

Science Planning Perspective on Improving Regional Climate Prediction for Services

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The vision of National Oceanic and Atmospheric Administration (NOAA) is to build a “Weather-Ready and Climate-Smart Nation”. It requires our operation services providing the public skillful and reliable prediction products at the local level. To take on the challenge, National Weather Service (NWS) Science and Technology Infusion (S&TI) Climate Mission works for years to identify key scientific issues/problems in climate prediction and service operations and synthesize research and development needs that contribute to the NWS S&T development strategic plan.

1. Background

The forecast skill has a direct bearing on service quality, which the user community concerns the most. Current short-term climate prediction skill is limited, giving less confidence for decision making.

The seamless prediction concept has been accepted by the weather-climate community. Palmer *et al.* (2008) drew an analogy between the prediction system and a chain, and call to focus on the weakest link that determines the strength of a chain. A further thought would be on where the weakest link is located.

This presentation is to address the challenges facing us. First, we look for clues from forecast outliers and unexpected failures that forecasters routinely see, and then have a discussion on how to get the most from current model output (low-hanging fruit) for better serving the user community. Lastly, a summary is given from the science planning perspective on the hope of improving regional climate prediction for services.

2. Puzzles

The unexpected prediction failures/outliers, which puzzled our forecasters in routine operation, could be just the right entrance point to find the key to move forward. Here are some examples.

2.1 Unexpected outcome

Figure 1 from Dr. van den Dool's presentation in 2012 shows that unexpectedly, the foremost weather forecast error is not due to random processes, nor to local factors, but rather to large-scale climate biases. However, by experimentally removing past N-days running-mean forecast errors, the overall levels of forecast skill are only modest. It becomes clearer that the weather and climate model development has to be unified to achieve breakthrough performance.

2.2 Forecast failure

Figure 2 demonstrates a forecast failure, a

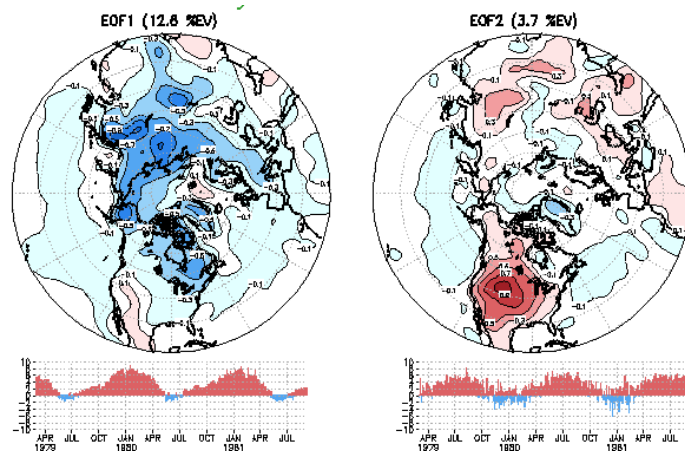


Fig. 1 The leading two EOF modes of 975 hPa temperature 5-day forecast error (1979-12) by NCEP Climate Forecast System (CFS) version 2. (van den Dool 2012)

week-2 forecast running to the opposite of the observation, reported by Mike Halpert in 2006. He looked at the near-range forecast and found that the 6-10 day forecast from 11/26 initial condition can correctly capture the 500 hPa height observed pattern, while that from 11/25 initial condition cannot. There were follow-up discussions between operation and research communities on what had been learned to improve the week-2 forecast, which pointed to key vulnerable spots that need research to focus on, such as upstream regimes of weather system development, Day-1 forecast errors and physical processes and interactions *etc.* This case and the summary of discussion were posted on the Board of Outstanding Open Problem, NWS S&TI Climate Bulletin (<http://www.nws.noaa.gov/ost/climate/STIP/r2o+o2r.htm>).

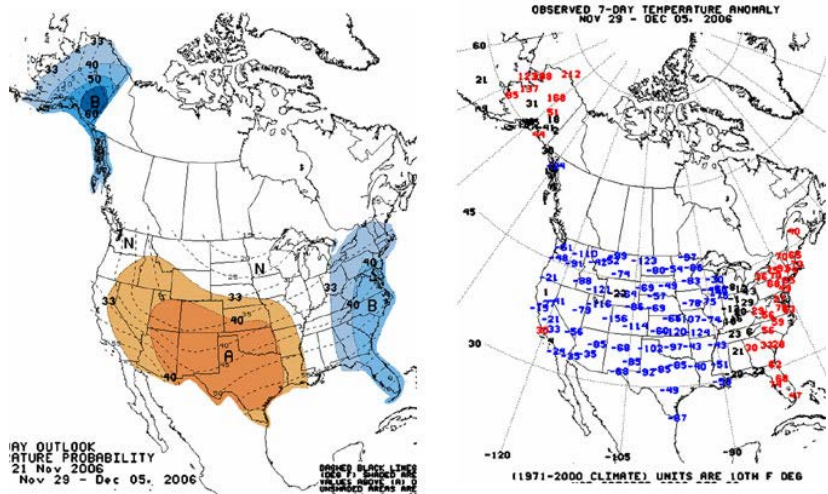


Fig. 2 Left: 8-14 day temperature forecast based on NCEP Global Forecast System (GFS) ensemble made on 11/21 for 11/29-12/5/2006. Right: The observation for verification in the same period. (Mike Halpert 2006)

2.3 Routine prediction outliers

Outliers are extreme deviations from the others seen in routine forecast. Figure 3 was taken from the week 2-4 tendency forecast experiment site maintained by Muthuvel Chelliah. It showed the tendency forecast outliers on 8/16 (week 1P, 6-10 days), 8/20 (Week 2) and 8/26 (week 3). All can be traced back to the initial state around 8/5-6. Here raised an outstanding issue for the data assimilation community to investigate - What is the critical factor to cause the forecast skill dropping off significantly?

2.4 Key predictors

According to our forecasters, seasonal prediction mainly depends on three factors, 1. ENSO, 2. Long-term trend, 3. summertime soil moisture.

For ENSO forecast, it is a long outstanding challenge to predict ENSO phase change. Models are too much like persistence. The events often start too late and then last beyond the time they should. Figure 4 shows the ENSO prediction plume in a recent forecast, from which we can see most models prefer to predict El Niño development. Comparing the performance of GFDL CM2 with that of ESSIC ICM, it is interesting to see that from August to September, when being closer to winter, ENSO development is accelerating predicted by both models but in opposite directions.

For the long-term trend, the warming stagnation has been detected since 1998. Models have difficulties to simulate that. Research speculations are due to underestimation of

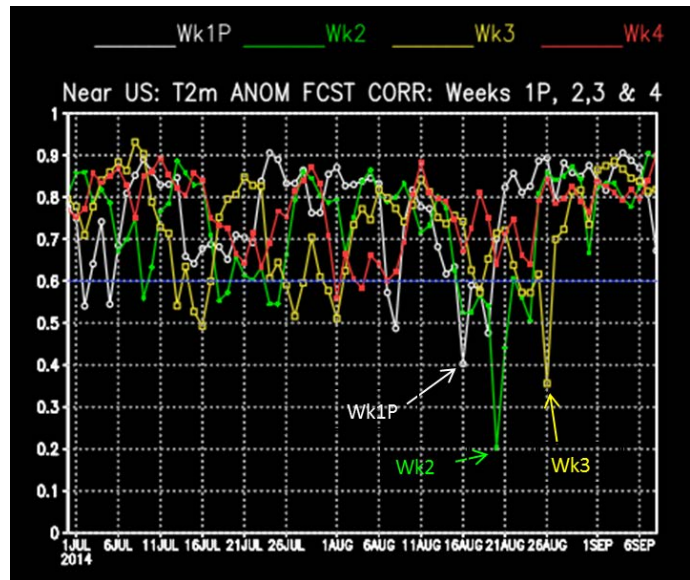


Fig. 3 Anomaly correlation skill of near US 2 meter temperature tendency forecast from late June to early September 2014 for 6-10 days (white), week 2 (green), week 3 (yellow), and week 4 (red). (Chelliah 2014)

internal natural climate variability on decadal and longer time scales, influence of unaccounted external forcing factors, overestimation of the model sensitivity to elevated greenhouse gas concentrations, and roles played by ocean *etc.* These puzzles need to be further explored.

3. Opportunities

Now, CFS v3 development is on the way. Before any model advancement being achieved, how can we get the most from current model outputs to better meet user needs? Following are some emerging opportunities.

3.1 Regional-global model hybrid

Research illustrates down-scaling by a good regional model does provide more useful information for service. But the large scale dynamics could be altered due to the domain constrain. Spectral nudging was used to prevent large unrealistic departures between the GCM driving fields and the RCM fields at the GCM spatial scales.

Instead of doing spectral nudging, Liu and Wang (2014) with Laing took a simpler approach, using CFS to drive CWRf, a climate version of WRF model with optimum multi-physics, and averaging the results of the two models. Preliminary result shows the prediction could not only beat CFS and CWRf individually, but also be comparable with current NMME. (See Figure 5. For illustration purpose, the figure shows each model with a single member.) Since only two models are involved, it is easier to implement in-house and also convenient to upgrade in future.

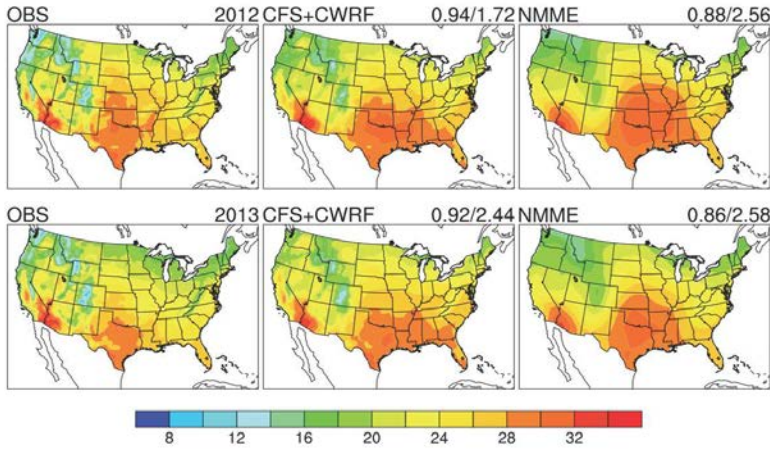


Fig. 5 JJA 2-m temperature (°C) of 2012 (upper) and 2013 (lower). From left to right are GDAS analysis, simulations by CFS and CWRf average and by NMME. The spatial correlation coefficient/RMS error is indicated at the top right corner of each panel for simulations. (Liu, Wang and Liang *et al.* 2014)

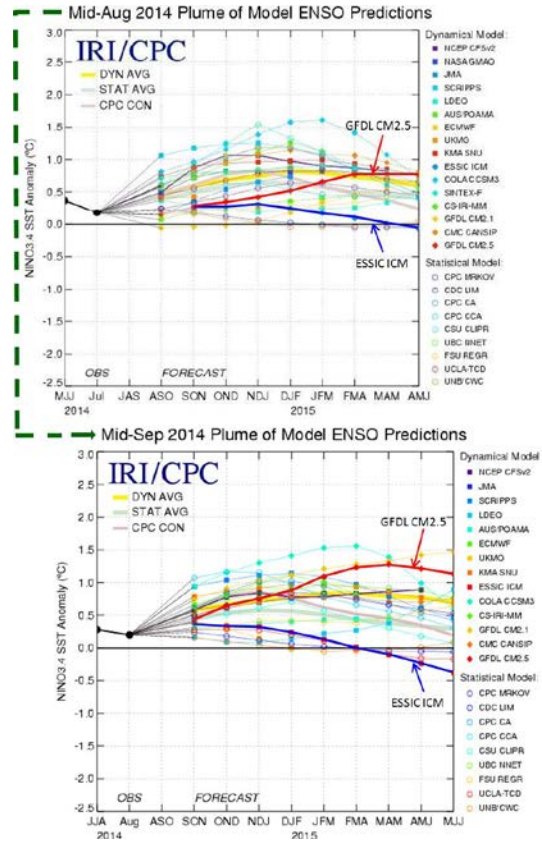


Fig.4 Plume of model ENSO prediction of mid-August (top) and mid-September (bottom).

3.2 Tendency forecast

Since the tendency correlation between the forecast and the observation is high¹ (Chelliah 2013), this information can be used as forecast supplement to meet particular user needs, such as providing information on when the temperature will cool down during an extraordinary, sustained heat wave event *etc.*

4. Summary

Science planning has to be ahead of the operational development, which requires sensitiveness to research advancement for stepping over existing barriers. Meanwhile, it is also important to communicate the obstacles that block our forecast improvement to research

¹ To be useful for applications, the tendency correlation between forecast and observation has to be well above 0.5 for a single forecast or 0.7 for an ensemble forecast with large members. (Delsole and Cash 2014, personal communication)

community. The NWS S&TI Board of Outstanding Open Problems is set for our research partners to shoot arrows at the targets, thus accelerating our model improvement for better serving the user community. The most challenging issue on effective climate service is to provide users skillful and reliable prediction information at the local level. To move our service beyond obstacles, we need research support and advocate collaboration and mutual development.

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