

Subseasonal Potential Predictability of Horizontal Water Vapor Transport and Precipitation Extremes over the North Pacific

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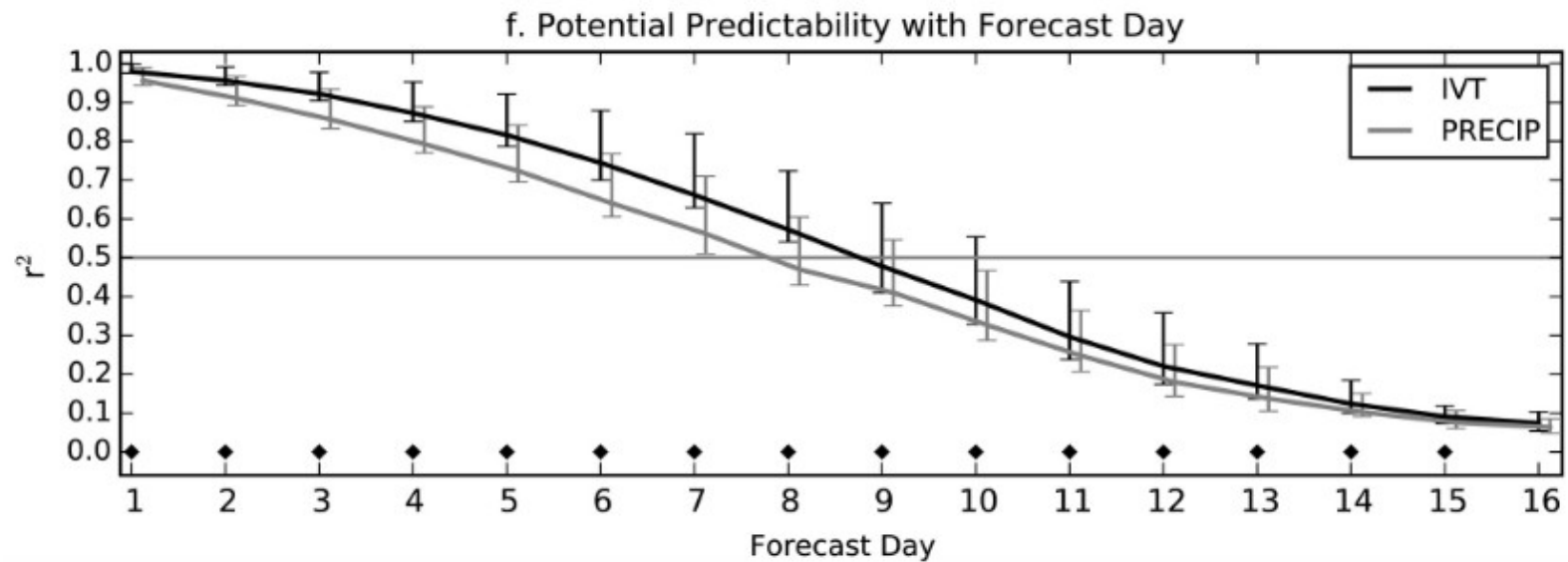
National Center for Atmospheric Research, Boulder, CO, USA²

European Centre for Medium-Range Weather Forecasts, Reading, UK³

July 1st, 2024

S2S Potential Predictability – Differences between IVT and Precipitation

Lavers et al. 2016 demonstrated these differences on the medium range, but these differences are still yet to be shown in the S2S range



Source: Lavers et al. (2016)

Project Goal

Determine whether differences between the predictability of IVT and precipitation exist in the subseasonal range and physically explain any potential differences

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Page(s): 833–846

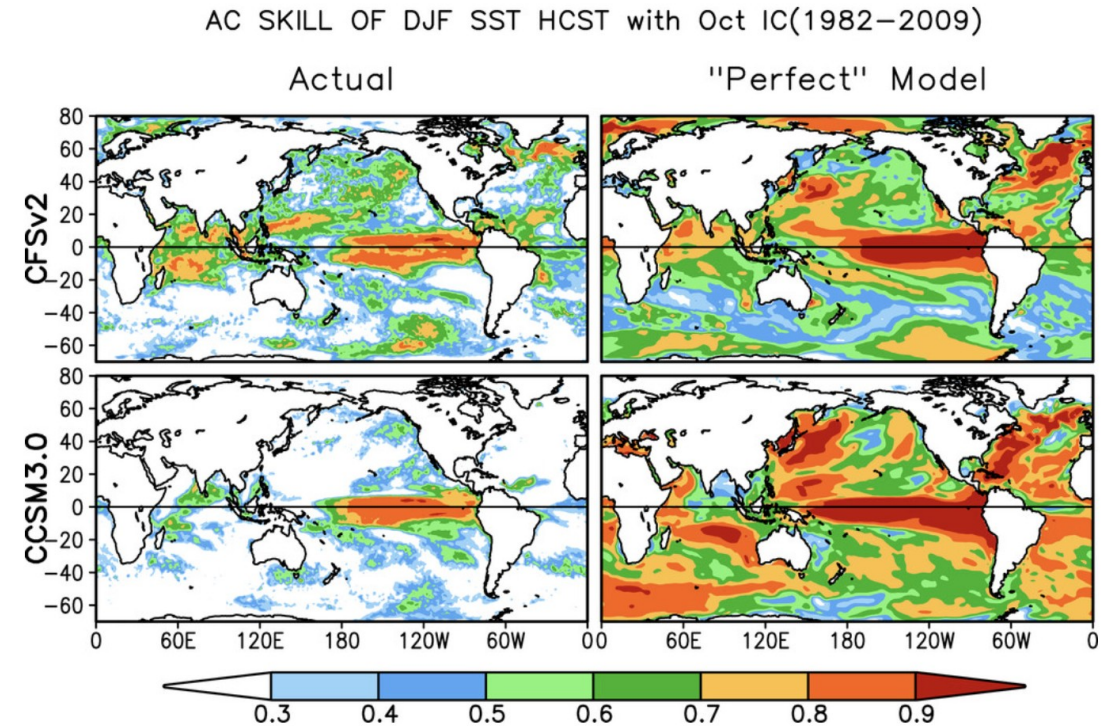
Our Approach

ECMWF reforecasts

Skill metric: ROC scores

Lead times: Week 3 and
Week 4

Target threshold: 90th
Percentile conditions



Traditional Predictability



= reanalysis



= ensemble member





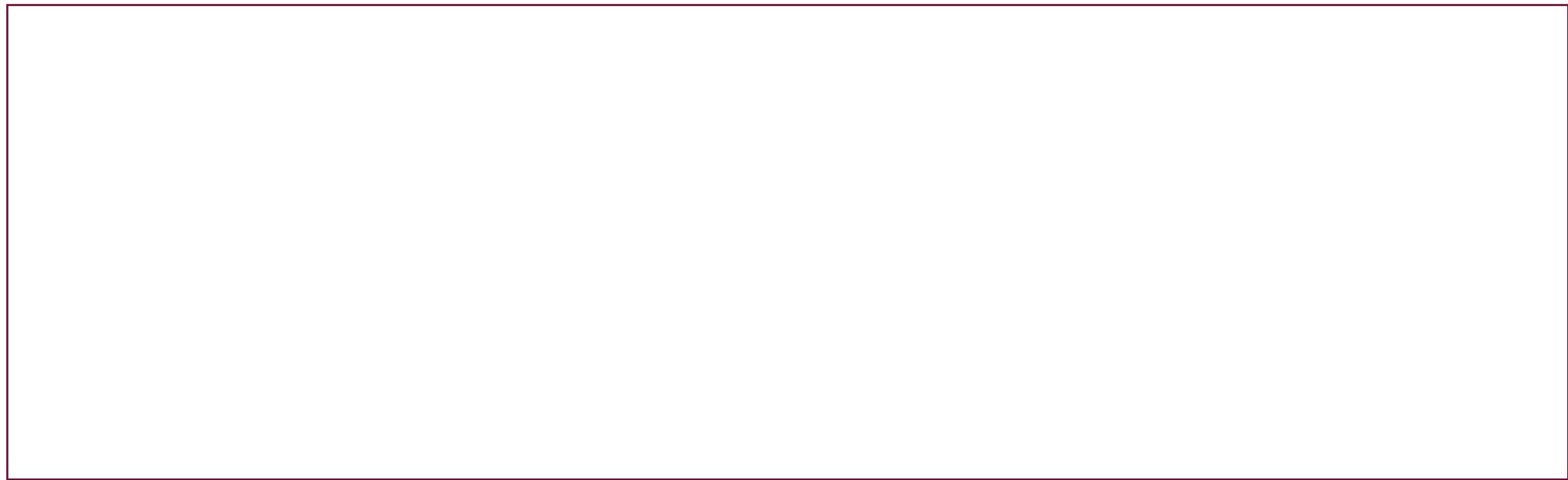
t = 0

t = n

Skill = Function  , $\text{mean}(\text{ } (n))$ 

Potential Predictability

 = "model-observation" ensemble member  = forecast ensemble member





$t = 0$

$t = n$

Skill(ens) = Function  (n),  n (n))

Potential Predictability

 = "model-observation" ensemble member  = forecast ensemble member





$t = 0$

$t = n$

Skill(ens) = Function  (n),  n (n))

Potential Predictability

 = "model-observation" ensemble member  = forecast ensemble member



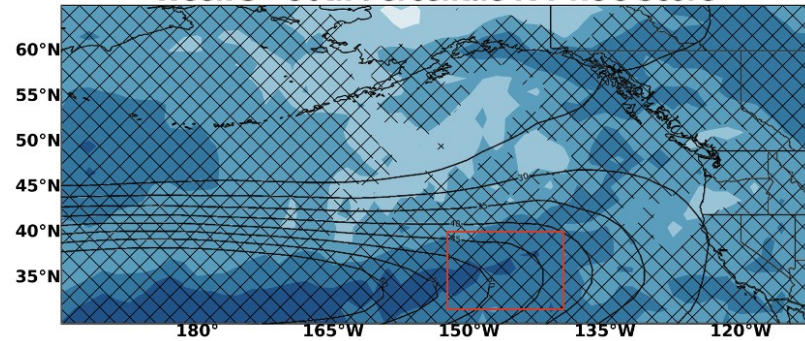
$t = 0$

$t = n$

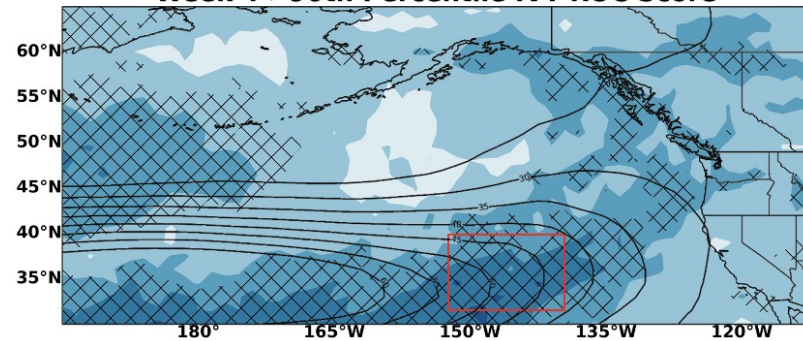
Skill(ens) = Function  (n),  n (n))

ROC Scores

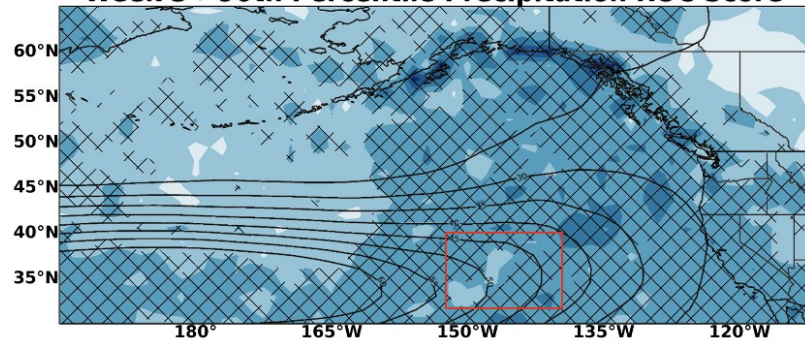
Week 3 >90th Percentile IVT ROC Score



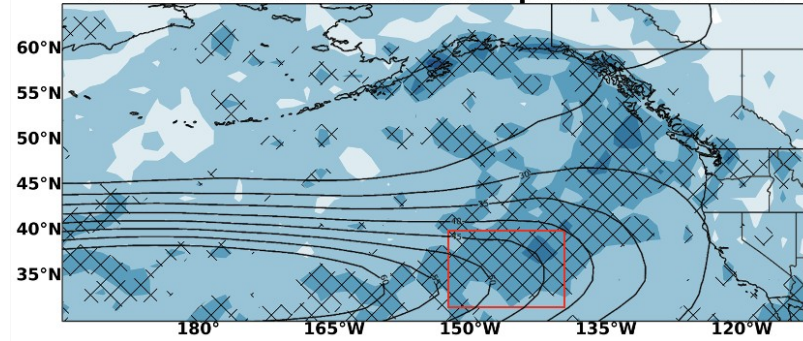
Week 4 >90th Percentile IVT ROC Score



Week 3 >90th Percentile Precipitation ROC Score

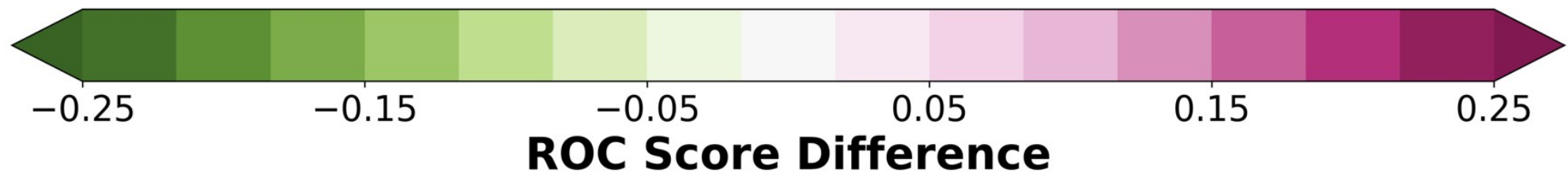
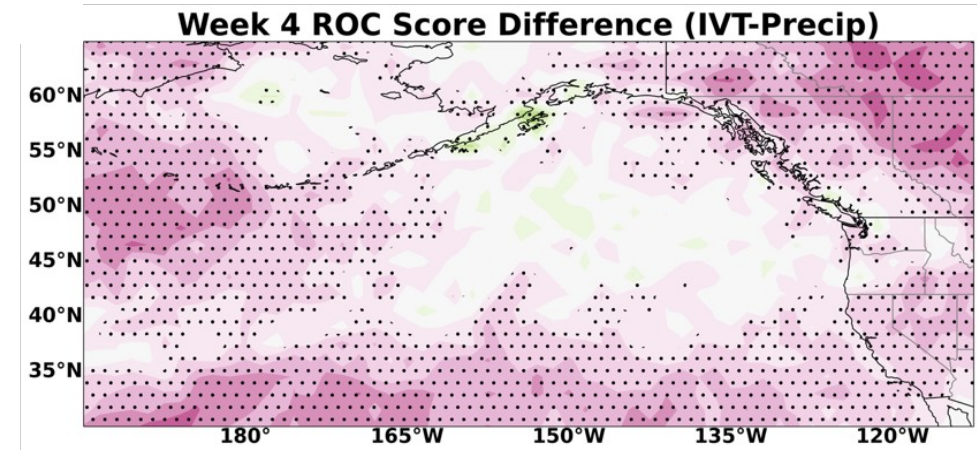
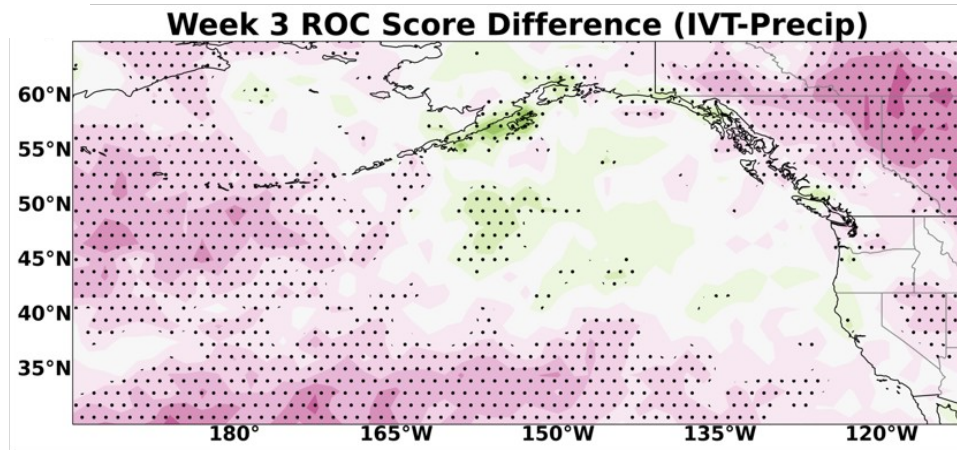


Week 4 >90th Percentile Precipitation ROC Score



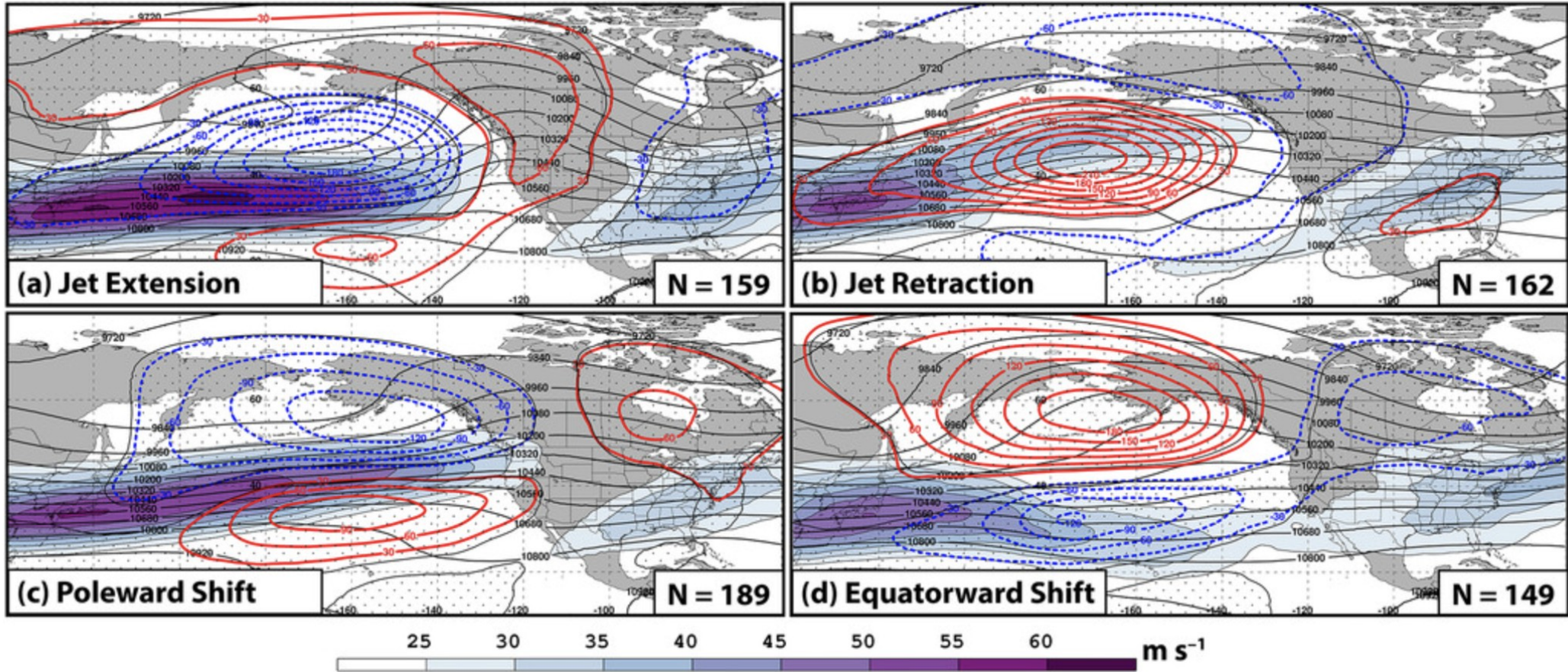
Skillful using
Mann-
Whitney U
test (Mason
and Graham
2002)

Differences in ROC Scores



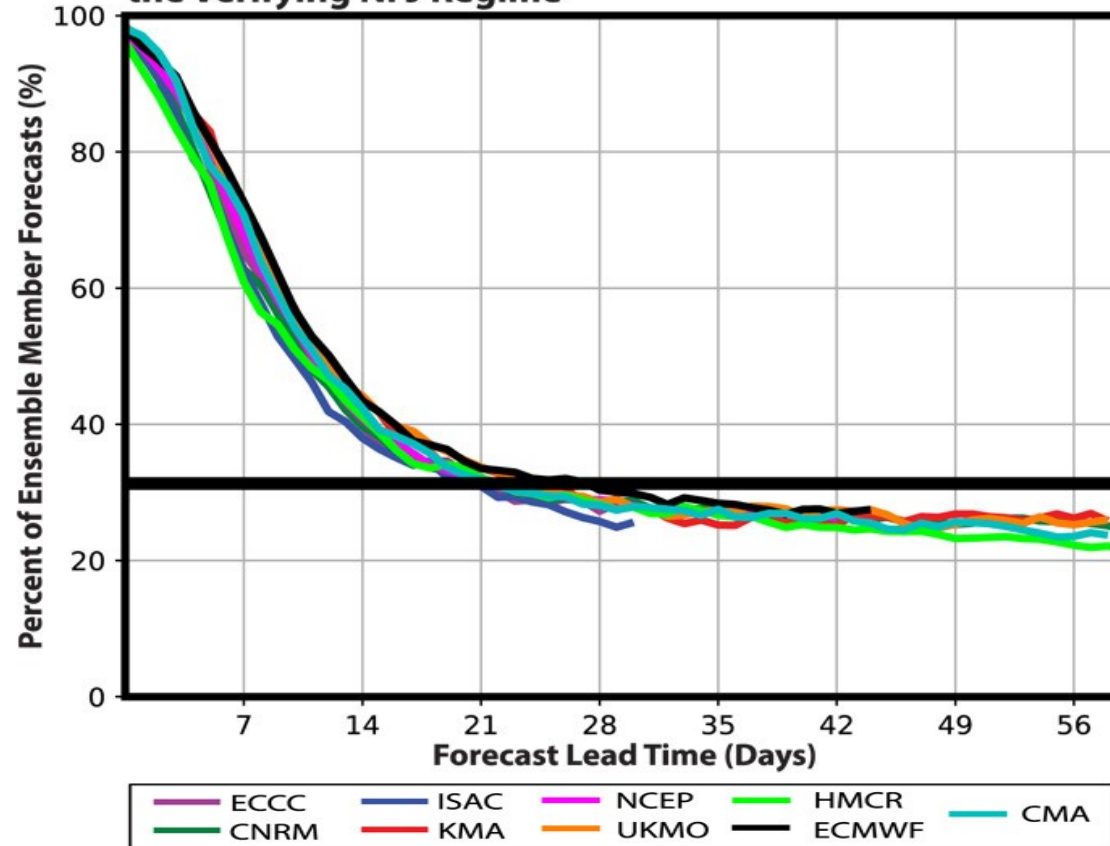
= Difference is significant at the 95% level using student t-test

NPJ EOFs (Winters, Keyser, and Bosart 2019)



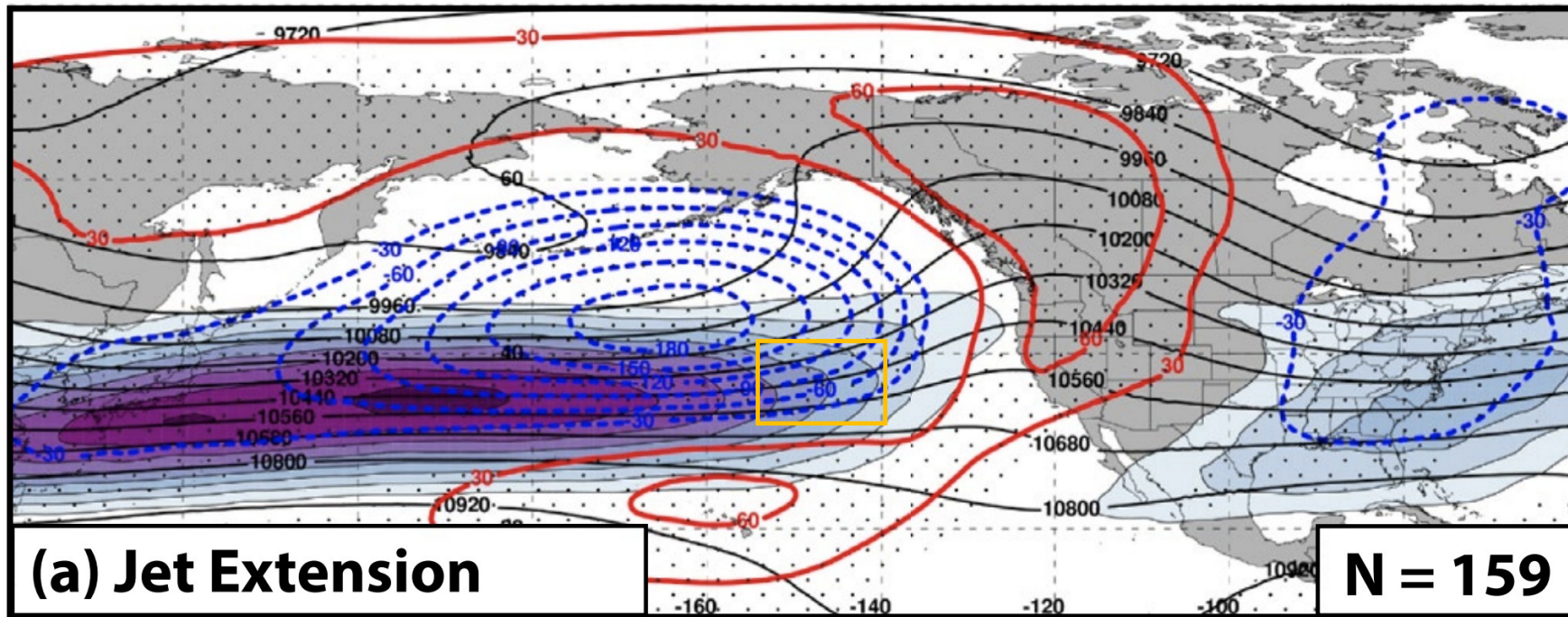
Subseasonal Forecast Skill of Jet Extension (Winters 2021)

(c) Percent of Ensemble Members that Correctly Forecast the Verifying NPJ Regime



Jet Exit Region

Source: Winters, Keyser, Bosart (2019)



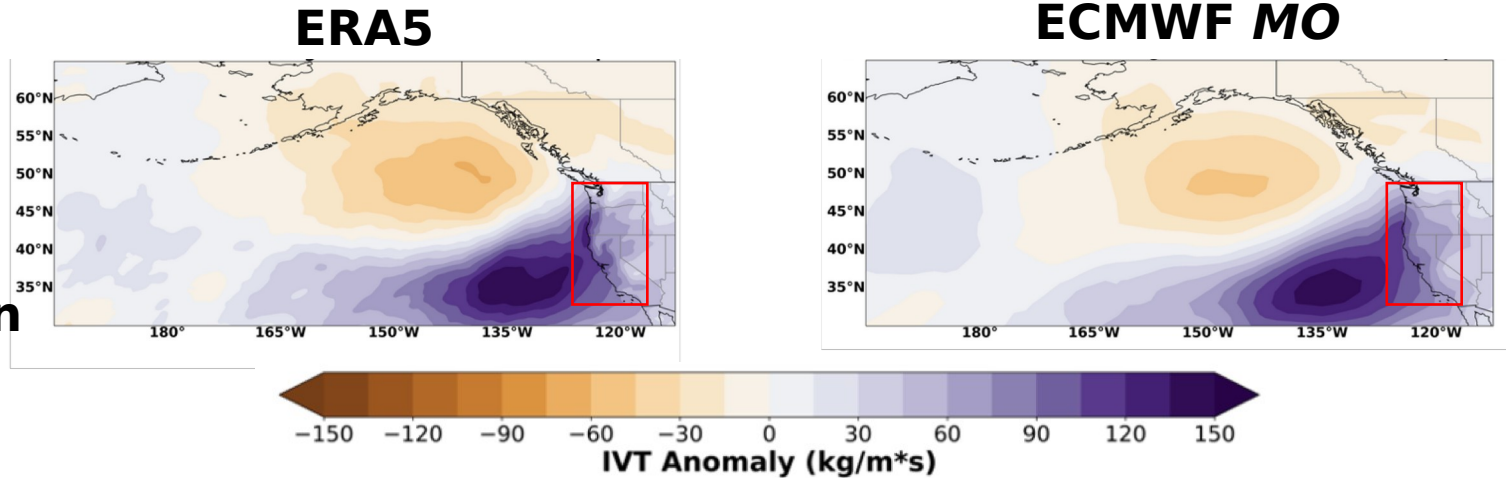
250 hPa geopotential heights - black contours

250 hPa geopotential height anomalies - colored contours: red (positive), blue (negative)

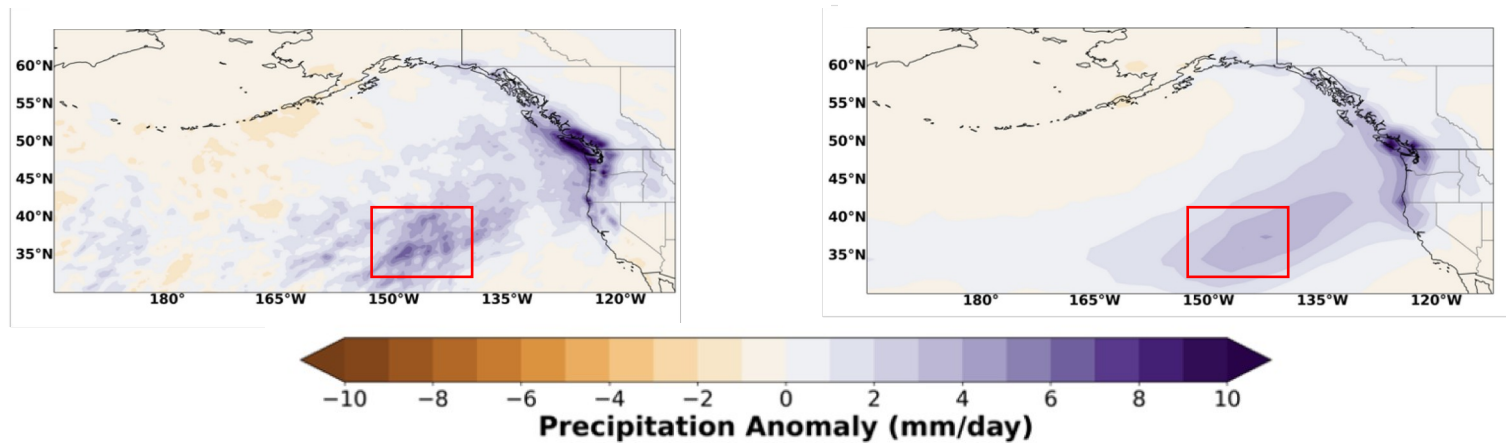
Wind speed - shaded

Importance of Predicting Jet Exit

**>90th
Percentile
Coastal
Precipitation**



**>90th
Percentile
Jet Exit IVT**

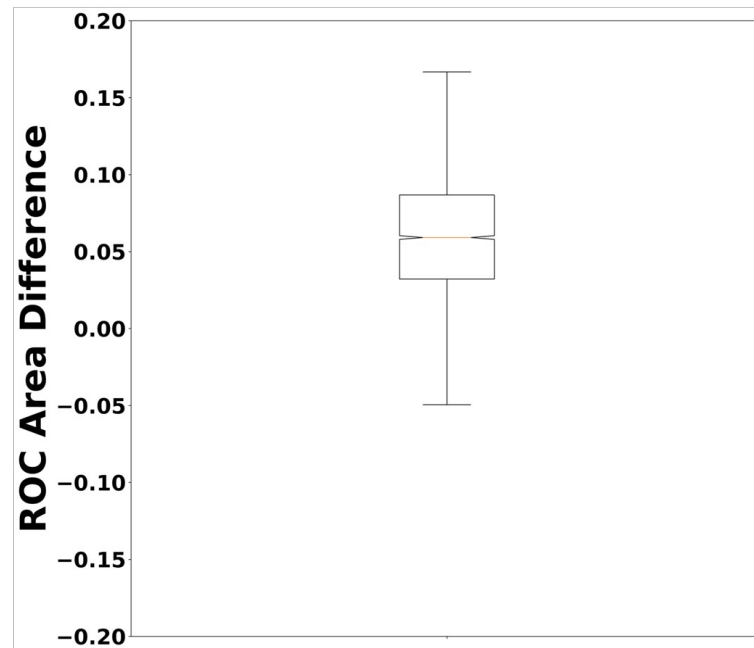


Change in Jet Exit ROC Scores (IVT-Precip)

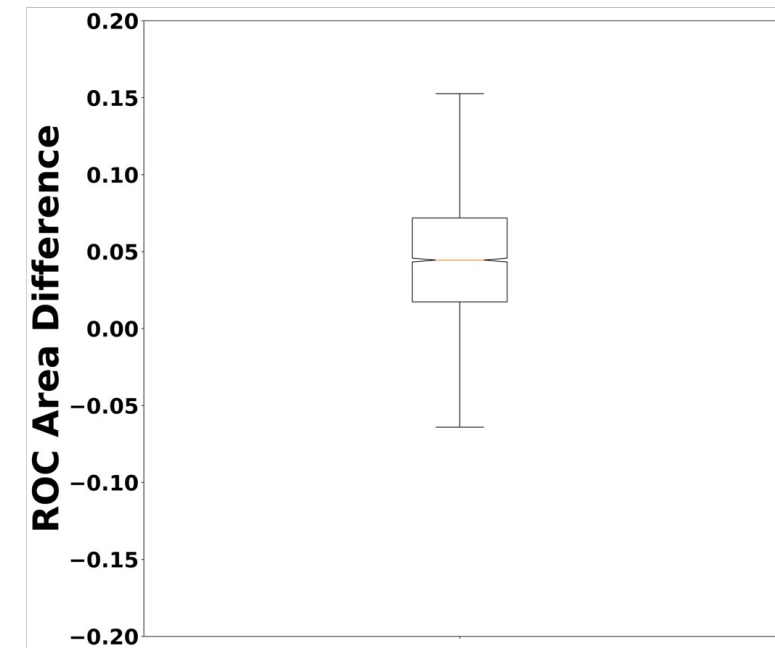
5000
Bootstraps

1000
Samples

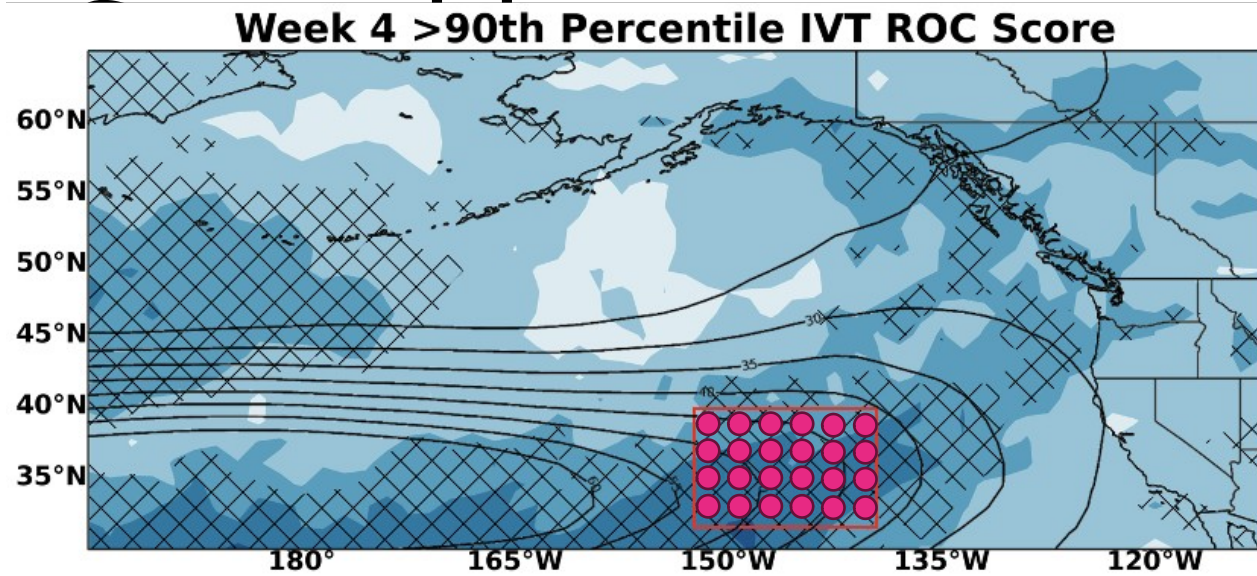
Week 3



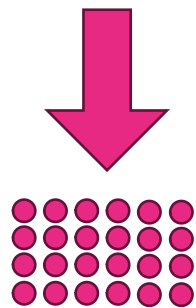
Week 4



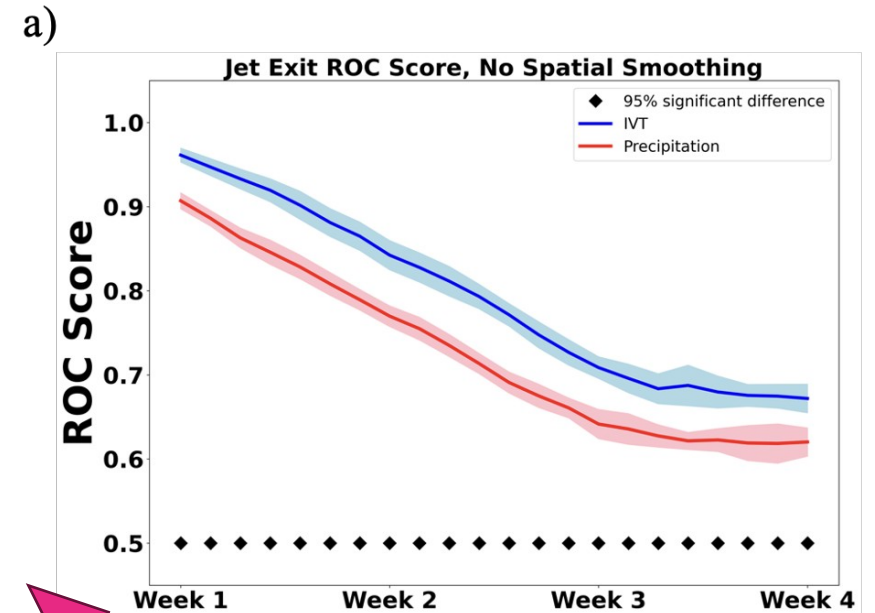
No Spatial



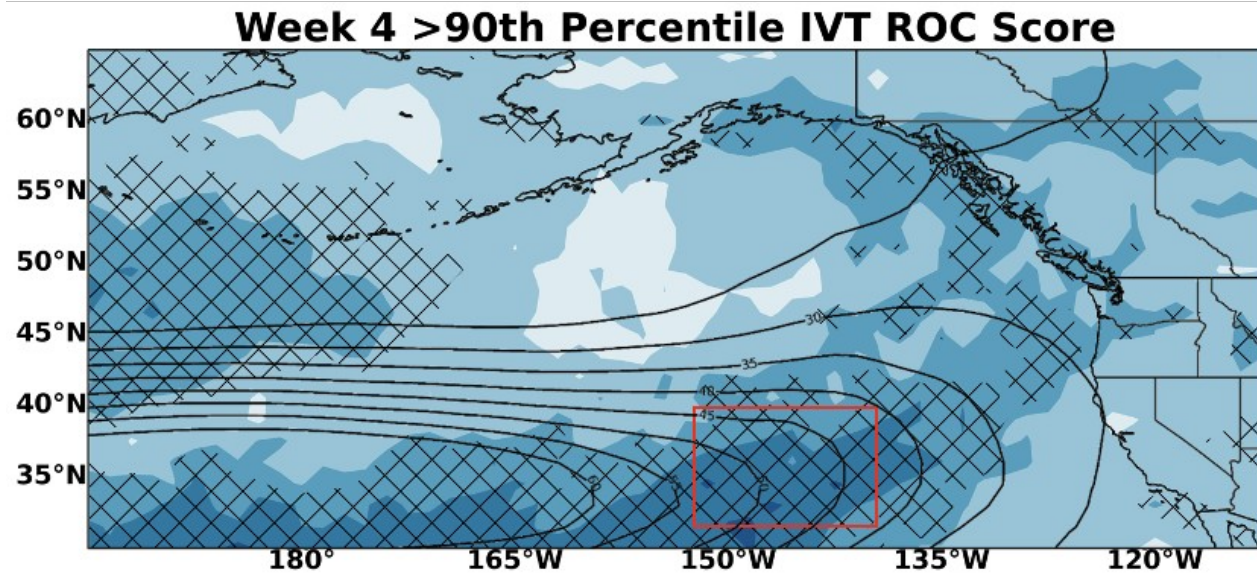
Compute ROC scores at each point



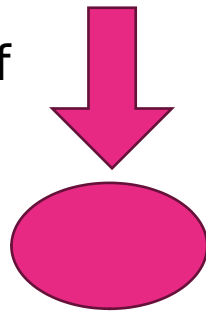
Compute Mean ROC score



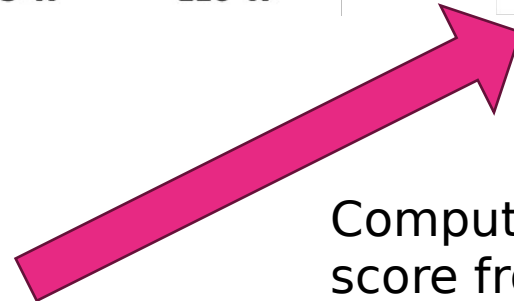
Spatial Smoothing



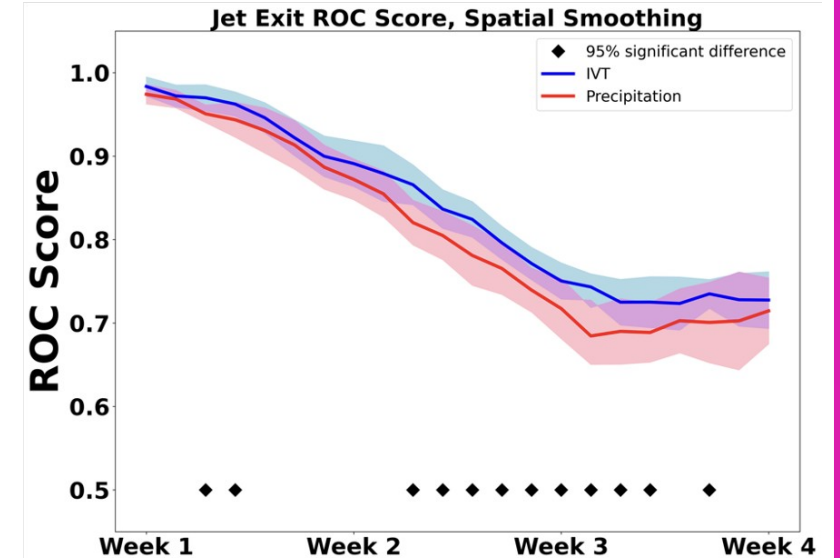
Compute mean of conditions over the entire area



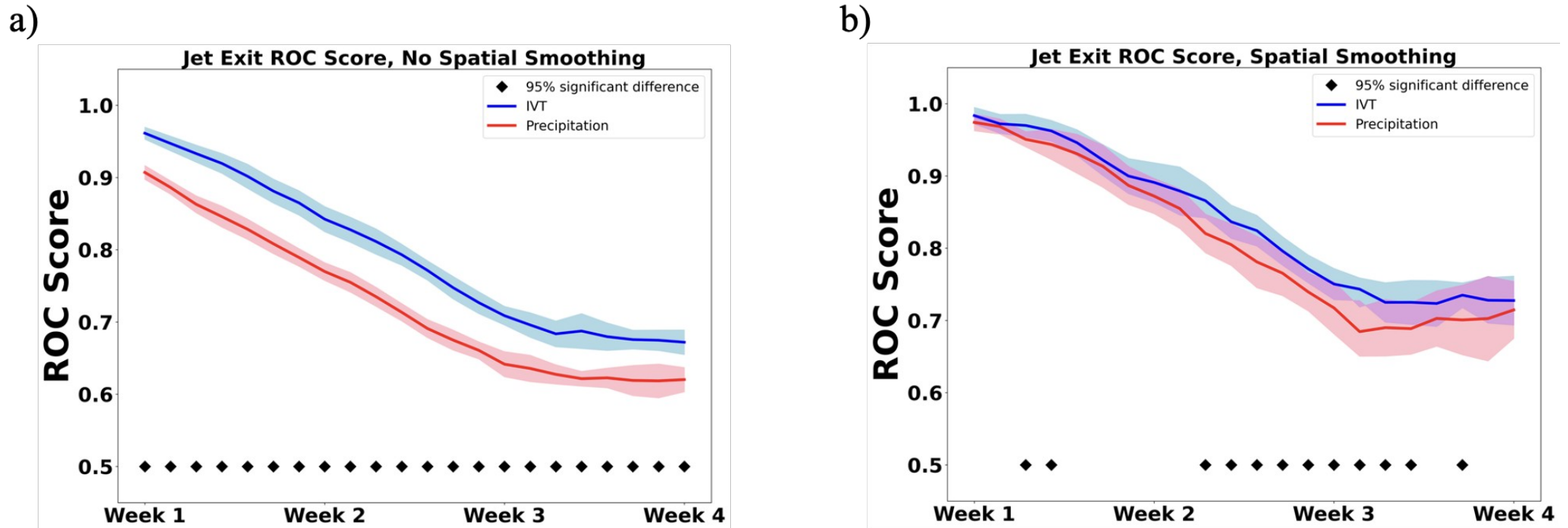
Compute ROC score from averaged area



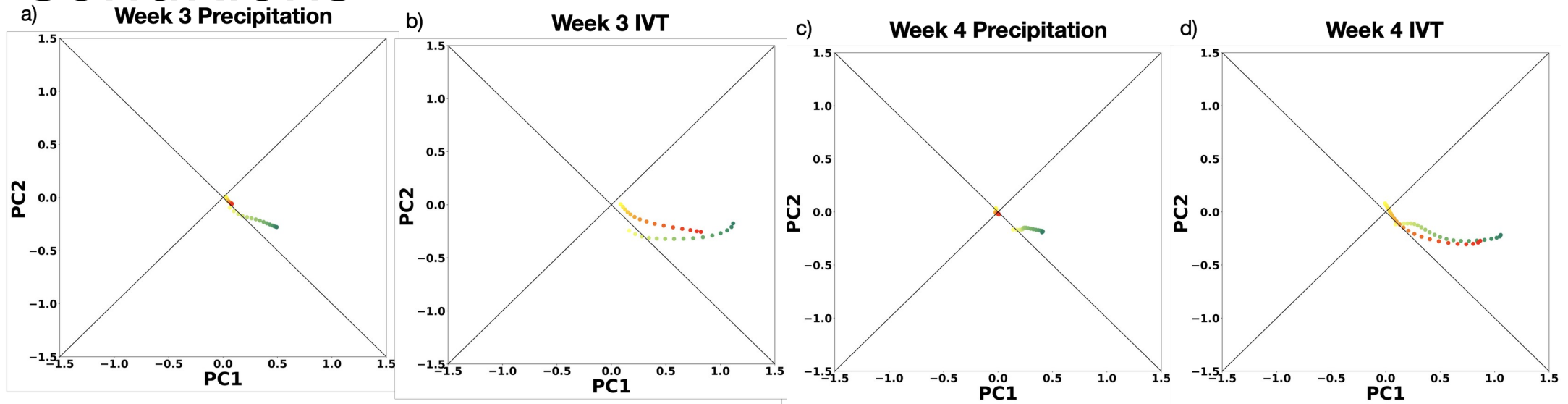
b)



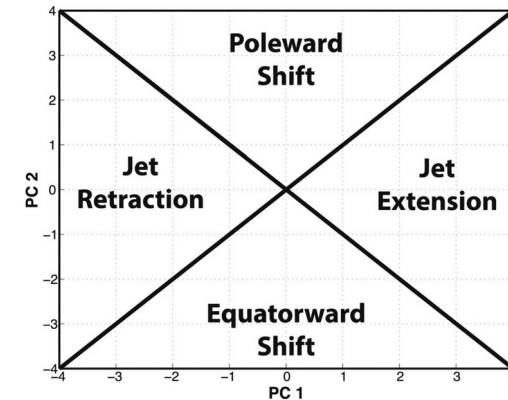
Impact of Smoothing Spatially



MO NPJ Regimes during $MO > 90^{\text{th}}$ Percentile Conditions



Red = unskillful forecasts
Green = skillful forecasts
Darker shades = longer lead times

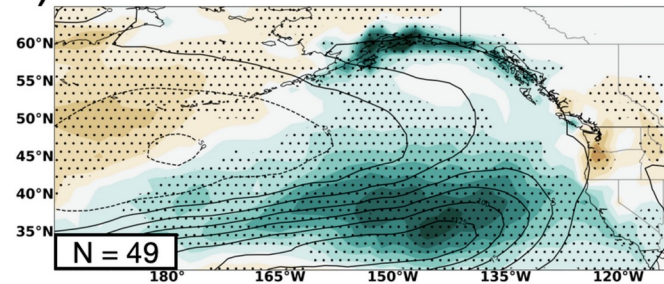


MO Conditions during MO 90th Percentile Jet Extension

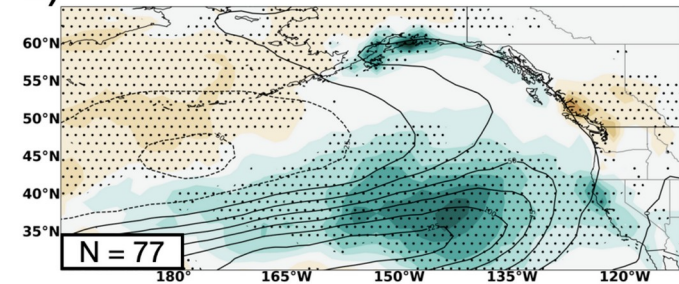


= significant at the 95% level using student t-test

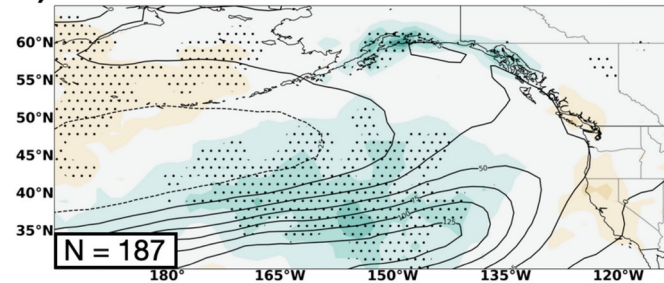
a) Week 3 Skillful Jet Extension Forecasts



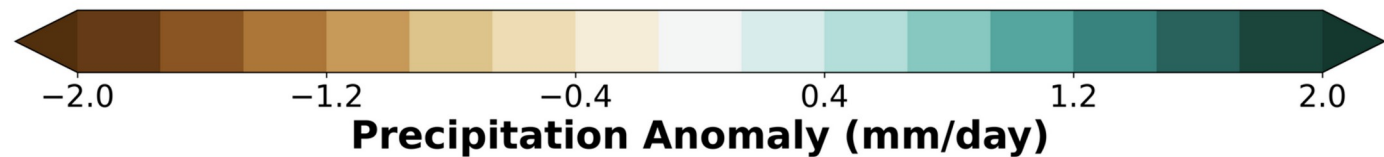
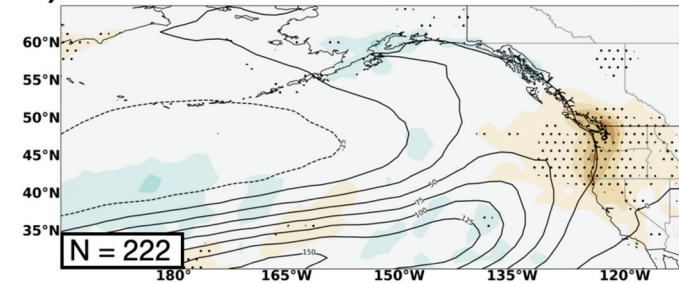
b) Week 4 Skillful Jet Extension Forecasts




c) Week 3 Unskillful Jet Extension Forecasts



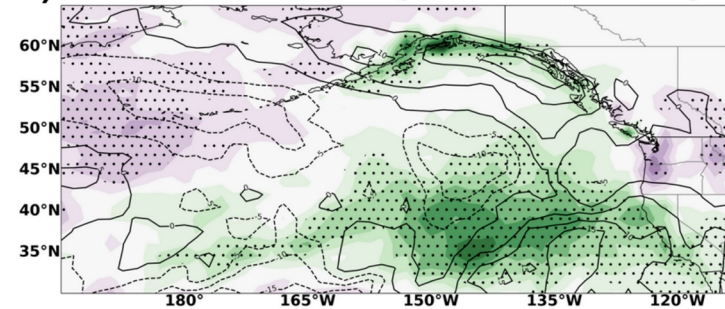
d) Week 4 Unskillful Jet Extension Forecasts



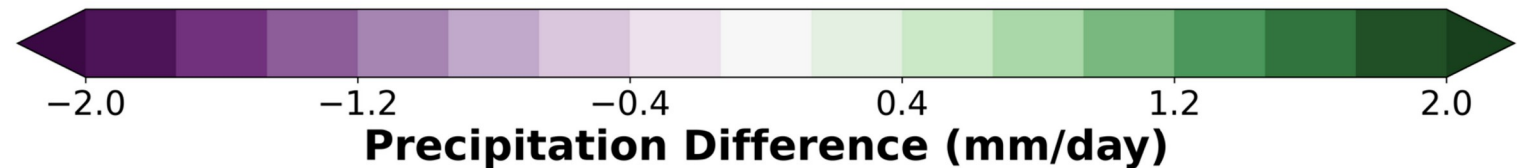
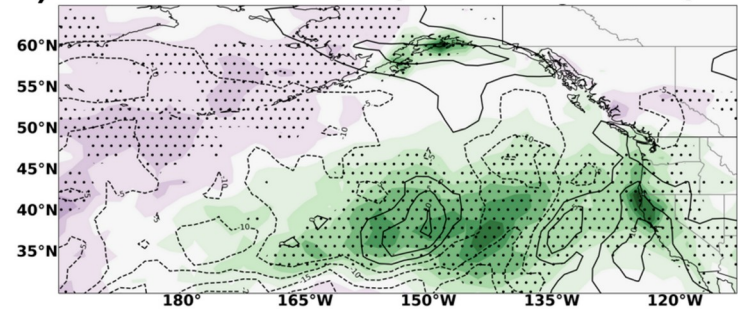
MO Conditions during MO 90th Percentile Jet Extension

 = Precipitation difference is significant at the 95% level using student t-test

e) Week 3 Difference (Skillful - Unskillful)



f) Week 4 Difference (Skillful - Unskillful)

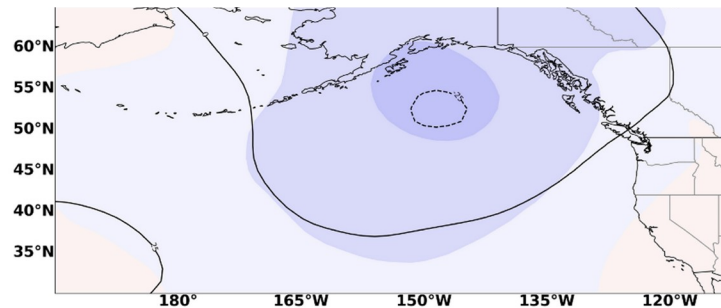


Forecasted Geopotential Height Anomalies during $MO > 90^{\text{th}}$ Percentile IVT in Week 4

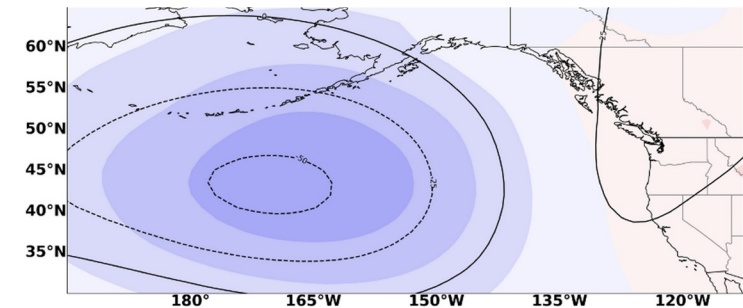
Line contours:
300 mb
geopotential height
anomaly

Shaded contours:
850 mb
geopotential height
anomaly

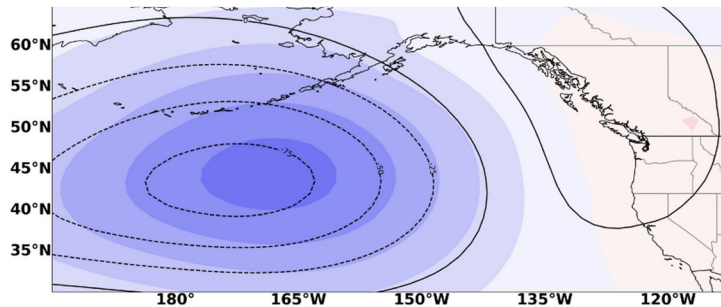
Week 1



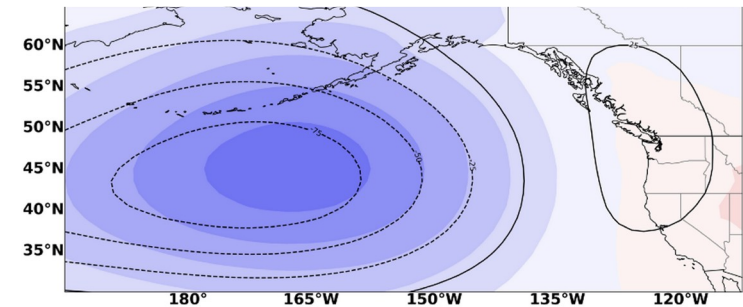
Week 2



Week 3

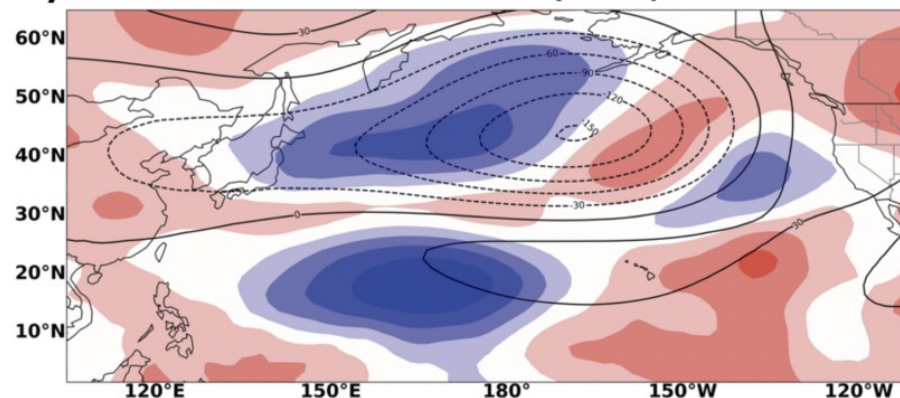


Week 4

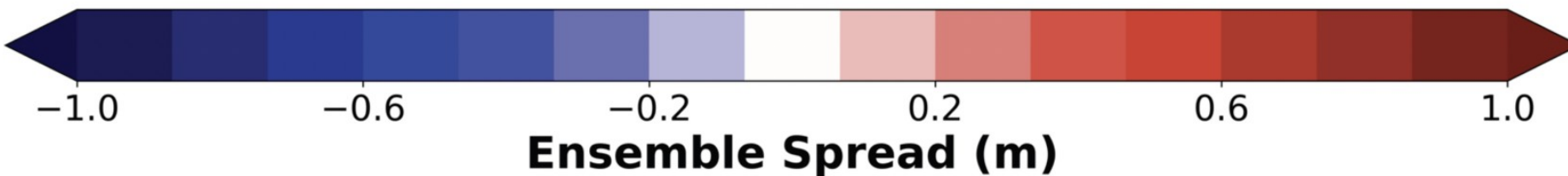
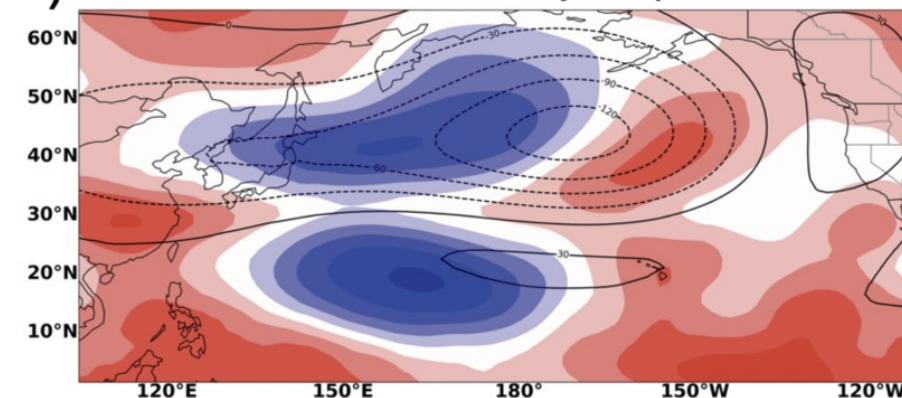


Standardized Ensemble Spread during Skillful Forecasts

a) Week 3 Standardized Ensemble Spread (Skillful Forecasts)

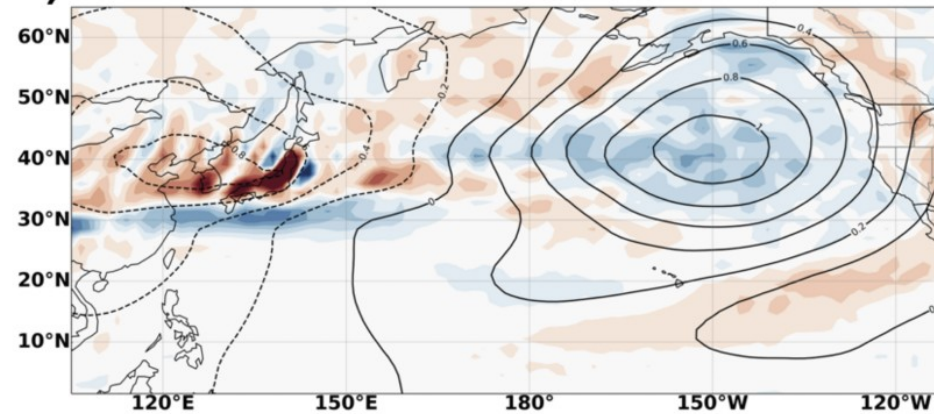


b) Week 4 Standardized Ensemble Spread (Skillful Forecasts)

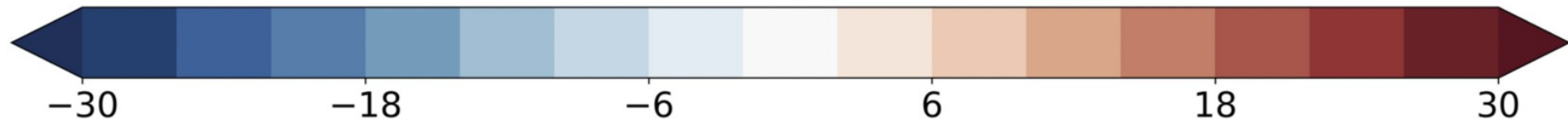
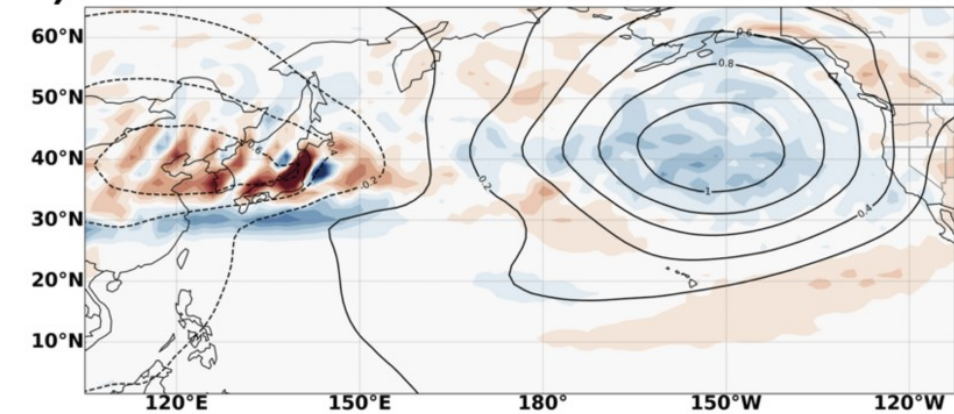


Rossby Wave Source during Skillful Forecasts

c) Anomalous RWS Week 3 Skillful Forecasts



d) Anomalous RWS Week 4 Skillful Forecasts



Rossby Wave Source (10^{-11}s^{-2})

Main Conclusions

There is some potential predictability of both $>90^{\text{th}}$ percentile IVT and precipitation weeks that exists out to week 4 in the jet exit region

IVT generally has more forecast skill than precipitation does over the North Pacific at subseasonal lead times

Local variability cannot fully explain differences in forecast skill

The strength of the NPJ can have a significant impact on the predictability of both IVT and precipitation in the subseasonal range

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