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# IPART: A Python Package for Image-Processing based Atmospheric River Tracking

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## Summary

An atmospheric river (AR) in the field of meteorology/climatology refers to enhanced water vapor content in the lower troposphere. The term was coined as an analogy to the terrestrial rivers in a sense that when viewed from satellite imagery or large scale atmospheric observation, they appear as narrow and elongated vapor filaments, representing transient intensified horizontal moisture fluxes (e.g. Gimeno, Nieto, VÃzquez, & Lavers (2014), Dettinger (2011)). A typical atmospheric river can carry 7-15 times the water in the Mississippi River (Ralph, Neiman, Kiladis, Weickmann, & Reynolds, 2011), and at any time in winter, there are four to five such systems in the Northern Hemisphere alone (Zhu & Newell, 1998), accounting for $80 - 90\,\%$ of the total north-south integrated vapor transport (Guan & Waliser, 2015; Zhu & Newell, 1998). Its dual hydrological role, both as a fresh water source for some water-stressed areas (Dettinger, 2011, 2013; Rutz & Steenburgh, 2012) and as a potential trigger for floods (Lavers & Villarini, 2013; Lavers, Villarini, Allan, Wood, & Wade, 2012; Moore, Neiman, Ralph, & Barthold, 2012; Neiman, Ralph, Wick, Lundquist, & Dettinger, 2008), has granted it increasing attention among the research community. Their long-term change in a warming climate also stands as a pressing research question. However, an important prerequisite to answer such questions is a robust and consistent detection method. As meteorologists and climatologists often deal with observational or simulation data in large sizes, an algorithmic method can ensure better efficiency, consistency and objectivity compared with human identification.

In many existing applications, a magnitude thresholding approach is used. For instance, Ralph, Neiman, & Wick (2004), Neiman et al. (2008), Hagos, Leung, Yang, Zhao, & Lu (2015) and Dettinger (2011) identified ARs by first locating regions where the Integrated Water Vapor (IWV) is greater than $20\,mm$. A $250\,kg/(m \cdot s)$ threshold on the Integrated Vapor Transport (IVT) was used by Rutz, Steenburgh, & Ralph (2014) and Rutz, Steenburgh, & Ralph (2015). However, an implicit assumption with this magnitude thresholding approach is that the atmospheric moisture level stays unchanged throughout the analysis period. Such an assumption may not be fully justifiable under a warming climate as the atmospheric moisture level is expected to increase.

In this package we propose a suite of new detection/tracking algorithms to help solve the above difficulties. Through a systematic analysis using 7 years of Reanalysis data (Dee et al., 2011), we have found that the proposed detection algorithm has reduced sensitivity to parameters and data resolution. Long-lived ARs spanning multiple days, having cross-continent or cross-basin tracks can be more reliably traced through their tropical/sub-tropical origins to high-latitude landfalls. As the research on ARs matures, new AR detection/tracking methods are been developed, and the inter-comparisons of various AR detection/tracking are carried out by, for instance, the Atmospheric River Tracking Method Intercomparison Project (ARTMIP) (Rutz et al., 2019; Shields et al., 2018). Using the terminology of ARTMIP (Shields et al., 2018), the proposed method is a "tracking" (Lagrangian approach) type, with length and shape geometrical requirements. It imposes no threshold on IVT/IWV, but instead imposes absolute thresholds on the spatio-temporal scale of AR-like systems. The detected ARs can be optionally time-stitched to identify coherent AR objects. We have performed some systematic comparisons with two magnitude thresholding based AR detection methods included in ARTMIP, and the proposed method displays better correspondence between North Hemisphere AR tracks and storm tracks, better identification of the strong mid-latitude AR-related moisture transports, and longer AR track durations. The detailed analysis is given in (Xu, Ma, Chang, & Wang, 2020).

`IPART` is therefore intended for researchers and students who are interested in the field of atmospheric river studies in the present day climate or future projections.

The `IPART` package includes a collection of Python functions/classes designed for an analysis workflow covering the detection of ARs, the simplification of the AR's geographical location, to the subsequent tracking through time. The algorithms are implemented using the Python programming language as a wrapper to some well-established numeric packages including `numpy`, `scikit-image` and `networkx` etc. The input and output data use the NetCDF format, an industry standard in the geoscience field. Optional graphical outputs can also be saved, making it suitable for production usage and educational purposes as well. A series of Jupyter notebooks are also included to help guide the users through the entire workflow, and some example scripts are provided as templates to help the user quickly build their own production scripts.

# Example use case

The AR detection algorithm is inspired and modified from the image processing algorithm *Top-hap by Reconstruction (THR)*, which consists of subtracting from the original image a *greyscale reconstruction by dilation* image (Vincent, 1993).

In the context of AR detection, the greyscale image in question is the non-negative IVT distribution, denoted as $I$. The greyscale reconstruction by dilation component corresponds to the background IVT component, denoted as $\delta(I)$. The difference $I-\delta(I)$ gives the transient IVT component, from which AR candidates are searched. Figure 1 shows this decomposition process. It could be seen that after this separation of background/transient components, it becomes trivial to locate AR-like features.

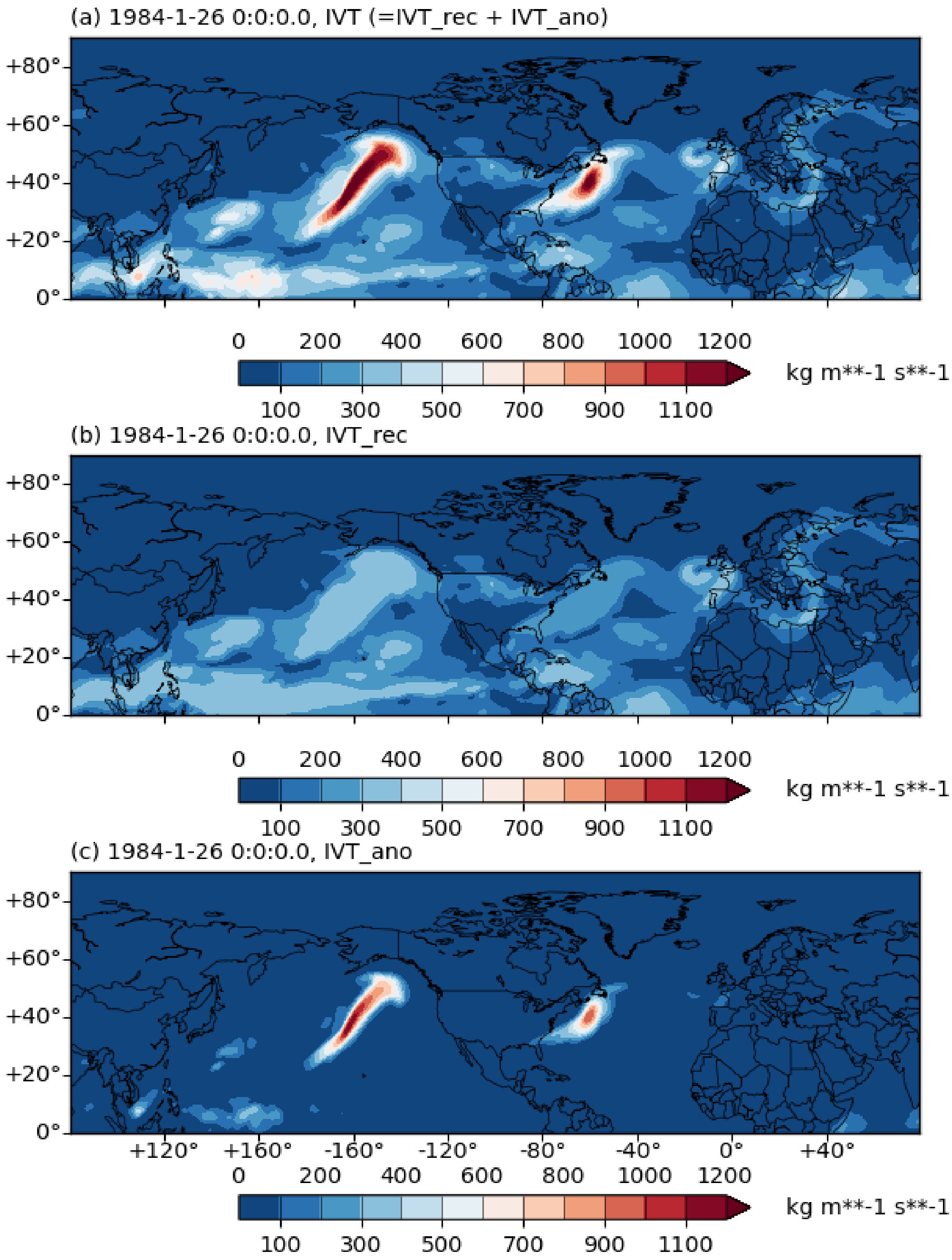


**Figure 1:** (a) The IVT field in $kg/(m \cdot s)$ at 1984-01-26 00:00 UTC over the North Hemisphere. (b) the IVT reconstruction field ($\delta(I)$) at the same time point. (c) the IVT anomaly field ($I - \delta(I)$) from the THR process at the same time point.

After locating ARs at various time steps, a single curve is sought for each AR as a summary of its location. A directed planar graph model is used in this process, and weighted Dijkstra path searching algorithm is used to find this "AR axis". Further details can be found in the documentation page.

Lastly, a modified Hausdorff distance definition is used as an inter-AR distance estimate, and an exclusive nearest neighbor approach is used to link ARs at consecutive time points. Figure 2 shows an example of this tracking process.

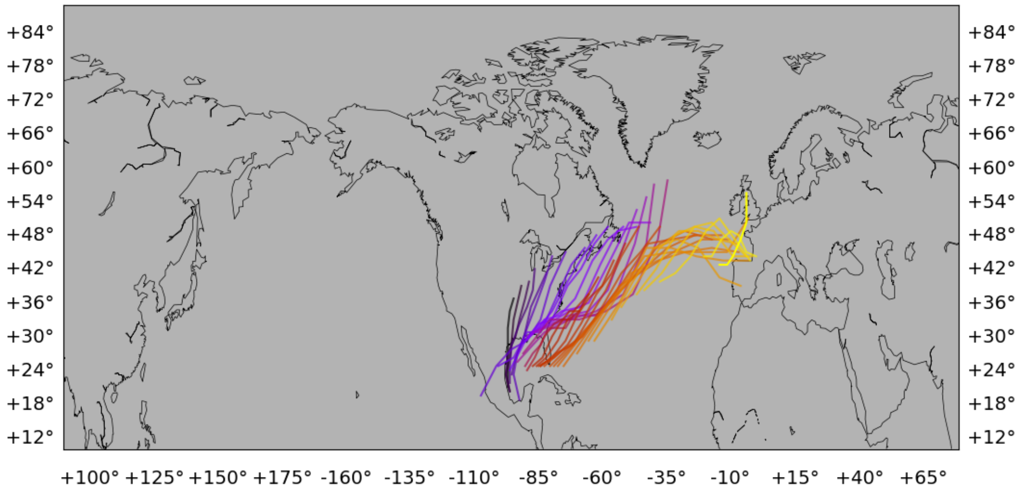


**Figure 2:** Locations of a track labelled "198424" found in year 1984. A color scheme of black to yellow through purple indicates the evolution, where black curves represent the AR at earlier times and yellow curves at later times.

# External libraries used

Manipulation of the NetCDF data is achieved using the Python interface of the `NetCDF` software (Unidata, 2020), `numpy` (van der Walt, Colbert, & Varoquaux, 2011) and `scipy` (Virtanen et al., 2020) packages. The detection process utilizes the image-processing package `scikit-image` (Walt et al., 2014). The AR axis finding process utilizes the `networkx` package (Hagberg, Schult, & Swart, 2008). Generated outputs are further manipulated with `pandas` (McKinney, 2010) and displayed using `matplotlib` (Hunter, 2007).

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