Hydrometeorological Accuracy Enhancement via Postprocessing of Numerical Weather

Forecasts in Complex Terrain

1. Introduction

* Post-processing techniques should maintain an balance between short learning period (to respond to changes faster) and long training period (for better stability)
* Systematic error in complex terrain: difference between actual and the model terrain. Poor physics parameterization
* Random error is associated with the chaotic nature of the atmosphere
* Temperature and Precipitation forecasts needed for hydrologic stream flow models.
* Postprocessing basics: statistical regression between NWP values and observations over a fixed period of time. Then use the regression for future NWP values. If successful, there should be reduced mean error.
* MOS based techniques: require long data archival periods.
* Next improvement: 14 day moving window of error calculations. (Moving-weighted-average methods)
* Kalman filtering uses preceding model-observation pair for the future forecast. So, it is an iterative, recursive process, but requires less database storage.

1. Data
   1. Temperature

* Six different post-processing techniques used:
  + Seasonal Mean Error (SNL): subtract seasonal mean error value (different for summer and the winter) of last year, from the forecast value.
  + Moving Average (MA): Each previous value gets the same weight.

Q: Is the average value same across seasons?

Q: temporal resolution: every year/month?

* + Linear Weighted Average (LIN): like MA, but recent error estimates are weighted heavily
  + Cos2 weighting function: similar as LIN but weighting based on cos2 weighting.
  + Best Easy Systematic Estimator (BES):
  + Kalman Filter (KF)
* Weighting Period:
  + Shorter period: captures recent changes in error due to weather changes.
  + Longer period: needed for statistical stability
* Error correction window:
  + Short: covers synoptic pattern and model changes
  + Long: statistical stability
* 14 day window chosen, as even for the Day 8 forecast, the mean absolute error had reached a stable value by that time
  1. Precipitation
* NWP forecasts using the CMC GEM model for days 1 – 8. Q. Ensemble or deterministic forecasts?
* Day-to-day variability is greater than compared to temp. forecasts.
* Simply subtracting the mean error can lead to negative values. So, use new method: Degree of Mass Balance (DMB)
* DMB must cover a period of time where some precip is observed, to avoid division by 0.
* LIN, Cos2 and KF are not suitable for DMB correction, as they need daily correction.
* 40 day window chosen for the postprocessing

1. Results
   1. Daily Temperature

* Mean error and Mean absolute error is calculated to check the deviation of the postprocessing method with respect to the Direct Model Output (DMO).
* All methods except SNL reduce DMO mean error for max. and min. temp to near zero (Fig. 5)
* All methods performed nearly equally in terms of Mean Absolute Error.
* MAE skill score: perfect forecast = 1, if 0 then it performed same as the DMO.
* SNL improves in terms of MAE skill score over longer lead times (day 5 – 8) because it has better statistical stability through the 6 month average
  1. Daily Precipitation
* Challenges of Quantitative-Precipitation Forecasting (QPF):
  + Specific Humidity is the basic variable for precipitation.
  + NWP models have a dry start. So, they need a certain spinup time.
  + Discontinuous variable in terms of both space/time
  + Greater day2day variability
  + Seasonal cycles, but no diurnal cycles
  + Precipitation could be in form of rain, hail or snow
  + Point observation (rain gauge) vs. gridded forecasts (10 km x 10 km grid)
  + Uncertainty of observations during windy conditions (e.g. rain gauge)
* MA and BES yield well-balanced DMB values (i.e. 1). So, they are a good post-processing method.
* Statistical Significance test to confirm the results
* SNL outperforms the other two in terms of MAE skill score for forecasts days 5 – 8. Because it has longer training period (6 mos. compared to 40 day window for the other two)

1. Summary and Conclusions
   1. All methods perform better than the DMO
   2. SNL is better than the other techniques for medium-range (day 5 – 8) precipitation and temperature forecasts, due to its longer training period
   3. Future work:
   * Use multivariate approach (introduce new variables) to weighting error estimates
   * Multi-model approach
   * Autoregressive-moving average (ARMA) modelling