NOAA's 43rd Climate Diagnostics & Prediction Workshop, 2018

Are Dynamical Sub-Seasonal Scale Forecasts Useful for Predicting Extreme Precipitation and Heat Wave Events in California and Nevada?

Shraddhanand Shukla Climate Hazards Center University of California, Santa Barbara sshukla@ucsb.edu

Motivation and Objective

- Hydrologic uncertainty is one of the primary contributors to uncertainty in the water management planning in California and Nevada, for various (often competing) sectors, operating at diverse spatial and temporal scale.
- Climate forecasts contribute to hydrologic uncertainty.
- Sub-seasonal scale forecasts are promising new tool.

This study examines the skill of sub-seasonal forecasts mainly in forecasting extreme precipitation and temperature events in California and Nevada.

Data and Methods

- Observed Precipitation, Tmax, Tmin:
 - OSU's PRISM dataset, spatially aggregated to 1X1 degree to match the spatial resolution of the dynamical models.
- North American Multimodel Ensemble (NMME) SubX forecasts:
 - 2 of the 7 models used for this analysis (*based on data availability and consistency in initial conditions)
 - Models used are GEOS5 and CCSM4, more models to be added in future.
- Winter (Nov-March) for P forecasts and Summer (JJA) for T forecasts (*based on data availability).
- The skill is analyzed for 1999-2016 period, at 1X1 degree and at the scale of Climate Divisions.

Skill in forecasting mean Precipitation, Tmax and Tmin

Mean P forecast skill

- 0 to 30 days mean P forecast skill exists mainly in parts of N. California, during JFM.
- Majority of the skill comes from the skill during 0 to 7 days, which dissipates quickly.
- The skill for the 15 to 30 days period is negligible.

Skill in forecasting mean Precip



-0.2 0.2

Correlation

-0.8

-0.7

-0.6

-0.5

-0.4

0.4

0.5

0.6

0.7

0.8

Mean Tmax and Tmin forecast skill during Summer

- Like P, most of the monthly mean skill comes from the 0 to 7 days period.
- Tmin forecasts appear to have higher skill than Tmax.
- Forecasts initialized in June are most skillful.
- Skill is generally highest for 3-4 weeks over N. Nevada.

Skill in forecasting mean Tmax



The skill at the spatial scale of Climate Division

Generally >0 skill at 3-4 weeks when aggregated to a greater spatial scale (e.g. Climate Division)

In some cases the skill at 3-4 weeks >0.3.



Skill in forecasting mean Tmax events



Skill in forecasting Precipitation, Tmax and Tmin extremes

Definition of extremes

• Extreme events: The days when P, Tmax, or Tmin is above 90%-ile of the climatological distribution.

• Climatological distribution taken from 1999-2016 period from 5 days window centered at the target day.

Observed Extremes in recent years



In terms of daily P extremes, March and Dec 2012, March 2014 and 2016 and Jan-Feb 2017, stand out.



Several T extreme events in the recent past. Mostly in 2014-2016.

More Tmin than Tmax extremes.

Number of Extreme Tmin Events Mar Aug Oct Nov Dec Feb Apr May Jul Sep lan lun 201 01 0 201 20

Comparison of Observed (left) and Forecasted (right) numbers of Tmax extremes between 2012-2016

Hit events: Aug, 2012 Jun, Jul 2013 Jun 2016.

False events: Aug, 2014, 2016.



Comparison of Observed (left) and Forecasted (right) numbers of Tmin extremes between 2012-2016

Forecasted Tmin Observed Tmin Jun Jul Jul Aug Jun Aug 2012 Hit events: 2012 Aug, 2012 Jun, Jul 2013, 2013 2013 Jul 2014 Jun 2015, 2016. 2014 2014 False events: Aug, 2014, 2015 2016. 2015 2016 2016 Number of events Number of events

Skill in forecasting extreme P events

- Skill in forecasting number of extremes over 30 days is limited.
- Highest skill at 0 to 7 days.
- Highest skill during JFM.

Skill in forecasting >90%-ile Precip events



Skill in forecasting extreme Tmax and Tmin events during Summer

- Skill is positive but limited over 0-30 days.
- Higher Tmin than Tmax skill.
- Higher skill over parts of N. Nevada.



-0.8 -0.7 -0.6 -0.5 -0.4 -0.2 0.2 0.4 0.5 0.6 0.7 0.8 Skill in forecasting >90%-ile Tmin events

34.5

0 to 6 days 7 to 14 days 15 to 31 days 0 to 14 days 0 to 30 days



Forecasting extremes at Climate Division scale



If we allow for spatial bias in forecasting extremes, in general, it doesn't increase the skill substantially at 3-4 weeks lead time.

Variation in skill (over CA and NV) based on threshold for extreme events and forecast IC month

Highest skill for >70%-ile events.

Difference in median skill for each thresholds is negligible at 15-30 days.

Higher skill during DJF than N.

In all cases median skill >0.



Skill in forecasting Precip Extremes

Skill in forecasting Tmax Extremes



Although skill of >70%-ile event is the highest, the difference in the median skill for different thresholds is lower for Tmax than Tmin.



0-6 days 7-14 days 15-31 days 0-14 days 0-30 days

Generally highest skill during June.

Summary

- Limited skill in forecasting mean P, Tmax and Tmin, at 0 to 30 days lead time.
 - \circ $\,$ Most of the skill present during the 0 to 7 days lead time.
 - Higher skill during JFM for Precipitation, and June for Tmax and Tmin.
 - Higher skill in forecasting Tmin than Tmax.
- Limited skill in forecasting P, Tmax, Tmin at 0 to 30 days lead time.
 - Most of the skill present during the 0 to 7 days lead time.
 - A number of recent monthly T extremes forecasted.
 - Skill increases for lower threshold for extreme events.
 - Skill is potentially useful although still limited if a coarse spatial scale (e.g Climate Division) is considered.

Future questions

- Is limited skill better than no skill (e.g. climatology)?
 - Perhaps depended on the needs of stakeholder?
 - In collaboration with stakeholder figure out applications and scale where the SubX forecasts can be applicable.
- Can limited skill in sub-seasonal forecasts be combined with the skill from initial hydrologic conditions, improve hydrologic forecasts skill beyond the current levels?
- How does skill change based on MJO, AO, PNA etc phases, and land surface conditions (dry vs wet)?
- How skillful are larger scale climate features that influence P and T?

Acknowledgement

- (1) California Nevada Applications Program (CNAP) team members at University of California, San Diego.
- (2) Funding support from NOAA RISA and NIDIS.
- (3) OSU for PRISM data, and IRI, and SubX team for the NMME SubX dataset.

Thank you!

sshukla@ucsb.edu