An evaluation of subseasonal hydrometeorological ensemble forecasts at different time scales

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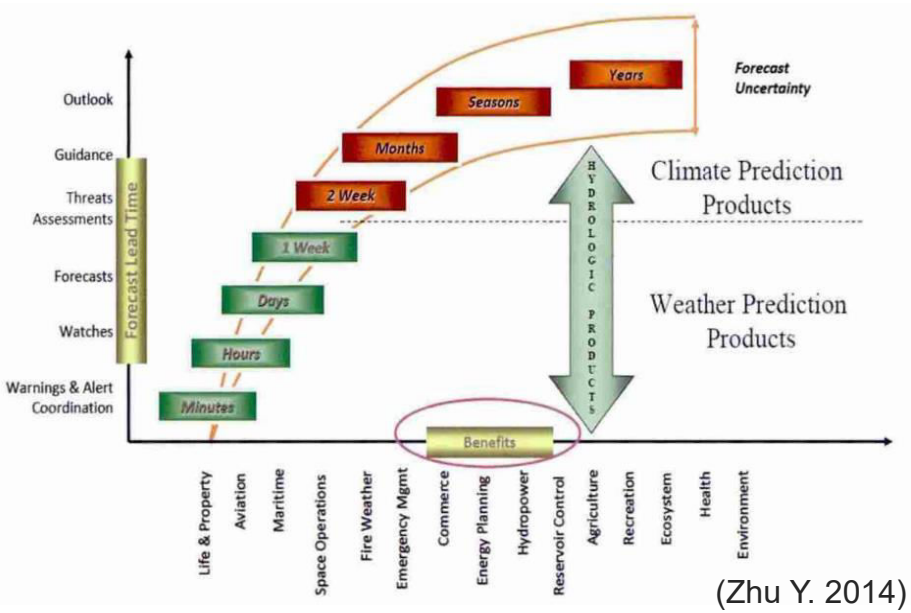
Background

- Medium-range weather forecasts usually focus on horizons within 2 weeks, while climate predictions extend to months and beyond.
- **Subseasonal to seasonal (S2S) predictions**, **with a time range spanning from 2 weeks to 6 months**, bridge the gaps between weather forecasts and climate predictions, deepening the collaboration between the weather and climate communities.



(Zhu Y. 2014)

Background

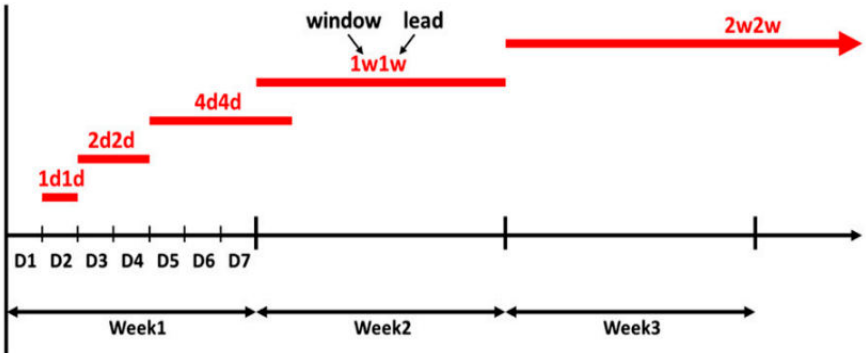
- **“The Butterfly Effect”**

The highly nonlinear atmospheric system has chaotic nature, and daily forecasting skills around the 7th to 10th lead days become poor.

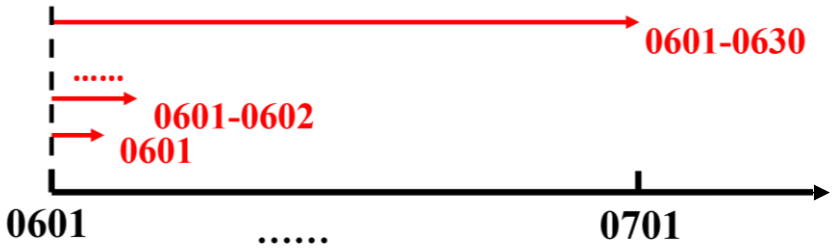
However, it doesn’t mean that forecasts with long lead times do not contain any valuable information.

- Meteorological researchers evaluate S2S forecasts for certain timescale. For example, Zhu et al. (2014) evaluated average precipitation during the 2nd week, or during the 3rd ~ 4th week.

- For hydrological applications such as reservoir scheduling, cumulative streamflow/precipitation forecasts from the first day are also meaningful.



(Zhu et al. 2014)



Cumulative precipitation forecasts from the first day

Background

- **Research questions:**

  - ✓ Compared to daily predictions, what is the prediction skill of S2S models for cumulative precipitation events? How do accumulative timescales affect the S2S precipitation prediction skill?

  - ✓ What is the prediction skill of cumulative streamflow events? Will the skill in cumulative precipitation forecasts transfer to skill in cumulative streamflow forecasts?

Data for evaluation of precipitation forecasts

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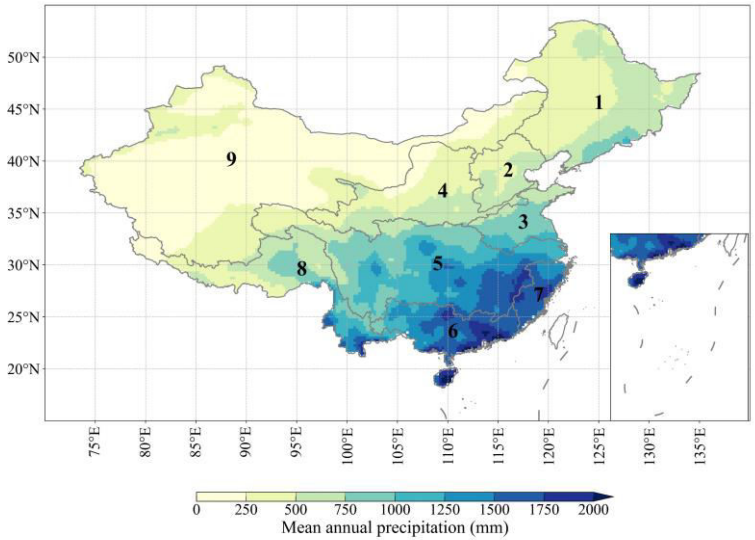
- **Study area**



The spatial distribution of mean annual precipitation during 1999-2009 in China. No available data in Taiwan Province.

Nine major river basins:

- 1. Songhua and Liao River Basin
- 2. Haihe River Basin
- 3. Huaihe River Basin
- 4. Yellow River Basin
- 5. Yangtze River Basin
- 6. Pearl River Basin
- 7. Southeast Basin
- 8. Southwest Basin
- 9. Inland River Basin

- **S2S reforecast dataset**

Model	Length of prediction	Reforecast period	Reforecast frequency	Ensemble size
CMA	Days 0-60	1994-2014	Daily	4
ECMWF	Days 0-46	Past 20 years (1995-2016)	Twice per week	11
NCEP	Days 0-44	1999-2010	Daily	4

(Vitart et al. 2017)

Common configurations:

- Length of prediction: Days 1-30
- Reforecast period: 1999-2009
- Spatial resolution: 1.5°×1.5°

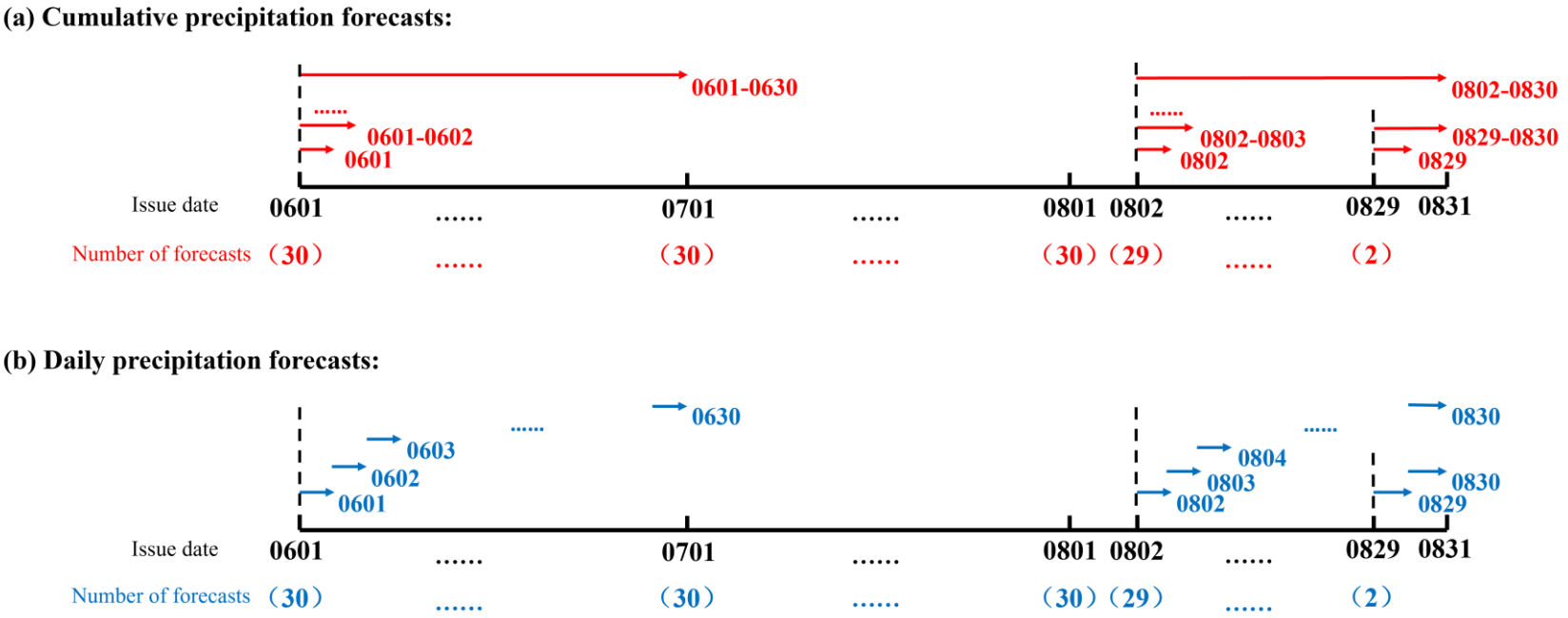
- **Reference dataset**

CN05.1, a gridded daily scale dataset with high spatial resolution that is based on observations from 2416 meteorological stations in China. (Wu and Gao 2013)

- Period: 1999-2009
- Spatial resolution:
  0.25°×0.25° (raw)
  1.5°×1.5° (after linear interpolation)

Methodology

- **Definition of cumulative timescales**
  - **Cumulative precipitation forecasts from the first day,** with cumulative timescales of 1-30 days
  - **Daily precipitation forecasts:** Lead times 1-30 days



Timescale setting for (a) cumulative precipitation forecasts and (b) daily precipitation forecasts, using summer (JJA) as an example.

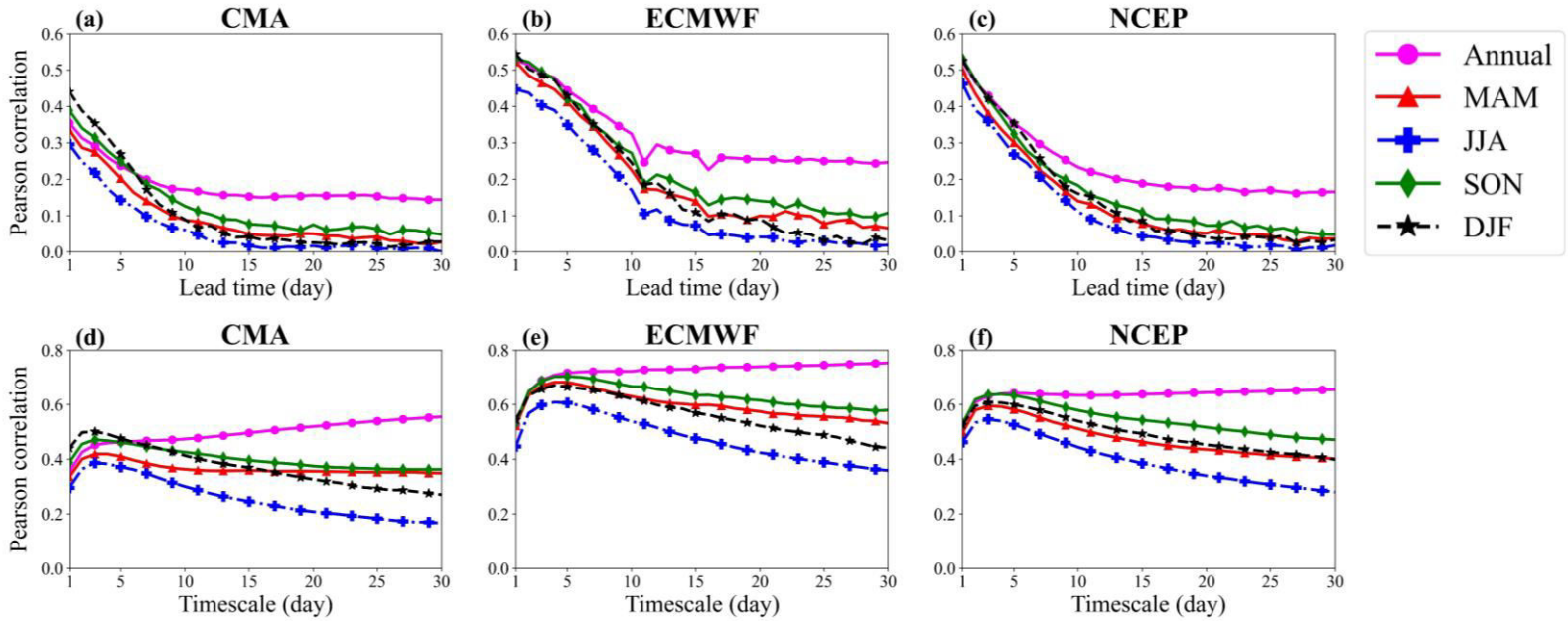
- **Evaluation metrics**
  - Pearson correlation coefficient (R)
  - Equitable threat score (ETS)

Results

- **Skill comparison between daily and cumulative precipitation predictions**

Daily Precipitation Forecasts

Cumulative Precipitation Forecasts

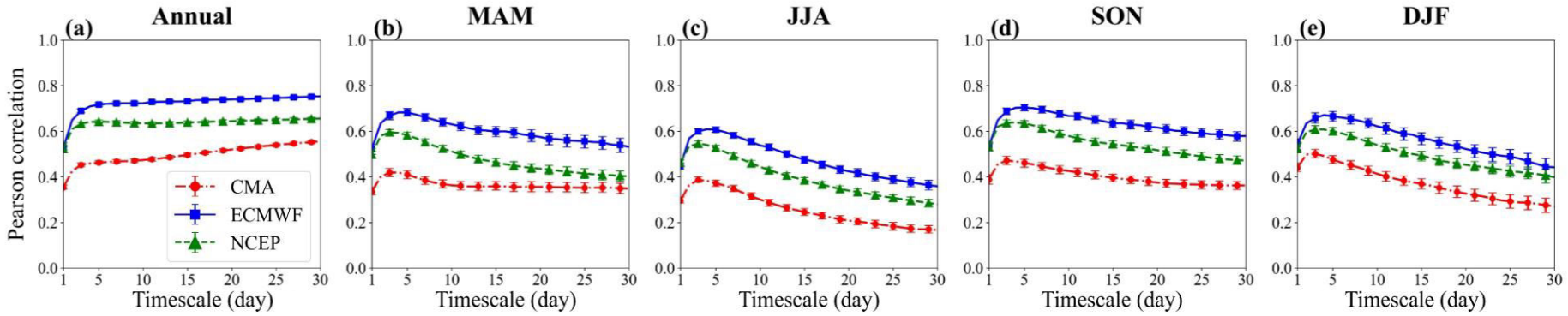


The variation of Pearson correlation coefficient (R) between three S2S models' daily predictions (top row), cumulative predictions (bottom row) and observations.

- The correlation between daily precipitation predictions and corresponding observations rapidly decreases as the lead time increases. The R of daily predictions after 10 days is essentially less than 0.2, which indicates that there is no prediction skill.
- The correlation between cumulative precipitation predictions and corresponding observations is notably better than that between daily predictions and observations.

Results

- **Correlation between cumulative precipitation predictions and observations**



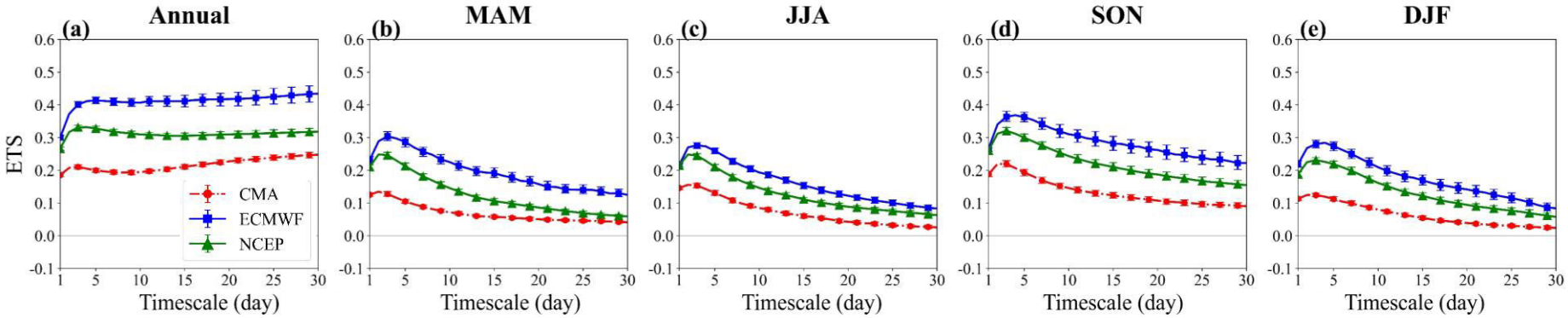
The variation of Pearson correlation coefficient (R) between the ensemble mean of cumulative precipitation predictions derived from three S2S models and corresponding observations at various timescales.

- If evaluate forecasts in each season: the S2S models' cumulative precipitation prediction skill exhibits an increasing trend followed by a decrease with timescale. The optimal skill usually occurs at a timescale of a half-week to one week rather than the first day after the forecast issued.

- ECMWF model performs the best, followed by NCEP and CMA models.

Results

- **The ETS for categorical cumulative precipitation predictions**



The variation of ETS of three S2S models for forecasting above-normal precipitation events at various timescales.

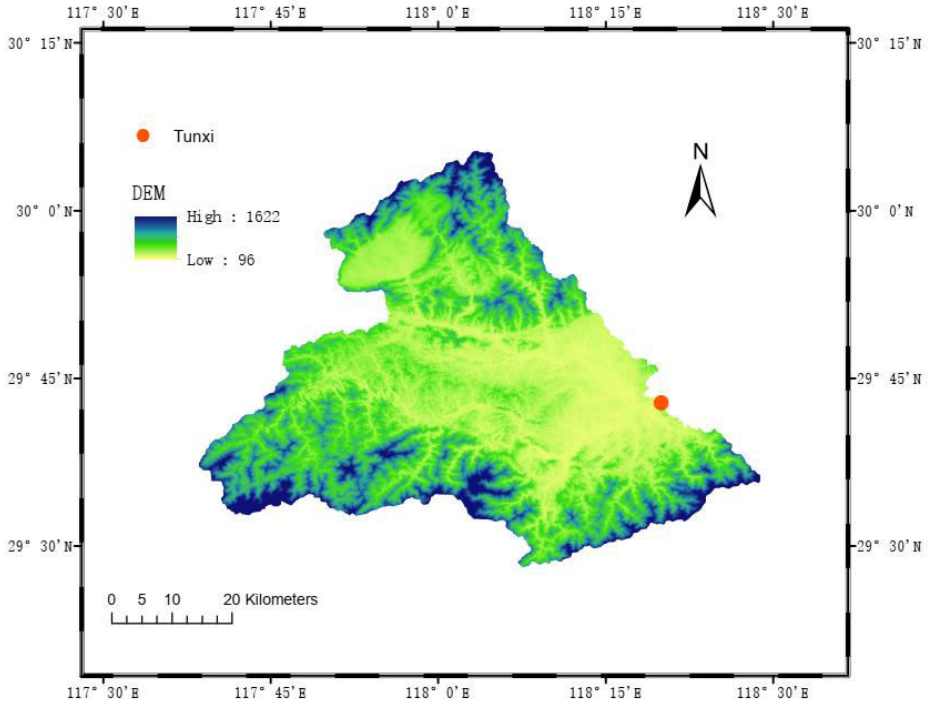
- The temporal variation of ETS also exhibits a trend of increase followed by decrease, which is similar to that of R.

Why "first increase, then decrease" with time scale?

- The temporal variation of cumulative precipitation prediction skill is the result of a trade-off between the following two factors:
  - Long-lead predictions introduce more error;
  - Time aggregation tends to average out this error.

Question 2: Will the skill in cumulative precipitation forecasts transfer to skill in cumulative streamflow forecasts?

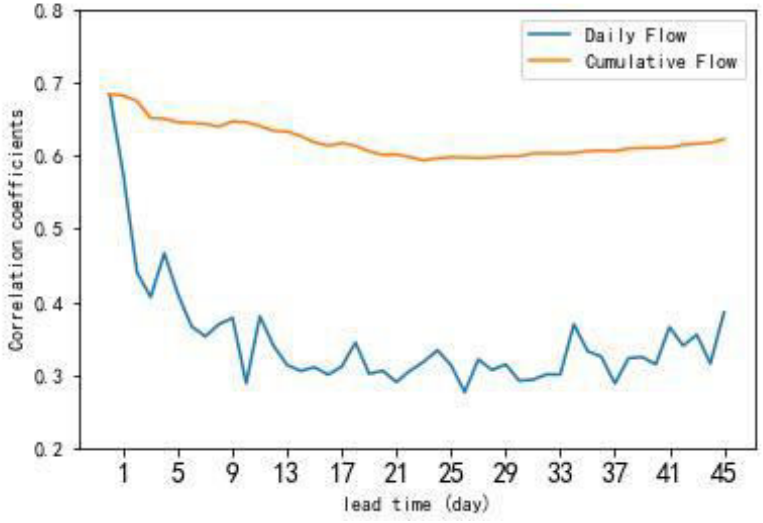
- Tunxi River Basin with area of 2697 km^2, is located in southern China, in a subtropical monsoon climate zone. The mean annual precipitation is around 1670mm in the region. The mean temperature is around 15°C.
- We use a lumped Xinanjiang (XAJ) rainfall-runoff model, which is developed by Prof. Zhao Renjun in 1970s.
- We downloaded 0.25° x 0.25° subseasonal precipitation forecasts from ECMWF and calculate mean areal precipitation in the basin. We post-processed precipitation forecasts by Bayesian joint probability (BJP) and generate 100 precipitation ensemble forecasts.
- Then we used post-processed precipitation forecasts as inputs to XAJ hydrological model, and generated hydrological ensemble forecasts in the basin.



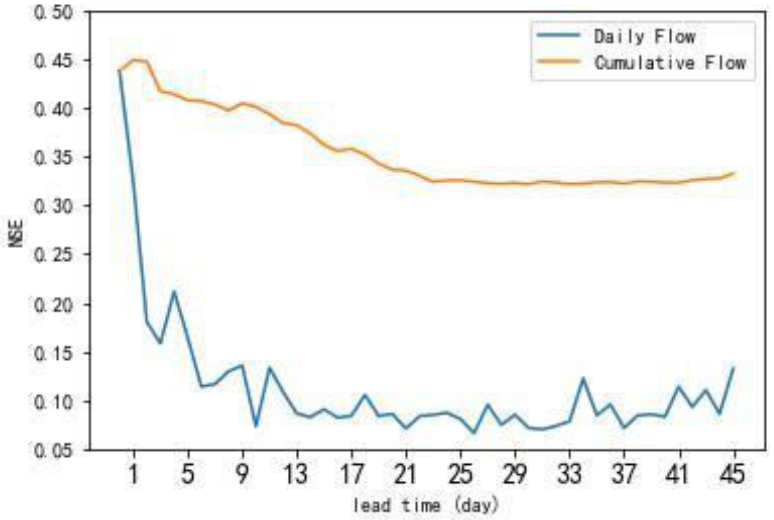
Daily VS cumulative streamflow forecast (preliminary results)

- Cumulative streamflow forecasts show higher skill than daily forecasts.

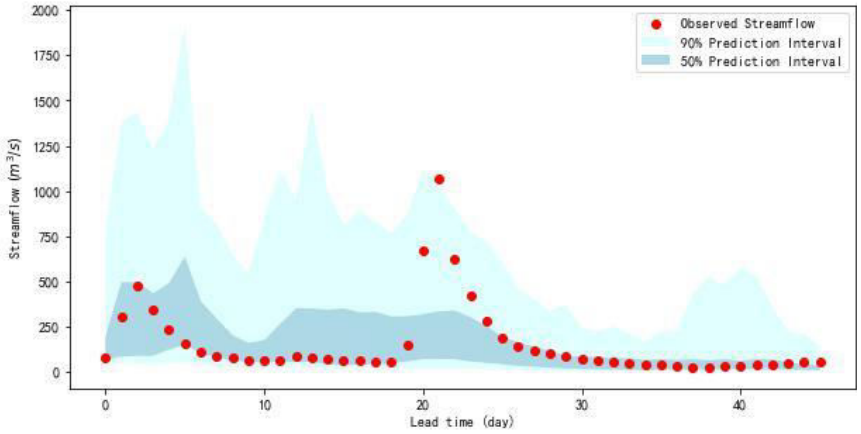
Correlation coefficients



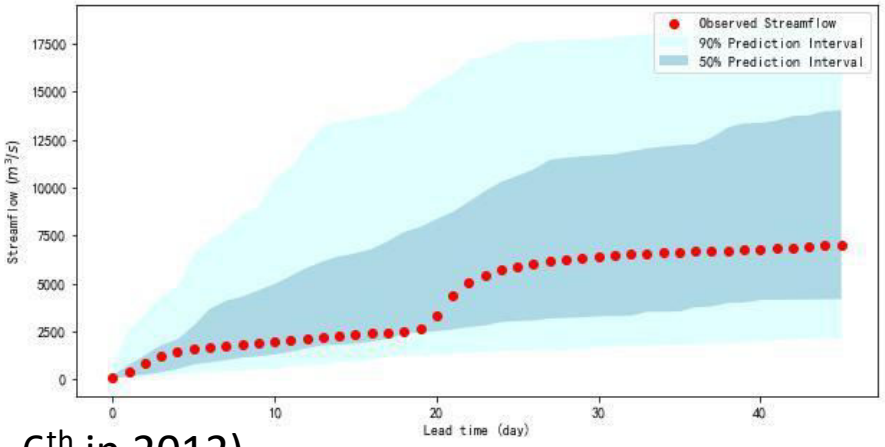
Nash–Sutcliffe efficiency



Daily streamflow forecasts



Cumulative streamflow forecasts



(Streamflow forecast example issued on Jun. 6th in 2012)

Summary

- The cumulative precipitation predictions are more skillful than daily predictions.
- For cumulative precipitation predictions, timescale is a nonnegligible factor affecting the prediction skill. The prediction skill shows an increasing trend followed by a decrease with timescale. The optimal skill usually occurs at a timescale of a half-week to one week.
- For streamflow predictions, preliminary results also show that cumulative streamflow predictions are more skillful than daily streamflow predictions. More investigations and applications of cumulative streamflow predictions will be conducted in the future.

Reference: Spatiotemporal variations in precipitation forecasting skill of three global subseasonal prediction products over China, Shiyuan Liu, Wentao Li, Qingyun Duan, Journal of Hydrometeorology (accepted)

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Thanks for listening!

Reference: Spatiotemporal variations in precipitation forecasting skill of three global subseasonal prediction products over China, Shiyuan Liu, Wentao Li, Qingyun Duan, Journal of Hydrometeorology (accepted)