Global co-occurring features and their contributions to total and extreme precipitation

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Overview

U.S. DEPARTMENT OF ENERGY **Regional & Global Model Analysis**

Precipitation remains among the most challenging variables for weather and climate models to simulate accurately, but is of crucial importance for societal impacts. This project builds on activities of an ad hoc DOE working group pursuing exploratory diagnostics and metrics to inform the improvement of these models. Coordinated projects led by UCLA and IU aim to bridge the gap between phenomenon-based diagnostics—involving the identification of features associated with weather phenomena including low pressure systems (LPS), mesoscale convective systems (MCS), frontal systems, and atmospheric rivers (AR)—and other leading diagnostic approaches: (1) spatiotemporal statistics of precipitation; (2) process-oriented diagnostics for the coupling of precipitation to its large-scale environment.

Task I	Task II	Task III
Create a standardized framework to provide atmospheric feature information by first identifying LPS, MCS, frontal systems, and ARs in observation/ reanalysis and then extend it for climate model output	Evaluate the contributions by different phenomena to total precipitation and contributions to the probability distributions of precipitation, both in current climate and future changes	Create process-oriented diagnostics for the relation of feature statistics to hypothesized leading factors in the large-scale thermodynamic and dynamic environment.

This project addresses the RGMA Topic Water cycle and Associated Extremes with respect to the influence the large-scale environment on extreme events, interactions between convective scales and the large-scale circulation, including environmental influence on mesoscale organization, and process-level identification of sources of uncertainty and feedbacks to help reduce biases in global model projections. It will expand the sustainable software capabilities of CMEC both in terms of standards and of hypothesis- driven process diagnostics.

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1. Coordinated identification of leading feature types and associated precipitation

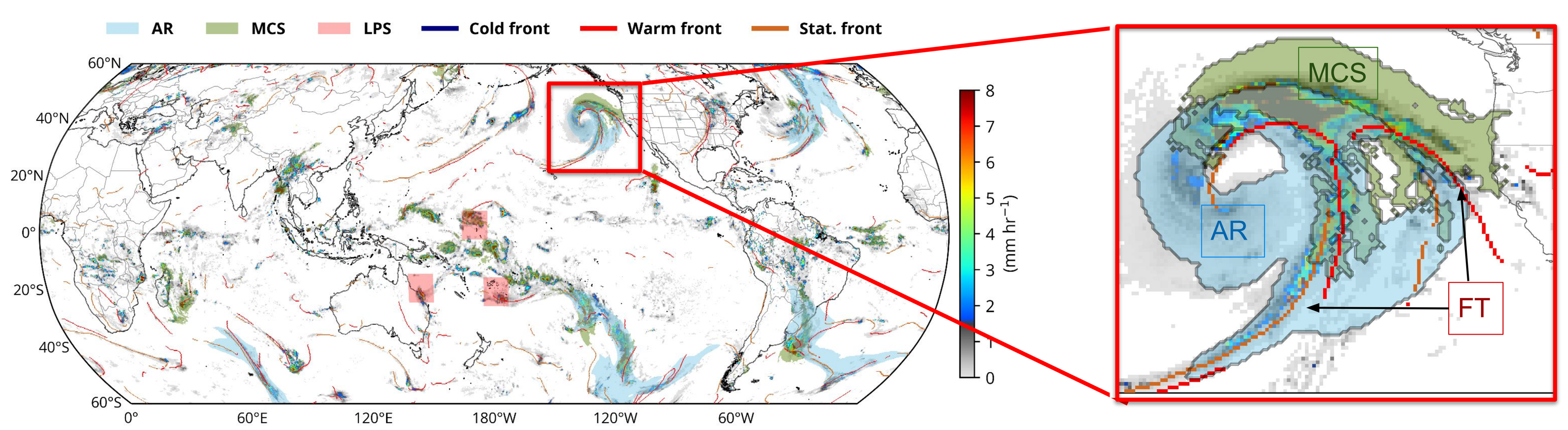

Figure. Global map of GPM-IMERG precipitation and identified features including atmospheric river (blue shading), front (contours), low-pressure system (red shading), and mesoscale convective system (green shading). The time is at 00Z January 8th, 2019. One synoptic-scale weather phenomenon- extratropical storm is highlighted that showsloi, clear feature co-occurrence (red box; subset). In many cases, feature co-occurrence is inherent to the phenomenon e.g. winds and water vapor increases associated with frontal baroclinic gradients And uplift associated with atmospheric River. Assignment precipitation according to individual algorithms and then evaluate co-occurrence.

❑ **A 19-year (2001-2019) integrated dataset of tracked features using reanalysis and satellite observations**

❑ ERA5 reanalysis (0.25-deg., hourly)
- **Atmospheric river (AR)** (**TECA-BARD**; O'Brien et al., 2020)
- **Front (FT)** (Catto et al., 2013; Sansom and Catto, 2022)
- **Tropical low-pressure system (LPS, 35S-35N)** (**TempestExtremes**; Ullrich and Zarzycki, 2017; Vishnu et al. 2020)

❑ GPM-IMERG + MERGE-IR (0.1-deg., hourly)
- **Mesoscale convective system (MCS)** (**FLEXTRKR**; Feng et al., 2021)

Table 1. Descriptions of selected features identified by individual algorithms and the post-defined features.

Feature catalogs	Acronym	Data	Variable	Object type	Algorithm
Atmospheric river	AR	ERA5	Vertically integrated vapor transport (IVT)	Connected grids	Toolkit for Extreme Climate Analysis - Bayesian AR Detector (TECA-BARD)
Front	FT	ERA5	wet-bulb potential temperature field at 850 hPa horizontal winds at 850 hPa	Grids projected by line segments	Sansom and Catto (2022)
Low-pressure system	LPS	ERA5	Stream function of horizontal winds at 850 hPa	Single grid	TempestExtreme
Mesoscale convective system	MCS	GPM-IMERG / MERGE-IR	Brightness temperature (T_b) & precipitation rate (P)	Connected grids	FLEXible object TRaKeR (FLEXTRKR)
Non-feature catalogs					
Deep convection	DC	GPM-IMERG / MERGE-IR	T_b < CC threshold, P ≥ 0.5 mm hr^{-1}	Single grid	-
Non-deep convection	ND	GPM-IMERG / MERGE-IR	T_b ≥ CC threshold, P ≥ 0.5 mm hr^{-1}	Single grid	-
Stratiform clouds	ST	GPM-IMERG / MERGE-IR	T_b < CC threshold, P < 0.5 mm hr^{-1}	Single grid	-
Drizzle	DZ	GPM-IMERG / MERGE-IR	T_b ≥ CC threshold, P < 0.5 mm hr^{-1}	Single grid	-

2. Frequency of identified leading feature types and their co-occurrences

❑ Frequency of individual atmospheric features

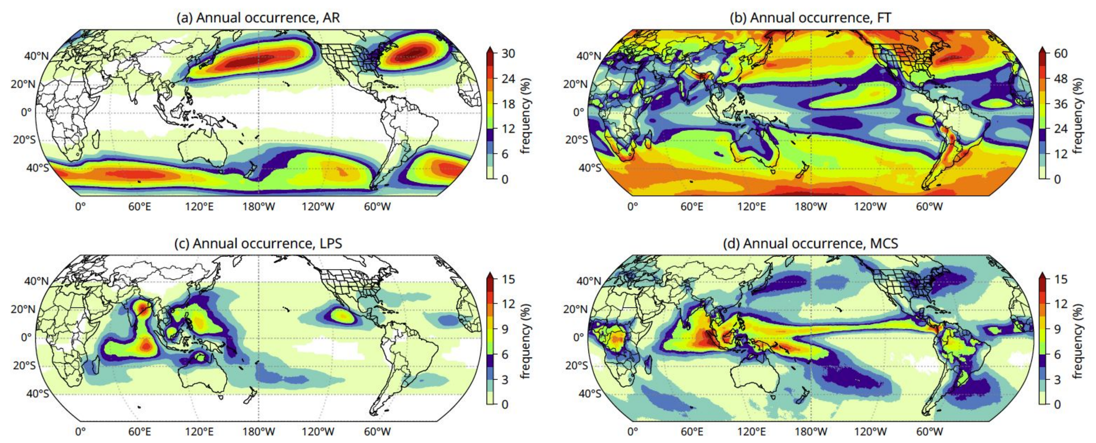

Figure. Mean annual frequency of four algorithm-identified features: (a) Atmospheric rivers (AR), (b) fronts (FT), (c) low-pressure systems (LPS), and (d) mesoscale convective systems (MCS). The annual frequency is defined as the ratio of counts in the feature mask to the total time steps in a year for 6-hourly data.

❑ Fraction of rainy times associated with feature co-occurrences: AR and FT are highly co-occurring

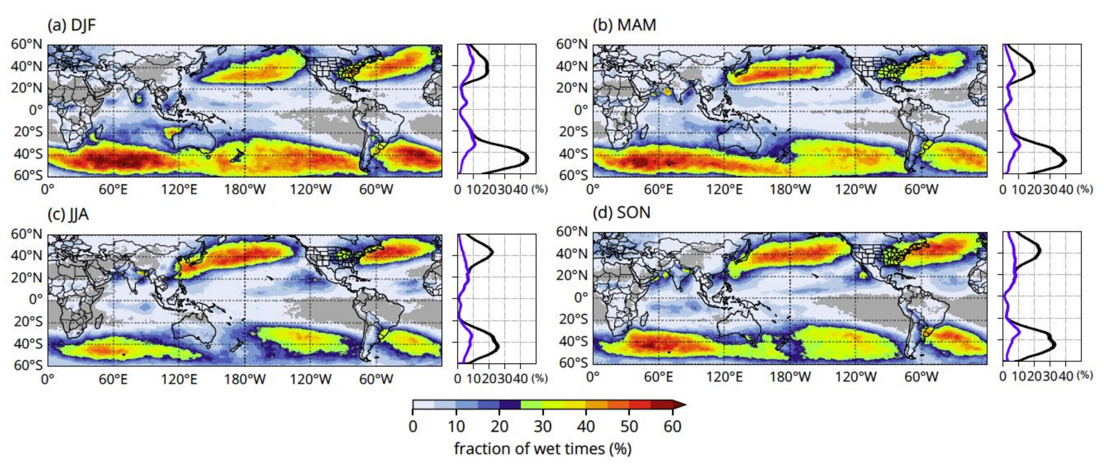

Figure. The fraction of seasonal wet times associated with feature co-occurrences for (a) DJF, (b) MAM, (c) JJA, and (d) SON. A wet time is defined when the GPM-IMERG precipitation rate is greater than 0 (mm hr^{-1}). The gray shading shows areas of no co-occurrence (fraction = 0). The right subset in each panel shows the zonal mean of the fraction (black) and the result from a sensitivity analysis merging AR and FT as one category (blue).

3. Generating global precipitation feature identifiers

❑ Co-occurrence and extreme precipitation of severe synoptic phenomena

Interpretations: → interactions/collective effects of different features lead to strong responses in rainfall
or → Individual trackers focusing on a particular criterion identify different parts of a single phenomenon

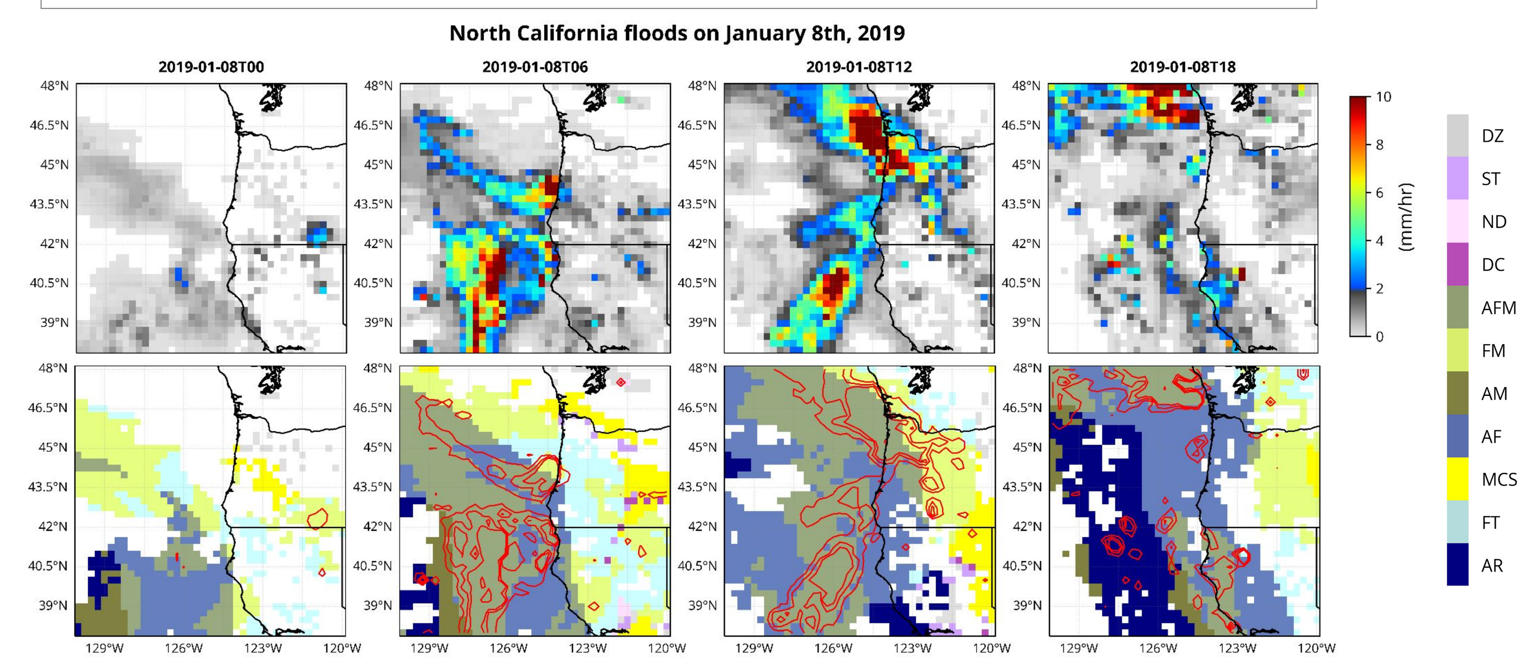

Figure. Time evolution of GPM-IMERG precipitation (top row) and corresponding precipitation feature identifiers (PFIDs, bottom row) during a severe weather phenomenon on January 8th over California and Pacific Northwest. (Bottom row) PFIDs of co-occurring features. Red contours indicates GPM precipitation rates of 2, 4, and 6 (mm/hr).

Precipitation feature identifiers (PFIDs)
- precipitating pixels > unique ID for single or co-occurring features
- e.g., Front = FT, AF = AR-Front, FM = Front-MCS,, AR-Front-MCS = AFM
- "non-feature" categories (precip. not claimed by any features): deep convection (DC), non-deep convection (ND), stratiform (ST), and drizzle (DZ). (Tb & P thresholds)
- quantitatively unpacking precipitation under a complex phenomenon

Global precipitation feature identifiers (available soon)	Feature-environment catalogues (in progress)
Tsai, Wei-Ming et al. (Forthcoming 2024). Precipitation identifiers for meteorological features combining global GPM-IMERG retrievals and ERA5 reanalysis [Dataset]. Dryad. https://doi.org/10.5061/dryad.v9s4mw73g	- define and create catalogues for environment variables, most appropriate for process-level studies of each feature

4. Analysis of precipitation contributions and rainfall intensity

Rainfall contributions from the leading features and their co-occurrences to total/extreme precipitation

❑ Total rainfall ❑ R95 extreme rainfall

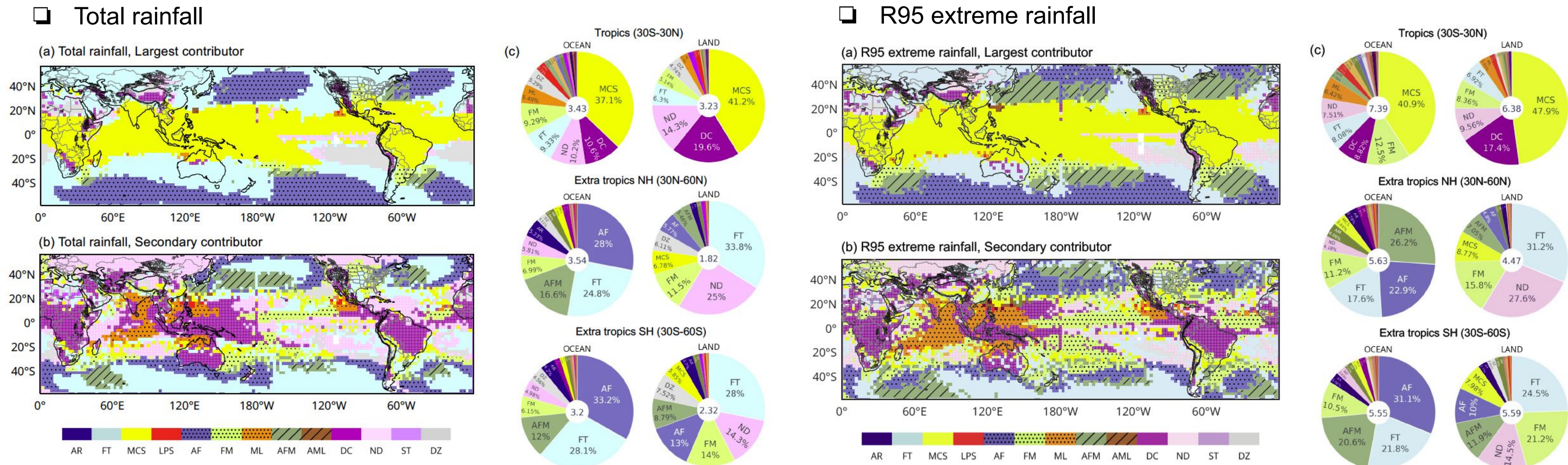

Figure. Global maps of PFIDs as (a) the largest and (b) the second largest contributor to the local precipitation during 2001-2019. The map presents the outcome computed on a 2.5-degree grid space based on the 0.25-degree data. (c) Pie charts of feature contributions to regional rainfall over land and oceans in the tropics (30S-30N, top), the northern hemisphere extra-tropics (30N-60N, middle), and the southern extra-tropics (30S-60S, bottom). The precipitation average of the latitude band is denoted at the pie chart center in the unit of mm day^{-1} (mm $hour^{-1}$ for R95 extremes)

A closer look at global precipitation based on PFIDs

In the tropics
- MCSs dominate the contribution of total rainfall, as well as R95 extremes (top 5% rainfall)
- LPS-MCS co-occurrences prevail over acknowledged monsoon regions

In the extratropics
- Greater contributions from co-occurring features over oceans compared to land, especially from those related to AR and FT
- AR-FT-MCS seems to be impactful for extremes, especially in the NH

→ overall provide observational benchmarks to Test climate model's ability to capture these leading features in terms of rainfall contributions

❑ Precipitation distributions of co-occurring features

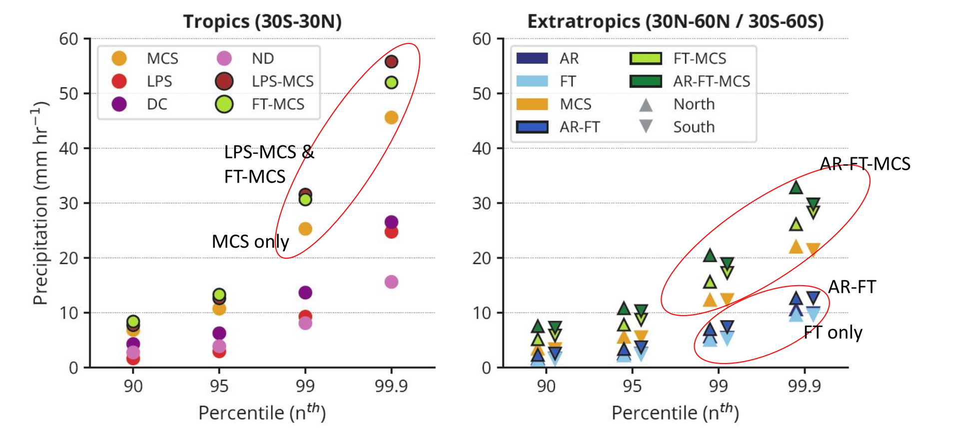

Figure. Precipitation intensities of selected PFIDs at the corresponding percentiles: 90, 95, 99, and 99.9, over the tropics (left) and the extratropics in the northern and southern hemispheres (right). Note that the single feature and its related co-occurrences (e.g., MCS v.s. LPS-MCS) are mutually exclusive as different samples.

- Co-occurring features systematically exhibit stronger rainfall compared to individual features,
- in part because feature trackers identify different aspects of a complex underlying phenomenon.
- What thermodynamic and dynamic conditions support these synergies?

5. Toward feature-environment diagnostics on the process level

❑ Characterizing key physical processes in features leading to extreme rainfall

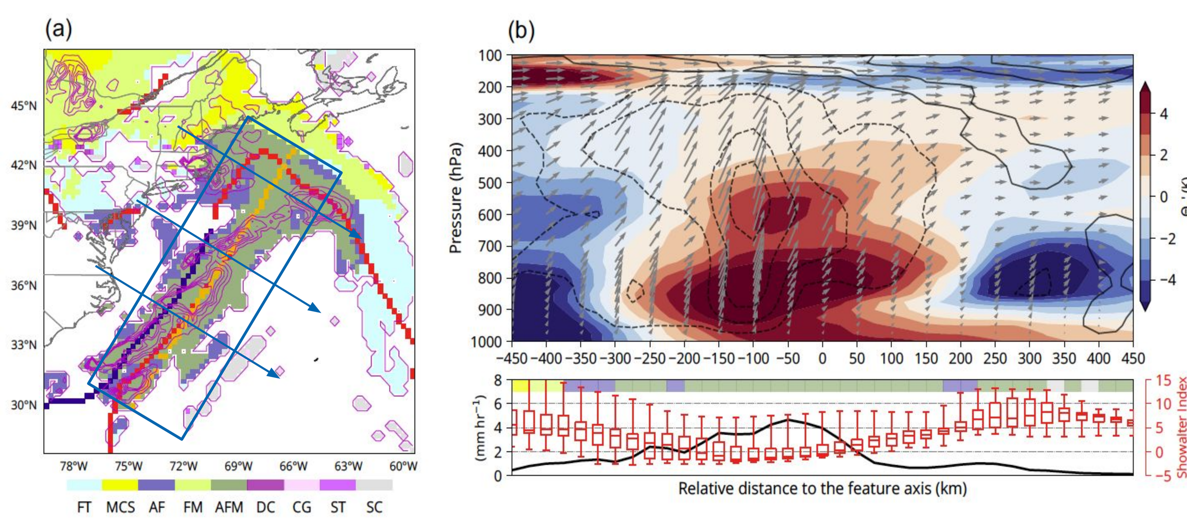

Figure. A feature-environment diagnosis showcase of the AR-FT-MCS feature includes (a) feature-associated precipitation identifiers and (b) the composite thermodynamics and dynamics from ERA5. Components in (a): GPM-IMERG precipitation (magenta contour, 0-10 mm hr^{-1}, interval=2), the identified fronts (red and blue contours), and the feature major axis (orange pixels). The major axis consists of pixels overlapped with a line that passes through the feature centroid determined by a least-squares fitting on the distance to all feature grids. Components in (b): (upper panel) the deviation of equivalent potential temperature (shading contour), and the vector of projected horizontal and vertical winds (arrow); (lower panel) GPM-IMERG precipitation (black), values of the Showalter Index distributed by the cross-sections (boxplot, including the median, the first and third quartiles), and the feature of the greatest fraction in the distance bin (shading bar).

- Heavy rainfall occurs ahead the front of the complex co-occurring feature
- Heavy rain seems to be substantially convective, reflected by the deep upwelling and conditional instability (Indicated by Showalter Index)
- A framework of feature-environment catalogues, which contains features and concurrent environments, can help characterize key processes and evaluate uncertainties in climate models

Check out a relevant poster on the diagnostics of MCSs and the thermodynamic environment:
Buoyancy-precipitation coupling in the life cycle of tropical mesoscale convective systems [Water Cycle and hydroclimate]

Animation of identified features

References: Feature algorithms & data sets: O'Brien, Travis A., et al. 2020, doi.org/10.5194/gmd-13-6131-2020; Feng et al. 2021, doi.org/10.1029/2020JD034202; Sansom and Catto 2022, doi.org/10.5194/gmd-2022-255; Ullrich and Zarzycki 2017, doi:10.5194/gmd-10-1069-2017; Vishnu et al. 2020 doi.org/10.1029/2020JD032977.
Results here: Tsai et al. (2024) Co-occurring atmospheric features and their contributions to precipitation extremes (under review)