Preliminary validation of extended WRF forecasts for plant pathogen dispersal and disease occurrence

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1. Introduction

Temperature and rainfall frequency are key environmental parameters affecting the spread of plant diseases during the growing season. For the past years, we have used WRF to generate mean monthly weather forecasts for plant disease models. Monthly averages are crucial to agricultural disease forecasts. Short range weather forecasts are traditionally identified as initial value problems, while long-range climate forecasts of mean quantities are considered to be boundary value problems. However, the sub-seasonal scale lies between the short range and climate scale and therefore sub-seasonal forecasts could depend on both initial conditions and boundary values. In terms of forecast products, the predictability on sub-seasonal scales needs to be well quantified before current generation of forecast models can reliably used to drive plant disease models. Our research attempts to assess the predictability and accuracy of the global WRF model in forecasting precipitation frequency and surface temperature at monthly time scale. Our goal is to classify the monthly forecasts as either primarily initial value problems or boundary value problems, if possible.

2. WRF model setup

The WRF used for this work is version 3.1 with default configurations for model physics and vertical resolution (Skamarock et al. 2008). The key physics parameter schemes include Kain-Fritsch (new Eta) for cumulus parameterization, SYU for boundary-layer physics, WSM 3-class simple ice for cloud microphysics, Dudhia (RRMT) for radiation, Monin-Obukhov for atmospheric surface layer, and thermal diffusivity for the land surface processes. The model atmosphere is 31 layers with finer resolution within the boundary layer and tropopause. The model was run using the Global version of WRF. There are three domains which correspond to the entire globe at 1.5^{o}x1.5^{o}, entire U.S. at 0.5^{o}x0.5^{o}, and the Central U.S. at 0.17^{o}x0.17^{o}, respectively. This presentation focuses on the U.S. domain.

Model simulations were initiated at weekly intervals and integrated for 31 days. The GFS (Global Forecast System) analysis was used for initial conditions. Since our main goal was to diagnostic atmospheric predictability at the subseasonal time scale using the global version of WRF, which is not coupled with the ocean, we used fixed sea surface temperature (SST) during the course of the 31-day integration. The fixed SST limits the source of atmospheric variability to uncoupled models. Nevertheless, we do not expect large SST variations over one month period.

3. Preliminary results

We produced 18 monthly forecasts each beginning at different weeks, consecutively. Each of the 18 forecasts was compared to observations. We focused on air temperature, rainfall amount and rainfall frequency.

3.1 Temperature

Figure. 1 shows that all of the monthly temperature forecasts have a systematic cold bias. The mean temperature of the 18 forecasts was 17^{o}C while that of observed was 20 ^{o}C. Figure.1 (b) shows the deviation of the forecast and observed plots from their respective mean over the 18 monthly periods.

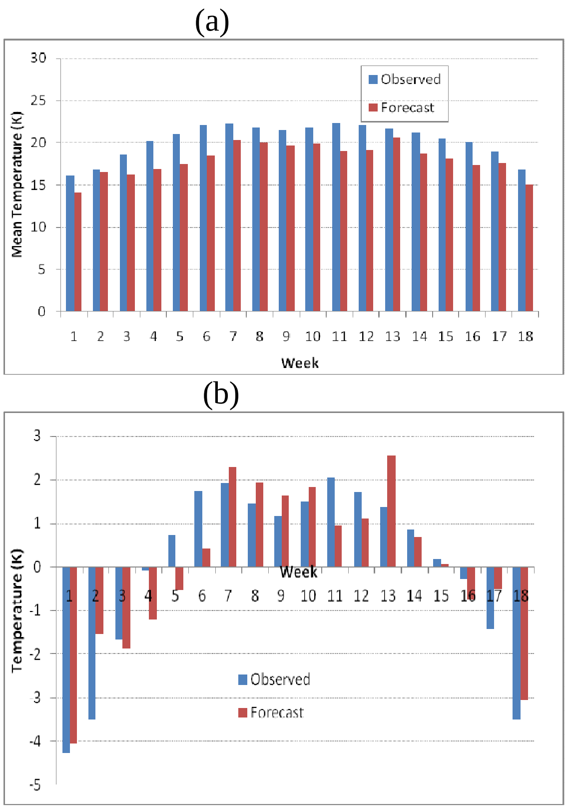

Fig. 1 Comparison of forecasted and observed temperature for the central U.S. for different weeks. The temperature are spatial averaged over the region bounded by 30-50^{o}N and 100-80^{o}W.
(a) mean temperature and (b) deviation of the forecasted and observed from each of their respective means over 18 forecasts.

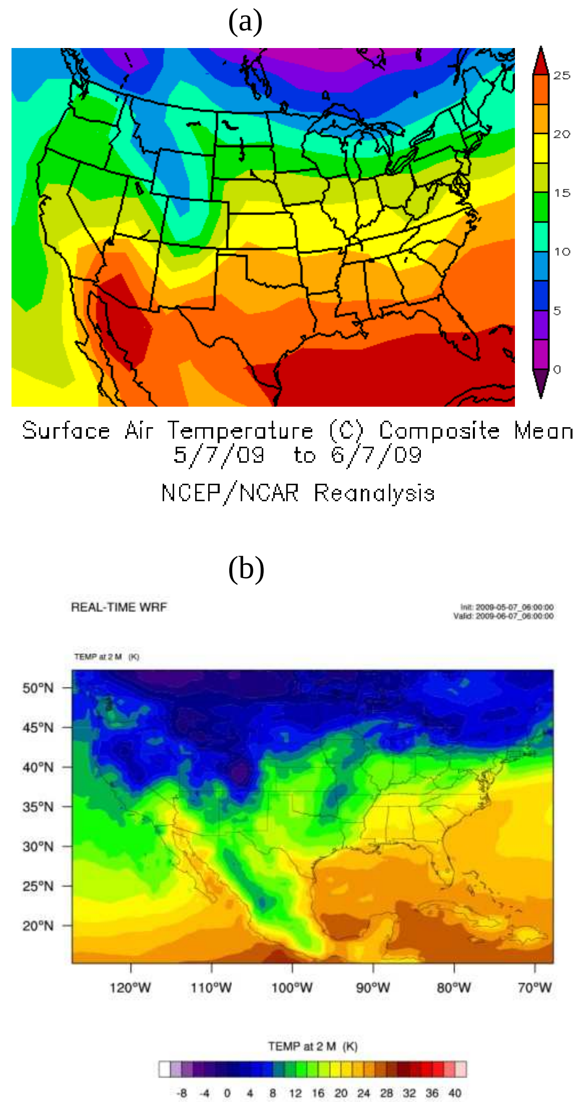

Fig. 2 Comparison of observed and forecast surface temperature for the first week(5/7/09 to 6/7/09). (a) observed temperature. (b) forecasted temperature.

Interestingly, there is a systematic and fairly constant bias in the model forecasts amongst the 18 differents runs suggesting that the monthly mean is fairly insensitive to the initial value. However, while the observed temperature decreased in August, the forecasted temperature exhibited the opposite trend, increasing with the peak on the 13th forecast (Fig. 3) during the same time period.

The spatially averaged temperature difference between (a) and (b) is about 3^{o}C with forecast temperature being lower. (Fig. 2)

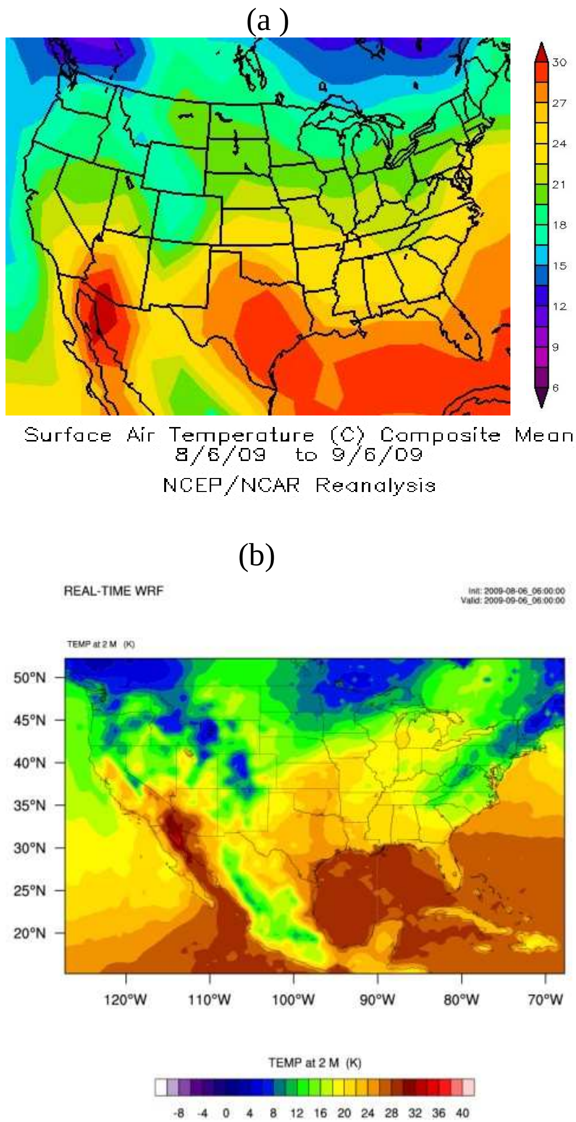

Fig. 3 Comparison of the observed and forecast surface temperature for the 13th week (8/6/09 to 9/5/09).

The averaged forecasted temperature achieved its peak value around 21°C. The averaged observed temperature was 22°C. (Fig. 3)

3.2 Rainfall amount

Spatial averaged rainfall amounts (Fig. 4) were over predicted by the model during growing season. However, daily precipitation rates were over predicted during light rain events. (Fig. 5) and under predicted during heavy events (Fig. 6).

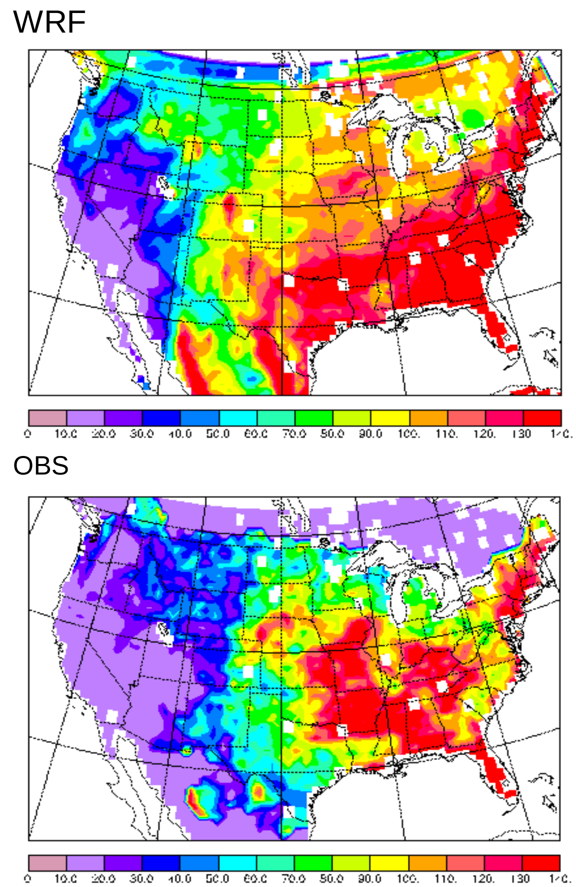

Fig. 4 Comparison of averaged forecasted and observed rainfall.

Heavy rainfall occurred over agricultural regions during the growing season. The deviation between averaged forecasted and observed rainfall amount is about -10mm. Heavier rainfall locations forecasted by the WRF model were located to the southeast of observed results. (Fig. 4)

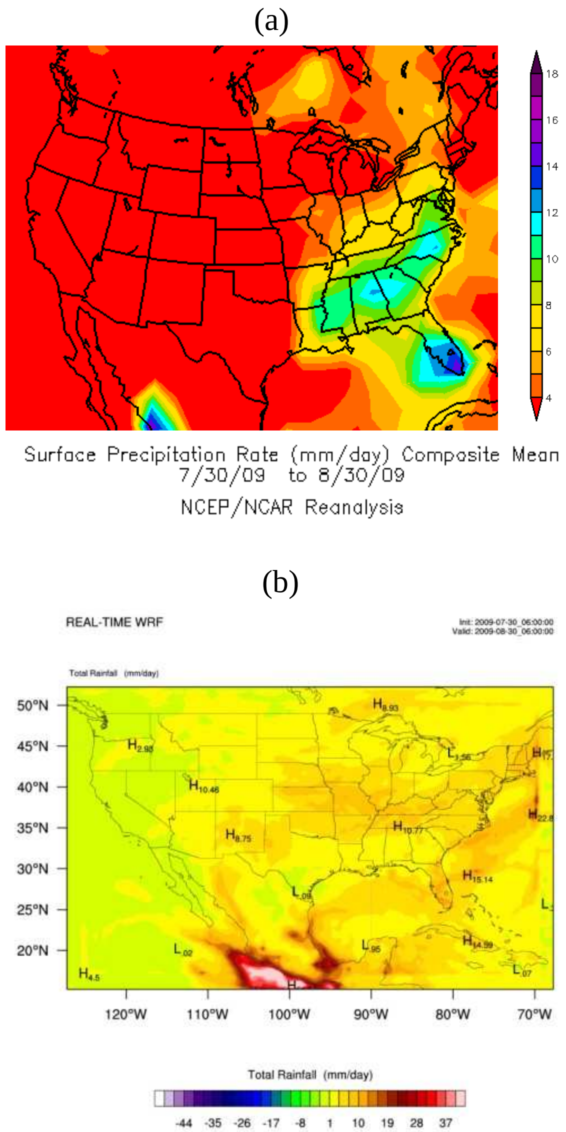

Fig. 5 Comparison of observed and forecasted mean precipitation rate (7/30/09 to 8/30/09). (a) observed precipitation amount. (b) WRF forecasted amount.

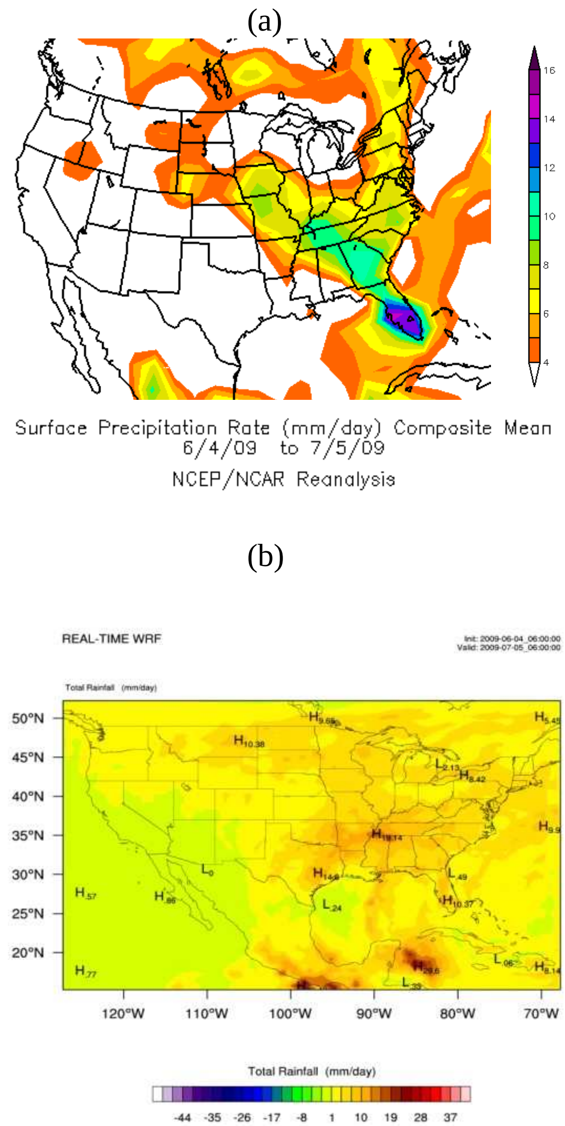

Fig. 6 Comparison of observed and forecasted mean precipitation rate from 6/4/09 to 7/5/09. (a) observed precipitation amount. (b)WRF forecasted amount.

During this forecast time period, most agricultural regions received light rainfall, less than 4mm/day. However total forecasted rainfall was more than observed rainfall. (Fig. 5)

During this forecast time period, agricultural regions received plentiful rainfall. Forecasted precipitation was less than observed by an average of 6mm/day. (Fig. 6)

3.3 Rainfall frequency

The number of rainfall days provided information about rainfall frequency which is crucial during the growing season. Figure. 7 shows the rainfall days during the 31-period averaged over 18 forecasts. The predicted number of rainy days had a positive bias which is probably caused by the model "drizzle" effect, which is well documented. Therefore, a careful selection of cutoff rainfall day amount can increase the accuracy of rainy day frequency noticeably.

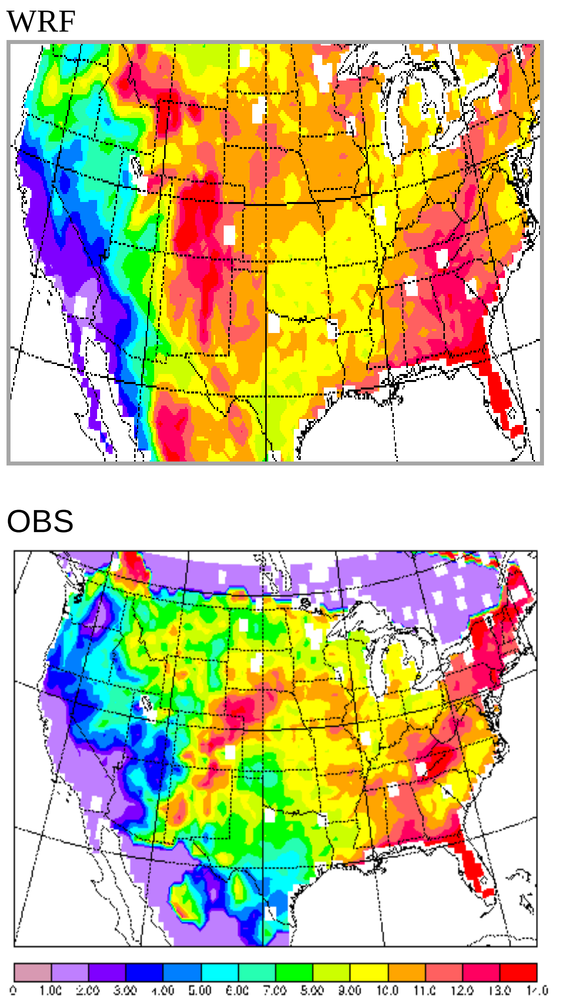

Fig. 7 Comparison of the averaged numbers of forecasted and observed rainfall days for each 31 days.

The higher forecasted frequency was located over the northern agricultural regions, although the forecast results for most agricultural regions were reliable. The averaged bias between forecasted and observed frequency was less than one day. (Fig. 7)

4. Summary and Discussions

Accurately forecasting weather at the subseasonal scale is crucial to producing accurate disease forecast.

The month-long temperature mean forecasts exhibited a systematic cold bias when started from different initial conditions. This suggests that the mean monthly temperature using the global WRF over the small domain is relatively insensitive to initial conditions. Although, this does not conclusively demonstrate that sub seasonal forecasts of mean temperature over the Midwest are boundary value problems, it does provide compelling evidence.

The WRF model over-predicted the precipitation amount and frequency except when the precipitation was heavy. This may be caused by model "drizzle " effect which is a common problem in modeling precipitation. These results did not deviate greatly from typical precipitation modeling results.

Since sub seasonal forecasts may depend on both initial conditions and boundary values, identifying which factor these forecasts are more sensitive to become an important problem for sub seasonal forecasts. For future study, two types of comparison experiments will be considered. We will produce forecasts in a small domain embedded in the global WRF model driven by initial data as well as forecasts for a small domain driven laterally by boundary data. Comparing the results of these runs to the observed data we will be able to identify the sensitivity of the monthly means to initial conditions in the context of the global WRF model. Also, we plan to extend forecast periods to several months to allow for more robust predictability studies in temperature and perhaps look at the sensitivity of monthly precipitation to initial data as well. Our goal is to determine what sort of model configuration is best suited to producing sufficiently accurate sub seasonal forecasts for use in disease spread models.

5. References

Skamarock, W. C., et al., 2008: A Description of the Advanced Research WRF Version 3. Tech. Rep. NCAR/TNC475+STR, NCAR, Boulder, Colorado.