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Citation: ZHANG, W. ... et al., 2017. Improved ENSO forecasting using Bayesian updating and the North American Multi Model Ensemble (NMME). Journal of Climate, 30(22), pp. 9007-9025.

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Metadata Record: https://dspace.lboro.ac.uk/2134/25955

Version: Accepted for publication

Publisher: © American Meteorological Society (AMS)

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Improved ENSO Forecasting using Bayesian Updating and the North American Multi Model Ensemble (NMME)

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Revision accepted by Journal of Climate
on August 1 2017

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Abstract

This study assesses the forecast skill of eight North American Multi Model Ensemble (NMME) models in predicting Niño3/3.4 indices and improves their skill using Bayesian updating (BU). The forecast skill that is obtained using the ensemble mean of NMME (NMME-EM) shows strong dependence on lead (initial) month and target month, and is quite promising in terms of correlation, root mean square error (RMSE), the standard deviation ratio (SDRatio) and probabilistic Brier Skill Score, especially at short lead months. However, the skill decreases in target months from late spring to summer due to the “Spring Predictability Barrier.” When BU is applied to eight NMME models (BU-Model), the forecasts tend to outperform NMME-EM in predicting Niño3/3.4 in terms of correlation, RMSE, and SDRatio. For Niño3.4, the BU-Model outperforms NMME-EM forecasts for almost all leads (1-12; particularly for short leads) and target months (from January to December). However, for Niño3, the BU-Model does not outperform NMME-EM forecasts for leads 7-11 and target months from June to October in terms of correlation and RMSE. Last, we test further potential improvements by preselecting “good” models (BU-Model-0.3) and by using principal components analysis to remove the multicollinearity among models, but these additional methodologies do not outperform the BU-Model, which produces the best forecasts of Niño3/3.4 for the 2015/2016 El Niño event.
1. Introduction

The El Niño Southern Oscillation (ENSO) phenomenon is a dominant atmospheric-oceanic mode in the tropical Pacific with a dominant timescale of 2-7 years (e.g., Philander, 1983; Rasmusson and Wallace, 1983; Trenberth, 1997; Wyrtki, 1975), strongly mediating global weather and climate (e.g., Alexander et al., 2002; Hoerling et al., 1997; Rasmusson and Wallace, 1983; Wang et al., 2000; Webster and Yang, 1992; Wyrtki, 1973; Zhang et al., 2013). The predictability of the global climate system strongly depends on the prediction of ENSO, which is the largest source of predictability for North Atlantic and Pacific climate, for U.S. precipitation and for the Asian summer monsoon (e.g., Kumar et al., 2017; Xue et al., 2013; Zhu et al., 2013). It is therefore crucial to advance our understanding and to make timely and reliable forecasts of ENSO.

In recent decades, major advancements have been made in understanding and forecasting ENSO (e.g., Cane et al. 1986; Battisti and Sarachik, 1995; Clarke, 2008; L'Heureux and Thompson, 2006; Philander, 1983; Sarachik and Cane, 2010; Stuecker et al., 2015; Wittenberg et al., 2014; Jia et al. 2015), due to the improved capability of fully-coupled climate models (e.g., Bellenger et al., 2014; Capotondi, 2013; Collins, 2000; Delworth et al., 2012; Vecchi and Wittenberg, 2010), better atmospheric and oceanic observations (e.g., McPhaden et al., 1998; White, 1995; Xie, 2004), and improved assimilation techniques to feed observations into climate models (e.g., Behringer et al., 1998; Chen et al., 1995; Jin et al., 2008; Latif et al., 1998; Zhang et al. 2007). However, the predictability of ENSO by climate models is still limited by error growth and model inadequacies (Jin et al., 2008; Kumar et al., 2017; Xue et al., 2013). For example, in early 2014, the forecasts using climate models or statistical methods falsely predicted an El Niño in the 2014/2015 winter (Ludescher et al., 2014; Tollefson, 2014), and a number of studies have
attempted to understand the underlying physical mechanisms for the failure of the 2014/2015 case
(e.g., Hu and Fedorov, 2016; Imada et al., 2016; Min et al., 2015; Zhu et al., 2016).

The North American Multi-Model Ensemble (NMME) project (Kirtman et al., 2014) has
advanced the forecasting of ENSO and relevant climate variables by integrating coupled models
from research centers across the United States and Canada. Kumar et al. (2017) assessed the
predictability of Niño3.4 in the NMME models. They found that the predictability of ENSO
strongly depends on seasonality, due to changes in ENSO’s predictable component, and is the
lowest in spring and summer because of the Spring Predictability Barrier (e.g., Webster and Yang,
1992). Although the prediction skill based on the ensemble mean of NMME models is promising,
it is of central importance to examine whether we can further improve the NMME forecasts by
using more advanced statistical methods to leverage the information from these models. For
instance, even though the NMME models have different numbers of ensemble members ranging
from 6 to 28, the focus of previous studies was on the use of the ensemble average (weighted
equally) to produce the final forecasts (Becker et al., 2014; Chen et al. 2017; Kirtman et al., 2014;
Kumar et al., 2017). Whether it is possible to improve the forecast skill by using all the individual
members (rather than their ensemble average) has not been examined in previous studies.

From a methodological perspective, Bayesian updating (BU) has proven skillful in
improving multi-model forecasts and provides a more realistic description of predictive
uncertainty accounting for between- and in-model variances (Bradley et al., 2015; Duan et al.,
2007; Hoeting et al., 1999; Luo and Wood, 2008; Min et al., 2007; Raftery et al., 2005; Slater et
al., 2017). BU implements Bayes’ theorem to update the probability distribution of a variable (e.g.,
NMME-based Niño3.4 forecasts) with the new observed information (e.g., observation-based
Niño3.4). The BU predictions are basically weighted averages of the individual forecasts of
climate variables (Luo and Wood, 2008; Luo et al., 2007; Wang et al., 2013). BU has been used to improved ENSO forecasts with the European Centre for Medium-Range Weather Forecasts (ECMWF) ensemble simulations (Coelho et al., 2004). We will use BU to further improve the NMME forecasting of ENSO by leveraging the forecasting skill of all of the individual members from eight NMME models.

The objectives of this study are twofold. First, we aim to evaluate the skill of the NMME models in predicting Niño3/3.4 indices. Second, we attempt to further improve the NMME forecasts for Niño3/3.4 indices by leveraging the forecasting skill of eight NMME models using BU. We evaluate the prediction of the 2015/2016 El Niño event using BU and compare the forecasts with the NMME models. This study aims to advance our understanding of the current status of the skill of the NMME models in forecasting ENSO and provides a new approach to improve forecasts using ensemble members, which has potential to be broadly applied.

The remainder of this paper is organized as follows. Section 2 presents the data and methodology, while Section 3 discusses the forecast results based on NMME and BU. Section 4 includes the discussion and summarizes the main conclusions.

2. Data and Methodology

2.1 NMME Models

The available period, ensemble size and lead months of the NMME models are summarized in Table 1, with eight climate models and up to 94 members (Becker et al., 2014; Kirtman et al., 2014). The hindcasts and forecasts of sea surface temperature (SST) at 1°×1° spatial resolution are available from the early 1980s to the present. We consider eight climate models: CCSM3 (Community Climate System Model, version 3) and CCSM4 (Community Climate System Model,
version 4 – subset of CESM1) from the National Center for Atmospheric Research (NCAR); Center for Ocean–Land–Atmosphere Studies (COLA), and Rosenstiel School for Marine and Atmospheric Science, University of Miami (RSMAS); CanCM3 (3rd Generation Canadian Coupled Global Climate Model) and CanCM4 (4th Generation Canadian Coupled Global Climate Model) from Environment Canada’s Meteorological Service of Canada - Canadian Meteorological Centre (CMC); CFSv2 (operational Climate Forecast System version 2) from National Centers for Environmental Prediction (NCEP); GEOS5 (Goddard Earth Observing System Model, version 5) from the National Aeronautics and Space Administration (NASA)’s Global Modeling and Assimilation Office (GMAO); GFDL CM2.1 (Climate Model, version 2.1) and FLOR B01 (Climate Model version 2.5) from National Oceanic and Atmospheric Administration (NOAA)’s Geophysical Fluid Dynamics Laboratory (GFDL). The observed estimates of SST are obtained from the Met Office Hadley Center (HadISST, version 1.1) (Rayner et al., 2003).

2.2 Niño3 and Niño3.4 Indices

We focus on the Niño3 and Niño3.4 indices in both the observations and NMME hindcasts/forecasts. These two indices are defined as the SST anomalies averaged over the Niño3 and Niño3.4 regions. The Niño3 region is bounded by 5°S-5°N and 150°W-90°W, while the Niño3.4 region is bounded by 5°S-5°N and 170°W-120°W. The SST anomalies in the observations are calculated by removing the seasonal cycle, which is based on the climatology of 1982-2015. The SST anomalies in the NMME models are calculated by accounting for the dependence on season and on forecast lead time with respect to the 1982-2015 period following Kumar et al. (2017).
2.3 Bayesian Updating (BU)

The Bayesian updating (BU) of the NMME forecasts is an implementation of Bayes’ theorem, in which the probability distribution of a variable, $Y$ (i.e., NMME-based Niño3.4 forecasts), is updated when new information (e.g., observation-based Niño3.4) becomes available. BU has also been used to improve the ensemble forecasts of the ECMWF model (Coelho et al., 2004), where it was applied to calibrate and combine both empirical and coupled model ensemble forecasts. This study employs BU to combine coupled model ensemble forecasts from the NMME project. The best estimates of the probability of different outcomes are defined by the climatology (i.e., the historical averages of the forecasted variable), represented here by the prior climatological density function $f(y)$. After a climate model forecast $\theta$ is available, the updated (or posterior) density function is given by Bayes' theorem to be:

$$f(y|\theta) = \frac{f_\theta(\theta|y)f(y)}{f_\theta(\theta)} \quad (1)$$

where $f_\theta(\theta)$ is the unconditional density of $\theta$, and $f_\theta(\theta|y)$ is the likelihood function. The posterior density $f(y|\theta)$ describes the conditional distribution of the variable given the climate model forecast $\theta$, and therefore represents a probability distribution forecast of the outcome. Here we apply Bayesian updating to a data sample, where $[y_i, i=1\ldots N]$ represents the historical observations of $Y$, i.e. a sample drawn from the prior density $f(y)$. We represent a sample drawn from the posterior density $f(y|\theta)$ using the likelihood function $f_\theta(\theta|y)$. By definition, the likelihood function $f_\theta(\theta|y)$ is the distribution of a given model forecast $(\theta)$ (e.g., July 2010) conditioned on the observed SST ($y$) for the same month. If we have a hindcasted sample (e.g., monthly observations from January 1982 to December 2015), the likelihood function can be estimated by a regression model:

$$\theta = \bar{\theta}(y) + \varepsilon \quad (2)$$
where $\bar{\theta}(y)$ is the expected value of the forecast given the observation $y$, and $\varepsilon$ is the residual model error. We apply the Bayesian updating using a linear regression approach, so we implement a simple linear regression model $\bar{\theta}(y)$ and assume that the residual errors are normally distributed with constant variance (see also Coelho et al. (2004)). The likelihood function $f_\theta(\theta|y)$ is then:

$$f_\theta(\theta|y) = \frac{1}{\sqrt{2\pi}\sigma_\varepsilon} \exp \left[ -\frac{(\bar{\theta}(y)-\theta)^2}{2\sigma_\varepsilon^2} \right]$$  \hspace{1cm} (3)

Using the likelihood function developed for each of the 94 individual model members or the ensemble average of the eight models, we assign a weight $w_i$ to each observation $y_i$ in the historical sample. The weight $w_i$ represents the likelihood of observing outcome $y_i$ given the climate forecast $\theta$. The historical sample is reweighted as:

$$w_i = \frac{f_\theta(\theta|y_i)}{\sum_{j=1}^{N} f_\theta(\theta|y_j)}$$  \hspace{1cm} (4)

where the sum of the weights $w_i$ is equal to 1. The collection of the weights for all historical observations for the given month (e.g., for the HadISST-derived Niño3.4 from January 1870 to December 2015, minus the forecast year) is thus similar to a discrete probability distribution forecast for each model or model member. This suggests that the weights show the likelihood of each discrete outcome given the climate model forecasts. Weights of $1/N$ indicate that there is no potential skill and produce the same distribution as the prior distribution before Bayesian updating, so the output is equivalent to a climatology forecast (i.e., the average historical conditions for the same months) and the member is automatically ignored. For models with a weak relationship between forecasts and observations, the Bayesian weights will be close to $1/N$, indicating that each outcome is equally likely. For models with a strong and significant relationship between forecasts and observations, the Bayesian weights will be greater than $1/N$, and will grow as the potential skill increases (thus giving more weight to the forecast). Any weights of less than $1/N$ indicate that
The outcome is less likely than the climatology. The weights for every single model are combined to yield a multi-model forecast.

The BU method may be dependent on the skill of the individual models of the NMME project. Here we assess whether the skill of the BU can be improved by selecting the models (“good candidates”) in which the value of the correlation coefficient between forecasted and observed Niño3/Niño3.4 indices is greater than a threshold value, selected to be 0.3 in this study (BU-Model-0.3). The threshold of 0.3 is selected experimentally based on the value of correlation coefficient at the 0.05 significance level for the study period. We tuned the threshold to be larger or smaller and the results did not change significantly. Moreover, because we cannot assume that all the GCMs are independent (i.e., similarities exist among different models, and some, like CCSM3/CCSM4 or CanCM3/CanCM4 are two different versions of the same model), we perform principal component analysis (PCA) on the forecasted Niño3/Niño3.4 indices for each NMME model to reduce the multicollinearity among individual forecasts (see also Slater et al. (2017) for an application to the seasonal forecasting of precipitation and temperature over Europe using the NMME data). Because the forecasts of the Niño indices with different NMME models are linearly correlated, the PCA which transforms the forecasts into orthogonal principal components, may improve the forecasts by reducing the multicollinearity. We then apply BU to the loadings of all the PCs (BU-Model-PCA). Similar to BU-Model-0.3, we also focus the Bayesian updating on the loadings of the PCs having correlation with the observed Niño3/Niño3.4 indices greater than 0.3 (BU-Model-PCA-0.3). The four BU methods are summarized in Table 2.

2.4 Forecast Verification Metrics

To quantify the skill of the different models and approaches with respect to the observations we use the correlation coefficient, the root mean square error (RMSE) and the
standard deviation ratio (SDratio) as deterministic metrics. SDratio represents the capability of the forecasts in capturing the dispersion of the observations (Barnston et al., 2015), and is defined as the standard deviation of the forecasted El Niño indices divided by the one for the observations.

We will refer to the correlation between the mean forecasted Niño indices (of all NMME members) and observations as “NMME-CorM”, and to the mean of all the individual correlations between every NMME-member and the observations as “NMME-MCor” (i.e., the correlation of the means vs the mean of the correlations). To be consistent with the calculation of other skills (e.g., RMSE and SDratio), we also use “NMME-EM” to denote the method based on the ensemble mean of all NMME members/models. NMME-CorM is a special case of NMME-EM for calculating correlation. Although NMME-CorM and NMME-MCor are forecast verification measures, we use them as forecast methods to be easily compared with BU hereafter.

In addition to deterministic verification metrics such as correlation and RMSE, we also employed the probabilistic verification metric Brier skill score (Wilks, 2011). Brier skill score is based on the Brier Score (BS), which is a scalar metric of the accuracy of a probabilistic forecast for dichotomous events and is defined as:

$$BS = \frac{1}{n} \sum_{i=1}^{n} (f_i - O_i)^2$$  (5)

where $n$ is the number of forecasts, $f_i$ is the forecast probability of the occurrence of an event for the $i^{th}$ forecast, and $O_i$ is the $i^{th}$ observed probability, which is defined to be 1 if the event occurs and 0 if it does not.

The Brier Skill Score is defined as:

$$BSS = 1 - \frac{BS_f}{BS_{cli}}$$  (6)

where $BS_{cli}$ denotes the Brier Score for climatological forecast (with a probability of 0.33 for each tercile), while $BS_f$ is the Brier Score for the forecast based on NMME or BU. For a climatological
forecast, the BSS is zero. In this study, a probabilistic forecast of an event in each tercile was
implemented. The three categories are defined as “above-normal”, “normal” and “below-normal”
based on the values of the Niño 3/Niño3.4 index in the forecasts. We focus on the forecast skill of
“above-normal” and “below-normal” events with warm/cold SST anomalies.

To test whether the differences in forecast skill among the different forecast methods are
statistically significant, we use the Wilcoxon signed-rank test. This test considers the magnitude
of the differences in forecast skills (DelSole and Tippett, 2014), and its statistic is defined as:

\[ W_T = \sum \text{when} d_n > 0 (\text{rank of } |d_n|) \]  

where \( d_n = 0 \) is assumed to never occur. The finite-sample distribution of this statistic is invariant
to the distribution of the loss differential if the distribution is symmetric about zero.

3. Results

Figure 1 shows the observed and predicted composite SST anomalies for the December-
February (DJF) El Niño and La Niña events between 1981 and 2016 based on observations and
NMME forecasts initialized in December. Overall, the NMME climate models successfully
predicted the SST anomalies in the tropical Pacific, especially in the Niño3 and Niño3.4 regions.
During El Niño years, the forecast SST anomalies in the Niño regions are slightly weaker than the
observations, with the exception of the GFDL CM2.1 and the NASA-GEOS5 (NASAGMAS)
climate models. During La Niña years, the SST anomalies in the NMME models tend to extend
farther west than the observations, with the exception of CFSV2 which predicts the SST anomalies
at locations similar to the observations. The negative SST anomalies in GFDL CM2.1, CanCM3,
CanCM4, CCSM3, and NASA-GEOS5 models are slightly stronger than those in the observations
(Figure 1).
The model biases during El Niño and La Niña years are shown in Figure S1, supporting the above discussions on SST anomalies. For example, GFDL CM2.1 has warm biases in the tropical Pacific, especially west of the Niño3.4 region during El Niño years. CanCM3, CanCM4 and CCSM3 also show weak warm biases west of the Niño3.4 region. Most of the models show cold biases in the Niño3 and Niño 3.4 regions during El Niño years. During La Niña years, most of the models feature cold biases in Niño3 and Niño 3.4 regions except CCSM4, with warm biases in the Niño3.4 region.

Figure 2 displays the temporal evolution of Niño 3.4 index during El Niño and La Niña years. Overall, the NMME models capture the temporal evolution of El Niño/La Niña period quite well, though there are some biases in all the NNME models. Given such biases in the SST anomalies and evolution, the BU could overcome some of these biases by integrating useful information from historical observations.

NMME-CorM shows higher correlation value for Niño3/ Niño3.4 than NMME-MCor (Figures 3 and 4), indicating that the ensemble mean of NMME forecasts is better than individual NMME forecasts. Figure 3 shows the skill of the Niño3 forecasts for target months from January to December and lead months from 1 to 12 with different forecast methods. Overall, BU performs better in target months from January to March than in other target months, consistent with the changes of forecast skill of NMME-CorM with respect to different target months. Overall, NMME-CorM performs better in target months during boreal autumn and winter than in target months during spring and summer in terms of correlation (Figure 3), consistent with Barnston et al. (2015) and Kumar et al. (2017) who found that the predictability of ENSO is the lowest in spring and summer. The skill of NMME Niño3 forecasts depends on the lead month, and the skill of NMME-CorM drops with increasing lead time (Figures 3). For example, the forecast skill of
NMME (i.e., NMME-CorM) for Niño3 in terms of correlation is close to 1 (e.g., 0.95-0.98) at lead
month 1 but drops to ~0.6 for target months from January to April, and to ~0.4 for target months
from May to December at lead month 12 (still significant at the 5% significance level). This
reduction in forecast skill with increasing lead time suggests that NMME-CorM produces
promising results for the Niño3 index in terms of correlation, with a strong dependence on lead
month and target month (Barnston and Tippett, 2013; Barnston et al., 2012, 2015; Jin et al., 2008;
Kumar et al., 2017; Tippett et al., 2012).

Figure 3 also shows the forecasts of Niño3 in all target and initialization months using the
four BU methods listed in Table 2. For target months from January to May, the BU-Model
generally outperforms the skill of NMME-CorM/NMME-EM. As expected, the forecast skill in
both NMME and BU forecasts drops for increasing lead times. Similar to the skill obtained from
the equal weighting of the NMME forecasts, the forecast skill with the BU-Model drops at a slower
rate in target months from January to April than in target months from May to December when the
lead month increases from 1 to 12. For example, the forecast skill of the BU-Model for Niño3 in
terms of correlation is around 0.95-0.98 at lead month 1, around 0.6 for target month from January
to April and around 0.4 at lead month 12 for May-December target months. For June-July target
months, the BU-Model performs slightly better than NMME-CorM for short lead months 1-4, after
which the opposite is true. BU-Model-PCA is developed by applying BU to the loadings of all the
PCs, and aims to improve the forecast skill of BU by removing collinearity (see Section 2 for
details). In these target months, the BU-Model-PCA does not outperform the BU-Model. For
August-December target months, the BU-Model generally performs better than the NMME-CorM
in forecasting Niño3 (Figure 3).
We build the BU model based on the NMME forecasts with a correlation of 0.3 or higher (BU-Model-0.3) to test whether we can improve the performance of BU by keeping only the forecasts having a higher correlation with observations. BU-Model-0.3 does not perform better than the BU-Model for almost any of the target months (Figure 3), and this statement holds for different threshold values of correlation coefficient (figure not shown). Thus, the skill does not improve by focusing on a subset of models that exhibit a stronger relationship between forecasts and observations. The BU-Model-PCA/BU-PCA-Model-0.3 can slightly outperform BU-Model/BU-Model-0.3 for very short lead months (Figure 3). However, BU-Model/BU-Model-0.3 performs much better than the BU-Model-PCA/BU-PCA-Model-0.3 for longer lead months (Figure 3). This suggests that the application of PCA to the NMME forecasts prior to BU does not lead to a consistent improvement in the forecast skill for all lead months.

Figure 4 shows the results for Niño3.4, which are similar to those shown for the Niño3 index (Figure 3). For example, the BU-Model/BU-Model-0.3 outperform the NMME-CorM in target months January-May and September-December (Figure 4). However, for June-August target months, the BU-Model/BU-Model-0.3 perform better than NMME-CorM only for short lead months. Previous studies have shown the difficulties in forecasting ENSO during June-August because of the “Spring Predictability Barrier” which presents a challenge (Barnston and Tippett, 2013; Barnston et al., 2012; 2015; McPhaden, 2003; Tippett et al., 2012). The Spring Predictability Barrier is responsible for the drop in forecast skill during boreal spring and for the drop in skill of the forecasts made during boreal spring for the following seasons. For example, the skill of forecasts initialized in boreal spring drops faster than that of the forecasts initialized in August or November (Jin et al., 2008). Previous studies have reported low forecast skill for target months June-August initialized during spring (e.g., Torrence and Webster, 1998; Jin et al., 2008;
Barnston et al., 2015). Because the BU-Model-0.3/BU-Model-PCA-0.3 do not outperform BU-
Model/BU-Model-PCA, respectively, we will focus on the performance of BU-Model and BU-
Model-PCA in forecasting Niño3/3.4 henceforth.

The forecast skill (correlation) for Niño3/Niño3.4 using the BU-Model generally
outperforms NMME-CorM for January-May and September-December target months (Figures 3
and 4). For June-August target months, the BU-Model does not show improvements in forecast
skill for Niño3/Niño3.4 with respect to NMME-CorM. Figure 5 shows a summary of the values of
the correlation coefficient between forecasted and observed Niño indices using NMME-CorM,
BU-Model and BU-Model-PCA. The Spring Predictability Barrier in forecasting El Niño/La Niña
is evident for all the forecasts, with diminished skill for target months in late boreal spring to boreal
summer. The dependence of skill on season and lead month is also obvious for all the forecasts.
Overall, the BU-Model outperforms NMME-CorM in forecasting Niño3/3.4, particularly for short
lead months 1-5. In general, the BCA-Model-PCA does not outperform BU-Model in forecasting
Niño 3/3.4 (Figure 5). Figure S2 illustrates the differences in forecast skill between BU-
Model/BU-Model-PCA and NMME-CorM for Niño3.4 and Niño3. In general, the BU-Model
outperforms NMME-CorM for almost all short lead months. However, the BU-Model shows some
weakness in forecasting Niño3.4/Niño3 for June-August target months after lead month 5. BU-
Model-PCA shows similar results compared with the BU-Model for short lead months. However,
the BU-Model-PCA performs worse than the BU-Model for August-September target months and
lead months 10-12 for Niño3.4, and for June-November target months and lead months 10-12 for
Niño3. The largest improvements in forecasting Niño3/3.4 made by BU/BU-PCA compared with
NMME-CorM lie in the August-December target months and lead months 1-7.
The SDratio measures the ability of the forecasts to capture the dispersion of the observations. We find the NMME-EM forecasts tend to be overdispersed in comparison with the observed values for long lead months, especially in the January-June and October-December target months (Figure 6, top panels). Moreover, the NMME-EM forecasts tend to underestimate the dispersion in the observations for lead months 1-4 and July-October target months. The BU-Model largely outperforms the NMME-EM forecasts in terms of SDratio for almost all lead and target months because the SDratio values in BU-Model are closer to 1 (Figure 6, middle panels). BU-Model-PCA improves the SDratio by reducing dispersion for very short lead months but increases dispersion for the longest lead months 10-12 (Figure 6, bottom panels). This suggests that BU-Model-PCA does not improve the forecasting of ENSO compared with the BU-Model.

The RMSE values of the NMME-EM forecasts of Niño3/3.4 tend to decrease as the lead month becomes shorter (Figure 7, top panels). The largest RMSE occurs in the lead months 11-12 and the target months October-December. For Niño3.4, there are large RMSE values in the NMME-EM forecasts in the January target month with 10-12 lead months (Figure 8, top panel). Overall, the RMSE is smaller for the BU-Model than for NMME-EM, particularly for the short lead months, consistent with the improvements in correlation in Figures 5 and 7 (middle panels).

Moreover, the RMSE in BU-Model-PCA is also slightly smaller than that in NMME-EM for short lead months (Figure 7, bottom panels). To support the above discussions, Figure S3 illustrates the differences in the RMSE values between the BU-Model and NMME-EM, and between BU-Model-PCA and NMME-EM. Overall, BU outperforms NMME-EM by producing a smaller RMSE in Niño3/3.4 indices, especially for short lead months; BU-PCA produces similar RMSE compared with BU. It is noted that BU performs much better than BU-PCA in terms of correlation coefficient between forecasted and observed Niño indices for long lead months (Figures 4, 5 and S2).
However, the differences in RMSE between BU-Model and BU-Model-PCA appear to be smaller compared with the difference in correlation.

We use the Wilcoxon signed-rank test (DelSole and Tippett, 2014) to test whether the differences in the forecast skill (e.g., correlation and RMSE) between BU and NMME are statistically significant. Figure 8 shows that the differences in RMSE for Niño3.4 between BU and NMME are statistically significant at the 5% level for lead months 1-5, identical to those between BU and PCA-NMME. For the forecasts of Niño3, the differences in RMSE between BU and NMME are significantly significant for lead month 1-6, and this is also true for differences between BU and PCA-NMME. For the correlation coefficient, the differences in Niño3.4 between BU and NMME are statistically significant at lead months 1-5 and this is also true for the differences between BU and PCA-NMME (Niño3.4), between BU and NMME for Niño3, and between BU and PCA-NMME for Niño3. There are some significant differences between BU and PCA-NMME for Niño3 and Niño3.4 at lead month 12.

In addition to the deterministic measures of skill (i.e., correlation and RMSE), we also use Brier Skill Score to measure the forecast skill with BU and NMME. We focus on the forecasts for the upper and lower terciles of the Niño3.4 and Niño3 indices. Overall, the BU method outperforms NMME for the upper tercile of Niño3.4 and Niño3 at shorter lead months (Figure 9) and for the lower tercile, especially at short lead months (Figure 10). Overall, the forecast skill for the lower tercile of Niño3.4 is higher than for Niño 3 (Figure 10).

The 2015/2016 El Niño event is one of the strongest El Niño events since 1870 (Blunden and Arndt, 2016). Here we use this El Niño event as a case study to show the capability of the BU-Model in forecasting the Niño3/3.4 indices. We focus on the observed Niño3/3.4 index averaged over October-December (OND) in 2015 with a value of 2.6. The Niño3/3.4 indices forecasted by
the BU model are generally much closer to the observations than those forecasted by NMME-EM up to the lead month 10 (Figure 11). The forecasts of Niño3/Niño3.4 indices obtained during the OND of 2015/2016 with the BU model also produce much smaller biases than those achieved by NMME-EM even for lead month 10. In the lead month 9 the forecasted Niño3 index with NMME-EM is ~0.5 while the index obtained with the BU-Model is ~1.3. In the lead month 8, the forecasted Niño3 index during OND 2015 with NMME-EM is ~1 while the forecasted Niño3 with BU-Model is ~2. Therefore, the BU model performs much better than NMME-EM in forecasting this most recent strong El Niño event.

We have also examined whether longer or more reliable observations of SST can influence the forecast skill of the El Niño events (e.g., 1982/1983, 1997/1998 and 2015/2016). To accomplish this, we use the observed SST over the period 1870-2015 (BU-1870) and 1940-2015 (BU-1940) for the BU for the three El Niño events (Figure S4). There are some differences in the forecasts based on BU-1870 and BU-1940; overall, BU-1870 produces better forecast skill than BU-1940 for the 2015/2016 El Niño event (Figure S4), while the skill of BU-1940 and BU-1870 for the 1997/1998 and 1982/1983 events appears to be similar. Based on these analyses, we cannot find an obvious improvement in the prediction skill obtained from BU-1870 compared with that from BU-1940. Future studies should examine this issue in more details.

4. Discussion and Conclusions

Timely and accurate ENSO forecasts are likely to have major societal and economic impacts (e.g., agriculture and fishing). The NMME project has advanced our capability of forecasting key atmospheric and oceanic variables. In this study, we have assessed the ability of a Bayesian updating approach (BU) to improve the forecasts of the Niño3/3.4 indices, and compared
the results with those of the equally-weighted ensemble average of the NMME forecasts (NMME-EM).

The forecast skill for Niño3/3.4 using NMME-EM shows strong dependence on lead (initial) month and target month and is promising in terms of correlation, RMSE and SDRatio, especially at short lead months. For example, the correlation coefficient between forecasted (NMME-EM) and observed Niño3/3.4 indices is close to 1 for short lead months, with very small RMSE errors. The skill in terms of correlation for Niño3/3.4 with NMME-EM drops to 0.4-0.7 at lead month 12. Moreover, the forecast skill of Niño3/3.4 with NMME-EM decreases in target months from late spring to summer, due to the Spring Predictability Barrier.

Overall, the BU-Model outperforms NMME-EM in predicting Niño3/3.4 for almost all the target months and lead months in terms of correlation, RMSE, and SDRatio. The BU-Model outperforms NMME-EM forecasts in Niño3.4 for almost all lead months and target months. However, it does show some weaknesses in forecasting Niño3.4/3 for June-August target months and long lead months (e.g., 7-10) in terms of correlation, and it does not outperform the NMME forecasts for Niño3 for June-October target months and lead months 7-11. A caveat of this study is that the ENSO forecast can vary over decadal scales (Barnston et al., 2012; Zhao et al., 2016), and we would need to study longer periods to obtain more robust comparisons between Bayesian updating and NMME. For the 2014/2015 event, the prediction skill of Niño3.4 during October-December with BU-model is higher than NMME-EM for lead months 1-5 and 10, consistent with a better skill of BU at shorter lead months (Figure S5). Overall, the BU-Model performs better than NMME-EM for Niño3/3.4 in terms of SDRatio; but focusing on a subset of GCMs that showed stronger relationship between forecasts and observations does not improve the overall forecast skill. We also used PCA to examine the potential impacts of correlation among models on forecast
skill, but we did not find any significant improvement. Meanwhile, the performance of BU in forecasting Niño4 (Figure S6) is slightly worse than for Niño3/3.4. This might be due to the intrinsic low predictability of Central Pacific El Niño events. Further studies are required to improve the BU for Niño4, possibly by using a more sophisticated likelihood function and prior distribution.

The prediction skill that is obtained using BU-EM is comparable to, or slightly better than, that of current prediction models/schemes for Niño3/3.4. For example, at a 3-month lead time in the eastern equatorial Pacific, an intermediate coupled climate model produces a correlation of ~0.75 (Zheng and Zhu, 2016), while the NMME-EM and BU-CorM produce a correlation of more than 0.85. The BU-Model forecast skill is comparable to the skill that is obtained using CFSv1 and CFSv2 (with biases adjusted) as reported in Barnston and Tippett (2013). Our forecasts of Niño3.4 are also comparable to or slightly better than those obtained in Saha et al. (2014), particularly for short lead months. Our BU-Model slightly outperforms the results based on statistical models and dynamic models reported in Barnston et al. (2012) in terms of correlation and RMSE.

ENSO plays a central role in exciting teleconnections that modulate global weather and climate, such as tropical cyclones, precipitation and air temperature (e.g., Alexander et al., 2002; Ropelewski and Halpert, 1986; Zhang et al., 2012; 2015; 2016a; 2016b). Thus, our future work will assess whether the improvements in the prediction skill of Niño3/3.4 indices using BU-Model can heighten the prediction skill of these ENSO-driven meteorological variables and phenomena.

Acknowledgements: The authors thank the NMME program partners and acknowledge the help of NCEP, IRI and NCAR personnel in creating, updating and maintaining the NMME archive, with the support of NOAA, NSF, NASA and DOE. This study was partly supported by NOAA's
Climate Program Office's Modeling, Analysis, Predictions, and Projections Program, Grant #NA15OAR4310073, and Award NA14OAR4830101 from the National Oceanic and Atmospheric Administration, U.S. Department of Commerce. GV also acknowledges funding by the National Science Foundation under CAREER Grant AGS-1349827, and the Broad Agency Announcement Program and the Engineer Research and Development Center–Cold Regions Research and Engineering Laboratory under Contract W913E5-16-C-0002. The authors acknowledge insightful comments by three anonymous reviewers which improved the quality of this paper.
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Figure 2. Evolution of Niño3.4 in observations (black) and in the NMME forecasts with climate models (red/blue for El Niño/La Niña respectively) for El Niño and La Niña events. ‘Jan(0)’ represents the January in mature El Niño/La Niña phases.

Figure 3. Skill of the Niño3 forecasts for target months from January to December and lead months from 1 (0.5) to 12 (11.5) with BU-Model (red solid), BU-Model-0.3 (red dashed), BU-Model-PCA (orange solid), and BU-Model-PCA-0.3 (orange dashed). “NMME-CorM” (black solid line) denotes the skill of the ensemble mean (equally weighted) of all the NMME members while “NMME-MCor” (blue solid) denotes the mean skill of all NMME members. The y-axis indicates the strength of the correlation between the forecasts and the observed Niño indices. In the boxplots, the circle and the red line within the box represent the mean and the median, respectively; the limits of the box represent the 25th and 75th percentiles, while the limits of the whiskers the 5th and 95th percentiles.

Figure 4. Same as Figure 2 but for the Niño3.4 index.

Figure 5. The correlation values (shading) in NMME-CorM/NMME-EM (the ensemble mean of NMME; top panels), BU-Model (BU; middle panels) and BU-Model-PCA (BU-PCA; bottom panels) for Niño3.4 (left panels) and Niño3 (right panels).

Figure 6. Standard deviation ratio (SDratio, shading) using forecasts/observations in NMME-EM (NMME, top panels), BU-Model (BU, middle panels) and BU-Model-PCA (BU-PCA, bottom panels) for Niño3.4 and Niño3. A value of 1 is the ideal value.

Figure 7. Root mean square error (RMSE, shading) in NMME-EM (NMME, top panels), BU-Model (BU, middle panels) and BU-Model-PCA (BU-PCA, bottom panels) for Niño3.4 and Niño3.

Figure 8. Wilcoxon signed-rank test results for RMSE (left) and correlation coefficient (right) in different BU versions and NMME for Niño3 and Niño3.4 indices at lead months 1-12. Dark-shaded regions indicate that the differences are statistically significant.

Figure 9. Brier skill score for the upper tercile in NMME-EM (NMME, top panels), BU-Model (BU, middle panels) and BU-Model-PCA (BU-PCA, bottom panels) for Niño3.4 and Niño3.

Figure 10. Brier skill score for the lower tercile in NMME-EM (NMME, top panels), BU-Model (BU, middle panels) and BU-Model-PCA (BU-PCA, bottom panels) for Niño3.4 and Niño3.

Figure 11. The observed values (black) and forecasts with BU (red) and NMME (blue) for (a) Niño3 and (b) Niño3.4 index averaged over the October-December (OND) of the 2015/2016 El Niño. The grey curves represent the Niño3/3.4 indices that were predicted by each of the eight available NMME models (mean of the members).
Table 1. The available period, ensemble size and lead months of the NMME climate models. The available period does not reflect the presence of gaps; the ensemble size indicates the largest number of members per model and does not reflect missing data for one or more members.

<table>
<thead>
<tr>
<th>Model</th>
<th>Available Period</th>
<th>Ensemble Size</th>
<th>Lead Times (months)</th>
</tr>
</thead>
<tbody>
<tr>
<td>CCCma-CanCM3</td>
<td>1981 - Present</td>
<td>10</td>
<td>0.5 – 11.5 (1-12)</td>
</tr>
<tr>
<td>CCCma-CanCM4</td>
<td>1981 - Present</td>
<td>10</td>
<td>0.5 – 11.5 (1-12)</td>
</tr>
<tr>
<td>COLA-RSMAS-CCSM3</td>
<td>1982 - Present</td>
<td>6</td>
<td>0.5 – 11.5 (1-12)</td>
</tr>
<tr>
<td>COLA-RSMAS-CCSM4</td>
<td>1982 - Present</td>
<td>10</td>
<td>0.5 – 11.5 (1-12)</td>
</tr>
<tr>
<td>NCEP CFSv2</td>
<td>1982 - Present</td>
<td>24</td>
<td>0.5 – 9.5 (1-10)</td>
</tr>
<tr>
<td>GFDL CM2.1</td>
<td>1982 - Present</td>
<td>10</td>
<td>0.5 – 11.5 (1-12)</td>
</tr>
<tr>
<td>GFDL FLOR B01</td>
<td>1980 - Present</td>
<td>12</td>
<td>0.5 – 11.5 (1-12)</td>
</tr>
<tr>
<td>NASA-GEOS5</td>
<td>1981 - Present</td>
<td>12</td>
<td>0.5 – 9.5 (1-10)</td>
</tr>
<tr>
<td>NCAR-CESM1</td>
<td>1980-2010 and 2016 to present</td>
<td>10</td>
<td>0.5 – 11.5 (1-12)</td>
</tr>
</tbody>
</table>
Table 2 Description of the four ways in which BU is applied in this study.

<table>
<thead>
<tr>
<th>BU Methods</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>BU-Model</td>
<td>BU is applied to the eight models in NMME</td>
</tr>
<tr>
<td>BU-Model-0.3</td>
<td>BU is applied to the NMME models for which the correlation with observed El Niño indices is greater than 0.3</td>
</tr>
<tr>
<td>BU-Model-PCA</td>
<td>BU is applied to the loadings of PCs for the eight models in NMME</td>
</tr>
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