Water Vapor Budget in Atmospheric Rivers: A Multi-model Evaluation

Bin Guan[1,2], Duane Waliser[2], and Marty Ralph[3]

[1]Joint Institute for Regional Earth System Science and Engineering, UCLA

[2]NASA Jet Propulsion Laboratory, Caltech

[3]Scripps Institution of Oceanography, UC San Diego

With key input/feedback from **Joel Norris** (SIO) and **Guang Zhang** (SIO)

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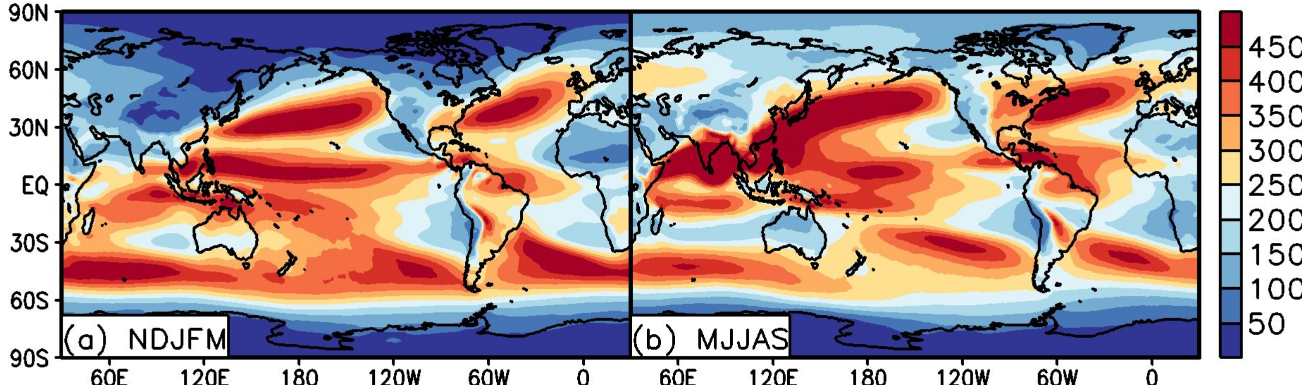
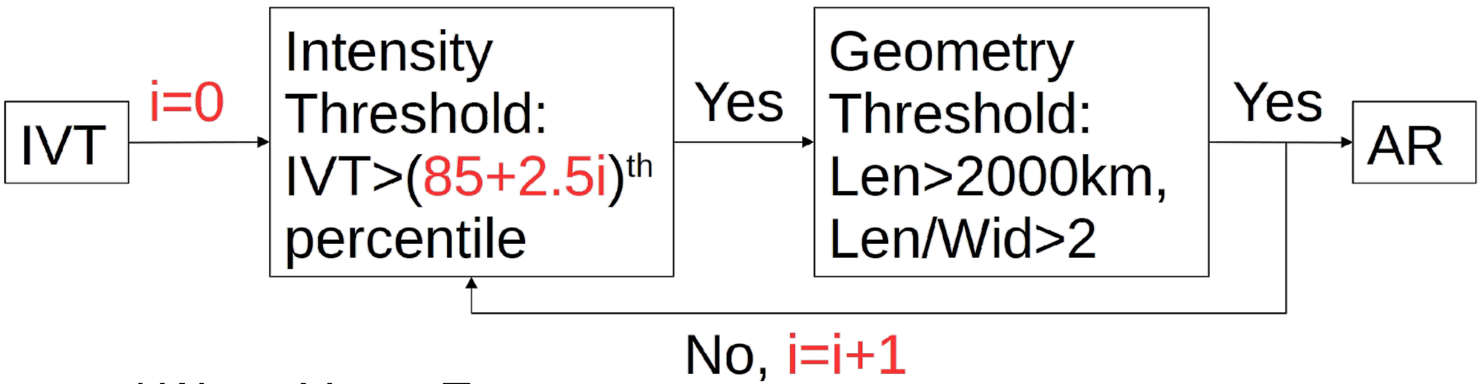
Key Motivations

- Process-level understanding of ARs; specifically, reanalysis depiction of AR water budgets and uncertainties (and where observational efforts like AREX could help the most)
- AR water budget in global weather/climate models: systematic biases and model spread?
- How biases in water budget relate to biases in bulk AR characteristics (e.g., frequency, geometry, …)

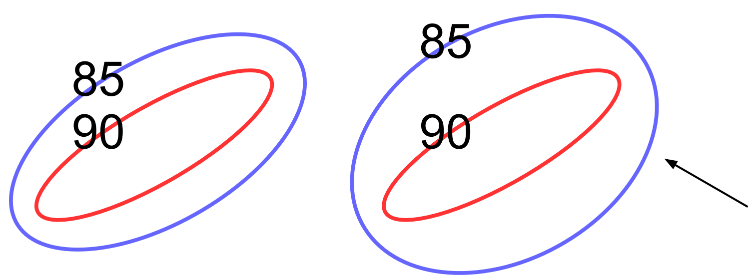
Global AR Detection Algorithm

Guan and Waliser 2015, Revision/refinement in Guan et al. 2018





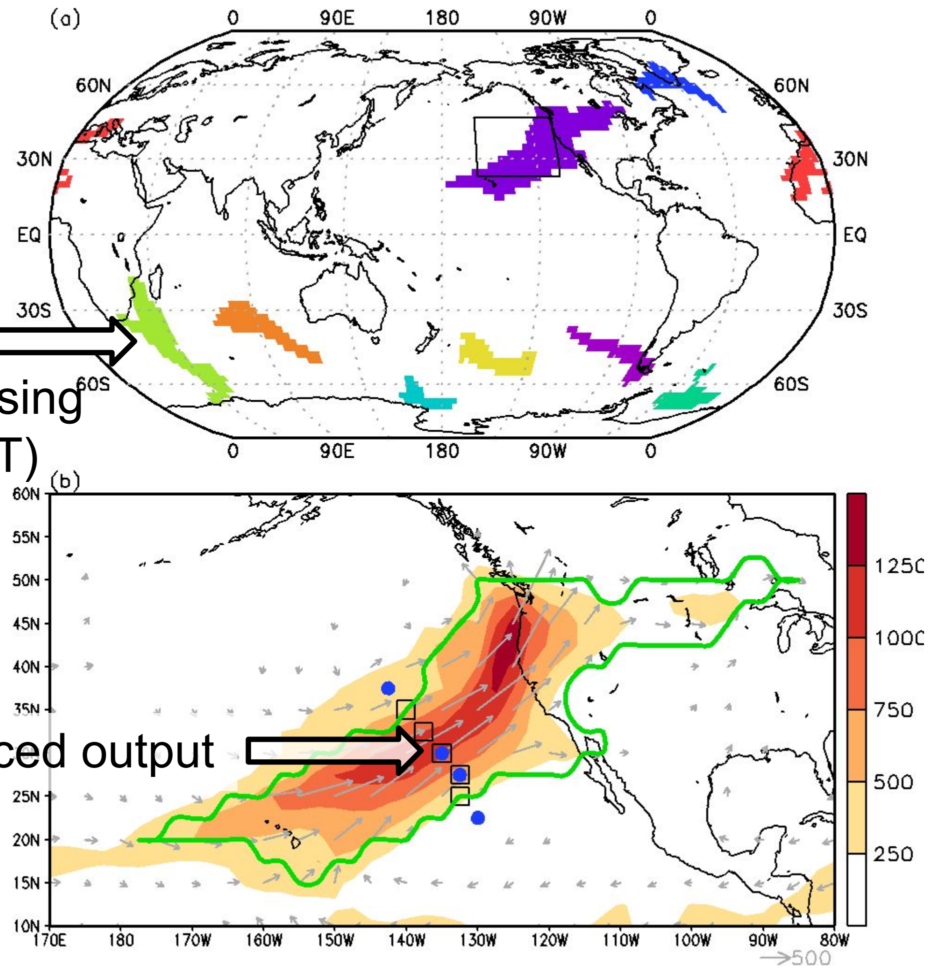
IVT=Integrated Water Vapor Transport



IVT Percentile Contours

Undetected (too "fat") if using a single threshold of 85th percentile

Example AR Detection Output

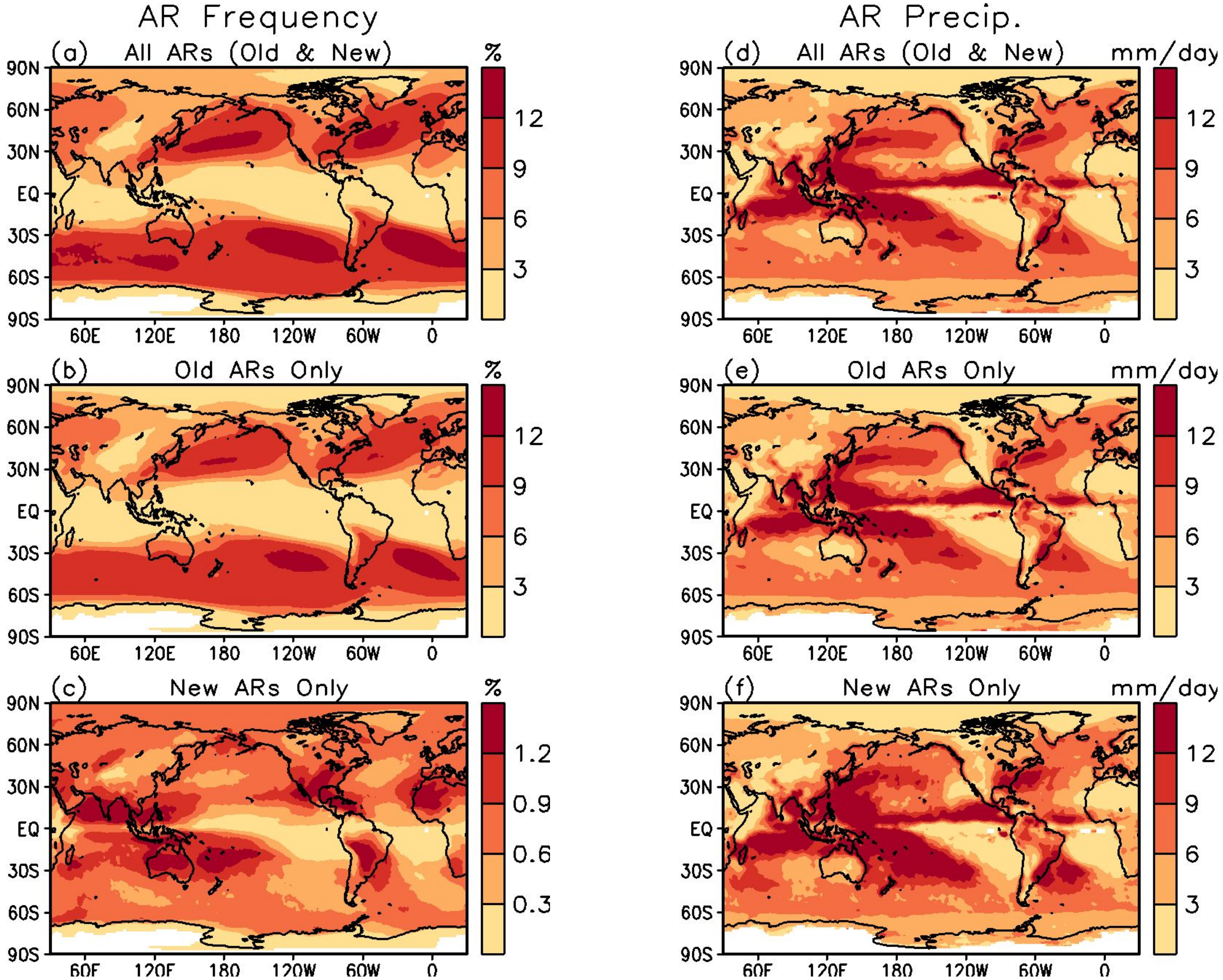


"New" AR
(i.e., undetected if using 85th percentile IVT)

Enhanced output

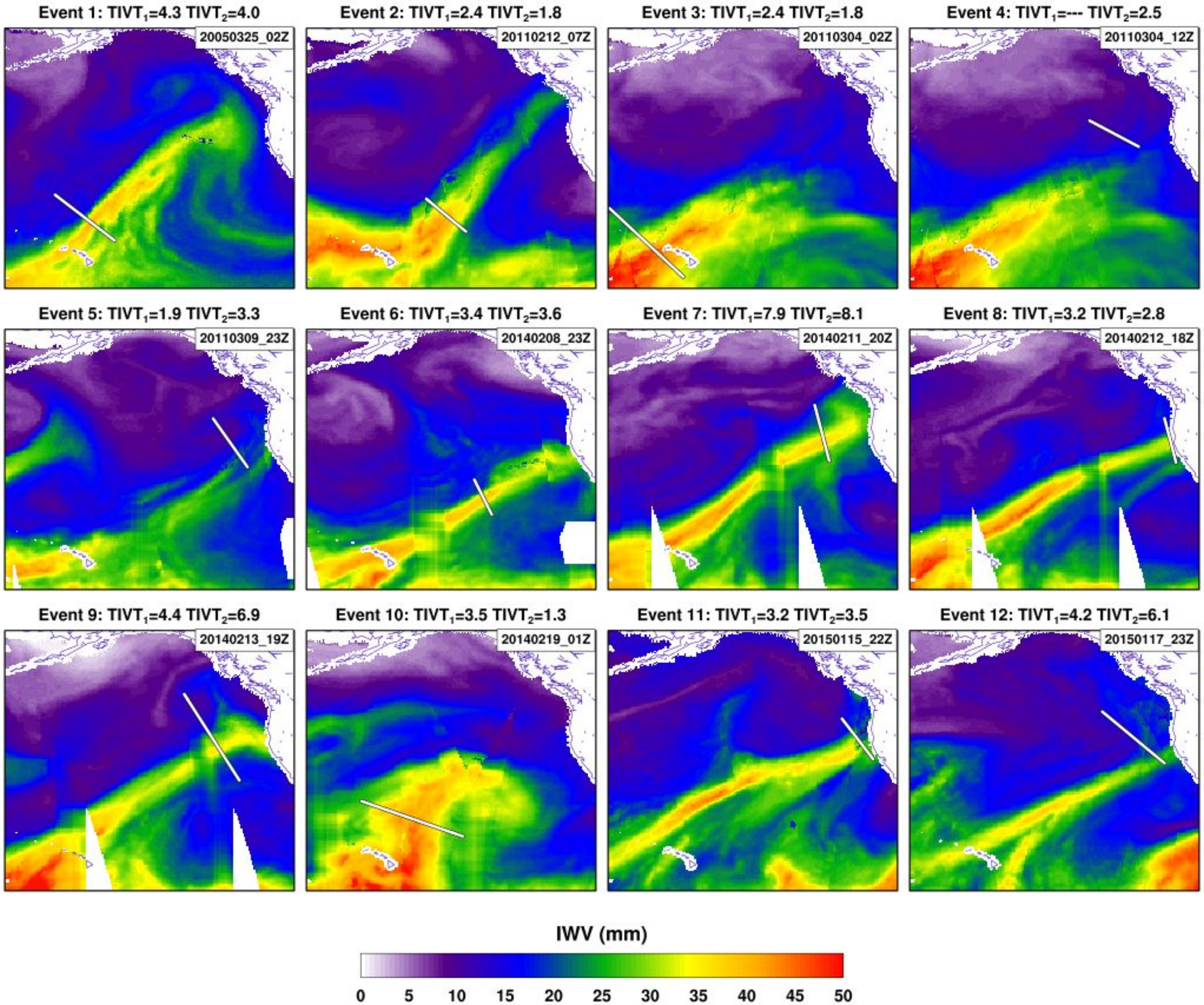
New capability/feature in revised algorithm

Multiple vs. Single IVT Threshold



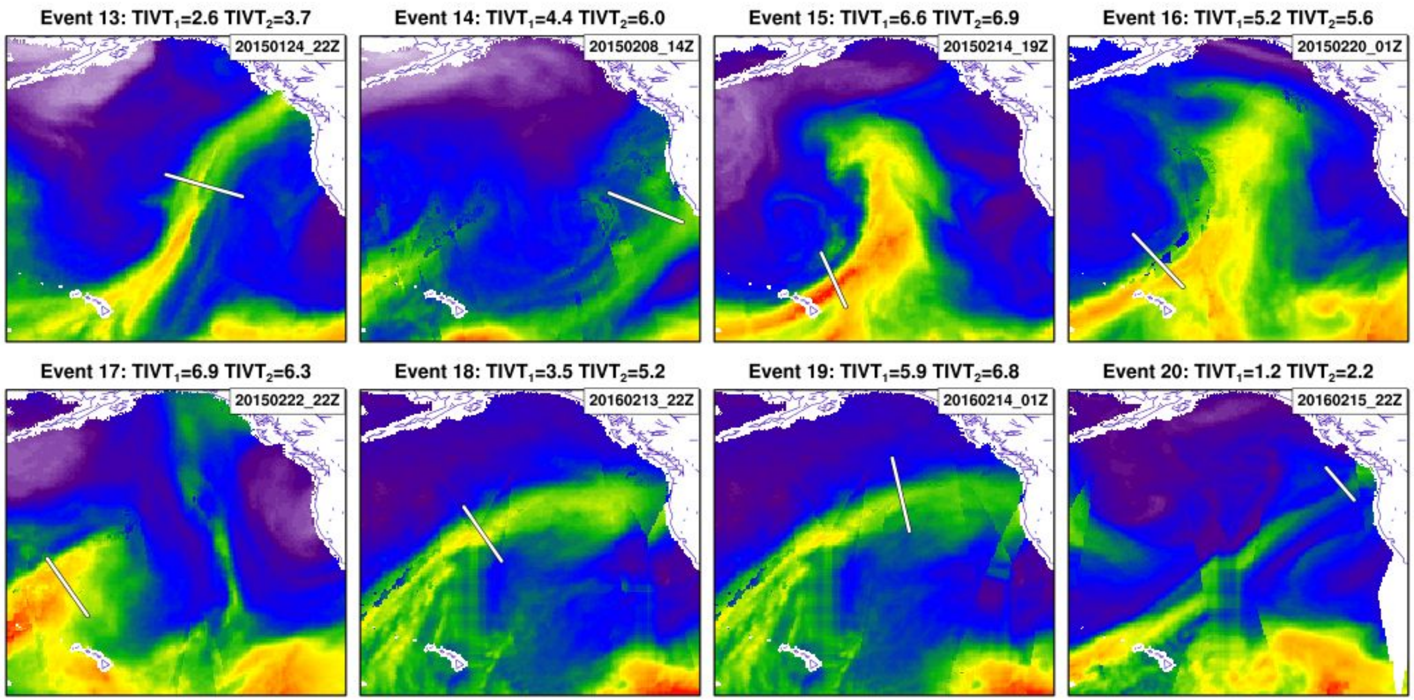
- Use of multiple IVT thresholds, i.e., 85-95th percentiles, detects roughly 2-3 more AR days per year compared to the use of a single threshold of the 85th percentile
- “New” ARs are as precipitating as “old” ARs

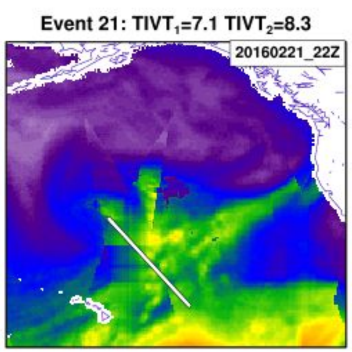
Ralph et al. 2017
Airborne Observations



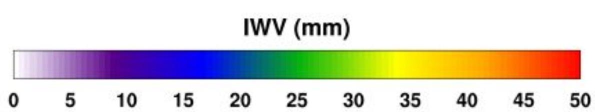
Ralph et al. 2017

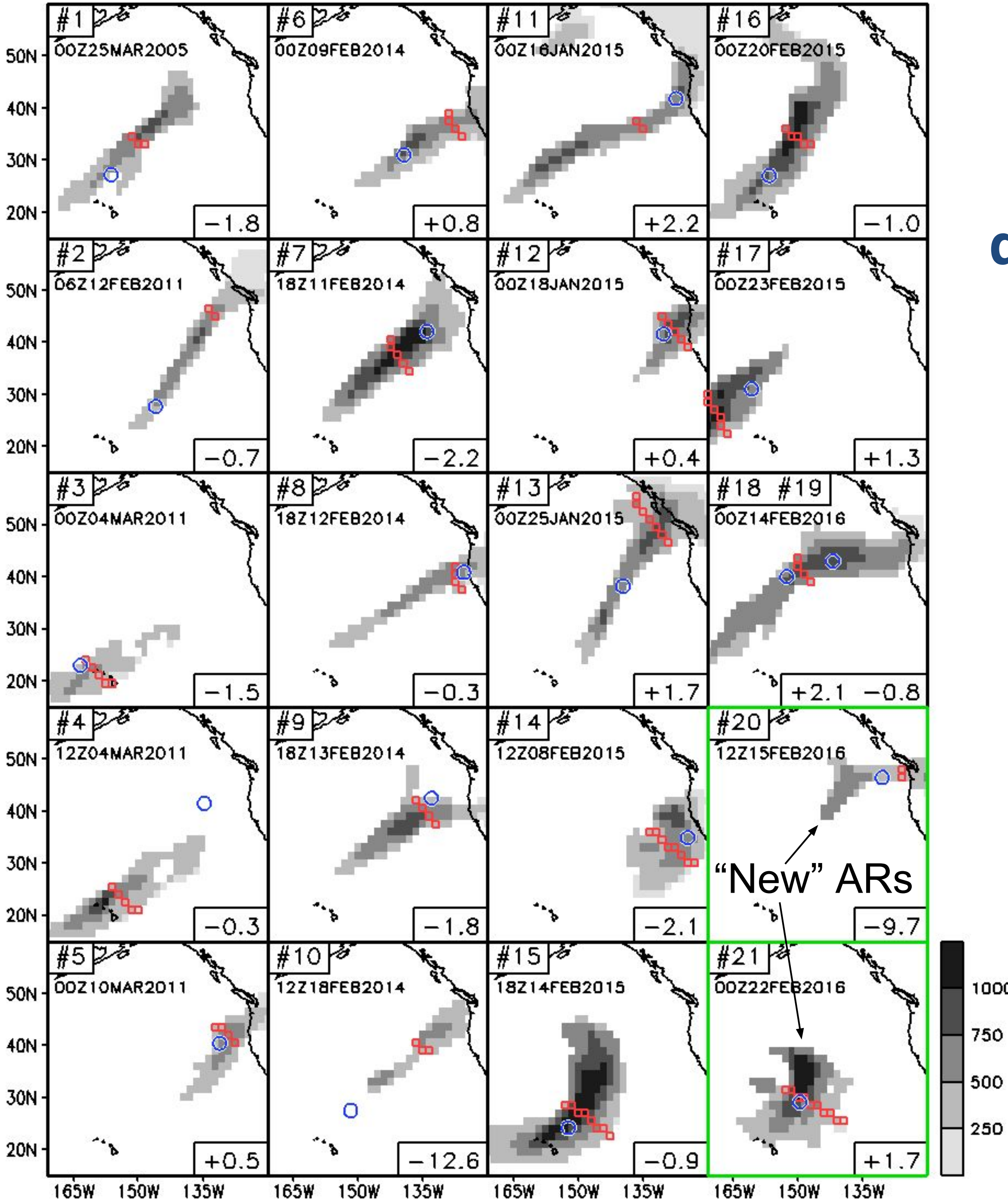
Airborne Observations





On average, each AR over NE Pacific has a flow rate of ~2.6 Amazon Rivers





Algorithm captures 21 dropsonde-observed ARs

Algorithm + Reanalysis

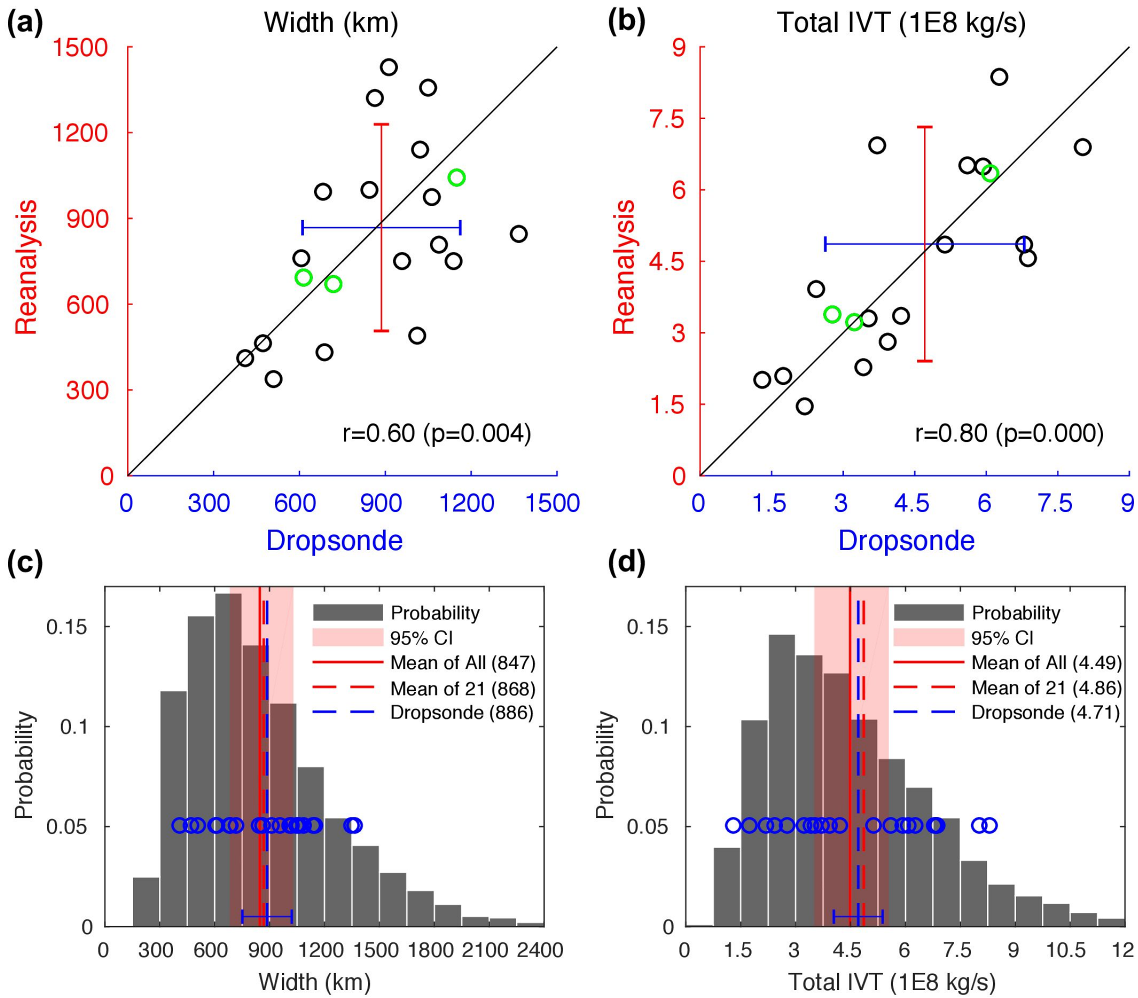
- Shading: AR shapes.
- Red: transect going through AR centroid.

Dropsonde

Blue: midpoint of AR transect.

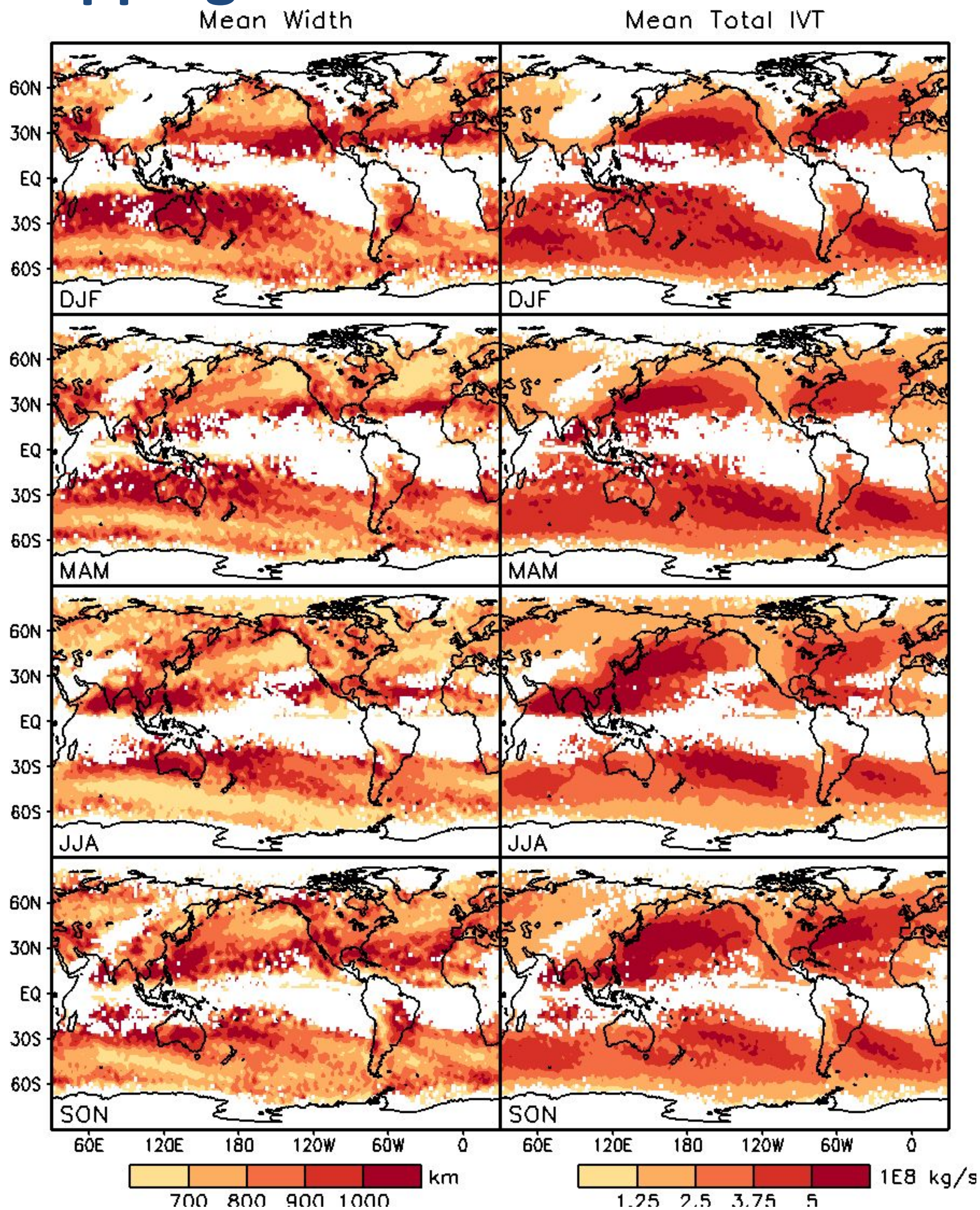
All 21 dropsonde ARs have a matching reanalysis AR; 19 of them matched within ±3 hours.

Remarkable Agreement Between Two Totally Independent AR Catalogs (Reanalysis vs. Dropsonde)

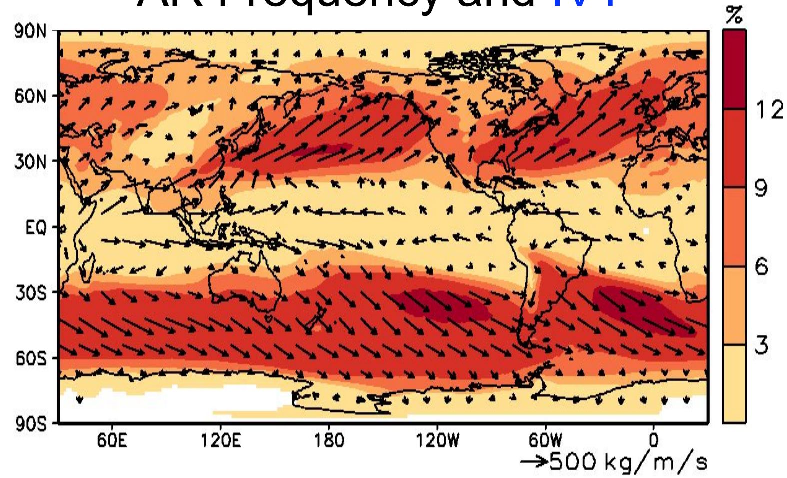


- Top: ERA-Interim-based AR width (-2% error) and total IVT (+3% error) validate well against dropsonde observations.
- Bottom: Dropsonde-observed AR width (5% difference) and total IVT (5% difference) well represent the entire population (21 vs. ~6000

Mapping AR Width and TIVT Globally



AR Frequency and IVT

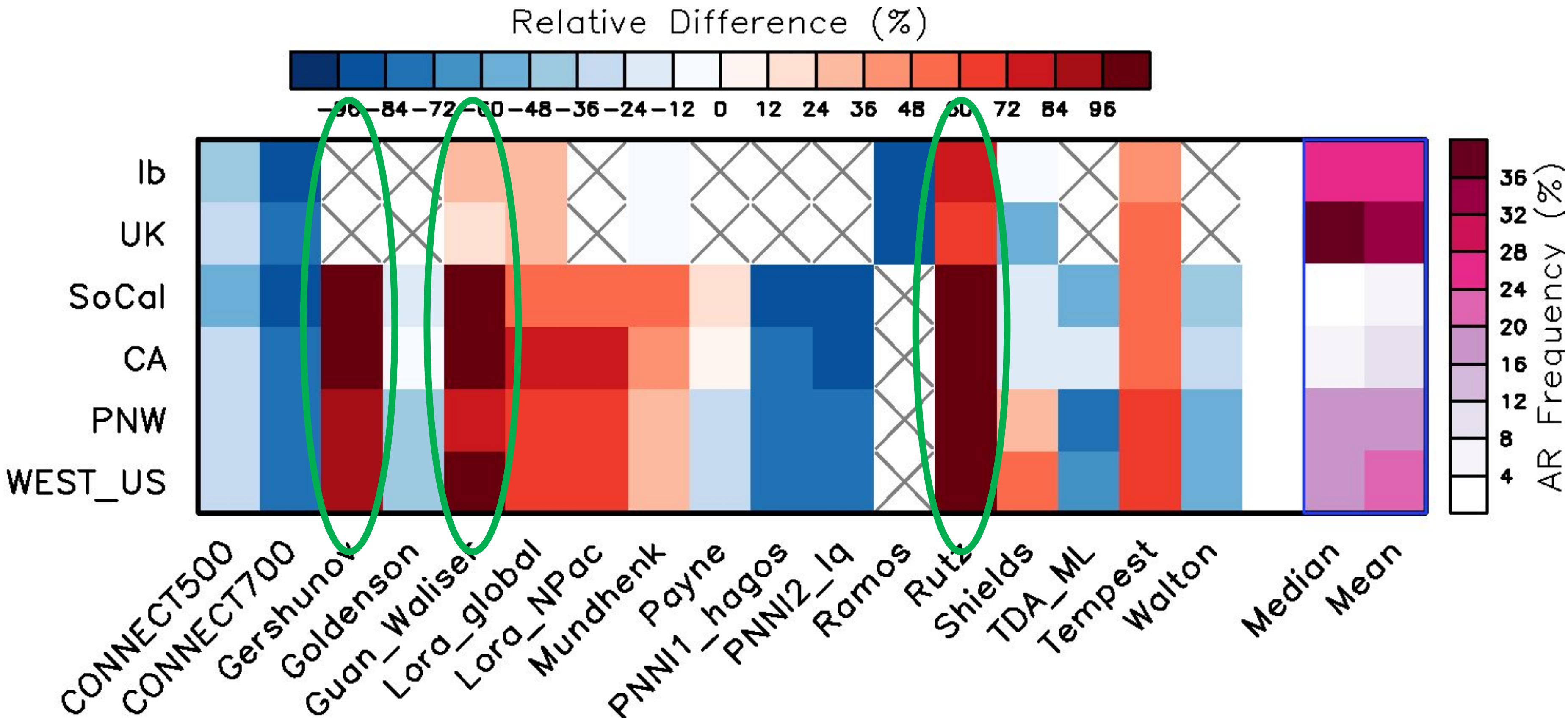


- AR width and TIVT (left) have considerable seasonal and geographical variations
- The largest values tend to occur in the subtropics and during cold seasons
- Complimenting AR IVT (above), TIVT (left) gives insight to individual ARs

Over ~90% Agreement in Detected AR Landfall Dates Compared to 3 Independent Studies

Study Area	Western North America (Neiman et al. 2008)	Britain (Lavers et al. 2011)	East Antarctica (Gorodetskaya et al. 2014)
Period	1997–2014, November–March	1997–2010, October–March (High-impact events only)	2009–2012, All Months (High-impact events only)
Variable for AR Detection	IWV from SSM/I and SSMIS Retrievals	900-hPa Specific Humidity from Twentieth Century Reanalysis Project	IWV from ERA-Interim Reanalysis
Percent Agreement	94%	89%	100%

AR detection result can be sensitive to detection methods: IVT (intensity) threshold among the key factors



Analysis under the auspices of the ARTMIP Project

20-year Simulations from Global Weather/Climate Models

GASS-YoTC Multi-model Experiment

Model Name	Native Resolution (Lon × Lat, # of Vertical Levels)	Remark
BCC-AGCM2.1	T42 (2.8°), L26	
ISUGCM	T42 (2.8°), L18	
SPCAM3	T42 (2.8°), L30	Super-parameterized, Daily Archive
UCSD-CAM3	T42 (2.8°), L26	
GISS-E2	2.5° × 2.0°, L40	
TAMU-CAM4	2.5° × 1.9°, L26	
FGOALS-s2	R42 (2.8° × 1.6°), L26	
ACCESS1	1.875° × 1.25°, L85	
MetUM-GA3	1.875° × 1.25°, L85	
MIROC5	T85 (1.5°), L40	
CNRM-AM	T127 (1.4°), L31	
EC-GEM	1.4°, L64	
MRI-AGCM3	T159 (1.125°), L48	
CAM5	1.25° × 0.9°, L30	
CAM5-ZM	1.25° × 0.9°, L30	
CFS2	T126 (1°), L64	
CWB-GFS	T119 (1°), L40	
ECEarth3	T255 (0.7°), L91	
GEOS5	0.625° × 0.5°, L72	
NavGEM1	T359 (0.42°), L42	
CanCM4	2.8°, L35	Coupled
SPCCSM3	T42 (2.8°), L30	Coupled, Super-parameterized, Daily Archive
ECHAM5-SIT	T63 (2°), L31	Coupled
ECHAM6	T63 (2°), L47	Coupled

● Grid cell size

Atmos.-only

Coupled

Atmospheric Water Vapor Budget

$$\text{IWV Tendency} = \text{IVT Convergence} + \text{Evap} - \text{Precip}$$

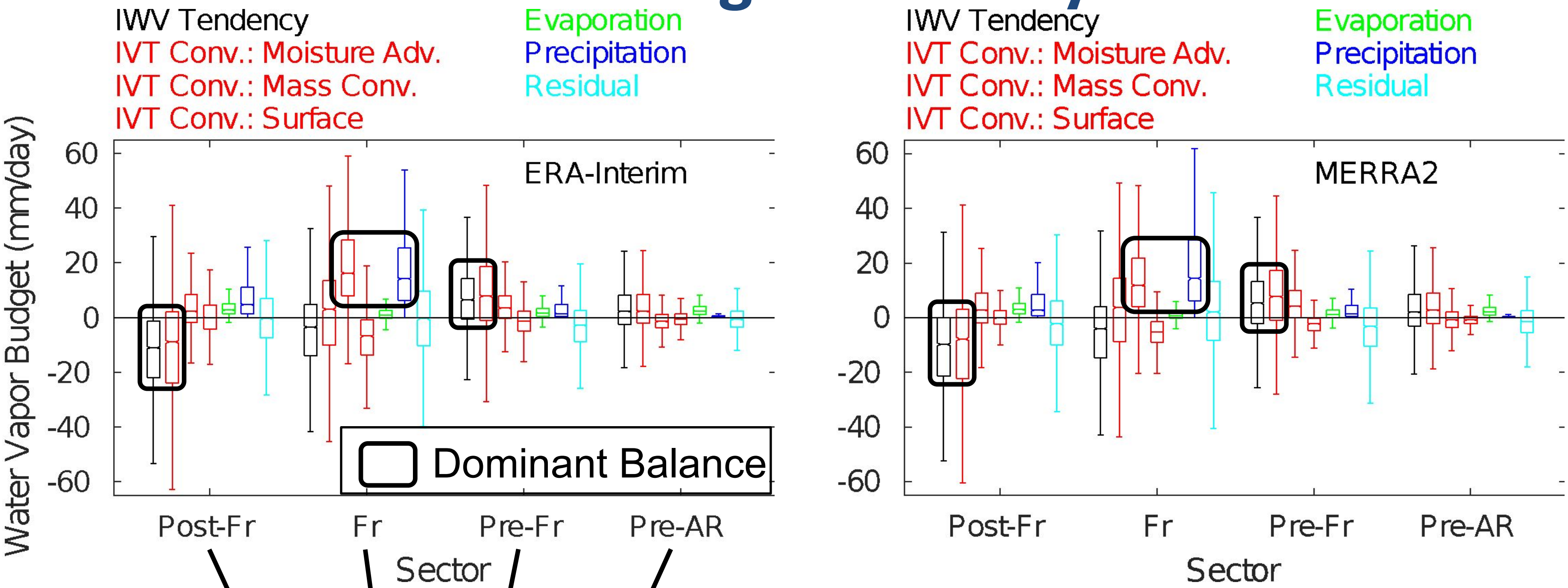
$$\frac{\partial}{\partial t}\int_0^{p_s} q\,dp = -\int_0^{p_s}(\underbrace{\mathbf{u}\cdot\nabla q}_{1} + \underbrace{q\nabla\cdot\mathbf{u}}_{2})dp - \underbrace{q_s\mathbf{u}_s\cdot\nabla p_s}_{3} + E - P$$

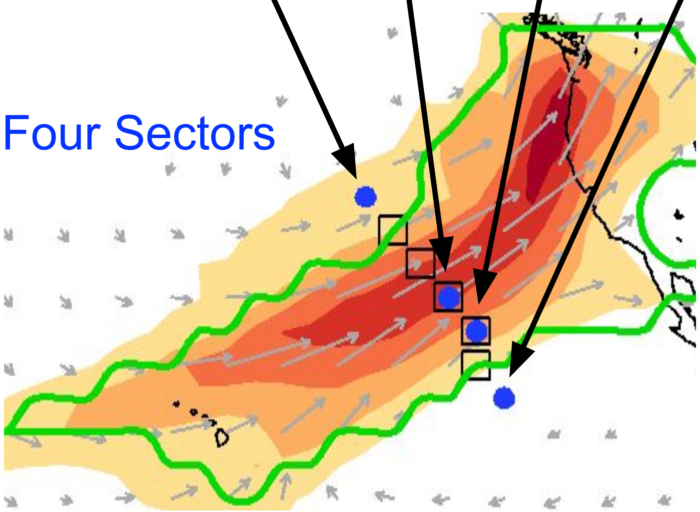
IVT Convergence due to

1. Moisture Advection
2. Mass Convergence
3. Surface process

Adapted from Eqn. 15 of Seager & Henderson (2013)

Water Budget: Reanalyses

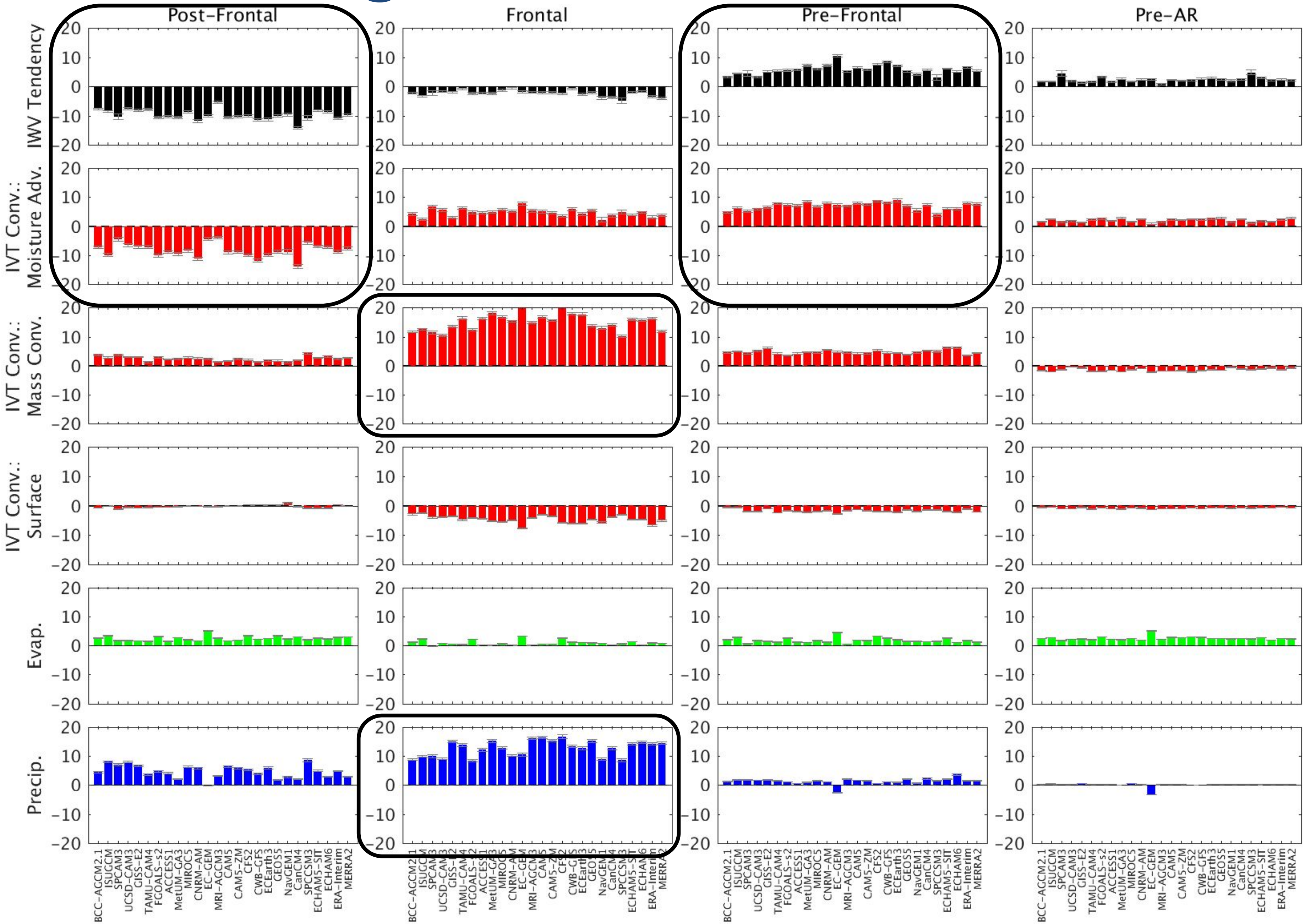




- Based on ~6000 ARs detected over northeastern Pacific during 1991-2010 NDJFM
- Overall, good agreement between ERA-Interim and MERRA-2
- Each sector of the four is unique relative to the others, with water budget dominated by different terms

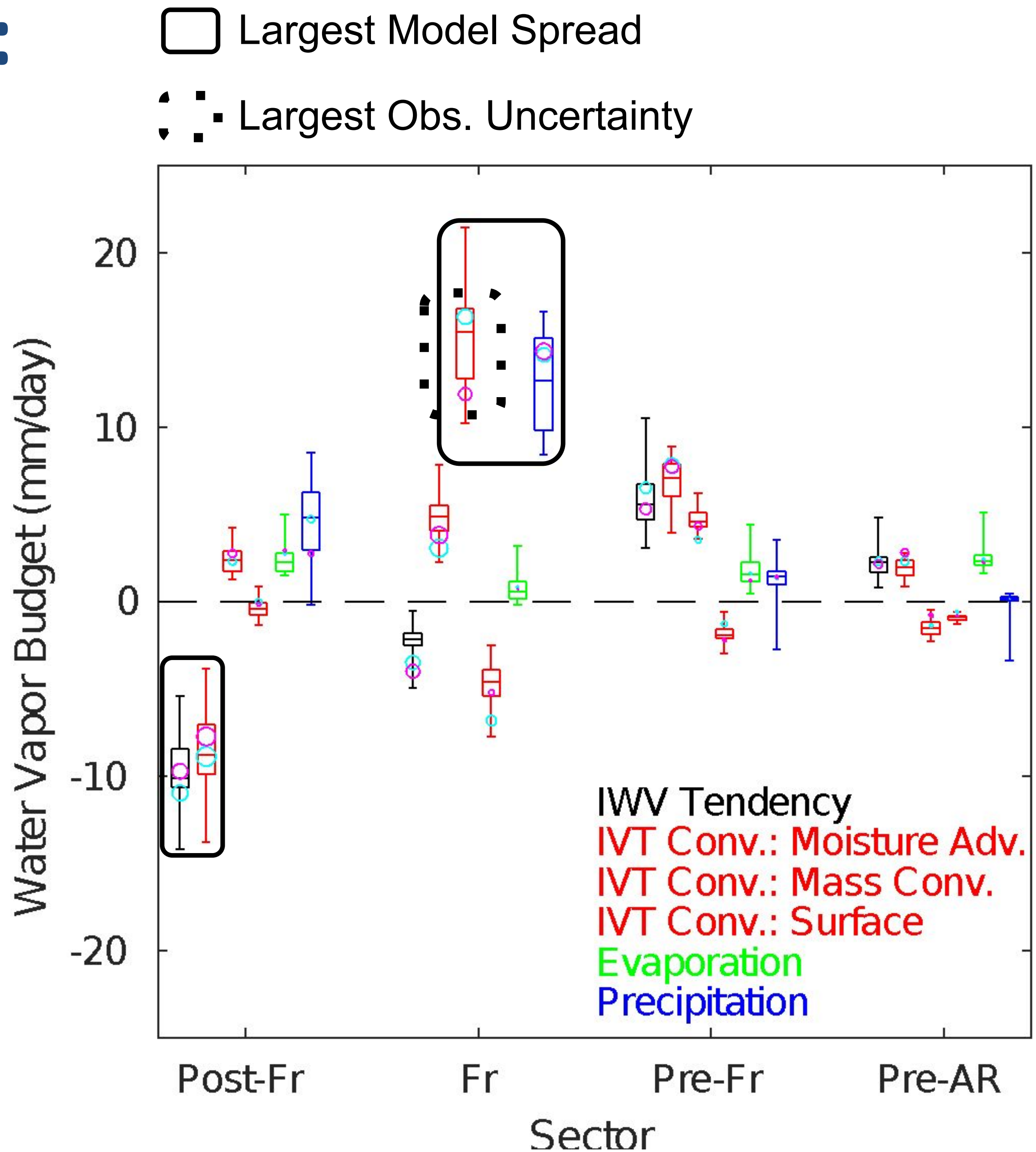
Water Budget: Models

Dominant Balance

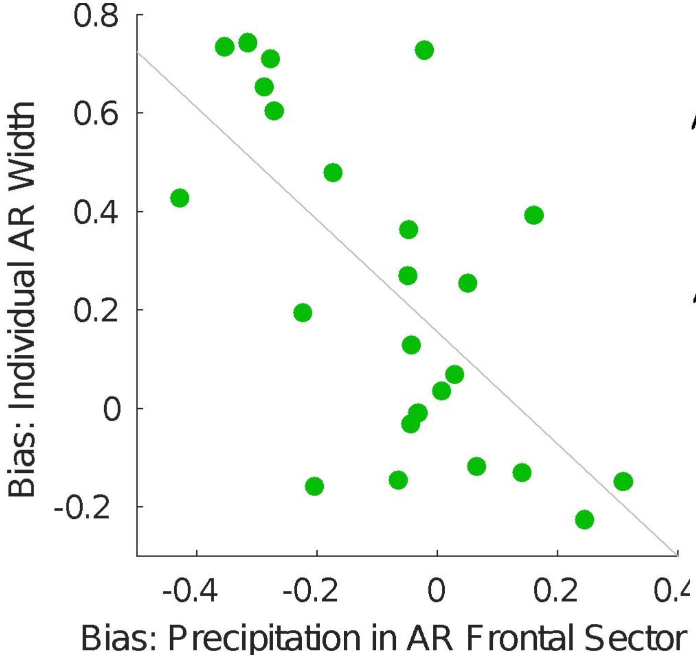


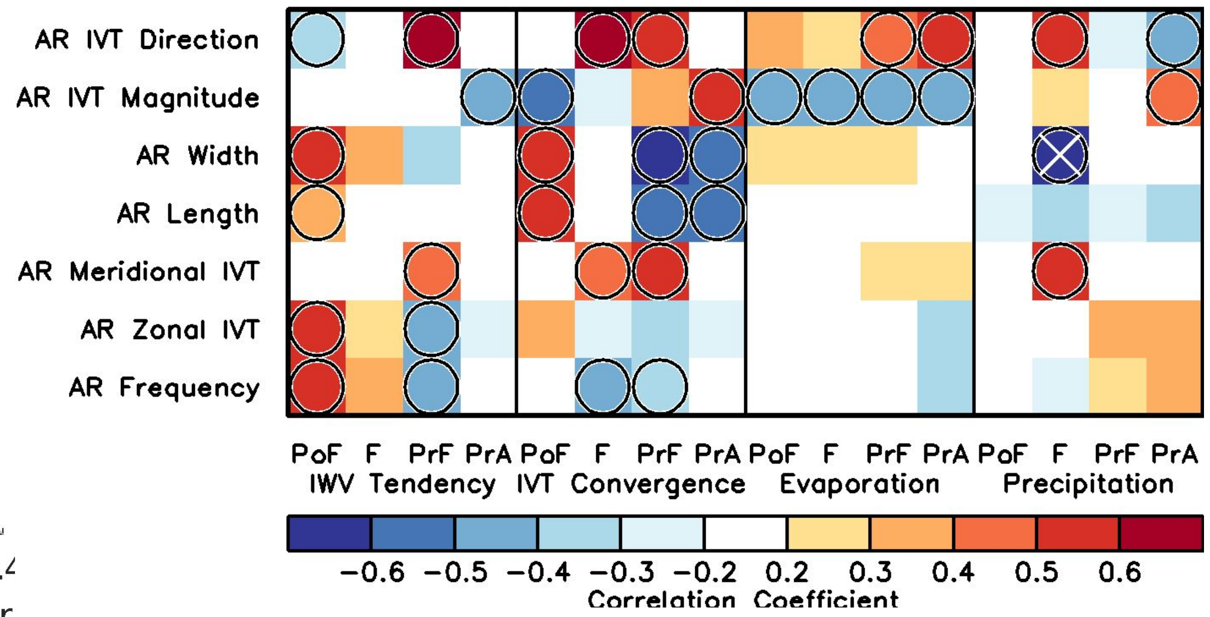
Water Budget: Model Spread

- Model spread (box-whiskers) is notable compared to observational uncertainty (diff. between two circles)
- Largest model spread occurs in post-frontal and frontal sectors in their respective dominant budget terms
- Largest observational uncertainty is associated with IVT convergence due to mass convergence in frontal sector



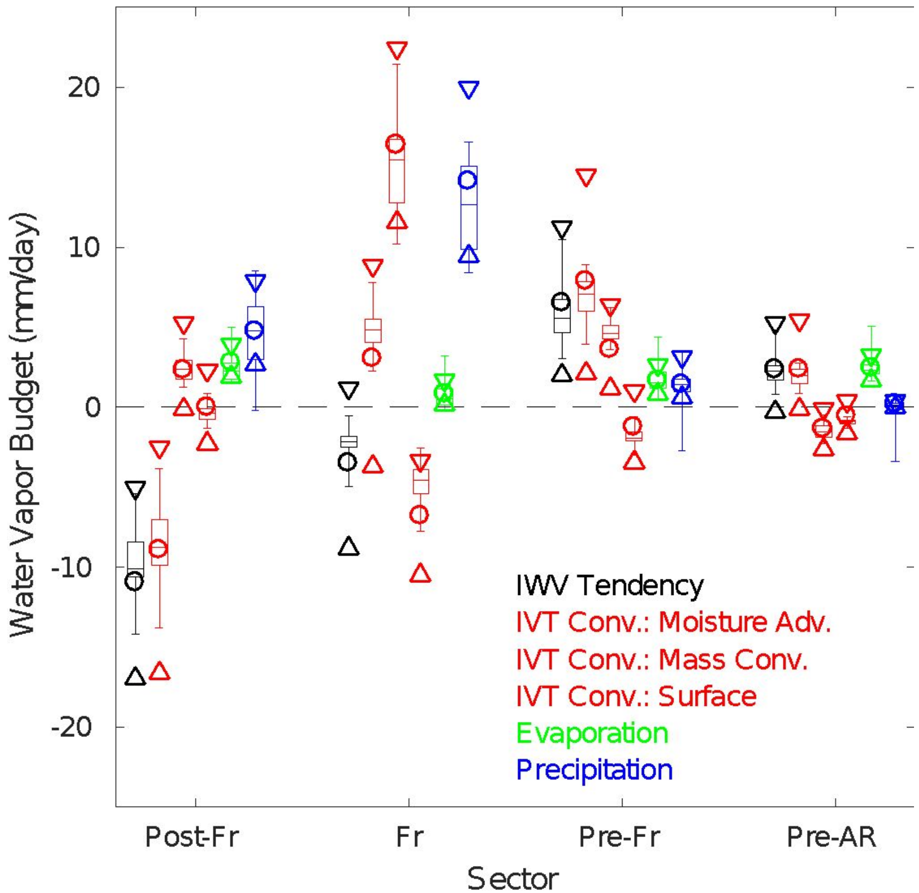
How does water budget bias relate to model fidelity in bulk AR characteristic?





- Example (left): Too much precipitation in AR frontal sector (i.e., bias in water budget) is related to too narrow ARs (i.e., bias in bulk AR characteristics)
- Examination of 4 terms @ 4 sectors and 7 bulk AR characteristics (right) indicates simulated bulk AR characteristics overall have larger sensitivity to biases in IVT convergence and IWV tendency compared to E/P (counting # of circles, i.e., significant correlations)

How can a small sample of observed ARs (e.g., from AREX) potentially help constrain climate models?



Even a small sample of observed ARs (here, 30) can potentially falsify a fraction of the global models (comparing model spread in box-whiskers to observational uncertainty in triangles)

Method

- A small sample of k ARs (with k mimicking # of anticipated observations) is drawn randomly from a total of ~6000 reanalysis ARs, and the median value of each budget term is obtained;
- The above is repeated 10,000 times, with 10,000 sets of median values obtained;
- The 5th, 50th, and 95th percentiles of the median values are plotted (the centers of the upward triangle, circle, and downward triangle, respectively) to represent observational uncertainty associated with a small sample;
- Model spread across 24 models based on ~6000 ARs (boxplots) is evaluated relative to above observational uncertainty

How can a small sample of observed ARs (e.g., from AREX) potentially help constrain climate models?

30 ARs @ 90% Conf. Lev.	Post-Fr	Fr	Pre-Fr	Pre-AR	Total
IWV Tendency	0	0	0	0	0
IVT Conv.: Moisture Adv.	0	0	0	0	0
IVT Conv.: Mass Conv.	0	3	0	0	3
IVT Conv.: Surface	0	4	0	0	4
Evaporation	9	10	5	2	15
Precipitation	7	5	4	3	15
Total	14	15	7	4	21

- **Main sector of table**: considering only the given sector and given parameter, # of models that fall outside of observational uncertainty associated with a random sample of k ARs
- **Rightmost column**: # of models that fail in at least one sector for the given parameter
- **Bottom row**: # of models that fail for at least one parameter in the given sector
- Red: # of models that fail for at least one parameter in at least one sector

Number of models (out of 24) a random observation of k ARs (i.e., kx4 sectors) can eliminate

k	20	30
@ 95% Conf. Lev.	9	16
@ 90% Conf. Lev.	16	21

Summary

- The Guan and Waliser (2015) global AR detection algorithm has been further developed and evaluated;
- Six water vapor budget terms at four AR sectors are compared between two reanalyses and 24 global weather/climate models;
- Each of the four AR sectors is uniquely dominated by different budget terms: largely agreed between ERA-Interim and MERRA-2;
- Model spread is notable relative to reanalysis uncertainty, the largest model spread being associated with the dominant budget terms in post-frontal and frontal sectors;
- Reanalysis uncertainty and model biases in key AR water vapor budget terms highlight the need for better constraining these terms, such as via dedicated field observations.

Bin.Guan@jpl.nasa.gov

Global AR databases and codes available at

ucla.box.com/ARcatalog