Subseasonal Prediction Skill from SubX

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Predictability of Week 3-4 Averages

Evidence of Sub-Seasonal Predictability

Pegion, Sardeshmukh (2011; MWR):	ψ and OLR (CFS, GEOS5, LIM)
Johnson et al. (2013; Wea. For.):	N. America T. (empirical)
Wang et al. (2014; Climate Dyn.):	MJO (CFSv2)
Vitard (2014; QJRMS):	MJO and NAO (ECMWF)
Li and Roberts (2015; MWR):	Summer P. (CFSv2, JMA, ECMWF)

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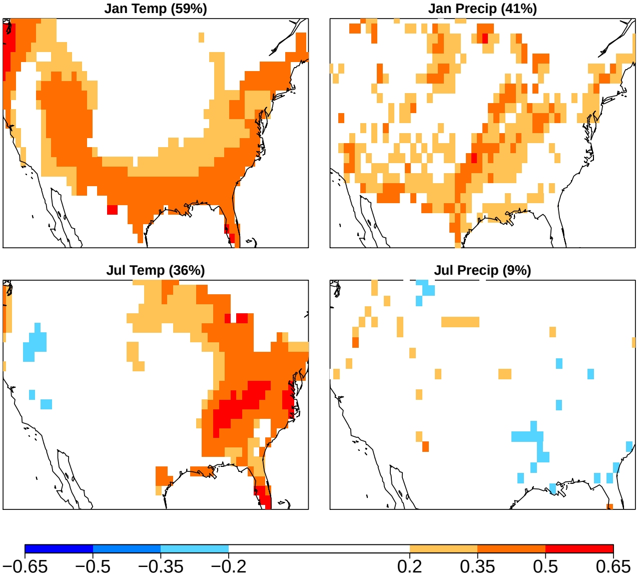
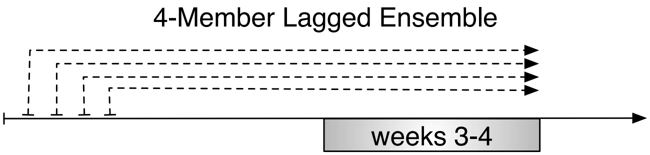
No clear demonstration of skill by dynamical models for predicting week 3-4 averages of T. or P. over North America.

Correlation Skill of CFSv2 Hindcasts

Week 3−4 Prediction; Lagged Ensemble= 4 days

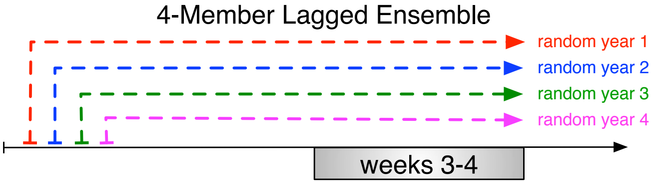


Data Details



- CFSv2 hindcasts initialized 0Z, 6Z, 12Z, 18Z each day 1999-2010.
- Consider only 14-day mean of weeks 3-4 (15-28d) hindcasts.
- Temperature validated with NCEP/NCAR reanalysis.
- Precipitation validated with CPC Unified Gauge-Based Analysis.
- Subtract out smoothed climatology conditioned on verification day.

Permutation Test



- Standard significance test is not appropriate because hindcasts initialized 6 hours apart are not independent.
- Under null hypothesis of no predictability, hindcasts are exchangeable for the same start day and lead.

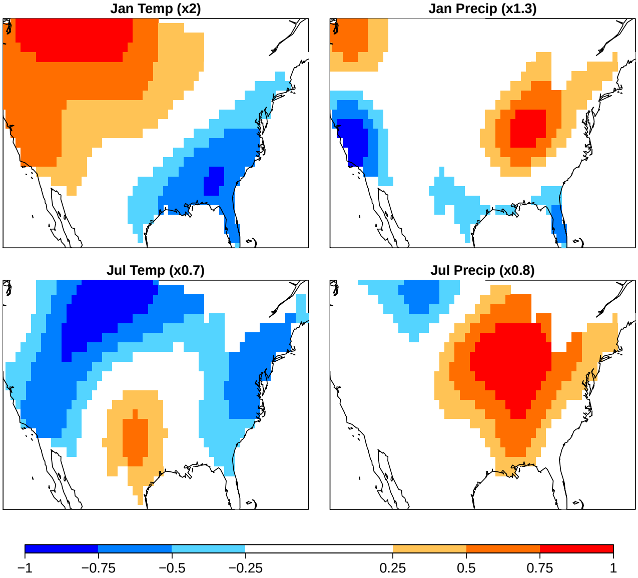
Predictable Component Analysis

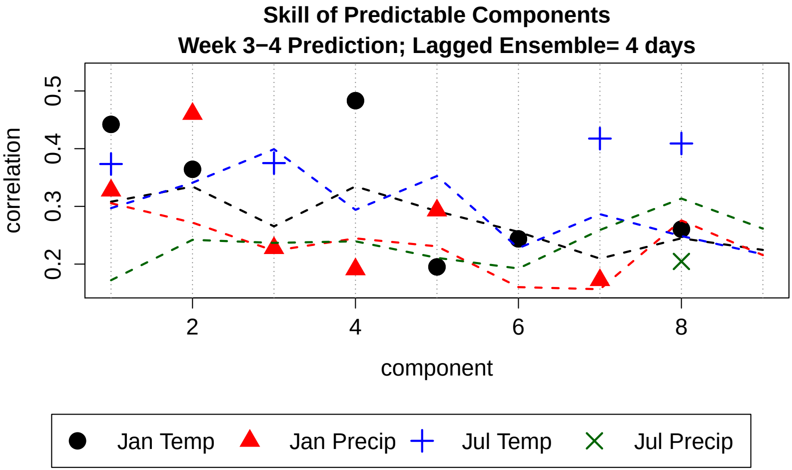
Determine linear combination of variables that maximizes S/N.

$$\begin{aligned} \text{signal} &= \text{variance of ensemble means} \\ \text{noise} &= \text{variance } \textit{about} \text{ the ensemble means} \end{aligned}$$

Most Predictable Component

Week 3−4 Prediction




Skill of Predictable Components
Week 3−4 Prediction; Lagged Ensemble= 4 days
correlation
0.2
0.3
0.4
0.5
2
4
6
8
component
Jan Temp
Jan Precip
Jul Temp
Jul Precip

SubX BY THE NUMBERS

7 Global Models

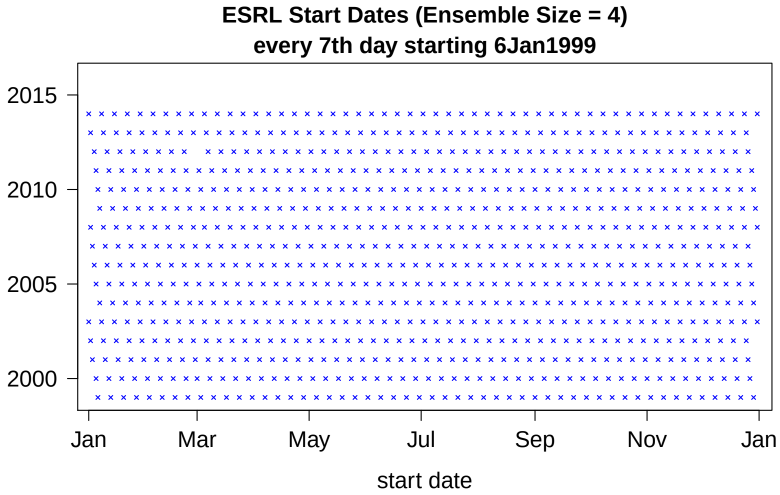
1 Year of ***Real-time*** Forecasts

17 Years of ***Retrospective*** Forecasts

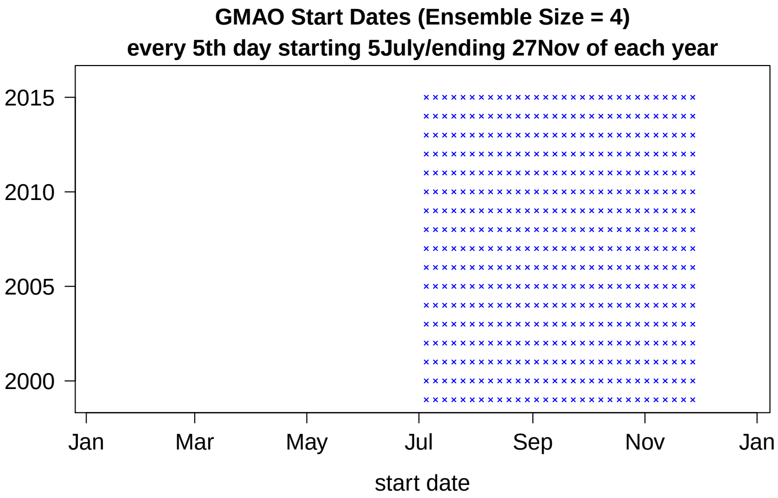
3-4 week guidance for Climate Prediction Center Outlooks

courtesy of Kathy Pegion

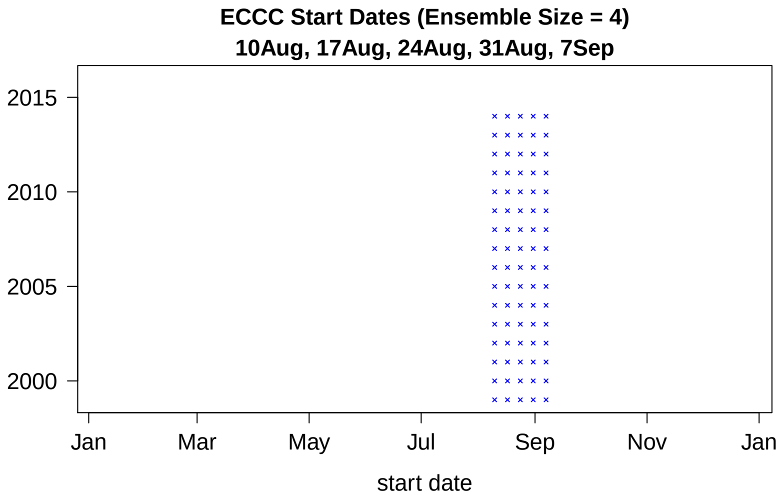
Model	Lead (d)	E	Time Steps	Initial Conds
$ECCC - GEM$	32	4	6976 10Aug1995-14Sep2014	only 4 IC dates every year: 10Aug, 17Aug, 24Aug, 31Aug, 7Sep
$EMC - GEFS$	35	11	914 02June1999-30Nov2016	every 7th day starting from 02June and ending at 30Nov of each year
$ESRL - FIMr1p1$	32	4	835 06Jan1999-31Dec2014	every 7th day starting from 06Jan1999 and ending at 31Dec2014
$GMAO - GEOS_V2p1$	45	4	5990 05Jul1999-27Nov 2015	every 5th day starting from 05July and ending at 27Nov of each year
$NRL - NESM$	45	1	5995 03Jul1999-30Nov2015	each set of 4 consecutive ICs starting from 03Jul1999 separated by 3 days
$RSMAS - CCSM4$	45	3	6569 07Jan1999-31Dec2016	every 7th day starting from 07Jan and ending at 29Apr of each year



2-3 samples per day

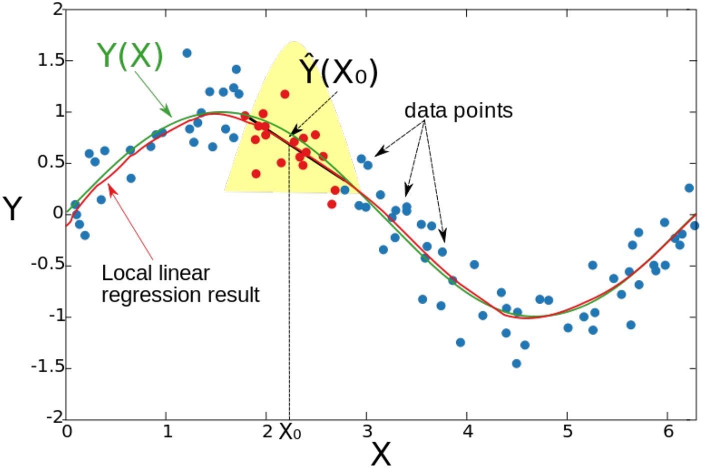


17 samples 1 day/week, 0 samples on other days of the week



16 samples 1 day/week, 0 samples on other days of the week

Local Linear Regression



Hastie, Tibshirani, Friedman, 2009, Elements of Statistical Learning

Monte Carlo Experiment

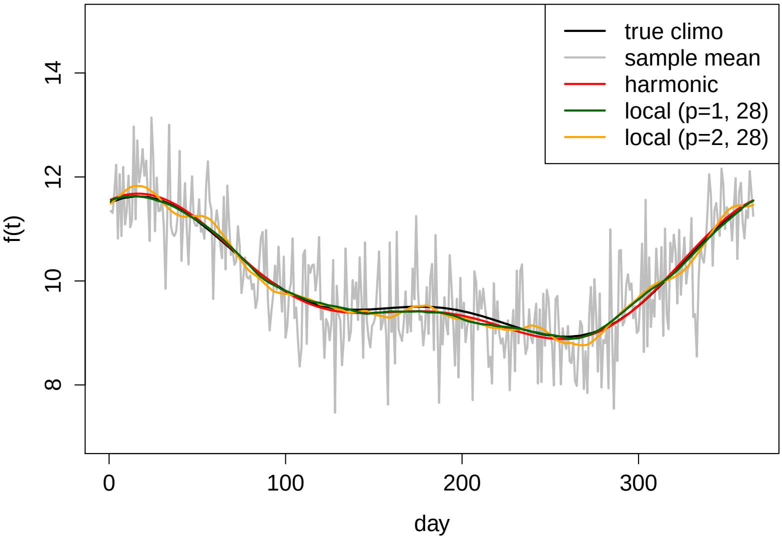
1. Synthetically generate data from the model

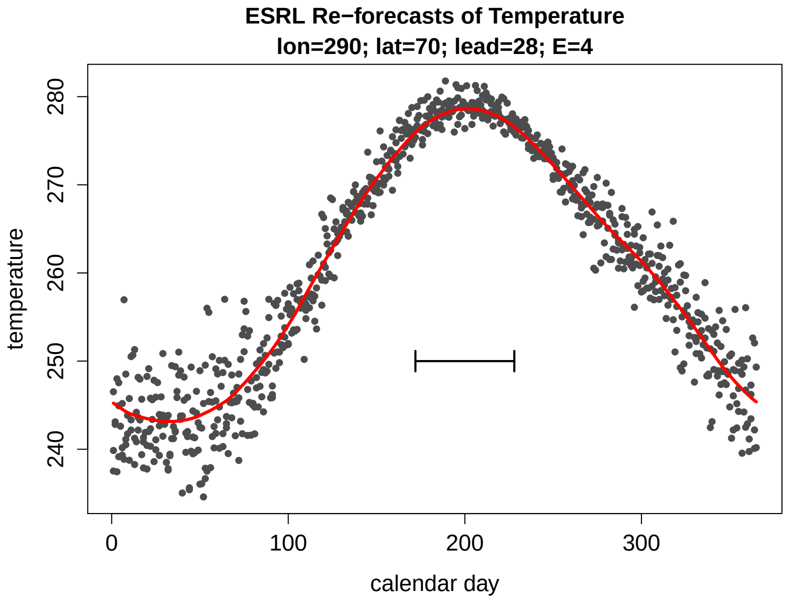
$$Obs(t) = \sum_{k=1}^{2} \left(a_k \cos\left(\frac{2\pi tk}{365}\right) + b_k \left(\frac{2\pi tk}{365}\right)\right) + noise$$

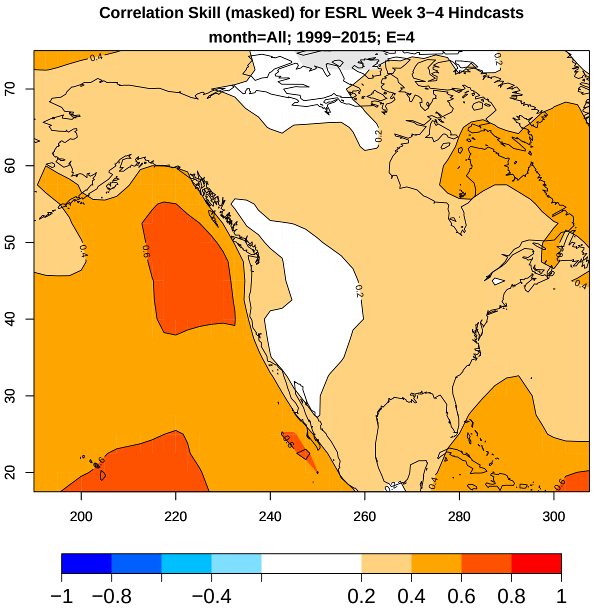
2. Subsample in a way similar to SubX (e.g., every 7 days for 16 years)
3. Test different methods for estimating climatology:

sample mean:	average of each calendar day
harmonic:	estimate parameters in (1) using least squares.
local (28)	local linear regression with 28-day window

16 years; IC every 7 days



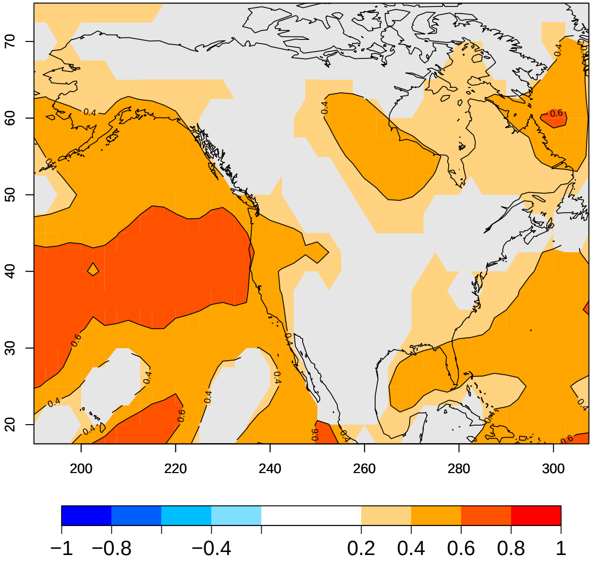

ESRL Re−forecasts of Temperature
lon=290; lat=70; lead=28; E=4
temperature
280
270
260
250
240
0
100
200
300
calendar day

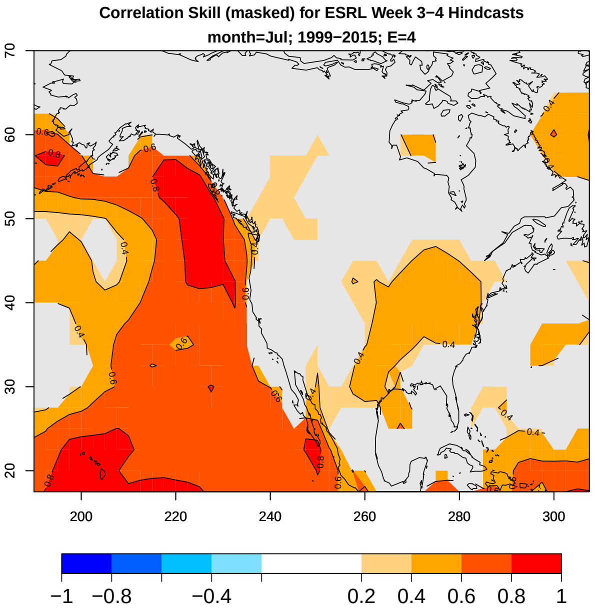


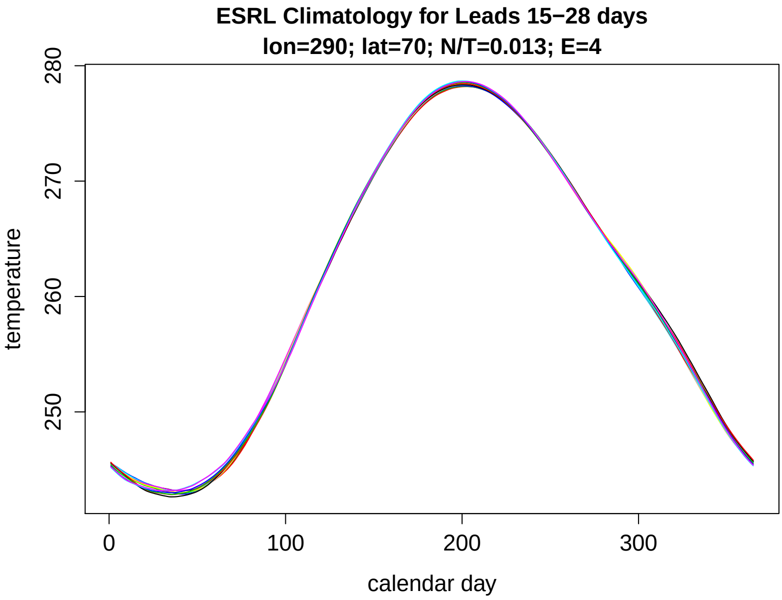
Correlation Skill (masked) for ESRL Week 3−4 Hindcasts
month=All; 1999−2015; E=4
70
60
50
40
30
20
200
220
240
260
280
300
0.2
0.4
0.6
−1
−0.8
−0.4
0.2
0.4
0.6
0.8
1

Correlation Skill (masked) for ESRL Week 3−4 Hindcasts

month=Jan; 1999−2015; E=4



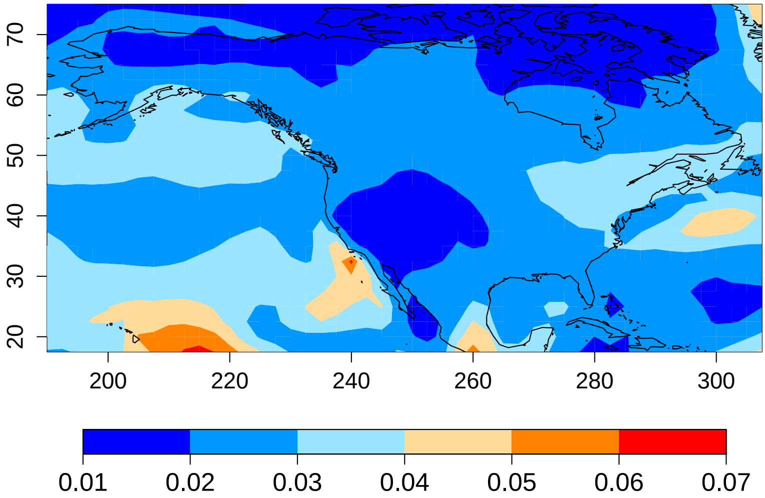

Correlation Skill (masked) for ESRL Week 3−4 Hindcasts
month=Jul; 1999−2015; E=4
70
60
50
40
30
20
200
220
240
260
280
300
−1
−0.8
−0.4
0.2
0.4
0.6
0.8
1

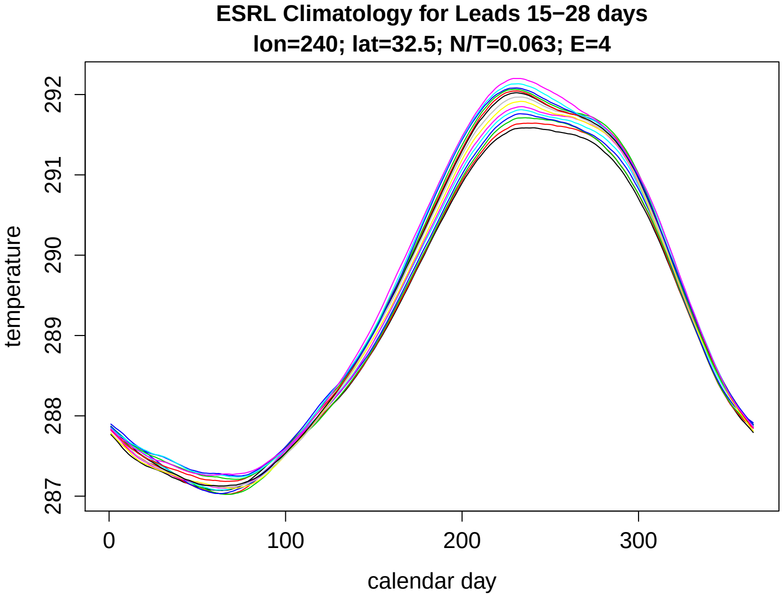

ESRL Climatology for Leads 15−28 days
lon=290; lat=70; N/T=0.013; E=4
temperature
280
270
260
250
0
100
200
300
calendar day

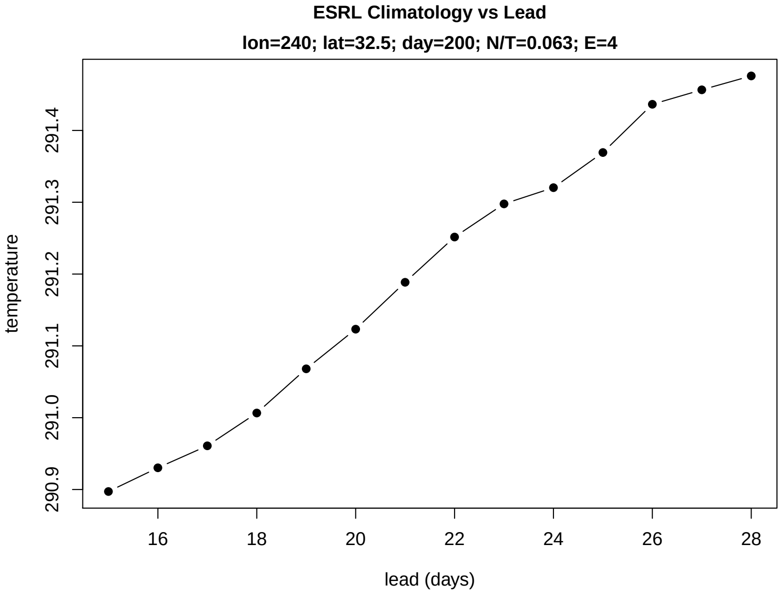
Measure of Lead-Time Dependence of Climatology

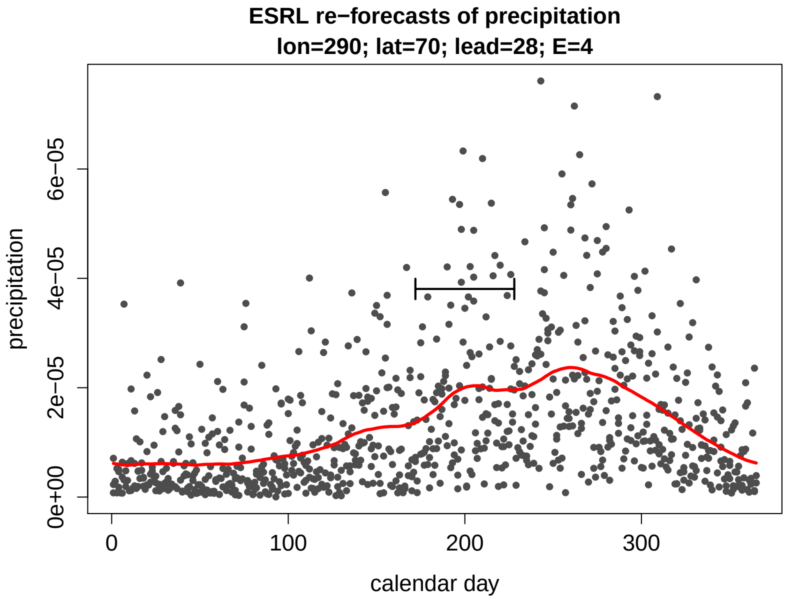
$$N/T = \frac{\text{standard deviation about each calendar-day mean}}{\text{standard deviation over all calendar days}}$$

Lead−time Dependence of ESRL Climatology
Leads= 15−28 days; E=4

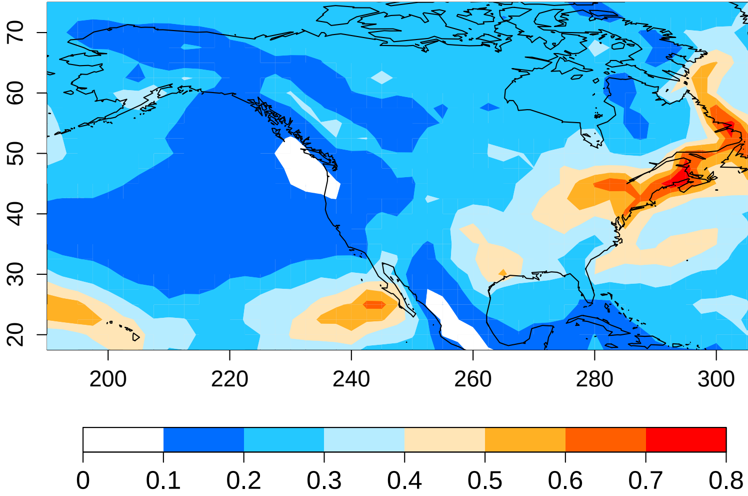


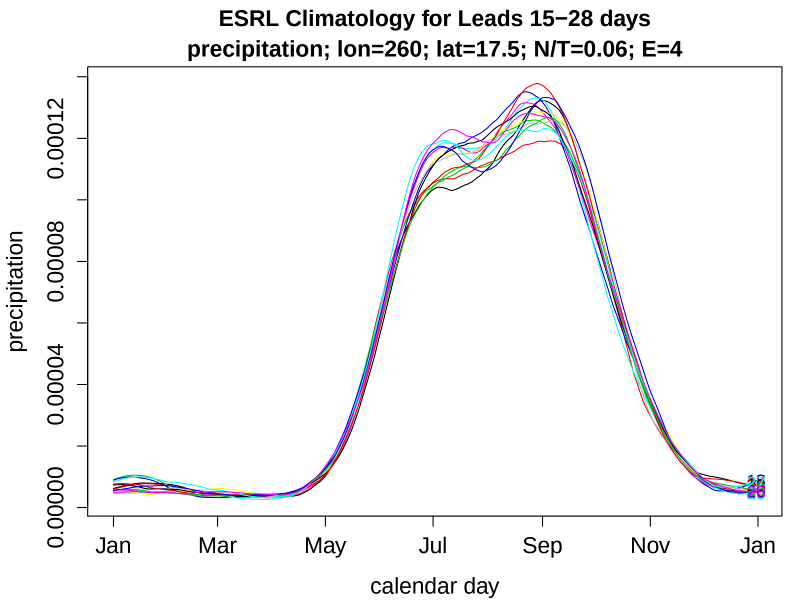

ESRL Climatology for Leads 15−28 days
lon=240; lat=32.5; N/T=0.063; E=4
temperature
287
288
289
290
291
292
0
100
200
300
calendar day


ESRL Climatology vs Lead
lon=240; lat=32.5; day=200; N/T=0.063; E=4
temperature
290.9
291.0
291.1
291.2
291.3
291.4
16
18
20
22
24
26
28
lead (days)

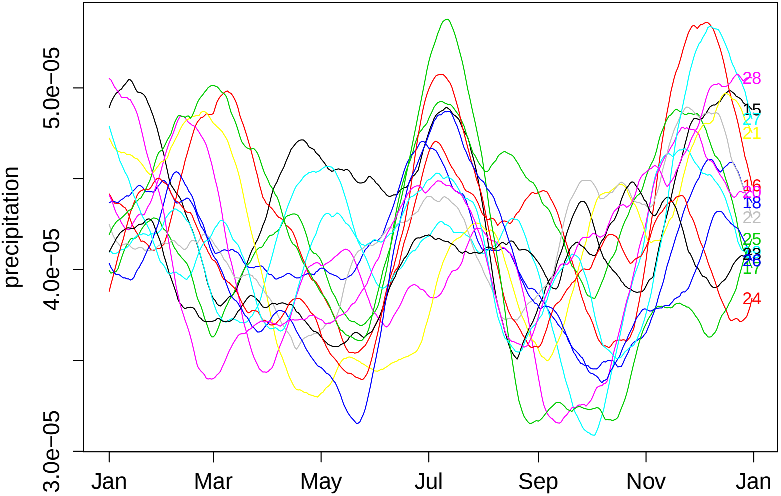

ESRL re−forecasts of precipitation
lon=290; lat=70; lead=28; E=4
precipitation
0e+00
2e−05
4e−05
6e−05
0
100
200
300
calendar day

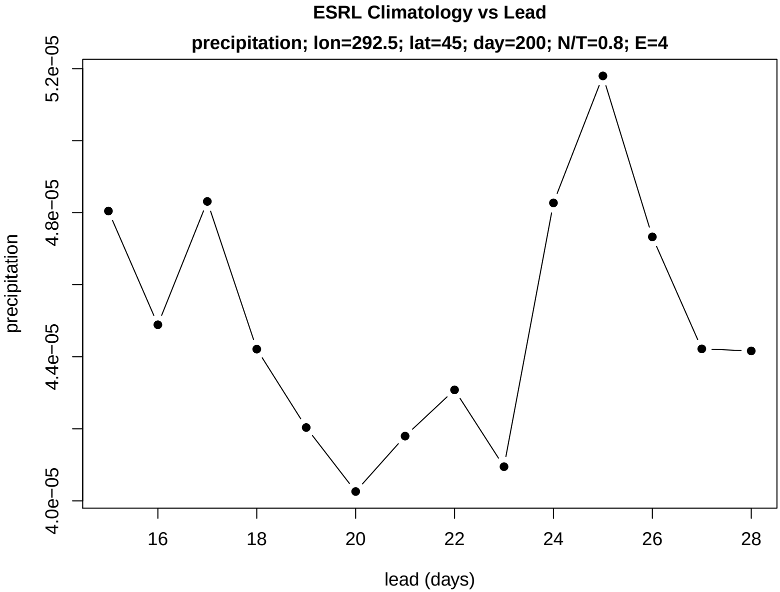
Lead−time Dependence of ESRL Climatology
precipitation; Leads= 15−28 days; E=4

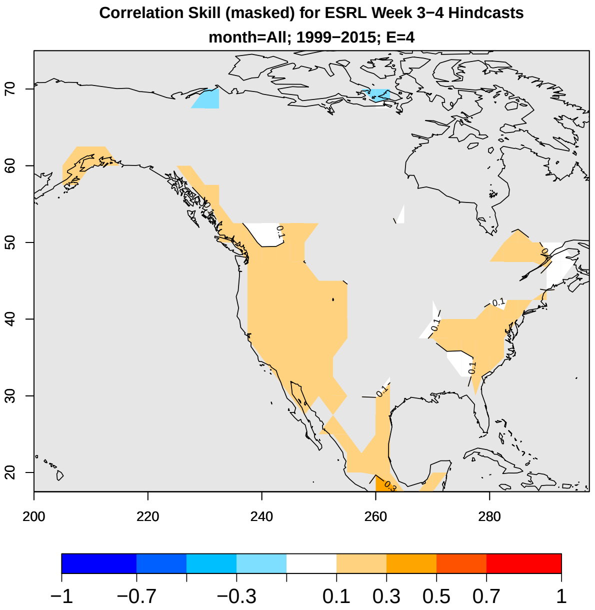



ESRL Climatology for Leads 15−28 days
precipitation; lon=260; lat=17.5; N/T=0.06; E=4
precipitation
0.00000
0.00004
0.00008
0.00012
Jan
Mar
May
Jul
Sep
Nov
Jan
calendar day

ESRL Climatology for Leads 15−28 days
precipitation; lon=292.5; lat=45; N/T=0.8; E=4




ESRL Climatology vs Lead
precipitation; lon=292.5; lat=45; day=200; N/T=0.8; E=4
precipitation
5.2e−05
4.8e−05
4.4e−05
4.0e−05
16
18
20
22
24
26
28
lead (days)


Correlation Skill (masked) for ESRL Week 3−4 Hindcasts
month=All; 1999−2015; E=4
70
60
50
40
30
20
200
220
240
260
280
−1
−0.7
−0.3
0.1
0.3
0.5
0.7
1

Summary

Predictability of Week 3-4 CFSv2 Forecasts over CONUS

- CFSv2 skillfully predicts week 3-4 temperature and precipitation.
- Significance of the skill determined by rigorous permutation test.
- Skill detected also using Predictable Component Analysis.
- Most predictable patterns are related to ENSO.
- Some predictability of winter precipitation related to MJO.

SubX over CONUS

- Data inhomogeneities complicate estimation of model climatology.
- Local linear regression (LOESS) appears very promising.
- Including lead-time dependence in climatology will be critical.
- ESRL has statistically significant skill for week 3-4 temperature.
- Subtracting climatology may not be best way to remove model precipitation biases.