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THESIS

**USING BAYESIAN STATISTICAL POSTPROCESSING
METHODS TO IMPROVE LOCAL WIND FORECASTS**

by

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March 2021

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IMPROVE LOCAL WIND FORECASTS**

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Submitted in partial fulfillment of the
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ABSTRACT

This thesis explores the use of Bayesian statistical postprocessing to rapidly train a highly accurate forecast from a 1 km resolution gridded WRF model forecast over a 100 km by 100 km area. These methods leverage three modeled forecast variables—10 m winds, sea-level pressure, and terrain elevation—in conjunction with downstream observations and prior model runs to identify model inaccuracies. Using only three days of data, a Bayesian corrected forecast is produced and analyzed for accuracy and improvement over the original model run relative to real-world observations. Over 90% of the resulting forecasts saw improvement over the raw model forecasts in root mean squared error, and over 87% of the forecasts saw improvement in mean error over the raw model forecasts. Extreme circumstances saw improvements in accuracy of over 9 knots while overall improvements were reliably seen both in accuracy and precision among Bayesian corrected forecasts. These findings are significant as they suggest that Bayesian statistical postprocessing methods work and should be both employable at rapid rates, and result in more accurate forecasts.

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TABLE OF CONTENTS

I.	INTRODUCTION.....	1
II.	BACKGROUND	5
	A. WHAT HAS BEEN DONE?	5
	B. WHAT HAS NOT BEEN DONE?.....	6
	C. WHY THIS IDEA?	7
	D. LIMITATIONS	8
	E. METHODS	8
III.	RESULTS	11
IV.	CONCLUSION	23
	LIST OF REFERENCES.....	25
	INITIAL DISTRIBUTION LIST	27

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LIST OF FIGURES

Figure 1.	Box and Whisker Plots of the Mean Error of Raw Model Forecasts (grey) versus the Bayesian Corrected Forecast (blue).	17
Figure 2.	Box and Whisker Plots of Mean Error of All 0000UTC Model Run Forecasts (grey) versus the Bayesian Corrected Forecast (blue).	18
Figure 3.	Box and Whisker Plots of Mean Error of All 1200UTC Model Run Forecasts (grey) versus the Bayesian Corrected Forecast (blue).	19
Figure 4.	Box and Whisker Plots of the Root Mean Squared Error of Raw Model Forecasts (grey) versus the Bayesian Corrected Forecast (blue).	20
Figure 5.	Box and Whisker Plots of Root Mean Squared Error of All 0000UTC Model Run Forecasts (grey) versus the Bayesian Corrected Forecast (blue).	21
Figure 6.	Box and Whisker Plots of Root Mean Squared Error of All 1200UTC Model Run Forecasts (grey) versus the Bayesian Corrected Forecast (blue).	22

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LIST OF TABLES

Table 1.	Forecast Error Page 1 of 5	12
Table 2.	Forecast Error Page 2 of 5	13
Table 3.	Forecast Error Page 3 of 5	14
Table 4.	Forecast Error Page 4 of 5	15
Table 5.	Forecast Error Page 5 of 5	16

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LIST OF ACRONYMS AND ABBREVIATIONS

ASOS	Automated Surface Observing System
ECMWF	European Centre for Medium-Range Weather Forecasts
EMOS	Ensemble Model Output Statistics
GALWEM	Global Air-Land Weather Exploitation Model
GFS	Global Forecast System
ICLAMS	Integrated Community Limited Area Modeling System
NAM	North American Mesoscale Model
NCEP	National Centers for Environmental Prediction
NPS	Naval Postgraduate School
PPD	Posterior Predictive Distribution
SREF	Short Range Ensemble Forecast
WRF	Weather Research and Forecasting Model
UTC	time zone indicator for Universal Time

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I. INTRODUCTION

Over the years, responding appropriately to weather has proven to be a factor of increasing importance for human and resource protection within the U.S. military. Take Hurricane Florence, for example. The resulting damage cost billions of dollars at Camp Lejeune, North Carolina, and could have cost the military billions more had protective measures not been taken (Smith 2019). In preparation for Hurricane Florence, the Navy sortied its ships to protect the fleet. As reported by *Navy Times*, “The Navy counted nearly 30 vessels from Naval Station Norfolk and Joint Expeditionary Base Little Creek leaving Monday before high winds and rain lash the mid-Atlantic coast” (Jowers et al. 2018). Leaving those ships in port would have been to risk billions of dollars in damage to U.S. military assets. Furthermore, to sortie 30 vessels undoubtedly cost the Navy millions of dollars. The action taken by the Navy is evidence of just how important and valuable those resources are.

Since weather greatly impacts military operations, it is crucial to improve the military’s knowledge of weather forecasting and its impacts. Take the U.S. Air Force’s 557th Weather Wing, for example. According to its mission statement, the 557th Weather Wing aims for “Maximizing America’s Power through the Exploitation of Timely, Accurate, and Relevant Weather Information; Anytime, Everywhere” (557th Weather Wing 2020). The goal is to forecast as accurately as possible and in a relevant manner, so that weather can be exploited against the enemy and anticipated to protect valuable assets and personnel.

On 16 June of 2017, a tornado-producing storm passed over Offutt Air Force Base. Caught off guard, the maintenance crew attempted to secure their most critical assets: two E-4B “Doomsday Jets.” Not only were lives put at risk in the attempt to secure the aircraft, but both E-4Bs still were damaged. Additionally, eight other aircraft were damaged with an appraisal of \$8.3 million worth inflicted on the E-4Bs alone (Liewer 2017). This event put Airmen’s lives at elevated risk, cost millions of dollars in damage, and temporarily reduced the Air Force’s capability by grounding two of only four aircraft tasked with the mission of “continuing national communications in the event of nuclear war” (Liewer

2018). The implications of such a reduction in capabilities is burdensome. In order to prevent more damage to U.S. resources, weather forecasting capabilities must be improved upon. The U.S. military is not only expected to forecast accurately in America. Rather, the military is expected to have global reach in its warfighting capabilities. As a result, the capability to forecast threats and weather-related catastrophes should not be limited to the nation's borders. Instead, superior weather forecasting capabilities should exist wherever U.S. forces may exist.

Improving forecast accuracy overseas presents its own set of challenges. With stateside resources, the United States has well-trained models, such as the North American Mesoscale Model (NAM), which can apply its seasoned data assimilation over small scales more accurately relative to global, large-scale models. When compared to the Global Forecast System (GFS) or the Global Air-Land Weather Exploitation Model (GALWEM), localized models such as the NAM outperform their global counterparts on a local scale. While localized grid point models such as the NAM may have more accuracy on localized scales, one big problem exists in relation to global reach: it is difficult to train high resolution models in data sparse regions. The abundance of tools such as radar, Automated Surface Observing Systems (ASOS), high-resolution weather satellites, and nationwide information sharing platforms in the United States allows American-tailored models to be highly trained, while pre-existing data collection infrastructure does not and may not ever exist overseas in an area as broad as North America. Additionally, when enough data does exist, the process of data assimilation can be a very time-consuming process.

For these reasons, the military often aims to use global forecasting models such as the GALWEM for their overseas forecasting purposes. As stated by Ralph Stoffler, acting Director of Weather for the United States Air Force, "Just a little time back; we had multiple models, multiple things serving different command and control architectures with different forecasts. We are now down to one model that serves everybody." Such a decision provides continuity among forecasts and allows for global reach. While migrating to a single global model provides the U.S. Air Force with global reach, relying on it solely will sacrifice accuracy at the local scale. Perhaps high-resolution models could be used to supplement local data on top of the synoptic scale data provided by global model forecasts

without decentralizing the organizational structure of weather support beyond its current state. If the U.S. military had the capability to use higher resolution forecasting models globally, would it truly be beneficial? Currently, the costs of using high-resolution models globally, at least in the Air Force, outweigh the benefits. What if a high-resolution model could be rapidly trained to forecast in a small, localized area anywhere in the world?

Theoretically, Bayesian statistics could be used to correct forecasts to become more accurate and effectively “train” the model at a more rapid rate. By applying the Naval Postgraduate School’s (NPS) Bayesian model to wind forecasts, this thesis is intended to explore the effectiveness of applying Bayesian statistical postprocessing methods to modern forecasting at the local scale. Its findings are intended to create more discussion on the feasibility of its employment and open the door to further research. If these methods work, they could indicate the potential to provide more reliable and timely resource protection for U.S. military assets through Bayesian statistical postprocessing of weather forecasts. The ability to deliver more accurate forecasts globally and at a local scale could re-shape the way weather is utilized in the U.S. military.

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II. BACKGROUND

A. WHAT HAS BEEN DONE?

As seen in Dale Poirier's research, Bayesian statistics have become increasingly more utilized in the solution of modern-day problems. Such evidence can be seen in the exponentially increasing number of articles mentioning "Bayes" or "Bayesian" throughout numerous commonly used academic databases over time. With a realization for its utility, Bayesian statistics are being used and researched in rapidly increasing proportions, especially among economists and statisticians (Poirier 2006). Bayesian statistics have even been utilized to model presidential elections with alarming accuracy (Alexander 2017). While the knowledge of Bayesian statistics continues to grow, its impact on meteorology also continues to grow. Included below are several examples in which Bayesian statistics have been used to further research in meteorology.

In one study, in order to find more accurate but also computationally more efficient forecasting methods for extreme weather events, two postprocessing correction methods were applied in weather forecasting: 1) simple linear regression and 2) Bayesian linear regression to dual model ensemble forecasts using the Weather Research and Forecasting (WRF) Model and the Integrated Community Limited Area Modeling System (ICLAMS) over a 2 km gridded region in the Northeastern United States. Using ASOS data for 13 significant weather events during the years 2004–2011 for model evaluation and error optimization and up to 10,000 variance sets as prior data, linear regression methods were used to adjust forecasts for four significant weather events occurring in the years 2011–2013. This test found that with up to 20 variance sets and 10–13 storms, forecast accuracy could be maximized using Bayesian linear regression over simple linear regression. Bayesian techniques outperformed raw model data up to 30% on average over the full gridded space and up to 60% at individual stations (Yang et al. 2017).

In 2017, Robert Travis Wendt wrote a dissertation in which he explored the efficacy of using Bayesian statistical postprocessing in order to "nudge" Ensemble Model Output Statistics (EMOS) toward greater accuracy. He found that when using downstream

observations as posterior beliefs in conjunction with forecast data from the National Centers for Environmental Prediction (NCEP) Short Range Ensemble Forecast Model (SREF), uncertainty could be identified using Bayesian statistics. The above methods combined with Markov Chain Monte Carlo sampling allowed for calibrated posterior predictive distributions (PPDs). His research yielded positive results in forecast accuracy when forecasting maximum and minimum surface temperatures as well as maximum wind speeds over 24-hour periods in relation to the raw model output at individual point forecast locations.

Jones (2018) used Wendt's algorithm to showcase the capability to correct ceiling and visibility forecasts from the NAM. Using 94 different forecast fields from each NAM forecast as the predictor variables and prior ASOS data for posterior distributions, Bayesian inference was used to adjust ceiling and visibility forecasts at a single grid point. Using 1183 hourly observations as training data, 196 hours' worth of corrected forecasts were produced. This experiment had significant findings in that error reduction and skill improvement were observed in the corrected forecasts relative to the raw NAM forecasts (Jones 2018). In a separate study by Cummings (2018), Wendt's machine learning algorithm was used to more accurately correct European Centre for Medium-Range Weather Forecasts (ECMWF) EMOS data using "B-Decks" or historical hurricane data as posterior data. Data assimilation was completed by using storm track and intensity data from the years 2010–2016 to train the ECMWF model and corrections were applied to 2017 ECMWF forecasts. These methods successfully removed model bias in most cases, resulting in more accurate forecasts (Cummings 2018).

B. WHAT HAS NOT BEEN DONE?

As seen in the examples above, Bayesian statistical postprocessing has been used in a wide variety of ways. Most common cases involve in depth research of strictly severe weather events, but many studies also focus on simple daily forecasting. Alternatively, Bayesian statistics have not yet been used in a multitude of ways in the weather community. This research is unique as it aims to use Bayesian statistics to more accurately forecast surface winds throughout an entire 100 km by 100 km gridded region while limited to the

use of only one high resolution forecasting model and downstream ASOS and other surface observations. Furthermore, statistical training will be completed using only three downstream observation periods prior to the forecast, and specific weather events will not be chosen as training or test data. Instead, training and forecasts will be completed over a pre-determined time period to limit “cherry picking” of like data for data assimilation. Such research has never been conducted prior to this thesis’ study.

C. WHY THIS IDEA?

This idea has numerous potential benefits. Although Wendt noted that “regardless of the data available for training, Bayesian models appear to offer better predictive performance,” the use of only significant or severe events to train a forecasting model should logically yield a model that will only forecast most accurately during severe events. Wendt also noted in his research that similar training data will yield more effective results. Simple logic implies that more recent or nearer weather events should relate more to current sensible conditions than events further away in time. Furthermore, diurnal trends should theoretically imply similar conditions at the same point in time during the day. By utilizing common sense patterns, and Wendt’s Bayesian algorithm, training time could theoretically be minimized, allowing for a shorter training period prior to the application to a high-resolution area forecast.

Higher resolution forecasting allows for the recognition of small-scale weather effects that can often be overlooked in larger scale forecasting. If small-scale weather effects can be recognized more reliably, and Bayesian statistical postprocessing can make forecasts more accurate, weather sensitive thresholds can be made more precise, and battlefield awareness can be maximized. Such capabilities could allow the military to use tools that are highly sensitive to weather conditions in austere environments more often. The identification of more precise thresholds would allow for greater security through more accurate forecasting, and minimal time requirements for data analysis would allow for more rapid employment. More accurate forecasting in austere locations would also allow for more accurate predictions of adversary capabilities. These benefits are what the current methods seek to help maximize one day through forecast improvement. These reasons

drive the potential desire for rapid data analysis, while avoiding the “cherry picking” of similar weather events, as customers would likely not have such luxuries. As a result, these methods seek to allow for a more accurate, high resolution forecasting method to be used in all conditions.

Additionally, the current research intends to rely on only one forecasting model. The military’s ability to operate with minimal resources such as fewer forecasting models could allow for the preservation of the model’s integrity as greater security can be focused on a single entity as opposed to many. Furthermore, one model achieves lower monetary cost, and less computational power requirements.

D. LIMITATIONS

This experiment will be limited by the tools used. For example, this research will rely on existing ASOS and other surface sites to gather observational data for both model training and model performance evaluation. Performance analysis can only be evaluated at points where surface observations can provide data for comparison. The ability to gather observations may be the single most restrictive factor in this experiment. Without observations, verification of forecast performance cannot be quantified. Time is another limitation. The amount of time it takes to analyze the training data and create a forecast will be crucial in determining the validity of these methods. Real world application would require that data be available well in advance of the onset of a weather condition. Should the data analysis and the process of creating the forecast take too long, these methods would prove useless as there is no need to forecast for the past.

E. METHODS

Using Wendt’s algorithm, 1 km grid resolution WRF data was used. Forecast fields were chosen to be used as predictor variables. Predictor variables used in this study were the WRF predicted 10 m winds, sea-level pressure, and terrain elevation. The experiment is conducted using a gridded model spanning 100 square kilometers in area, centered on the Monterey Bay in Monterey, California. Over the course of three days prior to the forecast, ASOS and other observations at approximately 50 locations were used for Bayesian inference. Only the approximate number of surface observations is given because

the availability of observational data varied throughout the course of the experiment. At times, data corruption, or temporary loss of services effected select surface observations in an inconstant manner. Using the observations, the algorithm analyzes modeled wind inaccuracies. Modeled winds and predictor variables can be compared to observed winds while the algorithm detects relationships between forecast fields and the resulting forecast. Once modeled error is recognized, the algorithm “nudges” the WRF forecast proportionally, based on the resulting PPD. The resulting windspeed (not direction) forecast in meters per second is then analyzed for accuracy relative to ASOS and other surface observations at the nearest grid point and compared to the forecast produced by the pure WRF data.

The current work initially used Wendt’s algorithm in a trial period where Bayesian inference was applied at every grid point across the entire extent of the forecast area. These methods proved to be inefficient as observations for verification could only be attained near a portion of the points. If verification could not be complete at unavailable locations, time could be saved by forecasting at only verifiable locations. As a result, the Bayesian inference was applied again but only at applicable grid points which could be paired with surface observation points. Removing the number of points at which the Bayesian inference was applied cut down on processing time and allowed for the use of less processing power.

To conduct the experiment, 20 days of surface data were chosen when WRF forecasts were available, which was a limiting factor in the experiment. These days span from 02 June to 22 June of 2018. These observations were used for statistical model training, and performance verification.

Statistical model training was completed by using three observation periods to train the algorithm, each taken during the three consecutive days prior to the upcoming forecast, at the same diurnal time as the forecast itself. For example, when referencing Row 1 on Table 1: *the forecast was a 3 hour long forecast valid at 0300 UTC, meaning that the forecast was made using model data from the 0000 or midnight UTC model run on the 7th. 0300 UTC surface observations were ingested in the Bayesian algorithm for June 4th, 5th, and 6th. Using the observations from days prior, and the 0000 UTC WRF model run for the*

7th, Bayesian inference was made on top of the WRF forecast, resulting in an adjusted forecast for the 7th valid at 0300 UTC.

All Bayesian corrected forecasts were compared alongside surface observations that were valid for the same time as the forecast. Mean error (ME) of the forecasts at all observable points was calculated relative to the surface observations given the assumption that any variation from the observation in the forecast was error. Root mean square error (RMSE) was also calculated at all observable locations. Finally, ME and RMSE were also calculated for all the forecasts when made using only pure WRF model data. Box and whisker plots and comparisons in performance among the WRF model forecasts alone and the Bayesian corrected forecasts were made. Both ME and RMSE were chosen so that biases in the methods used may become more apparent through comparison in results between the two. Additionally, using ME will allow for the analysis of negative results while RMSE does not preserve negative margins for resulting precision analysis.

III. RESULTS

In running a trial period, Wendt's algorithm was successful in nudging forecasts at all grid points across the entirety of the forecast area. Using minimal computing power (a laptop), it took approximately 3 hours to apply the Bayesian inference across the entirety of the forecast area. After pairing down the application to only applicable points where observations could be used, each model run took approximately 15 minutes on the same computer. Using the paired down application, 194 forecasts were produced with Bayesian inference. Assuming observations as ground truth at correlating points; 90.2062% of the forecasts saw overall improvement in the Bayesian application versus the raw WRF forecasts in RMSE. Additionally, 87.6289% of the forecasts saw overall improvement in the Bayesian application versus raw model forecasts in ME. Little correlation was found in forecast performance relative to the length or the valid hour of the forecast. As displayed in Tables 1 through 5, training days, forecast length, valid time, ME, and RMSE were calculated and recorded for both the pure model data and the Bayesian corrected data. As seen in Tables 1 through 5, when noted in the right two columns, a green highlight depicts an improvement of performance in the Bayesian corrected data over the pure model data while red depicts no improvements or a regression in performance.

Table 1. Forecast Error Page 1 of 5

Fcst hr	V hr	V Day	T Day 1	T Day 2	T Day 3	Fcst ME	Fcst RMSE	Bayes ME	Bayes RMSE
3	3	7	4	5	6	-2.0835743	3.1983794	0.558248	2.1970003
3	3	8	5	6	7	-1.5526328	2.4075250	0.5410155	1.8871266
3	3	9	6	7	8	-2.7787125	3.5691470	0.0043143	1.9890242
3	3	10	7	8	9	-3.7058162	4.9089287	0.0189103	2.829432
3	3	11	8	9	10	-2.2325494	3.8011887	0.752847	2.5430208
3	3	12	9	10	11	-1.2343466	2.2629011	0.8801707	2.0846805
3	3	13	10	11	12	-1.7837785	2.7211735	0.5419637	2.105744
3	3	14	11	12	13	-2.2863890	3.1384442	0.2313895	2.1325408
3	3	15	12	13	14	-2.6921483	3.4803484	-0.8936905	1.9491664
3	3	16	13	14	15	-2.7404259	3.3586743	-0.2303774	1.7063015
3	3	17	14	15	16	-3.5507760	5.2458902	0.8389056	2.7223856
3	3	18	15	16	17	-1.9868454	2.7960658	0.3431507	1.3282596
3	3	19	16	17	18	-1.6813573	2.4532686	1.0028686	1.9662625
3	3	20	17	18	19	-1.3008100	2.7841625	1.4865181	2.7218609
3	3	21	18	19	20	-1.1186498	3.2858192	1.652761	3.2821599
3	15	7	4	5	6	-1.4610217	2.3324344	0.1611455	1.6967548
3	15	8	5	6	7	-0.4321682	1.8321648	1.1114847	1.9520475
3	15	9	6	7	8	0.0615044	1.9462868	1.0475119	1.8817906
3	15	10	7	8	9	0.0173602	1.6417231	0.600304	1.7108949
3	15	11	8	9	10	-0.5341686	1.2788502	-0.1005869	0.9603329
3	15	12	9	10	11	-0.4739308	1.1201816	-0.3474983	1.0662538
3	15	13	10	11	12	-1.4928876	1.9536548	0.3251072	1.4999856
3	15	15	12	13	14	-1.8651663	2.6291003	0.0153563	1.5361105
3	15	16	13	14	15	-2.6381984	3.3026847	0.0388529	1.3706775
3	15	17	14	15	16	-1.1950170	1.8088878	0.4492624	1.1824386
3	15	18	15	16	17	-0.1486717	1.1202851	0.174938	0.8641129
3	15	19	16	17	18	-0.6594524	1.3827610	0.5270647	1.2996985
3	15	20	17	18	19	-2.1852198	3.0707490	0.0210101	1.4382353
3	15	21	18	19	20	-1.3086220	2.6602361	1.1196002	2.1208603
6	6	7	4	5	6	-1.7011097	2.6521439	0.3877079	1.5809531
6	6	8	5	6	7	-1.4588059	2.2530640	0.360421	1.6654502
6	6	9	6	7	8	-1.6809725	2.6582879	0.4099843	1.7200559
6	6	10	7	8	9	-2.5202091	3.5822840	0.3816724	2.2251576
6	6	11	8	9	10	-1.8528962	2.8698804	0.5205109	2.1255646
6	6	12	9	10	11	-0.9428421	1.7686586	0.3561436	1.6684685
6	6	13	10	11	12	-1.8873502	2.5745716	0.1313626	1.7436851
6	6	15	12	13	14	-1.1993015	1.9980953	0.0706336	1.3933961
6	6	16	13	14	15	-1.5942885	2.5942587	-0.1786738	1.7827532
6	6	17	14	15	16	-2.4666037	3.2793954	0.3808793	1.6500832
6	6	18	15	16	17	-0.0077167	1.4896390	0.7138938	1.5397851
6	6	19	16	17	18	-1.1834050	1.8318410	0.6241016	1.4219492
6	6	20	17	18	19	-1.7488537	2.5916970	-0.0817479	1.5980631
6	6	21	18	19	20	-1.0167391	2.8808329	1.4922091	2.9861733
6	18	7	4	5	6	-1.0131200	2.0847093	0.752142	1.7058041
6	18	8	5	6	7	-0.8691290	2.4625123	1.6644416	2.6510476
6	18	9	6	7	8	-2.0344858	3.2097637	0.4528813	2.3106637

Table 2. Forecast Error Page 2 of 5

Fcst hr	V hr	V Day	T Day 1	T Day 2	T Day 3	Fcst ME	Fcst RMSE	Bayes ME	Bayes RMSE
6	18	10	7	8	9	-1.9316578	2.5708412	0.2306889	1.6896336
6	18	11	8	9	10	-0.3970097	2.1563367	1.4341971	2.3683199
6	18	12	9	10	11	-1.1799981	2.1261548	0.8437362	1.9273694
6	18	13	10	11	12	-1.3686954	1.9345675	0.1541119	1.3514381
6	18	14	11	12	13	-1.2886296	2.3531054	0.4004534	1.7535973
6	18	15	12	13	14	-1.7172100	2.6121505	0.0450831	1.6377846
6	18	16	13	14	15	-2.2837371	3.4521749	0.6038727	1.9052258
6	18	17	14	15	16	-2.0404138	2.6475038	0.9786669	1.8738675
6	18	18	15	16	17	-0.3215397	1.7495687	1.8127237	2.6983052
6	18	19	16	17	18	-2.2029180	2.8118243	-0.4164214	1.4625065
6	18	20	17	18	19	-1.3540428	2.9840734	1.165684	2.2952818
6	18	21	18	19	20	-1.7160551	2.8811386	0.328762	2.1302328
9	9	7	4	5	6	-1.8077374	2.5879792	0.2707128	1.3476557
9	9	8	5	6	7	-1.2720771	2.2804091	0.3678495	1.6088739
9	9	9	6	7	8	-1.0321036	2.0630155	0.6563372	1.6576269
9	9	10	7	8	9	-2.0816137	3.3292711	0.4300987	1.9646456
9	9	11	8	9	10	-1.8632285	2.4248329	0.1054876	1.0337711
9	9	12	9	10	11	-0.9122188	1.6084654	-0.160689	1.4012521
9	9	13	10	11	12	-1.2122837	1.9391932	0.778714	1.8410795
9	9	15	12	13	14	-1.5547054	2.3305010	-0.2412018	1.440347
9	9	16	13	14	15	-1.3488992	2.0297984	0.0031977	1.3512394
9	9	17	14	15	16	-2.4157734	2.9787357	-0.0572914	1.4971975
9	9	18	15	16	17	-0.5758219	1.1263859	0.3395066	0.8793903
9	9	19	16	17	18	-0.4448936	1.2842629	0.4660156	1.4541529
9	9	20	17	18	19	-1.0845187	2.3749746	1.0102734	2.1173111
9	9	21	18	19	20	-1.5439432	2.7713406	0.2255906	2.0031123
12	0	6	2	3	5	-3.0134991	4.0304753	-0.0308513	2.6816638
12	0	7	3	5	6	-3.2709768	4.3969214	0.4151469	2.4392768
12	0	8	5	6	7	-3.6356832	4.6552688	0.7992889	2.4863291
12	0	9	6	7	8	-3.6328840	4.9802475	1.3082362	3.0792376
12	0	10	7	8	9	-5.1031496	5.8188014	1.754511	3.2829564
12	0	11	8	9	10	-4.8081113	5.9564539	1.1044844	3.1862601
12	0	12	9	10	11	-1.4480559	2.4563753	0.8880827	2.3367969
12	0	13	10	11	12	-2.1635128	3.1783558	0.560413	2.3761859
12	0	14	11	12	13	-1.5767113	2.9654958	1.2551289	2.6536964
12	0	15	12	13	14	-1.9618731	2.8365133	-0.2283042	1.8169229
12	0	16	13	14	15	-2.3852914	3.0803528	-0.0043063	1.7632712
12	0	17	14	15	16	-5.1553682	6.0879997	0.0929838	2.6432276
12	0	18	15	16	17	-3.6612829	4.2015303	0.6397377	1.8042988
12	0	19	16	17	18	-2.2854214	3.0985125	0.7259642	2.0097563
12	0	20	17	18	19	-2.0811824	3.5093782	0.890695	2.8374541
12	0	21	18	19	20	-1.2164946	3.2538064	1.7080068	3.2771861
12	0	22	19	20	21	-1.5545408	3.0262029	0.7115021	2.5624444
12	12	7	4	5	6	-1.7000239	2.6482545	0.2627025	1.4144854
12	12	8	5	6	7	-1.2164114	2.0190564	0.4045198	1.5568173
12	12	9	6	7	8	-1.3495051	1.8700408	0.1299997	1.1170377

Table 3. Forecast Error Page 3 of 5

Fcst hr	V hr	V Day	T Day 1	T Day 2	T Day 3	Fcst ME	Fcst RMSE	Bayes ME	Bayes RMSE
12	12	10	7	8	9	-1.6773468	2.5924937	0.0268116	1.6916342
12	12	11	8	9	10	-1.5542179	2.0735762	0.0885963	1.2318555
12	12	12	9	10	11	-1.0983812	1.5923489	-0.2701907	1.0411463
12	12	13	10	11	12	-0.8395794	1.7608330	1.055188	1.9385769
12	12	15	12	13	14	-1.1974862	2.0735382	0.0089847	1.5529158
12	12	16	13	14	15	-1.7239455	2.2862669	-0.2667241	1.2539922
12	12	17	14	15	16	-1.5730768	2.0361619	0.2451781	1.3135395
12	12	18	15	16	17	-0.0730369	1.1921205	0.4269934	1.2062843
12	12	19	16	17	18	-0.9676560	1.4308932	0.688615	1.4564249
12	12	20	17	18	19	-0.6811057	2.3577588	1.536844	2.6421965
12	12	21	18	19	20	-1.3785096	2.7028125	0.2091616	1.9081685
15	3	7	3	5	6	-2.3321145	3.3129710	0.6325256	2.0796653
15	3	8	5	6	7	-2.5165512	3.6250013	0.3581448	1.9711387
15	3	9	6	7	8	-2.8027752	3.6966280	0.8038381	2.1519304
15	3	10	7	8	9	-4.3230564	5.3068435	1.0728411	3.0247715
15	3	11	8	9	10	-3.2398396	4.5389510	0.6311175	2.5348095
15	3	12	9	10	11	-1.5328257	2.3278513	0.5806522	2.1687236
15	3	13	10	11	12	-1.7030808	2.7187782	0.7222266	2.2718133
15	3	14	11	12	13	-2.3177409	3.1384644	0.5135659	2.187826
15	3	15	12	13	14	-1.5099517	2.2450230	-0.1697335	1.6308631
15	3	16	13	14	15	-2.1570238	2.9666571	-0.164851	1.7111758
15	3	17	14	15	16	-3.7269881	4.7031682	0.1453781	2.4313131
15	3	18	15	16	17	-2.8318440	3.3194534	-0.0042212	1.2341276
15	3	19	16	17	18	-1.2858701	2.4068563	0.8504547	2.0365562
15	3	20	17	18	19	-1.6067151	3.0173926	1.378483	2.6588168
15	3	21	18	19	20	-0.9586473	3.4447310	1.78705	3.4106664
15	3	22	19	20	21	-1.5025192	2.9170775	0.333946	2.2701527
15	15	7	4	5	6	-1.3336937	2.1403697	0.2463911	1.5332881
15	15	8	5	6	7	-0.8720049	1.7432657	0.6263298	1.4587439
15	15	9	6	7	8	-0.8927369	1.9870916	1.049365	1.8104826
15	15	10	7	8	9	-1.8498121	2.5795987	0.1033433	1.5599785
15	15	11	8	9	10	-1.2372934	1.8083822	0.0519946	1.0456748
15	15	12	9	10	11	-1.0497181	1.5794395	-0.5687479	1.2604946
15	15	13	10	11	12	-0.7918222	1.4842616	0.8829698	1.5851119
15	15	15	12	13	14	-0.7252552	2.0959574	0.5163668	1.826618
15	15	16	13	14	15	-1.7689237	2.6838178	0.0089822	1.3302494
15	15	17	14	15	16	-1.8570032	2.3512369	0.112899	1.0790034
15	15	18	15	16	17	-0.5424769	1.2688781	-0.0914535	0.8394442
15	15	19	16	17	18	-0.5156323	1.2452722	0.603401	1.3409716
15	15	20	17	18	19	-1.4202575	2.3645228	0.3280135	1.4470023
15	15	21	18	19	20	-1.5929764	2.7170609	0.850284	1.9700603
18	6	7	3	5	6	-2.2894359	3.0640705	0.1585425	1.5143155
18	6	8	5	6	7	-2.0700755	2.7712187	0.1477903	1.6342915
18	6	9	6	7	8	-1.9213078	2.8538991	0.4359234	1.8067426
18	6	10	7	8	9	-4.2305752	4.9579658	0.3538718	2.306179
18	6	11	8	9	10	-2.1010454	3.3246752	0.7238881	2.1946223

Table 4. Forecast Error Page 4 of 5

Fcst hr	V hr	V Day	T Day 1	T Day 2	T Day 3	Fcst ME	Fcst RMSE	Bayes ME	Bayes RMSE
18	6	12	9	10	11	-1.6095983	2.2131385	0.084871	1.6629019
18	6	13	10	11	12	-1.4844825	2.2324425	0.5550299	1.8406797
18	6	15	12	13	14	-1.8548371	2.3969681	-0.115045	1.3151301
18	6	16	13	14	15	-1.4370039	2.4495579	0.1845952	1.6551899
18	6	17	14	15	16	-2.4648325	3.0564059	0.1135849	1.6617125
18	6	18	15	16	17	-0.7205698	1.6054846	0.6949319	1.55275
18	6	19	16	17	18	-1.1863901	1.8650625	0.42733	1.5302418
18	6	20	17	18	19	-2.1164167	3.0014293	0.0253513	1.6168571
18	6	21	18	19	20	-1.2642925	3.2057057	1.6768291	3.0893284
18	6	22	19	20	21	-1.6718068	2.8077756	0.2747376	1.9179332
21	9	7	3	5	6	-1.8742980	2.6645511	0.2786666	1.379419
21	9	8	5	6	7	-1.7535342	2.6447568	0.0357563	1.5164665
21	9	9	6	7	8	-1.9064722	2.6676329	0.2923702	1.4472874
21	9	10	7	8	9	-2.5489239	3.6726600	0.4423737	2.0451308
21	9	11	8	9	10	-2.5077311	3.2412514	0.0016241	1.075682
21	9	12	9	10	11	-0.5961004	1.3276883	0.2286683	1.487114
21	9	13	10	11	12	-1.0879109	1.9559517	0.9825003	2.0257311
21	9	15	12	13	14	-1.6697568	2.4214298	-0.4283802	1.5988903
21	9	16	13	14	15	-1.2461560	1.9470598	0.0653676	1.3136521
21	9	17	14	15	16	-2.1244472	2.6605966	0.3341861	1.4579945
21	9	18	15	16	17	-1.0361649	1.4591603	0.1461445	0.7213278
21	9	19	16	17	18	-1.2727912	1.7625956	0.5338494	1.370196
21	9	20	17	18	19	-1.3917666	2.7581224	0.6224325	1.9596425
21	9	21	18	19	20	-1.4486344	2.8262761	0.3944358	2.077483
21	9	22	19	20	21	-1.2921467	2.5483578	0.3109992	1.7167001
21	21	7	4	5	6	-1.7115822	2.9813302	1.0730757	2.567383
21	21	8	5	6	7	-1.4268381	2.9016988	1.7349237	3.0024997
21	21	9	6	7	8	-3.9368514	4.8883649	-0.067486	2.7651752
21	21	10	7	8	9	-4.2665707	5.1256712	-0.3643389	2.7505665
21	21	11	8	9	10	-2.2377886	2.8351463	0.802154	2.1492311
21	21	12	9	10	11	-1.7280800	2.6453182	1.1414963	2.3562976
21	21	13	10	11	12	-1.9379922	2.9550875	0.9832436	2.0938357
21	21	14	11	12	13	-1.9513116	2.6610622	0.0906136	1.7291674
21	21	15	12	13	14	-2.4126975	3.3692812	-0.1018043	2.0525218
21	21	16	13	14	15	-4.1431986	5.2669836	1.1158927	2.6235143
21	21	17	14	15	16	-2.7702939	3.6449889	1.3918866	2.7136462
21	21	18	15	16	17	-2.0653610	2.8024079	0.4965581	1.8783968
21	21	19	16	17	18	-1.8248194	3.0521608	0.9264642	2.6061848
21	21	20	17	18	19	-1.1317210	2.9949974	1.1805146	3.0024988
21	21	21	18	19	20	-1.8672681	3.1255726	0.338765	2.3757782
24	0	7	3	5	6	-2.7553538	4.0885252	0.1799516	2.4601865
24	0	8	5	6	7	-2.5177994	3.6126806	0.7042882	2.3721379
24	0	9	6	7	8	-2.9792718	4.3790138	0.9323325	2.956355
24	0	10	7	8	9	-5.0473139	5.7948236	1.0592845	2.8864005
24	0	11	8	9	10	-4.8173890	5.9816015	0.7886772	3.1060004
24	0	12	9	10	11	-1.9560309	2.9328022	1.0300611	2.3239905

Table 5. Forecast Error Page 5 of 5

Fcst hr	V hr	V Day	T Day 1	T Day 2	T Day 3	Fcst ME	Fcst RMSE	Bayes ME	Bayes RMSE
24	0	13	10	11	12	-2.2888199	3.1712627	0.3797224	2.4877473
24	0	14	11	12	13	-2.1912849	3.7294852	1.2912605	2.7142521
24	0	15	12	13	14	-1.9737862	2.6338122	-0.1198687	1.7844891
24	0	16	13	14	15	-2.3710229	3.1877710	-0.0931757	1.9122442
24	0	17	14	15	16	-3.9368041	5.1611597	0.5384198	2.8047744
24	0	18	15	16	17	-3.8599242	4.6263057	0.1899619	1.9233974
24	0	19	16	17	18	-1.9141394	2.9914240	0.7390004	2.1664962
24	0	20	17	18	19	-1.7683647	3.1902394	1.1227186	2.7899825
24	0	21	18	19	20	-1.3313747	3.2856304	1.7144445	3.2471705
24	0	22	19	20	21	-1.8955280	3.2441175	0.5261539	2.4793179

Table 1–5 Legend: Error indices relative to each individual forecast. Fcst_hr is the length of the forecast in hours, V_hr is the valid time of the forecast, V_Day is the day in which the forecast is valid, T_Day_1 is the first day used for data assimilation in the Bayesian inference algorithm, T_Day_2 is the second day used for data assimilation in the Bayesian inference algorithm, T_Day_3 is the third day used for data assimilation in the Bayesian inference algorithm, Fcst_ME is the mean error calculated for the raw model forecast at all observable points assuming surface observational data is the truth, Fcst_RMSE is the root mean squared error for the raw model forecast at all observable points relative to surface observations, Bayes_ME is the mean error of the Bayesian corrected forecast relative to surface observations color coded green if improvement is seen over Fcst_ME and red if more error than Fcst_ME is seen, Bayes_RMSE is the root mean squared error of the Bayesian corrected forecast relative to surface observations color coded green if improvement is seen over Fcst_RMSE and red if greater root mean squared error than Fcst_RMSE is seen. All errors are given in units of m/s.

For all tabulated data, box and whisker plots were produced as seen in Figures 1 through 6. For each time period, plots were produced to analyze performance among time periods and forecast length. It is helpful to note that when analyzing these box and whisker plots, the plots' location relative to zero quantifies the amount of error. The farther the box or the "mean line" is from zero, the more error was seen in forecasts, or the nearer the line is to zero, the less error. While box placement depicts forecast accuracy, the size of the box helps depict precision among forecasts. If forecasts remain consistent; meaning they show bias or less variance, boxes will appear smaller. Ideally, results should show an improvement in accuracy and precision, meaning that plots should be smaller, and closer to zero. RMSE should appear closer to zero to depict performance improvement while the size of the box will depict precision less reliably since only non-negative numbers result from the calculation. In analyzing differences between ME and RMSE, it is nice to note that a single anomaly of greater magnitude will appear to effect RSME to a greater degree than ME. If ME plots show minor differences between raw model forecasts and Bayesian

forecasts but RMSE plots depicts a significant difference between the two, the disparity is likely the result of a relatively large anomaly among one or only a few outlier forecasts.

As seen in Figure 1, an overall improvement in forecast accuracy was seen in ME among the Bayesian corrected forecasts versus the raw model forecast when analyzing the mean of all conglomerate forecasts. On average, forecasts saw approximately 1.4 m/s improvement in accuracy while outliers saw margins of improvement of up to 5.1 m/s, an improvement in accuracy of over 9 knots.

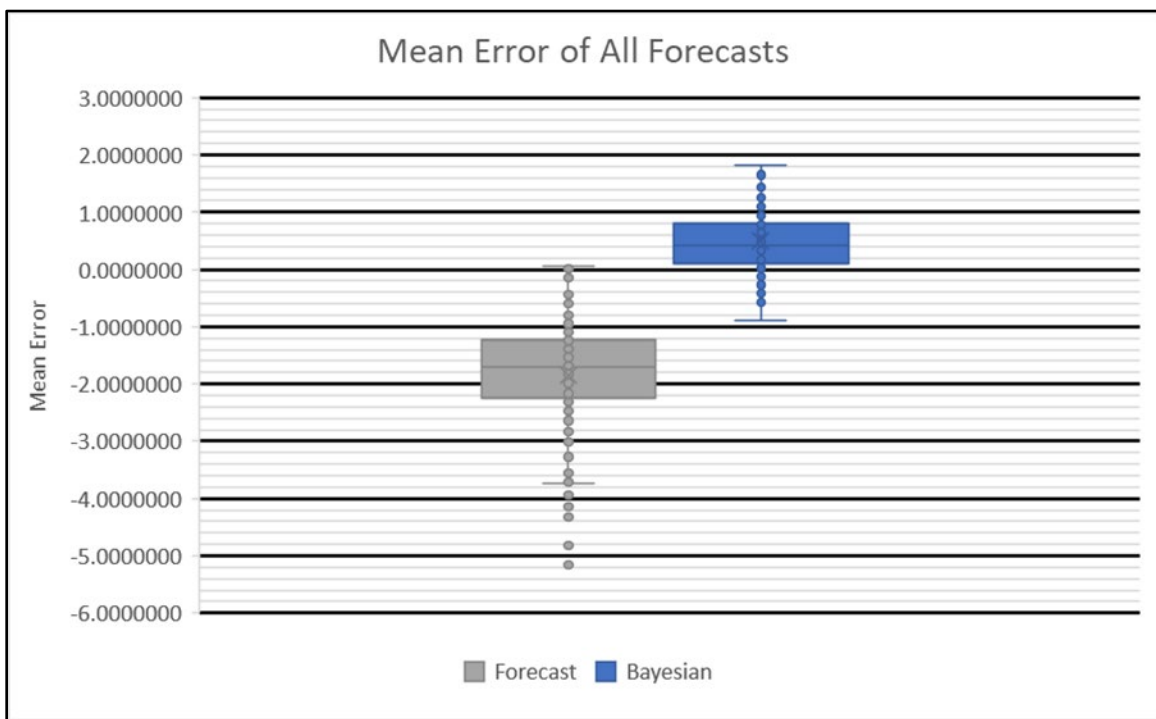


Figure 1. Box and Whisker Plots of the Mean Error of Raw Model Forecasts (grey) versus the Bayesian Corrected Forecast (blue).

As seen in Figure 2; among all 0000UTC model run forecasts, all Bayesian corrected forecasts were more accurate than the correlating raw model forecasts in respects to ME. Such an observation can be seen by the “Bayesian” box’s closer location to zero relative to the correlating raw model “Forecast” box. Additionally, a tighter spread or a smaller box in nearly all 0000UTC Bayesian forecast plots relative to the raw model forecast plot suggests an improvement in forecast precision. The only plot depicting only

marginal suggested improvements in precision over the raw model forecast can be seen in the 21-hour forecast.

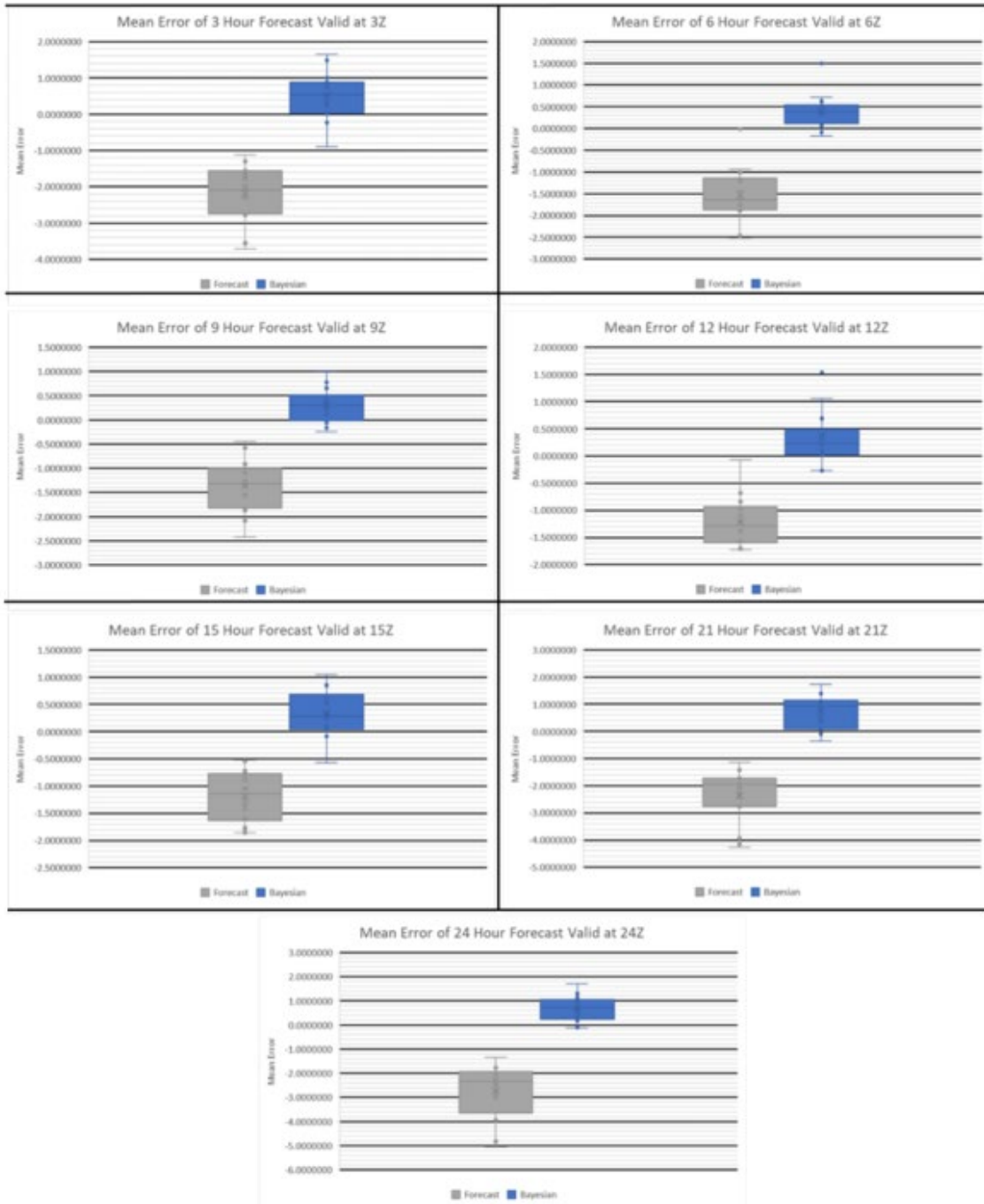


Figure 2. Box and Whisker Plots of Mean Error of All 0000UTC Model Run Forecasts (grey) versus the Bayesian Corrected Forecast (blue).

Much like Figure 2, Figure 3 depicts all Bayesian corrected forecasts produced by the 1200UTC model run in ME. All plots in Figure 3 show an improvement in accuracy over the correlating raw model forecasts. A tighter spread or a smaller box in nearly all 1200UTC forecast plots can also be observed in the “Bayesian” box relative to the associated “Forecast” box in Figure 3 with exception to the 6-hour forecast where improvements in the Bayesian forecast precision were relatively marginal.

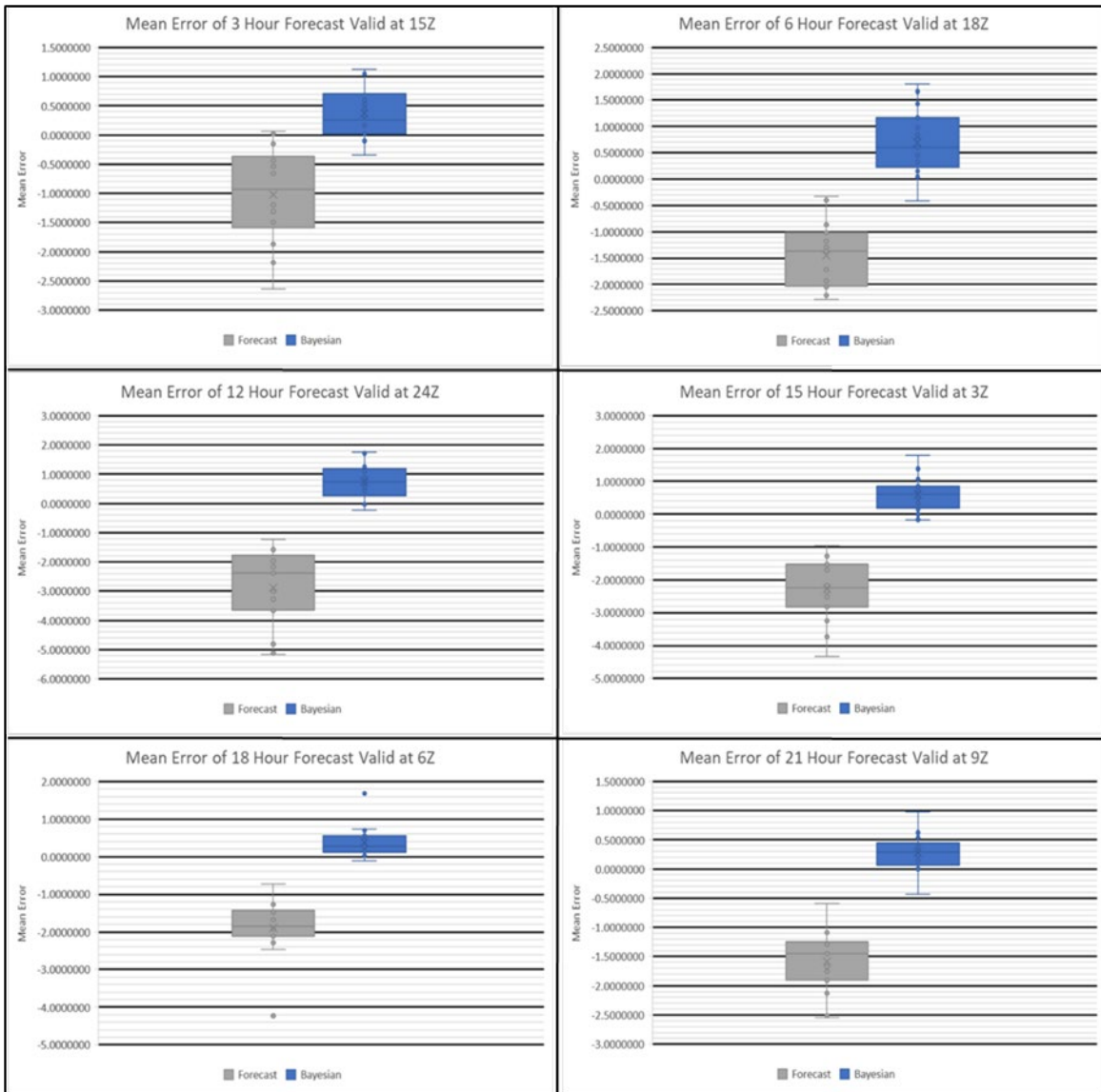


Figure 3. Box and Whisker Plots of Mean Error of All 1200UTC Model Run Forecasts (grey) versus the Bayesian Corrected Forecast (blue).

Among the conglomerate of all forecasts as seen in Figure 4, the “Bayesian” box is closer to zero relative to the raw model forecast. As a result, one can conclude that the Bayesian adjustments resulted in more accurate forecasts. Mean lines were found at 2.7 for the raw forecast and 1.9 for the Bayesian forecast depicting on average an improvement of 0.8 m/s in RMSE. Outliers depict an improvement of up to 2.9 m/s among Bayesian forecasts versus the raw model forecasts.

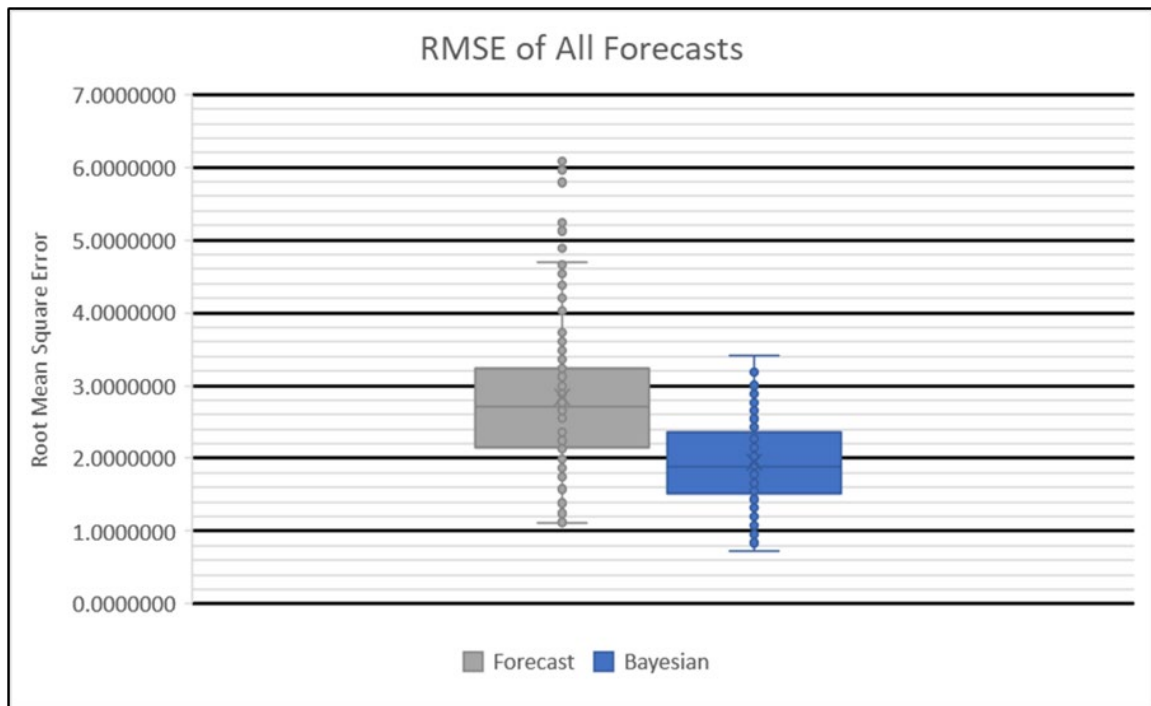


Figure 4. Box and Whisker Plots of the Root Mean Squared Error of Raw Model Forecasts (grey) versus the Bayesian Corrected Forecast (blue).

Finally, as observed in Figures 5 and 6, all Bayesian corrections resulted in more accurate forecasts at all forecast periods both from the 0000UTC and the 1200UTC model runs, respectively. Greater forecast accuracy once again can be seen by a relatively closer positioning to zero among box plots.

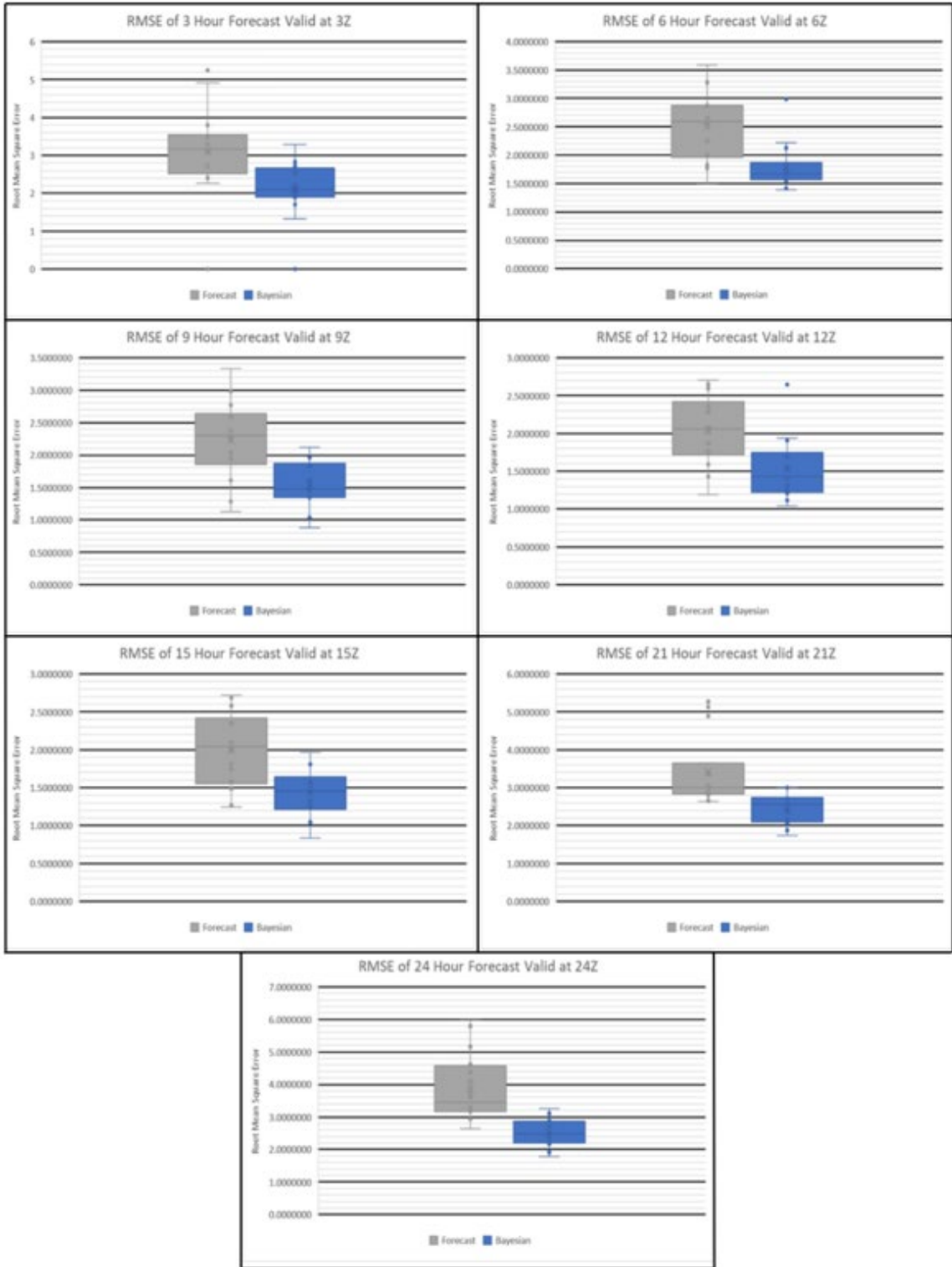


Figure 5. Box and Whisker Plots of Root Mean Squared Error of All 0000UTC Model Run Forecasts (grey) versus the Bayesian Corrected Forecast (blue).

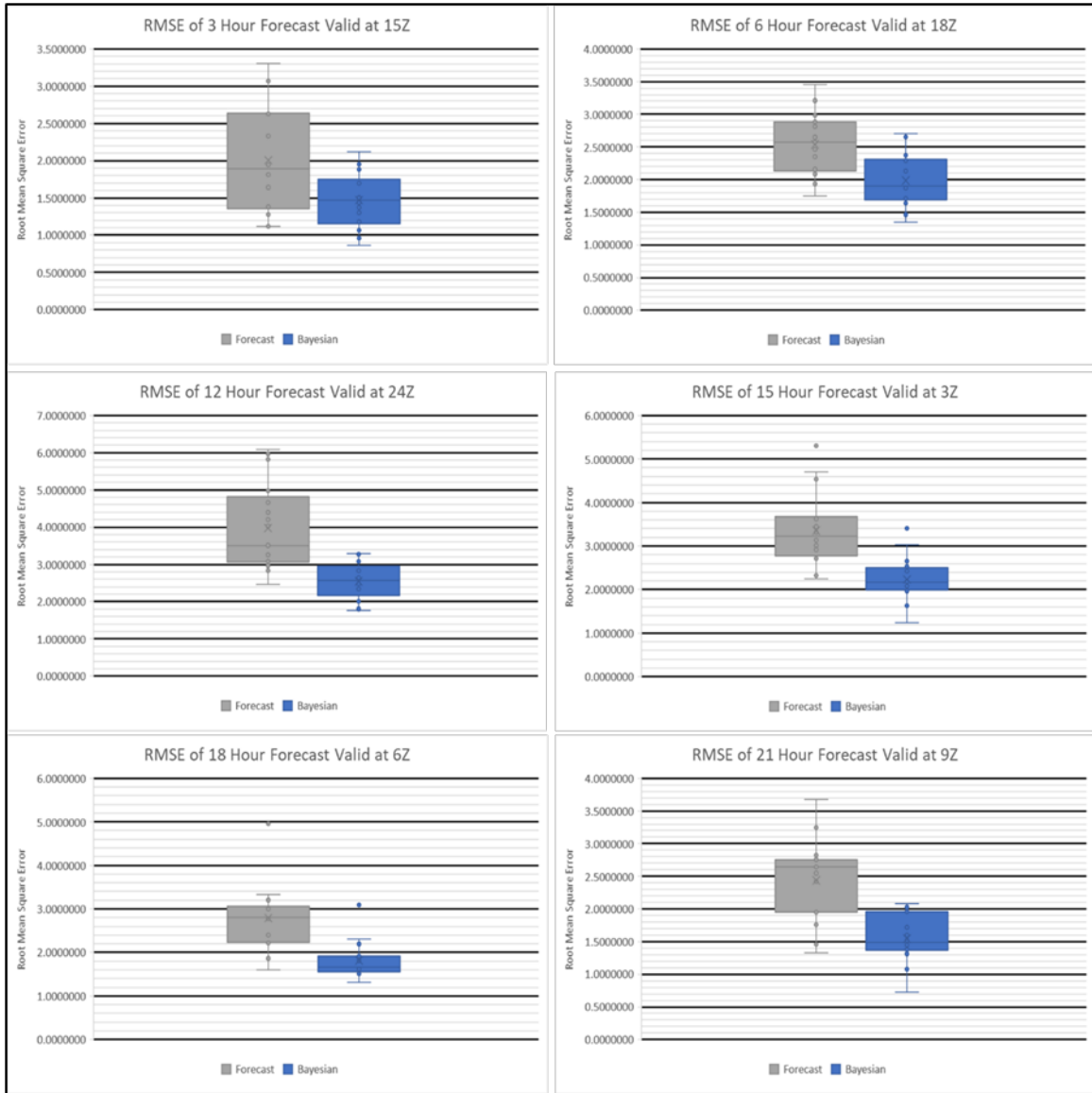


Figure 6. Box and Whisker Plots of Root Mean Squared Error of All 1200UTC Model Run Forecasts (grey) versus the Bayesian Corrected Forecast (blue).

IV. CONCLUSION

This research yielded promising results in searching for more accurate wind forecasting methods using Bayesian statistical postprocessing. Using only 3 days of observations at numerous ASOS and other surface observation locations as a training period and one high resolution gridded model, these methods successfully exhibit how effective Bayesian statistical postprocessing can be in finding operationally relevant solutions to current weather forecasting problems. Not only does this method display the potential to rapidly train a high-resolution model, but it also showcases a way to forecast with greater accuracy and precision. Analysis of forecasting methods showed improvement in ME of up to 5.1 meters per second or over 9 knots. Such a disparity in forecast accuracy is operationally significant in the military. Often, the military uses “go-no go” thresholds to preserve operational risk management. If a forecast is said to break a threshold, operations may be stopped due to the risks of operating under conditions at or above those thresholds. An error of 9 knots in a forecast will likely result in operations being stopped when they could have continued safely, or the assumption that operations are safe to conduct when they are dangerous. A 9-knot difference in wind speed among forecasts can also change boundary layer processes. Such a change could impact the error of other modeled predictions or forecast variables.

Furthermore, the ability to conduct this research with minimal computing power promises the potential for these methods to translate to the operational field. The computing time needed to apply these methods on a simple laptop computer allowed for sufficient time to deliver a full area forecast, making its application possible in almost any circumstance. Further research is recommended to find the most efficient methods possible, but this research lays the groundwork for a promising future in using Bayesian statistical postprocessing to more accurately produce a rapidly trainable high-resolution forecast.

For an eager student looking to further this study, more research would prove beneficial in focusing on answering these following questions: How effective is this process at improving forecasts in locations distant from observation points used during model training? Where does this process work the best? Where does this process work the

worst? What is the optimal number of prior days to use for model training prior to the forecast? What is the optimal spacing and number of prior observations to use to yield the most efficient or accurate training? What effect will extreme weather events have on the accuracy? Will these methods work in forecasting all forecast fields? What forecast fields yield the best or most efficient results? Are other predictor variables needed and how much improvement occurs with them? What interpolation methods will maximize accuracy when using observation points that do not fall exactly at the grided forecast point.

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