Subseasonal predictability of precipitation

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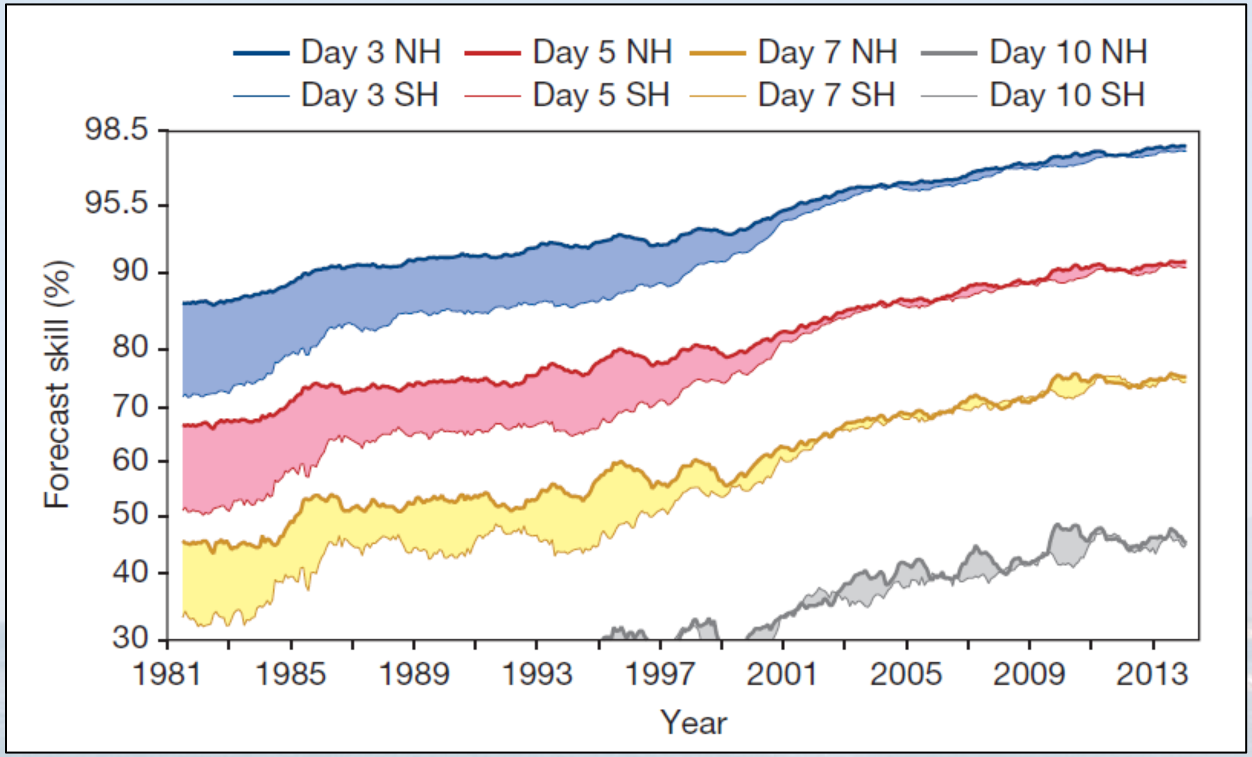
ICTP/ECMWF/Univ. L'Aquila Workshop on OpenIFS

5-9 June 2017

Outline

- ❑ Overview of Subseasonal-to-Seasonal (S2S) Project
- ❑ Predictive skill of precipitation in the subseasonal range (2-8 week leads)
  - ○ Forecast skill and precipitation intensity
  - ○ Winter season over the United States
  - ○ Summer season over South America
- ❑ Conclusions

Weather Forecasts in the Short-to-Medium Range



Predictability ⟷ **Initial Conditions**

Figure 1 | A measure of forecast skill at three-, five-, seven- and ten-day ranges, computed over the extra-tropical northern and southern hemispheres. Forecast skill is the correlation between the forecasts and the verifying analysis of the height of the 500-hPa level, expressed as the anomaly with respect to the climatological height. Values greater than 60% indicate useful forecasts, while those greater than 80% represent a high degree of accuracy. The convergence of the curves for Northern Hemisphere (NH) and Southern Hemisphere (SH) after 1999 indicates the breakthrough in exploiting satellite data through the use of variational data[100].

The quiet revolution of numerical weather prediction

doi:10.1038/nature14956

Peter Bauer[1], Alan Thorpe[1] & Gilbert Brunet[2]

Seasonal Forecasts

Seasonal Forecasts became operational

IRI/CPC Pacific Niño 3.4 SST Model Outlook

Most models favor El Niño by the late Northern Hemisphere summer 2017, with the dynamical models favoring onset during the summer of 2017.

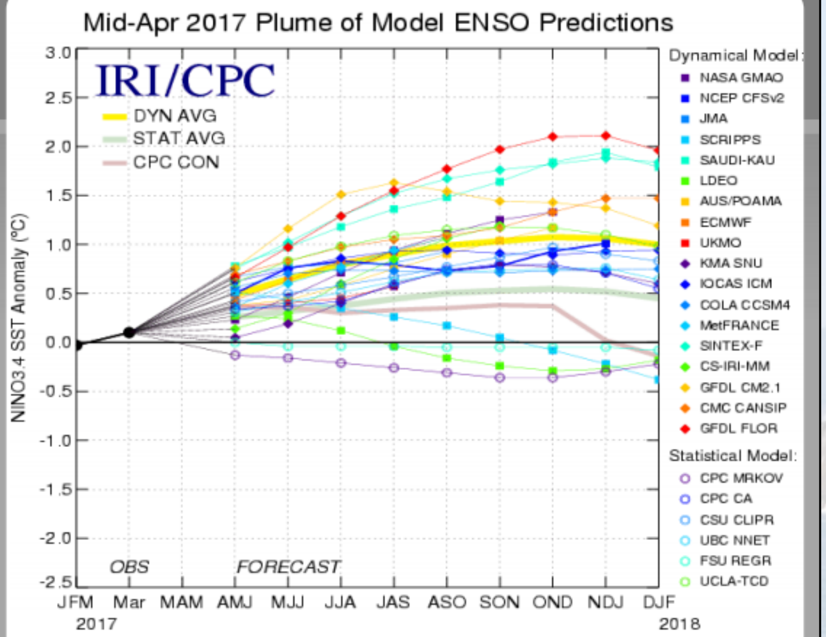
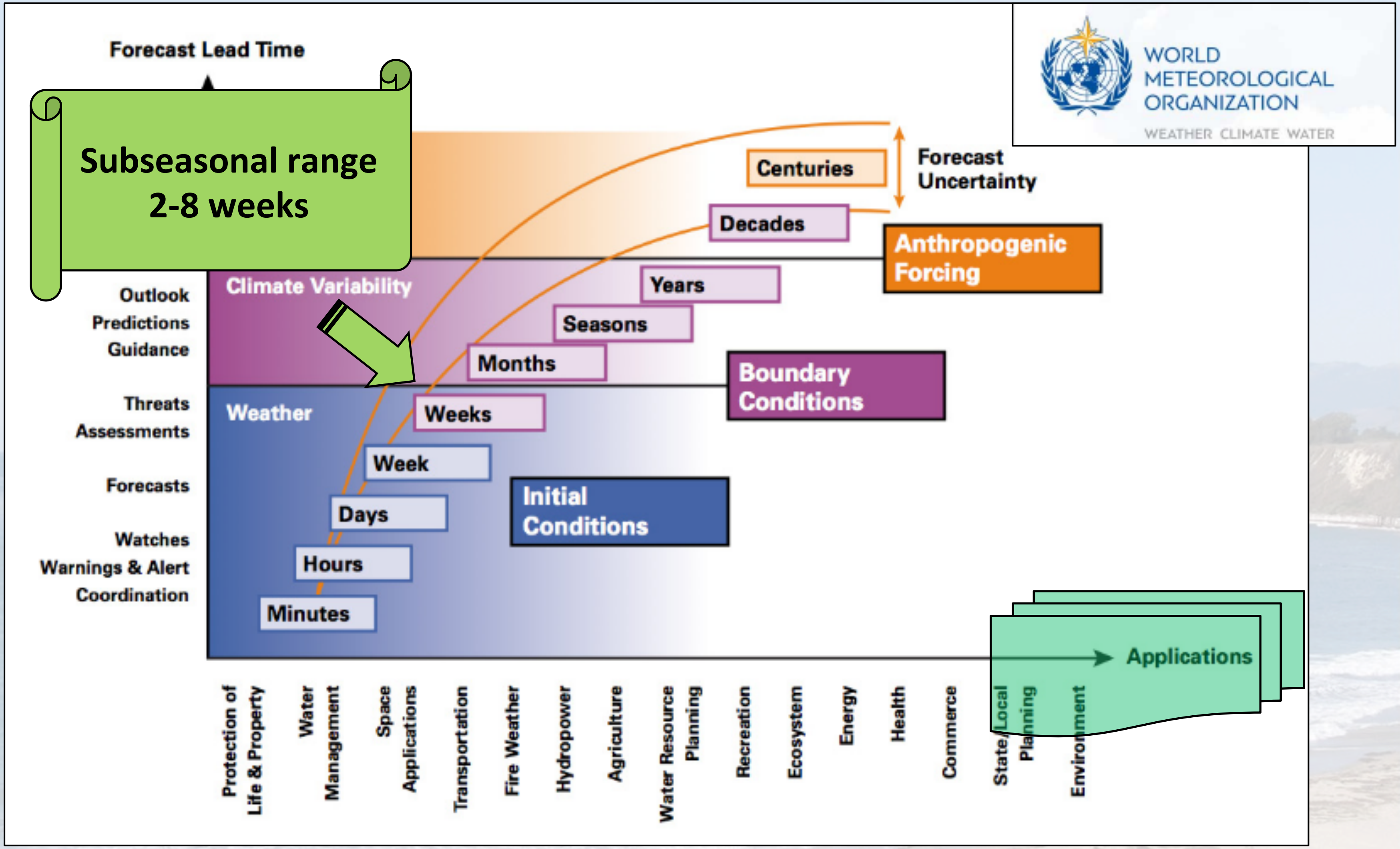


Figure provided by the International Research Institute (IRI) for Climate and Society (updated 18 April 2017).

Predictability ⟷ **Boundary Conditions**

Seamless weather-climate prediction



Subseasonal to Seasonal (S2S) Prediction Research Project

- *"**Improve forecast skill** and understanding on **sub-seasonal to seasonal** timescales - emphasis on **high-impact weather events**"*
- *"Promote the initiative's uptake by operational centers and **exploitation by the applications community**"*
- *"Capitalize on the expertise of **weather** and **climate** research communities to address issues of importance to the Global Framework for Climate Services"*

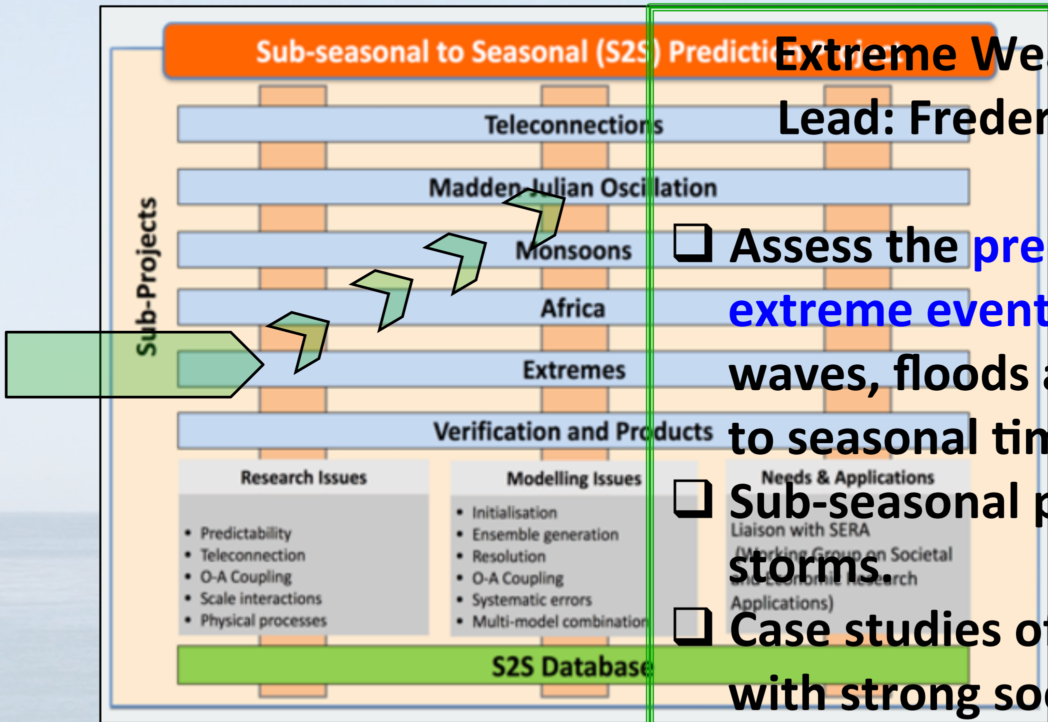
Focus: 2 weeks-1 season forecast range

WWRP WCRP World Climate Research Programme THORPEX A World Weather Research Programme

Sources of Potential Predictability in the Subseasonal Range

- ❑ **Madden Julian Oscillation**
- ❑ **Stratospheric initial conditions**
- ❑ **Land/ice/snow initial conditions**
- ❑ **Sea surface temperatures**

S2S Subprojects



Extreme Weather Subproject
Lead: Frederic Vitart ECMWF

- Assess the predictability of extreme events such as heat, cold waves, floods at the sub-seasonal to seasonal time scale
- Sub-seasonal prediction of tropical storms.
- Case studies of extreme weather with strong societal impact

ECMWF Spaces Calendars

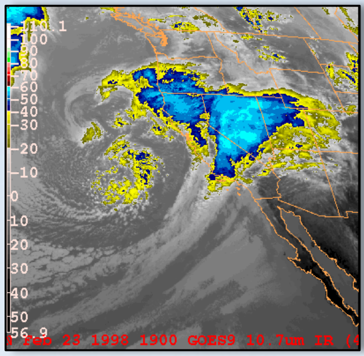
S2S

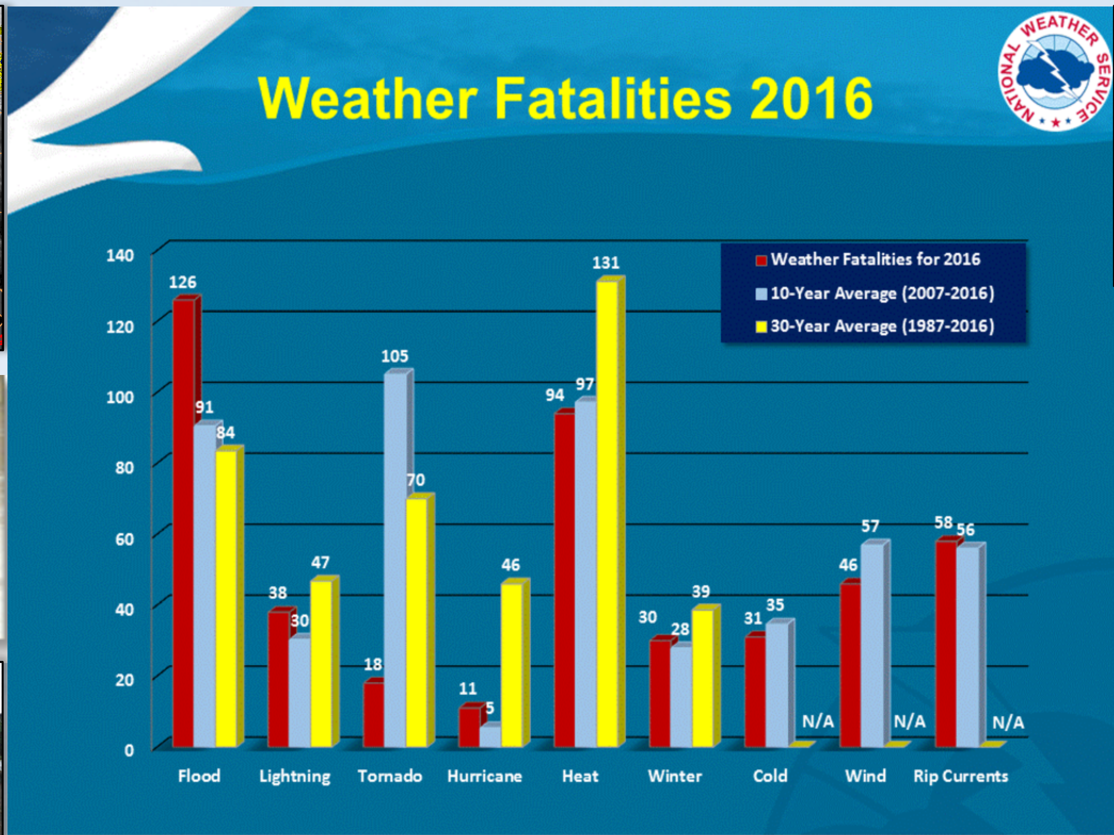
Pages / Home / Description

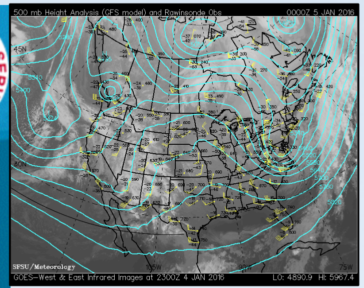
Models

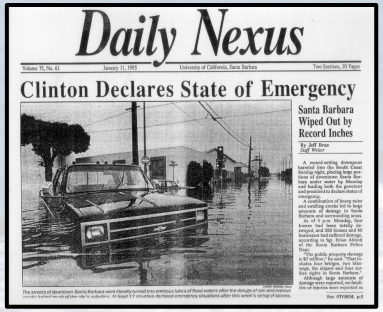
Status on 10th March 2016	Time range	Resolution	Ens. Size	Frequency	Re-forecasts	Rfc length	Rfc frequency	Rfc size	Volume of real-time forecast per cycle	Volume of reforecast per update
	Lead		Near real time			Reforecasts				
BoM (ammc)	d 0-62	T47L17	33	2/week	fix	1981-2013	6/month	33		6 TB
CMA (babj)	d 0-60	T106L40	4	daily	fix	1994-2014	daily	4		
CNR-ISAC (isac)	d 0-31	0.75x0.56 L54	41	weekly	fix	1981-2010	every 5 days	1		
CNRM (lfpw)	d 0-32	T255L91	51	weekly	fix	1993-2014	2/monthly	15		6.75 GB/start date
ECCC (cwao)	d 0-32	0.45x0.45 L40	21	weekly	on the fly	1995-2014	weekly	4		
ECMWF (ecmf)	d 0-46	Tco639/319 L91	51	2/week	on the fly	past 20 years	2/week	11		
HMCR (rums)	d 0-61	1.1x1.4 L28	20	weekly	on the fly	1985-2010	weekly	10		
JMA (rjtd)	d 0-33	T319L60	25	2/week	fix	1981-2010	3/month	5	3.8 GB	900 GB
KMA (rksl)	d 0-60	N216L85	4	daily	on the fly	1991-2010	every 8 days	3		
NCEP (kwbc)	d 0-44	T126L64	16	daily	fix	1999-2010	day	4		
UKMO (egrr)	d 0-60	N216L85	4	daily	on the fly	1993-2015	4/month	3		

Extreme precipitation





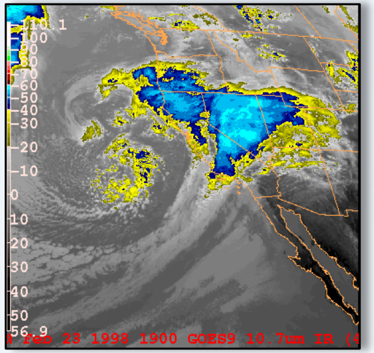



Daily Nexus

Clinton Declares State of Emergency

Santa Barbara Wiped Out by Record Inches

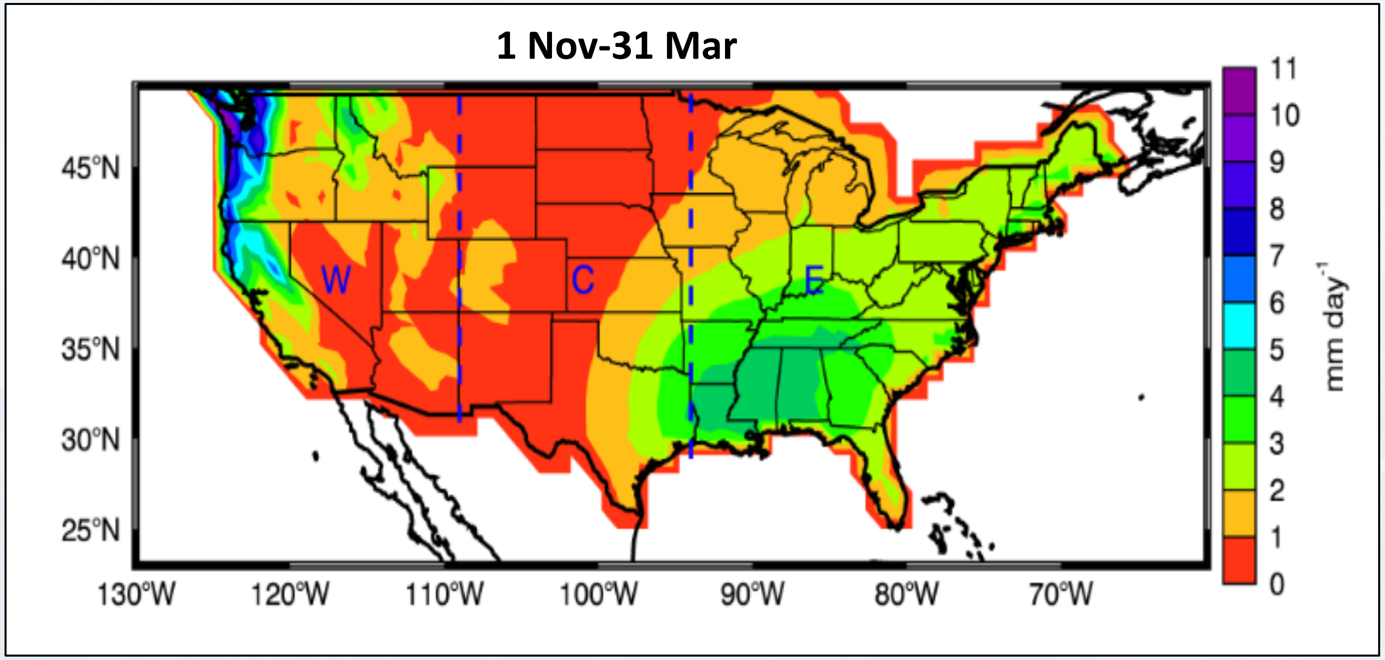
Research Questions



- Is there **skill** in probabilistic forecasts of precipitation in the **subseasonal range**?
- How does the **predictive skill** of precipitation vary **as a function of precipitation intensity**?
- Is **heavy precipitation more predictable** than light-to-moderate precipitation?
- How does the **predictability of heavy precipitation** vary across different **climatic regimes?**

Objective: **Examine S2S probabilistic forecast skill of precipitation in the contiguous United States**

Winter Precipitation Climatology



NCEP/CPC Unified Gridded precipitation

Probabilistic forecasts of precipitation

Methodology

- ❑ **Reforecast data**

Model	Forecast range	Spatial resolution	Members	Frequency
ECMWF (CY41R2)	46 day	1° lat/lon	11 (control + 10 Perturbations)	2 Initializations per week (M, H)

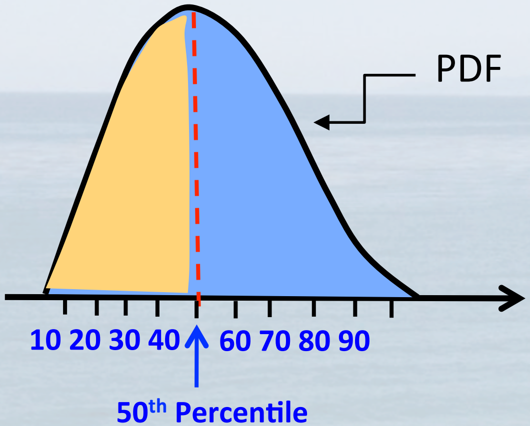
- ❑ **Period: 1 November – 31 March, 1995-2015 (20-yrs)**
- ❑ **Verification: CPC Unified precipitation gridded data**
- ❑ **Intermediate steps**
  - **Interpolate model forecasts to CPC Unified precipitation grid**
  - **Estimate daily mean model bias (lon, lat, lead)**
  - **Remove daily mean model bias from forecasts**

Probabilistic forecasts of precipitation

Methodology

- Subseasonal Emphasis ⇒ compute weekly mean precipitation (to reduce noise)
- Fit Gamma Probability Distribution Function

Nov-Mar Precipitation



Probability forecast categories

➢ $\text{Prob} = Prec < P_{perc}^{th}$	10th 20th 30th 40th Percentiles
➢ $\text{Prob} = Prec > P_{perc}^{th}$	50th 60th 70th 80th 90th Percentiles

- Validation data
- Forecasts: 1-week lead

Probabilistic forecasts of precipitation

Probability forecast categories

➢ Prob $= Prec < P_{perc}^{th}$	10th 20th 30th 40th Percentiles
➢ Prob $= Prec > P_{perc}^{th}$	50th 60th 70th 80th 90th Percentiles

$$Prob = Number\ of\ members\ forecasting\ event / total\ number\ of\ members$$

- ❑ **Validation: 1 Nov-31 Mar, 1995-2015**
- ❑ **Each season:**
  - ○ **44 Initializations**
  - ○ **Each initialization ⇒ forecasts out to 1-6 week leads**
- ❑ **Total: 880 forecasts for each lead**

Validation of Probabilistic forecasts

For a given **precipitation forecast category** $(P_{erc^{th}})$ and lead time:

Forecast Probabilities $Y_k : \{Y_1, Y_2, Y_3 \ldots Y_k \ldots Y_N\}$ $\quad Y_k \in [0,1]$

Observations $O_k : \{O_1, O_2, O_3 \ldots O_k \ldots O_N\}$ $\quad O_k =$ 0 ≡ No event; 1 ≡ Event

Brier Score $$BS = \sum_{k=1}^{N} (Y_k - O_k)^2 / N$$

Brier Skill Score $$BSS = 1 - BS/BS_{Ref}$$

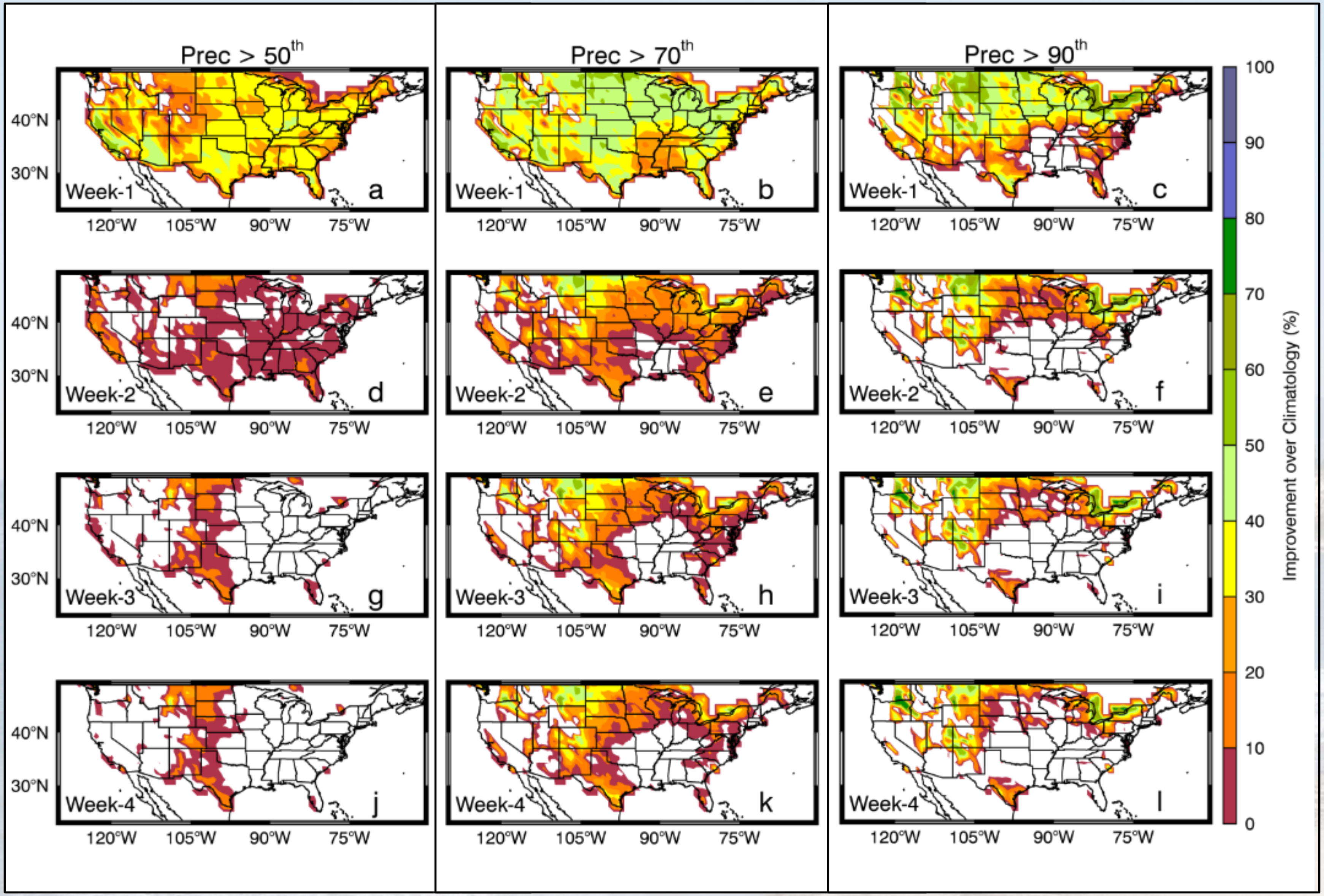
$$BS_{Ref} = Prob_{Clim}(1 - Prob_{Clim})$$

$Prob_{Clim} \equiv$ *Climatological probability*


Is there skill in probabilistic forecasts of precipitation in the subseasonal range?

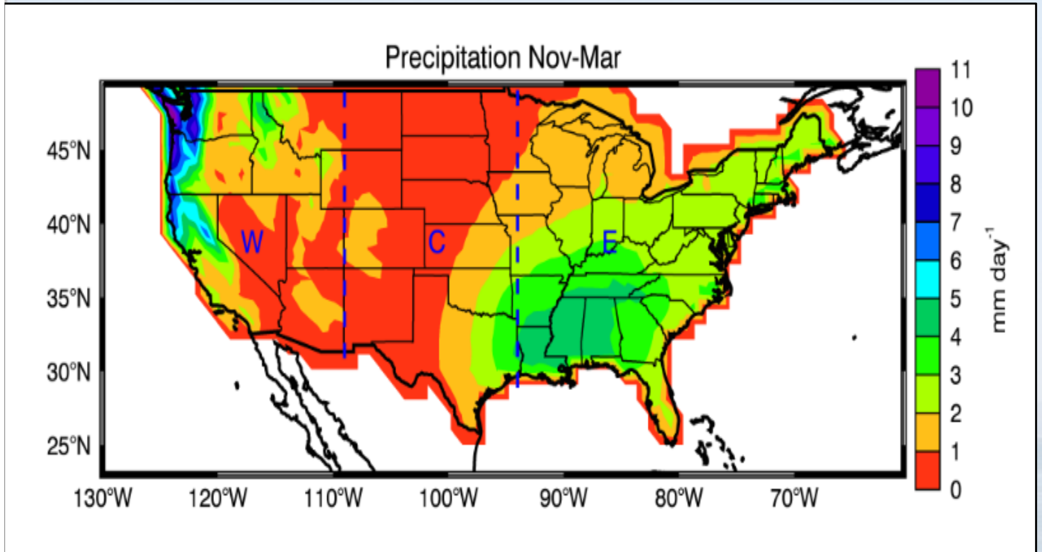
Brier Skill Score

$$BSS = 1 - BS/BS_{Ref}$$

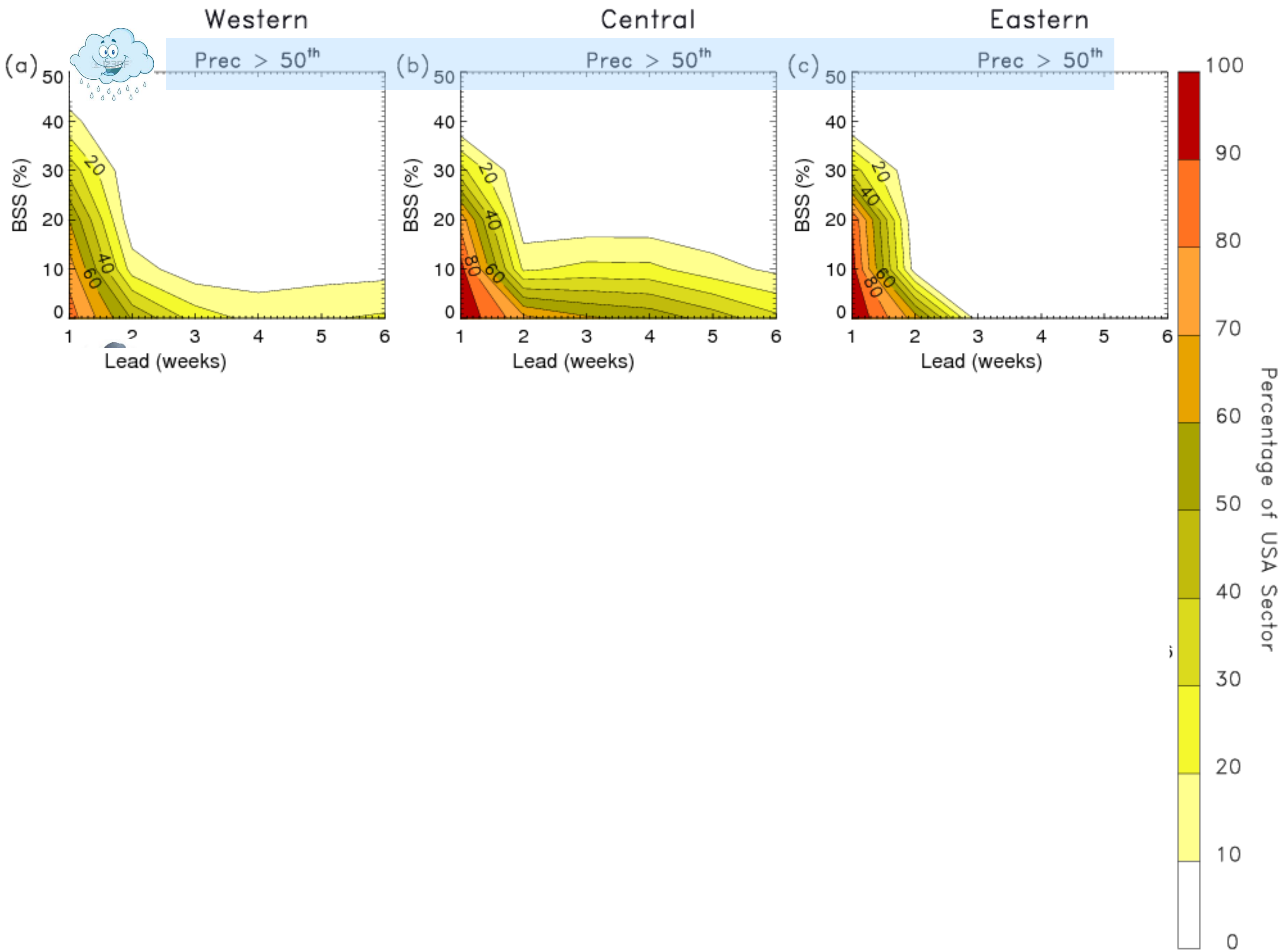


Brier Skill Score

Another way to look at it



- **Divide USA in three sectors**
- **Compute percentage of sector with BSS > Threshold**


Western
Central
Eastern
(a)
(b)
(c)
Prec > 50th
Prec > 50th
Prec > 50th
BSS (%)
Lead (weeks)
Percentage of USA Sector
20
40
60
80

Probabilistic forecast skill

Forecast Probabilities $Y_k: \{Y_1, Y_2, Y_3 \ldots Y_k \ldots Y_N\}$

Observations $O_k: \{O_1, O_2, O_3 \ldots O_k \ldots O_N\}$

Forecast Quality: { BSS (single number) , **Reliability Diagram** }

Conditional Average Observation: $O_i = P(O_1 / Y_i) = 1/N_i \sum_{k \in N_i} O_k$

$0_1 \equiv$ yes event

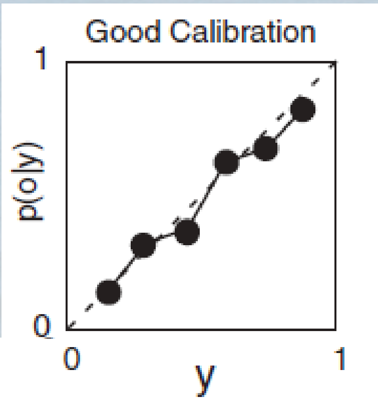
"It tells how well each forecast is calibrated"

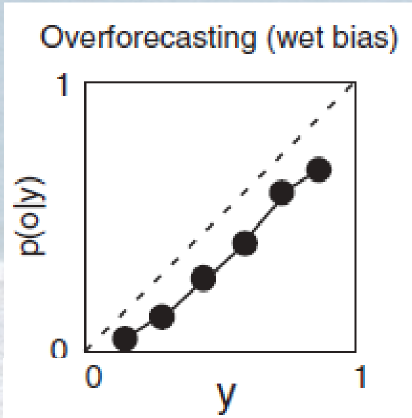
Refinement Distribution: $P(Y_i) = N_i / N$

$N_i \equiv$ number times each prob. forec. was used

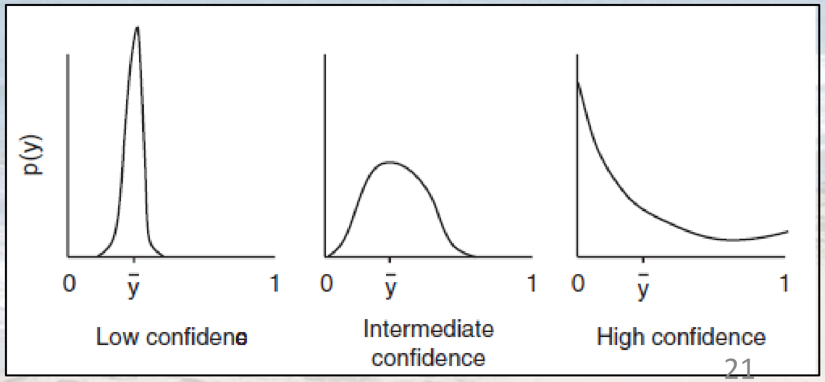
"It tells if model discerns different outcomes"

Reliability Diagrams





Refinement Distributions

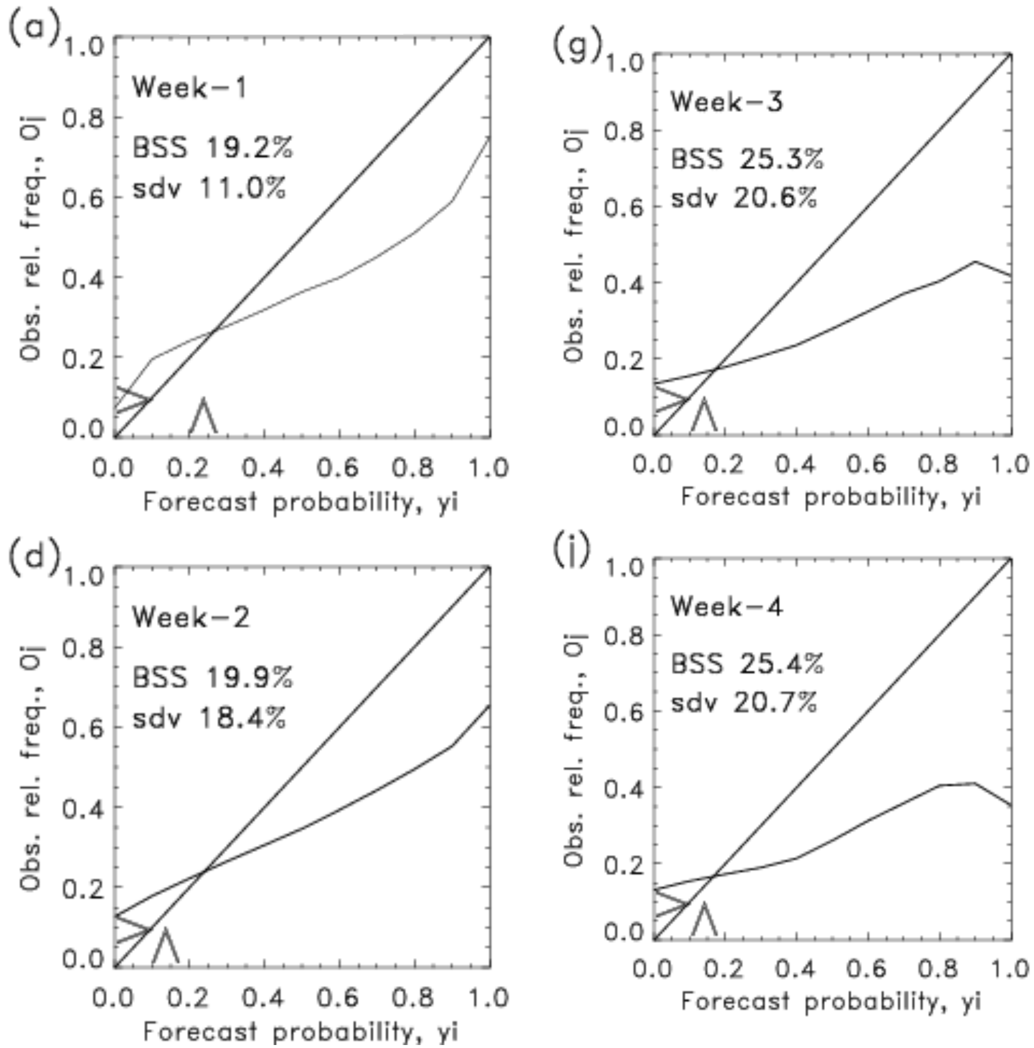


Wilks 2011

Reliability Diagrams

Average over USA

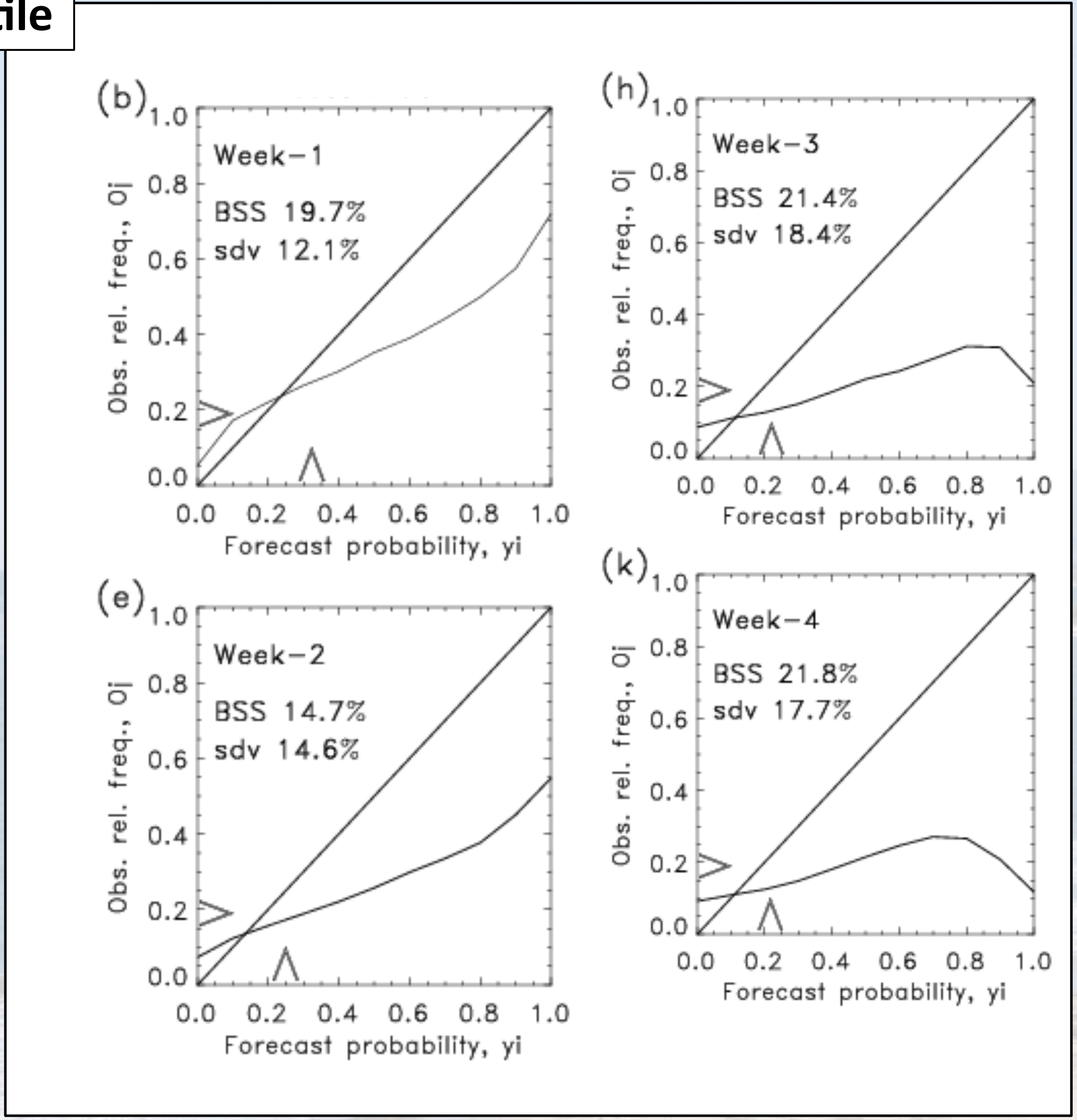
Prec > 50th Percentile



Reliability Diagrams

Average over USA

Prec > 70th Percentile



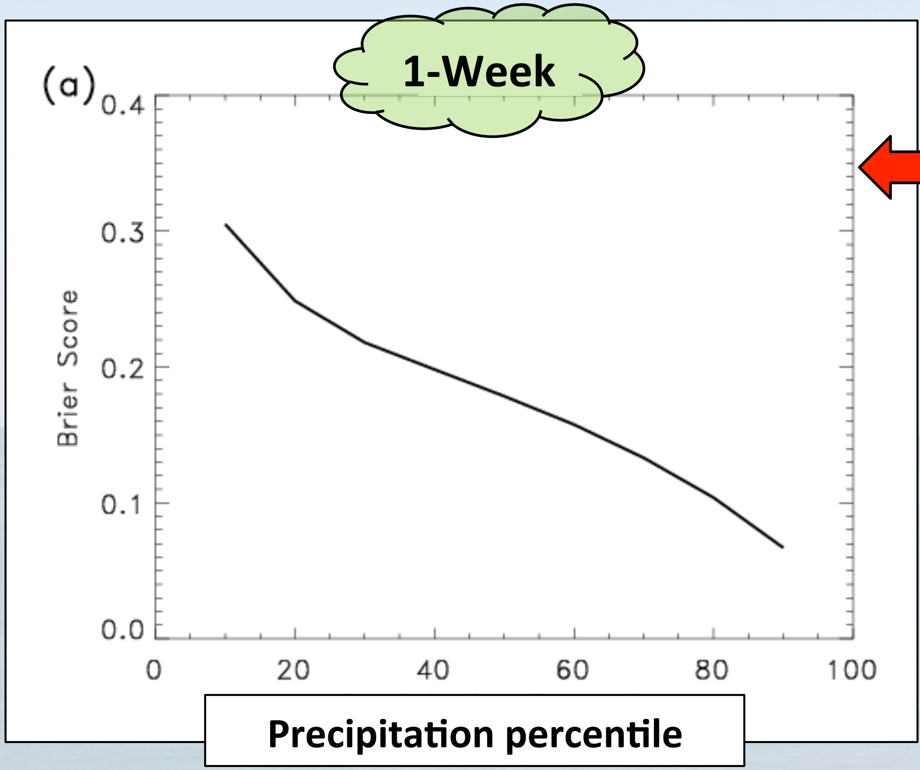
Is there skill in probabilistic forecasts of precipitation in the subseasonal range?

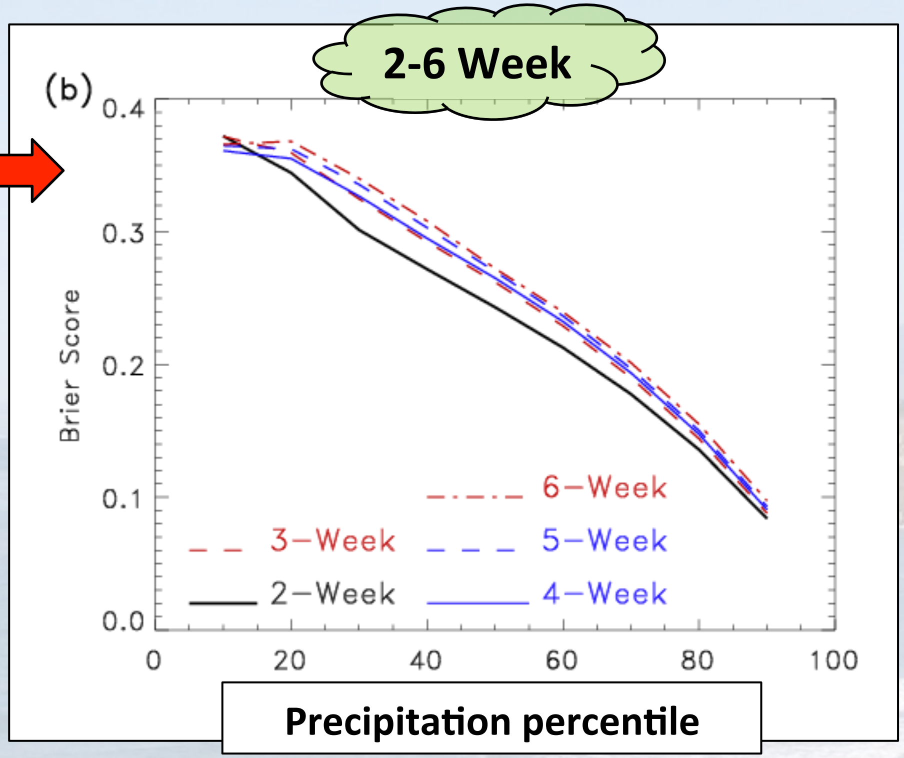
Probably Yes but forecasts need calibration


How does the predictive skill of
precipitation vary as a function of
precipitation intensity?

How does the **predictive skill** of precipitation vary **as a function of precipitation intensity**?

Brier Score $BS = \sum_{k=1}^{N} (Y_k - O_k)^2 / N$

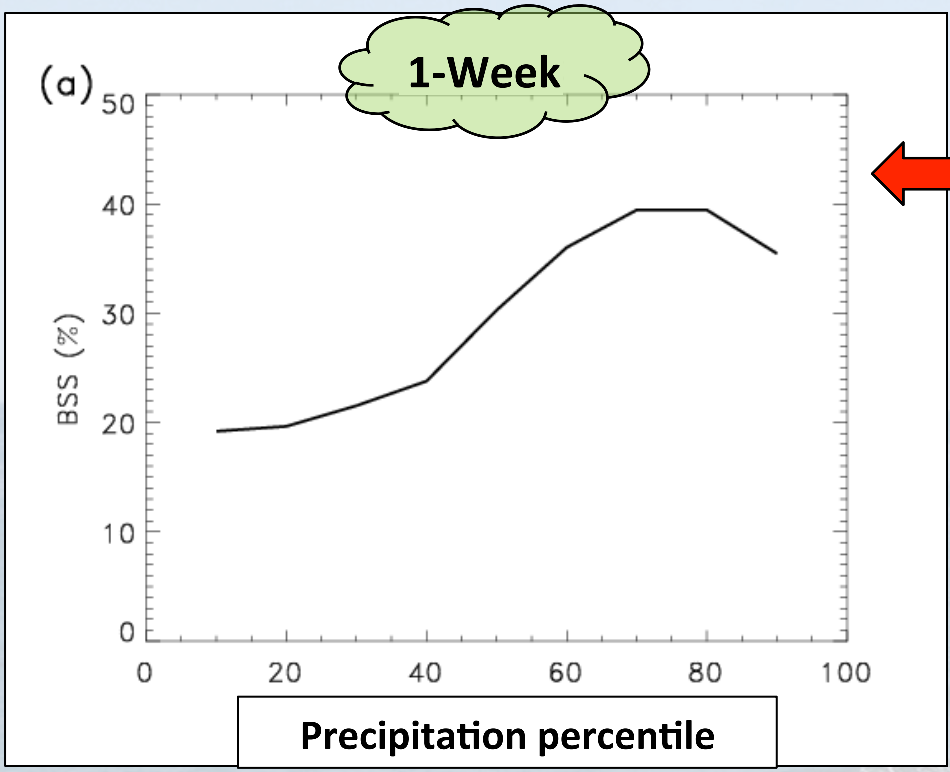


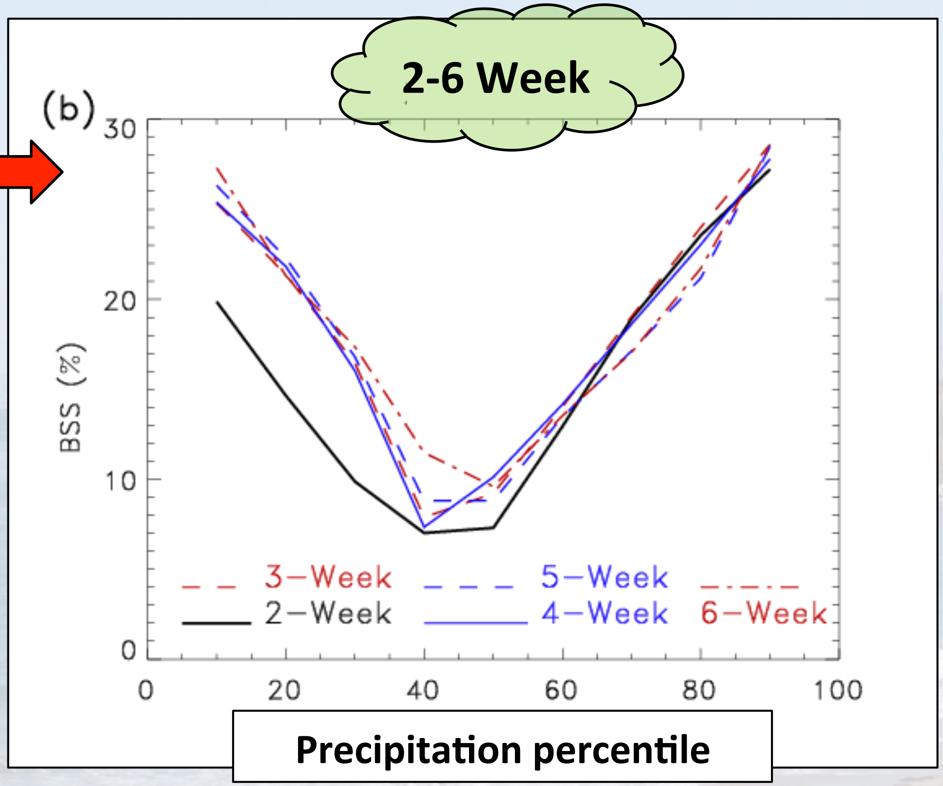


Average BS over the USA

How does the **predictive skill** of precipitation vary **as a function of precipitation intensity**?

Brier Skill Score $BSS = 1 - BS/BS_{Ref}$

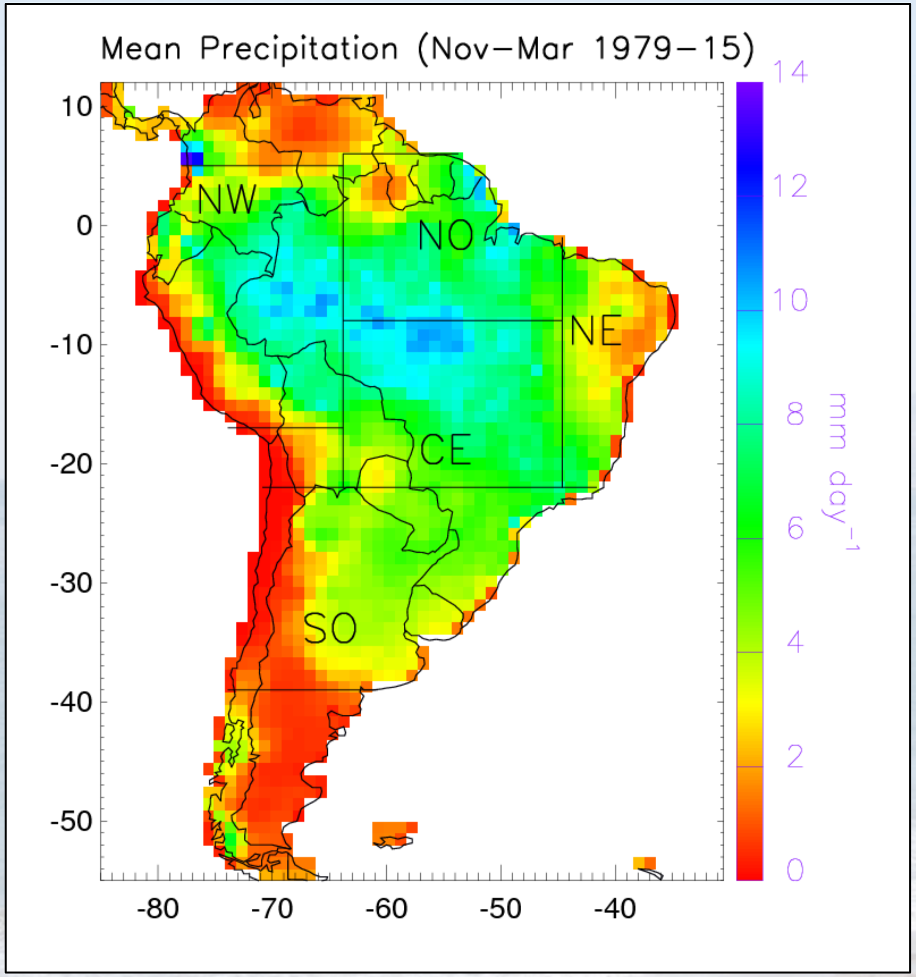




Average BSS over the USA where BSS > 0

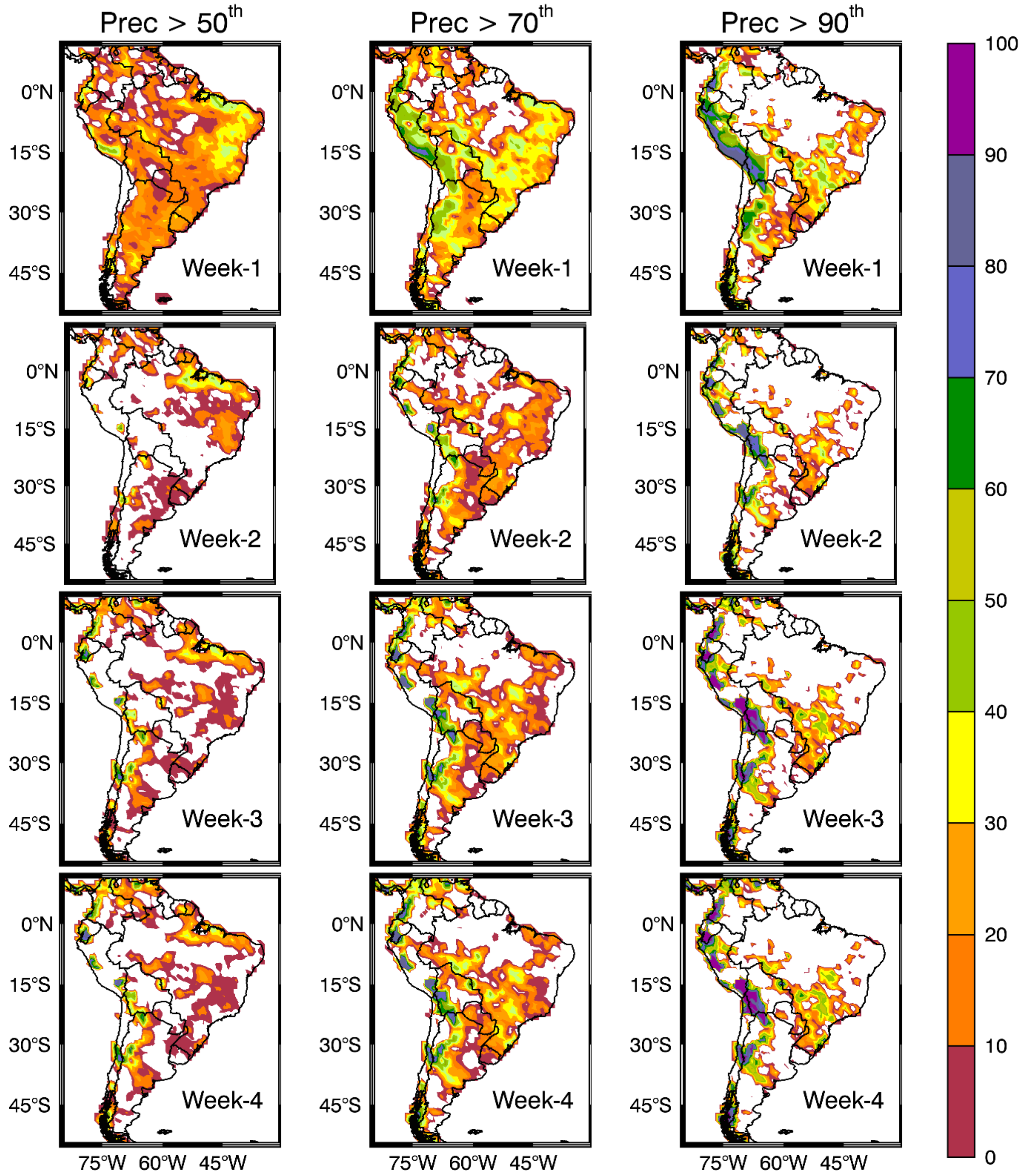
How does the predictability of heavy precipitation vary across different climatic regimes?

Objective: Examine S2S probabilistic forecast skill of precipitation in South America



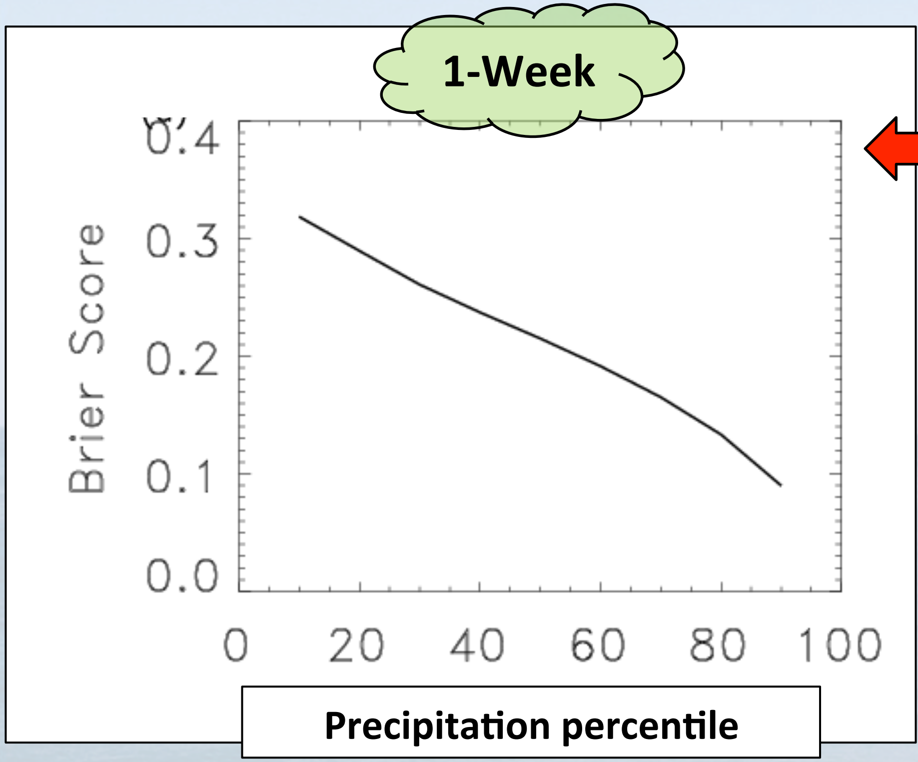
- ECMWF model
- Same analysis
- Different climate

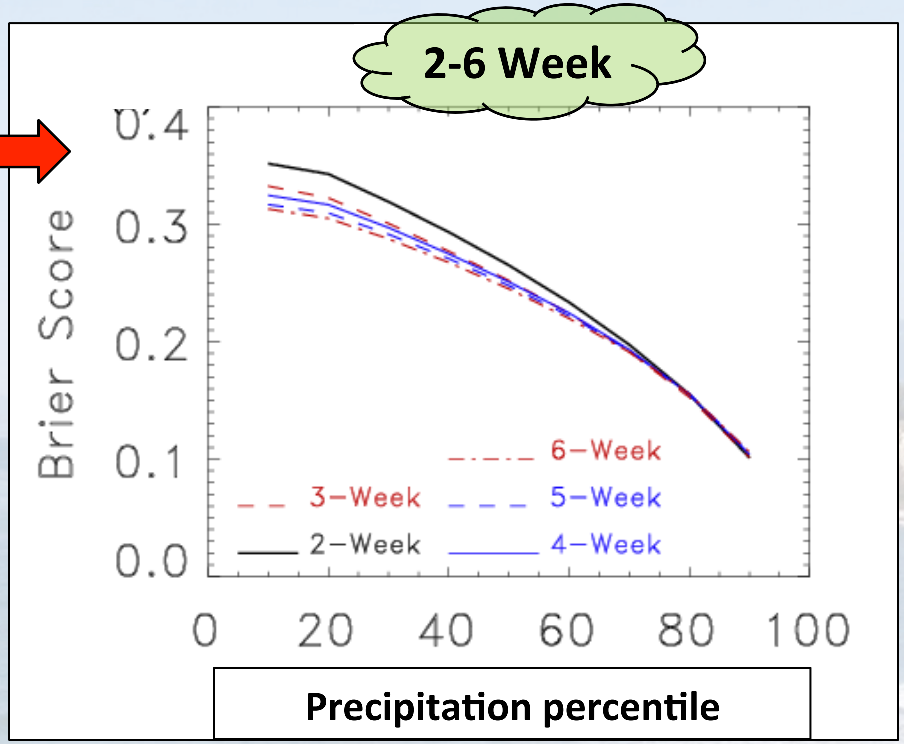
Brier Skill Score



How does the **predictive skill** of precipitation vary **as a function of precipitation intensity**?

Brier Score $BS = \sum_{k=1}^{N} (Y_k - O_k)^2 / N$

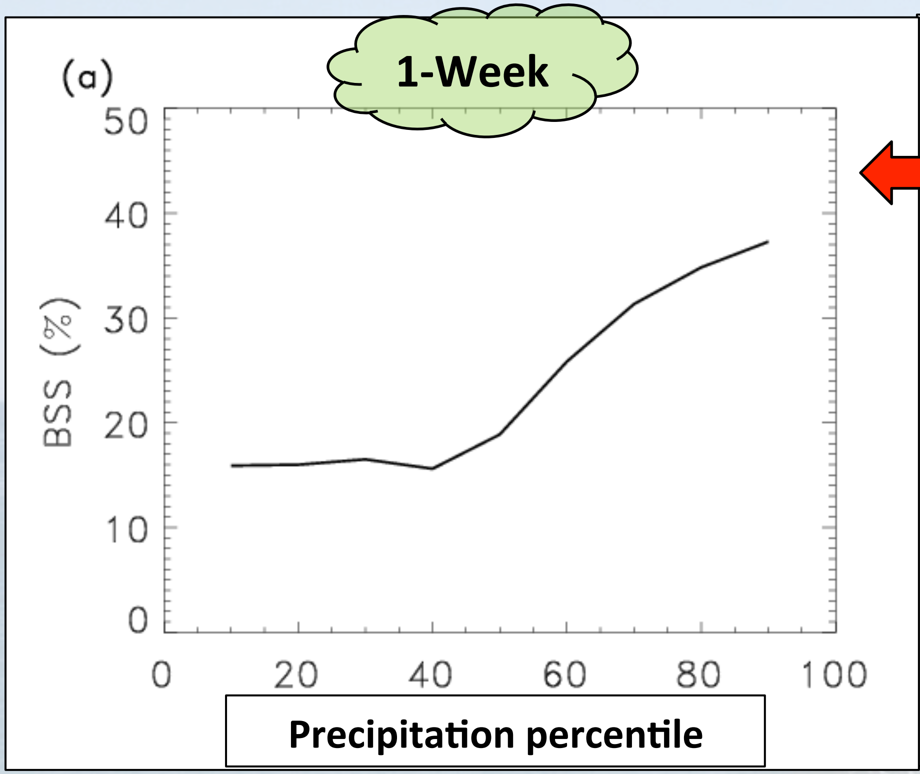


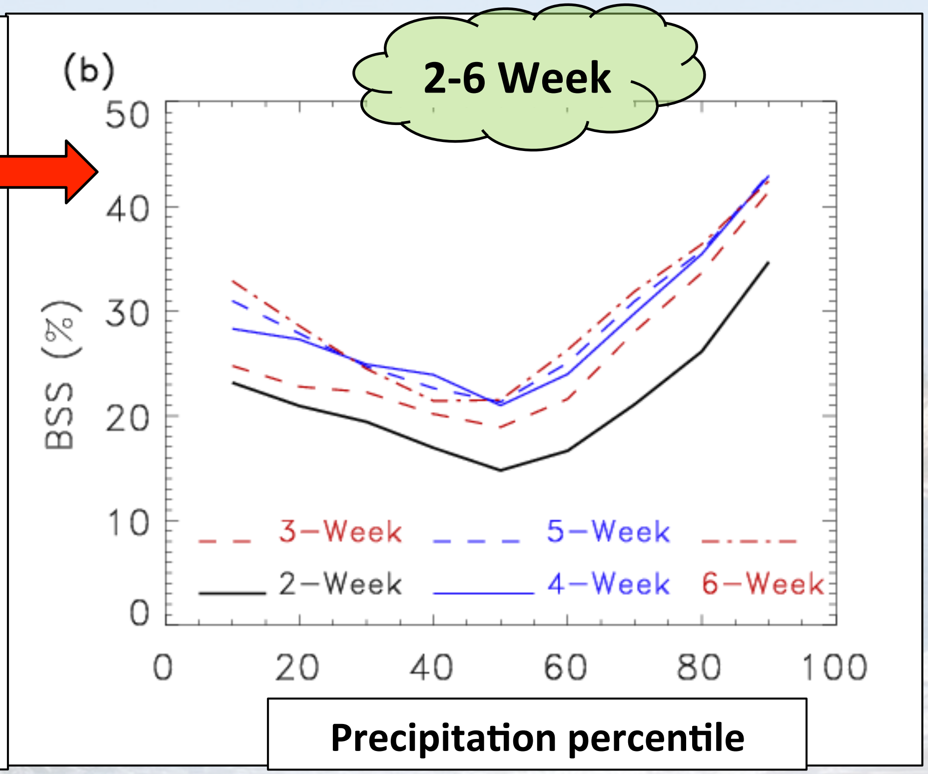


Average BS over South America

How does the **predictive skill** of precipitation vary **as a function of precipitation intensity**?

Brier Skill Score $BSS = 1 - BS/BS_{Ref}$





Average BSS over South America where BSS > 0

Conclusions

<u>Probabilistic forecasts of precipitation over the USA</u>

- ECMWF model shows high skill at 1-week lead
  - BSS up to 40% for Prec > 50^{th} percentile
  - BSS up to 80% heavy precipitation (Prec > 70^{th}, 90^{th} percentiles)
- ECMWF model shows skill at ~2-4 week leads
  - Higher skill for heavier precipitation (Prec > 70^{th}, 90^{th} percentiles)
  - Probabilistic forecasts ⇒ conditional biases ⇒ calibration
- Distinct behavior in forecast skill *versus* precipitation intensity
  - 1-week lead ⇒ BSS_{Max} at ~70-80 percentiles
  - 2-6 week leads ⇒ BSS increases linearly with P^{th} (BSS Min ~40^{th} 50^{th})

<u>Probabilistic forecasts of precipitation over South American Monsoon</u>

- Somewhat similar behavior in forecast skill *versus* precipitation intensity

Jones, C., J. and J. Dudhia, 2017: Potential predictability during a Madden-Julian Oscillation event. *J. Climate* (In Press)

Forecasts errors on scales not directly related to the MJO grow fast in time and propagate to extratropics ⇒ impact forecasts

Ongoing Research

Predictability experiments with OpenIFS

- ❑ Forecast errors on MJO and non-MJO scales
- ❑ Propagation of forecast errors

  Tropics ⇔ Extratropics

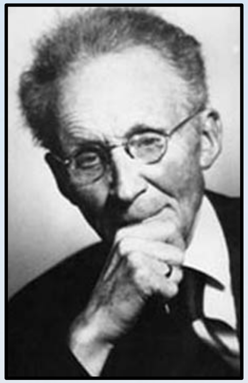
- ❑ Predictability in the subseasonal range

  Atmospheric circulation

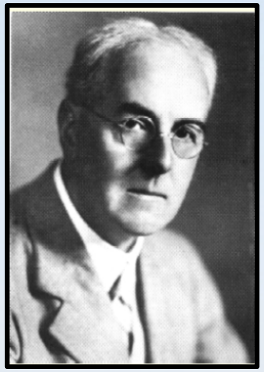
  Precipitation

Thanks for the attention

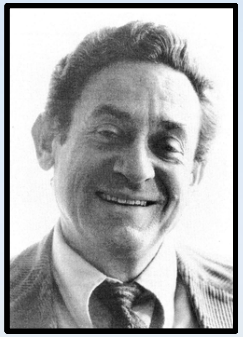
Tremendous progress in short-medium range numerical weather prediction



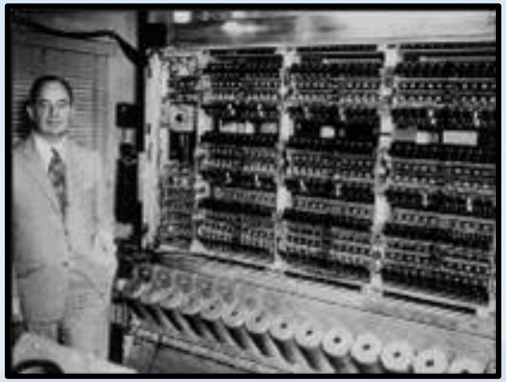
Vilhelm Bjerknes
(1862-1951)



Lewis Richardson
(1881-1953)



Jule Charney
(1917-1981)



John von Neumann and the ENIAC computer.