Disentangle the North American Monthly Precipitation Predictive Skill from Different Time-scales and Initial Conditions

Lantao Sun
Department of Atmospheric Science, Colorado State University

Acknowledgement: Yaga Richter, Anne Sasha Glanville, Teagan King (NCAR), Martin Hoerling, Andrew Hoell, Arun Kumar (NOAA), Marybeth Arcodia, James Hurrell (CSU)

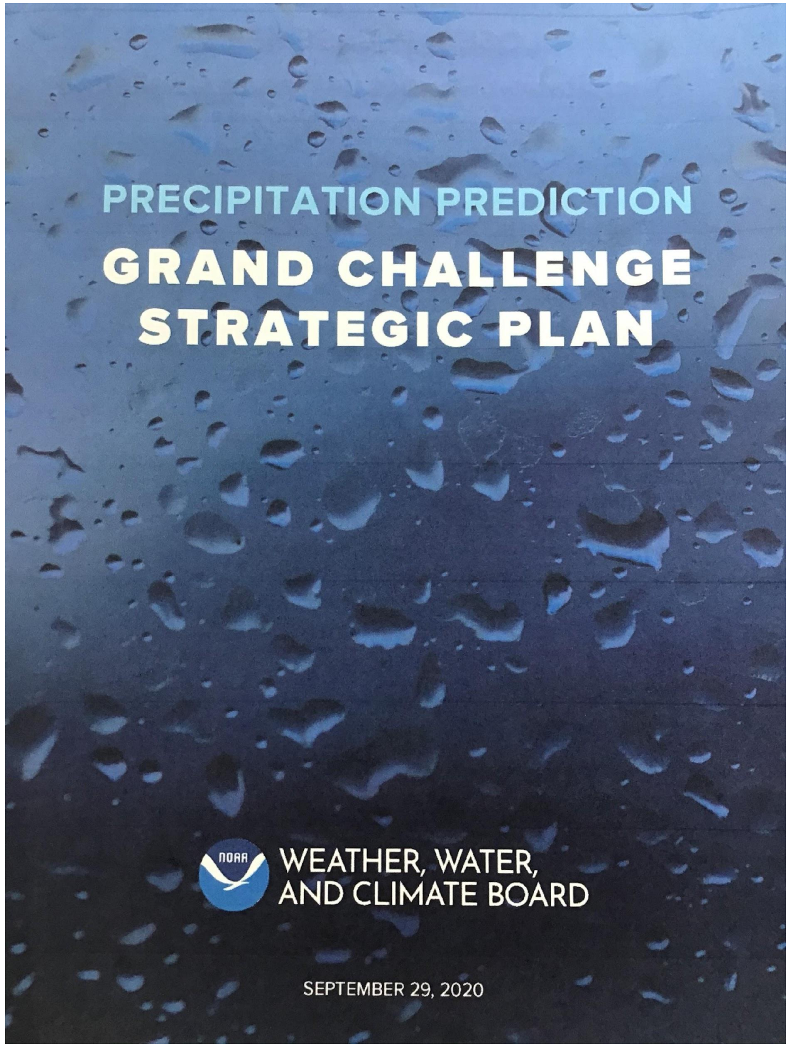
CESM workshop, June 13, 2023

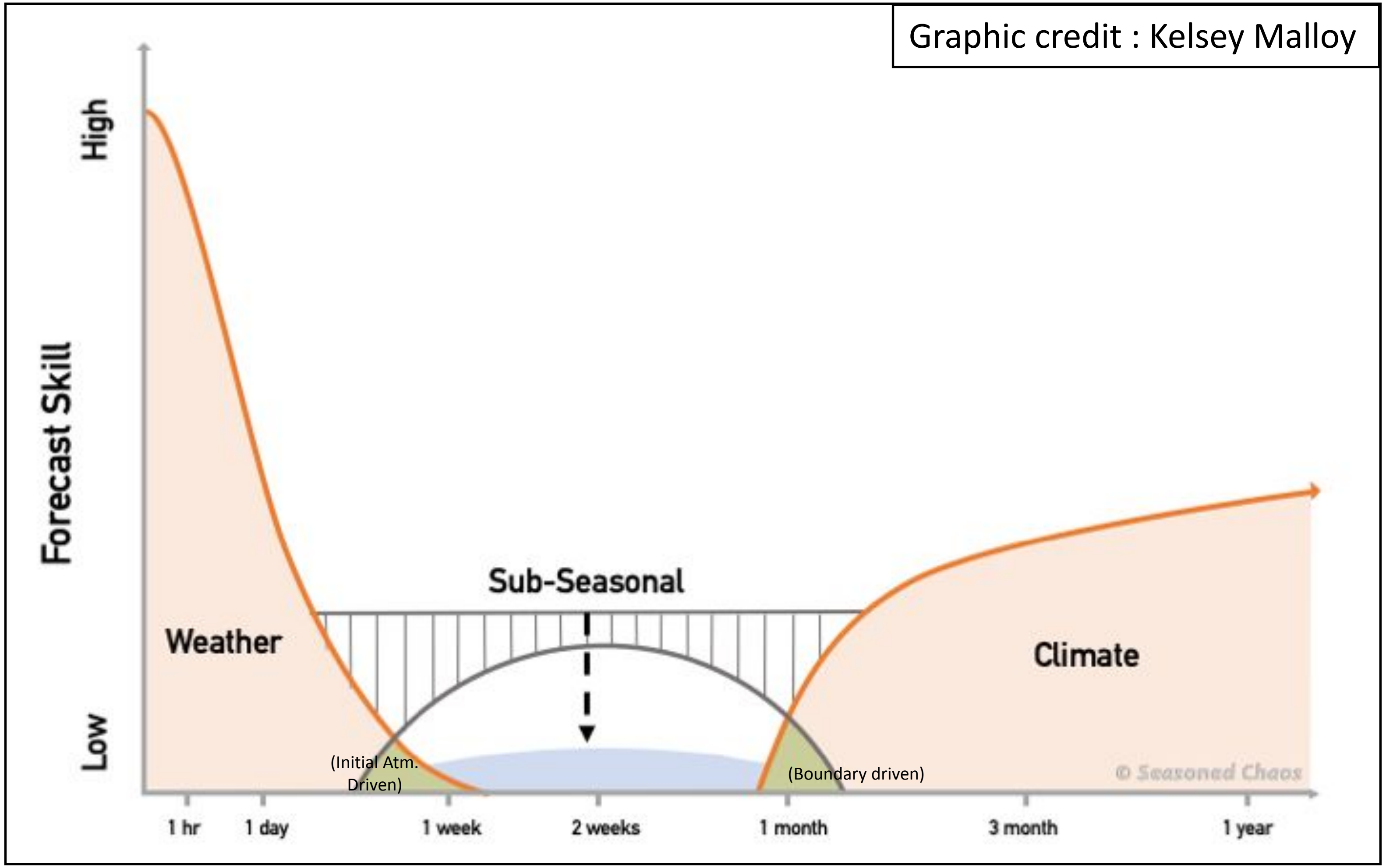
NCAR

NATIONAL OCEANIC AND ATMOSPHERIC ADMINISTRATION
NOAA
U.S. DEPARTMENT OF COMMERCE

Contents

Practical and Theoretical Importance for Understanding Monthly Precipitation Forecast Skill



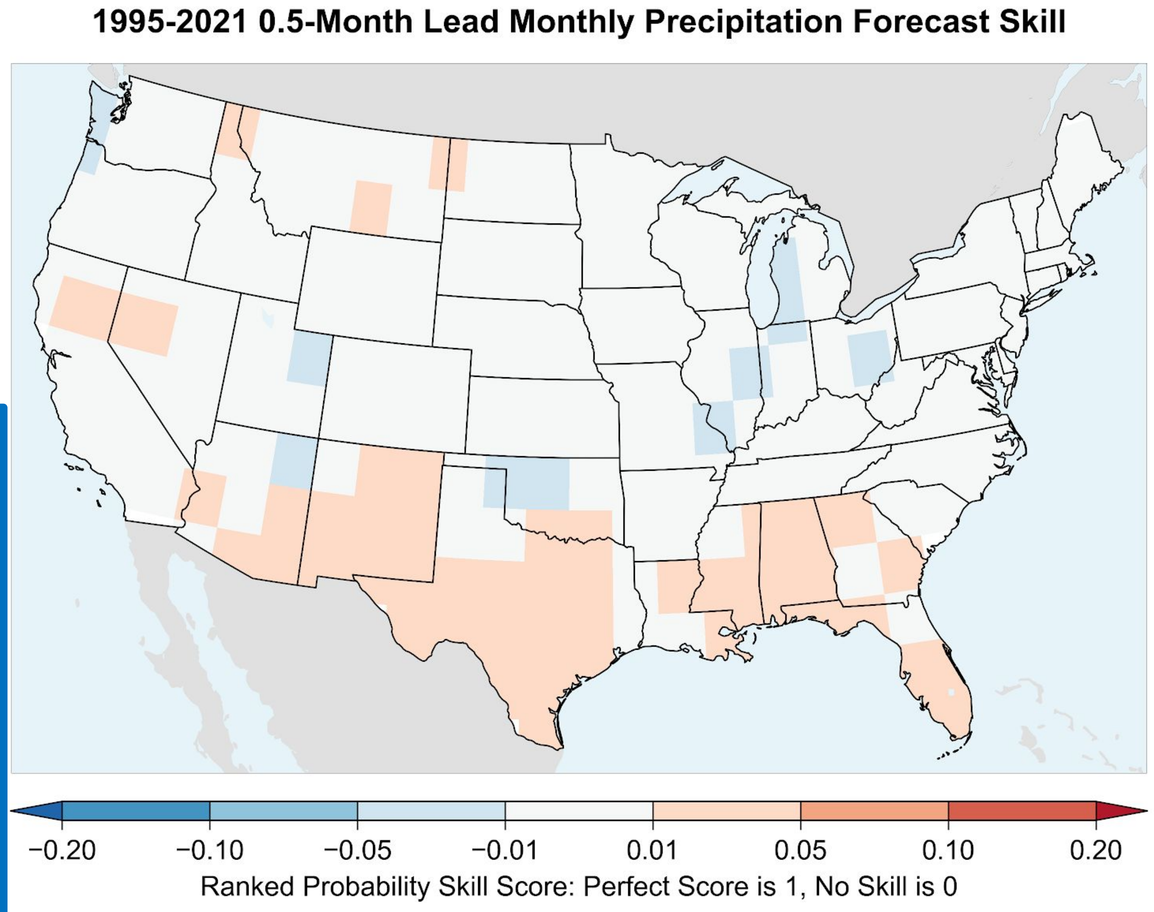


CPC's monthly precipitation forecasts

- Forecasts issued at the beginning of each month (0-day lead) to predict the entirety of that month.
- Forecasts issued in the middle of each month (0.5-month lead) to predict the following month.

Sun, L., M. Hoerling, J. H. Richter, A. Hoell, A. Kumar and J. Hurrell, (2022): Attribution of North American Subseasonal Precipitation Prediction Skill, *Weather and Forecasting*, doi: 10.1175/WAF-D-22-0076.1.

- Seasonal and regional variations in monthly precipitation predictive skill
- Substantial impact of ENSO on monthly precipitation skill at lead time of 0.5 months.



Research Goal

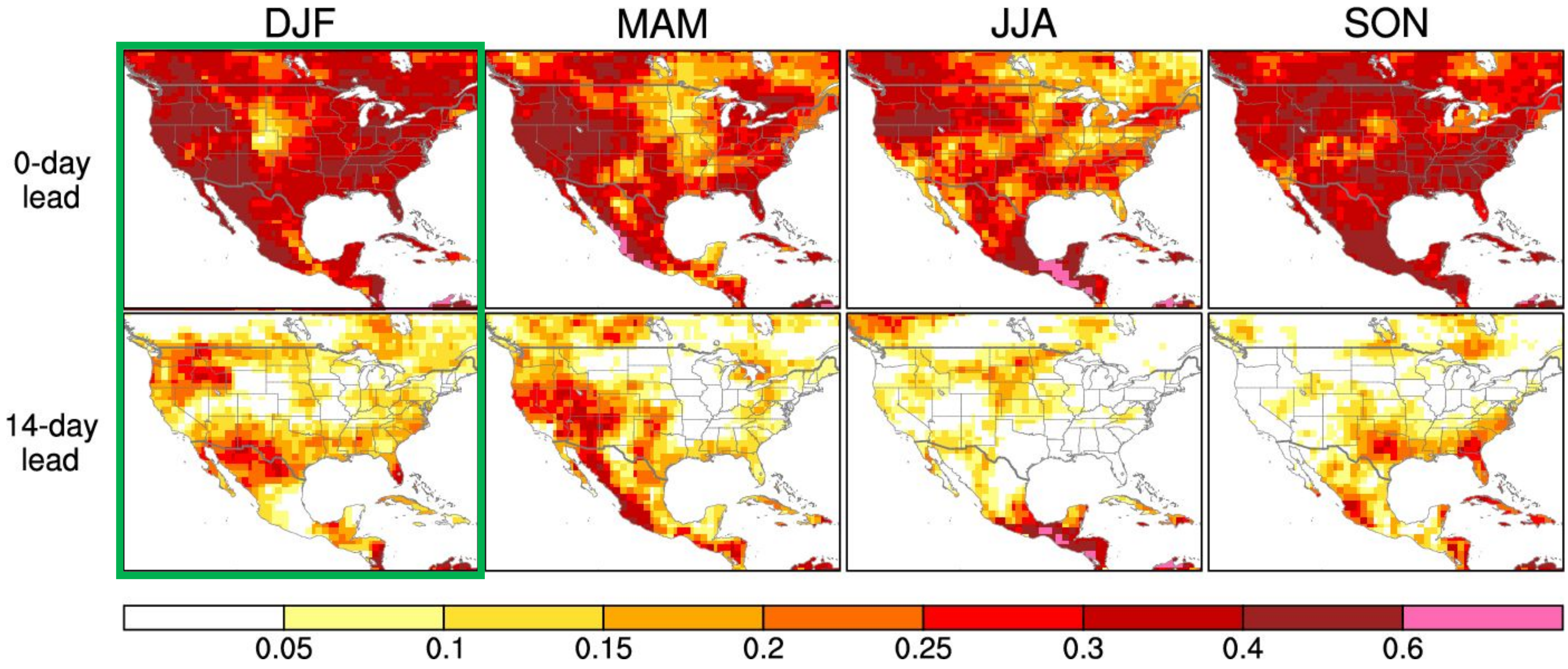
Expanding on our previous analysis of North American monthly precipitation predictive skill, this study aims to:

1. Examine the separate skill components of monthly precipitation: seasonal versus subseasonal timescales.
2. Investigate the impacts of atmospheric, oceanic, and land initial conditions on monthly precipitation skill.

Subseasonal reforecast with CESM2 (Richter et al. 2022)

- 11-member reforecast spanning 1999-2020, with forecasts up to 45 days, initialized every Monday.
- Initialization method based on previous decadal prediction (Yeager et al., 2018).
  - Atmospheric: CFSv2 reanalysis.
  - Land: CLM5 spin up with CFSv2.
  - Ocean and sea-ice: JRA55-do.
- Evaluated the anomaly correlation coefficient (ACC) skill for monthly precipitation at 0-day lead (*average for weeks 1-4*) and 14-day lead (*average for weeks 3-6*).

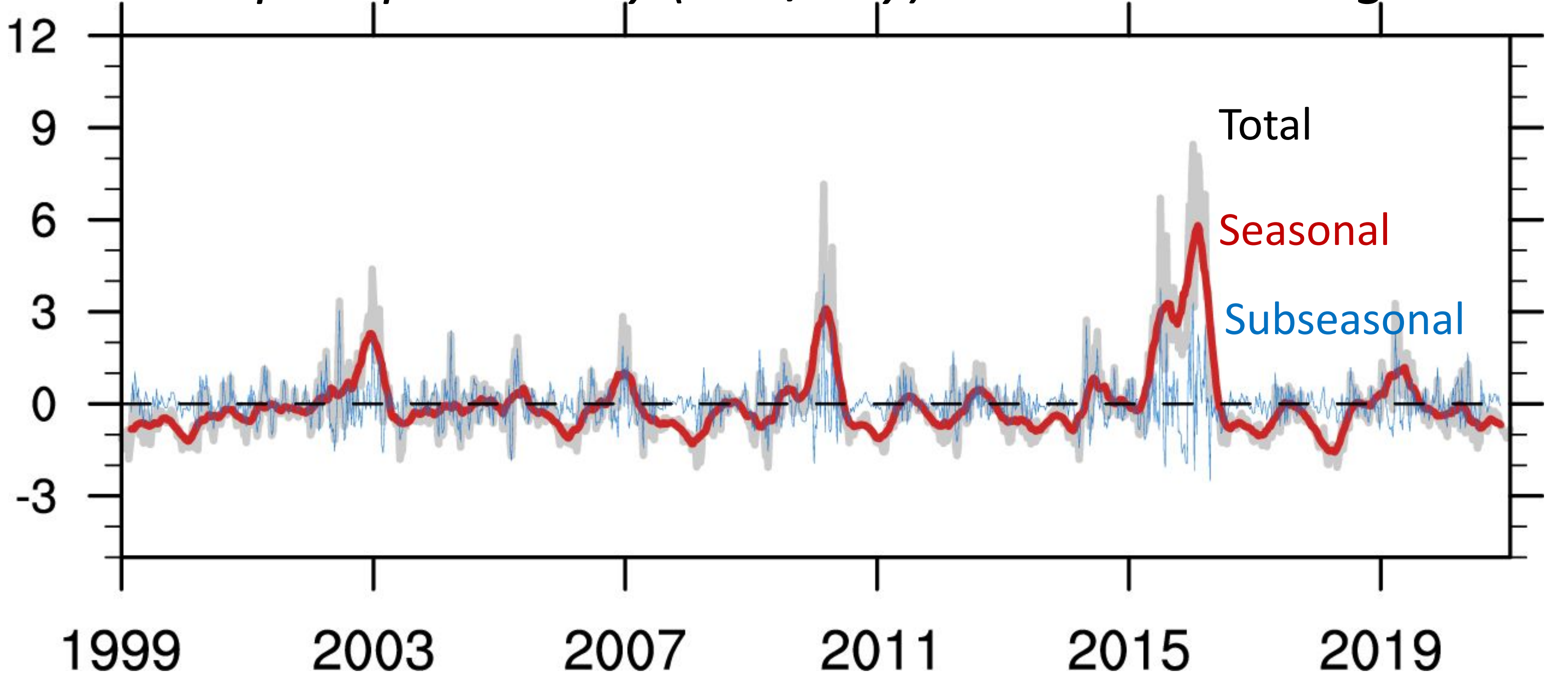
North American monthly precip predictive ACC skill in CESM2



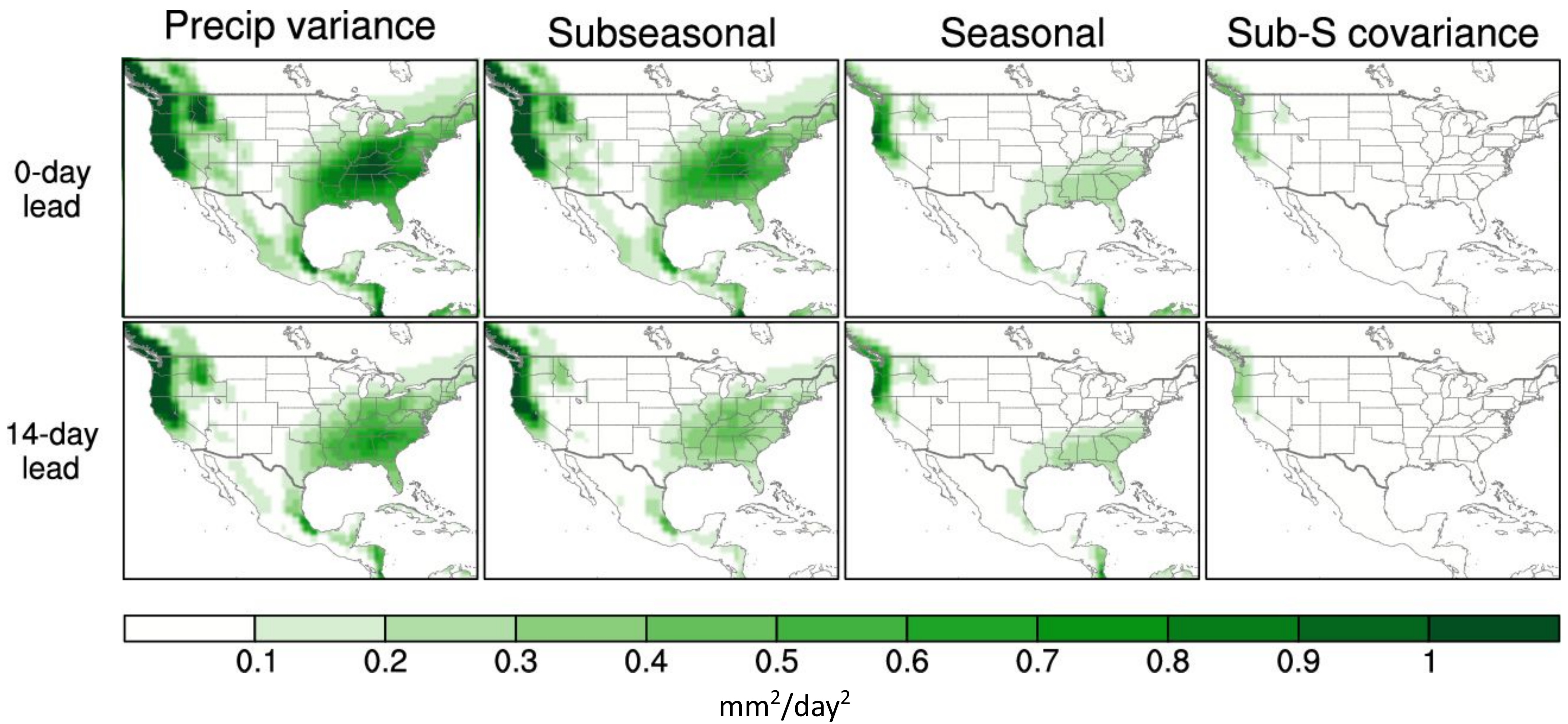
Separation the CESM2 reforecast anomaly into seasonal and subseasonal components

Our methodology involves calculating the forecast weekly anomaly time series (i.e., week 1, 2, … 6) for the period 1999-2020. Subsequently, we apply a 17-week running mean to extract the seasonal components, while considering the residual anomaly as the subseasonal components (Arcodia et al., 2020).

week-1 precip anomaly (mm/day) over Niño 3.4 region



DJF monthly Precipitation variance at different timescale



Separate the DJF monthly precipitation predictive skill into seasonal and subseasonal components

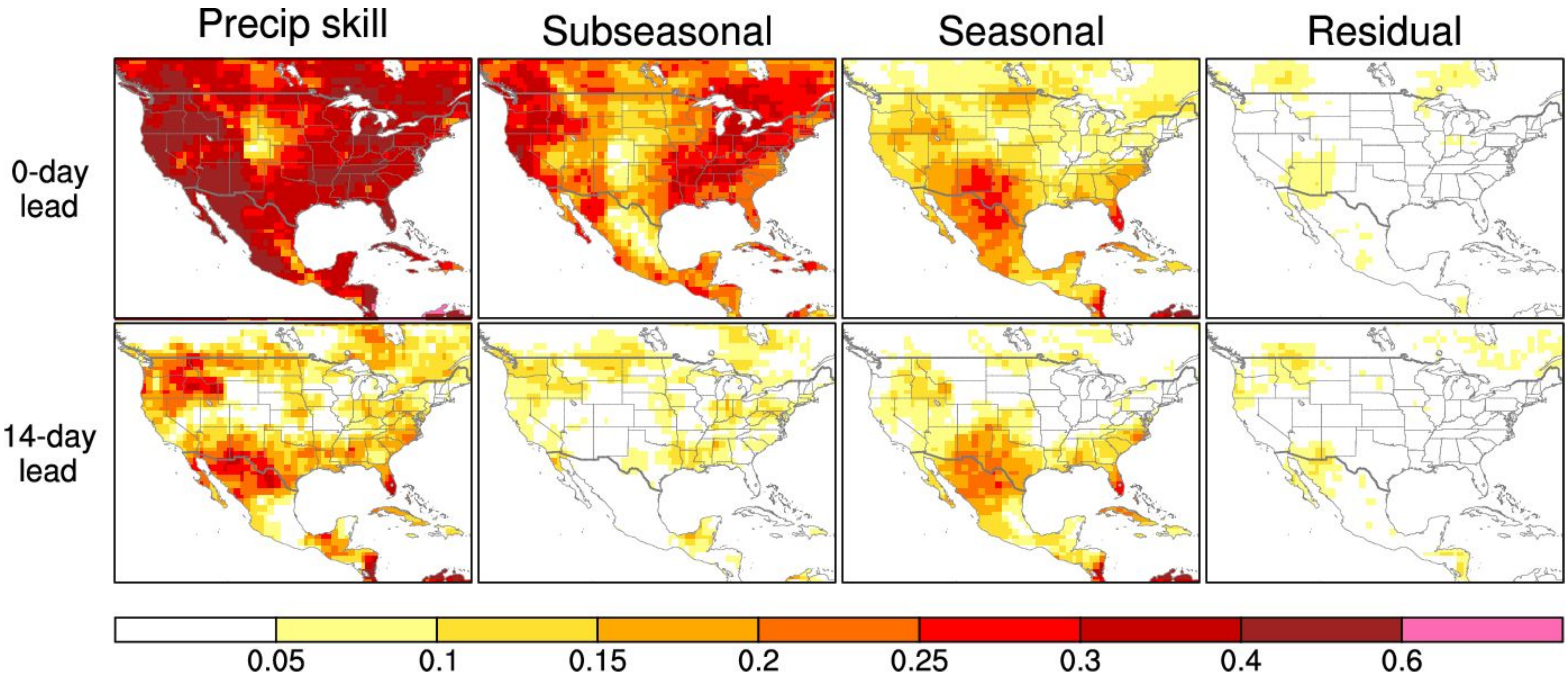
$$ACC_{standard}(x,y) = \boxed{\frac{ACC_{season}}{\sqrt{(1+\frac{1}{r_m})(1+\frac{1}{r_o})}}} + \boxed{\frac{ACC_{subseason}}{\sqrt{(1+r_m)(1+r_o)}}} + \varepsilon$$

Seasonal component

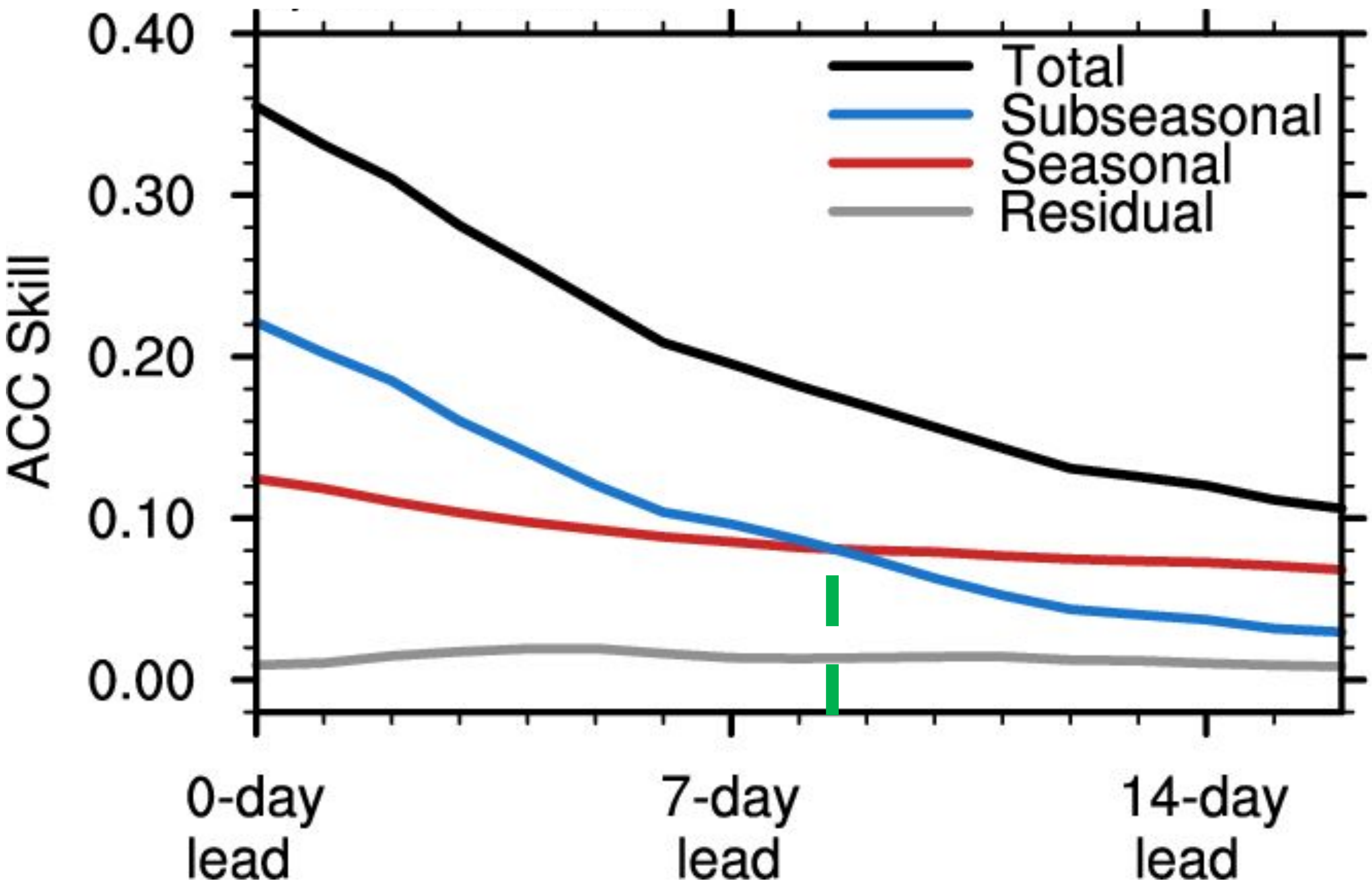
Subseasonal component

where ACC_{season} and $ACC_{subseason}$ represent the seasonal and subseasonal predictive skill, respectively. r_m indicates the ratio of the variance between seasonal and subseasonal components in model reforecast and r_o is for the observations. ε is the residual term related to the covariance term.

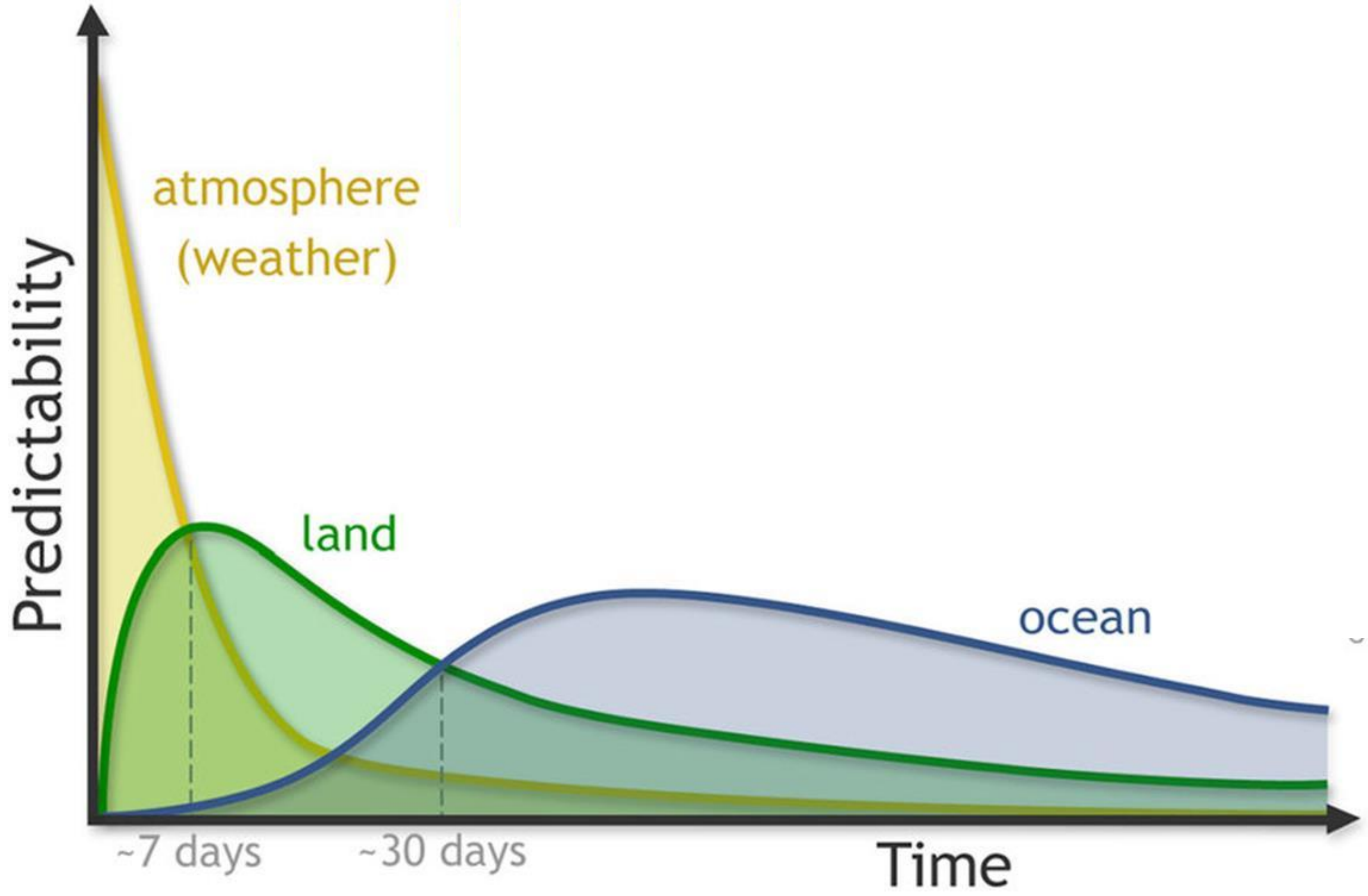
Separate the DJF monthly precipitation predictive skill into seasonal and subseasonal components



DJF monthly precipitation predictive skill averaged over North America



Potential sources of the subseasonal predictive skill



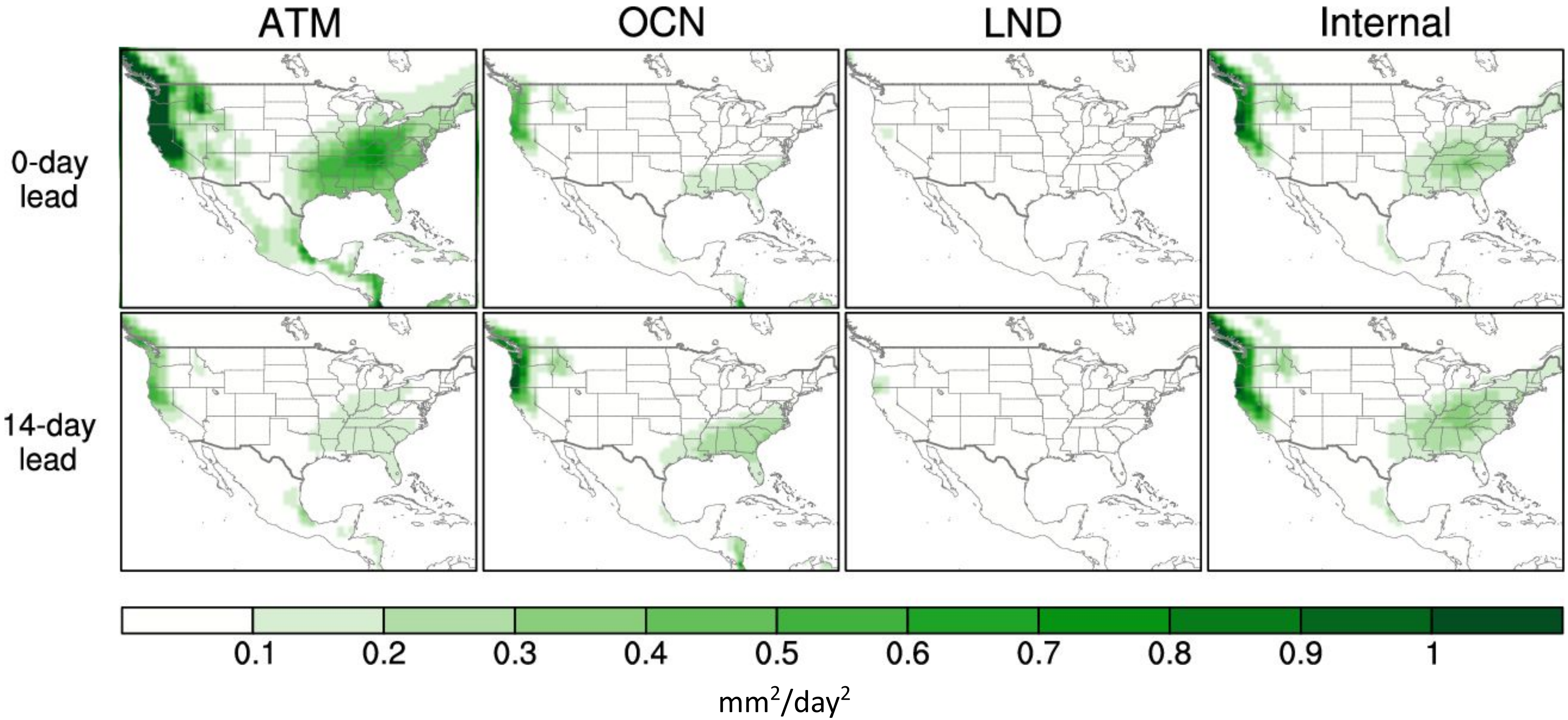
Credit: NOAA Climate.gov graphic, adapted from original by Paul Dirmeyer.

CESM2 idealized initialize reforecast

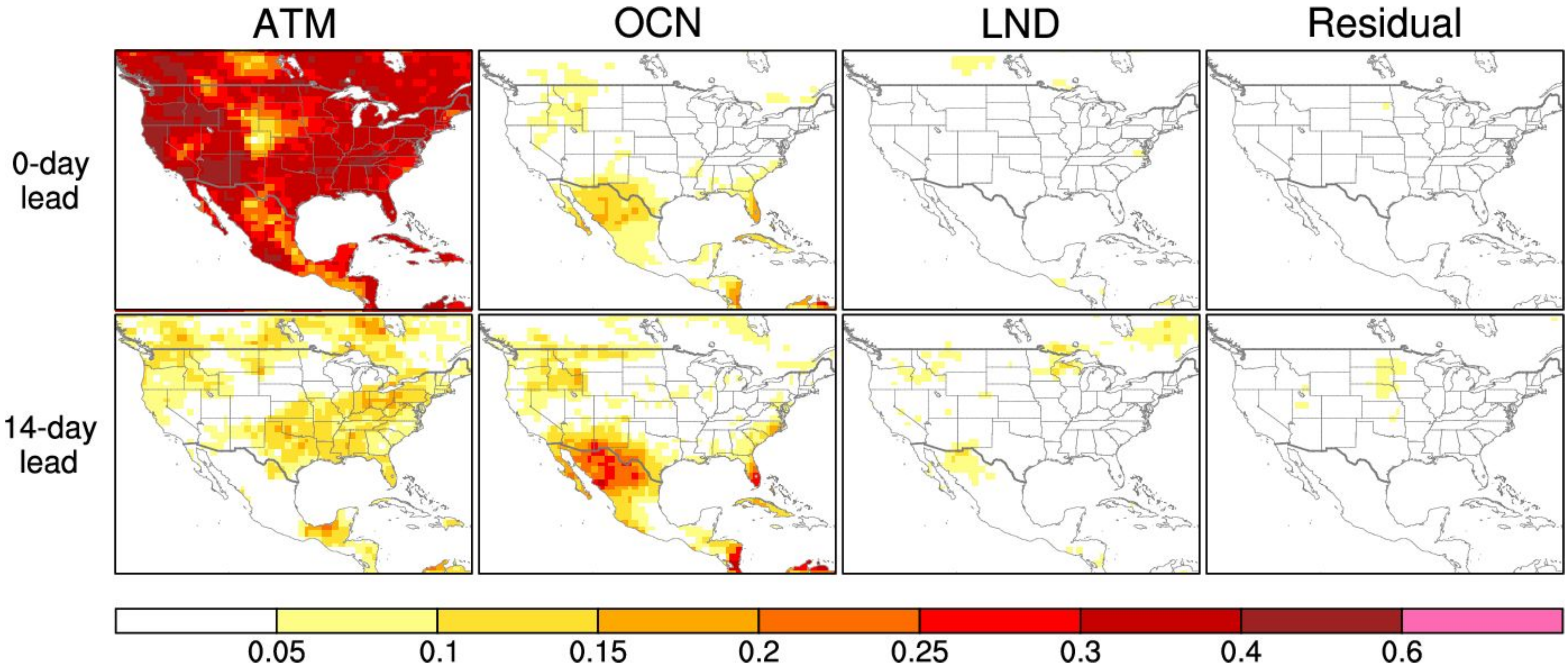
Initialize some component(s) to climatology for the reforests (Table)

Reforecasts experiments	Atmosphere initial condition	Ocean initial condition	Land Initial condition
S2SHINDCASTS (Standard)	CFSv2	JRA55-do	CLM5 spin up with CFSv2
S2SHINDCASTSclimoLND	CFSv2	JRA55-do	climatology
S2SHINDCASTSclimoOCN	CFSv2	climatology	CLM5 spin up with CFSv2
S2SHINDCASTSclimoATM	climatology	JRA55-do	CLM5 spin up with CFSv2
S2SHINDCASTSclimoOCNclimoLND	CFSv2	climatology	climatology
S2SHINDCASTSclimoATMclimoLND	climatology	JRA55-do	climatology
S2SHINDCASTSclimoOCNclimoATM	climatology	climatology	CLM5 spin up with CFSv2
S2SHINDCASTSclimoALL	climatology	climatology	climatology

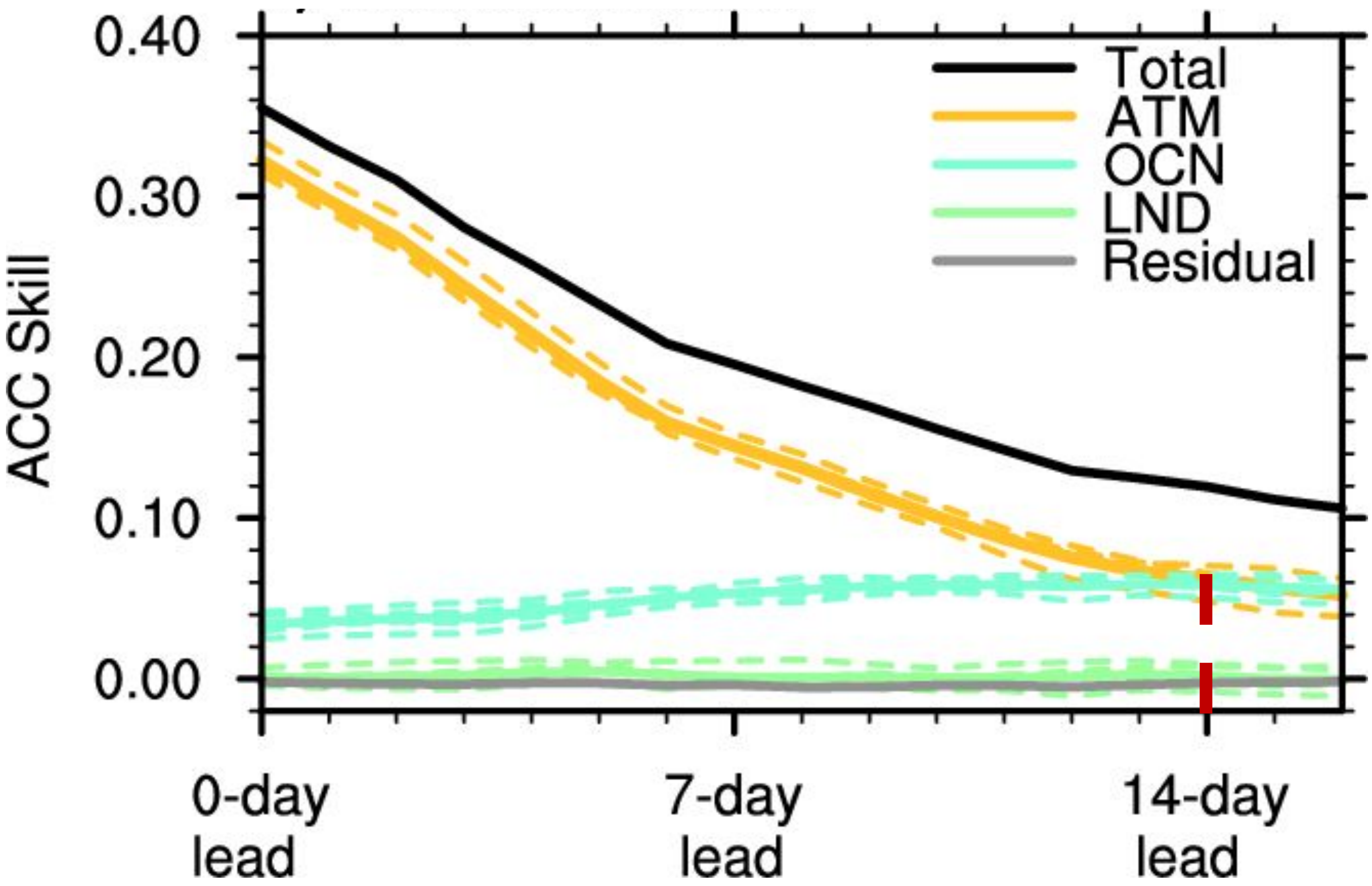
DJF monthly Precipitation variance due to initial conditions



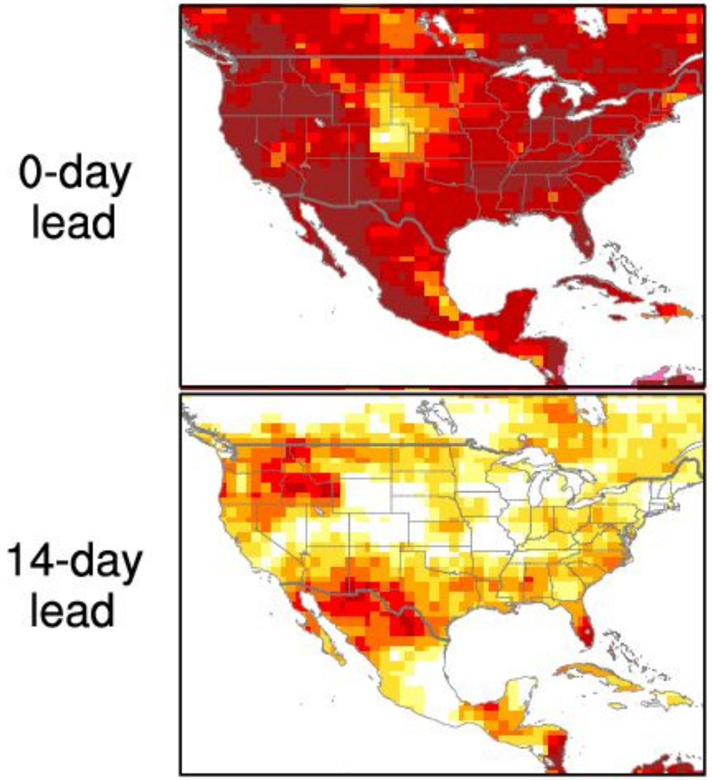
Decompose the predictive skill into contributions from initial conditions



DJF monthly precipitation predictive skill averaged over North America



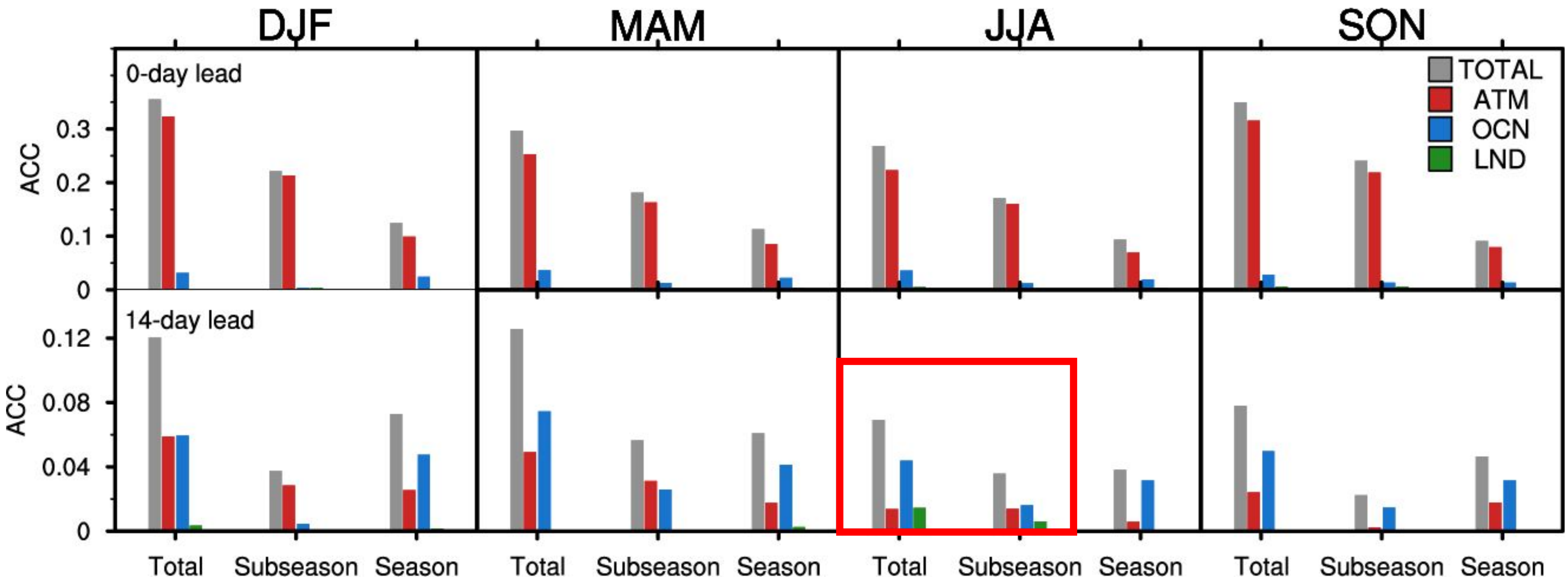
Disentangle the North American Monthly Precipitation Predictive Skill from Different Time-scales and Initial Conditions



- Seasonal and subseasonal skills display distinct spatial patterns, with different relative magnitudes observed at the 0-day and 14-day leads.
- At the 0-day lead, the atmospheric initial condition predominantly influences monthly precipitation skill. Conversely, at the 14-day lead, both atmospheric and oceanic initial conditions contribute comparably, yet with spatial variations.

Email: Lantao.sun@rams.colostate.edu

Supplementary figures



DJF
MAM
JJA
SON
0-day lead
14-day lead
ACC
0
0.1
0.2
0.3
0.04
0.08
0.12
TOTAL
ATM
OCN
LND
Total
Subseason
Season

Decompose the predictive skill into contributions from initial conditions

$$ACC_{standard}\,(x,y) = \frac{\sum_{t=1}^{T} X'_{atm} X'_{obs}}{\sqrt{\sum_{t=1}^{T} X'^{2}_{model} \sum_{t=1}^{T} X'^{2}_{obs}}} + \frac{\sum_{t=1}^{T} X'_{ocn} X'_{obs}}{\sqrt{\sum_{t=1}^{T} X'^{2}_{model} \sum_{t=1}^{T} X'^{2}_{obs}}} + \frac{\sum_{t=1}^{T} X'_{lnd} X'_{obs}}{\sqrt{\sum_{t=1}^{T} X'^{2}_{model} \sum_{t=1}^{T} X'^{2}_{obs}}} + \varepsilon$$

ATM OCN LND