jsmetrics v0.~~1.1~~.2.0: a Python package for metrics and algorithms used to identify or characterise atmospheric jet-streams.

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Abstract. The underlying dynamics controlling ~~this planet's~~ the 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.~~ We propose that there have been three broad strategies for characterising jet streams in the literature, including statistics that isolate a single value from the wind speed profile (*jet statistics*), methods for quantifying the sinuosity of the upper air (*waviness metrics*), and algorithms that identify the coordinates of fast flowing wind (*jet core algorithms*). 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 *jsmetrics* version ~~0.1.1~~0.2.0, a new open-source Python 3 module with standardised versions of ~~16~~17 metrics that have been used for jet stream characterisation. We demonstrate the application of this library with two case studies derived from ~~ERA-5~~ERA5 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

25 in data (see recent reviews in Maher et al., 2020; Bösiger et al., 2022). As such, many strategies have been adopted to capture aspects of the jet stream. ~~The most popular~~ Among the most commonly used approaches 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 scale. ~~Among the most popular approachescurrently used~~ Of these common approaches, we identify 3 broad types:

30 1. *Jet statistics* — Statistics for isolating ~~various~~ single quantities synonymous with the jet stream from upper-level wind speed within a given time window (e.g. latitude, speed, width; Section 2.1);

   2. *Waviness metrics* — Statistics and ~~indices~~ algorithms for determining the sinuosity or 'waviness' of upper-level mean flow within a given time window (Section 2.2);

   3. *Jet core algorithms* — ~~Two-step process for isolating and then characterising cores (also known as centres) of fast wind~~
35 ~~speeds in the upper-level wind~~ Methods that produce a multidimensional mask of coordinates corresponding to the jet stream within the atmosphere within a given time window (Section 2.3):

   4. *~~Identification~~* ~~— based on wind speed thresholds and/or locality/neighbours.~~

   5. *~~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
40 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 identifi-
45 cation. The tool we introduce, *jsmetrics*, is an open-source Python 3 package built from *xarray* that implements ~~16~~ 17 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

50 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~~ are 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
55 the thermally-driven Hadley Cell; Held and Hou, 1980).

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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, narrow, and less latitudinally variable (Harnik et al., 2014; Lachmy and Harnik, 2014; Madonna et al., 2017; Menzel et al., 2019; Stendel et al., 2021). The position of the thermally-driven processes are connected to the edges of the Hadley Cell, although recent work suggests this only a loose connection (Menzel et al., 2019).

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 (Lee and Kim, 2003; Manney et al., 201). 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; Held and Hou, 1980; Madonna et al., 2017). The *jsmetrics* package, introduced in this paper, focuses exclusively on metrics for tropospheric jet streams.

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 important that we are able to assess uncertainties involved in representing the jet streams in data, and further, to know how they are responding to climate change (Gulev et al., 2021; Lee et al., 2019).

2 Strategies for characterising jet streams

Understanding how jet streams operate between seasons, between phases in climate oscillations, and in response to human activities could enable projections about the regimes of (extreme) surface weather across timescales (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 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 streams' form, position, or trends over time and space. In this version of *jsmetrics* (v0.2.0), we include 17 methods from the literature. These have become the initial set of metrics included based on firstly, their ease to implement into Python, and secondly on their relative popularity in the wider literature. In Section 1, we made a distinction between metrics of three broad categories, discussed in further detail in this section.

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
Archer and Caldeira (2008) (AC08)	u, v	100-400	Monthly
Woollings et al. (2010) (W10)	u	700-925	Daily
Barnes and Polvani (2013) (BP13)	u	700-850	Daily
~~Barnes and Polvani (2015)~~ Grise and Polvani (2014) (GP14)	u	850	Daily
Barnes and Polvani (2015) (BP15) [1]	u	700-925	Daily
Barnes and Simpson (2017) (BS17)	u	700	10-day average
~~Grise and Polvani (2017)~~ Bracegirdle et al. (2018) (B18)	u	850	~~Daily Quadratic interpolation of max wind speed Brace~~
Ceppi et al. (2018) (C18) [2]	u	850	Monthly
~~Kerr et al. (2020)~~ Zappa et al. (2018) (Z18) [2]	u	850	Monthly
Kerr et al. (2020) (K20) [3]	u	500	Daily

[1] adapted from Barnes and Polvani (2013); [2] extended to include jet speed in Screen et al. (2022) [3] adapted from Barnes and Fiore (2013).

2.1 Jet statistics

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 ridges, but instead to capture the general climatological characteristics of ~~the jet (position, speed, operational range, etc.) in the atmospheric column~~ a jet stream, such as its position and speed (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~~ 10 jet latitude metrics from the literature that feature in the *jsmetrics* package.

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 dominate 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~~ However, by isolating lower-level winds, these methods ~~suffer if the~~ may miss aspects of jet streams whose eddy-driven

components do not extend throughout the atmospheric column ~~towards the surface~~ within the method's given time window. They also do not capture any behaviour near the level of maximum wind speed, nor the presence of multiple jet streams (Melamed-Turkish et al., 2018; Manney et al., 2021).

In each case, the jet statistics available in *jsmetrics* all centre around extracting single quantities from upper-level wind to characterise the jet stream in a given temporal and spatial frame. Most commonly, this involves extracting 'latitude' and 'speed' quantities at 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~~ either for an entire study region (all metrics expect K20), or by longitude (K20). Whilst, each jet statistics produces outputs that are directly comparable to each other, a degree of variation is provided by how each method achieves their outputs. Metrics from ~~Grise and Polvani (2017), Barnes and Simpson (2017), Bracegirdle et al. (2018) and Ceppi et al. (2018)~~ GP14, BS17, B18, C18, and Z18 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)~~ W10, BP13, and BS17 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 they 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 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 (Manney and Hegglin, 2018), such as cold-air outbreaks~~(Manney and Hegglin, 2018)~~. Further, these metrics are developed to find a single-jet structure (one stream), so they 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~~ propagation 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~~ nor do they diagnose the eddy or thermal processes driving them (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

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) (FV15)	u, v	500	Daily	Meridional circulation index
Cattiaux et al. (2016) (C16)	zg	500	Daily	Sinuosity metric

140 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~~ that a 'wavier' jet stream ~~leading~~ leads to more extreme (winter) weather in response to the warming world is a highly

145 contested topic ~~(Cohen et al., 2020, 2021)~~(Francis, 2017; Manney and Hegglin, 2018; 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. Robust conclusions about changes in jet waviness so far have been difficult to establish due to variation in the region and years studied, as well as the methodology used (e.g. Barnes, 2013; Barnes and Simpson, 2017; Blackport et al., 2019; Blackport

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2.3 Jet core algorithms

Jet core algorithms are rule-based methods which isolate ~~the jet stream~~ coordinates associated with jet streams in the upper-air wind~~as a~~. Their outputs consist of a multidimensional collection of points ~~in the atmosphere called~~ describing coordinates associated with the main body of the jet streams, known variously as 'jet cores', 'jet occurrences' or 'jet centres' (here we refer

155 to them all as jet cores). ~~They achieve this by using a given~~ Using these coordinates, it is possible to then mask/extract further dynamical information e.g. pressure, altitude, or speed at the locations of the jet cores. Most commonly, the jet core algorithms extract coordinates using wind-speed ~~threshold before using~~ thresholds before applying further rule-based algorithms to classify ~~a location~~ the jet cores further (e.g. into ~~a type of jet occurrence, a~~ types of jet core occurrence, into local maxima, ~~etc). 5~~ into zonally continuous structures, etc.). We review the 6 jet core algorithms ~~feature~~ featured in the *jsmetrics* package ~~(Table 3)~~in

160 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 ~~,~~than the other types of strategies outlined in this research. However, they provide ~~a relatively more comprehensive~~ relatively more detail about the features in the jet streams at a synoptic scale (Molnos et al., 2017; Kern et al., 2018). We note that, the implementations of SO9, M11, PO13, and K14 can provide three-dimensional outputs for each

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

	Study	Variable(s)	Pressure-level (hPa)	Temporal
	Koch et al. (2006) (K06)	u, v	100-400	Daily
	Archer and Caldeira (2008) (AC08)[1]	u, v	100-400	Monthly
	Schiemann et al. (2009) (S09)	u, v	100-500	6-hourly
	~~Pena-Ortiz et al. (2013)~~ Manney et al. (2011) (M11)[2]	u, v	100-400	Daily
	Pena-Ortiz et al. (2013) (PO13)	u, v	700-850	Month-Yearly
	Kuang et al. (2014) (K14)[3]	u, v	200-250	any

~~Manney et al. (2014)[1] u, v 100-400 Daily Wind speed maxima and jet core separation~~ height

[1] also include a method for extracting the jet latitude statistic; [2] method refined in Manney and Hegglin (2018) to include physically-based method to distinguish subtropical and polar jets; [3] adapte

time step including altitude coordinates about the jet cores they extract, and K06 and ACO8 instead return mass-weighted output which provide two-dimensional jet cores for each time step.

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 27-40 ms^-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)~~(local wind-speed maxima; Schiemann et a, 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~~ discount the influence of multiple streams of ~~jets~~jet streams, 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, in climate regimes different from the present (e.g. SSP5-8.5), and within different phases of the given climate oscillations ~~(e.g. Woollings et al., 2010; Madonna et al., 2017; Manney and Heg~~ (e.g. Woollings et al., 2010; Madonna et al., 2017; Manney and Hegglin, 2018; Manney et al., 2021). 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)~~, although this relationship also expresses significant regional variation (Manney and Hegglin, 2018; Maher et al., 2020; Manney et al., 202.

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

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to separate them. ~~Pena-Ortiz et al. (2013)~~ K06 subdivide jet core 'events' by depth. PO13 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 jetcore 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.~~

, but were only able to separate the Northern Hemisphere subtropical jet in Jan-Feb. The M11 method was extended by Manney and Hegglin (2018) which introduces a physical-based identification of the subtropical jet (based on the thermal tropopause altitude), to more robustly separate it from the polar jet. Manney et al. (2014) found that separating the M11 cores by a latitude criterion to be effective only at a climatological scale. Finally, we also note that are some methods that have been developed exclusively for the subtropical jet (see Maher et al. (2020) for a review of such methods), and envisage these could be incorporated in a future release of *jsmetrics*.

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 ~~(?)~~(due to its ability to interface with NetCDF4 and GRIB data formats; Hoyer et al., . 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. Unfortunately, this flexibility requires making all base functions as simple and one-use as possible, which has sometimes led to a decrease in readability. For example, it became necessary to keep some base functions more specific, which may make some of these harder to use, without a familiarity with the package nor more advanced Python knowledge. We hope to have alleviated any loss of readability, with the use of more verbose naming conventions throughout the package and detail in the individual method's docstrings.

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 If there are any adjustments or difference between the literature's implementation and the (Python) implementation provided by *jsmetrics* is described in the , we have made of note of these in the metric's dosctring under 'Notes', available in the online 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.

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

| File	Purpose
higher-level of abstraction	
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.
lower-level of abstraction	
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.
specification file	
details_for_all_metrics.py	Stores all the data sub-setting specifications and descriptions for each algorithm and metric
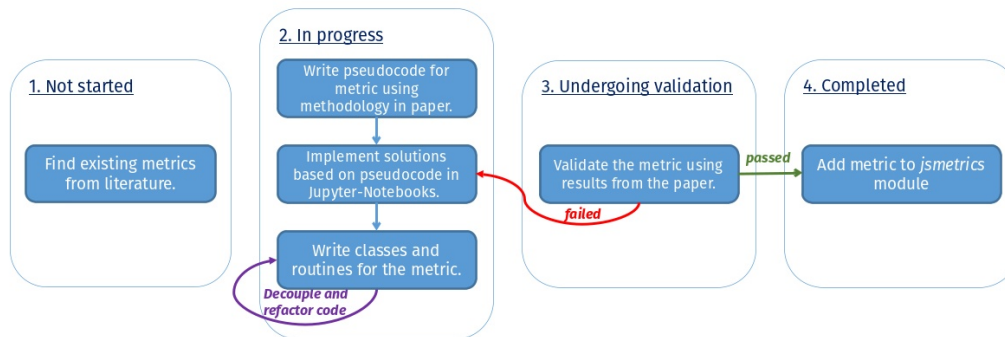
Figure 1. Stages involved with developing the *jsmetrics* package.

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

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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~~ 0.2.0, ten jet statistic metrics, two jet waviness metrics and ~~five~~ six 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 ~~ERA-5~~ ERA5 (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 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 ~~29~~16th ~~December 2022~~October 2023). To introduce the features of the package, we look at two case studies using data from ~~ERA-5~~ ERA5 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 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 lower tropospheric *u*-component wind data (in m/s) from the ~~ERA-5~~ ERA5 climate reanalysis to compare the ~~monthly averaged latitudinal position and speed~~ daily latitudinal position of the jet stream over the North Atlantic, North Pacific, and Southern Hemisphere as determined by ~~7 metrics~~ 8 jet statistics available in *jsmetrics* (Figure 2~~&~~ ~~??~~). The data is in NetCDF version 4.0 and details ~~2.5~~1.0° by ~~2.5~~1.0° global u-component wind speed for each winter ~~month~~ day (DJF or JJA) between 1st January 1979 and 31st January ~~1959 and December 2021 (189 months)~~2022 at the pressure levels: 700, 775, 850 and 925 hPa. In ~~these figures~~this figure, each violin plot is produced from ~~189~~3912 (DJF) or 3956 (JJA) data points representing the ~~monthly averages of 3 winter months during this 63-year~~ daily winter day averages during this

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290 43-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)~~AC08, as this method uses *v*-component wind speed, and ~~Kerr et al. (2020)~~K20, 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.~~
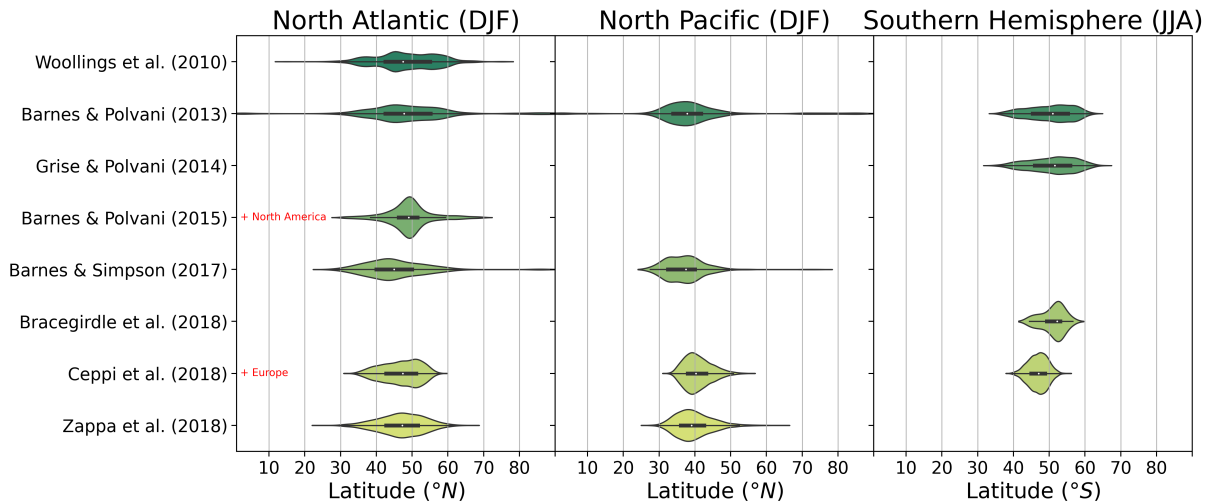

Figure 2. A comparison of the ~~monthly averaged~~ daily mean position of the jet stream during the winter months between 1st January ~~1959~~ 1979 and ~~December 2021~~ 31st January 2022 in three study regions as specified by ~~7~~ 8 jet latitude metrics available in the *jsmetrics* package. The region 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)~~(Data: ERA5 climate reanalysis product; Hersbach et al., 2020).

295 ~~As for Figure 2, but for 6 jet speed metrics available in the *jsmetrics* package (Data: ERA-5 climate reanalysis product; Hersbach et al., 20~~

As shown in ~~these figures~~this figure, the distribution of ~~monthly averaged latitude and speed~~ daily latitude of the jet stream in the winter is shown to be relatively wider in the North Atlantic region (Interquartile Range (IQR) varying between 5.32-12.5°N across the metrics) than in the North Pacific (IQR=5.14-7.79°N) and Southern Hemisphere ~~across all~~ (IQR=3.85-9.94°S)

300 across 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 value of the mean jet latitude (Figure 2) .~~ For the North Atlantic, we show that the degree of uncertainty arising from choice of jet latitude statistic (or the *metric uncertainty*) on the mean position is 3.81°N (between 45.26-49.08°N). In contrast, the uncertainty arising from internal variability, for which we use IQR as a proxy, is 7.18°N (between 5.32-12.5°N) across the metrics, implying the internal variability has a relative larger impact on uncertainty associated with the jet position.

305 The mean position of the jet stream across 1979-2022 is shown to be between 37.24-40.81°N for the North Pacific and between 46.85-51.01°S for the Southern Hemisphere, as estimated by these metrics.

~~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 ms^{-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 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)~~ In Figure 2, some general differences between the metrics may arise due to differences in the region definition, e.g. BP15 & C18, and differences in pressure level from which the metric has been calculated, e.g. BS17 (see Table 1). Further, while W10, BP13 and BP15 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) and Bracegirdle et al. (2018)~~ GP14, BS17, C18, Z18, and B18 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 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 ms^{-1} at an instantaneous scale; Riehl~~

~~.~~

We hope to express that when viewing jet latitude ~~and speed~~ estimations in this manner, researchers may be able to evaluate ~~structural~~ metric uncertainties arising from ~~metric definitions within the estimation of~~ differences in methods used to characterise jet streams. These figures highlight ~~the divergence in structural uncertainty when quantifying the jet stream in~~ some preliminary divergence in metric uncertainty across different regions of the globe~~using~~, arising from various existing 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 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~~ ERA5 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 wind speed at 250 hPa to 5 jet core algorithms from the *jsmetrics* package in Figure 3.

We note that the vertical resolution and grid spacing of the data used in this case study, may not be adequate for the methods to effectively capture jet cores (see a discussion of vertical resolution and grid spacing in Manney et al. (2017)). Instead, the data has been selected based on faster algorithm run time and reproducibility on the figures included in this section. Finally, we have selected jet cores at 250 hPa from M11 and PO13 for comparison with wind speed and K14, but we acknowledge that these two algorithms also return jet core outputs at different altitudes.
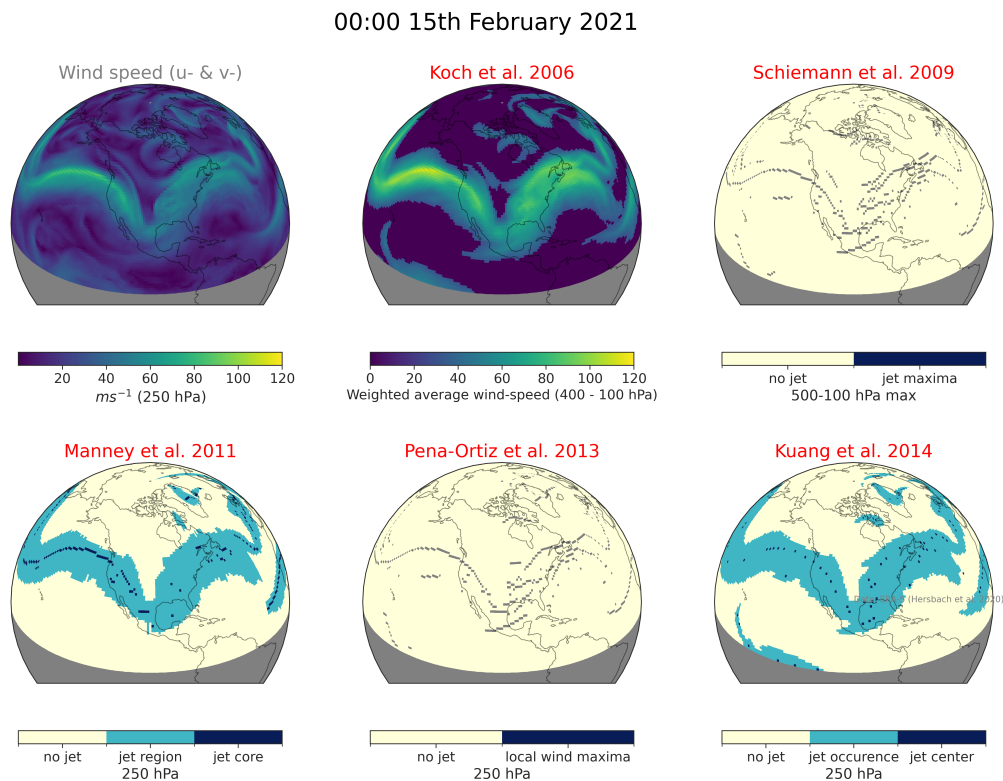

Figure 3. Comparison of the estimation of the jet stream position during the *North American Cold Wave* event at 00:00 on the 15th February 2021 as estimated by 5 ~~jet core~~ jet core algorithms available in the *jsmetrics* package. The top left panel shows the 250 hPa resultant wind speed as calculated from *u*- and *v*- component winds ~~(Data: ERA-5 climate reanalysis product; Hersbach et al., 2020)~~ (Data: ERA5 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~~ 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~~ that 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)~~ S09, M11, P013,

14

350 and K14 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)~~ S09, and PO13 set stricter conditions for ~~jet-cores to be identified and hence isolate a thinner band. Schiemann et al. (2009) use the~~ features they extract, only selecting cells of local 'maxima', and M11 and K14 create boundary regions around each core/maxima. There are only slight visual differences between the jet cores in P13 and S09, because both algorithms make use of a wind-speed threshold of 30 ms^{-1} ~~but isolate~~ to extract local maxima in the altitude/latitude plane, but S09 isolate

355 ~~jet-coresto be only those~~ *jet cores* only 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~~ M11 use an additional algorithm after initial discovery of local maxima to divide jet cores occurring within the same local maxima region based on whether: (1) the two or more cores are more than 15°of latitude apart and (2) whether the wind speed drops more than 15 ms^{-1} between

360 those cores, otherwise these jet cores in the same region will be considered part of 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)~~. As such, the jet core output from M11 at 250 hPa may vary slightly from other similar methods (e.g. S09 & PO13), as the jet cores may be associated with different altitudes. K14

365 also relies on checking for local maxima, but within the longitude/latitude plane. The methodology checks for jet occurrence ~~centers (here jet centers)~~and 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: 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).

370 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.

Next, we look at two waviness metrics during the *Texas Cold Wave* event in Figure 4. As estimated by FV15, a large negative MCI (MCI less than 0 indicates Northerly flow) patch is shown over Western North America during the 10-day period

375 encompassing the *Texas cold wave event*. C16 provides a more limited view of the event, but shows some variation in the temporal profile of the upper air sinuosity (jet waviness) during the *Texas cold wave* event, with relatively higher and more sustained sinuosity in the upper-air flow being associated between 00:00 13th February - 18:00 15th February.
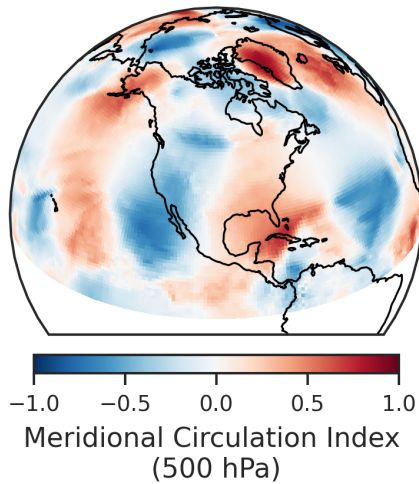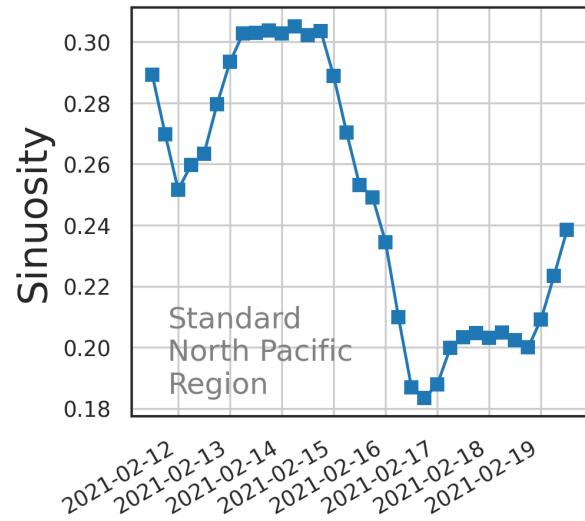
Figure 4. A comparison of jet waviness during the *Texas Cold Wave* event between 12:00 11th-19th February 2021 as estimated by two waviness metrics available in *jsmetrics*. The metric from Francis and Vavrus (2015) is a mean of MCI calculated for each 6 hour time step between 12:00 11th-19th February 2021. When MCI is 0, the wind is purely zonal, and when MCI is 1 (-1), the flow is from the South (North). (Data: ERA5 climate reanalysis product; Hersbach et al., 2020).

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
380 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:

1. ~~structural~~ metric uncertainty — by comparing the estimations of the jet stream using multiple ~~metrics~~ statistics or algorithms on a single dataset.

385
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.

In Figures 5 and 6, we demonstrate a simple evaluation of ~~structural~~ metric uncertainty using the same dataset and metrics
390 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~~15-75°N ~~—75~~ & 60-0°~~N & 60~~W~~—0W~~), North Pacific (~~0~~0-90°N

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~~—90 N~~ & 120°~~E—120~~E-120°W), Northern Hemisphere (~~00-90°-90~~N), Southern Hemisphere (~~00-90°-90~~S). We ~~exclude Bracegirdle et al. (2018) from this analysis, as it is developed for a single pressure level.~~ <ins>include the extension to C18 and Z18 proposed by Screen et al. (2022), to produce an associated jet speed for those methods. To demonstrate the sensitivity of</ins> the jet statistics to parameters in their definition, we also show in Figure 6 the distribution of jet speed over the various regions used the respective studies (see Table 1), rather than a single common region.
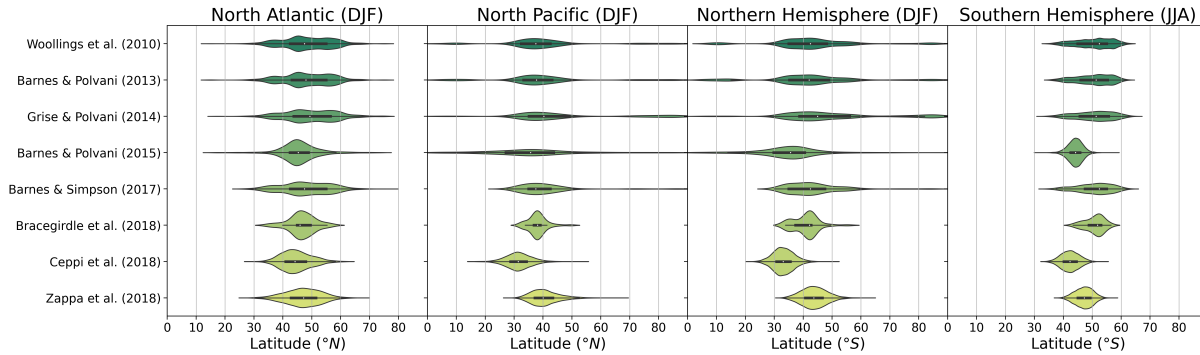

Figure 5. A comparison of the 700-925 hPa winter ~~monthly~~ <ins>daily</ins> mean position of the jet stream between <ins>1st</ins> January ~~1959~~ <ins>1979</ins> and ~~December 2021~~ <ins>31st January 2022</ins> in four <ins>standard</ins> regions as estimated by ~~6~~ <ins>8</ins> jet latitude metrics available in the *jsmetrics* package ~~(Data: ERA-5 climate reanalysis product; Hersbach et al., 2020)~~<ins>(Data: ERA5 climate reanalysis product; Hersbach et al., 2020).</ins>
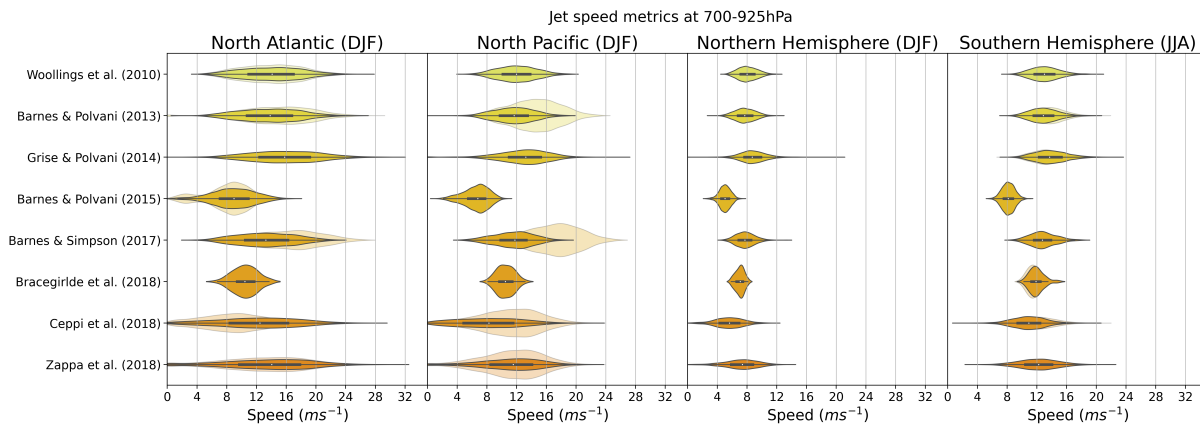

Figure 6. ~~As for Figure 5, but for 5~~ <ins>A comparison of the 700-925 hPa winter daily mean</ins> jet speed <ins>between 1st January 1979 and 31st January 2022 in four standard regions as estimated by 8 jet speed</ins> metrics available in the *jsmetrics* package ~~(Data: ERA-5 climate reanalysis product; Hersbach et al., 2020)~~<ins>(Data: ERA5 climate reanalysis product; Hersbach et al., 2020). Where the original studies used a different regional definition (see Table 1), the distribution of jet speed using that altered region is shown underneath the distribution determined from the common standard region.</ins>

~~The comparison shows~~ As shown in these figure, there are clear divergences in the distribution of ~~monthly mean~~ daily jet latitude position and jet speed estimated by the various metrics ~~from~~ using the same dataset. ~~This demonstrates that~~ In Figure 5, the estimation of mean jet position is shown to vary more in the Northern Hemisphere (33.22-49.75°N) than in the North Atlantic (44.62-49.55°N), North Pacific (31.57-46.81°N), or Southern Hemisphere (42.37-50.59°S). The estimation of jet mean position from C18 over this period is found to perform less similarly to the other jet latitude statistics, showing the most equatorward estimation in each region.

In Figure 6, the fastest and most variable jet speed estimations are shown in the North Atlantic (8.92-15.31 ms^{-1}), versus the North Pacific (6.56-11.51 ms^{-1}), Northern Hemisphere (5.04-7.77 ms^{-1}) or Southern Hemisphere (8.15-13.07 ms^{-1}). We also find that the BP13, BS17, and C18 methods are sensitive to the original definitions of the North Pacific region (Figure 6).

In viewing the jet statistics in this manner, we hope to have demonstrated that using any one metric in isolation is associated with a significant level of ~~structural~~ metric 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~~ As such, the *jsmetrics* package could be used to evaluate the sensitivity of each metric to varying definitions of regions.

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)~~(e.g. Maher et al., 2020; Bösiger et al., 2022, and references therein). Therefore, in the next example, we explore the effect of *input uncertainty* by using a jet core algorithm on data with different ~~temporal aggregations~~time averaging periods. We use the ~~metric in case study 2 by Kuang et al. (2014) (Section 4.2)~~K14 metric, which classifies jet occurrence centres in the upper-air wind (200-250 hPa). These centres 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~~ time averaging periods (which all centre on 12:00 15th February 2021) 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 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~~ broader time scales if the weather system ~~dissipates~~ remains and the features of the jet ~~break off or evolve~~to stay in place over a region. Note that, this metric finds jet features over Greenland at the finer time scales, but these features are lost with ~~aggregation~~temporal averaging.
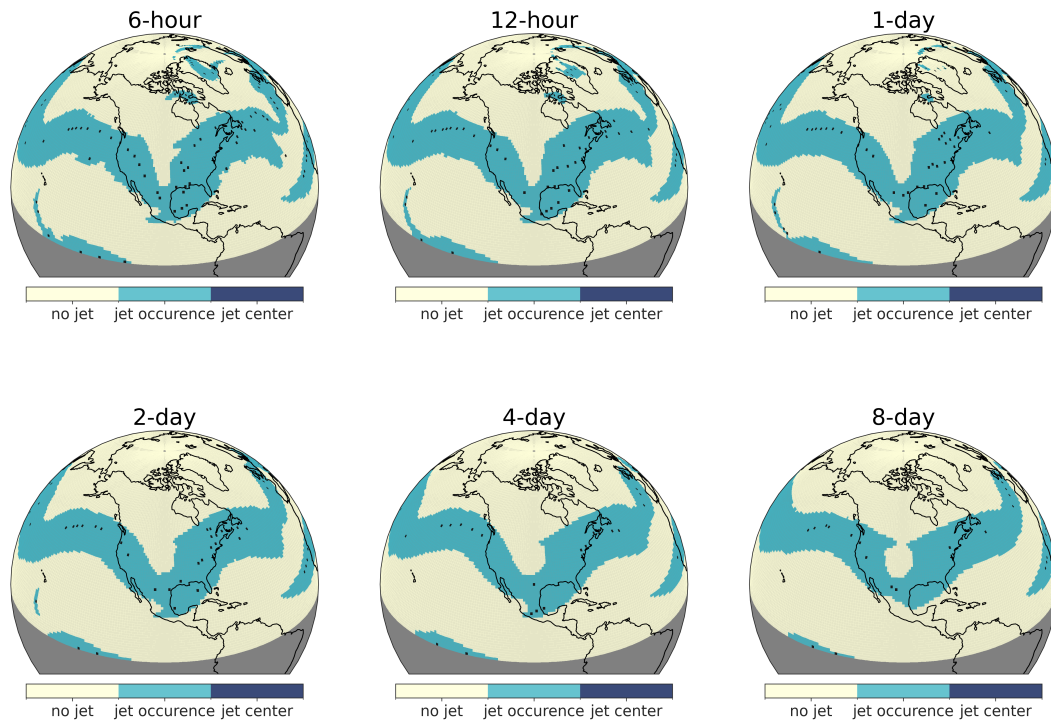
Figure 7. Jet occurrence and jet occurrence centre points as determined by the algorithm from Kuang et al. (2014) at 250 hPa at 6-hour, 12-hour, 1-day, 2-day, 4-day and 8-day ~~time scales~~ averaging periods during the *North American Cold Wave* event centring on 12:00 15th February 2021 ~~(Data: ERA-5 climate reanalysis product; Hersbach et al., 2020)~~(Data: ERA5 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 from K14 around the *North American 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~~time averaging: important features are diluted using the *mean*, while *counts* show more detail but can also include unimportant features.

These examples highlight the care needed in study design. Using only one temporal scale, without considering the effect of temporal ~~aggregation~~averaging 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.
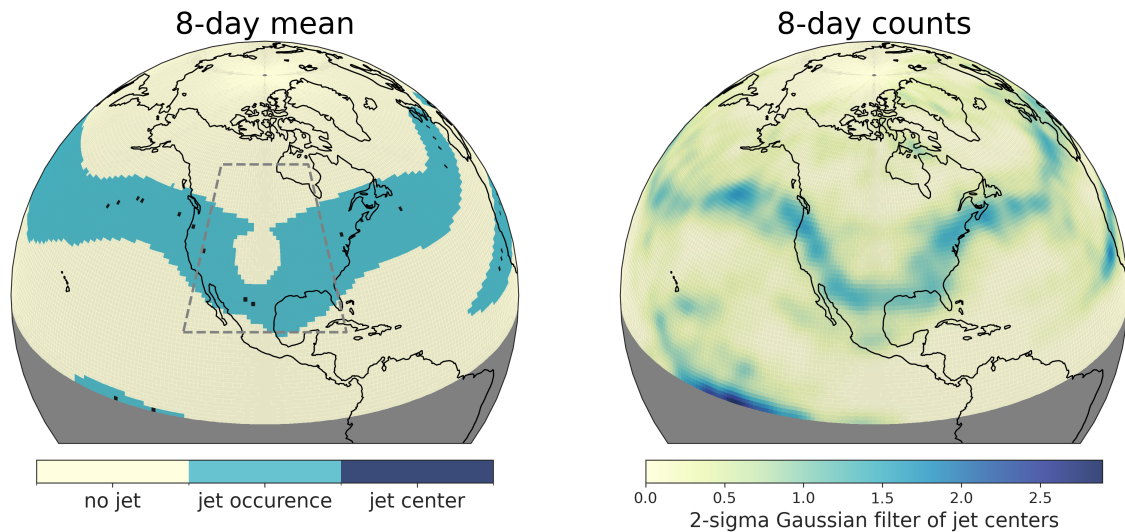
Figure 8. A comparison of 8-day daily counts versus mean of jet occurrence centres as determined by the algorithm from Kuang et al. (2014) during the *North American Cold Wave* event centring on 12:00 15th February 2021 (Data: ERA-5 climate reanalysis product; Hersbach et al., 2020)(Data: ERA5 climate reanalysis product; Hersbach et al., 2020).

435   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 7 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 (120-80°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 jet cores using a given algorithm and use these locations as a mask to extract wind speed

440 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 at the native resolution. 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) We note that the papers that spawned some jet core algorithms e.g. M11 & PO13 provide their own jet latitude extraction method, but these have not yet been implemented in *jsmetrics*. AC08, BS17 & B18 all produce a single value of jet latitude due to the

445 temporal resolution used . for this example. These estimates are 37.42°N, 32°N, & 31.78°N, respectively. This figure shows the jet latitude to be generally more polewards as determined by the jet core algorithms compared with the jet latitude metrics. This is most likely due to the altitude of the methodology (Tables 1 & 3). 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.
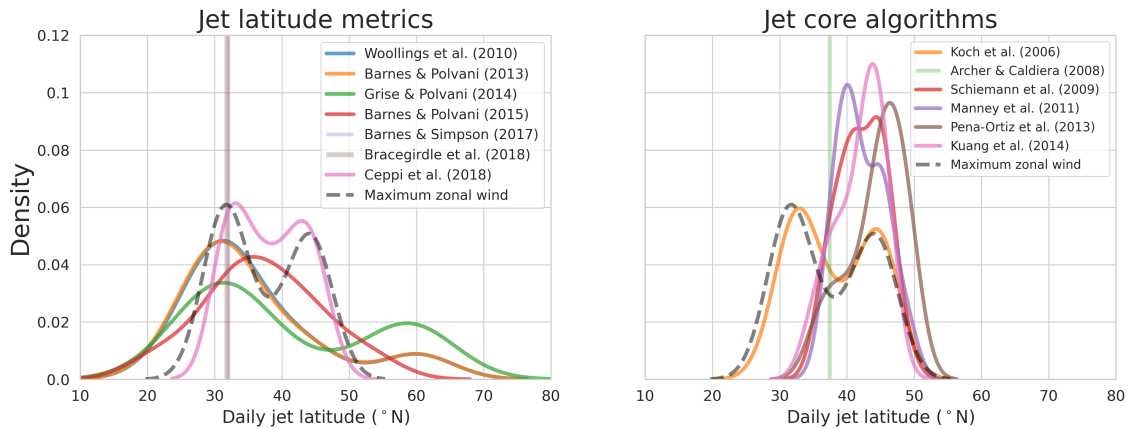
Figure 9. A comparison of 6-hourly latitude of maximum wind speed estimations from jet latitude metrics and jet core algorithms available in *jmsetrics* during the *North American Cold Wave* event between 80–120°W and 20–60°N between 12:00 11th & 19th February 2021. *Maximum zonal wind* is the zonally-averaged maximum wind speed, calculated using *u*- and *v*-component wind ~~(Data: ERA-5 climate reanalysis product; Hersbach et al., 2020)~~(Data: ERA5 climate reanalysis product; Hersbach et al., 2020).

5 Future Work

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 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~~ metric and parametric uncertainty associated with the estimations 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 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.

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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: 4~~accessed: 16th ~~January~~ October 2023). This project is a strictly open-source project and has a strong copyleft 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~~ that can be shared with similar metrics ~~i.e.~~ e.g., 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~~ that 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; Bösiger 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~~ that 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~~17 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

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; zg refers to the gravity-adjusted geopotential height)

Study	Variable(s)	Pressure-level (hPa)	Temporal
Jet statistics			
Strong and Davis (2007) [1]	u-, v-	100-500	6-hourly
Barton and Ellis (2009)	u-	300	Daily
Harnik et al. (2014)	u-	300 hPa	Daily
Messori and Caballero (2015)	u-, v-	200–400 & 700–925	any
Simpson et al. (2018)	u-	700	Monthly
Liu et al. (2021)	u-	250 & 850	Daily
Mangini et al. (2021) [2]	u-	700-900	Daily
Blackport and Fyfe (2022)	u-	700	Daily
Hallam et al. (2022)	u- ~~, v-~~	250	Daily
Jet waviness metrics			
Screen and Simmonds (2014) [3]	zg	500	Daily
Martineau et al. (2017) [4]	zg	500	Daily
Jet core algorithms			
Gallego et al. (2005)	zg	200	Daily
~~Limbach et al. (2012) u-, v-, w- 100-1000 any jet stream tracking algorithm~~ Chenoli et al. (2017)	u-, v-	100-300	Daily
~~Molnos et al. (2017) u-, v- 150-500 6-hourly Dijkstra shortest path~~ Spensberger et al. (2017) [5]	PV	280-380 K PVU	6-hourly
Rikus (2018)	u-	0-1000	any

[1] adapted from Strong and Davis (2005, 2006); [2] adapted from Madonna et al. (2017); [3] adapted from Screen and Simmonds (2013); [4] adapted from Chen et al. (2015); Huang and Nakamura (201

500 software can open up new avenues for researchers for evaluating both the location and characterisation of the jet streams and also open up a more comprehensive quantification of various uncertainties associated with using different methods, datasets, and specifications (~~structural~~metric, 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
505 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 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.

510 *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 ERA-5 climate re-analysis available from the Climate Data Store.

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