2014) checks for jet occurrence centers (here jet centers), which are defined in grid cells whereby wind speeds above 30 ms^{-1} are local maxima (so they have a higher wind speed than all



the surrounding 8 grid cells). As such, this algorithm distinguishes between two different categories of jet stream occurrences:
295 making the assumption that the centres of jet streams are important features in their own right, as opposed to regions where a
given wind threshold is exceeded (Kuang et al., 2014).

With this case study, we demonstrate the slight differences in the estimations of the jet stream from various jet core algorithms, and suggest that the difference at the 6-hourly scale will likely be amplified when aggregating into coarser time resolutions.

300 4.3 Other potential uses

The *jsmetrics* package is designed to be flexible with both the inputs and the calculation, of a given metric. While a user can change the exact specifications by which some metrics are calculated (e.g. changing wind-speed thresholds and filter window sizes), users can also pass different subsets/specifications of data into the metrics (e.g. different spatial-temporal regions and resolutions). As such, this opens up the possibility to do sensitivity analysis to explore or evaluate:

- 305 1. *structural uncertainty* — by comparing the estimations of the jet stream using multiple metrics on a single dataset.
2. *parametric uncertainty* — by comparing the estimation of the jet stream from a given metric using slightly different specifications, i.e. filter window-sizes, thresholds, etc.
3. *input uncertainty* — by comparing the estimation of the jet streams in different domains (pressure levels, spatial-temporal resolution) and with different datasets.

310 In Figures 5 and 6, we demonstrate a simple evaluation of *structural uncertainty* using the same dataset and metrics as case study 1 (Section 4.1: winter jet latitude and speed), but with a single set of specifications: vertical levels of 700-925 hPa, for the four fixed regions of North Atlantic (15°N —75 °N & 60°W—0°W), North Pacific (0°N —90 °N & 120°E—120°W), Northern Hemisphere (0°-90°N), Southern Hemisphere (0°-90°S). We exclude Bracegirdle et al. (2018) from this analysis, as it is developed for a single pressure level.

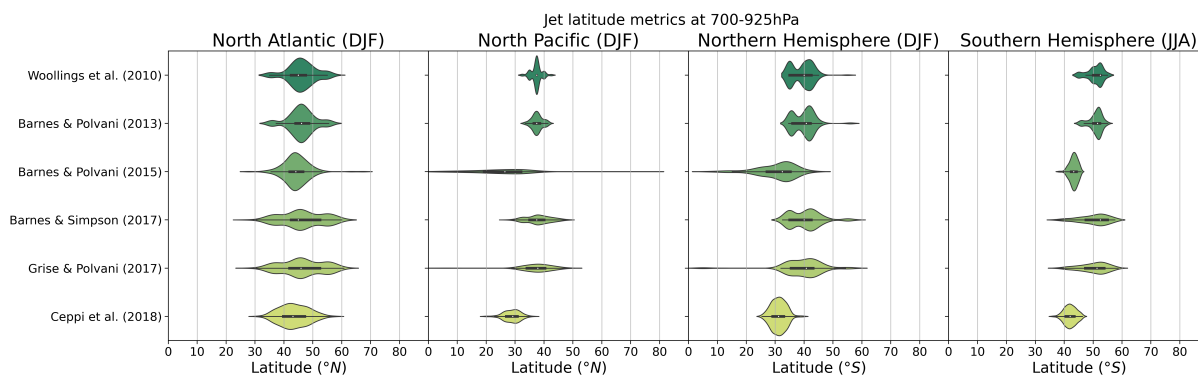


Figure 5. A comparison of the 700-925 hPa winter monthly mean position of the jet stream between January 1959 and December 2021 in four regions as estimated by 6 jet latitude metrics available in the *jsmetrics* package (Data: ERA-5 climate reanalysis product; Hersbach et al., 2020).

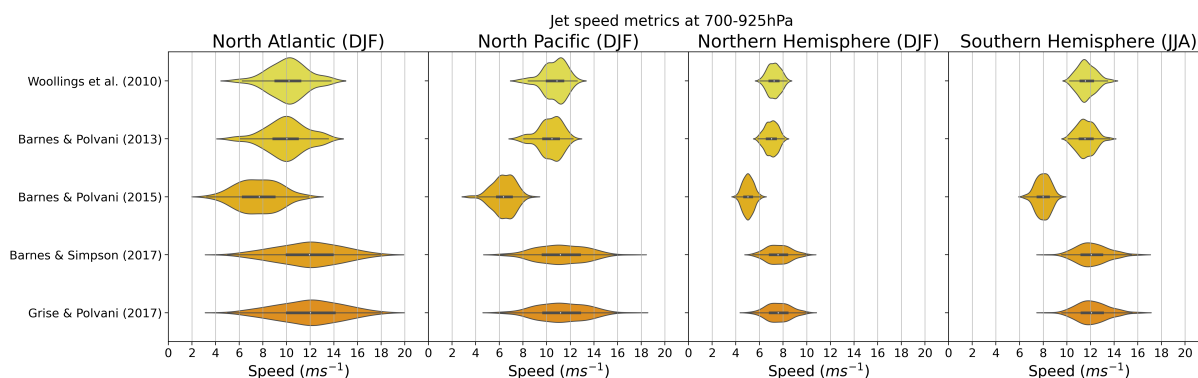


Figure 6. As for Figure 5, but for 5 jet speed metrics available in the *jsmetrics* package (Data: ERA-5 climate reanalysis product; Hersbach et al., 2020).

315 The comparison shows clear divergences in the distribution of monthly mean jet latitude position and jet speed estimated by the various metrics from the same dataset. This demonstrates that using any one metric in isolation is associated with a significant level of structural uncertainty — so estimates of how much a jet has shifted will strongly depend on the metric. In particular, Figure 5 shows that some metrics give more consistent and well-defined estimates across multiple regions than others (and this finding also holds at different pressure levels). The *jsmetrics* package could be used to evaluate the sensitivity of each metric to varying definitions of regions.

320

Jet streams are chaotic actors in the atmosphere, and as such, there is no universal strategy to capture their features at any timescale in data (Maher et al., 2020; Bösiger et al., 2022). Therefore, in the next example, we explore the effect of *input uncertainty* by using a jet core algorithm on data with different temporal aggregations. We use the metric in case study 2 by Kuang et al. (2014) (Section 4.2), which classifies jet occurrence centres in the upper-air wind (200-250 hPa). These centres



325 are defined as grid cells where wind speed is above 30 ms^{-1} and a local maxima compared with the surrounding eight grid cells. We examine the effect of six different temporal aggregations on characterisation of the *North American Cold Wave* event in February 2021, using the same data detailed in Section 4.2.

Figure 7 shows a clear trough in upper-level jet occurrence and jet occurrence centres extending south towards Texas in mid-February, but the extent to which this feature is visible depends on the timescale used. This feature is robust up to about 330 4 days, but a trough structure becomes less clear in the jet occurrences and jet centers beyond that. We expect large-scale and persistent features of the jet stream (in this case a stationary/standing wave over North America) to be more defined/stable at finer time scales before the weather system dissipates and the features of the jet break off or evolve. Note that, this metric finds jet features over Greenland at the finer time scales, but these features are lost with aggregation.

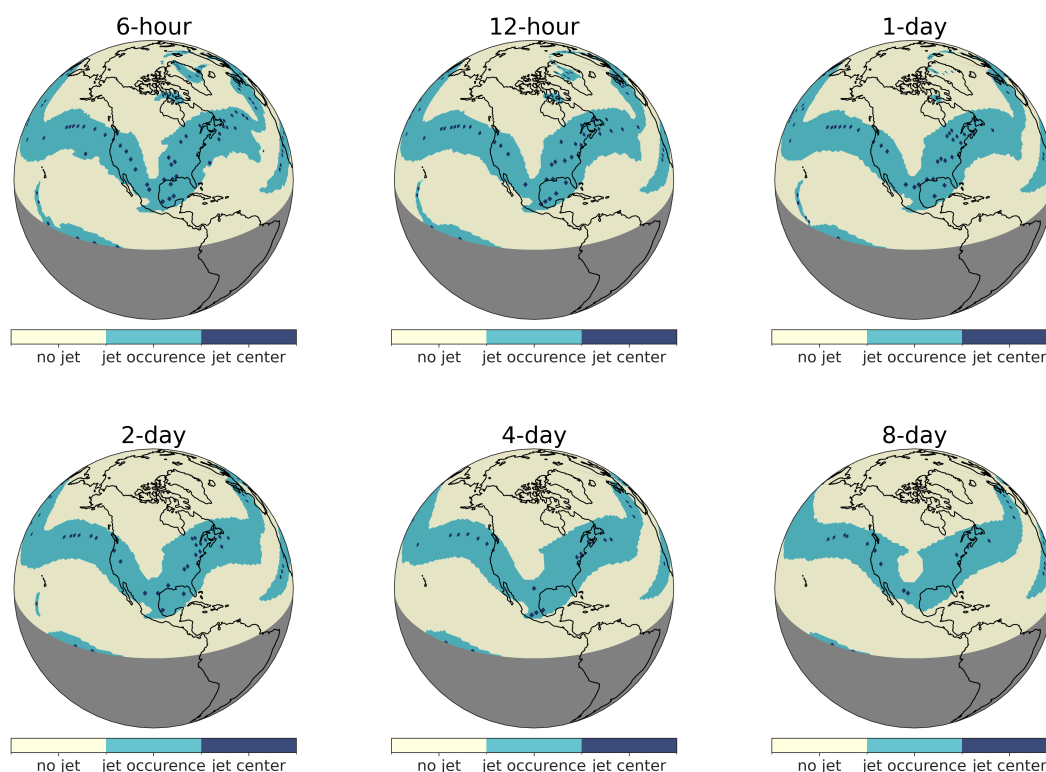


Figure 7. Jet occurrence and jet occurrence centre points as determined by the algorithm from Kuang et al. (2014) at 250 hPa at 6-hour, 12-hour, 1-day, 2-day, 4-day and 8-day time scales during the *North American Cold Wave* event centring on 12:00 15th February 2021 (Data: ERA-5 climate reanalysis product; Hersbach et al., 2020).

Next, we compare the 8-day mean with the count of 6-hourly means of the jet occurrence centres around the *North American* 335 *Cold Wave* event from the 11th of February 2021 to the 19th of February 2021. We use a 2-sigma Gaussian filter around the 32 6-hourly jet centres to smooth the counts in each 1° by 1° grid cell. The comparison (Figure 8) demonstrates the losses and



gains of each temporal aggregation: important features are diluted using the *mean*, while *counts* show more detail but can also include unimportant features.

340 These examples highlight the care needed in study design. Using only one temporal scale, without considering the effect of temporal aggregation on jet features (given the current lack of knowledge about which scales are appropriate for a given purpose), is likely to underestimate uncertainty in estimation of the jet streams.

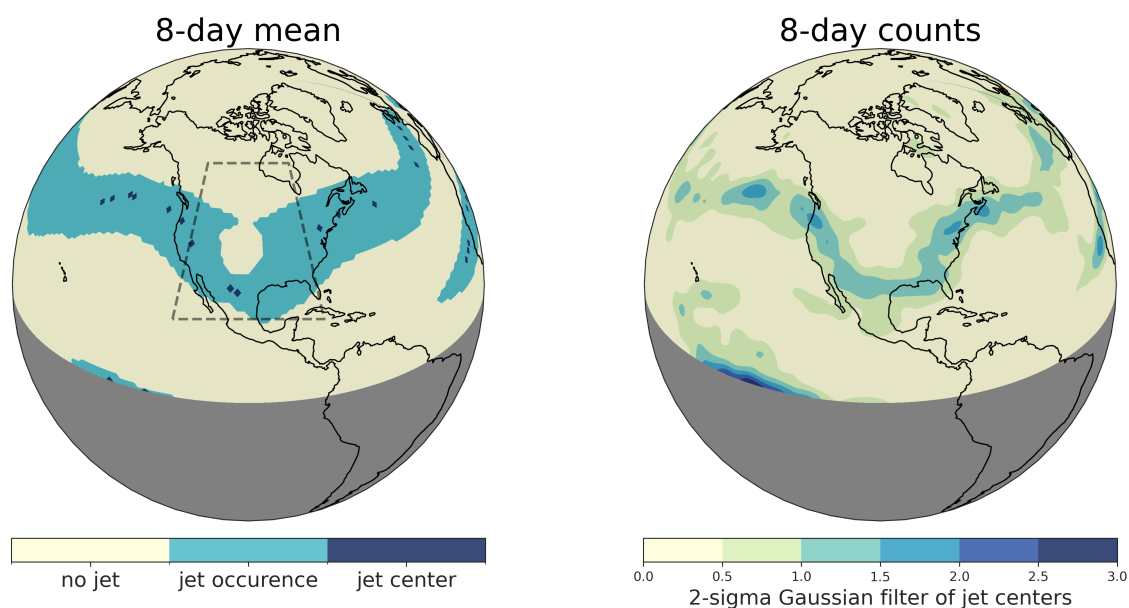


Figure 8. A comparison of 8-day daily counts versus mean of jet occurrence centres as determined by the algorithm from Kuang et al. (2014) during the *North American Cold Wave* event centring on 12:00 15th February 2021 (Data: ERA-5 climate reanalysis product; Hersbach et al., 2020).

In our last example, we extract a single value – the latitude of the jet stream over a study area – to compare the estimations of 6 jet core algorithms to the estimation of the latitude of the jet stream to 5 metrics available in *jsmetrics* which are purpose-built for extracting a jet latitude. We use 8 days of the 2021 *North American Cold Wave* and the region outlined in Figure 8 (120-345 80°W, 20-60°N) to do this (Figure 9). To create an estimate for jet latitude from the jet core algorithms, we first compute the estimation of the jet stream position using a given algorithm and use these locations as a mask to extract wind speed values for each day. Using these values, we then extract the zonally-averaged maximum wind speed and define the associated latitude as the jet latitude value. For this purpose, (resultant) wind speed has been calculated using *u*- & *v*-component wind. The metrics from Barnes and Polvani (2015), Bracegirdle et al. (2018) and Archer and Caldeira (2008) all produce a single value of jet 350 latitude due to the temporal resolution used. This figure shows the jet latitude to be generally more polewards as determined by the jet core algorithms compared with the jet latitude metrics. Notably, only a few of the metrics produce a bimodal distribution of the jet latitude, which is observed in the maximum zonal wind speed profile during this period, but this includes none of the jet core algorithms which use a wind speed threshold.

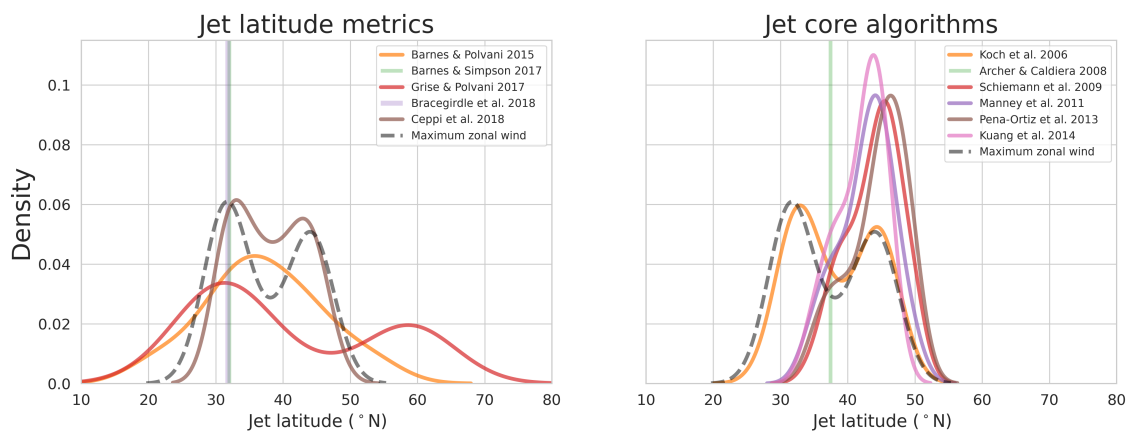


Figure 9. A comparison of 6-hourly latitude of maximum wind speed estimations from jet latitude metrics and jet core algorithms available in *jsmetrics* during the *North American Cold Wave* event between 80–120°W and 20–60°N between 12:00 11th & 19th February 2021. *Maximum zonal wind* is the zonally-averaged maximum wind speed, calculated using *u*- and *v*-component wind (Data: ERA-5 climate reanalysis product; Hersbach et al., 2020).

5 Future Work

355 The *jsmetrics* package is a work in progress, but aims to be a flexible and useful research tool for comparing and refining existing jet metrics, as well as a platform for developing new metrics in the future. Apart from adding new metrics to the module, detailed in section 5.1, there are a few directions for the current use of the *jsmetrics* package. As a package, *jsmetrics* provides no scripts for running analysis of various jet stream metrics in combination, as we have demonstrated in section 4. Therefore, one direction for the use of *jsmetrics* is scripts or a module built on top of *jsmetrics* that is made to run a comparison of multiple
 360 metrics. For the analysis in section 4, we used scripts that make use of specification files (like *details_for_all_metrics.py*) which detail the data sub-setting, expected input variables and the function to run. We then wrote a script containing an ‘AnalysisRunner’ class to actually handle the experiment and loop over and calculate the metrics in a manner specified by the specification files on a given dataset. As outlined in section 3, this is made possible as the package does not attempt to subset the input data: instead it is expected that the user handles the quality and specification of data passed into *jsmetrics*. Running metrics in combination opens up the possibility of evaluating the input, structural and parametric uncertainty associated with the estimations
 365 of the jet stream latitude, speed, waviness, or location (depending on the experiment, and which metrics are currently in the package).

Another direction is to write a script to run the analysis on multiple datasets, built on top of modules using specification files. This could be used not only to evaluate jet stream estimates in different observational datasets, but also in multiple
 370 climate model projections (e.g. the CMIP6 multi-model ensemble; Eyring et al., 2016), to search for coherent patterns and emergent observational constraints of future jet-stream behaviour.



Other metrics libraries and packages are written in Python and developed for use with NetCDF4 and xarray datasets. There is the potential to include various metric implementations within Python's xclim — a Python library of derived climate variables and climate indicators, based on xarray (Logan et al., 2022). Further, a comparison of various jet stream metrics as calculated with the *jsmetrics* package has the potential to be integrated as a recipe for the ESMVal Tool for evaluating CMIP6 model data (Andela et al., 2022).

5.1 Adding metrics

The *jsmetrics* package has a guide to contributing available on ReadTheDocs (<https://jsmetrics.readthedocs.io/en/latest/contributing.html>, last access: 4th January 2023). This project is a strictly open-source project and has a strong copy-left licence (GNU General Public Licence v3.0). The *jsmetrics* package is designed to be easy to contribute to and there is an emphasis on future metrics being built upon a collection of generalised sub-functions which can be shared with similar metrics i.e. for calculating zonal mean wind speed or applying a low-pass filter. Because of the inherent similarity of some existing metrics currently implemented in *jsmetrics*, we recommend first looking for similar metrics that have been implemented and viewing how they are defined within this package. The aim of adding any new metric should be to try to minimise the amount of repeating code and to standardise the components of the metrics as much as possible so that they can run with slightly altered inputs i.e. with different wind speed thresholds, different filter window sizes etc. We recommend experimenting with various designs of any prospective addition to *jsmetrics* in a Jupyter-notebook and to prioritise fast and simple implementations of that given metric.

We have leant into the capabilities of GitHub to log the progress of any given metrics. We open a new GitHub Issue to log and describe a new potential metric and GitHub Projects to track the progress of a given metric in a manner explained in Section 3.2 and in Figure 1. In Table 5 we outline some further metrics which are in the process of being implemented or could be implemented in the future. It is possible that as the package expands, there is an opportunity to refine the categories developed to contain and define different types of metrics and also those that look at different types of jet streams i.e. low-level, eddy-driven, thermally-driven jets etc. Finally, we note that some metrics may be too complex for the remit of this package (e.g. Kern et al., 2018; Kern and Westermann, 2019; Bösigler et al., 2022), those variables which look at different aspects of the upper-level flow synonymous with (characteristics of) jet streams such as wind shear (e.g. Lee et al., 2019) and magnitude of atmospheric waves (e.g. Chemke and Ming, 2020) and also any potential metrics which require a training element to run and those that are currently very computationally expensive (e.g. Limbach et al., 2012; Molnos et al., 2017).

6 Conclusions

In this work, we have introduced the features of *jsmetrics* — a Python package containing an implementation of 15 metrics or algorithms used to identify atmospheric jet streams, and we have demonstrated its use on climate reanalysis data. The motivation for developing this software comes from a desire to standardise, and make openly available, various methods used to identify and characterise jet streams such that they can be used in combination, compared and contrasted. It is hoped that this software can open up new avenues for researchers for evaluating both the location and characterisation of the jet streams and



Table 5. Techniques for identification or characterisation of jet streams in the literature not yet implemented in the *jsmetrics* package (*u*-, *v*- and *w*- refer to the zonal, meridional and vertical wind components; *z_g* refers to the gravity-adjusted geopotential height)

Study	Variable(s)	Pressure-level (hPa)	Temporal	Method
Jet statistics				
Strong and Davis (2007) ¹	<i>u</i> -, <i>v</i> -	100-500	6-hourly	Surface of max wind speed
Barton and Ellis (2009)	<i>u</i> -	300	Daily	Latitude of maximum wind speed
Messori and Caballero (2015)	<i>u</i> -, <i>v</i> -	200–400 & 700–925	any	Jet Angle Index & Jet Latitude Index
Simpson et al. (2018)	<i>u</i> -	700	Monthly	20-year running mean zonal wind
Mangini et al. (2021) ²	<i>u</i> -	700-900	Daily	Jet clusters using K-means
Hallam et al. (2022)	<i>u</i> -, <i>v</i> -	250	Daily	Maximum wind speed
Jet waviness metrics				
Screen and Simmonds (2014) ³	<i>z_g</i>	500	Daily	Wave amplitude metrics
Martineau et al. (2017) ⁴	<i>z_g</i>	500	Daily	Local finite wave activity
Jet core algorithms				
Gallego et al. (2005)	<i>z_g</i>	200	Daily	Geo-strophic stream-line algorithm
Limbach et al. (2012)	<i>u</i> -, <i>v</i> -, <i>w</i> -	100-1000	any	jet stream tracking algorithm
Chenoli et al. (2017)	<i>u</i> -, <i>v</i> -	100-300	Daily	Extends Pena-Ortiz et al. (2013)
Molnos et al. (2017)	<i>u</i> -, <i>v</i> -	150-500	6-hourly	Dijkstra shortest path
Spensberger et al. (2017) ⁵	<i>PV</i>	280-380 K PVU	6-hourly	Jet axis algorithm
Rikus (2018)	<i>u</i> -	0-1000	any	Discrete object algorithm

¹ adapted from Strong and Davis (2005, 2007); ² adapted from Madonna et al. (2017); ³ adapted from Screen and Simmonds (2013); ⁴ adapted from Chen et al. (2015); Huang and Nakamura (2016); ⁵ adapted from Berry et al. (2007);

also open up a more comprehensive quantification of various uncertainties associated with using different methods, datasets
405 and specifications (structural, parametric, input uncertainty, respectively)

We have tried to keep the package as simple to use and install as possible for those who wish to use the package as a research
tool, but there is also a lot of scope for the package to be built upon and extended. As we outline in Section 5.1, the process of
adding new metrics to the package is relatively formulaic and extensively logged on GitHub. The package provides a collection
of generalised functions which form components of the metrics, so it is easy enough to edit aspects of existing metrics included
410 in the module and also to develop new metrics from these generalised functions. Furthermore, the metrics included in the
package make no explicit attempt to change or subset the input data to the original specifications of the paper they stem from,
so they are adaptable to different regions, times, scales, and to future data products.

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Code and data availability. The up-to-date version of *jsmetrics* is available at: <https://github.com/Thomasjkeel/jsmetrics>. *jsmetrics* is also accessible on PyPi via the Python **pip** package manager. It is archived at: <https://zenodo.org/record/7377570>. All data used is available from
415 ERA-5 climate re-analysis available from the Climate Data Store.

Author contributions. TK undertook this research under the supervision of CB & TE. All author contributed to writing the manuscript.

Competing interests. The authors declare that they have no conflict of interest.



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