

1 **The System for Classification of Low-Pressure Systems**
2 **(SyCLOPS): An All-in-One Objective Framework for**
3 **Large-scale Datasets**

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7 **Key Points:**

- 8 • The first all-inclusive low-pressure system (LPS) detection and classification frame-
9 work for climate data and model outputs is proposed
10 • The framework substantially extends LPS track lengths while improving tropical
11 cyclone detection skills
12 • The framework is useful to study the frequency, structure, development, wind im-
13 pact, and precipitation contribution of each type of LPS

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14 Abstract

15 We propose the first unified objective framework (SyCLOPS) for detecting and clas-
 16 sifying all types of low-pressure systems (LPSs) in a given dataset. We use the state-of-
 17 the-art automated feature tracking software TempestExtremes (TE) to detect and track
 18 LPS features globally in ERA5 and compute 16 parameters from commonly-found at-
 19 mospheric variables for classification. A Python classifier is implemented to classify all
 20 LPSs at once. The framework assigns 16 different labels (classes) to each LPS data point
 21 (node) and designates four different types of high-impact LPS tracks, including tropi-
 22 cal cyclone (TC) tracks, Monsoon System (MS) tracks, subtropical tropical-like cyclone
 23 (STLC) tracks, and polar low (PL) tracks. The classification process involves disentangling
 24 high-altitude and drier LPSs, differentiating tropical and non-tropical LPSs using
 25 novel criteria, and optimizing for the detection of the four types of high-impact LPS. We
 26 compare our labels to those in the International Best Track Archive for Climate Stew-
 27 ardsip (IBTrACS) and find that they are in good agreement. TC detection using SyCLOPS
 28 produces better tropical cyclone detection skill compared to the previous algorithms. Fi-
 29 nally, we demonstrate that the output of SyCLOPS is valuable for investigating various
 30 aspects of LPSs, such as the evolution of a single LPS track, patterns and trends in LPS
 31 activities, and precipitation or wind influence associated with a particular LPS class.

32 Plain Language Summary

33 We create a new objective framework (SyCLOPS) that can detect, track, and cat-
 34 egorize different kinds of cyclones (low-pressure systems) in datasets. We use an advanced
 35 software called TempestExtremes to spot cyclones globally in ERA5 reanalysis and then
 36 use a Python program to sort all cyclones into 16 different groups based on their char-
 37 acteristics. We also identify four types of significant cyclone tracks: tracks of tropical
 38 cyclones, monsoon systems, subtropical cyclones, and polar lows. The framework can
 39 recognize cyclones over high-elevation areas and dry cyclones. It can also efficiently sep-
 40 arate tropical low-pressure systems and extratropical (non-tropical) systems using a novel
 41 method. We compare our results against existing archives and find that the framework
 42 produces objectively tracked tropical cyclones that better match the observations, and
 43 the labels given by the framework are in good agreement with those given in the sub-
 44 jective archives. Finally, we show that SyCLOPS can help us understand various aspects
 45 of low-pressure systems, like how they develop over time, changes in their activity trends,
 46 and their related extreme weather.

47 1 Introduction

48 Objective feature detection has emerged as a key tool for detecting and tracking
 49 various meteorological features in large-scale datasets, and responds to the growing need
 50 for advanced impacts-relevant model and climate data analysis. Researchers give con-
 51 siderable attention to detecting and tracking low-pressure systems (LPSs), or cyclones,
 52 which are often drivers for high-impact weather including high winds and extreme pre-
 53 cipitation. Some more significant LPSs, such as tropical cyclones (TCs), monsoon lows
 54 (MLs) or monsoon depressions (MDs), subtropical cyclones (SCs), and extratropical cy-
 55 clones (EXs), are commonly tracked using specialized tracking algorithms in reanalysis
 56 and climate model outputs to derive their climatology and perform climate projections(e.g.,
 57 Guishard et al., 2009; Neu et al., 2013; Hurley & Boos, 2015; Roberts et al., 2020). Tropical-
 58 like cyclones (TLCs) in the subtropics and the polar region, including Mediterranean hur-
 59 ricanes and polar lows (PLs), are capable of producing significant coastal hazards (Toomey
 60 et al., 2022), but more rigorous automated tracking has only occurred relatively recently
 61 because of advances in model resolution and observations (e.g., Stoll et al., 2018; Zhang
 62 et al., 2021; Stoll, 2022; Flaounas et al., 2023).

63 TempestExtremes (TE; Ullrich & Zarzycki, 2017; Ullrich et al., 2021) is an all-inclusive,
 64 state-of-the-art automated Lagrangian feature tracking software package. It is designed
 65 to robustly and efficiently detect, track, and analyze any nodal or areal features in large-
 66 scale datasets with user-friendly command lines and using parallelized C++. TE has been
 67 optimized for TC detection using geopotential thickness and mean sea level pressure closed
 68 contour criteria (Zarzycki & Ullrich, 2017). Bourdin et al. (2022) found that TC detec-
 69 tion using TE outperforms other methods for the reanalysis dataset ERA5 (Hersbach
 70 et al., 2020). Vishnu et al. (2020) used TE to track monsoon systems (MLs and MDs,
 71 or MSs) in the North Indian Ocean across different reanalysis products, and observed
 72 high success rates. TE has also been combined with the cyclone phase space (CPS) of
 73 Hart (2003), which classifies storms based on thermal wind and thermal asymmetry pa-
 74 rameters. For example, Zarzycki & Ullrich (2017) used TE and CPS to track both TCs
 75 and post-TCs (EXs) based on LPSs’ thermal structure, and detect extratropical transi-
 76 tion (EXT). Zhang et al. (2021) used a similar approach to detect Mediterranean hur-
 77 ricanes.

78 Although TE’s algorithms are powerful for LPS detection, when applied standalone
 79 they have similar restrictions and drawbacks as other specialized methods. Their main
 80 restriction stems from the fact that these algorithms exclusively target a single type of
 81 LPS using strict thresholds on physical variables. Consequently, detection criteria need
 82 to be quite stringent, and controls like seasonality, topographical masks, and latitudi-
 83 nal bounds are required to avoid polluting the dataset with incorrect detections (i.e., false
 84 alarms). With these criteria, tracks often end abruptly at regional or temporal bound-
 85 aries and are shorter in length than analogs in manually tracked datasets, which means
 86 that information from the complete LPS lifespan is not available. While the CPS approach
 87 has the ability to classify the thermal structure evolution of an LPS throughout its life-
 88 time, it is not designed for LPS classification, as different types of LPS often share sim-
 89 ilar thermal structures. For example, mature TCs, some post-TCs, EXs experiencing warm
 90 seclusion, and some subtropical or hybrid cyclones can all be categorized as shallow or
 91 deep symmetric warm-core systems according to the CPS (Hart, 2003). Hence, warm/cold
 92 core criteria are likely insufficient to effectively classify global LPSs.

93 Instead, we propose a new objective framework, called the System for Classifica-
 94 tion of Low-Pressure Systems (SyCLoPS), to detect, track, and classify all non-negligible
 95 LPSs worldwide at once, without any spatial or seasonal limitations. We test our frame-
 96 work in ERA5, and focus exclusively on surface-level LPSs (so upper-level disturbances
 97 and lows are out of our scope). The detection and tracking are completed using TE com-
 98 mands, and the classification is done in a separate Python classifier that assigns 16 dif-
 99 ferent types of LPS labels/classes (TD, TC, ML, EX, SC, PL, etc.) and 4 types of high-
 100 impact LPS tracks, which are TC Track, MS Track, and two types of TLC Tracks (sub-
 101 tropical TLC and PL tracks). The classification process is based primarily on conven-
 102 tional definitions, observations, and physical (dynamic/thermodynamic) intuition, and
 103 is simplified to the extent possible. The atmospheric variables used for classification are
 104 commonly found in reanalysis and climate model outputs. Basic machine learning tech-
 105 niques and mathematical optimization are used to refine our thresholds against archives
 106 of observed and subjectively identified LPSs. The resulting framework involves only thresh-
 107 olds on basic meteorological fields and includes no “black box” elements.

108 This new framework produces considerably extended LPS track lengths because
 109 of the low detection threshold. The labeled LPS nodes can be compared to the subjec-
 110 tive LPS status (labels) in the TC observation archive IBTrACS (Knapp et al., 2010).
 111 Labeled tracks is also comparable to subjective TC, MS, and TLC track archives. The
 112 framework maintains or improves LPS detection skill without implementation of the above-
 113 mentioned restrictions. For example, other TC detection frameworks will often pick up
 114 some stronger warm-core extratropical or subtropical systems that were not recorded in
 115 IBTrACS even if latitudinal bounds were enforced (Bourdin et al., 2022). The new al-

116 gorithm addresses this problem, leading to a noticeable increase in TC detection skill
 117 without further post-processing.

118 The manuscript is structured as follows. Section 2 summarizes all the datasets we
 119 use to verify our classification thresholds and LPS detection skills. Sections 3-5 explain
 120 the general detection and classification processes and justify each of the conditions we
 121 set for classification. In section 6, we include some highlights from the classified LPS cat-
 122 alog and discuss potential applications from the SyCLOPS framework. Section 7 concludes
 123 the paper and addresses known limitations.

124 2 Data

125 We detect, track, and classify LPSs throughout 1979 to 2022 in ERA5 at 3-hour
 126 frequency. ERA5 is used for testing our classification algorithms since SyCLOPS includes
 127 small or mesoscale features like early-stage TCs and TLCs, which require finer data res-
 128 olution. Although SyCLOPS is developed using ERA5, it uses a small number of com-
 129 monly output meteorological fields and so is intended to be applicable to other global
 130 or regional meteorological datasets. Additionally, alternative paths are identified if some
 131 data or fields are unavailable in regional models or at certain pressure levels. SyCLOPS
 132 uses TE’s closed contour (hereafter, CC) criteria as much as possible since the CC cri-
 133 teria are designed to be insensitive to model resolution (Ulrich & Zarzycki, 2017). Pos-
 134 itive (negative) CC criteria use graph search to make sure that all paths along the un-
 135 structured grid in a field from a field’s local maximum (minimum) lead to the greatest
 136 possible decrease (increase) before reaching a specified great-circle distance (GCD). A
 137 list of ERA5 variables used in SyCLOPS is given in Table S1 of supporting information
 138 (SI).

139 To verify detection skill for the four selected types of LPS, we use four subjective
 140 datasets for verification. TCs are verified against the widely-used IBTrACS. However,
 141 only 3510 main-type tracks that reach 34 knots (17.5 m s^{-1}) from the period of 1979-
 142 2021, inclusive, are kept for verifying TC detection skills in IBTrACS. We refer to this
 143 dataset as IB-TC. For MSs, we use the Sikka archive Sikka (2006), which provides manually-
 144 identified North Indian Ocean monsoon system positions on historic surface weather maps
 145 at daily frequency, digitized by Hurley & Boos (2015). Few subjective datasets are avail-
 146 able for the two types of TLCs we wish to detect. Elsewhere in the literature, subtrop-
 147 ical TLCs (STLCs) may be referred to as subtropical storms (SSs), which is regarded
 148 as the most intense category of SCs (Evans & Braun, 2012). Mediterranean TLCs (hur-
 149 ricanes) may be viewed as being among global STLCs, and they are perhaps most well
 150 studied, with relatively more observational data available. However, existing subjective
 151 datasets for Mediterranean TLCs are still very incomplete. To reconstruct a more cred-
 152 ible subjective archive for Mediterranean TLCs or STLCs, we obtain the subjectively
 153 tracked data from Flaounas et al. (2023), wherein trained meteorologists identify and
 154 track Mediterranean cyclones, including TLCs and other noticeable systems in the re-
 155 gion, using ERA5’s mean sea level pressure (MSLP) field. We then use the cyclone in-
 156 formation table provided in Flaounas et al. (2023) and two online sources (see Open Re-
 157 search section) to select tracks that can be potentially classified as TLCs, while avoid-
 158 ing weaker systems. We also observe that IBTrACS contains a few subtropical storm records,
 159 which agencies tend to record when they have the potential to transform into TCs. How-
 160 ever, these records are largely incomplete and can often be confused with weaker TCs,
 161 so we do not separate them from TC records. For PLs, we use the well-known STARS
 162 (Sea Surface Temperature and Altimeter Synergy for Improved Forecasting of Polar Lows)
 163 archive (Noer et al., 2011), which includes 185 subjectively identified polar lows from 2002-
 164 2011 in parts of the Nordic Seas. Of course, this is also not a complete list of all the PLs
 165 in this region due to insufficient observations.

In our objectively tracked LPS dataset, we match our tracks to the tracks in each subjective dataset using different matching algorithms, described in SI text S1. To avoid misclassification of MSs, we also use an objectively tracked North Atlantic easterly wave (EW) dataset (Q. A. Lawton et al., 2022) to construct a corresponding surface LPS dataset (also see SI text S1). These matched TC, MS, STLC, PL, and EW datasets are later used in the classification and data analysis process.

3 The Overall Workflow

MSLP is the starting point for our LPS node detection. Although prior research has also employed 850 hPa vorticity or streamfunction fields to detect monsoon systems or cyclones (e.g., Hodges, 1994; Hurley & Boos, 2015; Vishnu et al., 2020), we consider MSLP a preferable variable for two reasons: (1) local minima/maxima of MSLP are widely used in meteorological agency operations to locate surface pressure systems, including LPSs in IBTrACS; and (2) there is a global agency consensus on the definition of MSLP (Knapp et al., 2010). Further, low-level vorticity or streamfunction data may not be directly available in many datasets when intersecting with the surface, and they have opposite signs for cyclonic systems in the North and South Hemispheres, which could lead to tracks across equatorial regions becoming disconnected if they are not detected and tracked twice using different signs. These factors all contribute to the computational burden of detecting LPSs globally without spatial limitations.

MSLP signals may be generally weaker in the tropics, which makes it difficult to differentiate some weaker LPSs associated with tropical waves. To capture these features in the tracker, we consider the lowest reasonable detection threshold. Namely, an LPS node is flagged at a local minimum MSLP if the MSLP value is lower than the surrounding by at least 10 Pa (0.1 hPa) within 5.5° GCD (a 10-Pa delta positive CC criterion). Although we find this is an extremely low threshold, very weak EWs (particularly those over land) that don't have the minimal surface closed MSLP contour will not be detected.

The pointwise feature detection is performed using the *DetectNodes* function in TE. Besides the MSLP CC criterion, we also require that nodal candidates located within 6° GCD of each other merge into a single node, preserving the one with the lowest MSLP value by specifying the argument `--mergedist "6.0"`, which aligns with the specification in Zarzycki & Ullrich (2017). *DetectNodes* also computes 15 parameters (data columns) directly from input variable fields that are later utilized in the LPS classification process. A summary of those data columns and their abbreviations is included in Appendix A. Please refer to SI Text S5 for a brief explanation for the selection of specifications in the parameters. To construct LPS tracks, we then employ the *StitchNodes* function, which requires the following specifications to connect consecutive nodes in time and form non-negligible LPS tracks (all the TE command details are available in Appendix C):

1. `--mintime "18h"`: LPSs must at least sustain for a time span of 18 hours (equivalent to 7 three-hourly time steps in TE) to avoid too many weak, short-lived, diurnal lows.
2. `--range "4.0"`: Node candidates in two consecutive time steps must be located within 4° GCD distance of each other. This specification is chosen based on the fact that the translation speed of the fastest EXs rarely go over 40 m s⁻¹, or about 140 km per hour (Bernhardt & DeGaetano, 2012; Lodise et al., 2022).
3. `--maxgap "12h"`: A maximum allowable gap of 12 hours (equivalent to 5 time steps) within a track is implemented. A longer gap time is not preferred because it may include too many weak diurnal lows.
4. `"--threshold MSLCC, >=, 100.0, 5"`: To exclude negligibly weak LPS tracks, a track must contain at least 5 time steps during which MSLP includes a closed contour of depth 100 Pa over a 5.5° GCD (MSLCC ≥ 100 Pa) distance from the candidate node.

217 A total of 7,781,105 data points (nodes) and 379,301 distinct tracks are identified
 218 in the 44-year period from 1979 to 2022. The whole tracking process takes about 2 hours
 219 using 2 NERSC Perlmutter nodes (each with 128 threads). This forms the input (LPS)
 220 catalog for classification, structured in accordance with our description in Appendix A.
 221 Subsequently, we employ Python classifier codes (available via Zenodo, see the open re-
 222 search section) to classify each LPS node and assign them labels from the 16 distinct classes,
 223 following the workflow illustrated in the accompanying flowchart (Fig. 1). We call the
 224 output of this classification workflow the classified (LPS) catalog. The structure of this
 225 catalog can be found in Appendix A. Both catalogs are available for download via Zen-
 226 odo. All the required TE command lines for this framework are printed in SI text S6 and
 227 via Zenodo.

228 Note that we use the LPS catalogs mainly for testing our classification conditions,
 229 so the provided catalogs may not be the most comprehensive global LPS dataset con-
 230 sidering the data scalability and computation workload. Our detection specifications should
 231 be enough for general high-impact LPSs; however, some very small and short-lived high-
 232 impact systems, such as some PLs, can be missed because of the 3-hourly detection rate,
 233 the 18 hour mintime, or the rather large `mergedist`. For these cases, users may select
 234 their own regions and LPS features of interest and run *DetectNodes* and *StitchNodes* with
 235 alternative specifications before performing classification.

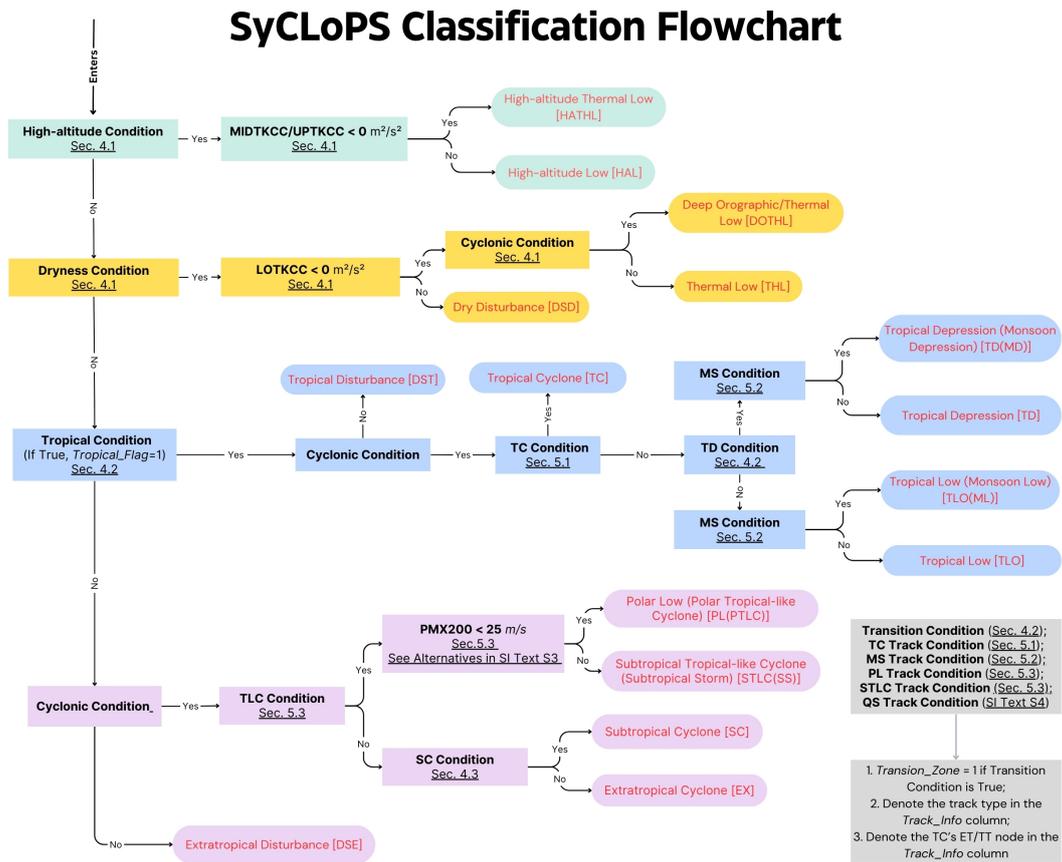


Figure 1. A depiction of the LPS classification workflow. The workflow begins in the top-left. A complete list of parameters is given in Appendix A, and a complete list of conditions is provided in Appendix B. Section numbers are noted in the figure below each condition to indicate where details can be found in the text.

Figure 1 shows the LPS classification flowchart. The workflow flows from top to bottom through five major branches to disentangle each major class of LPS. Boxes with red text indicate the final LPS classification labels (full labels and short labels). Details of the conditions applied in the flowchart can be found in Appendix B. The first branch (green) is the high-altitude branch, where we apply the high-altitude condition to extract those LPSs with a surface elevation higher than the 850 hPa (typically around 1500 m) from the input catalog, given that most of the more influential LPSs occur at a lower altitude. Although not as important, some of these high-altitude lows can be major contributors to precipitation over or near global plateaus (Tucker, 1999; L. Li et al., 2019). The second branch (yellow) is the dry branch. In this branch, we segregate those LPSs that hardly produce any precipitation due to their dry, low-level circulation. This generally includes thermally-driven shallow thermal/heat low systems, which can affect local cold fronts and heat waves (Reeder et al., 2000; Spengler et al., 2005). Third is the tropical branch (blue), which contains several recognizable and impactful features such as TCs, MDs, and MLs. At this level, the remaining unclassified LPSs will be determined to be tropical or non-tropical based on the tropical condition. The fourth branch (purple) is the extratropical branch, where we segregate TLCs (STLCs and PLs) and then differentiate SCs from the most typical EXs.

The gray workflow in the bottom-right of Fig. 1 is used in the second step of the classification. It provides additional useful information for reference purposes, but it does not affect any LPS node labels assigned in the first step: if a track meets a specific track condition using a time step threshold, one or more types of the four high-impact LPS tracks will be labeled in the `Track_Info` column of the classified LPS catalog. For example, if a track with a unique TID is determined to be both a “TC track” and “MS track”, then in the `Track_Info` column, every node/data point of that track will be denoted “Track_TC_MS.” We also introduce the quasi-stationary (QS) track condition that can identify those LPS tracks that stay relatively stationary and bounce around topographic features (see SI Text S3 for information on how we establish the thresholds) so that they can be filtered out or selected when needed. As there’s no hard cut-off between a tropical and non-tropical system, we additionally establish the transition condition along with the tropical condition to define a transition zone to address the ambiguity of the more hybrid and marginal tropical systems potentially under transition. The tropical condition must be fulfilled before the transition condition can be justified. The `Tropical_Flag` column and the `Transition_Zone` column in the classified LPS catalog will be set to 1 (or otherwise 0) if an LPS satisfies the tropical condition and transition condition, respectively. Extratropical and tropical transition (EXT and TT) completion nodes are also noted in the `Track_Info` column for TC tracks. We define EXT completion nodes as the first LPS nodes along the track with a non-tropical label after the last tropical-system node, and TT completion nodes as the first TC node before the last non-TC node in TC tracks that originate as a non-tropical LPS or within the transition zone defined in section 4. Users may choose their own standards to redefine EXT and TT positions based on the provided data. Details of the conditions used in the classification process will be discussed further in the next section.

4 Justification for Classification Conditions

4.1 High-altitude and Dry Branch Conditions

In the high-altitude branch, two classes are given based on the mid-level/upper-level warm core criterion (MIDTKCC/UPTKCC). MIDTKCC (UPTKCC) is the negative CC criterion of geopotential thickness between 500 hPa and 700 hPa (300 hPa and 500 hPa) over a 6.5° GCD, from the maximum thickness within 1.0° GCD of an LPS node. Geopotential thickness is used instead of temperature to detect warm cores for the same reasons listed in Zarzycki & Ullrich (2017). Hence, if MIDTKCC or UPTKCC is less than $0 \text{ m}^2 \text{ s}^{-2}$, it indicates that a high-altitude LPS is warm-cored at these levels (same for

the low-level warm-core criterion LOTKCC) and potentially thermally-driven. If this condition is met, the “High-altitude Thermal Low (HATHL)” label will be given; otherwise, the “High-altitude Low (HAL)” label will be used.

The dryness condition determines whether an LPS node will enter the dry branch: It requires that RHAG850 (average 850 hPa relative humidity over a 2.5° GCD) is greater than 60%. This threshold is determined by the lowest track-maximum RHAG850 (the maximum RHAG850 of all nodes within a track) in the matched PL and STLC dataset, chosen to prevent misclassification of significant non-tropical systems in the relatively drier subtropical/extratropical regions. Therefore, we consider RHAG850 at 60% a safe threshold to separate dry convective systems from moist convective systems. Next, the LOTKCC $< 0 \text{ m}^2 \text{ s}^{-2}$ criterion is used to examine LPSs’ low-level warm cores. If the condition is not met, the node will be classified as a “Dry Disturbance (DSD)” ; otherwise, we check the cyclonic condition.

The cyclonic condition uses VOR500 (average relative vorticity over a 2.5° GCD) to determine if an LPS has cyclonic circulation beyond mid-level (500 hPa). A typical heat low is considered to have a dry and warm low-level core and is shallow in nature (Smith, 1986; Hoinka & Castro, 2003). Hence, if an LPS node does not qualify for the cyclonic condition, it will be labeled as a “Thermal Low (THL).” However, some deeper THLs still emerge near elevated topography in the daytime, such as the type II southwest vortex in southwest China (Feng et al., 2016), so the remaining LPSs in the dry branch are labeled “Deep Orographic/Thermal Lows (DOTHL).”

4.2 Tropical Branch Conditions

The next step in the classification framework focuses on tropical systems. Traditionally, tropical systems have been identified using a warm-core criteria (e.g., Zarzycki & Ullrich, 2017; Roberts et al., 2020). However, in the course of this work we found that this criterion is often satisfied outside of the tropics and so lends to many false alarms in the classification. This observation motivated us to examine other fields. We would also like to avoid deterministic temperature thresholds as much as possible since they can be sensitive to global warming, and various types of LPSs can exist over similar sea surface temperatures (SSTs) in the subtropical oceans. Consequently, we found that RH100 (maximum relative humidity at 100 hPa within 2.5° GCD of LPS node) is more reliable and flexible for disentangling tropical and extratropical systems as a proxy of “tropicality.” There are two reasons that physically ground this choice. First, RH at 100 hPa is distinctly higher in the tropics. This is because only in the tropics is the tropopause often found above 100 hPa, as a result of active moist convection in the tropics. RH is high there because of the low tropopause temperature and presence of upper-level moisture. RH100 also decreases sharply in the subtropics, reflecting the dynamics of the troposphere and the transition between the tropics and subtropics near the edge of the Hadley cells (see SI Fig. S1 for an illustration of the 1979-2022 global mean RH100). Second, higher RH100 values indicate the presence of deep convection associated with a tropical system, and so this parameter is sensitive to EXT scenarios during which it decreases rapidly while TCs gradually lose their deep convective cores and become post-tropical.

To illustrate the behavior of RH100 during EXT, we examine a recent EXT case (2023 hurricane “Lee”) plotted with RH at 100 hPa in Fig. 2. In Fig 2a, the system was embedded in a region of high-level 100 hPa RH two days before EXT completion (between 00-06 UTC, Sep 15) as defined by the National Hurricane Center (NHC). In Fig. 2b, less than one day before EXT completion, the surrounding RH had dropped as the hurricane enters the subtropics. However, a belt of higher RH remains stretched out from the deep tropics, indicating the system’s remaining “tropicality.” RH100 is still over 90% at this point, as indicated by the bluish color within the 2.5° GCD circle. In Fig. 2c, hours

338 after EXT completion, we can see that the 100 hPa environment near the hurricane had
 339 become warm and dry, leading to a dramatic decrease in RH100.

340 In addition to RH100, DPSH (average deep-layer wind speed shear between 200
 341 hPa and 850 hPa over a 10.0° GCD) is also used to distinguish tropical systems in the
 342 subtropics, especially during EXT. Deep-layer shear is a good physics-related indicator
 343 of baroclinicity or an unfavorable environment for tropical deep convection. Post-TCs
 344 and general SCs/EXs primarily derive energy from baroclinic sources and are often sur-
 345 rounded by much more intense wind shear compared to tropical systems.

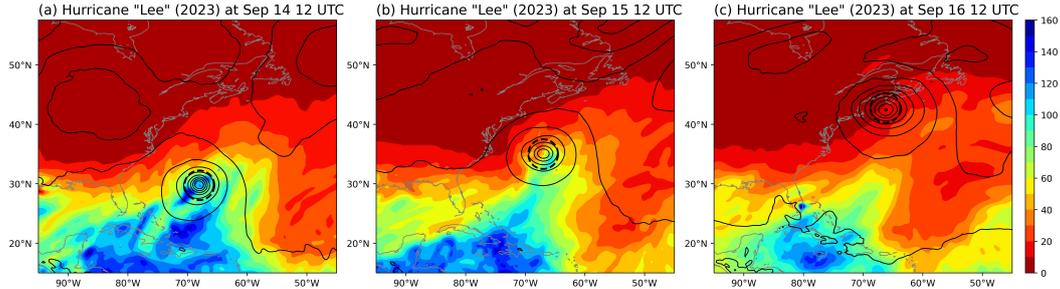


Figure 2. ERA5 Relative Humidity (RH) at 100 hPa during an example of a EXT case (Hurricane “Lee” of 2023) at (a) one day before EXT, (b) during EXT, and (c) soon after EXT. MSLP is shown using black contours. Note that RH at 100 hPa can exceed 100% in some datasets, reflecting supersaturation.

346 The tropical (and transition) condition with RH100 and DPSH is constructed as
 347 follows. First, we use two LPS node clusters that are hard to distinguish from SST or
 348 warm-core criteria. One consists of all the matched tropical systems recorded in IBTrACS
 349 in the subtropics (the tropical cluster), and the other consists of potential subtropical
 350 systems over relatively warm SSTs that are not recorded anywhere in IBTrACS (the sub-
 351 tropical cluster). Note that both clusters (especially the unverified subtropical cluster)
 352 will inevitably include some misclassified or transitional LPSs. Details of how we select
 353 these two clusters can be found in SI Text S2. We then apply the decision tree classi-
 354 fier over RH100 and DPSH using Gini index splitting criteria to the nodes in the two
 355 clusters with a tree depth of 2. Results in Fig. 3 show that the tropical and subtropi-
 356 cal clusters can be successfully differentiated by a minimum RH100 threshold of about
 357 20% (rounded off to the nearest 5%) and a maximum DPSH of 10 m s⁻¹. The accuracy
 358 score for this decision near 80%. We perform a sensitivity test as demonstrated in SI Text
 359 S2 and Fig. S2. These two thresholds are determined to be relatively stable and insen-
 360 sitive to a sensitive standard (the SST requirement) we choose for selecting the two clus-
 361 ters. The elongated outer contours of the tropical cluster towards the left are likely made
 362 up of some LPSs near or after EXT/TT (for reference, about 5% of labels in IBTrACS
 363 are “Extratropical”), but also some “drier” tropical systems in drier or less convective
 364 basins. For example, while only 6 or 0.6% of Western North Pacific (WNP) TC tracks
 365 have a track-maximum RH100 under 50%, 94 or 17% of TC tracks in the North Atlantic
 366 fall into this range, with 24 tracks falling under 20%. According to these results, the 20%
 367 RH100 threshold will serve as the minimum RH100 requirement in the tropical condi-
 368 tion, and the 10 m s⁻¹ DPSH threshold will be the minimum DPSH requirement in the
 369 transition condition, as stronger tropical systems can tolerate a much greater DPSH value,
 370 such as in many EXT cases, and DPSH of some weak LPSs closer to the equator can slightly
 371 exceed the 10 m s⁻¹ threshold due to the tropical easterly jet. The cores of tropical easterly
 372 jets at 200 hPa are most commonly found near 5° N to 15° N (Lu & Ding, 1989).

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Hence, we impose that the transition condition will not be triggered when an LPS is within 15° latitudes of the equator.

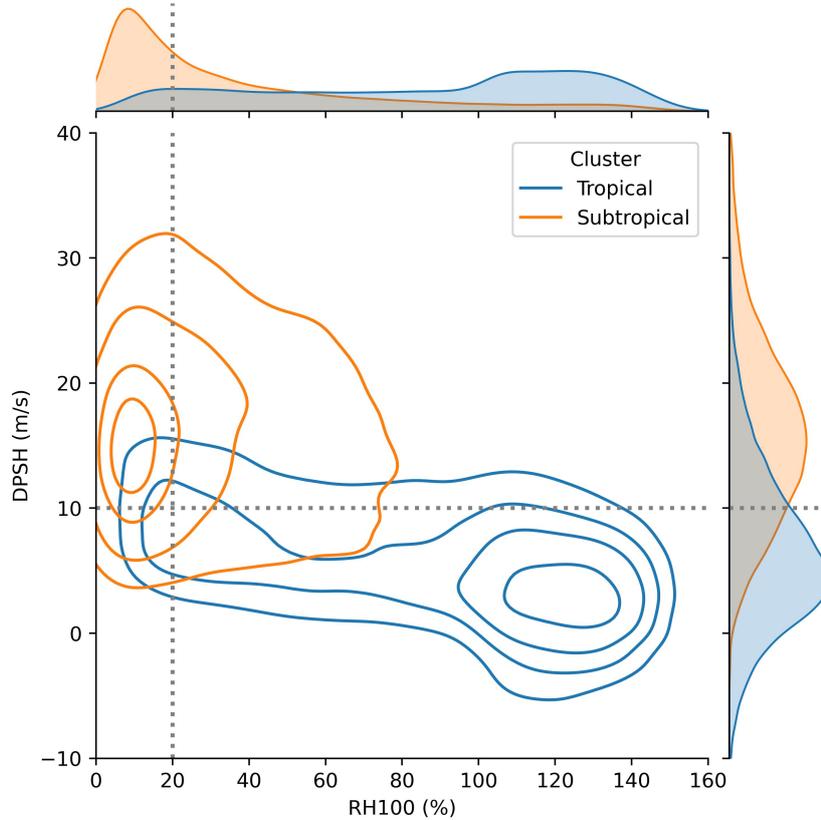


Figure 3. Kernel Density Estimate (KDE) on the RH100-DPSH plane for the tropical cluster and the subtropical cluster. The KDE levels are 0.25, 0.5, 0.75, and 0.9. Grey dotted lines indicate the classification thresholds determined by the decision tree classifier.

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To find the upper limit of DPSH for the tropical condition, we select 885 EXT tracks from the matched TC datasets whose pairs in IBTrACS have a “ET (Extratropical)” or “MX (Mixture, contradicting nature reports from different agencies)” label following the last “TS (Tropical System)” label in the *NATURE* column, and here we define the time of the last “TS” label as the EXT completion time of each EXT track. The pre-EXT cluster is defined by those nodes that are 3 to 24 hours before the EXT completion, and the post-EXT cluster is made up of those that are 3 to 24 hours after the EXT completion. We apply the decision tree classifier based on DPSH to find the boundary between the two clusters. With an accuracy score of 64%, the results show that the optimal DPSH threshold to distinguish the two clusters is around 18 m s^{-1} . The accuracy score is not high, but it is to be expected—most TCs gradually transform into EXs, so there isn’t a hard cut-off. We do not round off the DPSH threshold to the nearest 5 m s^{-1} since environmental wind shear typically changes slowly in magnitude along an LPS track. This result is also stable to small changes in the selection of the time range for each cluster.

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Finally, we consider 55% as the upper limit of RH100 for the transition condition for three reasons: (1) If we apply the decision tree classifier based solely on RH100 to separate the tropical and non-tropical cluster, the threshold for RH100 will be about 55% with a 74% accuracy score; (2) the median RH100 is about 55% at the time of EXT com-

393 pletion as defined above, and (3) the median track-minimum RH100 in the matched EW
 394 dataset (the matched tropical LPS dataset with the lowest average RH100) is also about
 395 55%. In summary, the tropical condition refers to $\text{RH100} > 20\%$ and $\text{DPSH} < 18 \text{ m s}^{-1}$.
 396 Upon fulfillment of the tropical condition, the transition condition is satisfied when $\text{RH100} < 55\%$
 397 or $\text{DPSH} > 10 \text{ m s}^{-1}$, and the latitude is poleward of 15° .

398 If only the RH100 and DPSH thresholds are included in the tropical condition, we
 399 find that a small number of polar systems could also satisfy the tropical condition. As
 400 shown in SI Figure S1, polar regions can also feature a relatively higher 100 hPa RH that
 401 potentially exceeds the RH100 threshold in our tropical condition. This is mostly the
 402 result of persistent darkness during polar wintertime, which allows the upper air tem-
 403 perature to fall to exceptionally low values despite a lack of moisture. On the other hand,
 404 DPSH also tends to be quite low in polar regions, as they are not in the main baroclinic
 405 zone. However, a plot of the T850 (Air temperature at 850 hPa at the node) distribu-
 406 tion for all systems satisfying the RH100 and DPSH thresholds indicates that tropical
 407 systems and polar systems are separate from each other by a $\sim 15 \text{ K}$ (270 K to 285 K)
 408 gap (see SI Fig. S3a). Hence, an additional T850 criteria ($\text{T850} > 280 \text{ K}$) is included to
 409 further distinguish the two systems. We expect this condition is sufficient even under
 410 the most extreme global warming scenarios.

411 Further down the tropical branch, the cyclonic condition determines whether an
 412 LPS is shallow and so should be tagged as a ‘‘Tropical Disturbance (DST).’’ The next
 413 step involves the TC condition, which identifies tropical cyclones (TCs). The conditions
 414 for this step are obtained by parameter optimization and discussed in section 5.1.

415 Tropical depressions (TDs) are sometimes referred to as the weakest TCs below the
 416 tropical storm category. Therefore, the TD condition requires an LPS to at least have
 417 weak upper-level warm cores ($\text{UPTKCC} < 0$). We do not require a low-level warm core
 418 for TDs as many weaker tropical systems develop a upper-level warm core before a stable
 419 low-level warm core is established (Reed et al., 1977; Hunt et al., 2016). We addi-
 420 tionally require MSLCC (the greatest positive closed contour delta of MSL over a 5.5° GCD)
 421 to exceed 160 Pa, determined by the median LPS node’s MSLCC at the IBTrACS track
 422 start time of each matched TC track, as agencies tend to start recording LPSs when they
 423 are reaching TD intensity. Regardless of whether an LPS satisfies the TD condition, the
 424 MS condition is also applied to separate monsoonal and non-monsoonal LPSs. The MS
 425 condition is obtained by optimization and discussed in section 5.2. After both the TD
 426 and MS conditions have been checked, the classifier assigns one of the four TD and Trop-
 427 ical Low (TLO) labels accordingly, as shown in Figure 1.

428 4.3 Extratropical Branch Conditions

429 LPS nodes that do not satisfy the tropical condition are non-tropical (extratrop-
 430 ical) systems in the extratropical branch. The cyclonic condition separates ‘‘Extratrop-
 431 ical Disturbances (DSE)’’ before they are examined under the TLC condition obtained
 432 by optimization. The conditions for identifying TLC labels, which include ‘‘STLC(SS)’’
 433 and ‘‘PL(ETLC)’’, will be discussed in section 5.2. The remaining LPS nodes will go through
 434 the SC condition which follows the general definition of a typical SC—a shallow, warm-
 435 cored, non-frontal LPS that features an upper-level cold low isolated/detached from the
 436 midlatitude westerlies extending its circulation to the surface in the subtropics (U.S. Navy,
 437 1994; Evans & Braun, 2012). Our SC condition states that an LPS must: (1) have a Z500CC
 438 greater than $0 \text{ m}^2 \text{ s}^{-2}$ to satisfy the upper-level cold low characteristic; (2) have a LOTKCC
 439 less than 0 to guarantee that the low-level is warm-cored; and (3) have a PMX200 (the
 440 maximum poleward 200 hPa wind speed within 1.0° GCD longitude) of greater than 30
 441 m s^{-1} (an effective minimum wind speed for identifying jet streams, see Koch et al. (2006))
 442 to increase the likelihood of the system being equatorward of the polar jet. Since PMX200
 443 might not be reliable in some regional models, alternatives to PMX200 thresholds used

444 in SyCLOPS are listed and explained in SI Text S4. We do not require EXs to be cold-
 445 cored since many Shapiro-Keyser EXs can be warm-cored due to the warm seclusion in
 446 their mature stage (Schultz & Keyser, 2021).

447 5 Criteria Optimization for High-impact LPS Detection

448 As discussed in section 4, the criteria for TCs, MSs (MDs and MLs), and TLCs all
 449 rely on parameter optimization. Since our optimization criteria are based on compar-
 450 ison to subjectively labeled LPS tracks, the parameter optimization procedure also la-
 451 bels LPS tracks by track conditions using the node count parameter (the count of nodes
 452 with a specific label within a track) to more stably define an LPS track. Considering that
 453 many datasets have a 6-hourly temporal resolution instead of three, the minimum node
 454 count we try in this section is 2. We optimize detection skills against different skill met-
 455 rics discussed below to find the best selected parameter combination upon satisfying con-
 456 ditions upstream of the workflow for each type of LPS. The selection of these parame-
 457 ters is primarily based on physical intuition and previous studies. In this section, we de-
 458 scribe the optimization procedure for these four classes of LPS.

459 5.1 TC Condition Optimization

460 The TC condition follows the cyclonic condition in the tropical branch. To iden-
 461 tify variables for the optimization procedure, we require CMSLCC (the greatest posi-
 462 tive closed contour delta of MSLP over a 2.0° GCD) to satisfy some minimum value and
 463 UPTKCC to satisfy some maximum value, since TCs are generally characterized by com-
 464 pact MSLP contours and deep warm cores. We choose a CMSLCC criterion over a max-
 465 imum wind speed criterion because the latter is much more sensitive to model resolu-
 466 tion and can be more easily distorted by complex topography. We also demand the node
 467 count of TC-labeled nodes within a track to have some minimum value to define a TC
 468 track. Evenly spaced values of these three parameters (over 3000 combination) are con-
 469 sidered to find the maximum detection skills.

470 A “test” TC dataset is constructed based on each possible 3-parameter combina-
 471 tion for the 1979-2021 period, and it is compared to the reference dataset IB-TC. A “hit”
 472 occurs if the test dataset is matched to a track in the reference dataset by appearing within
 473 2° GCD from a reference dataset data point at the same timestamp. A “miss” occurs
 474 if a track in the reference dataset does not have a match in the test dataset. A “false alarm”
 475 is a track found in the test dataset but are not matched to any tracks in the reference
 476 dataset. The TC detection skill metric used here is the hit rate (HR) minus false alarm
 477 rate (FAR), expressed as HRMFAR. HR is defined as the ratio of hits to the total num-
 478 ber of hits plus misses, and FAR is defined as the ratio of false alarms to the total num-
 479 ber of detected/selected tracks.

480 Figure 4a shows the detection skill of all chosen combinations of the CMSLCC and
 481 UPTKCC thresholds, with the optimal node count shown at the top of each combina-
 482 tion. The best detection criteria combination found is UPTKCC $< -107.8 \text{ m}^2 \text{ s}^{-2}$ (-11 m),
 483 CMSLCC $< 215 \text{ Pa}$ (although 210 Pa is also acceptable since it yields near-identical score),
 484 and TC-labeled node count > 8 with HRMFAR reaching 64%. More Details about the
 485 TC detection performance are discussed in 6. The CMSLCC and UPTKCC thresholds
 486 are used to support the TC condition, and the node step threshold specifies that there
 487 must be at least 8 time steps of TC-labeled nodes within a track for the track to be a
 488 TC track (the TC track condition).

489 5.2 MS Condition Optimization

490 For MS detection optimization under global detection and without seasonal con-
 491 straints, we demand criteria that could separate MSs from other weaker tropical LPSs,

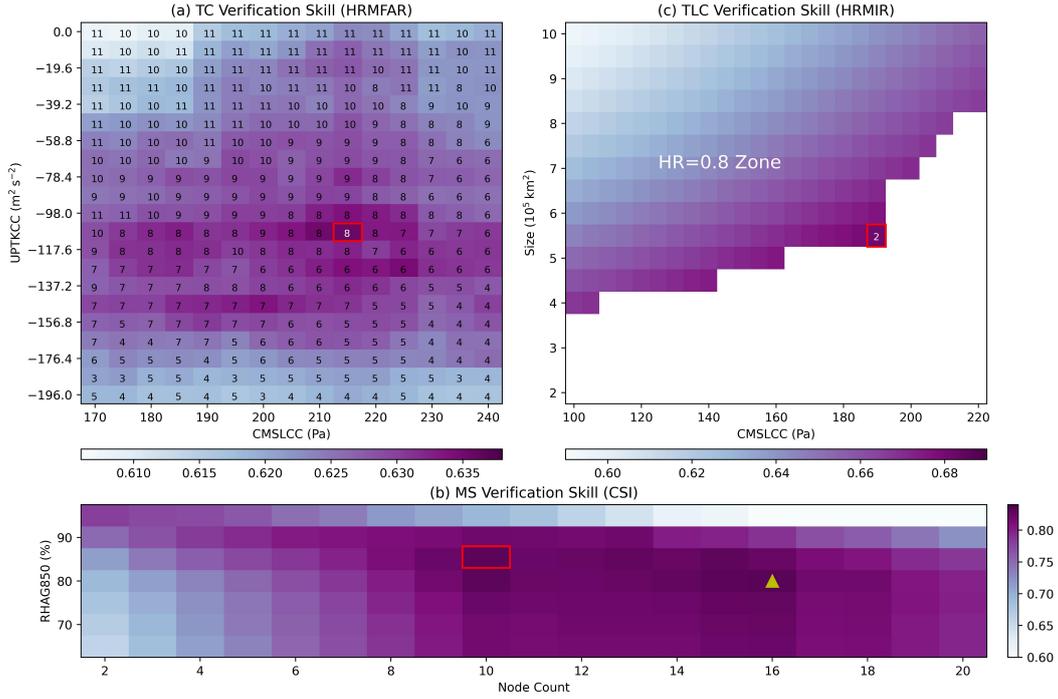


Figure 4. Detection skill optimization for (a) TC, (b) MS, and (c) TLC using different parameter threshold combinations and detection skills metrics shaded by their metric scores. The numbers in (a) and (c) represent the optimized time step for each combination (the optimal node count in (c) is uniform for every combination). The red rectangle in (a) and (b) indicate where the metric scores are maximized and consequently the final thresholds chosen. The metric score shading is only shown for the HR=0.8 zone in (b). In (c), the yellow triangle indicates the maximized score, and the red rectangle marks the final thresholds chosen.

492 such as EWs. MSs are considered to be born within monsoon troughs as opposed to the
 493 intertropical convergence zone (ITCZ) or upper-level easterly waves. According to NHC
 494 (n.d.)’s definition, monsoon troughs are characterized by their westerly flow south of the
 495 trough, compared to easterly trade winds on both sides of the ITCZ. Furthermore, on-
 496 sets of regional summer monsoons are often defined as a pattern of a change in wind speed
 497 and direction toward stronger westerlies (e.g., Qian & Lee, 2000; Gan et al., 2004). Thus,
 498 we develop the UDF850 parameter, which is the difference between the weighted area
 499 mean of the positive and negative values of 850 hPa U-component wind over a 5.5° GCD.
 500 This allows us to determine whether westerly winds (positive U-component wind mag-
 501 nitudes) or easterly winds (negative U-component wind magnitudes) dominate the lo-
 502 cal 850 hPa environment of a system. The plot of the UDF850 distribution for the MS
 503 and EW matched datasets shows that UDF850=0 m s⁻¹ effectively segregates the two
 504 clusters (see SI Fig. S3b). Hence, we select UDF850>0 as a minimal requirement for the
 505 MS condition.

506 As implied by the matched MS and EW datasets, MSs in the North Indian Ocean
 507 usually have a higher RHAG850 than North Atlantic EWs. This is not surprising, as mon-
 508 soonal regions are generally considered to have more convective activity and larger mois-
 509 ture transport. Given that Vishnu et al. (2020) also used parameters related to averaged
 510 850 hPa RH to exclude non-monsoon systems, we decide to include a minimum RHAG850
 511 threshold in the MS condition with the threshold undetermined. We compute the Crit-

512 ical Success Index (CSI) as defined below by Vishnu et al. (2020) of all the selected thresh-
 513 old combinations to find where CSI is maximal.

$$\text{CSI} = \frac{\text{hits}}{\text{hits} + (\text{misses} + \text{false alarms})/2} \quad (1)$$

514 A “hit” here is defined as a track in the test dataset having at least one node that
 515 is within 3.0° great-circle distance (GCD) of a track point in the Sikka dataset on the
 516 same date, and the track must also exist in the matched MS dataset. Since TCs are in-
 517 cluded in the Sikka dataset and are considered the most intense monsoon systems by the
 518 Indian Meteorological Department, tracks that already satisfy the TC track condition
 519 and are in the matched MS dataset are automatically considered matched (hits). We ap-
 520 ply the detection optimization over the same domain (the North Indian Ocean) and sea-
 521 son (June to September) as Vishnu et al. (2020), except that we incorporate the entire
 522 available data period rather than just a portion of it. The result shown in Fig. 4c sug-
 523 gests that the maximum CSI reaches 0.83 for RHAG850 = 80% and MS time step = 16.
 524 Our best CSI is thus identical to the value found in Vishnu et al. (2020), in support of
 525 the framework’s ability to detect weaker tropical systems. We finally choose the second
 526 highest CSI (also over 0.83) combination, RHAG850 = 85% and MS time step = 10, for
 527 the desired thresholds because we would like to include shorter MS tracks. Following these
 528 results, the MS condition is set as RHAG850 > 85% and UDF850 > 0 m s^{-1} . A node sat-
 529 isfying the MS condition as a MS (TD/TLO) node could be either “TD(MD)” if the TD
 530 condition is met at the same time, or “TLO(ML)” if the TD condition is not met. A track
 531 is considered to be a MS track only if it has 10 or more MS-labeled nodes. The MS track
 532 label highlights those weaker tropical LPS tracks that are more stably labeled as MSs,
 533 although they can also coincide with TC-labeled tracks per our standards. Complemen-
 534 tary to this, the “TLO” or “TD” label is given if an LPS fails the MS condition as a (non-
 535 MS) TD/TLO node. For global detection, weak tropical LPSs associated with EWs, among
 536 other types of tropical waves, are likely included in these two categories as well as in other
 537 dry or shallow systems/disturbances (i.e., DST and THL). One may make the assump-
 538 tion that weak (non-TCs) tropical (`Tropical_Flag=1`) non-MS LPS nodes in non-MS
 539 LPS tracks in some specific regions are (mainly) EWs.

540 5.3 TLC Condition Optimization

541 “Tropical-like” refers to LPSs that resemble “real” TCs in certain ways. For instance,
 542 a mature Mediterranean hurricane may have a distinct eyewall and a deep warm-core
 543 structure despite lower SSTs and greater baroclinity in a non-tropical environment (Pytharoulis
 544 et al., 2000). PLs (sometimes referred to as Arctic hurricanes) and Mediterranean hur-
 545 ricanes (STLCs), although still vaguely defined, may all be described as a group of mesoscale
 546 (small), intense, and short-lived (in terms of their TLC-stage lifespan) LPSs that can be
 547 classified as “tropical-like.” The most noticeable difference might be that polar lows are
 548 generally defined to develop north of the polar front or the main baroclinic zone in cold
 549 air masses (Moreno-Ibáñez et al., 2021), compared to STLCs emerging from the subtrop-
 550 ics. The term “hurricane-like extratropical cyclone” is also used in Romero & Emanuel
 551 (2017) to group Mediterranean hurricanes and North Atlantic PLs together. Here, we
 552 adopt a similar view that STLCs and PLs (which may be viewed as polar TLCs or PTLCs)
 553 are comparable to one another but different from the typical EXs/SCs and could be flagged
 554 under the same TLC condition. The conventional definition of PLs as being north of the
 555 polar front can then be used to distinguish between them. SyCLOPS offers a means for
 556 objective global identification of all TLC systems, which includes not only Mediterranean
 557 hurricanes and PLs but also the more intense subtropical/extratropical storms world-
 558 wide.

559 Similar parameters, such as CMSLCC and LOTKCC, are used to detect TLCs as
 560 we did to detect TCs. We expect TLCs to have, on average, a shallower/weaker warm-

561 core structure compared to TCs. Hence, we first impose a minimum requirement for the
 562 two warm core criteria ($\text{LOTKCC} < 0$ and $\text{MIDTKCC} < 0$). Static-stability or open-water
 563 criteria used in previous PL detection studies (Zappa et al., 2014; Stoll et al., 2018; Stoll,
 564 2022) are not considered here as they appear too restrictive to global TLC detection. For
 565 example, PLs may also appear closer to the baroclinic zone in a more sheared environ-
 566 ment (Montgomery & Farrell, 1992; Terpstra et al., 2016), and intense storm activity can
 567 often occur over Antarctic sea ice (Hepworth et al., 2022). The other significant distinc-
 568 tion between TLCs is their small or mesoscale sizes. Thus, we generate LPS size blobs
 569 and compute the `LOWSIZE` parameter conveniently using `TE`, as described in Appendix
 570 C, in addition to the parameters computed by `DetectNodes` to evaluate the extent of
 571 LPSs. `TE` commands with instructions and the Python script for calculating `LOWSIZE`
 572 are provided in SI text S6 and via Zenodo, respectively.

573 We use the combined matched STLC and PL dataset, which consist of 174 tracks,
 574 as our reference dataset for optimization. We concede that it’s difficult to evaluate or
 575 compare global TLC detection skills because TLCs’ records are limited and regional in
 576 scope, and their definition inexact. To overcome this, we first remove 12 tracks in the
 577 reference dataset that have a track-maximum `CMSLCC` lower than 215 Pa (the `CMSLCC`
 578 standard for TCs) to further avoid including tracks that are too weak to be considered
 579 TLCs. Second, we acknowledge that some TLCs could be embedded within a synoptic-
 580 scale circulation or trough in the background, sometimes with a twin low nearby (see SI
 581 Fig. S4 for an example) and thus will appear large (or be zero if embedded in a system
 582 with lower MSLP) using our size detection method. To work around this observation,
 583 we determine that LPSs that have a `CMSLCC` > 420 Pa (90% percentile of detected non-
 584 tropical non-shallow LPSs’ `CMSLCC`) and a `CMSLCC` to `MSLCC` ratio greater than 0.5
 585 (reflecting that a dominant and more compact LPS core exist within the larger system)
 586 are exempt from `LOWSIZE` requirements. Third, since the scope and quality of the refer-
 587 ence dataset is constrained, `FAR` becomes rather meaningless and is replaced by the
 588 infrequency rate (given that TLCs are infrequent), defined as the fraction of selected TLC
 589 tracks among all detected tracks that have at least one node that passes the cyclonic con-
 590 dition in the extratropical branch. Hence, the detection skills metric we use for the TLC
 591 condition is the `HR` minus infrequency rate (`IR`), or `HRMIR`. Here, `HR` is simply defined
 592 as the fraction of tracks that are detected (hits) in the reference dataset. Given the lim-
 593 ited sample size, `HR` is rounded to the nearest tenth (i.e., 0.750 and 0.849 will be rounded
 594 to 0.8) to roughly reflect its 90% confidence interval (`CI`) and potential sampling errors.

595 We iterate the selected range of `CMSLCC` and `LOWSIZE` threshold combinations
 596 for TLC condition optimization. The best `HR` attained is at the 0.8 level as shown by
 597 the shading in the upper left zone of Fig. 4b. Within this zone, the TLC condition is
 598 optimal when `IR` is the smallest (11.9%) at `CMSLCC` > 190 Pa and `LOWSIZE` $< 5.5 \times 10^5$
 599 km^2 (given that `LOWSIZE` is nonzero) on top of the other thresholds we mentioned above.
 600 The `LOWSIZE` threshold chosen here agrees with the meso- α scale range (i.e., roughly
 601 a 4-500 km LPS radius), which aligns with the upper size range of many studied TLCs
 602 (e.g., Holland et al., 1987; Rasmussen & Turner, 2003; Fita et al., 2007). Due to the short-
 603 lived nature of TLCs, `HRMIR` in all combinations maximizes when the node count equals
 604 two. LPS nodes that have been tagged as TLC will then be further classified as “PL(ETLC)”
 605 or “STLC(SS)” depending on whether they are located further north to the polar jet ($\text{PMX200} < 25$
 606 m s^{-1}). Tracks with two TLC-labeled nodes (PL or STLC) and at least one PL (STLC)-
 607 labeled node are then assigned PL (STLC) track labels. For an alternative test, we re-
 608 move the embedded TLC alternate condition and perform the optimization. The results
 609 show an identical `HR`, a slightly lower `IR`, and 72% overlapped detected TLC tracks when
 610 `CMSLCC` > 145 Pa and `LOWSIZE` $< 7.0 \times 10^5$ km^2 . Thus, it may be treated as an alter-
 611 native TLC condition, although it risks excluding many embedded TLC nodes.

6 Results and Applications

6.1 Main Results

In Fig. 5a, we plot the kernel density estimate (KDE) on the RH100-DPSH coordinate of all 6-hourly-sampled LPS nodes that have passed the second branch and meet the cyclonic condition, to verify the efficacy of our tropical and transition conditions. Our results demonstrate the validity of using RH100 and DPSH thresholds as the foundation for these conditions. The KDE clearly depicts two main clusters, separated by RH100 and DPSH. The solid-line and dash-line boundaries delineate the tropical and transition conditions. The RH100 transition threshold cuts through the narrowest part of the KDE. The cluster centered inside the tropical condition bounds is the tropical system cluster, while the cluster centered outside the box is the non-tropical system cluster, which is apparent from Fig. 5b, where the KDEs of the five matched datasets are placed on the RH100-DPSH coordinate. Within the tropical system cluster, the TC cluster spans the widest range as it includes LPSs undergoing EXT and at post-TC stage, whereas the MS and EW clusters have the highest and lowest mean RH100 values, respectively. Most of the matched tropical LPSs are within the transition boundaries (which may be deemed as the deep tropics). Inside the non-tropical system cluster, the STLC cluster has higher mean DPSH values than the PL cluster. The red filled contours in Fig. 5a depict the KDE of warm-core systems, defined as the previously selected LPS nodes that meet the criterion of $\text{UPTKCC} < -58.8 \text{ m}^2 \text{ s}^{-2}$ (-6 m). The KDE shows that warm-core systems can exist in both tropical and non-tropical clusters, and thus, the warm-core criteria may not be ideal for classifying LPSs across the spectrum. According to the classified catalog, the vast majority of the labeled tropical systems are confined within 40 degrees of the equator.

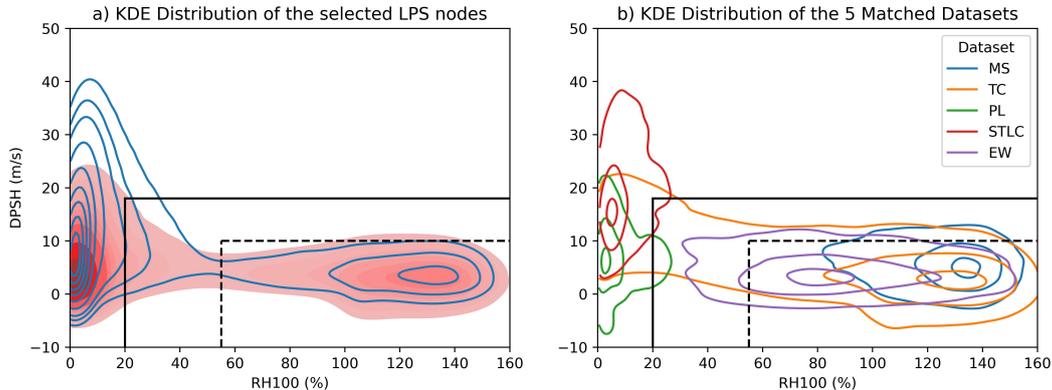


Figure 5. (a) The 10 KDE levels evenly distributed between 0 and 1 of all the selected detected LPS nodes (blue contours) and the warm-core LPS nodes (red filled contours); and (b) the 3 KDE levels set at 0.1, 0.5, and 0.9 of the five matched datasets on the RH100-DPSH coordinate.

SyCLOPS LPS labels are generally in good agreement with the labels in IBTrACS. Two types of labels are provided in IBTrACS: first, the WMO-assigned labels in the `NATURE` column, and second, the labels assigned by US meteorological agencies in the `USA_STATUS` column. The WMO labels are more general than the USA labels, as the USA labels include more classes based on LPSs' intensity. Miscellaneous labels that are vaguely defined and have a small sample size are not included in the comparison. Information about the two agencies' labels can be found on the IBTrACS website and in Landsea & Franklin (2013). Labels are compared when LPS nodes in our dataset and IBTrACS track points

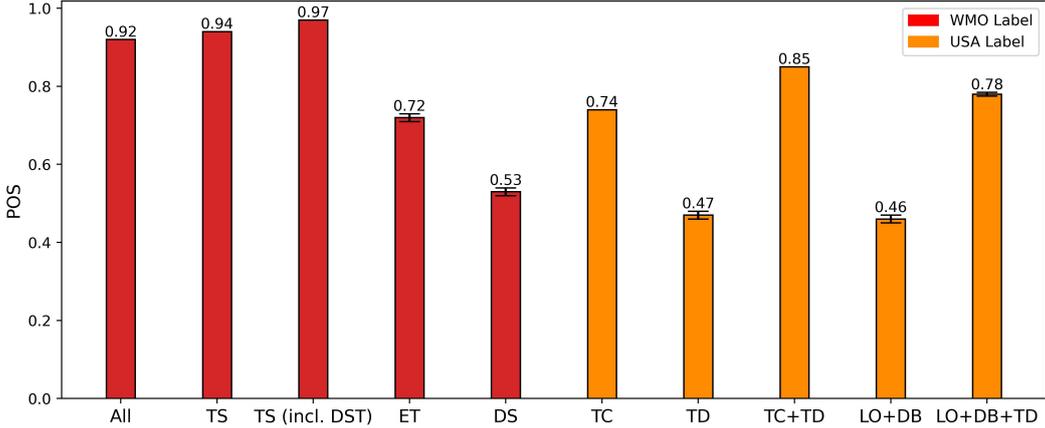


Figure 6. POS of our labels when compared to labels given by WMO (red bars) and USA agencies (blue bars). See text for details. POS values are shown on the top of bars with 95% confidence level error bars denoted.

lie within 2.0° GCD of each other at the same timestamp. 6 shows the probability of success (POS) for correctly labeling an LPS node of a particular class (setting IBTrACS labels as ground truth). Overall, 92% of the matched nodes are in agreement with the WMO labels, mainly contributed by the high “TS” POS of 94% (WMO’s “TS” label refers to “tropical system”). Since WMO’s “DS (disturbance)” label also exists, we regard “TS” as all non-shallow tropical systems, which is equivalent to all TC and TD/TLO labels in our labeling system. If all our labeled tropical LPSs are considered “TS”, the POS increases to 97%, suggesting that very few tropical systems are mistakenly labeled as non-tropical systems by our classification. The extratropical system (EX, SC, STLC, and PL) POS is at 72% when compared to the “ET (extratropical)” label of WMO. The majority of the extratropical records in IBTrACS are post-TCs immediately after EXT. Therefore, it suggests a rather small error in the EXT completion time justified by our classification when compared to IBTrACS. Breaking down the tropical systems, our TC POS remains at a relatively high level of 74% against TC labels given by USA agencies, while TD has a much lower POS of 47%. We find that TDs (TD and TD(MD)) are almost equally likely to be misclassified as TC and TLOs (TLO and TLO(ML)), which reflects ambiguity in their definitions and inevitable biases in LPS intensity evaluations by agencies, reanalysis, and our classification. If TDs are considered a category of TCs for both our labels and IBTrACS’s, the POS of “TC+TD” rises to 85%. The weakest system labels in IBTrACS, including LO (low) and DS/DB (disturbance), are more vaguely defined. They are often used at the start of TC tracks, and the labeled LPSs may not have a discernible surface center (Landsea & Franklin, 2013; NHC, n.d.). Hence, we treat them as the same label, which is equivalent to TLOs, DS (DST, DSD, and DSE), and THL (THL, DOTHL, and HATHL) in our labeling system. POS of about 50% is realized for this category compared to labels of WMO and USA agencies. Similarly, they are subject to biases in intensity evaluations and their exact definitions. If TDs are included in this class for both our labels and IBTrACS’s, the POS increases to 78%.

TC detection skill is improved using SyCLOPS when compared to the previous TE algorithm (Zarzycki & Ullrich, 2017, the ZU method;). For the ZU method, TC tracks are identified when nodes in a track that satisfy $UPTKCC < -58.8 \text{ m}^2 \text{ s}^{-2}$ (-6 m), $MSLCC > 200 \text{ Pa}$, WS (maximum wind speed at 10 m within 2.0° GCD) $> 10 \text{ m s}^{-1}$, and $ZS < 150 \text{ m}^2 \text{ s}^{-2}$ are detected for at least some certain time steps equatorward of 50° latitude. The HRMFAR of SyCLOPS is the same as the optimal HRMFAR mentioned in 5.1 after we re-

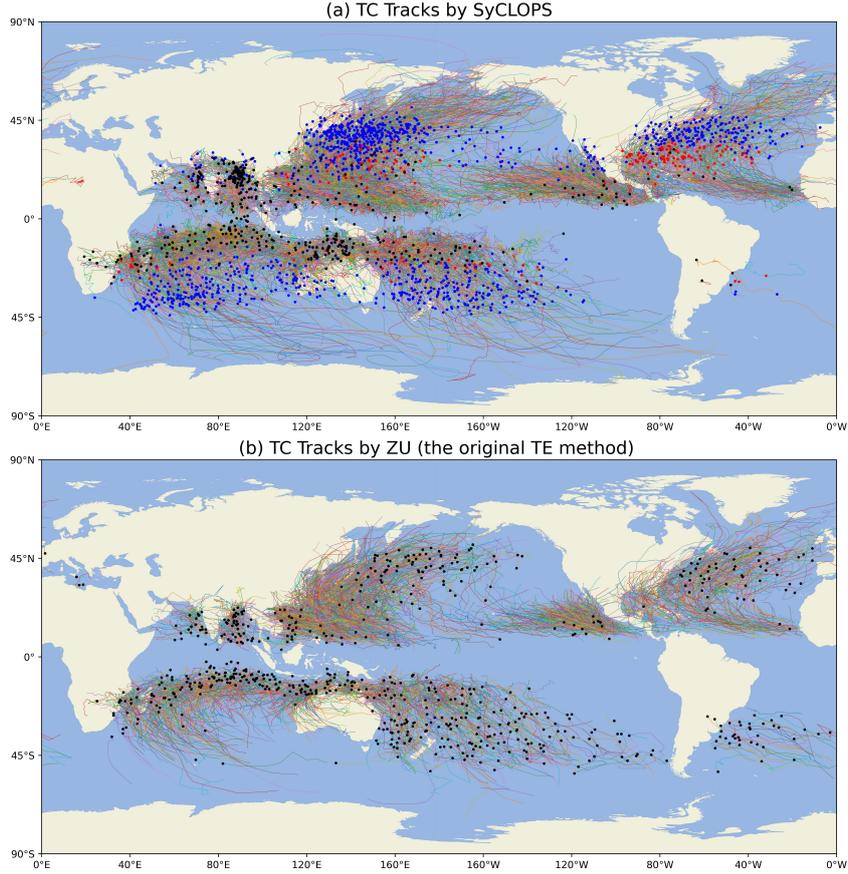


Figure 7. 1979-2021 TC tracks as tracked by (a) SyCLOPS, and (b) the ZU method. Black dots are the first locations of false alarm tracks. Blue and red dots are EXT and TT completion locations indicated by SyCLOPS. 1259 EXT cases and 195 TT cases are detected.

Table 1. Detection skill comparison between SyCLOPS and the ZU method

Method	HR	FAR	HRMFAR	Mean start time difference (hr)	Mean end time difference (hr)
ZU	76.2%	20.1%	56.1%	28	-30
SyCLOPS	78.2%	14.6%	63.6%	-49	30

677 sample the dataset at a 6-hourly frequency to match the frequency of ZU. The HRM-
 678 FAR of ZU is computed against the same IB-TC for the period of 1979-2021 using the
 679 same definition of hits and false alarms mentioned in 5.1. Table 1 summarizes the TC
 680 detection skill metrics of both methods. The mean start (end) time differences in the ta-
 681 ble refer to the time differences between the start (end) time of the detected TC track
 682 and the corresponding IB-TC track’s start (end) time. To summarize, the detection skill
 683 improvements are: (1) HRMFAR is increased by 7.5% due to a 5.5% decrease in FAR
 684 and a 2% increase in HR; and (2) the early detection of the pre-TC stage and late de-
 685 tection of the post-TC stage are significantly improved, extending TC track length by
 686 an average of 137 hours. The effects of these improvements are revealed in Fig. 7. Tracks
 687 detected using SyCLOPS are visibly longer at both ends (the pre-TC stage and the post-
 688 TC stage) compared to those tracked by ZU. Notably, the new approach more closely

689 matches IBTrACS observations in the South Atlantic and the Southeast Pacific, among
 690 other subtropical oceans, by largely reducing false alarms in those regions. We also notice
 691 that many official wind data in IBTrACS’s tracks are missing in earlier years in basins
 692 of the Indian Ocean (so they are not included in IB-TC) due to the fact that some agencies
 693 did not accept their regional responsibility until the early 1990s. Hence, many false
 694 alarms in the tropical Indian Ocean for both methods could actually be real TCs (hits).
 695 Discrepancies in wind measurement standards, observations, and operational procedures
 696 among agencies for different basins are also noted in Schreck et al. (2014), suggesting the
 697 presence of a “TC gray zone” due to these biases – i.e., a range of parameter values where
 698 different experts would draw different conclusions on the classification of a feature. Therefore,
 699 perfectly matching a subjective TC dataset is likely impossible. The blue and red
 700 dots show the EXT and TT completion positions of applicable TC tracks. 39% of the
 701 identified TC tracks undergo EXT, which is consistent with the global EXT fractions
 702 reported in Datt et al. (2022). The new method’s HRMFAR may be further elevated through
 703 post-processing operations such as eliminating QS tracks or marginal TC tracks that primarily
 704 reside in the transition zone. We advise being cautious when eliminating any marginal
 705 TCs since they can reside in the “TC gray zone.” As an example, the 2001 Australia “Duck”
 706 is a classic marginal (debatable) TC (see Garde et al., 2010). Although this storm was
 707 not recorded by the agency and it does not satisfy our TC track condition, it is labeled
 708 as “TC” at four timesteps under our classification. See SI Fig. S8 for a labeled track map
 709 of this special case.

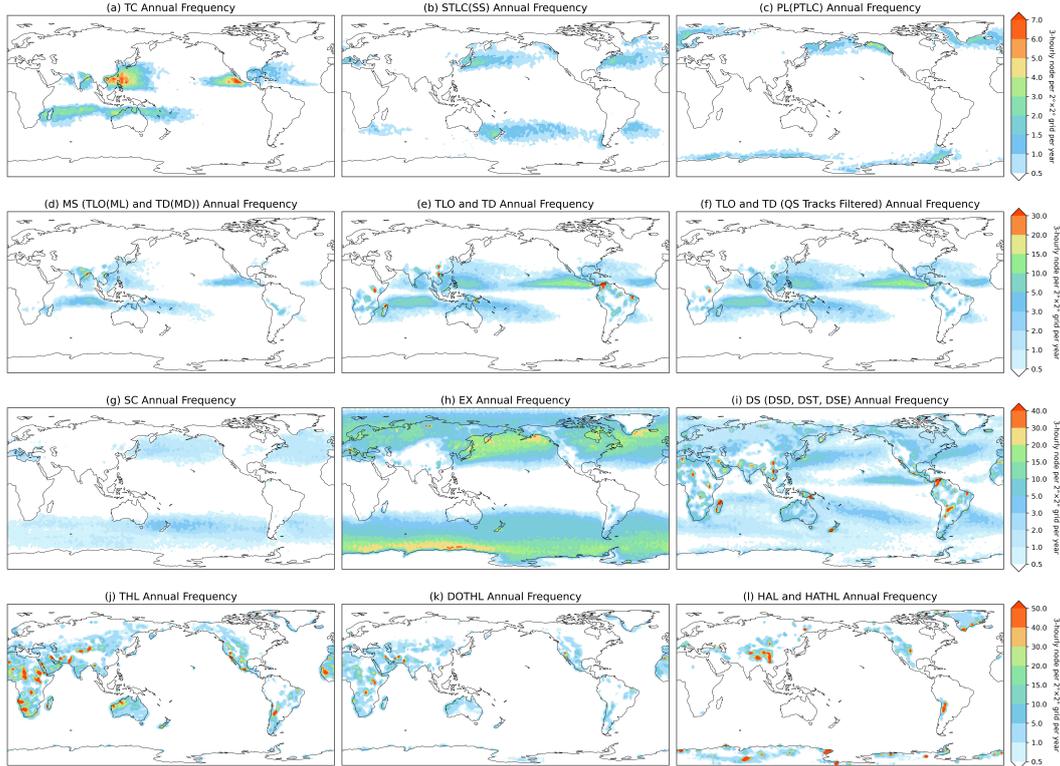


Figure 8. 1979–2022 annual frequency of (a) TC, (b) STLC(SS), (c) PL(PTLC), (d) MS (TLO(ML) and TD(MD)), (e) TLO and TD, (f) TLO and TD with QS track nodes filtered, (g) SC, (h) EX, (i) disturbances, (j) THL, (k) DOTHL, and (l) high-altitude LPS nodes per $2^\circ \times 2^\circ$ grid.

Major globally detected LPS annual frequencies for the different classes of LPSs are shown in Figure 8. In general, the frequencies of these systems are in accordance with observations. Please refer to SI Fig. S5 for a frequency bar plot of all LPS classes. The first row of Fig. 8 contains the least frequent LPS classes, followed by MS in the second row, which are all high-impact LPSs that can be considered extremes. TC frequencies are consistent with their track activity in the tropics and before EXT (Fig. 8a). In Fig. 8b, STLCs/SSs are more frequent in the Mediterranean Sea, the most studied hotspot for these features. They are also commonly found in the storm-track regions (the WNP and the northwestern Atlantic, as defined in Blackmon et al. (1977)), the southwest Atlantic, the southeast Pacific, the Japan Sea, and the Tasman Sea close to Southeast Australia. Those regions are all well known for their intense or tropical-like LPS activities, which include Australian east-coast cyclones, Chilean storms, Japanese south-coast explosive cyclones, TLCs/mesocyclones in the Sea of Japan and the Yellow Sea, and subtropical storms across the Atlantic (see e.g., Heo & Ha, 2008; Guishard et al., 2009; Iwao et al., 2012; Winckler et al., 2017; Gozzo et al., 2014; Shimada et al., 2014; Cavicchia et al., 2018). We expect that successful classification of STLCs is effective for reducing TC false alarms in our framework. PL activity reaches as far south as the Sea of Japan, and they are most prevalent in the Nordic Seas, the Gulf of Alaska, and over or near the sea ice of the Southern Ocean (Fig. 8c). Intense post-TCs are sometimes classified as TLCs, and removing them has only a minor impact on the frequencies of STLCs and PLs. MSs are mainly constrained in the tropical monsoon region defined in (J. Li & Zeng, 2003) and have two evident hotspots in the North Indian Ocean and near the Gulf of Tonkin in the South China Sea (Fig. 8d). Other TLOs and TDs are found throughout the tropics, with some overlap with MS activity and evidence of QS tracks shown by localized high frequencies mainly near rainforest regions (Fig. 8e). After filtering those QS tracks labeled by the QS track condition, strong LPS occurrences largely disappear, leaving other features mostly untouched. SCs are more widespread but less concentrated compared to STLCs (Fig. 8g). EX is the most common type of LPS labeled, and it is omnipresent outside of the tropics (Fig. 8h). Disturbances are found globally across latitudes, and THLs and DOTHLs are located primarily on arid lands. Finally, high-altitude LPSs occupy mountainous areas, including parts of the Antarctic continent.

We show the vertical cross section composites at the latitude of LPS's center for the six selected LPS classes in Figure 9. TCs feature a classic dumbbell-like structure resembling the shape of a cumulonimbus, as indicated by the two RH maxima at the lower- and the upper-level (Fig. 9a). Diabatic heating or latent heat release in TCs, as suggested by the cyclonic potential vorticity (CPV) contours, is evident throughout the lower-level and upper-level. The deep warm-core structure suggested by the potential temperature contours is most evident in the TC composite. Fig. 9b shows that a typical THL features a classic warm and dry low-level core, which is largely constrained to the boundary layer. As shown in Figures 9c and d, weaker tropical systems have far less developed convection and warm cores compared to TCs. MSs have comparatively higher RH at each level and a slightly more developed lower-level circulation than the other weaker tropical LPSs. An eastward tilt of the RH field below 300 hPa is noticeable in the non-MS weak tropical LPS (TD and TLO) composite in Fig. 9d. CPV contours stretching down from the subtropical tropopause in the STLC composite (Fig. 9e) imply that some STLCs undergo a downward development pathway, extracting CPV from upper-level PV anomalies or PV streamers, which agrees with the Mediterranean hurricane development mechanisms described in Flaounas et al. (2022). The warm core and the diabatic heating are more constrained to the lower level for PLs, as depicted in Fig. 9f. Despite the fact that both TCs and TLCs (STLCs and PLs) have relatively deeper warm cores, the upper-level RH of STLCs and PLs is significantly lower than that of TCs and other tropical systems. This distinction supports our choice of the RH100 criterion in the tropical condition.

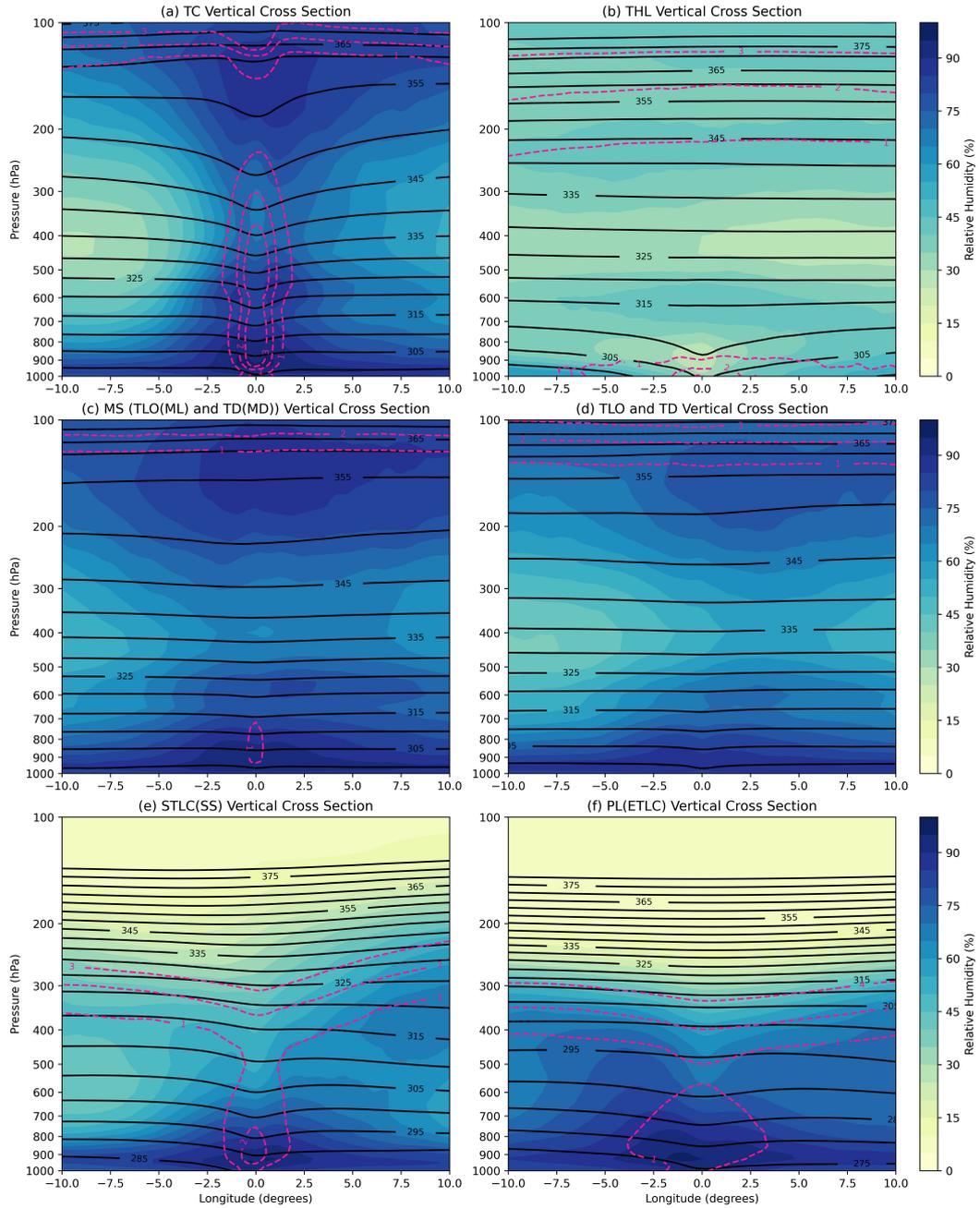


Figure 9. Vertical cross section composites of (a) TC, (b) THL, (c) MS (TLO(ML) and TLO(MD)), (d) TLO and TD, (e) STLC(SS), and (f) PL(PLTLC)-labeled LPS nodes. Dark pink dashed lines are contours of cyclonic potential vorticity (PVU), and black contours are potential temperature (K). The TC, MS, STLC, and PL composites are each based on 1000 randomly chosen nodes tagged with the specific type of label in the specific type of LPS track (i.e., 1000 TC-labeled nodes in TC-labeled tracks). The TLO/TD composite is based on 1000 randomly chosen nodes labeled “TLO” or “TD”, except for those in MS or QS tracks. The THL composite is based on 1000 randomly chosen THL-labeled nodes.

6.2 Other Applications

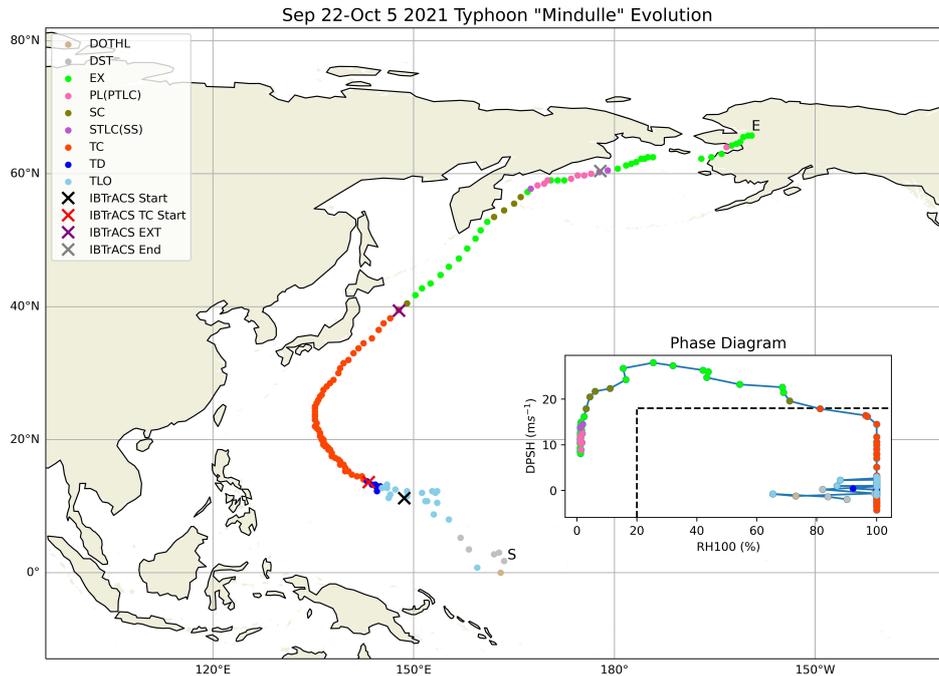


Figure 10. An example of different LPS labels in a TC (2021 Typhoon “Mindulle”) lifetime. The phase diagram shows its evolution on the RH100-DPSH coordinate with the tropical condition threshold outlined in dashed lines. We convert all instances of supersaturation of RH100 to 100% in the phase diagram. S and E indicates the start and the end of the track. The cross marks indicate the position of the start of IBTrACS record (black), the first IBTrACS TC record (red), IBTrACS EXT completion (purple), and the end of IBTrACS record (gray).

We now show some simple applications based on the classified catalog produced by SyCLOPS. One major benefit of SyCLOPS is that it can reveal a fairly complete history of each LPS track, so that the evolution of an LPS can be effectively traced. Thus, a useful application is showing a track along with its labeled nodes, such as the example in Figure 10. The example depicts the track history of the WNP typhoon Mindulle in 2021. Mindulle is first detected as a disturbance near the equator, then gradually intensifies as a non-MS TLO/TD before it becomes stably labeled as TCs. It completed its EXT around 40° N and later develops into a STLC and PL before dissipating as a EX in Alaska. The genesis time (the first TD label time), the first TC record time, and the EXT completion time are all within 12-hours of the corresponding IBTrACS records, while the record given by SyCLOPS further extends the IBTrACS track length. A phase diagram displayed by the DPSH-RH100 coordinate is attached to the figure. The phase evolution shows that the RH100 of the TC stays at a high level while the environmental wind shear gradually increases. The system’s RH100 decreases sharply during EXT, which is completed when the TC no longer satisfied the DPSH criteria from the tropical condition. In its final stage, the system enters a lower-sheared environment with very low RH100. More examples like this of different LPS classes (including North Atlantic hurricanes, the “Duck”, an MS, and TLCs) can be found in Figs. S7-9 in SI.

The labeled nodes can also be combined with the LPS size blobs we generated when computing LOWSIZE to derive the accumulated integrated kinetic energy (IKE; Powell & Reinhold, 2007) of targeted LPSs. SI Fig. S6 shows an illustration of the labeled

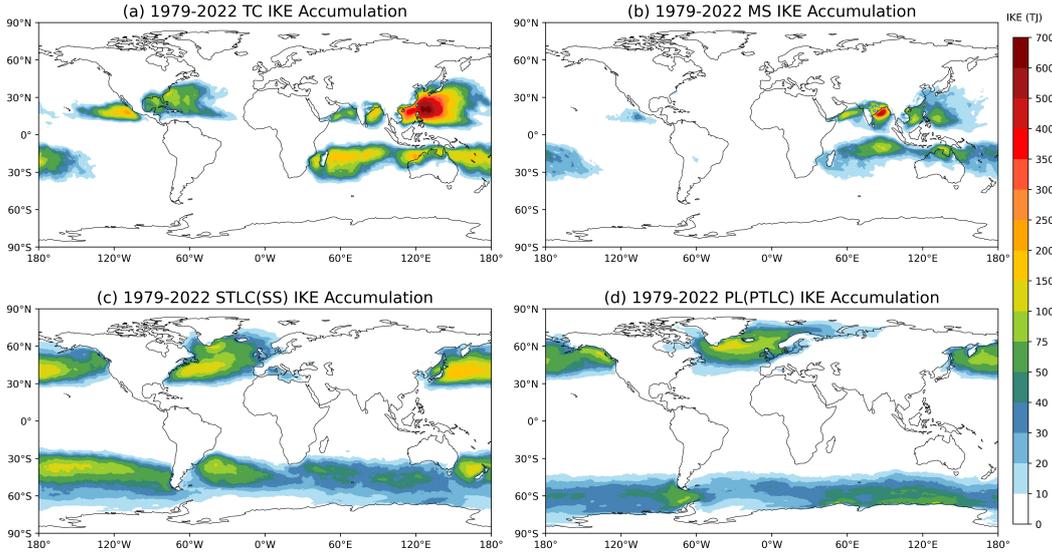


Figure 11. IKE of (a) TC, (b) MS, (c) STLC(SS), and (d) PL(PTLC) accumulated over the 1979-2022 period.

875 LPS size blobs. IKE is directly correlated with the potential destructiveness of LPSs,
 876 as it takes the size parameter into account. The IKE of an LPS is defined as the 1 m-
 877 deep mean kinetic energy at the surface level (here approximated by the 925 hPa level)
 878 within the LPS extent we define for LOWSIZE. Accumulated IKE of an LPS can be use-
 879 ful to study trends in LPS activity (Kreussler et al., 2021). In Figure 11, we show the
 880 accumulated IKE (in trillion joules, TJ) of the four types of high-impact LPS nodes from
 881 1979 to 2022. Specifically, we select blobs associated with TCs (TC nodes) in TC-labeled
 882 tracks, all (MS and non-MS) TDs and TLOs in MS-labeled tracks, STLCs in STLC-labeled
 883 tracks, and PLs in PL-labeled tracks are selected, respectively, for their IKE accumu-
 884 lations. The results indicate that TCs have the most widespread and severe wind impact
 885 over land, while the kinetic energy of MSs accumulates the most along the coast
 886 of the Bay of Bengal. STLCs are kinetically active in several hotspots globally. The in-
 887 fluence from their winds extends to places including the east coast of the United States,
 888 southeast Australia and New Zealand, southern Chile, northern Japan, and the Mediter-
 889 ranean coasts, among other. Besides the Antarctic region, PLs pose the greatest threats
 890 to the coasts of the Nordic Seas and the Gulf of Alaska. IKE’s spatial distribution pat-
 891 terns may appear different from the LPS frequencies because IKE is storm size-sensitive.
 892 For example, even though high TC frequencies are found concentrated in the Eastern
 893 Pacific basin (Fig. 8a), TC IKE is far more prominent in the WNP basin due to its largest
 894 mean observed TC size among all major basins (Chavas & Emanuel, 2010). Similarly,
 895 IKE for STLC in the Mediterranean Sea appear much smaller compared to other hotspots
 896 like the WNP and the northwest Atlantic, as TLCs in an open ocean basin can be rela-
 897 tively larger without topographic constraints. Those larger TLCs can possibly be em-
 898 bedded TLCs or “twin-cyclones” like the one shown in SI Fig. S4, and their existence
 899 is documented in many case studies in the two basins (e.g., Yamamoto, 2012; Fu et al.,
 900 2018; Yokoyama & Yamamoto, 2019).

911 Objectively tracked LPSs are often used in fractional precipitation contribution stud-
 912 ies to tease out the contribution of each LPS type to the total precipitation (e.g., Prat
 913 & Nelson, 2013; Prein et al., 2023). The outputs from our framework could be a good
 914 source for this purpose, as precipitation blobs can be derived and labeled in a similar man-
 915 ner as for the size blob. Blobs (areas) that satisfy the smoothed 850 hPa CRV thresh-

816 old ($CRV > 2 \times 10^{-5} \text{ s}^{-1}$) and a minimum 3-hourly total precipitation threshold of 0.3
 817 mm per 3 hours (0.1 mm hr^{-1}) are highlighted as LPS-associated precipitation and tagged
 818 with LPS labels (see SI Fig. S6). We consider this dynamic precipitation detection method
 819 more flexible than a fixed or uniform radius method that was often implemented in pre-
 820 vious studies (e.g., Dare et al., 2012; Stansfield et al., 2020). We select each class of high-
 821 impact LPS nodes and their associated precipitation blobs in the same way as we do for
 822 IKE. We demonstrate the fractional contribution of precipitation from the four types of
 823 high-impact LPS nodes in Figure 12. The results suggest that TCs contribute over 40%
 824 of total precipitation along the coasts of northwestern Australia and south of Baja Cal-
 825 ifornia. MSs are responsible for a larger fraction of total precipitation than TCs through-
 826 out South Asia and inland China. STLCs make up about 5% of total precipitation along
 827 the coastal region of the Mediterranean Sea and about 6-7% near northern Japan and
 828 the coasts along the Japan Sea. PLs are responsible for several percent of total precip-
 829 itation in the United Kingdom, northern Europe, and along the coast of Alaska. Since
 830 TLCs are active in the winter season, one may expect heavy snowfall as the form of their
 831 precipitation.

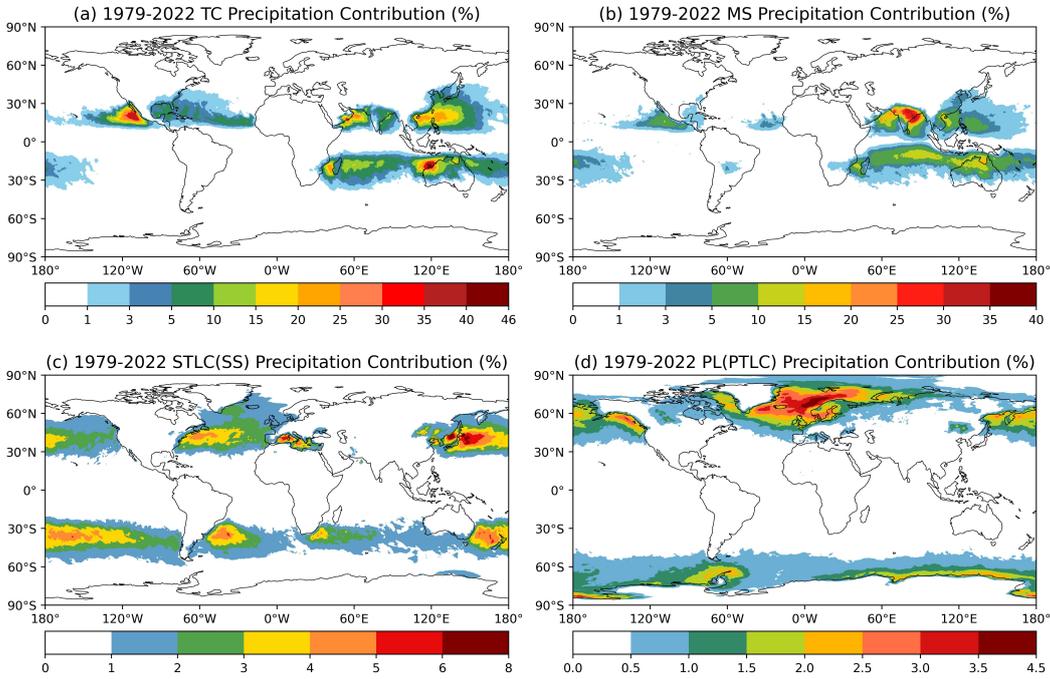


Figure 12. Fractional precipitation contributions from (a) TC, (b) MS, (c) STLC(SS), and (d) PL(PTLC) for the 1979-2022 period.

7 Final Remarks

832
 833 In this study, we propose an all-in-one detection and classification framework that
 834 combines multiple sole-purpose LPS detectors which we refer to as the System for Clas-
 835 sification of Low-Pressure Systems (SyCLoPS). SyCLoPS is developed atop the Tem-
 836 pestExtremes software package. It is tuned and subsequently applied to the ERA5 re-
 837 analysis. To the authors' best knowledge, this work represents the first attempt to clas-
 838 sify all LPSs in a single global dataset. Because a single intuitive workflow is employed,
 839 no LPS node is repeated or doubly classified. No topographical, latitudinal, or tempo-
 840 ral restrictions need to be applied in order to use this framework, and the detection thresh-

old is low enough to include very weak LPS nodes in the detected LPS tracks. As a result, a much more complete LPS lifecycle can be obtained for each LPS track, and its phase evolution can be traced using the labeled nodes. Our results show that the unified framework improves upon previous TC detection skill in TE by both increasing HR and lowering FAR. Detection skill for MSs is comparable to the previous study. SyCLOPS also features the first global TLC system detection. Upon comparing the labels given SyCLOPS to corresponding IBTrACS labels, we observe that SyCLOPS can reasonably label the LPS status in different stages of a TC. We also demonstrate that the resulting classified catalog can be used to study the annual frequencies, vertical cross section composites, track evolution, IKE accumulation, and fractional precipitation contribution of each LPS class. These potential applications could be valuable if applied to climate model outputs to investigate the effects of climate change. SyCLOPS may also be applicable in real-time operations and weather model outputs.

With the classified catalog, the parameter outputs, and the provided software codes, users may personalize the framework to meet their own needs. For example, the detection procedure for a single type of LPS in a given dataset can be easily isolated following a single path from the workflow. More LPS sub-classes may be derived from the provided data and the detection of other atmospheric features. For example, weaker tropical LPSs may be separated into different classes by matching them to distinct tropical wave systems, and polar lows may be divided into those that develop in a front-shear environment versus a reverse-shear environment. Users may also modify the TE specifications and classification conditions to optimize detection under alternate definitions of some LPS classes.

There are some limitations in SyCLOPS worth noting. Firstly, we have only applied SyCLOPS to the global ERA5 dataset, so the thresholds and parameter choices could be biased if applied directly to another global or regional dataset. While we have proposed some suggestions that would enable SyCLOPS’s adaptation to different datasets, more fine-tuning in the detection and classification processes may be required. It should also be noted that a dataset with a resolution coarser than ERA5 may be insufficient for detection and classification of smaller features such as early-stage TCs and TLCs. Second, although SyCLOPS features detection and classification of LPSs over any terrain, signals in MSLP or any low-level atmospheric fields can be distorted by elevated topography. Detection over or near those regions are subject to greater errors especially for weak systems. Third, ultimately, the hard cut-off threshold we impose between LPS phases is somewhat arbitrary: namely, there is always a gray zone or transition zone when it comes to the thresholds for a given LPS. Nonetheless, objective LPS detection and classification reduces biases introduced by human error and subjectivity because an objective standard can be strictly followed. However, by nature an LPS can exist in an “impure” and somewhat ambiguous state, which is contrary to fixed thresholds. This conflict is most obvious when a detected LPS persists at the edge of our defined thresholds, leading to its classification jumping between two labels. And lastly, confidence in detecting and classifying global TLC systems is still low due to a lack of global observations. The method for calculating LPS size in TE as described in Appendix C for classifying TLCs can be further improved to more accurately represent the size of a smaller TLC in a larger circulation or the background flow. We expect that there will be other deficiencies discovered and questions raised in the practical use of this experimental framework. Hence, we aim to address some of these remaining issues and evolve the algorithms for future versions of this framework.

Appendix A Catalog Column Documentation

Table A1 is the column documentation of the input (the upper portion) and the classified (the lower portion) LPS catalogs of SyCLOPS. Repeated column names for the classified catalog are skipped.

Table A1. Column Documentation

Column	Unit	Description
TID	-	LPS track ID (0-based) of the input and the output catalog
ISOTIME	-	The UTC timestamp (datetime) of the node
LAT	°	Latitude of the LPS in both the input and the output catalog
LON	°	Longitude of the LPS in both the input and the output catalog
MSLP	Pa	Minimum mean sea level pressure of the system
CMSLCC	Pa	Greatest positive closed contour delta of MSLP over a 2.0° GCD (the core of an LPS)
MSLCC	Pa	Greatest positive closed contour delta of MSLP over a 5.5° GCD
DPSH	m s ⁻¹	Mean deep-layer wind speed shear between 200 hPa and 850 hPa over a 10.0° GCD
UPTKCC	m ² s ⁻²	Greatest negative closed contour delta of the upper-level thickness between 300 hPa and 500 hPa over a 6.5° GCD, referenced to the minimum value within 1.0° GCD
MIDTKCC	m ² s ⁻²	Greatest negative closed contour delta of the middle-level thickness between 500 hPa and 700 hPa over a 3.5° GCD, referenced to the minimum value within 1.0° GCD
LOTKCC ^a	m ² s ⁻²	Greatest negative closed contour delta of the lower-level thickness between 700 hPa and 925 hPa over a 3.5° GCD, referenced to the minimum value within 1.0° GCD
Z500CC	m ² s ⁻²	Greatest positive closed contour delta of geopotential at 500 hPa over a 3.5° GCD referenced to the minimum value within 1.0° GCD
VOR500	s ⁻¹	Mean relative vorticity over a 2.5° GCD
RH100	%	Maximum relative humidity at 100 hPa within 2.5° GCD
RHAG850	%	Mean relative humidity over a 2.5° GCD at 850 hPa
T850	K	Air temperature at 850 hPa at the node
Z850	m ² s ⁻²	Geopotential at 850 hPa at the node
ZS	m ² s ⁻²	Geopotential at the surface at the node
UDF850	m s ⁻¹ sr	Difference between the weighted area mean of positive and negative values of 850 hPa U-component wind over a 5.5° GCD
PMX200	m s ⁻¹	Maximum poleward value of 200 hPa wind speed within 1.0° GCD longitude
LOWSIZE	km ²	The adjusted defined size of the LPS at the current time step
WS	m s ⁻¹	Maximum wind speed at the 10-m level within 2.0° GCD
Short_Label	-	The abbreviation of the Full_Label
Full_Label	-	The full label name of the LPS based on the classification
Tropical_Flag	-	1 if the LPS is designated as a tropical system, otherwise 0
Transition_Zone	-	1 if the LPS is in the defined transition zone, otherwise 0
Track_Info	-	“TC”, “MS”, “STLC”, “PL”, “QS” denoted for TC, MS, STLC, PL, and QS tracks; “EXT”, “TT” denoted for EXT and TT completion node
RAWSIZE	km ²	The raw defined size of the LPS at the current time step
IKE	TJ	The integrated kinetic energy computed based on RAW-SIZE’s extent (LPS size blob)

^a 925 hPa may be replaced by 850 hPa if data at this level is scattered in some datasets.

Appendix B Condition List**Table B1.** Classification Conditions

Condition Name	Conditions
High-altitude Condition ^a	Z850<ZS
Dryness Condition	RHAG850<60%
Cyclonic Condition	VOR500 ≥ 0 s ⁻¹ if LAT $\geq 0^\circ$; VOR500<0 s ⁻¹ if LAT<0°
Tropical Condition	RH100>20%; DPSH<18 m s ⁻¹ ; T850>280 K
Transition Condition	Tropical Conditon=True; DPSH>10 m s ⁻¹ or RH100<50%
TC Condition	CMSLCC>215 Pa; LOTKCC<0 m ² s ⁻² ; UPTKCC<-147 m ² s ⁻²
TD Condition	MSLCC>160 Pa; UPTKCC<0 m ² s ⁻²
MS Condition	UDF850>0 m s ⁻¹ ; RHAG850>85%
TLC Condition ^b	CMSLCC>190 Pa; MIDTKCC<0 m ² s ⁻² ; LOTKCC<0 m ² s ⁻² ; (LOWSIZE<5.5 × 10 ⁵ km ² ; LOWSIZE>0 km ²) or (CMSLCC>420 Pa; CMSLCC/MSLCC>0.5)
SC Condition	LOTKCC<0 m ² s ⁻² ; Z500CC>0 m ² s ⁻² ; PMX200 ^c >30 m s ⁻¹
TC Track Condition	At least 8 TC-labeled nodes in an LPS track
MS Track Condition	At least 10 TLO(ML) or TD(MD)-labeled nodes in an LPS track
STLC Track Condition	At least 2 TLC-labeled nodes (STLC(SS) or PL(PTLC)) and 1 STLC-labeled node in an LPS track
PL Track Condition	At least 2 TLC-labeled nodes (STLC(SS) or PL(PTLC)) and 1 PL-labeled node in an LPS track
QS Track Condition	See SI text S3 for details

^a It can be simply checking Z850 data availability (null or not) in some datasets.

^b See Sec. 5.3 for a potential alternative.

^c PMX200 thresholds used in this framework may be supplemented by other parameters in some regional models. See SI Text S4 for details.

Appendix C LOWSIZE Computation

To calculate LPS size, we refer to the definition of TC size which is typically determined by a TC's outer surface wind radius. We first use TE's `DetectBlobs` to detect blobs (areas) of smoothed 850 hPa cyclonic relative vorticity (CRV) $> 2 \times 10^{-5} \text{ s}^{-1}$ and 925 hPa wind speed $> 12 \text{ m s}^{-1}$. An alternative condition to this detection requirement is CRV $> 4 \times 10^{-5} \text{ s}^{-1}$ so that TC eyes and EXs' central weaker wind areas can be captured. Wind speed from 925 hPa is used for this calculation, for it is a commonly found lower model level above the surface level. Surface level winds are not used since they can be greatly distorted by complex topography. The 12 m s^{-1} threshold is obtained using a log wind profile from the 8 or 9 m s⁻¹ surface outer wind speed threshold often found in TC-size-related studies using ERA5 or climate models(e.g., Stansfield et al., 2020; Bian et al., 2021). The smoothed CRV field is used to control the boundary of an LPS so that the outer wind fields are less likely to connect with an unrelated system nearby. Each detected size blob is then assigned to a detected LPS node if the node is within 5° GCD of the centroid of the blob at the same timestamp, or otherwise within the region bounded by the minimum/maximum latitude/longitude (extent) of the blob. Information on the centroid, extent, and size of each blob can be directly output by TE's `BlobStats`. If multiple nodes are found for one blob, the blob is assigned to the node with the lowest MSLP. Next, the sizes of all the blobs paired with each node are added together as raw LPS sizes. For a quick comparison, the sizes of 2010-2021 WNP TCs computed by our method and the sizes given by the Japan Meteorological Agency (JMA) in IBTrACS have a reasonably high correlation coefficient of 0.63, with very high statistical significance. To avoid misclassifying EXs/SCs as TLCs near shorelines with elevated topography, we adjust the

917 raw LPS size if the LPS is close to those shorelines with its wind field largely affected
 918 by topography. Specifically, we multiply the raw LPS size by two if only 30 to 70% of
 919 surface geopotential within 5° GCD of an LPS is smaller than $7000 \text{ m}^2 \text{ s}^{-2}$ (approx-
 920 imately the 925 hPa level). This adjusted LPS size is defined as LOWSIZE. The non-adjusted
 921 (raw) LPS size computed by this method is included as the RAWSIZE column in the clas-
 922 sified catalog.

923 Open Research

924 The latest version (version 2.2.2) of TempestExtremes (TE) can be installed from
 925 <https://github.com/ClimateGlobalChange/tempestextremes> (Ullrich, 2024). The
 926 input and the classified catalog created in this study, the shell script for required TE com-
 927 mands, the Python Classifier, the Python script for calculating LOWSIZE, and other
 928 useful information about this new framework are all available via the Zenodo repository
 929 at <https://doi.org/10.5281/zenodo.10906285>. The ERA5 dataset was obtained from
 930 the Research Data Archive at the National Center for Atmospheric Research ([https://](https://doi.org/10.5065/BH6N-5N20)
 931 doi.org/10.5065/BH6N-5N20). The IBTrACS archive can be retrieved from [https://](https://www.ncei.noaa.gov/products/international-best-track-archive)
 932 www.ncei.noaa.gov/products/international-best-track-archive. The STARS pol-
 933 ar low list (Noer et al., 2011) is available at: [https://projects.met.no/polarlow/](https://projects.met.no/polarlow/stars-dat)
 934 [stars-dat](https://projects.met.no/polarlow/stars-dat). The following two websites were used to evaluate the status of tracked Mediter-
 935 ranean cyclones: https://meteorologia.uib.eu/medicanes/medicanes_list.html
 936 maintained by the meteorology group of the University of the Balearic Islands and [http://](http://medicanes.altervista.org)
 937 medicanes.altervista.org run by Daniele Bianchino. The objectively tracked east-
 938 erly wave dataset is downloaded from <https://doi.org/10.17605/OSF.IO/J4HPQ> pub-
 939 lished by Q. A. Lawton et al. (2022).

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