CWRF Downscaling Improves Precipitation Prediction for Optimizing Farmers Profit

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Cai, X., J. Ryu, X.-Z. Liang, P. Kumar, M. Svoboda, C. Knutson, M. Sittler, and D.A. Wilhite: Developing Seasonal Predictive Capability for Drought Mitigation Decision Support System. NASA NNX08AL94G

Liang, X.-Z., and K.E. Kunkel: CWRF Downscaling Seasonal Climate Prediction over the United States. NOAA NA08OAR4310575

Liang, X.-Z., and K.E. Kunkel: Optimal Ensemble Mesoscale Downscaling Prediction of USA Seasonal-Interannual Climate Variations. NOAA NA08OAR4310875

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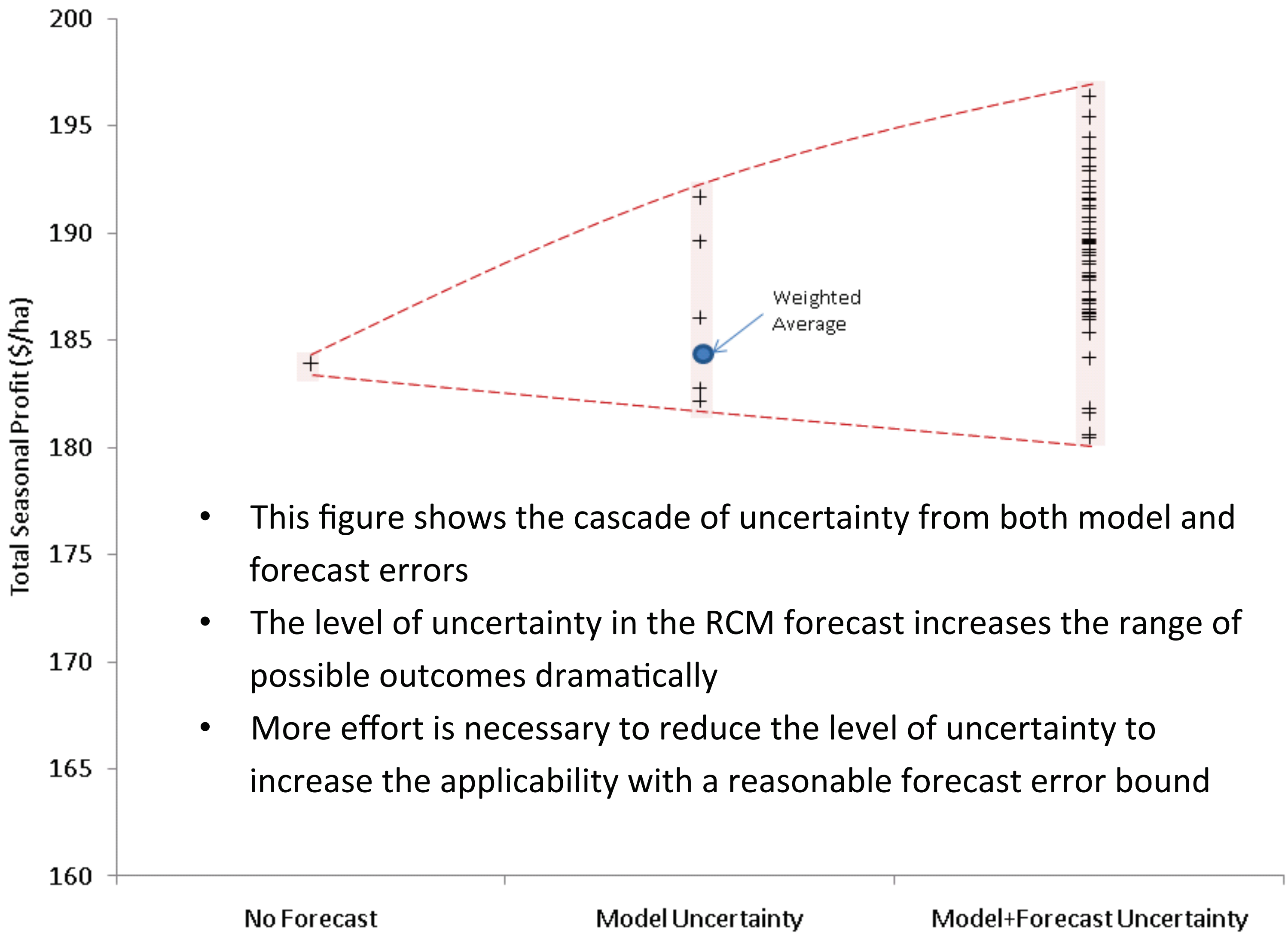
Stakeholders Ask for Higher Forecast Skill Than Current Models Can Deliver

- A survey with stakeholders indicates that improved forecasts will affect farmers' decision making if the statistical confidence is increased to **at least 75-80%**
- Current model forecast skills are at **66/67%** for daily min/max temperature and **33%** for daily total precipitation
- Meanwhile, a decision modeling exercise shows that NASA's remote sensing products can improve short and mid-term forecasts
- Aptly applied, such improved forecasts can increase farmers' net profit by **25-40%** (Cai et al. 2011; Ryu et al. 2010).

Ryu et al. 2010: Finding Potential Extents for ENSO-Driven Hydrologic Drought Forecasts in the United States. *Climatic Change*, 101, 575-597.

Cai et al. 2011: The value of probabilistic weather forecasts–An assessment by real-time optimization of irrigation scheduling. *J. Wat. Resou Plan. Managt.*, in press.

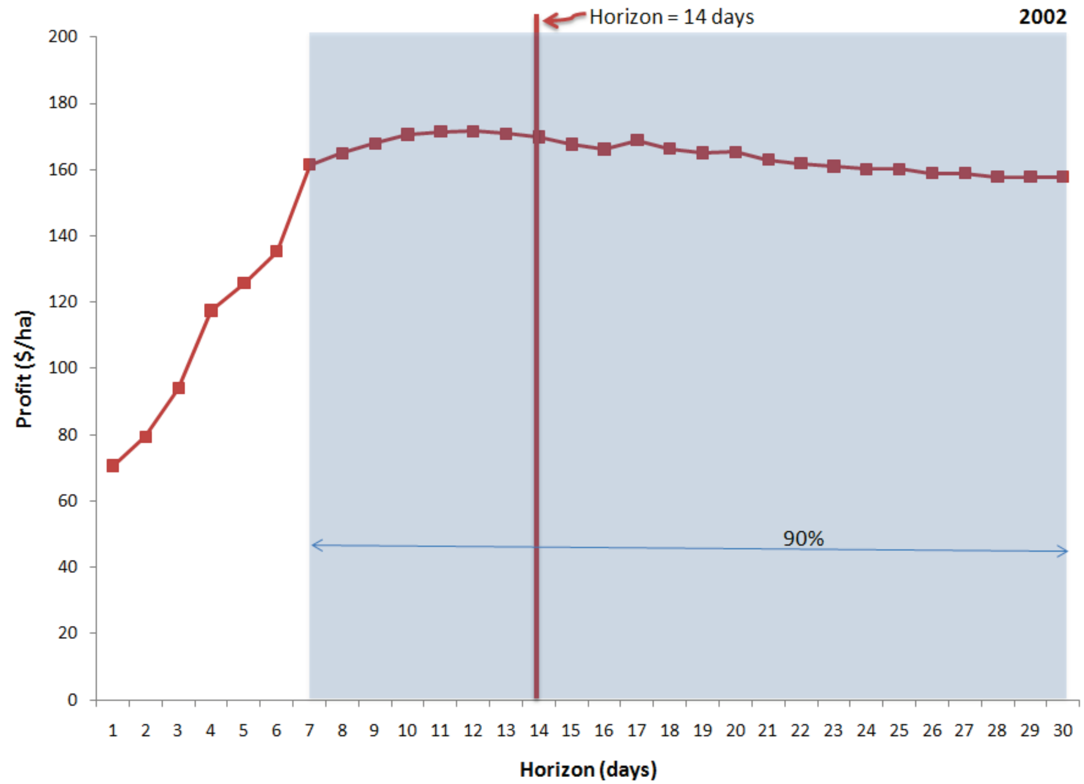
Propagation of uncertainty from model and forecast errors onto total seasonal profit in year 2004



- This figure shows the cascade of uncertainty from both model and forecast errors
- The level of uncertainty in the RCM forecast increases the range of possible outcomes dramatically
- More effort is necessary to reduce the level of uncertainty to increase the applicability with a reasonable forecast error bound

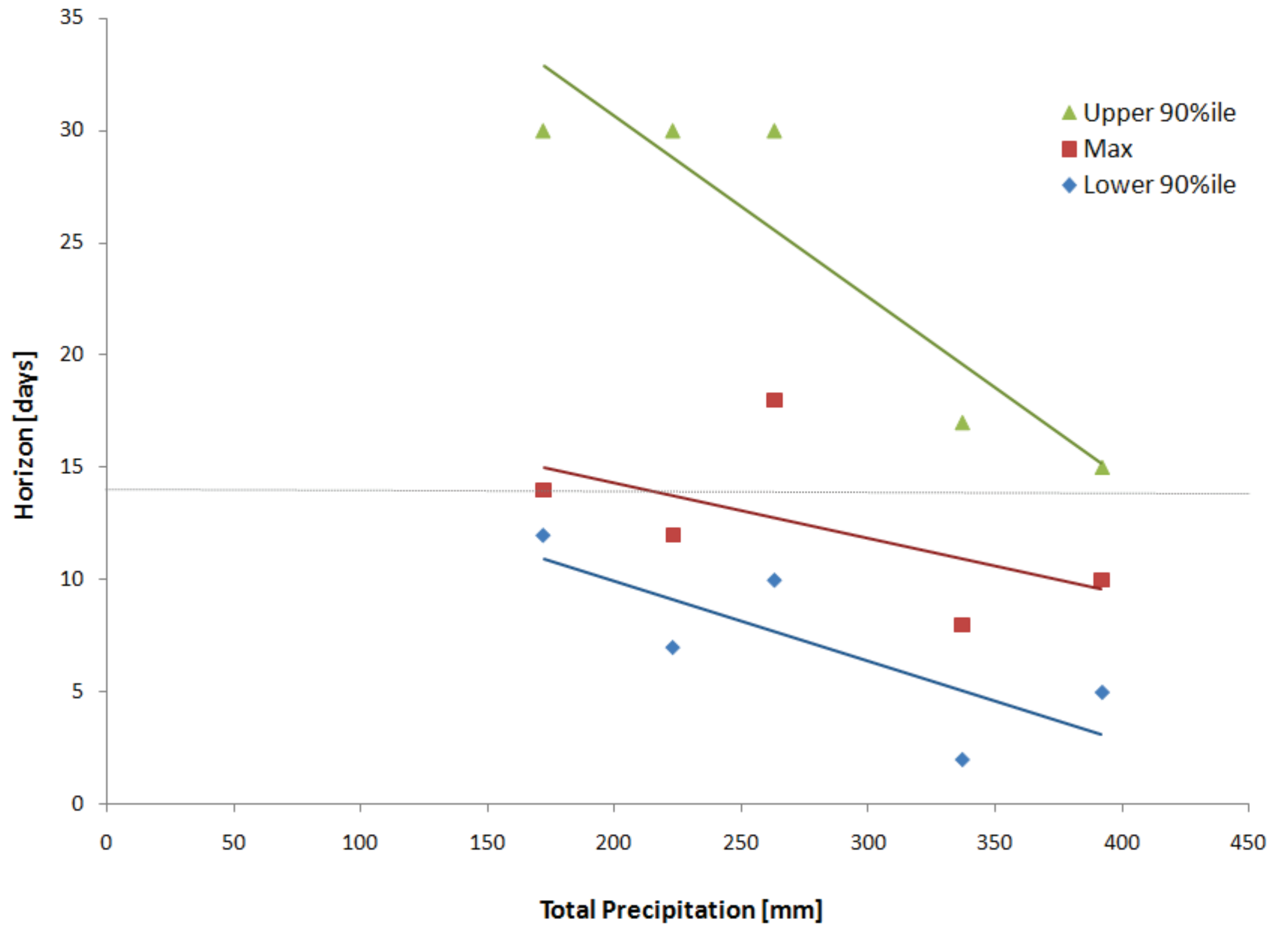
Impact of forecast horizon on the overall seasonal profit

- To determine the optimal forecast horizon and the incremental approach, we tested the no forecast scenario with incremental horizons between 1 day and 30 days
- The right figure shows the seasonal profit from optimizing farmers' decisions in year 2002 with different horizons



- If the horizon is too short (< 7 days), the incremental objective function underestimates the potential seasonal profit. One plausible explanation is that when irrigation occurs on a particular day, the benefit of the additional soil moisture is reaped over a longer time period than a single day
- If the horizon is too long (> 30 days), the benefit from irrigation might be slightly off-set due to a slight diminishing ratio of actual to potential evapotranspiration
- It is important to identifying the horizon range in which the sequential optimization of the incremental objective leads to near optimal seasonal profit

Impact of forecast horizon on maximum seasonal profit

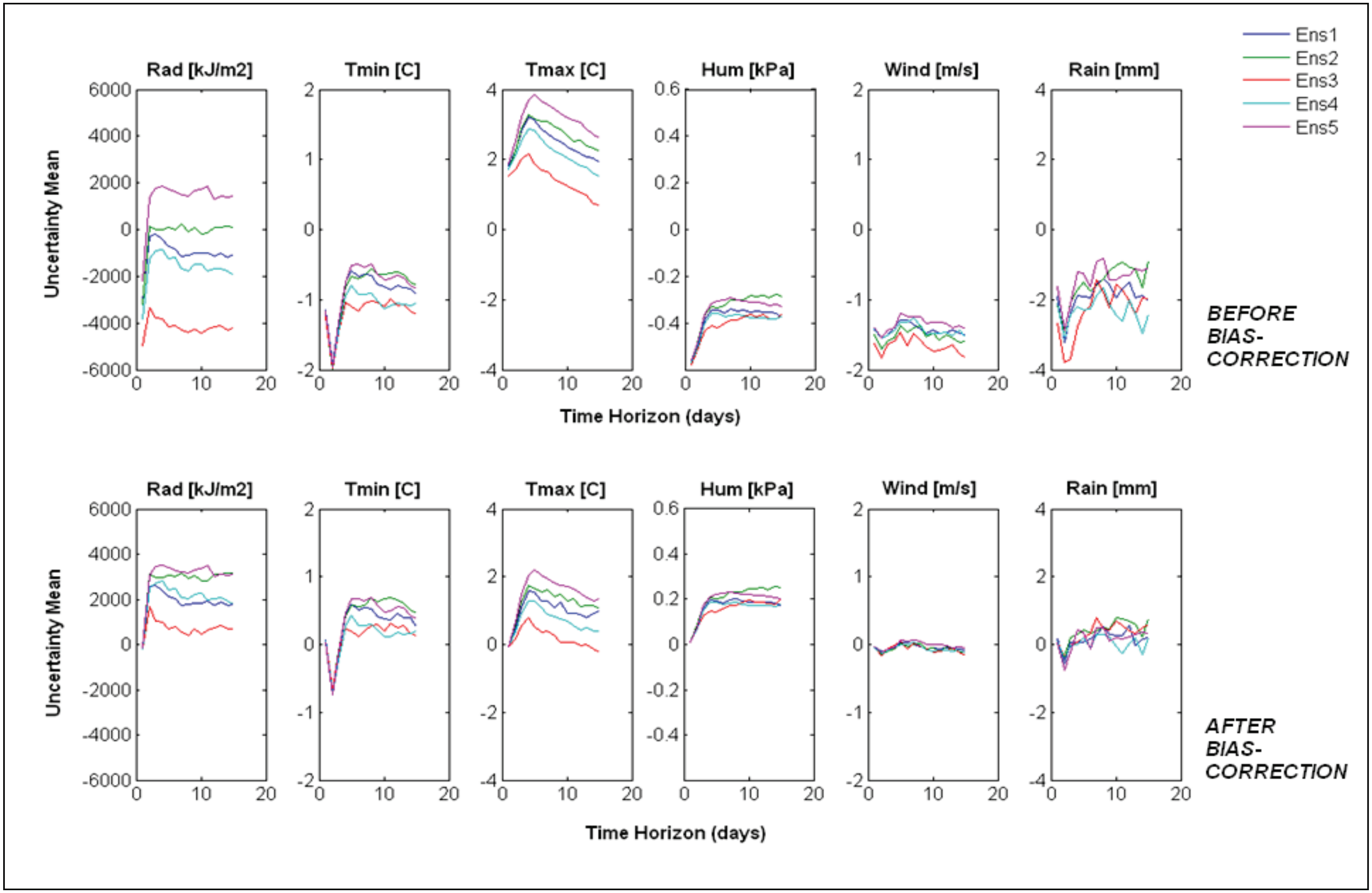


- Relation between the incremental horizon range in which 90% of the maximum seasonal profit is attained and the total precipitation in a season
- A 14-day forecast falls well within the range for all five years (2000-2006)

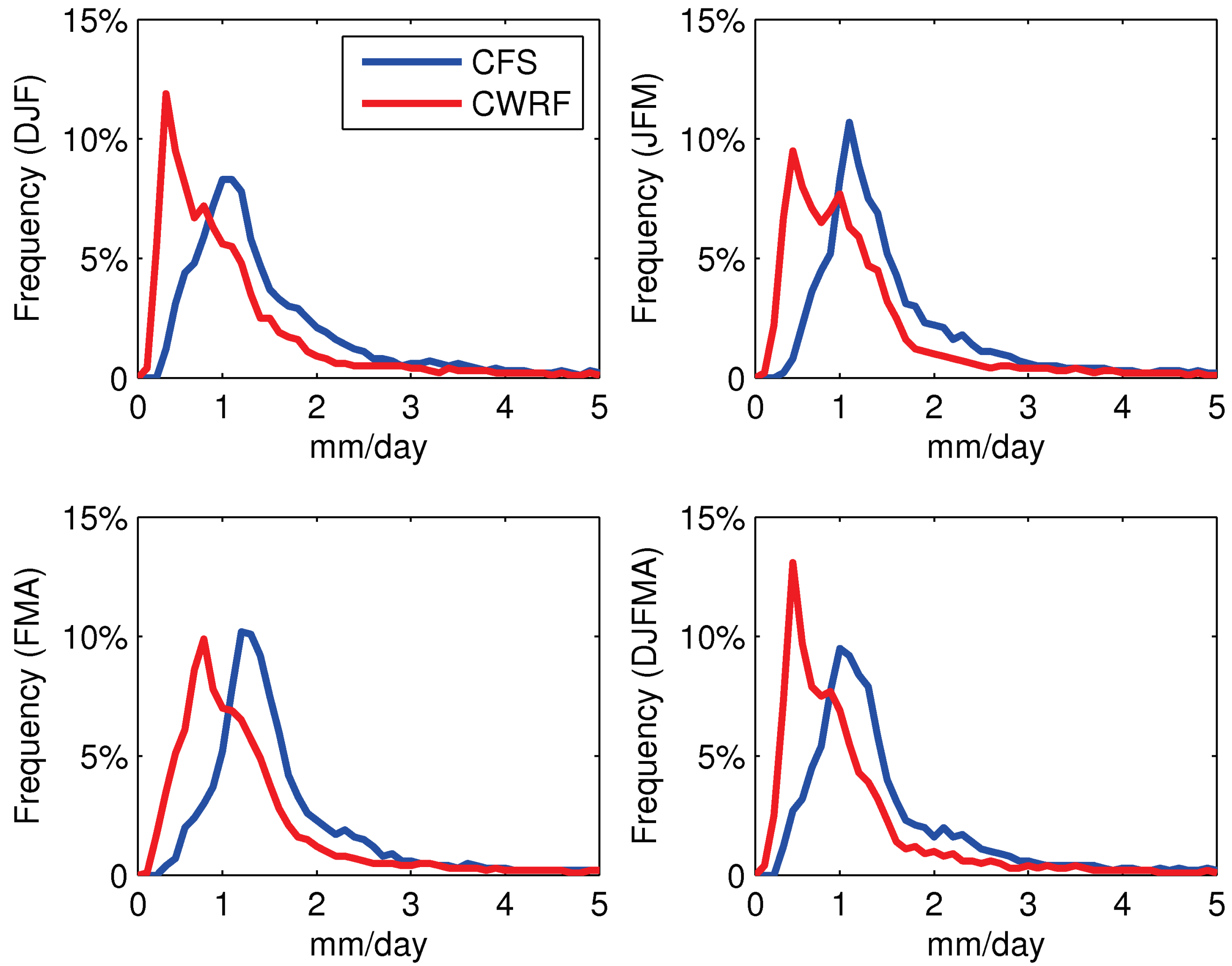
Summary for forecast horizon and seasonal profit

- We demonstrate the importance of selecting the appropriate horizon when assessing the incremental gain from real time irrigation decisions
- Selecting too short of a horizon would lead to a substantial gap between the outcome of the sequential real-time simulation-optimization framework and the resulting total seasonal profit
- Selecting too long of a horizon could lead to sub-optimal decisions that could lead to some reduction in seasonal profit
- A horizon range of 12-15 days would ensure achieving 90% of the optimal seasonal solution based on the five years (2002-2006)
- The applicability of the identified range to other cases and different objective functions remains open for further research

Correcting Model Biases to Bring Closer to Zero

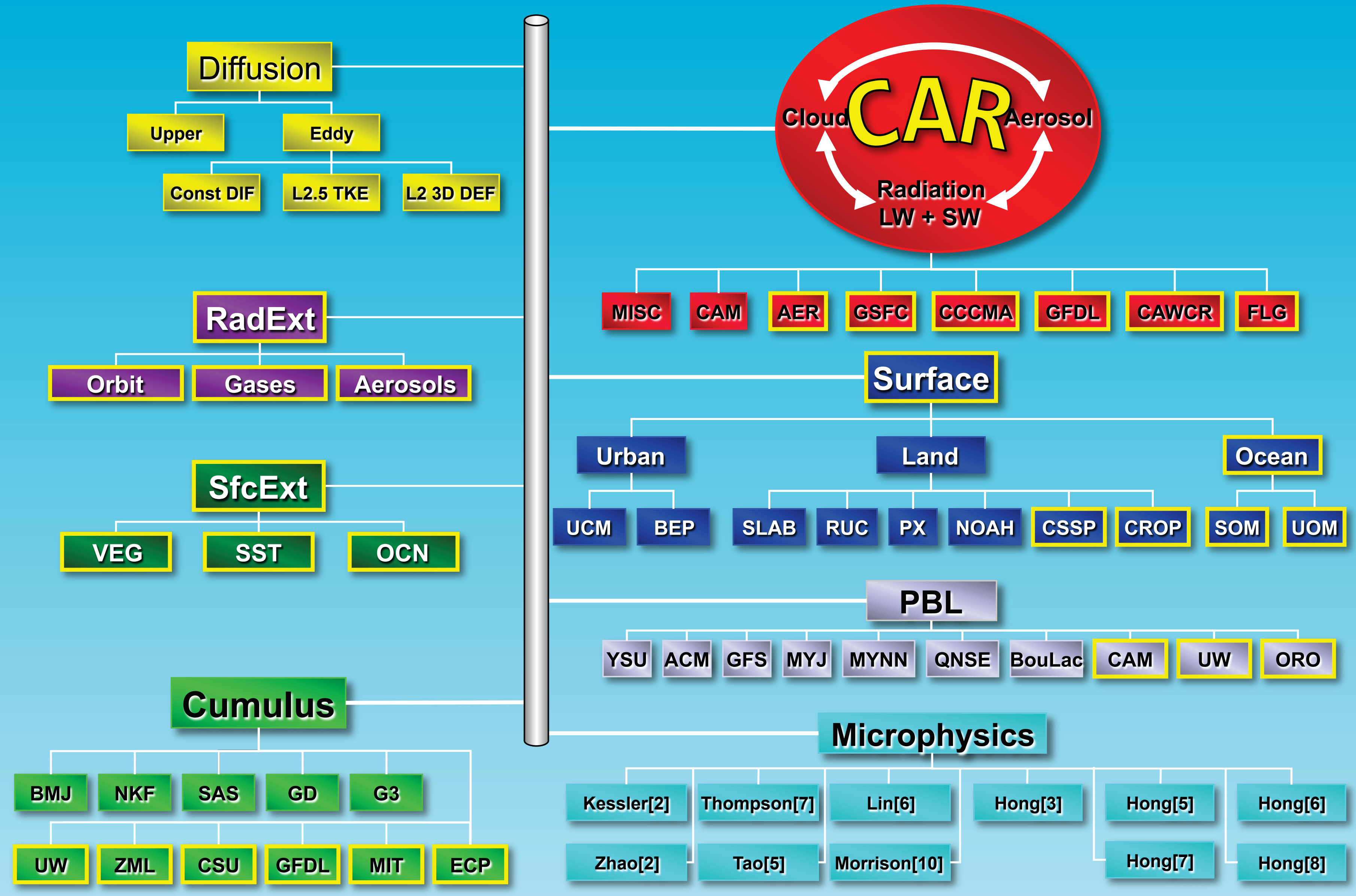


RCM Improves Seasonal Climate Prediction

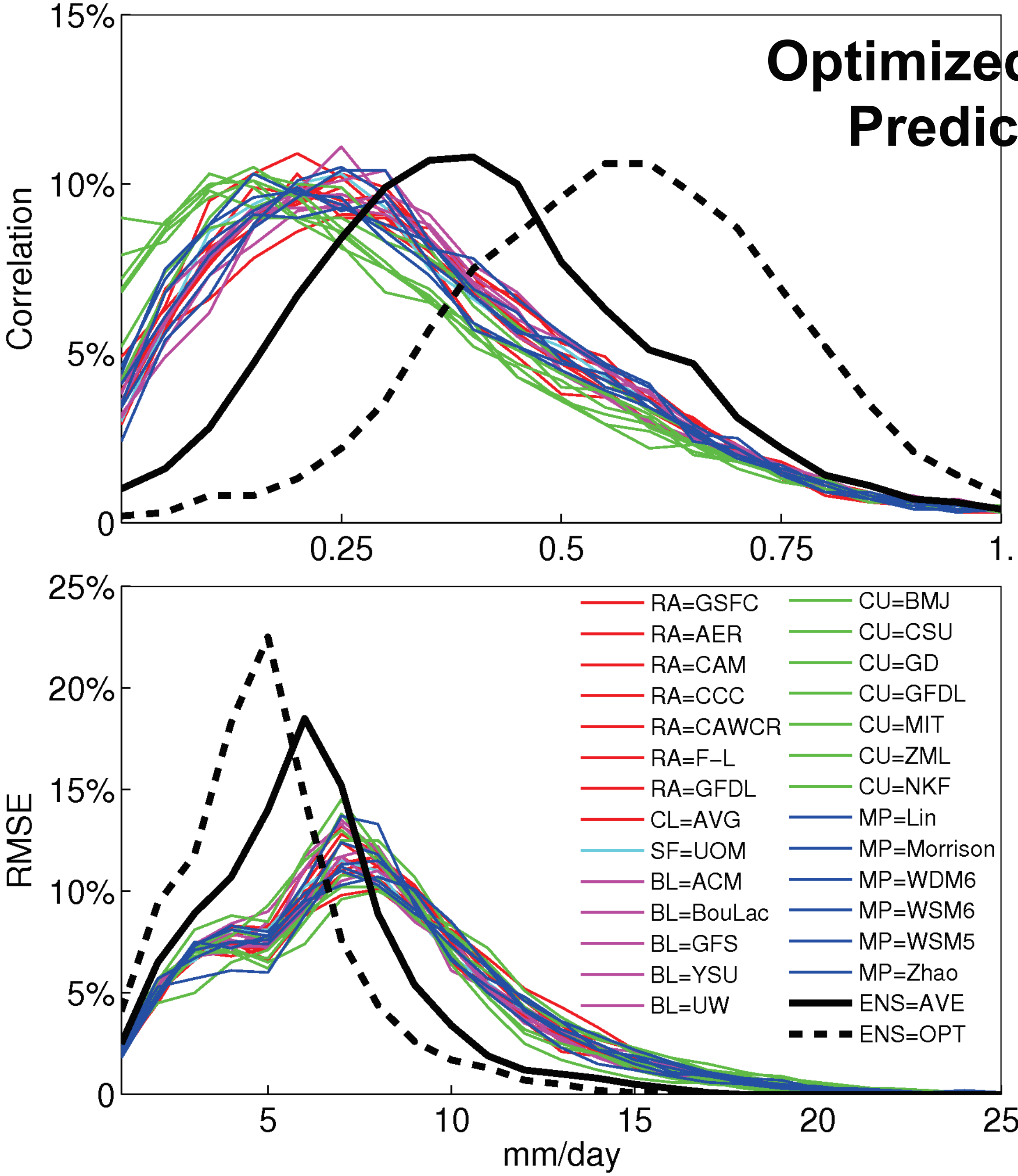


Frequency distribution of root mean square errors (RMSE, mm/day) for the interannual variations of seasonal precipitation over land predicted by the CFS and CWRF based on 5 ensemble members during wintertime of 1982-2008. Seasonal precipitation is binned at an interval of 0.1 mm/day. *From* Yuan and Liang 2011 (GRL).

CWRF Physics Options



Optimized Physics Ensemble Prediction of Precipitation In summer 1993

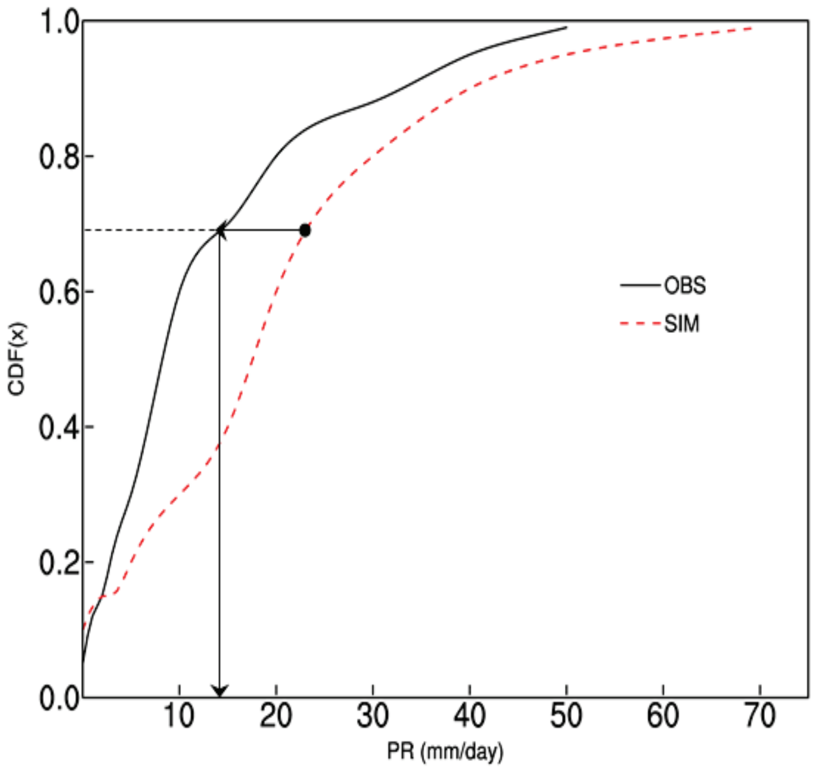


The physics ensemble mean substantially increases the skill score over individual configurations, and there exists a large room to further enhance that skill through intelligent optimization.

Spatial frequency distributions of correlations (*top*) and rms errors (*bottom*) between CWRF and observed daily mean rainfall variations in summer 1993. Each line depicts a specific configuration in group of the five key physical processes (*color*). The ensemble result (ENS) is the average of all runs with equal (Ave) or optimal (OPT) weights, shown as *black solid* or *dashed* line.

Liang et al. 2011

Quantile Mapping Method



The QM method relies on the empirical probability distributions of observed and simulated values to remove bias from the model simulation results. It replaces the model values with the corresponding observed values that possess the same non-exceedance probability.

Here the QM is based on point-wise and daily constructed empirical cumulative distribution functions (CDF) of modeled and observed datasets in a previous training window from t_1 to t_2. It transfers original model daily precipitation output $X_{i,t}$ to the corrected estimate:

$$Y_{i,t} = CDF^{-1\text{obs}}_{i,t_1,t_2}[CDF^{\text{sim}}_{i,t_1,t_2}(X_{i,t})]$$

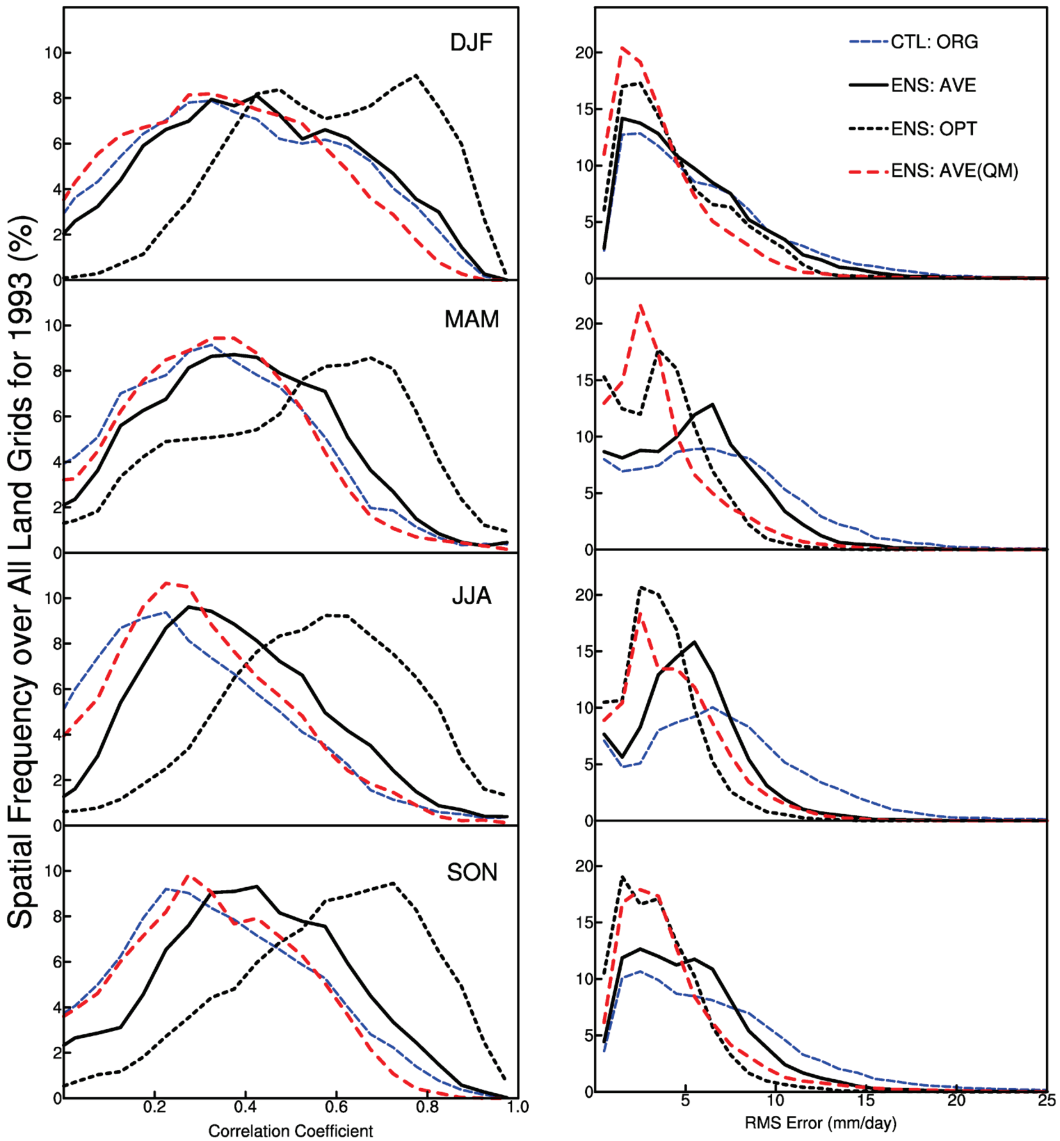
where CDF^{-1} represents the inverse CDF, and i depicts a grid point.

Let wl for the training window length and fl for the forecast lead, then

$$t_1 = t - fl - wl + 1 \text{ and } t_2 = t - fl$$

Here the training window has a moving length of wl.

Performance of Quantile Mapping Method



Forecast Lead = 10 days

Spatial frequency distribution of point-wise correlation coefficients and root mean square errors of daily mean precipitation as compared with observations for 4 seasons of 1993 over the U.S. land grids simulated by the CWRF using the control physics configuration (CTL: ORG), the average of all original CWRF output (ENS: AVE), the hindcast ensemble optimization (ENS: OPT), and the average of bias-corrected results with quantile mapping method from all 40 physics configurations with the training window length of 20 days and the forecast lead of 10 day (ENS: AVE(QM)).

Summary for CWRF Downscaling Skill Enhancement

- CWRF downscaling significantly enhance predictive skill
- CWRF Physics Ensemble further improves predictive skill
- Quantile Mapping for bias correction adds more skill
- Substantial gaps still exist from the optimal limit
- There is a hope: large room for further improvement
- More so: if NASA satellite data are assimilated