Seasonal forecasting of precipitation-relevant weather types over the United States

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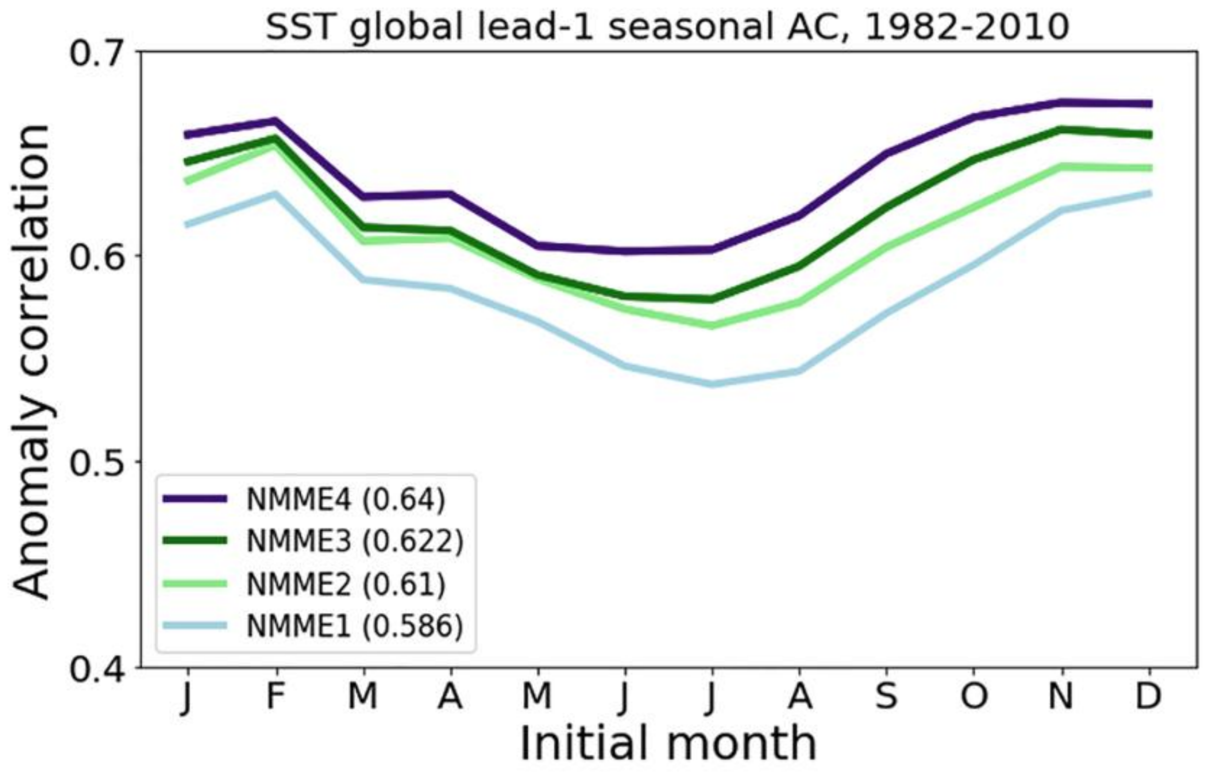
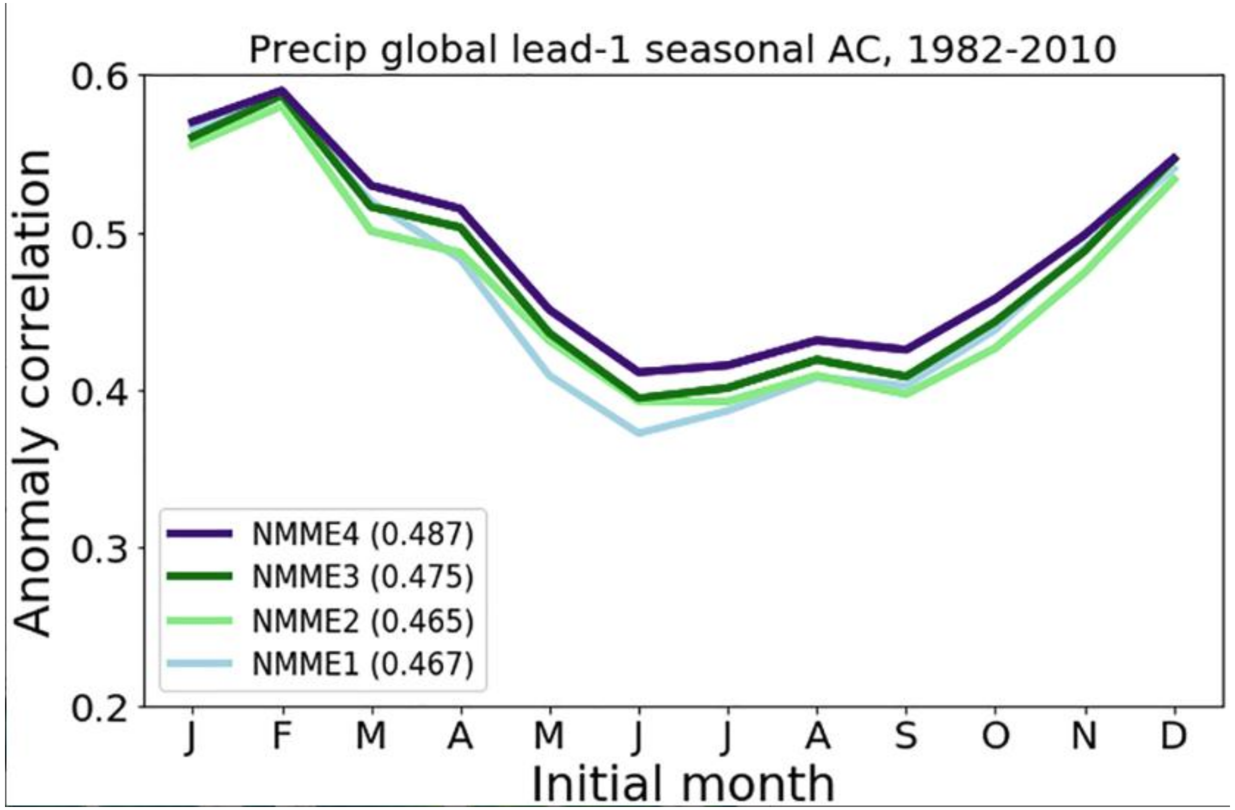
2025 Improving Sub-seasonal to Seasonal Precipitation Forecasting Workshop
Western States Water Council (WSWC), San Diego, CA (virtual)

Sea Surface Temperatures (SSTs) – a main source of seasonal predictability – have shown skill improvements, but have not led to commensurate improvements in precipitation.

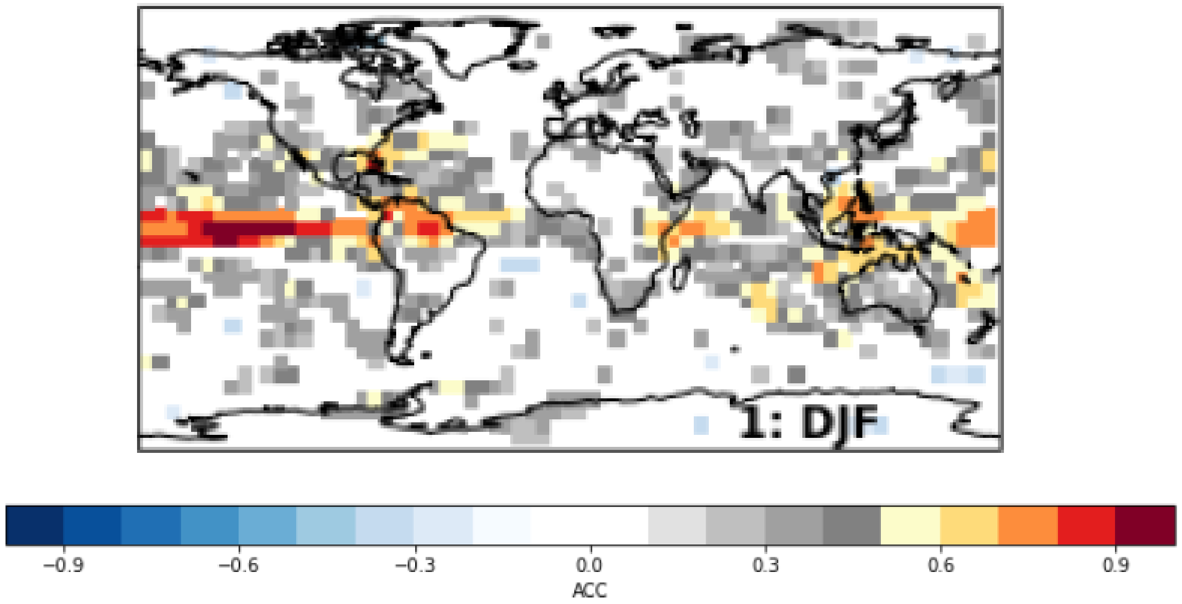




NMME = North American Multi-Model Ensemble

Becker et al. 2020 *GRL*

Seasonal precipitation forecast skill varies spatially.



Anomaly correlation coefficient (ACC) for winter precipitation (initialized in November) from SMYLE (Seasonal-to-Multiyear Large Ensemble generated using the NSF NCAR's CESM2)

(Yeager et al. 2022)

Alternative approach to predicting precipitation directly is to predict atmospheric patterns that are associated with precipitation.

Weather *Regimes* vs Weather *Types*

Weather *Regimes*

- Smaller number of patterns
- More persistent
- Broad (larger) region

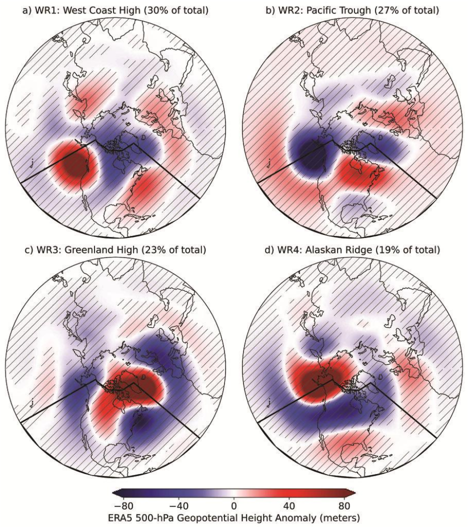


Figure: Molina et al. (2023).

Weather *Types*

- Larger number of patterns
- Vary on a daily basis (less persistent)
- Defined (smaller) domain

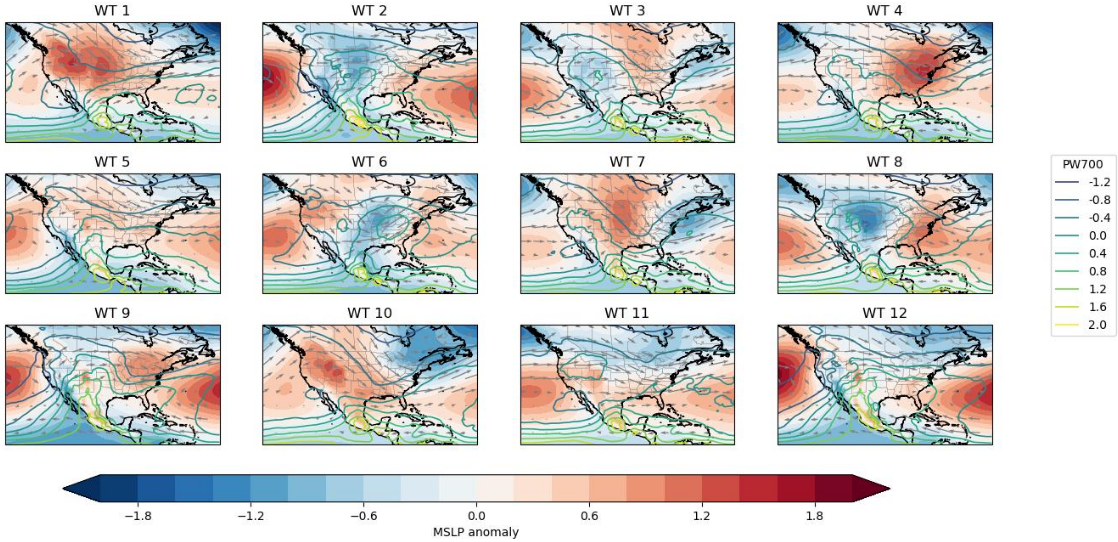


Figure: Towler et al. (minor rev).

In North America, subseasonal predictability of persistent ***winter*** weather regimes* has been explored.

4 *Winter* regimes have been evaluated using:

- European Centre for Medium-Range Weather Forecasts (ECMWF; Vigaud et al. 2018)
- National Centers for Environmental Prediction (NCEP) Climate Forecast System, version 2 (CFSv2; Robertson et al. 2020)
- NSF National Center for Atmospheric Research (NCAR) Community Earth System Model, version 2 (CESM2; Molina et al. 2023).

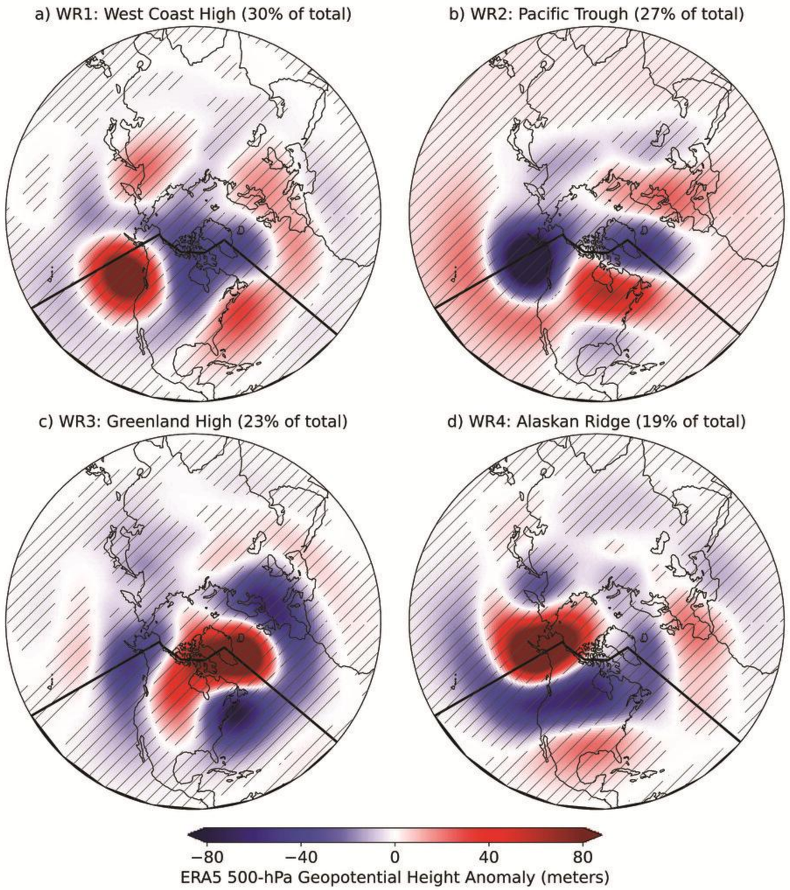
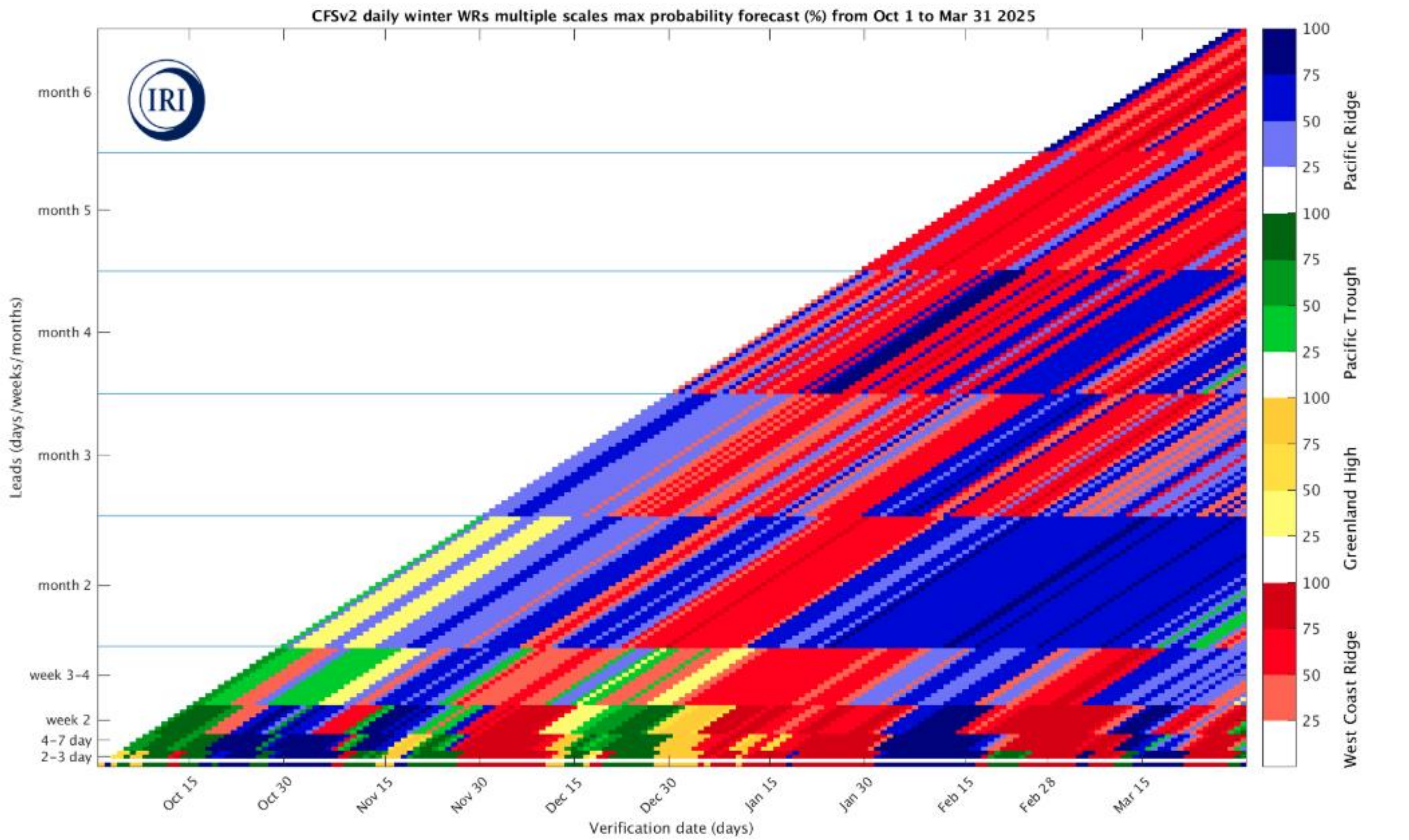


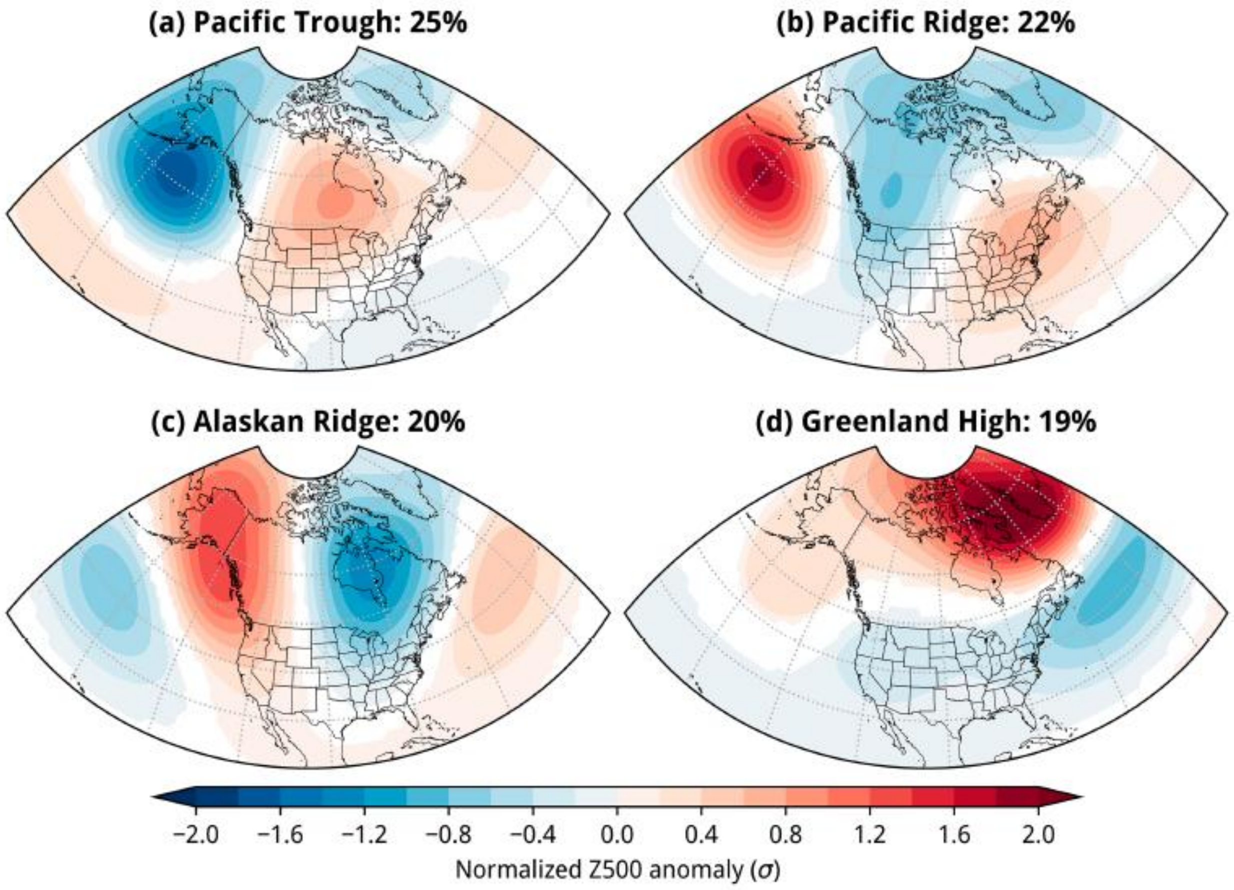
Figure: Molina et al. (2023).

IRI NOAA CFSv2 weather regimes forecasted in real-time (winter).



https://wiki.iri.columbia.edu/index.php?n=Climate.S2S-WRs

Year-round weather regimes* for North America have been developed, but not evaluated using forecast products.



** 4 regimes and a “no regime” state*

Lee et al. 2023

Weather types have been developed over the UK.

30 UK WTs (medium range)

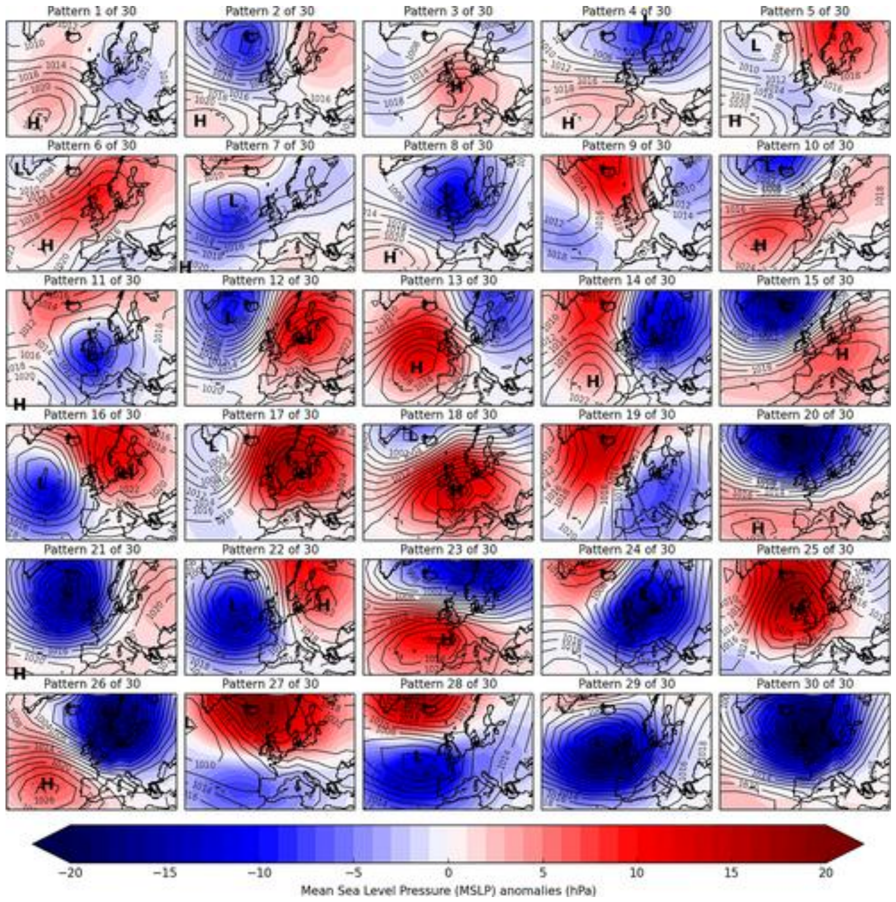


Figure: Neal et al. (2016, 2024).

8 UK WTs (monthly/seasonal)

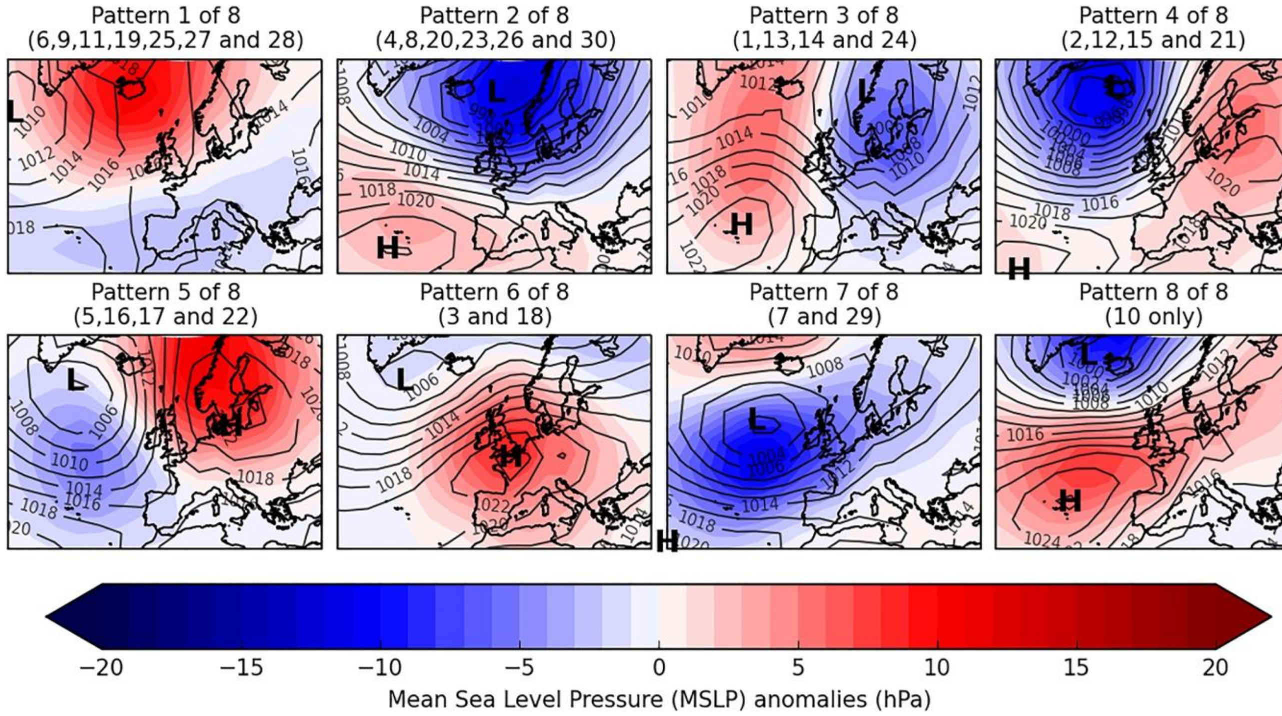
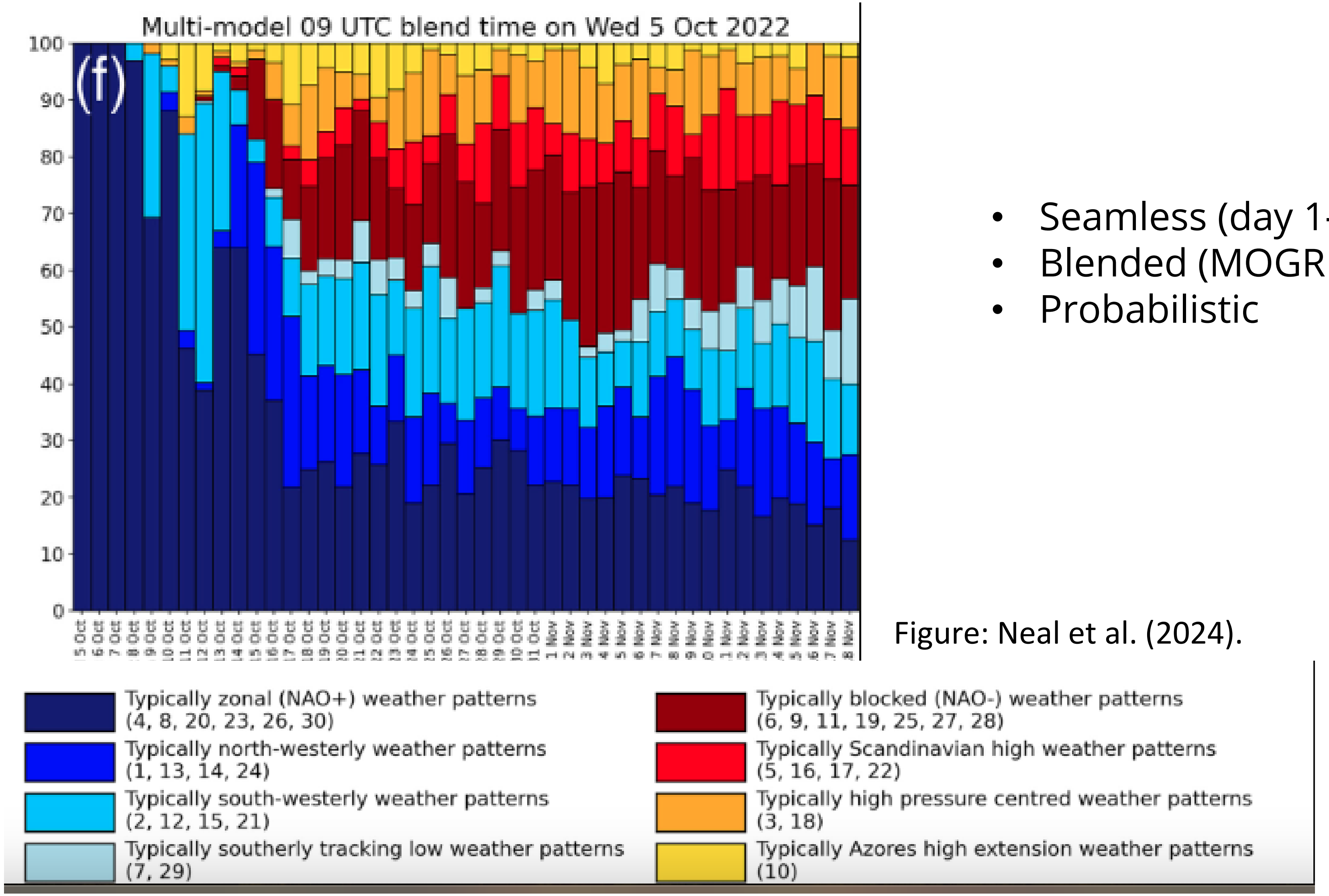


Figure: Neal et al. (2016, 2024).

WTs used in operational multi-model ensemble tool: Met Office "Decider".



- Seamless (day 1-45)
- Blended (MOGREPS-G, ECMWF, GEFS, GloSea)
- Probabilistic

Figure: Neal et al. (2024).

Year-round weather ***types*** for the CONUS* have been developed to be precipitation-relevant.

* contiguous United States

AGU PUBLICATIONS

Geophysical Research Letters

RESEARCH LETTER

10.1002/2015GL066727

Key Points:
- Changes in weather types correlate to increasing anticyclonic conditions in the U.S. Southwest
- The U.S. Southwest's climate might

Running dry: The U.S. Southwest's drift into a drier climate state

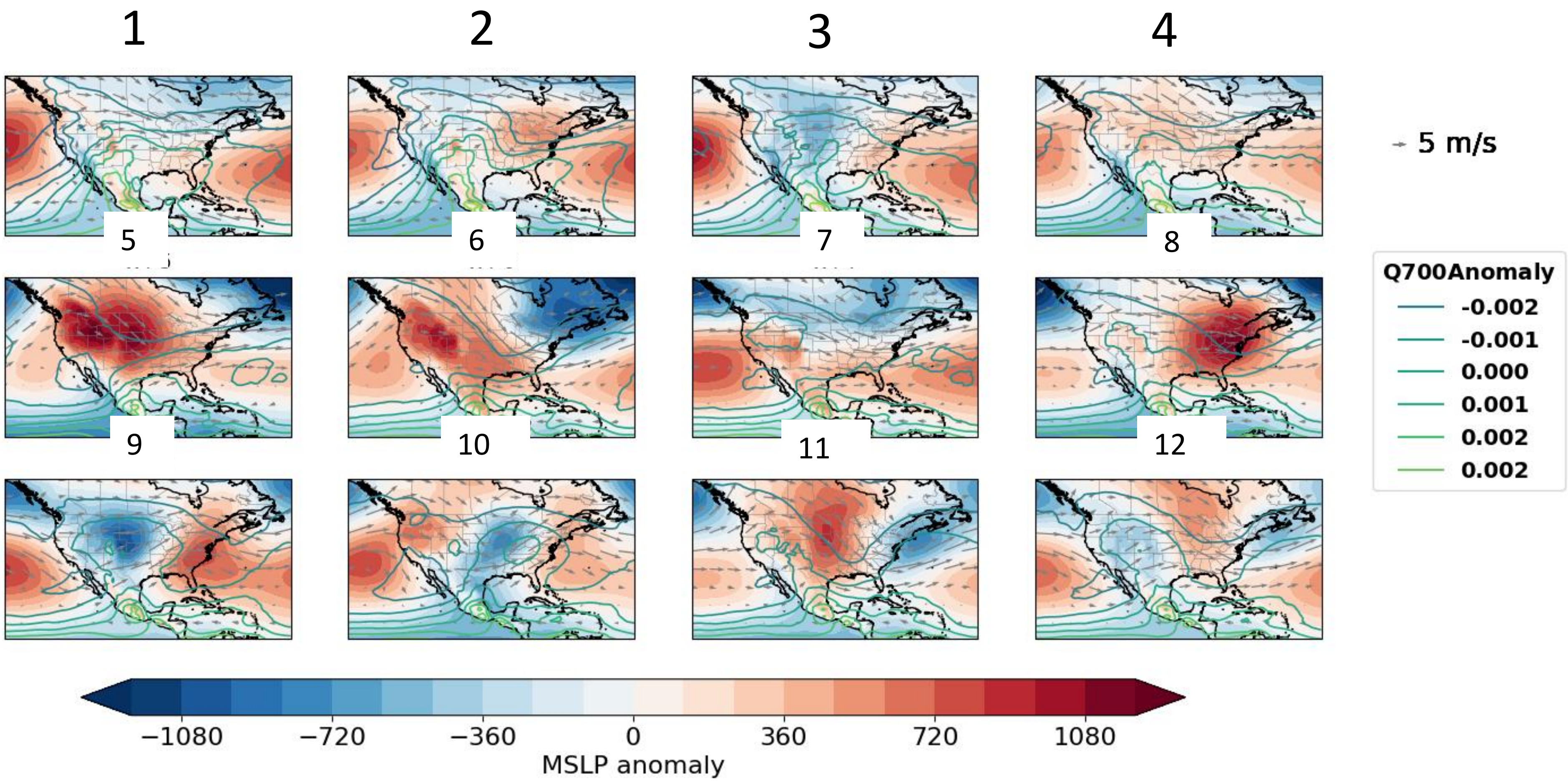
Andreas F. Prein[1], Gregory J. Holland[1], Roy M. Rasmussen[1], Martyn P. Clark[1], and Mari R. Tye[1]

[1]National Center for Atmospheric Research, Boulder, Colorado, USA

(Prein et al. 2016)

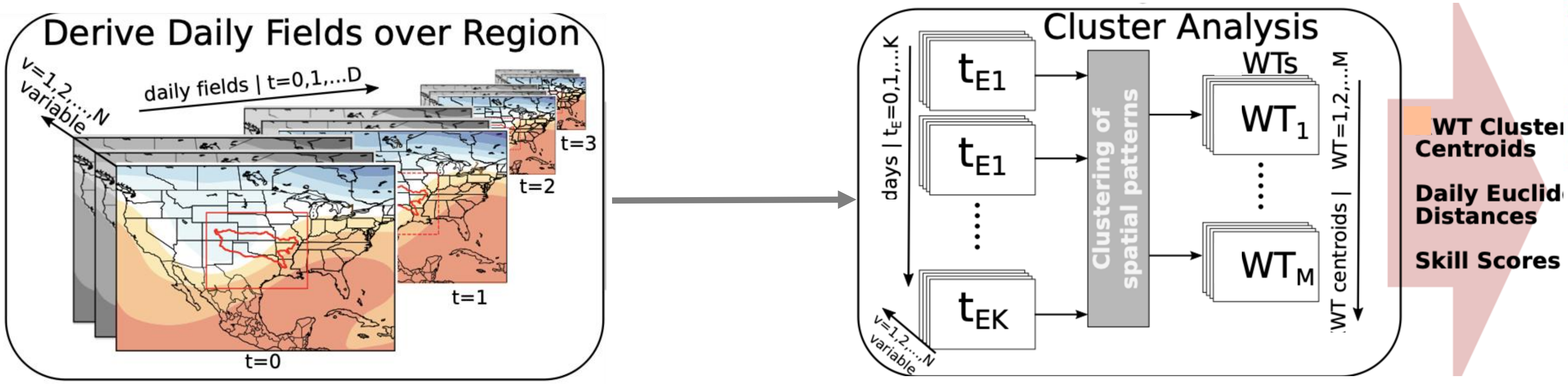
How well do forecast products predict the **seasonal** frequency of weather types associated with precipitation?

Weather types (WTs) categorize recurring large-scale atmospheric patterns.

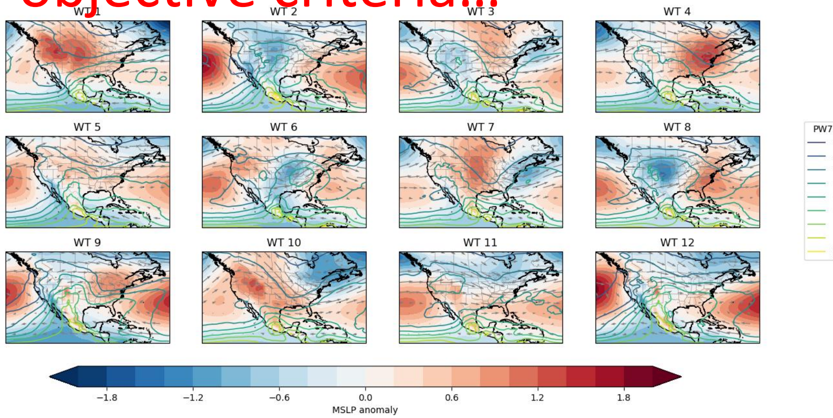


(WTs reproduced from Prein et al. 2022; Fig from Towler et al. WAF minor revision)

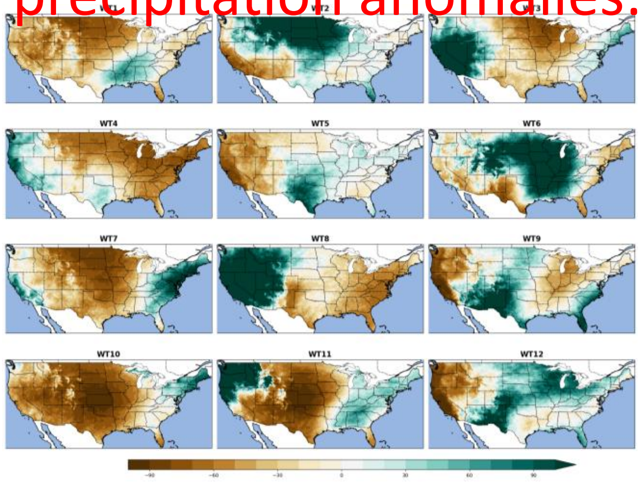
Weather types (WTs) are developed using clustering algorithm that tests large-scale predictor combinations & number of clusters.



Number of WTs optimized using objective criteria…



… based on associated precipitation anomalies:



Objective Criteria

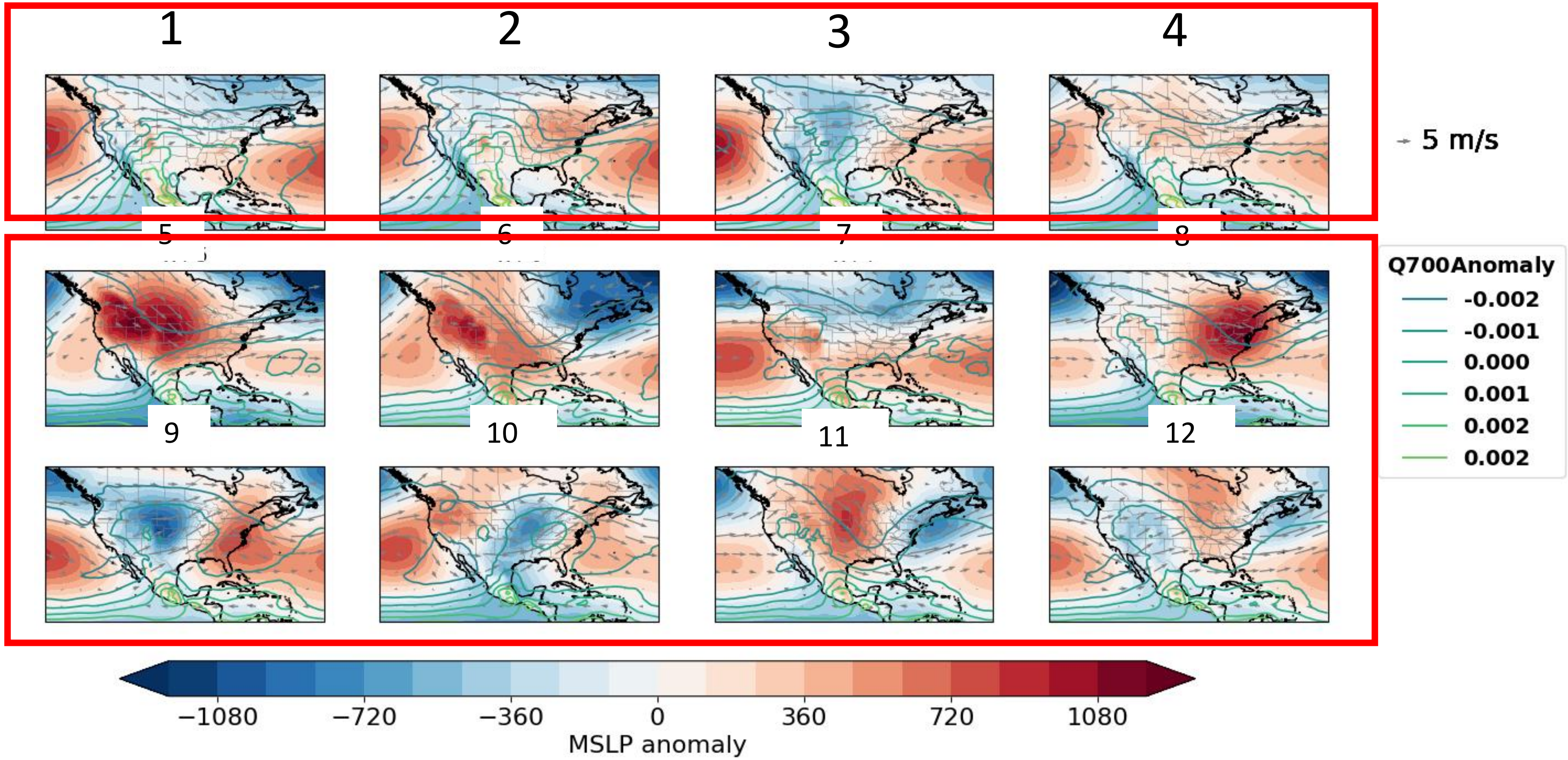
1. Each precipitation pattern is as distinct as possible (maximize absolute precipitation anomalies in clusters)
2. Precipitation variance as similar as possible within a cluster, and distinct from other clusters (minimize the ratio of inter cluster precipitation standard deviation to intra-cluster precipitation standard deviation)

Fig. Mod. from Prein and Mearns 2021

12 Weather Types are identified using 3 predictors: Sea Level Pressure, precipitable water, and winds

4 occur in summer

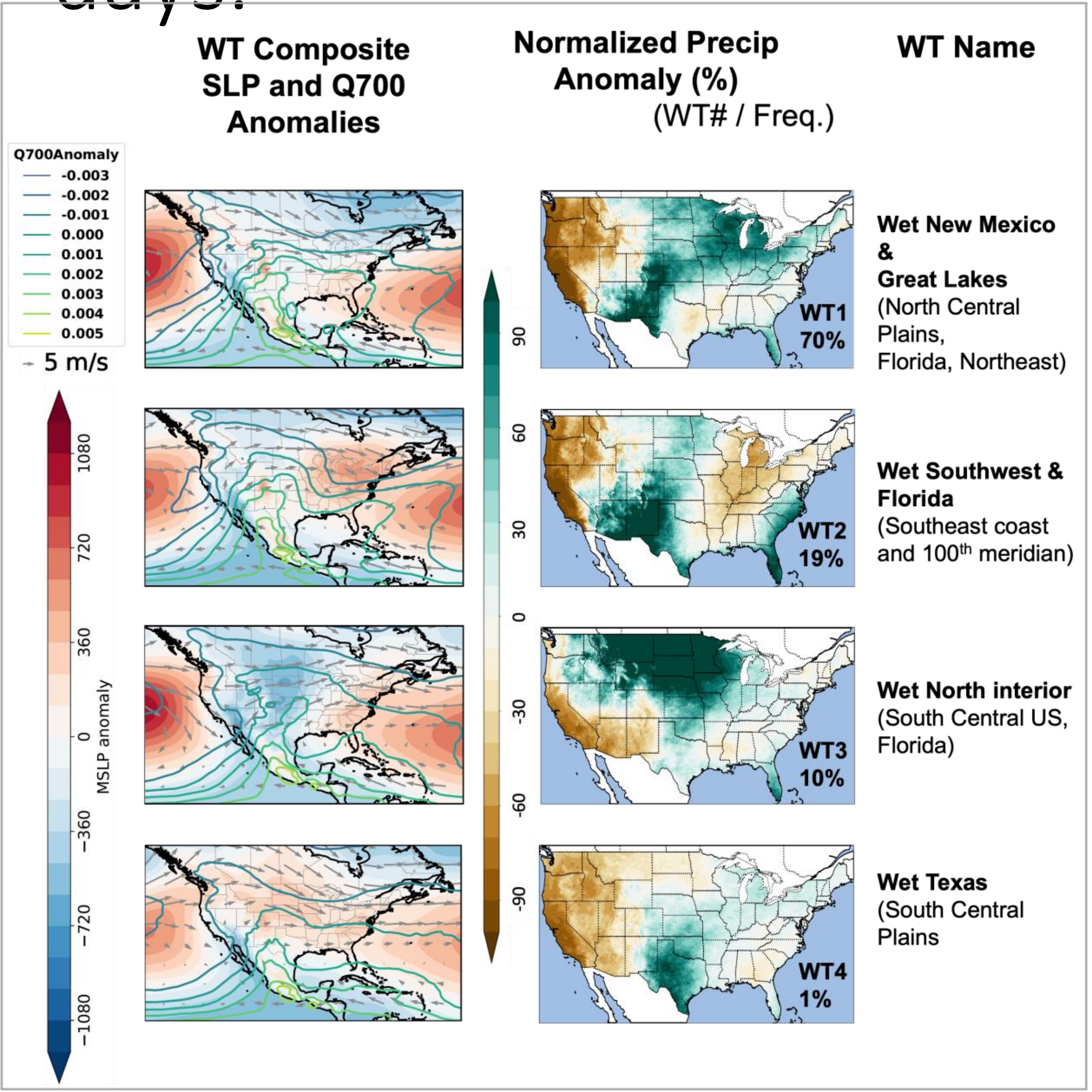
8 occur in winter



(WTs reproduced from Prein et al. 2022; Fig from Towler et al. WAF minor revision)

Four CONUS WTs* are identified for summer (JJA) days.

*Predictors: Sea Level Pressure (SLP), Precipitable Water (Q700), & winds (Prein et al. 2016)



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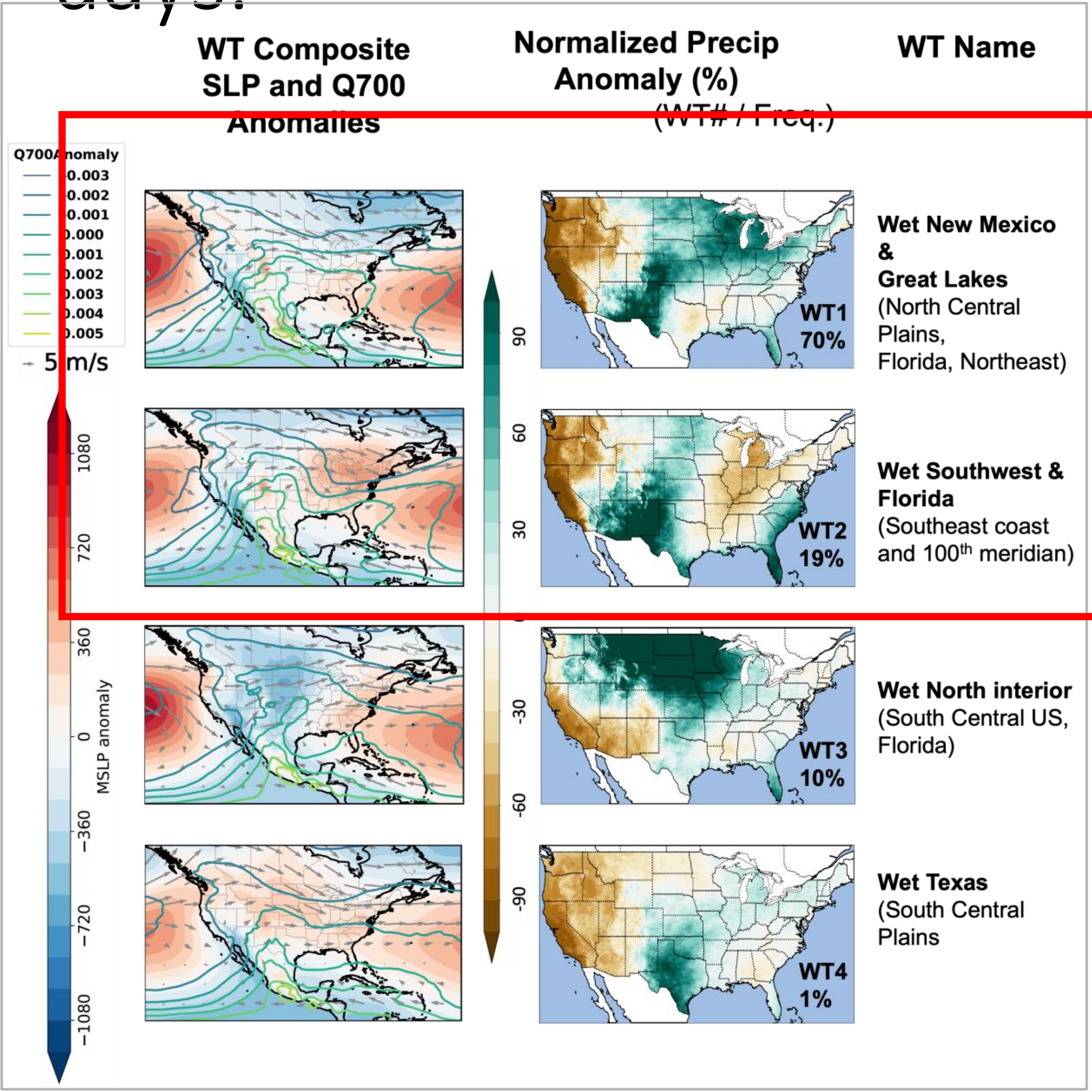
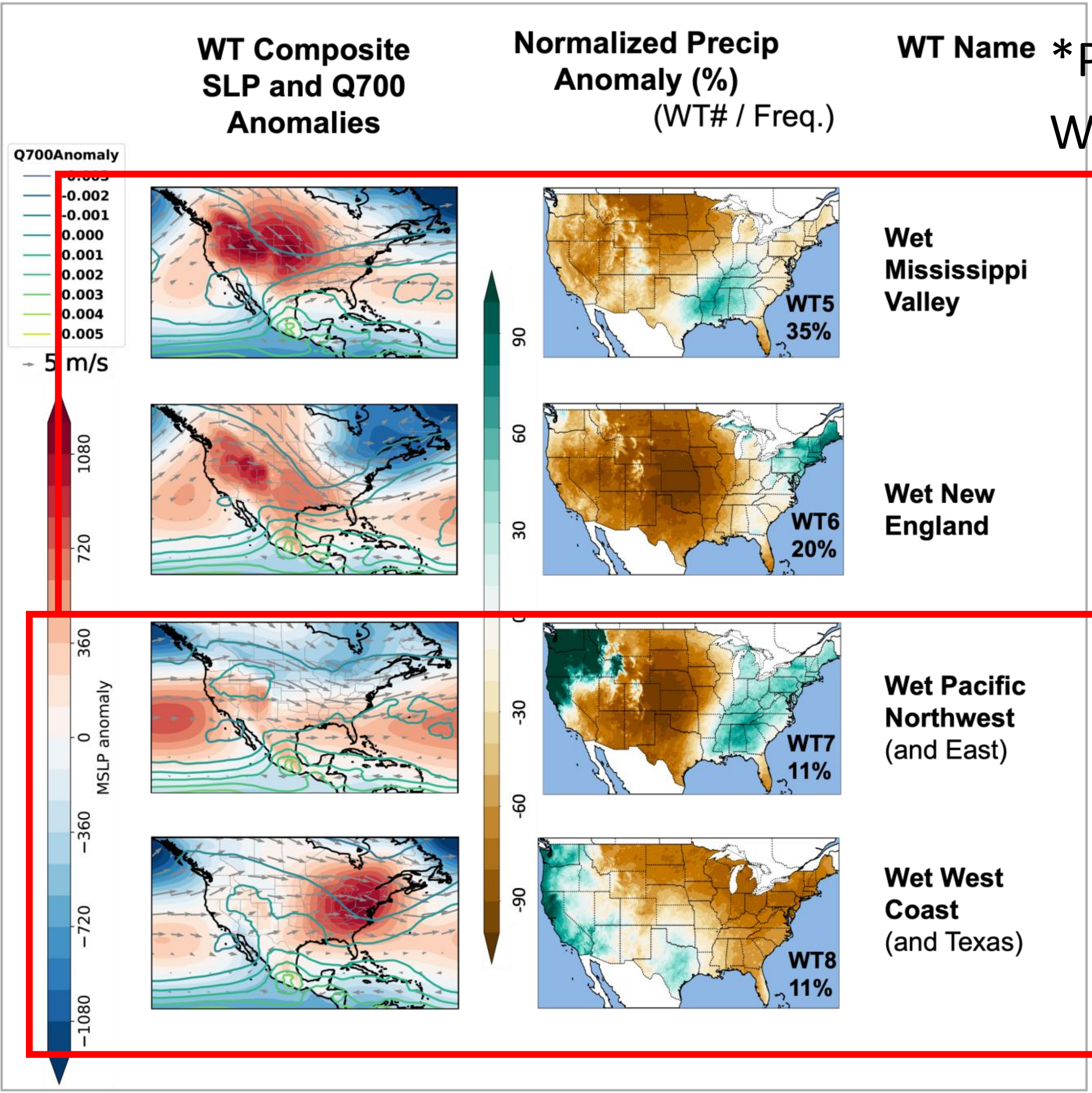


- Wet NM/GL: rich supply of Gulf moisture and generally lower than normal surface pressures across CONUS.
- Wet SW/FL: similar wet anomalies, lower (higher) pressure in West (East), richer moisture to the south.

Eight CONUS WTs* are identified for winter (DJF) days.

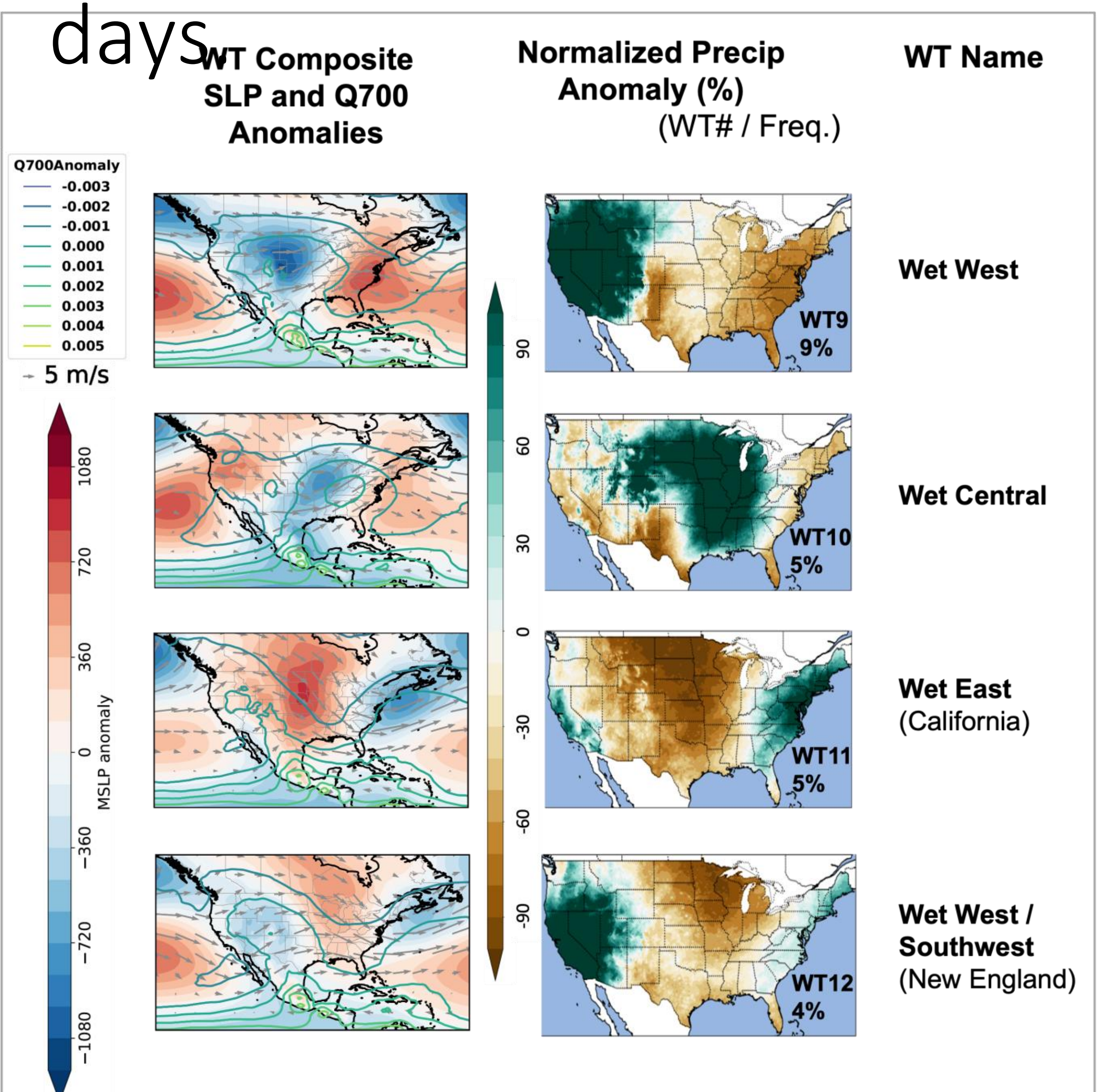


*Predictors: Sea Level Pressure (SLP), Precipitable Water (Q700), & winds (Prein et al. 2016)

- For the Western US, regions of anomalously high surface pressure are anomalously dry

- Relatively low surface pressures and high low-level moisture result in wet anomalies.

Eight CONUS WTs* are identified for winter (DJF) days



Several additional, but less frequent WT "flavors", where regions of anomalously high surface pressure are anomalously dry and regions of anomalous troughing and low-level moisture are anomalously wet.

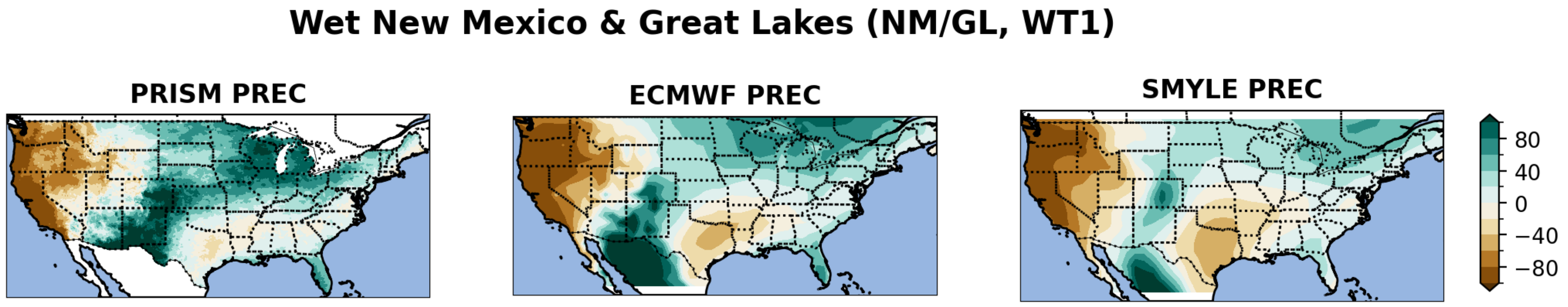
How well are these patterns captured by forecasting systems from different sides of the weather/climate and operations/research spectrum?

- Weather/operations: ECMWF (European Centre for Medium-Range Weather Forecasts (IFS Version 5 from Copernicus Climate Change Service)
- Climate/research: Seasonal-to-Multiyear Large Ensemble (generated using the NSF NCAR’s CESM2; Yeager et al. 2022)

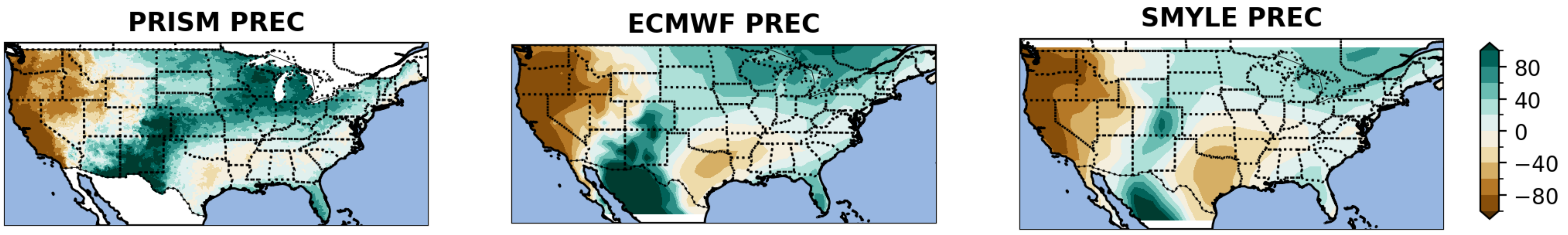
Clustering algorithm applied to hindcasts from two seasonal forecast systems (ECMWF and SMYLE), & evaluated against PRISM (precipitation) and ERA-Interim (large-scale predictors).

- Results are from ”lead 1”: e.g., May initialized for summer (JJA)
- Evaluate predictability of the **frequency** of precipitation-based WTs over 3-month season
- Used retrospective forecasts (hindcasts) from 1993-2019 (n = 27 years)
- Used ensemble average (SMYLE had 20 members; ECMWF had 25 members).
- 1 degree resolution.

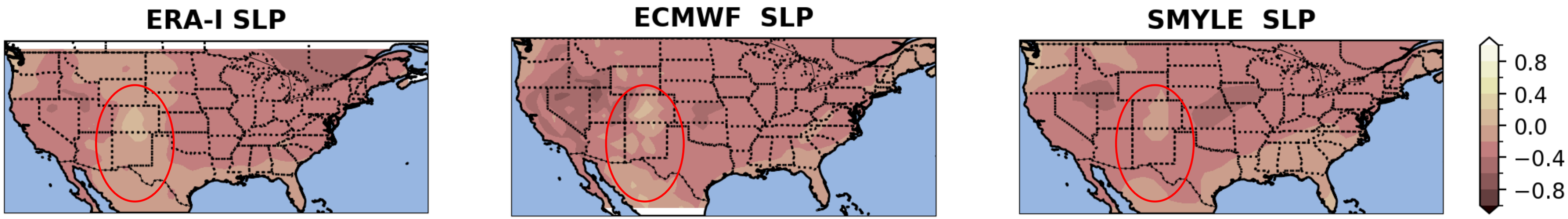
Visually, ECMWF precipitation is closer to PRISM than SMYLE

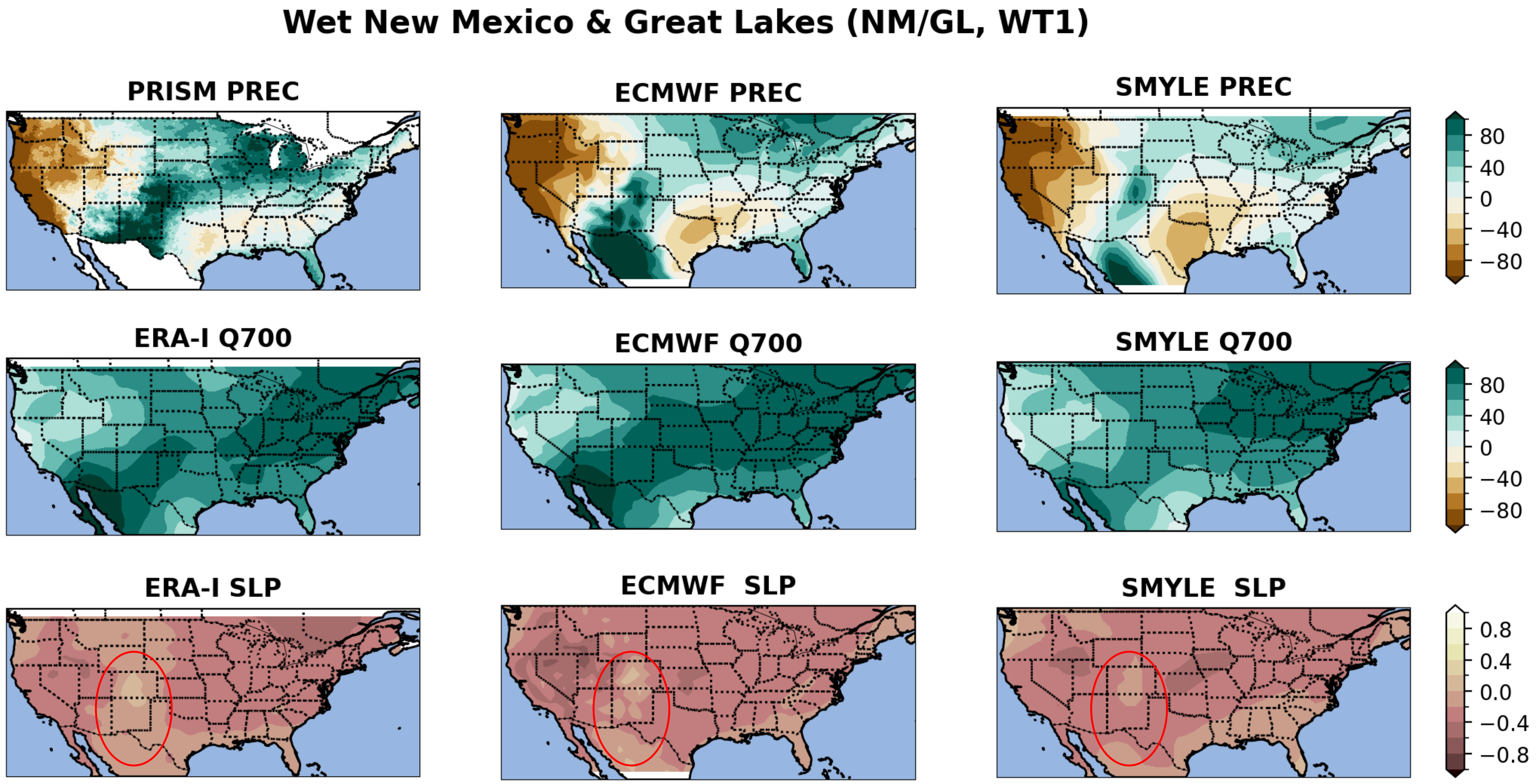


Wet New Mexico & Great Lakes (NM/GL, WT1)



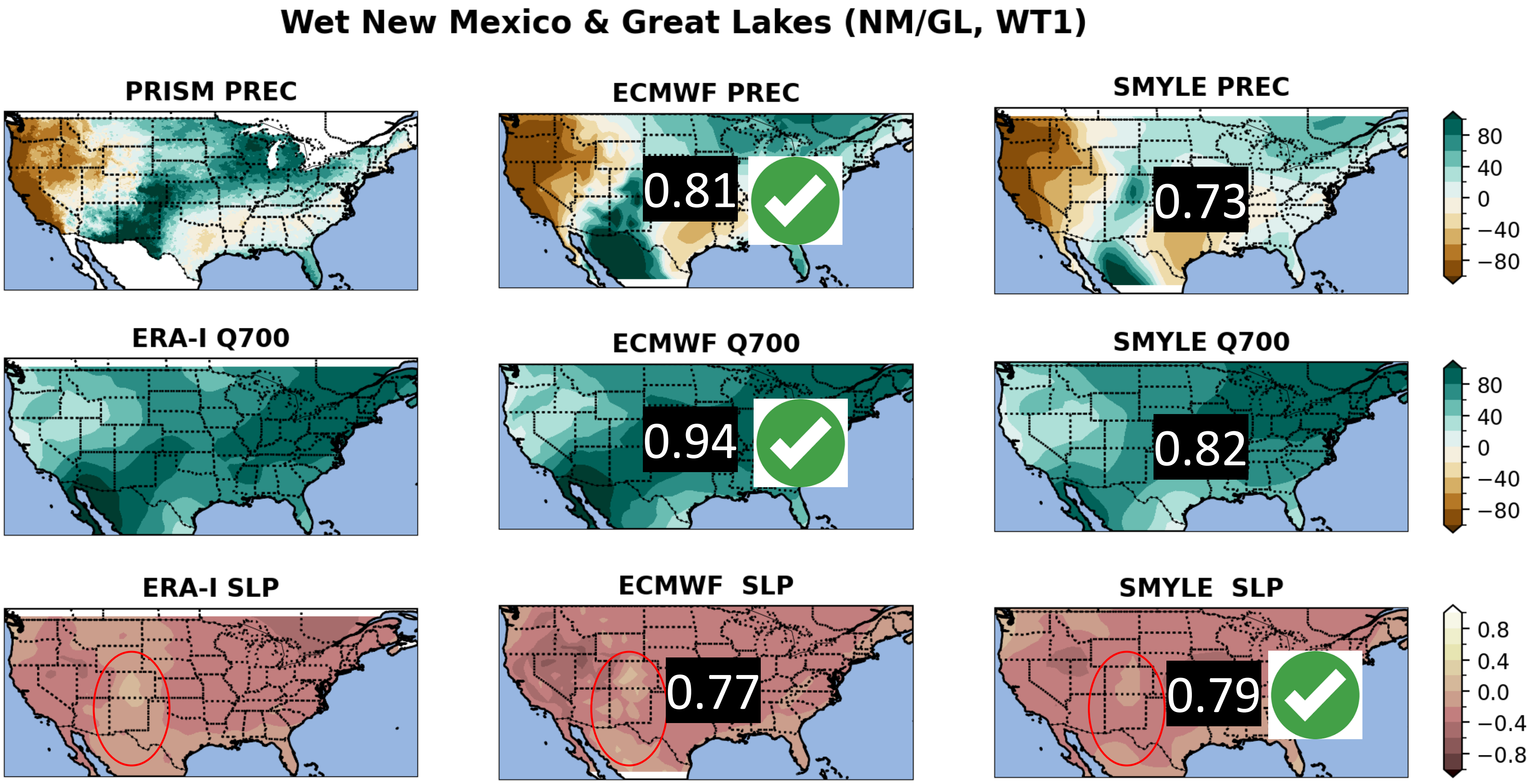
SLP is similar, ECMWF does a slightly better job capturing the low pressure over NM/Colorado





Wet New Mexico & Great Lakes (NM/GL, WT1)
PRISM PREC
ECMWF PREC
SMYLE PREC
ERA-I Q700
ECMWF Q700
SMYLE Q700
ERA-I SLP
ECMWF SLP
SMYLE SLP
80
40
0
−40
−80
80
40
0
−40
−80
0.8
0.4
0.0
−0.4
−0.8

Pattern correlations:



For average pattern correlation, ECMWF is slightly better than SMYLE, and large-scale predictors are better captured than precipitation.

	Precipitation		Q700		SLP	
	ECMWF	SMYLE	ECMWF	SMYLE	ECMWF	SMYLE
Average	0.82	0.74	0.96	0.92	0.97	0.96

We can also evaluate the *number of days* forecasted for each WT.

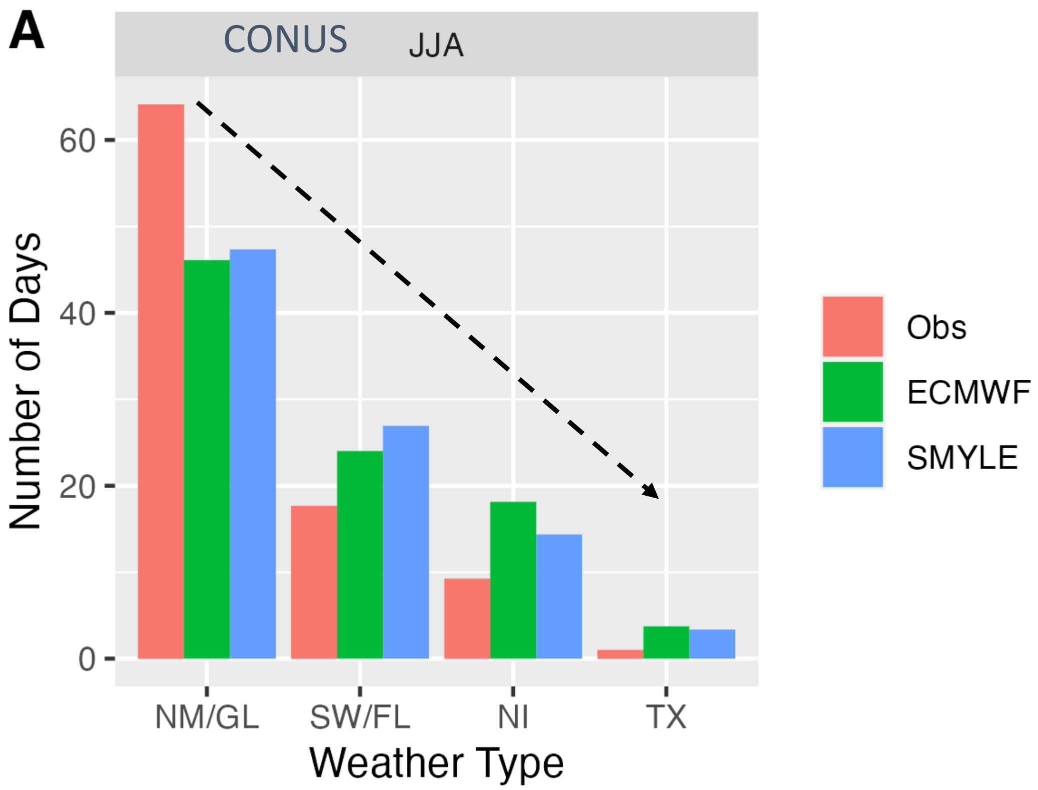
ERA-Interim

European Centre for Medium-Range Weather Forecasts (IFS Version 5 from Copernicus Climate Change Service)

Seasonal-to-Multiyear Large Ensemble (generated using the NSF NCAR's CESM2; Yeager et al. 2022)

Summer WTs: Both forecast systems capture rank;

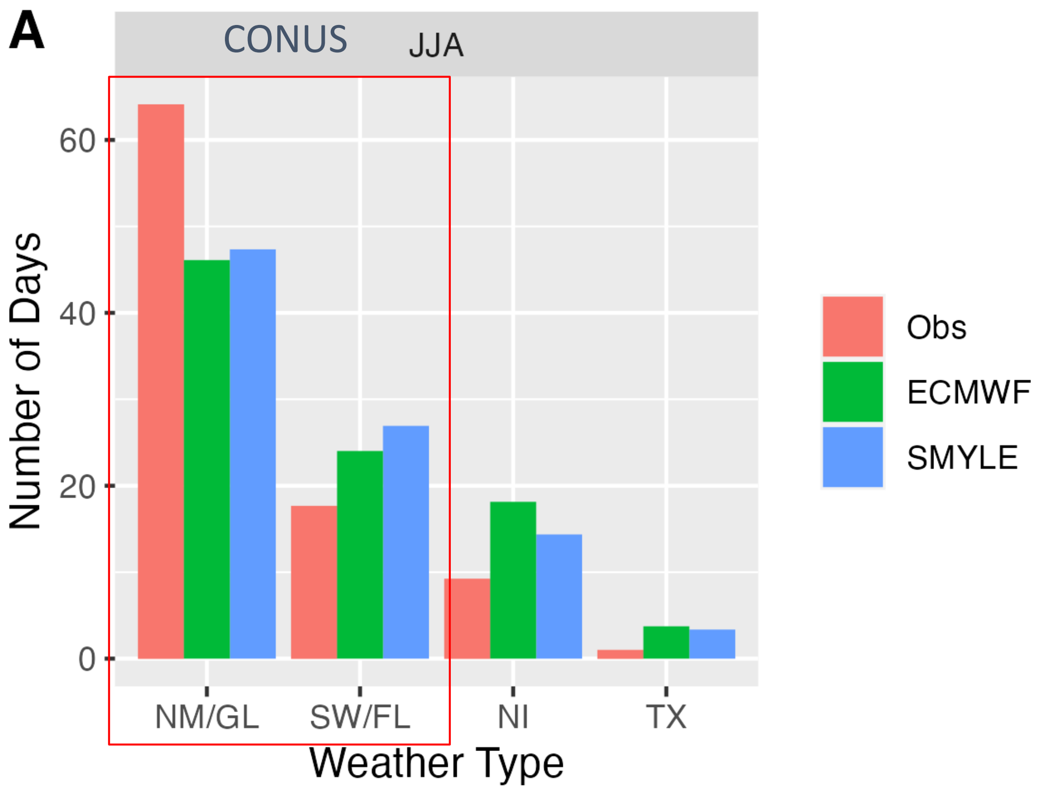
Average frequency (days)



Towler et al. (WAF Minor Revision)

Summer WTs: Both forecast systems capture rank; underestimate avg freq of NM/GL, and over-estimate SW/FL.

Average frequency (days)



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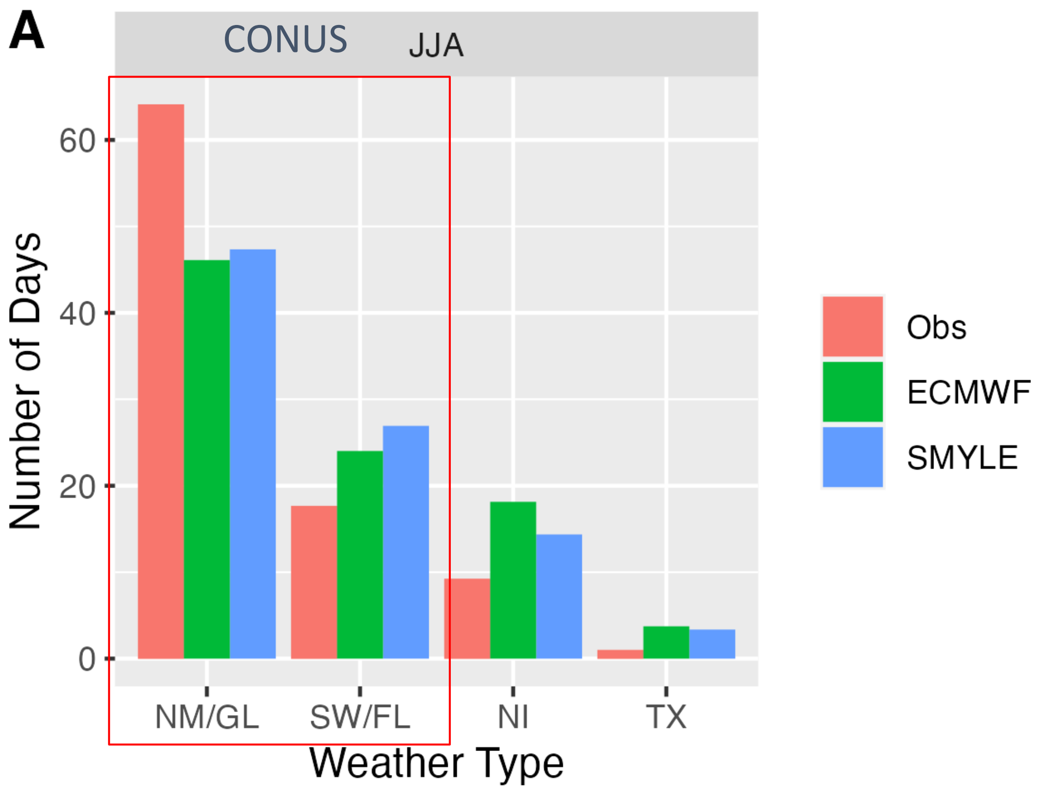
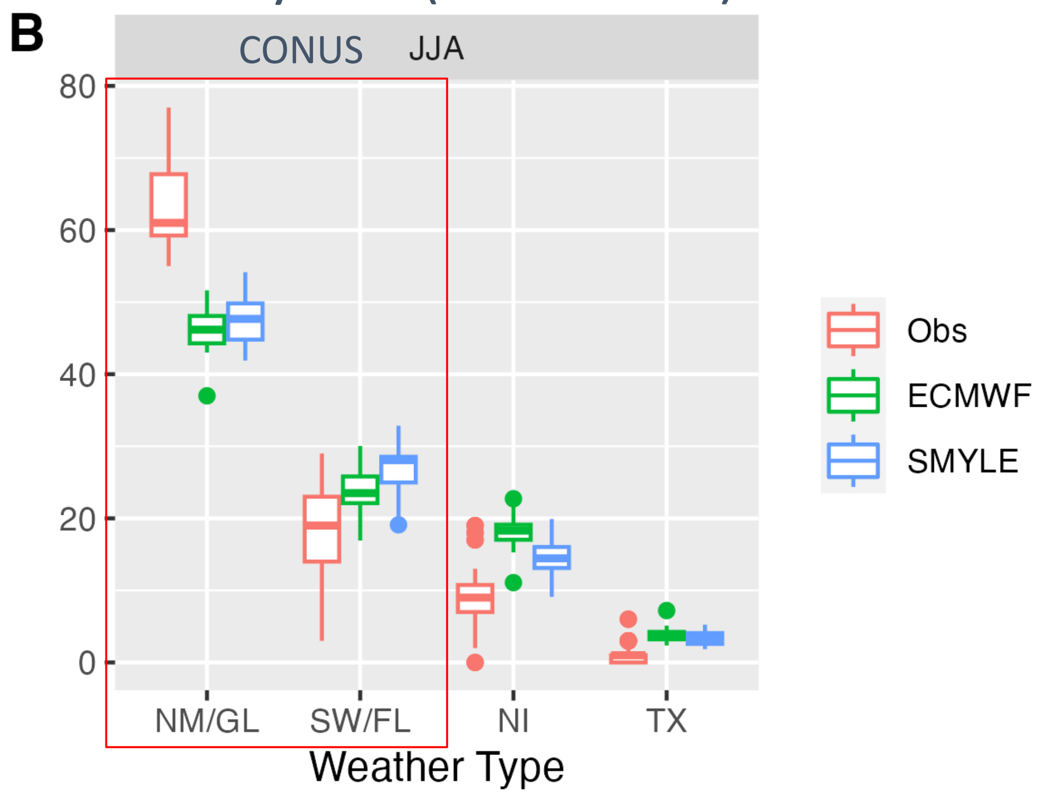


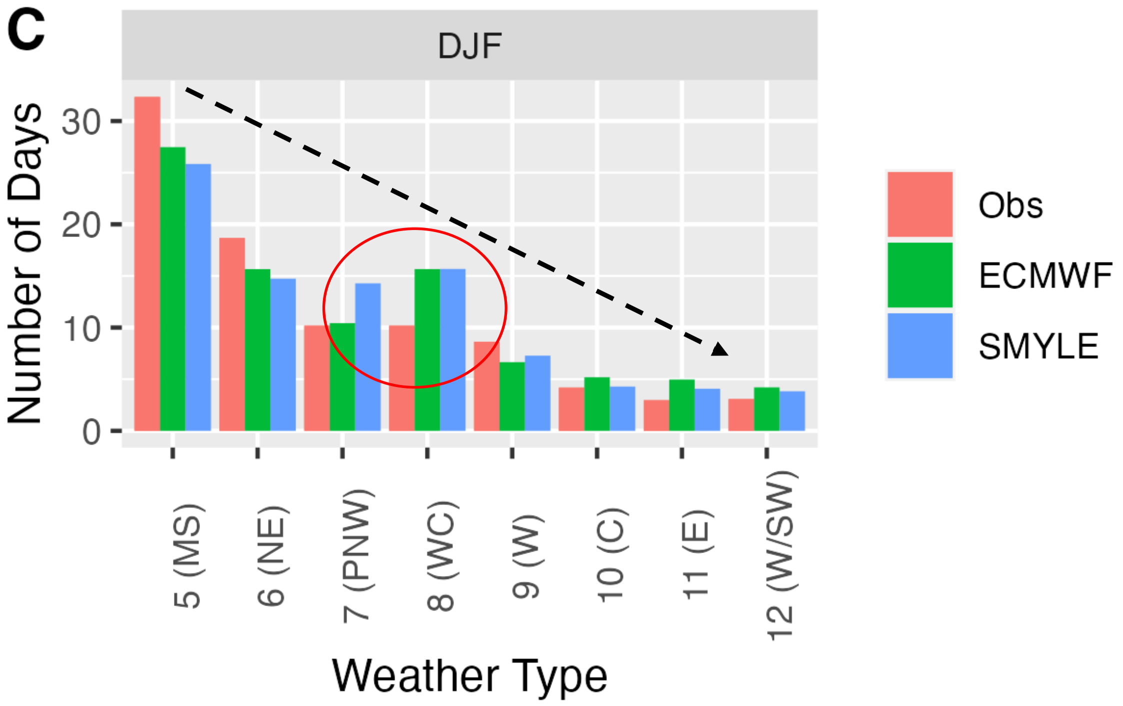
Annual frequency (days), n = 27 years (1993-2019)



Towler et al. (WAF Minor Revision)

Winter WTs: Both forecast systems generally capture descending rank, overestimating of WT7 and 8.

Average frequency (days)



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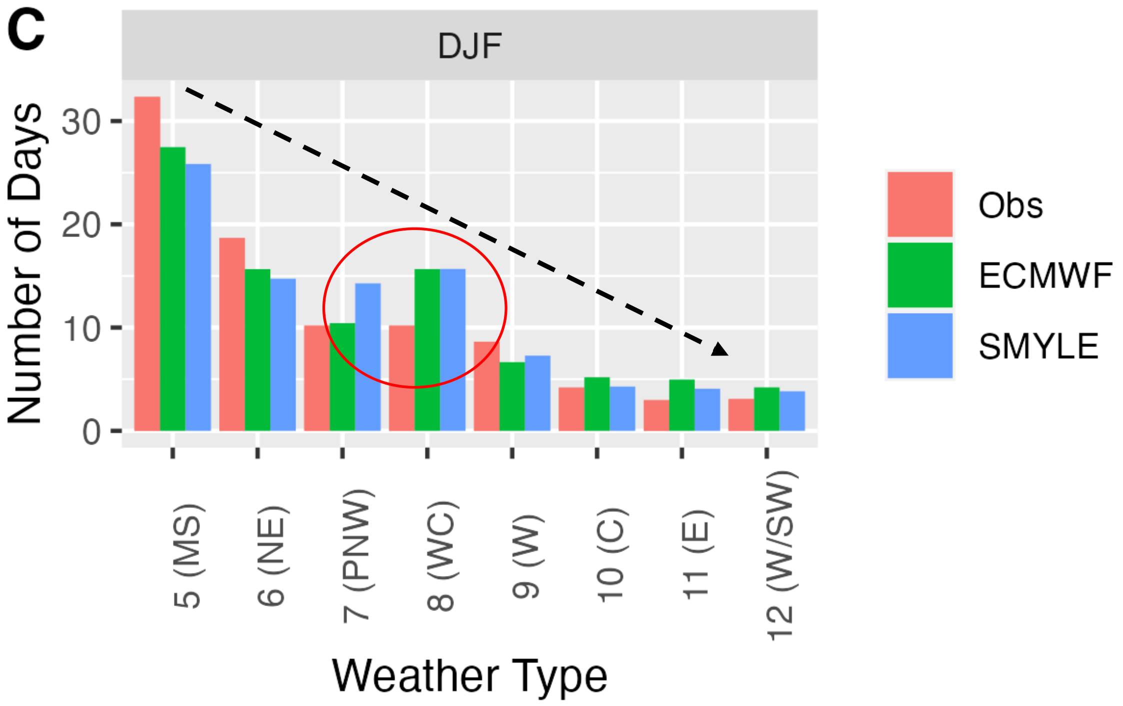

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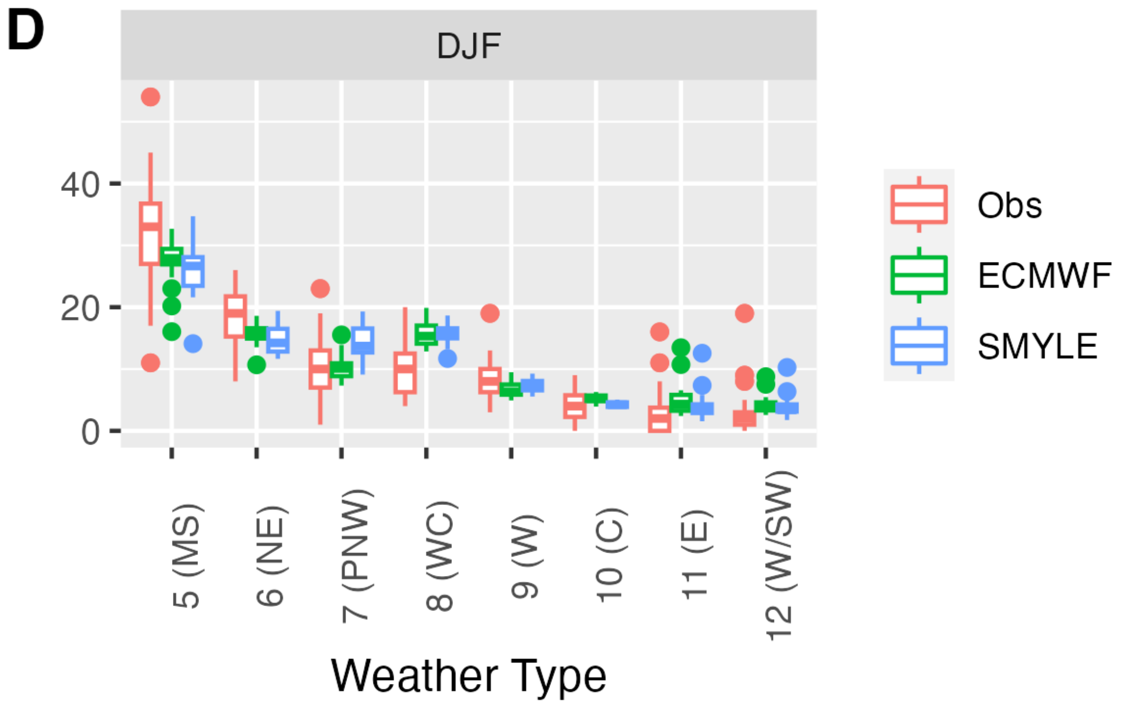
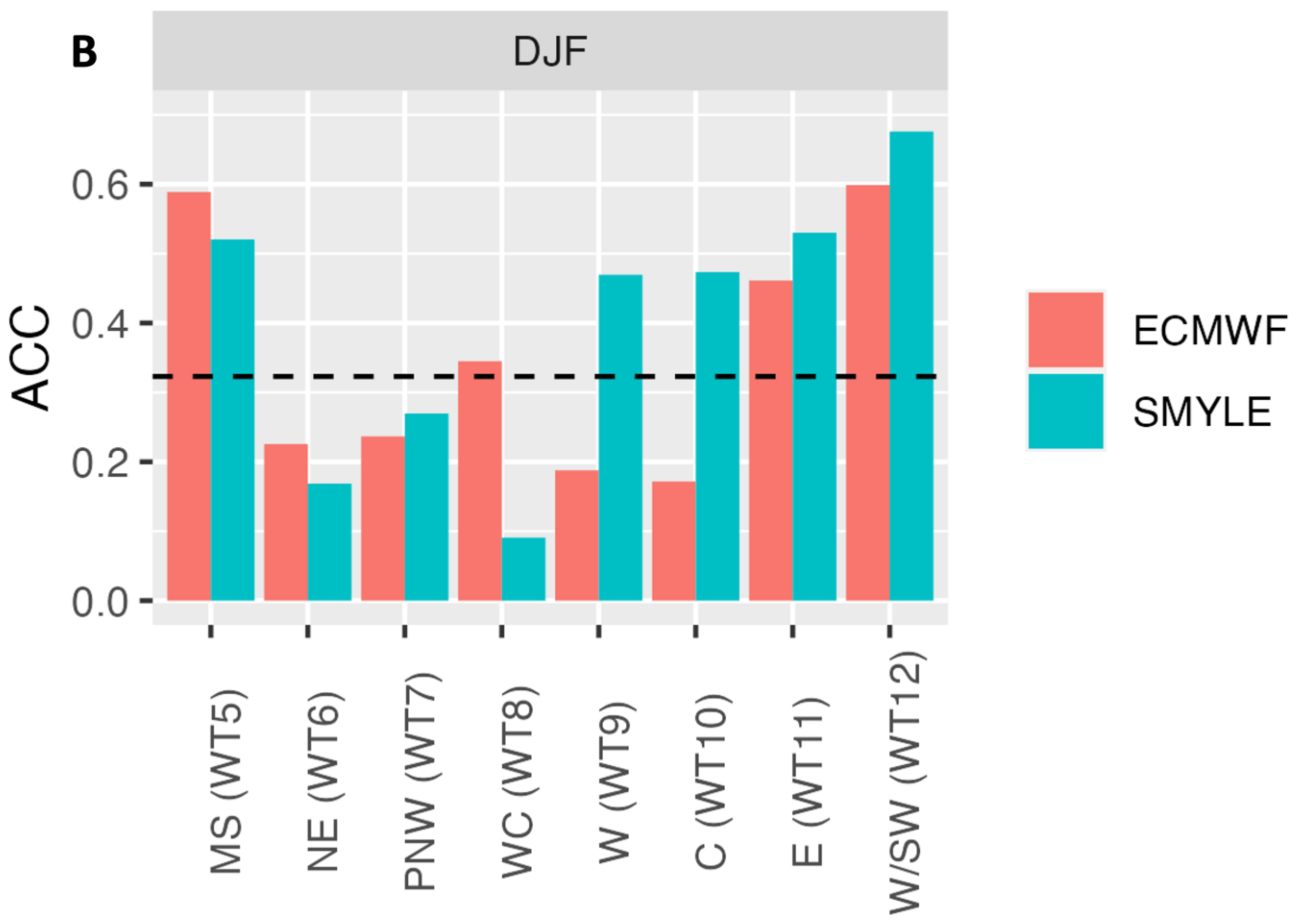


Towler et al. (WAF Minor Revision)

For the Winter WTs, there is at least one forecast system for 6/8 WTs statistically significant (ACC > 0.32, p=.1)

ACC for Annual frequency



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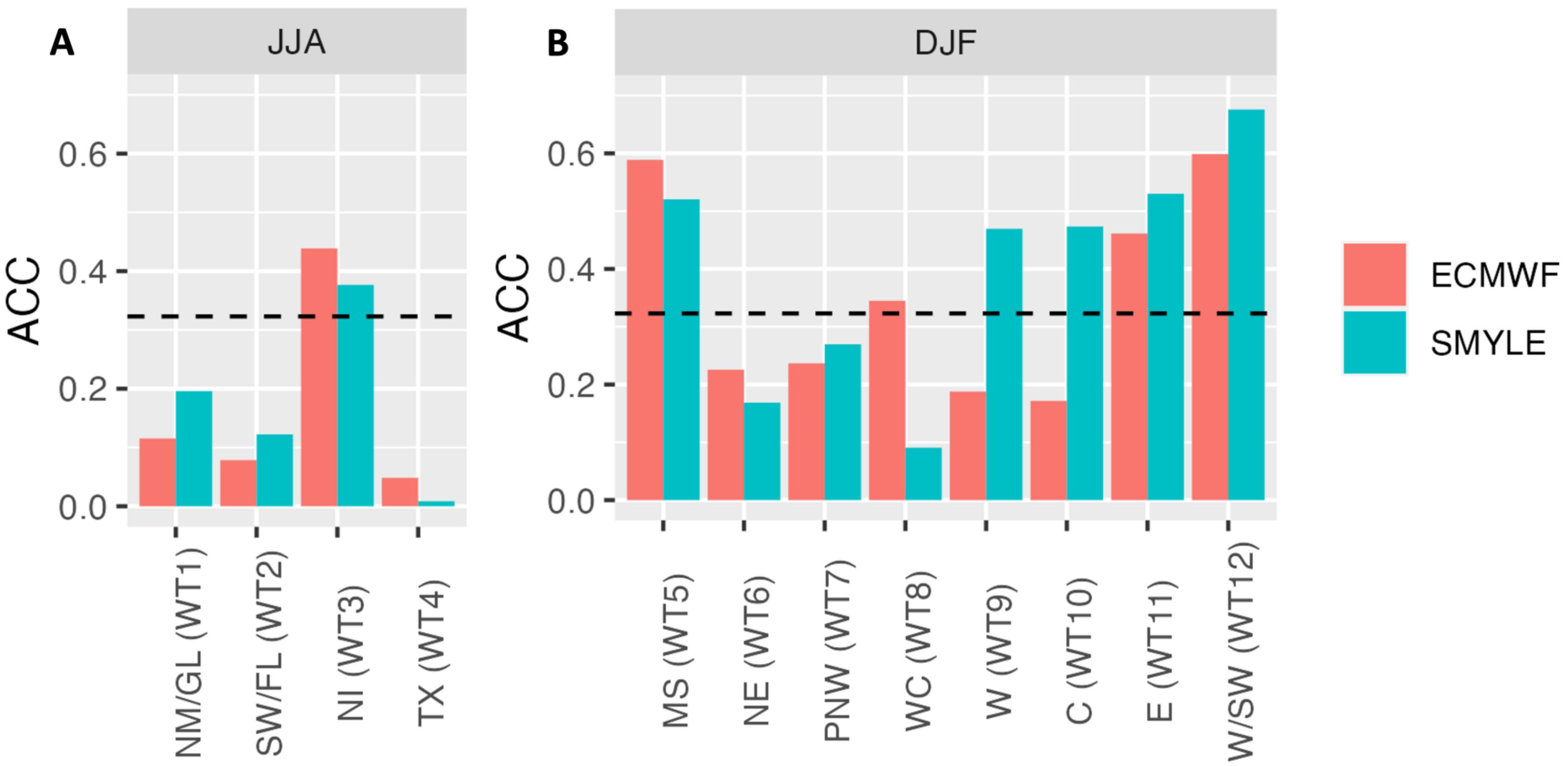
Summer: lower ACC values and only WT3 is significant.

ACC for Annual frequency



Towler et al. (WAF Minor Revision)

Sidebar:

Does skill improve with weather types developed for smaller domains/seasons?

US SW** WTs

(Prein, Towler et al. 2022)

** United States Southwest

Geophysical Research Letters

ADVANCING EARTH AND SPACE SCIENCE

RESEARCH LETTER

10.1029/2021GL095602

Key Points:

- Seasonal forecasting models do not have skill in simulating North American Monsoon (NAM) rainfall
- We use a data driven weather type (WT) algorithm to identify synoptic situations associated with NAM

Sub-Seasonal Predictability of North American Monsoon Precipitation

Andreas F. Prein[1], Erin Towler[1], Ming Ge[1], Dagmar Llewellyn[2], Sarah Baker[3], Shana Tighi[3], and Lucas Barrett[2]

[1]National Center for Atmospheric Research (NCAR), Boulder, CO, USA, [2]Bureau of Reclamation (Upper Colorado Region), Albuquerque, NM, USA, [3]Bureau of Reclamation (Lower Colorado Region), Boulder, NV, USA

Three WTs are identified for summer (JJA) for several US SW regions:

- Arizona West
- Arizona East
- New Mexico South
- New Mexico North

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- **Arizona West**
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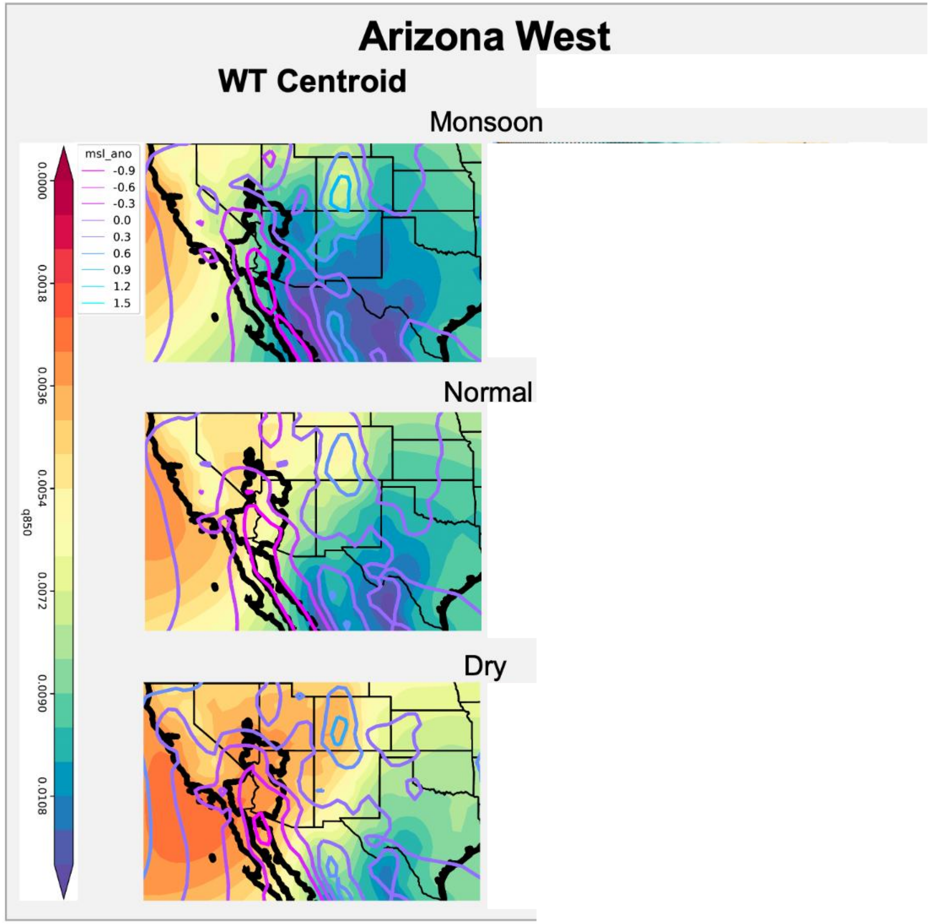

*Predictor: Low level moisture (Q850) (Prein et al. 2022)

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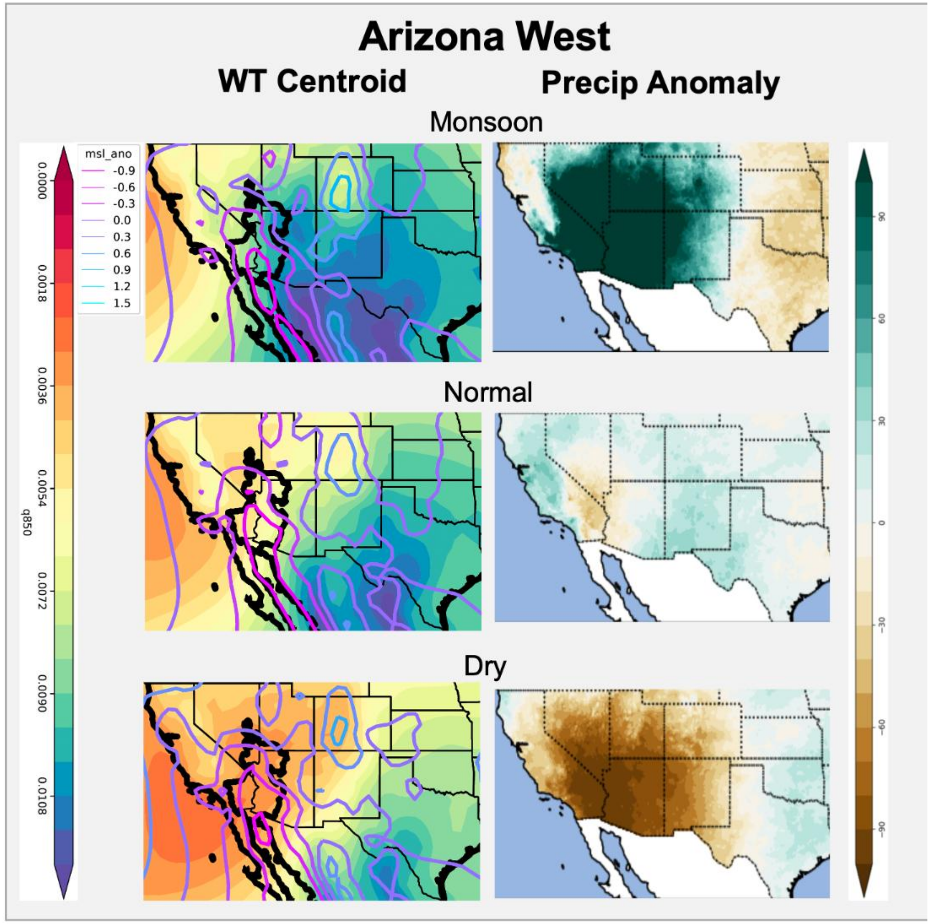


*Predictor: Low level moisture (Q850) (Prein et al. 2022)

For each US SW region, there is at least one forecast system that outperforms the CONUS WTs in terms of ACC*, but most are not statistically significant**

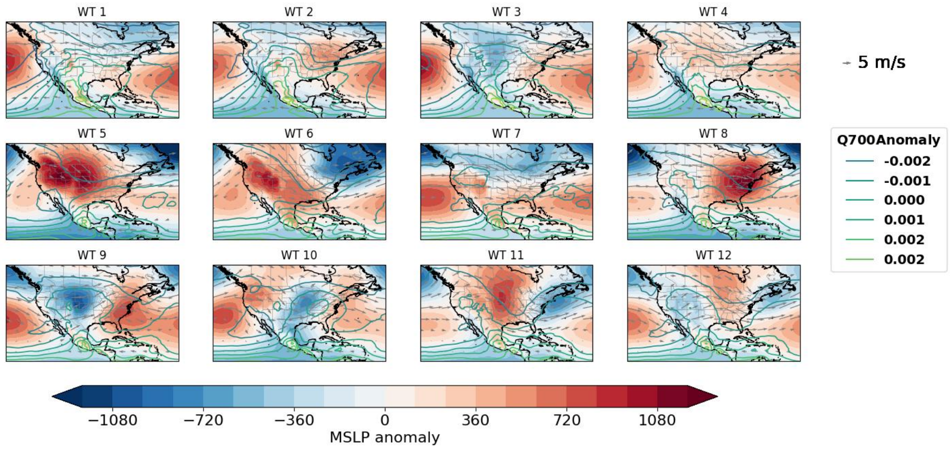
*Anomaly correlation coefficient

** at p=.1, ACC>0.32

<table>
<tr><th></th><th colspan="4">US SW</th><th colspan="4">CONUS</th></tr>
<tr><th></th><th colspan="2">Dry (US SW)</th><th colspan="2">Monsoon (US SW)</th><th colspan="2">NM/GL (CONUS)</th><th colspan="2">SW/FL (CONUS)</th></tr>
<tr><th></th><th>ECMWF</th><th>SMYLE</th><th>ECMWF</th><th>SMYLE</th><th>ECMWF</th><th>SMYLE</th><th>ECMWF</th><th>SMYLE</th></tr>
<tr><td>AZ-East</td><td>0.13</td><td>0.23 ✓</td><td>0.29 ✓</td><td>0.09</td><td rowspan="4">0.12</td><td rowspan="4">0.20</td><td rowspan="4">0.078</td><td rowspan="4">0.12</td></tr>
<tr><td>AZ-West</td><td>0.11</td><td>0.21 ✓</td><td>0.21 ✓</td><td>0.06</td></tr>
<tr><td>NM-North</td><td>0.04</td><td>0.13</td><td>0.29 ✓</td><td>-0.21</td></tr>
<tr><td>NM-South</td><td>0.41 ✓</td><td>0.32</td><td>0.31 ✓</td><td>0.09</td></tr>
</table>

Towler et al. (in prep)

Back to the CONUS WTs!



The power divergence (PD) statistic tests if forecasted frequency distribution is statistically different than observed distribution.

(Read and Cressie 1988; Gilleland et al. 2023)

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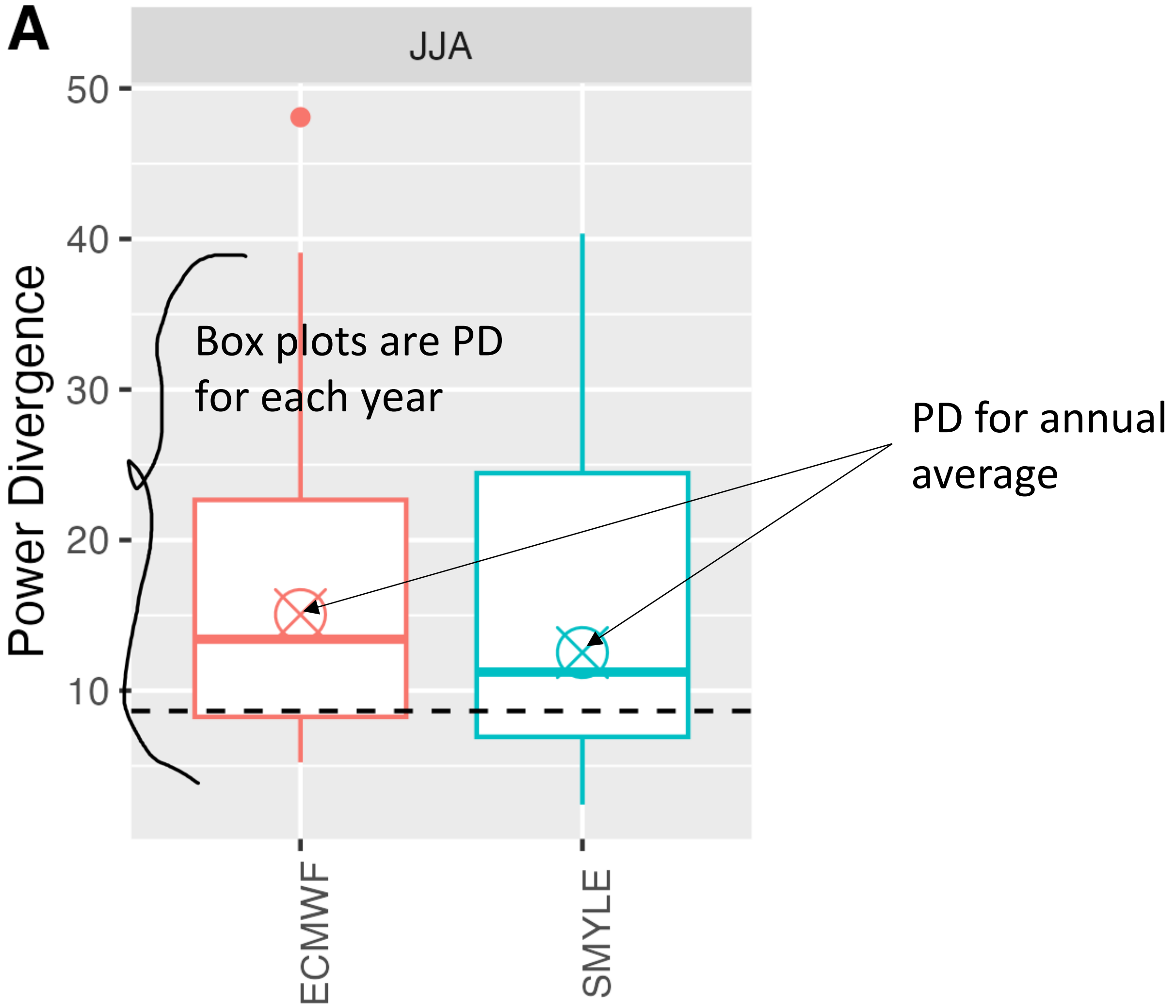

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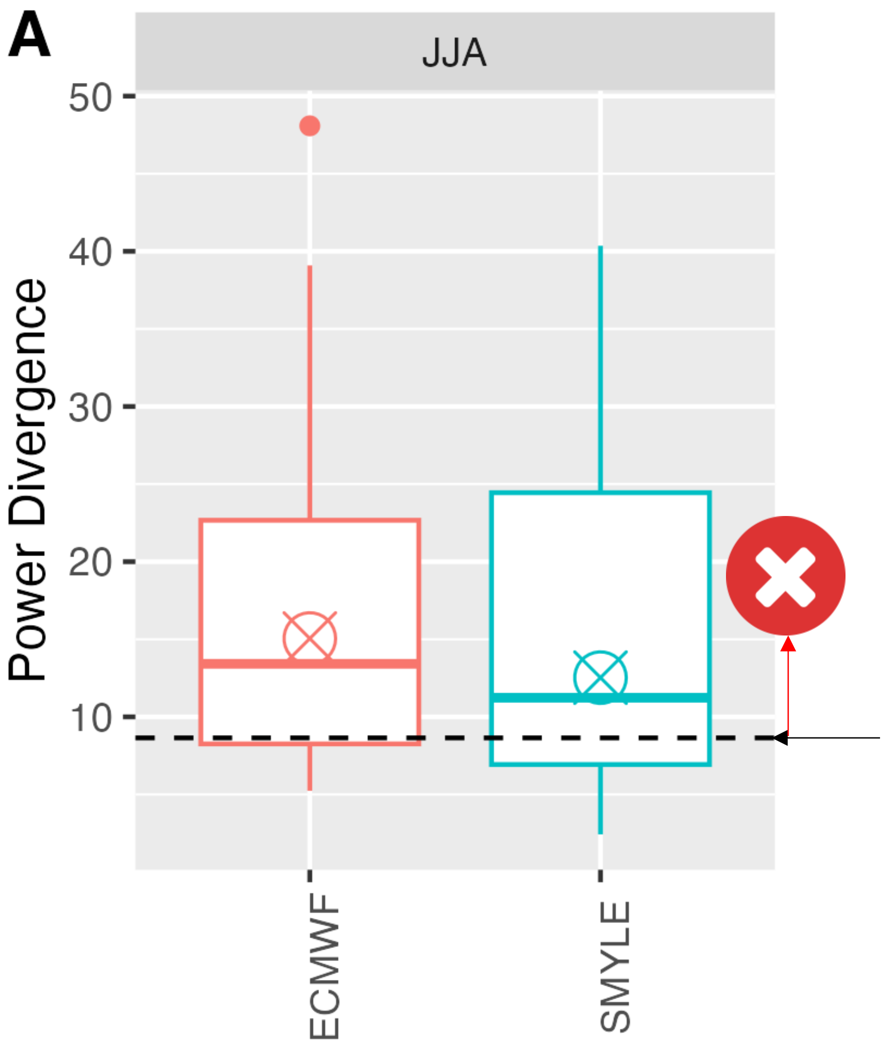


95% significance critical value

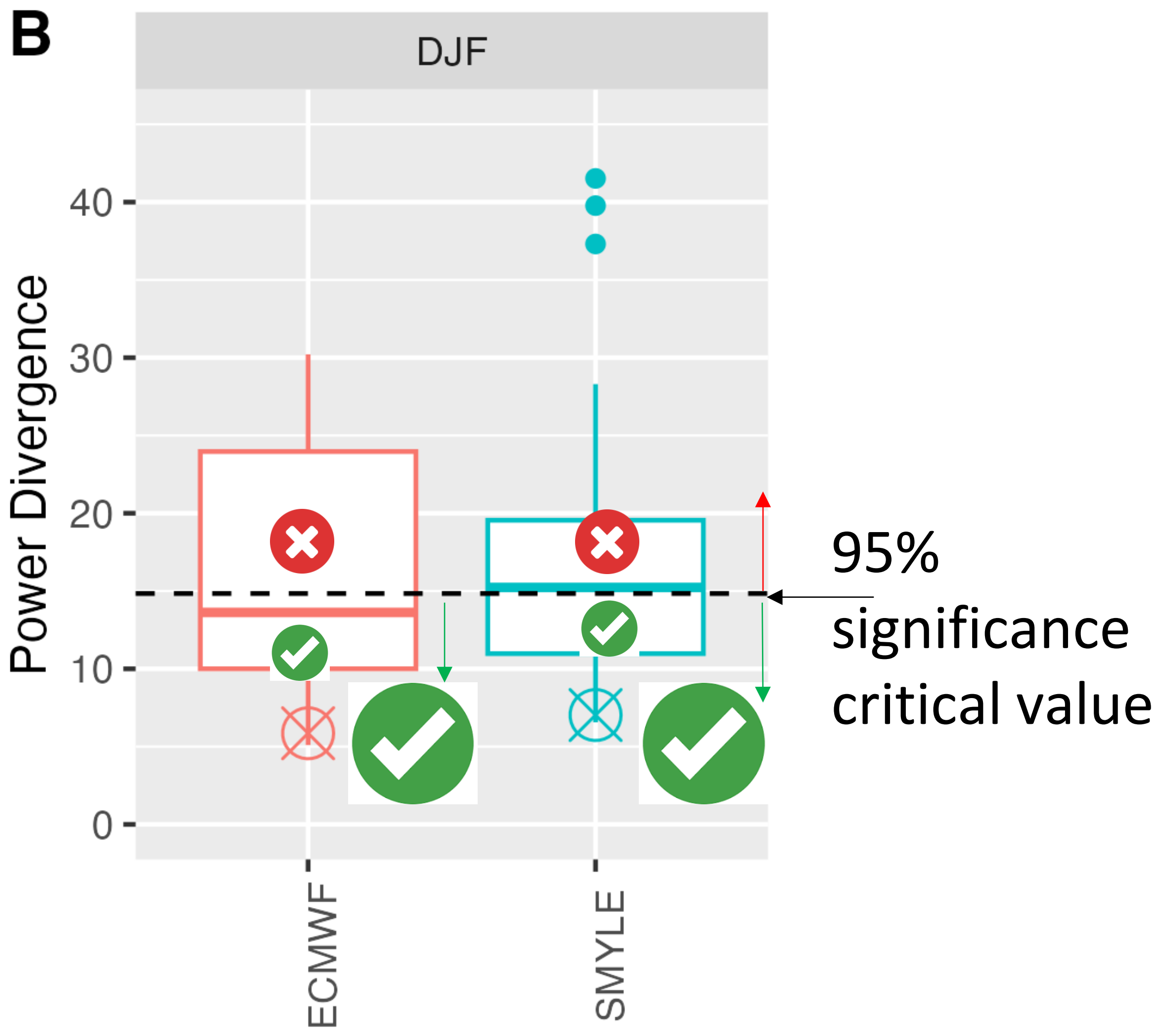
Summer WTs: PD generally above statistically significant line, indicating that neither forecast system captures frequency distribution…

(Read and Cressie 1988; Gilleland et al. 2023)

The power divergence (PD) statistic tests if forecasted frequency distribution is statistically different than observed distribution.

Winter WTs: Average PD is below line, indicating both systems capture frequency distribution…

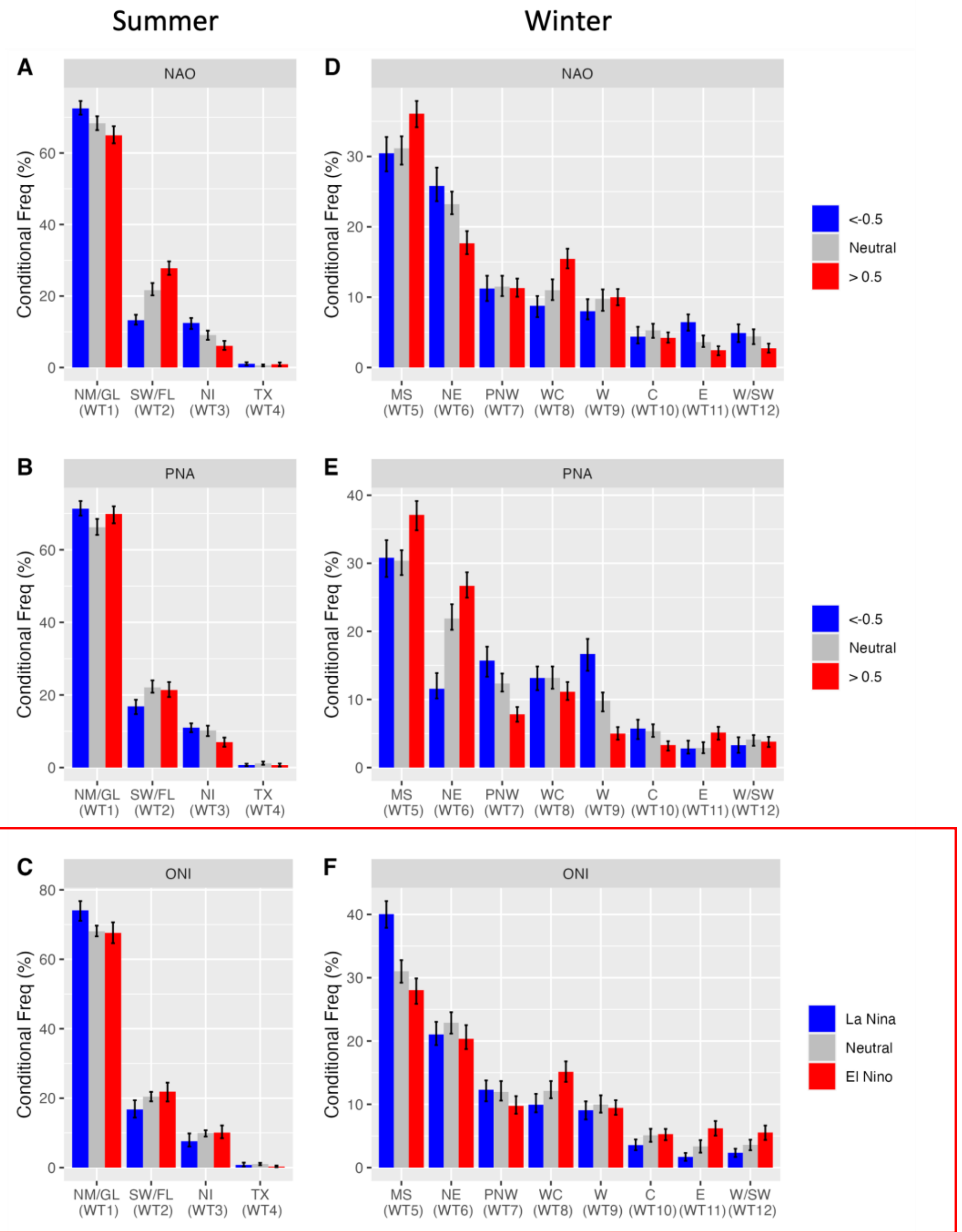
For annual frequency, ~half above, ~half below.



Summer and winter weather type probabilities conditional on NAO, PNA, and ENSO.

- Climate indices influence the WT frequencies, but a variety of WTs can be found in different index states.

- Forecasting these indices alone not enough to capture all of the associated precipitation variability.



Conclusions

- Seasonal forecast products can reproduce dominant weather patterns, can capture frequency on average, but struggle with year-to-year variability
    - Forecast systems (SMYLE and ECWMF) show similar results (encouraging for multi-models).
        - Better at large-scale patterns than precipitation.
        - Winter is better than summer.
    - Low variability could be due to ensemble averaging (and/or forecast products tending to be underdispersed).
- In summer, WTs tailored to US SW regions may help improve skill.
- Precedent for using WTs in operational forecasting.

Thank you!
Questions?

Contact:
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References

Becker, E., B.P. Kirtman, and K. Pegion, 2020: Evolution of the North American Multi-Model Ensemble. *Geophysical Research Letters*, 47 (9), e2020GL087408, https://doi.org/10.1029/2020GL087408

Gilleland, G., D. Muñoz-Esparza, and D. D. Turner, 2023: Competing Forecast Verification: Using the Power-Divergence Statistic for Testing the Frequency of "Better". *Weather and Forecasting*. 38 (9), 1539-1552, https://doi.org/10.1175/WAF-D-22-0201.1

Lee, S. H., M. K. Tippett, and L. M. Polvani, 2023: "A new year-round weather regime classification for North America." *Journal of Climate*, 36(20): 7091-7108.

Molina, M. J., J. H. Richter, A. A. Glanville, K. Dagon, J. Berner, A. Hu, and G. A. Meehl 2023: Subseasonal Representation and Predictability of North American Weather Regimes Using Cluster Analysis. *Artificial Intelligence for the Earth Systems*, 2, 1–25. https://doi.org/10.1175/AIES-D-22

Neal, R., D. Fereday, R. Crocker, and R. E. Comer, 2016: A flexible approach to defining weather patterns and their application in weather forecasting over Europe. *Meteor. Appl.*, 23, 389–400, https://doi.org/10.1002/met.1563.

Neal, R., J. Robbins, R. Crocker, D. Cox, K. Fenwick, J. Millard, and J. Kelly, 2024: A seamless blended multi-model ensemble approach to probabilistic medium-range weather pattern forecasts over the UK. *Meteor. Appl.*, 31 (1), DOI: 10.1002/met.2179

Prein, A.F., G. J. Holland, R. M. Rasmussen, M. P. Clark, and M. R. Tye, 2016: Running dry: The US Southwest's drift into a drier climate state. *Geophys Res Lett*, 43 (3), 1272–1279

Prein, A.F., E. Towler, M. Ge, D. Llewellyn, S. Baker, S. Tighi, and L. Barrett, 2022: Sub-Seasonal Predictability of North American Monsoon Precipitation. *Geophys Res Lett*, 49(9), https://doi.org/10.1029/2021GL095602.

Read, T. R. C., and N. A. C. Cressie, 1988: *Goodness-of-fit Statistics for Discrete Multivariate Data*. 1st ed. Springer-Verlag, New York, N.Y., 211 pp.

Robertson, A. W., N. Vigaud, J. Yuan, and M. K. Tippett, 2020: Toward identifying subseasonal forecasts of opportunity using North American weather regimes. *Monthly Weather Review, 148*(5), 1861–1875, https://doi.org/10.1175/MWR-D-19-0285.1

Towler E, Done JM, Ge M, Gilleland E, Prein AF (Minor Revision), Seasonal forecasting of precipitation-relevant weather types over the United States, *Weather and Forecasting*.

Vigaud, N., A. W. Robertson, and M. K. Tippett, 2018: Predictability of recurrent weather regimes over North America during winter from submonthly reforecasts. *Monthly Weather Review*, 146 (8), 2559–2577, https://doi.org/10.1175/MWR-D-18-0058.1

Yeager, S. G., et al 2022: The Seasonal-to-Multiyear Large Ensemble (SMYLE) prediction system using the Community Earth System Model version 2. *Geoscientific Model Development*, *15*(16), 6451–6493, https://doi.org/10.5194/gmd-15-6451-2022