Upskilling – Uncertainty reduction and representation in seasonal forecasting

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• A specific mission to foster the links between communities of research and practice in hydro-meteorological prediction

• An international initiative in hydrology since 2004

• Several community activities, including online resources, mailing list and a blog

hepex.org #HEPEX
Upcoming events/activities

- HESS special issue on seasonal hydrological forecasts
- Seasonal forecasting testbed
- EGU 2016 – April
- General HEPEX Workshop in Quebec, Canada, 6-8 June 2016
- AOGS 2016 – July 31

hepex.org  #HEPEX
Two sources of predictability

- **State of the catchment**
  - Glacier, snow, soil moisture, groundwater, in-stream storages, ...

- **State of the climate**
  - Atmosphere, ocean, land
Challenges

• High quality forecasts - Skill and reliability
• Meeting user needs
The Bayesian joint probability (BJP) method

- Predictors --> Predictands

- Issues
  - Heteroscedasticity
  - Zero value
  - Data

- The BJP solution
  - Transformations
  - Censored data
  - A joint probability model, with Bayesian inference

Wang, Robertson and Chiew (2009) *Water Resources Research*
Wang and Robertson (2011) *Water Resources Research*
Wang, Shrestha, Robertson and Pokhrel (2012) *Water Resources Research*
Robertson and Wang (2013) *Water Resources Management*
Probabilistic forecasts

Unregulated Inflow to Hume Dam
Forecast period: Sep-Nov 2015

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Unregulated Inflow to Hume Dam
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44 72.264 0
45 73.979 0
46 74.132 0
47 74.507 0
48 75.136 0
49 76.356 0.177
50 77.234 2.643
51 77.937 3.011
52 77.952 6.152
53 78.276 6.986
54 78.721 7.312
55 80.045 9.099
56 81.461 12.313
57 81.537 13.697
58 82.374 14.536
59 82.676 16.977
60 82.754 17.938
61 84.262 18.258
62 85.438 19.29
63 86.43 21.252
64 86.505 22.814
65 87.163 24.639
66 89.975 24.976
67 90.277 25.415
Cross validation
Key learnings

• Forecasts highly reliable
• Skill varying with locations and seasons
Model selection and combination

• Many candidate predictors
  • State of climate
    SOI, NINO3, NINO3.4, NINO4, ENSO Modoki;  IOD, IOE, IOW, II;
    TSI, SAM
  • State of catchment
    Antecedent streamflow;  Antecedent rainfall

• The best model approach

• The model combination approach (BMA)

Robertson and Wang (2012)  *Journal of Hydrometeorology*
Wang, Schepen and Robertson (2012)  *Journal of Climate*
Pokhrel, Wang and Robertson (2013)  *Water Resources Research*
Bennett, Wang, Pokhrel and Robertson (2014)  *Natural Hazards and Earth System Sciences*
Key learnings

• Two or fewer predictors in each BJP model
• Selecting the best model based on predictive ability - a good idea
• Model combination - preferred
  • Taking advantage of strengths of different models
  • Moderating worst forecast errors
Incorporating dynamical model outputs

• **Issues**
  • Antecedent streamflow or rainfall → Not always good indicators
  • Do climate model outputs add value?

• **Incorporating dynamical model outputs to the BJP model**
  • Hydrological model
  • Climate model

Robertson, Pokhrel and Wang (2013) *Hydrology and Earth System Sciences*
Pokhrel, Wang and Robertson (2013) *Water Resources Research*
Skill gain

CRPS skill scores

CRPS skill score of forecasts made using WAPAD and lag-1 streamflow (%) vs. CRPS skill score of forecasts made using selected predictors (%)
Key learnings

• **Incorporating hydrological model outputs**
  Forecast improvement when catchment is
  • wetting up
  • Drying down
  • near saturation

• **Incorporating climate model outputs**
  • Marginal skill increase when using precipitation forecasts
  • No additional benefit when using forecast SST

• **Hydrological model + BJP = Practical option**
What about fully dynamical models?

- **Advantages**
  - Conceptually more attractive
  - Ensemble time series forecasts useful for practical applications

- **Disadvantages**
  - Modelling more complex
  - Uncertainty handling much challenging

- **Overall**
  - The way to go
Merging statistical and dynamical forecasts

• The Bureau of Meteorology service
  • Currently the BJP is used for operational forecasting
  • The Bureau has also developed a dynamic model (DM)
  • The two models offer complementary skill
Complementary skill
Merging statistical and dynamical forecasts

• The Bureau of Meteorology service
  • Currently the BJP is used for operational forecasting
  • The Bureau has also developed a dynamic model (DM)
  • The two models offer complementary skill
  • Future service will adopt merged forecasts

• Bayesian model averaging (BMA)
  • Generally works well
  • On rare occasions, merged forecasts too wide and even bi-modal

• Quantile model averaging (QMA)

Wang, Schepen and Robertson (2012) *Journal of Climate*
Two examples
Key learnings

• QMA merged forecasts are preferable
• Merging brings out the best skill
Merging brings out the best skill

![Graph showing the correlation between skill scores of QMA forecasts and the better of BJP and DM forecasts.](image)
Improving climate forecasts

• Available forecasts are generally of low skill and unreliable

• BJP + BMA: A versatile duo!

Schepen, Wang and Robertson (2011) *Journal of Climate*
Wang, Schepen and Robertson (2012) *Journal of Climate*
Hawthorn, Wang, Schepen and Robertson (2013) *Water Resources Research*
Schepen and Wang (2014) *Journal of Hydrology*
Peng, Wang, Schepen, Pappenberger et al. (2014) *Journal of Geophysical Research*
Peng, Wang, Bennett, Pokhrel and Wang (2014) *Journal of Hydrology*
Schepen, Wang, Everingham (2015) *Weather and Forecasting*
**CBaM** for post-processing GCM forecasts

- **C**alibration
- **B**ridging
- **M**erging
The FoGSS model

• For generating **Forecast Guided Stochastic Scenarios**

• Ensemble forecasts of monthly volumes of streamflow out to 12 months

• The forecasts become more like natural stochastic scenarios as skill decreases with lead time
Generating a forecast

- CBaM → Climate forecasts
- WAPABA → Streamflow forecasts
- ERRIS → Revised streamflow forecasts
  - Conditional bias correction
  - Updating, injecting and propagating hydrological uncertainty to next lead time

Wang, Pagano, Zhou, Hapuarachchi, Zhang and Robertson (2011) *Journal of Hydrology*
Wang, Shrestha, Robertson and Pokhrel (2012) *Water Resources Research*
Li, Wang and Bennett (2013) *Water Resources Research*
Pokhrel, Robertson and Wang (2013) *Hydrology and Earth System Sciences*
Li, Wang, Bennett and Robertson (2015) *Hydrology and Earth System Sciences*
Li, Wang, Bennett and Robertson (HESS) *Water Resources Research*
Example forecasts
Key learnings

• Maximizing skill
  • Extracting the most out of climate model outputs
  • Hydrological modelling: Hydrological model, conditional bias correction, updating
Key learnings

• **Maximizing skill**
  • Extracting the most out of climate model outputs
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• **Achieving reliability**
Reliability - monthly

- Jan, 0 months
- Jan, 3 months
- Jan, 6 months
- Jan, 9 months

- Jul, 0 months
- Jul, 3 months
- Jul, 6 months
- Jul, 9 months

Probability integral transform

Standard uniform variate
Reliability - cumulative

![Graphs showing reliability data for January and July with different time periods (1, 3, 6, and 12 months). The graphs illustrate the cumulative probability distribution of various months, with standard uniform variate on the x-axis and probability integral transform on the y-axis.](image-url)
Key learnings

• **Maximizing skill**
  - Extracting the most out of climate model outputs
  - Hydrological modelling: Hydrological model, conditional bias correction, updating

• **Achieving reliability**
  - Reliable climate forecasts
  - Hydrological uncertainty handling
Key learnings

• **Maximizing skill**
  - Extracting the most out of climate model outputs
  - Hydrological modelling: Hydrological model, conditional bias correction, updating

• **Achieving reliability**
  - Reliable climate forecasts
  - Hydrological uncertainty handling

• **FoGSS for water management**
  - Forecast guided stochastic scenarios of monthly streamflow out to 12 months
  - Monthly volume skilful only at short lead times
  - Cumulative volume skilful to longer lead times
Current and future work

• New BJP
• New CBaM
• FoGSS adoption
• Flood and short-term forecasts
• Seamless forecasts
• Ensemble climate surfaces (ESDIIM)