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A COMPARISON OF PREDICTORS FOR FIRST-GUESS WIND SPEED ERRORS

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A Comparison of Predictors For First-Guess Wind Speed Errors

by P. A. Jacobs and D. P. Gaver

Abstract

Numerical meteorological models are used to assist in the prediction of weather. Each run of a numerical model produces forecasts of meteorological variables which are used as preliminary predictions of the future values of these variables. These initial predictions are referred to as *first-guess* values. Estimation of the mean-square first-guess error is required in the optimal interpolation process in the numerical prediction of atmospheric variables. Several predictors for the mean-square error of the first-guess wind speeds are studied. The results suggest that prediction using observed covariates tend to be better than those using first-guess covariates. However, observed covariates are not always available. Predictions using first-guess covariates are better at the 250 mb level than the 850 or 500 mb levels. Of those first-guess covariates studied, first-guess wind speed appears to be the best.

1. INTRODUCTION AND SUMMARY

Numerical meteorological models are used to assist in the prediction of weather. Each run of a numerical model produces forecasts of meteorological variables which are used as preliminary predictions of future values of these variables. These initial predictions are referred to as first-guess values. In this paper first-guess values will refer to the most recent 12-hour forecasts.

In certain areas of the world, observations of forecasted variables become available. Prior to the next run of the numerical model a multivariate optimal interpolation analysis updates a first-guess value of a variable by adding to it a weighted observed value of the variable if it is available. The weight multiplying the observed value depends on estimates of the mean-squared error of the first-guess value and the mean-squared error of the observation; cf. Goerss et al., [1991, a, b]. Thus it is of importance to predict the first-guess mean-squared errors.

The general problem of modeling and predicting mean-square errors is important but not widely studied; see Davidian and Carroll (1987), Nelder and Lee (1992), Aitken (1987), McCullagh and Nelder (1983).

In Jacobs and Gaver (1991, 1992) statistical models for the error of the first guess are used to predict mean-square error for first-guess wind components. The models assume that the error of the first guess has a normal distribution with mean 0 and variance which is a function that is log-linear with covariates. Details of the model are presented in Appendix A.

In this paper we use data from February 1991 to compare the predictive ability of various models. The data consist of measurements and 12 hour forecasts (first-guess values) of u and v wind components at the 850 mb, 500 mb and 250 mb pressure levels from 93 stations in North America 25N–75N for the month of February 1991. The forecasts are produced using the NOGAPS Spectral Forecast Model; cf. Hogan et al., (1991). Each station has measurement and first-guess values for every 12 hours; there are some missing observations. These missing values are deleted from the data set. The measurement values are subtracted from the first-guess values to obtain observations of the error of the first-guess value.

Let $U(o;t)$, (respectively $V(o;t)$), be the observed u-wind, (respectively v-wind) component at time t. Let $U(f;t)$, (respectively $V(f;t)$), be the first-guess u-wind (respectively v-wind) component at time t; $U(f;t)$, (respectively $V(f;t)$)

is the forecasted value of the u-wind (respectively v-wind) component made 12 hours previously. The first-guess error for the u-wind (respectively v-wind) component is

$$Y_U(t) = U(f;t) - U(o;t); \text{ (respectively } Y_V(t) = V(f;t) - V(o;t)). \tag{1.1}$$

The following covariates are considered in the log-linear model for the mean-square error of the first guess.

$$r(o;t) = \left[(U(o;t) - U(o;t-1))^2 + (V(o;t) - V(o;t-1))^2 \right]^{\frac{1}{2}} \tag{1.2}$$

$$w(o;t) = \left[U(o;t)^2 + V(o;t)^2 \right]^{\frac{1}{2}} \tag{1.3}$$

$$r(f;t) = \left[(U(f;t) - U(f;t-1))^2 + (V(f;t) - V(f;t-1))^2 \right]^{\frac{1}{2}} \tag{1.4}$$

$$w(f;t) = \left[U(f;t)^2 + V(f;t)^2 \right]^{\frac{1}{2}}. \tag{1.5}$$

$$r^*(t) = \left[(U(f;t) - U(o;t-1))^2 + (V(f;t) - V(o;t-1))^2 \right]^{\frac{1}{2}} \tag{1.6}$$

$$a(o,U;t) = |U(o;t) - U(o;t-1)|, \quad a(o,V;t) = |V(o;t) - V(o,t-1)| \tag{1.7}$$

$$a(f,U;t) = |U(f;t) - U(f;t-1)|, \quad a(f,V;t) = |V(f;t) - V(f,t-1)| \tag{1.8}$$

$$a^*(U;t) = |U(f;t) - U(o;t-1)|, \quad a^*(V;t) = |V(f;t) - V(o,t-1)| \tag{1.9}$$

$$m(f;t) = \max(U(f;t), V(f;t)) \tag{1.10}$$

The resultant wind $r(o;t)$, (respectively $r(f;t)$ and $r^*(t)$), is a measure of the observed (respectively forecasted), change in the wind. The variable $w(o;t)$, (respectively $w(f;t)$), is the observed, (respectively forecasted), wind speed. Higher wind speeds suggest more activity in the atmosphere. The change in magnitudes $a(o,U;t)$, $a(f,U;t)$ and $a^*(U;t)$ (respectively $a(o,V;t)$, $a(f,V;t)$ and $a^*(V;t)$ will be used to predict $Y_U(t)$, (respectively $Y_V(t)$).

The data are randomly divided into two sets called DA and DB. Maximum likelihood estimates of the parameters of the models using different covariates are computed using data DA (respectively DB). Nonparametric models based on binning are also considered. The models are then used to predict the mean-square first-guess errors in data set DB (respectively DA). Log-likelihood functions and the empirical distribution of the first-guess errors normalized by their predicted mean-square errors are used to evaluate the models' predictive ability. Details are given in Section 2.

In general, models which use observed covariates, e.g. $w(o)$, $a(o)$, have more predictive ability than those that use first-guess covariates, e.g. $w(f)$, $a(f)$, $m(f)$. The models applied at the 250 mb level appear to have more predictive ability than those for 500 mb and 850 mb.

Among the one-variate models for the 250 mb pressure height, the models that statistically appear to have the most predictive ability have as their covariate $w(o)$, $a(o)$ or $r(o)$. Those that have less but some predictive ability have as their covariate a^*, $w(f)$, $m(f)$ or r^*. Finally, one-variate models using variates $r(f)$ and $a(f)$ appear to have little predictive ability. Among those models for the 250 mb pressure height that use one first-guess covariate, $m(f)$ or $w(f)$ appear to have the most predictive ability.

2. THE DATA ANALYSIS

In this section we describe the data analysis. Let $U_i(o;t)$ and $U_i(f;t)$, (respectively $V_i(o;t)$ and $V_i(f;t)$) be the observed and first-guess u-wind (respectively v-wind) component at location $i = 1, \ldots, S$ at time t. By data we mean the vector $(U_i(o,t), U_i(f,t), V_i(o,t), V_i(f,t), U_i(o,t-1), U_i(f,t-1), V_i(o,t-1), V_i(f,t-1))$. The data set contains missing values. Vectors containing these missing values are deleted from the data set. Once missing values are deleted, there are 3618 vectors at the 850 mb level, 4100 at the 500 mb level, and 3744 at the 250 mb level. The observed values are subtracted from the first-guess values to obtain observations of the first-guess errors for each wind component

$$Y_i(U;t) = U_i(f;t) - U_i(o;t)$$

$$Y_i(V;t) = V_i(f;t) - V_i(o;t).$$

The remaining data are randomly divided into two sets called DA and DB without regard to the values of the data, the time t, or the location. Thus, data from the same location for different times may be in different data sets. Models are estimated for each pressure level using only covariates for that pressure level. The covariates considered for each wind component appear in Appendix B. The general statistical model is described in Appendix A.

The model is estimated using data sets DA, DB, and all the data for each pressure level. The estimated values for the parameters for selected models appear in Tables 3A, 4A, 3B, 4B, 3C and 4C. Note that the parameter estimates are usually positive. Hence increased values of the covariates are associated with higher variance of the first-guess errors.

The models estimated from DA (respectively DB) are used to predict the first-guess errors in data set DB (respectively DA). One measure used for assessing a model's goodness of fit and predictive ability is the value of $\tilde{\ell}$, the log-likelihood function up to addition of constants given in Appendix A (A.4); the log-likelihood for predicting mean-square errors in DB using a model estimated using DA uses the first-guess error and covariate(s) from DB and the parameter estimates from DA. Values of $\tilde{\ell}$ are computed for data DA (respectively DB) using the parameters estimated using DB (respectively DA); these values assess each model's predictive ability. Values of $\tilde{\ell}$ are also computed for data DA (respectively DB) using parameters estimated using DA (respectively DB); these values assess each model's goodness of fit.

Tables 1A, 1B, 1C present the values of $\tilde{\ell}$ for one-variate models for the different pressure levels. Also displayed are the values of $\tilde{\ell}$ for a model in which the first-guess errors are independent normally distributed with mean 0 and constant variance e^{α}.

Tables 2A, 2B, 2C present values for $\tilde{\ell}$ for two-variate models.

Compare the value of $\tilde{\ell}_c$ for the model with constant variance (no covariates) for DA (respectively DB) fit using DA (respectively DB) with the values of $\tilde{\ell}$ for DA (respectively DB) using models with parameters estimated using the other half of the data DB (respectively DA). A value of $\tilde{\ell}$ greater than $\tilde{\ell}_c$ indicates that the corresponding model fit with the other half of the data describes the data better than the best constant variance model fit with the same data it is used to summarize. For 850 mb data those one-variate models for which $\tilde{\ell} > \tilde{\ell}_c$ for DA and DB for both wind components are those with variate r^*, a^*, r, and $w(o)$. For 500 mb the one-variate models are those with variate r^*, $a(o)$, r, $w(o)$, and $w(f)$. For 250 mb, the models are those with variate r^*, $a(o)$, r, $w(o)$, $w(f)$, and $m(f)$.

To compare the predictive ability of the models, the fraction of increase in $\tilde{\ell}$, $(\tilde{\ell}-\tilde{\ell}_c)/|\tilde{\ell}_c|$ is computed where $\tilde{\ell}_c$ is the maximum value of $\tilde{\ell}$ for the constant variance model (with no covariates) estimated using data DA (respectively DB) compared to the value of $\tilde{\ell}$ for DA using one-variate models estimated using the other half of the data DB (respectively DA). The values of percentage of increase appear in Table 5 for the one-variable models with variate r^*, a^*, r, $w(o)$, $w(f)$, and $m(f)$. Note that the fraction increase tends to be larger for the 250 mb for the covariates using observed data, r, $w(o)$, and $a(o)$. The fraction also tends to be larger for the first-guess covariates $w(f)$ and $m(f)$ at the 250 mb level.

Another measure of predictability is the distribution of the first-guess errors divided by their predicted standard deviations. Table 6 displays the moments of the first-guess errors of the wind components DA (respectively DB) divided by the standard deviations that are predicted for it using the model fit using data of DB (respectively DA). Recall that the models assume that these errors are normally distributed with mean 0. Thus, if a model were perfect then the mean (respectively standard deviation, skewness, and kurtosis) of the normalized first-guess errors would be 0, (respectively 1, 0 and 3). Of particular interest is the kurtosis. In this application, the kurtosis can be thought of as a measure of the variability of the variance (cf. Cramér page 356). Hence, the smaller the kurtosis, the better the prediction of the model.

Table 6 presents not only results for the model of Appendix A with various covariates but also results for a nonparametric one-variate model. This nonparametric model is as follows. The data in DA (respectively DB) are binned into N bins according to the value of the ordered covariate. For each bin, the mean of the square of the wind speed errors corresponding to the covariates in that bin is computed. To evaluate the predictive ability of the model, the other data set DB (respectively DA) is used. The predicted mean-square error for a data point in DB (respectively DA) is the mean of the square of the wind speed errors for the bin determined from DA (respectively DB) the data point's covariate lies in.

Table 6 presents selected results using data for the 250 mb level. Results for parametric models of Appendix A with parameters estimated by maximum likelihood (MLE) and the nonparametric models with bins are presented. Also displayed are the sample moments of the first-guess errors in the row labeled "none". Displayed in the row labeled "constant" are the sample moments for the first-guess errors divided by the predicted standard deviation for a model with constant variance e^{α} fit using the other half of the data.

The values of the kurtosis suggest the following. Once again, models using the observed covariates $a(o)$ and $r(o)$ appear to make the best predictors. Among the first-guess covariates, $m(f)$ and $w(f)$ appear to have comparable predictive ability. If a nonparametric model using a first-guess variate is being considered, then using first-guess wind speed as the covariate seems to be a good choice.

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APPENDIX A

THE STATISTICAL MODEL

In this Appendix we describe the statistical model. Let $U_i(o;t)$ (respectively $V_i(f;t)$) denote the observed u-wind component (respectively first-guess wind component) at location i at time t; $i = 1, \ldots, S$. Let $V_i(o;t)$, (respectively $V_i(f;t)$) denote the observed v-wind component (respectively first-guess wind component) at location i at time t. The first-guess error of the u-wind (respectively v-wind) component at location i at time t is

$$Y_i(U;t) = U_i(o;t) - U_i(f;t)$$

(respectively, (A.1)

$$Y_i(V;t) = V_i(o;t) - V_i(f;t)).$$

The model is that $\{Y_i(U;t), i = 1, \ldots, S\}$ and $\{Y_i(V;t), i = 1, \ldots, S\}$ are independent random variables having a normal distribution with mean 0. The variance of $Y_i(U;t)$ is log-linear with a number of covariates. That is

$$Var\left[Y_i(U;t) \middle| X_i(1;t) = x_i(1), \ldots, X_i(p;t) = x_i(p)\right]$$
$$= \exp\left\{\alpha + \sum_{j=1}^{p} \beta_j(t) x_i(j;t)\right\}. \quad \text{(A.2)}$$

The likelihood function for this model is (up to multiplication by constants)

$$L(\alpha, \beta_1, \ldots, \beta_p)$$
$$= \prod_t \prod_i \exp\left\{-\frac{1}{2}\left[\alpha + \sum_{j=1}^{p} \beta_j(t) x_i(j;t)\right]\right\} \exp\left\{-\frac{1}{2} y^2 \exp\left\{-\left(\alpha + \sum_{j=1}^{p} \beta_j(t) x_i(j;t)\right)\right\}\right\} \quad \text{(A.3)}$$

The log-likelihood function is (up to addition by constants)

$$\tilde{\ell}\left(\alpha,\beta_1,\ldots,\beta_p\right)$$

$$= \sum_t \sum_i -\frac{1}{2}\left[\alpha + \sum_{j=1}^{p} \beta_j(t) x_i(j;t)\right] - \frac{1}{2} y^2 \exp\left\{-\left(\alpha + \sum_{j=1}^{p} \beta_j(t) x_i(j;t)\right)\right\} \tag{A.4}$$

The recursive procedure used to estimate the parameters (α, β_1, ..., β_p) is described in Gaver and Jacobs [1991].

APPENDIX B

THE COVARIATES

In this Appendix we list the covariates that were considered. As before let $U_i(o;t)$ and $U_i(f;t)$, (respectively $V_i(o;t)$ and $V_i(f;t)$) denote the observed and first-guess u-wind (respectively v-wind) component at time t for location i, $i = 1, \ldots, S$. The covariates considered for the first-guess error of the u-wind component are

$$a_i(o,U;t) = |U_i(o;t) - U_i(o;t-1)|$$

$$a_i(f,U;t) = |U_i(f;t) - U_i(f;t-1)|$$

$$a_i^*(U;t) = |U_i(f;t) - U_i(o;t-1)|$$

$$w_i(o;t) = \left[U_i(o;t)^2 + V_i(o;t)^2\right]$$

$$w_i(f;t) = \left[U_i(f;t)^2 + V_i(f;t)^2\right]$$

$$r_i(o;t) = \left[[U_i(o;t) - U_i(o;t-1)]^2 + [V_i(o;t) - V_i(f;t-1)]^2\right]^{\frac{1}{2}}$$

$$r_i(f;t) = \left[[U_i(f;t) - U_i(f;t-1)]^2 + [V_i(o;t) - V_i(f;t-1)]^2\right]^{\frac{1}{2}}$$

$$r_i^*(t) = \left[[U_i(f;t) - U_i(o;t-1)]^2 + [V_i(f;t) - V_i(o;t-1)]^2\right]^{\frac{1}{2}}$$

$$m(f;t) = \max(U(f;t), V(f;t)).$$

The covariates considered for the first-guess error of the v-wind component are

$$a_i(o,V;t) = |V_i(o;t) - V_i(o;t-1)|$$

$$a_i(f,V;t) = |V_i(f;t) - V_i(f;t-1)|$$

$$a_i^*(V;t) = |V_i(f;t) - V_i(o;t-1)|$$

$w_i(o;t), w_i(f;t), r_i(o;t), r_i(f;t)$, and $r_i^*(t)$.

TABLE 1A
Log-Likelihood
850 mb. Height/February Data

One-Variate Models

Wind Comp	Data	Model	Const	$r^*(t)$	$r(f;t)$	$a(o;t)$	$a(f;t)$	$a^*(t)$	$r(t)$	$w(o;t)$	$w(f;t)$	$m(f;t)$
u	A	A	-6226.6	-6183.6	-6226.6	-6109.6	-6226.6	-6167.1	-6162.3	-6174.4	-6217.1	-6221.5
	B	B	-6439.8	-6331.3	-6434.9	-6327.7	-6403.8	-6307.6	-6377.8	-6312.1	-6412.9	-6439.0
	B	A	-6452.9	-6347.4	-6452.5	-6341.0	-6450.1	-6319.6	-6390.2	-6333.9	-6426.7	-6455.0
	A	B	-6238.8	-6196.0	-6241.6	-6121.9	-6257.0	-6176.1	-6173.8	-6193.8	-6228.6	-6235.7
v	A	A	-6445.9	-6356.9	-6441.4	-6440.5	-6443.6	-6362.4	-6406.9	-6275.3	-6435.8	-6442.9
	B	B	-6343.7	-6297.4	-6343.1	-6287.4	-6343.5	-6317.6	-6258.1	-6201.8	-6327.9	-6343.7
	B	A	-6346.5	-6302.2	-6347.3	-6316.4	-6349.4	-6326.4	-6271.6	-6207.2	-6332.2	-6336.7
	A	B	-6448.8	-6362.4	-6446.0	-6470.7	-6450.5	-6373.7	-6422.0	-6280.7	-6440.4	-6451.4

$$r(f;t) = \left[\left(U(f;t) - U(f;t-1)\right)^2 + \left(V(f;t) - V(f;t-1)\right)^2\right]^{1/2}$$

$$a(f;t) = \left|U(f;t) - U(f;t-1)\right|$$

$$r^*(t) = \left[\left(U(f;t) - U(o;t-1)\right)^2 + \left(V(f;t) - V(o;t-1)\right)^2\right]$$

$a(o;t) = \left|U(o;t) - U(o;t-1)\right|$ for u - wind component error

$a(o;t) = \left|V(o;t) - V(o;t-1)\right|$ for v - wind component error

$a^*(t) = \left|U(f;t) - U(o;t-1)\right|$ for u - wind component error

$a^*(t) = \left|V(f;t) - V(o;t-1)\right|$ for v - wind component error

$$r(t) = \left[\left(U(o;t) - U(o;t-1)\right)^2 + \left(V(o;t) - V(o;t-1)\right)^2\right]^{1/2}$$

$$w(o;t) = \left[U(o;t)^2 + V(o;t)^2\right]^{1/2}$$

$$w(f;t) = \left[U(f;t)^2 + V(f;t)^2\right]^{1/2}$$

$$m(f;t) = \max\left(U(f;t), V(f;t)\right)$$

TABLE 2A
Log-Likelihood
850 mb. Height/February Data

Two-Variate Models

Wind Comp	Data	Model	Const	$r^*(t), a(o;t)$	$r(f;t), a(f;t)$	$r^*(t), a^*(t)$	$r^*(t), a(f;t)$	$r(t), w(o;t)$	$r(t), w(f;t)$
u	A	A	-6226.6	-6085.7	-6226.6	-6164.6	-6177.0	-6137.0	-6160.4
	B	B	-6439.8	-6240.0	-6394.5	-6299.0	-6329.4	-6294.8	-6362.8
	B	A	-6452.9	-6262.5	-6449.6	-6312.4	-6367.9	-6318.9	-6379.3
	A	B	-6238.8	-6102.3	-6263.4	-6174.8	-6202.6	-6158.7	-6173.6
v	A	A	-6445.9	-6356.8	-6441.1	-6353.6	-6344.2	-6260.1	-6404.2
	B	B	-6343.7	-6271.4	-6339.1	-6297.1	-6267.8	-6181.7	-6257.1
	B	A	-6346.5	-6304.1	-6345.6	-6306.5	-6277.0	-6190.3	-6270.8
	A	B	-6448.8	-6396.3	-6448.7	-6365.0	-6355.1	-6270.2	-6419.7

$$r(f;t) = \left[(U(f;t) - U(f;t-1))^2 + (V(f;t) - V(f;t-1))^2\right]^{1/2}$$

$$a(f;t) = |U(f;t) - U(f;t-1)|$$

$$r^*(t) = \left[(U(f;t) - U(o;t-1))^2 + (V(f;t) - V(o;t-1))^2\right]$$

$a(o;t) = |U(o;t) - U(o;t-1)|$ for u - wind component error

$a(o;t) = |V(o;t) - V(o;t-1)|$ for v - wind component error

$a^*(t) = |U(f;t) - U(o;t-1)|$ for u - wind component error

$a^*(t) = |V(f;t) - V(o;t-1)|$ for v - wind component error

$$r(t) = \left[(U(o;t) - U(o;t-1))^2 + (V(o;t) - V(o;t-1))^2\right]^{1/2}$$

$$w(o;t) = \left[U(o;t)^2 + V(o;t)^2\right]^{1/2}$$

$$w(f;t) = \left[U(f;t)^2 + V(f;t)^2\right]^{1/2}$$

TABLE 3A
One-Variate Models
Parameter Estimates
(Standard Errors)
850 mb. February Data

Wind Comp	Data Set	$r^*(t)$ α	$r^*(t)$ β	$r(f;t)$ α	$r(f;t)$ β	$a(o;t)$ α	$a(o;t)$ β	$a(f;t)$ α	$a(f;t)$ β	$a^*(t)$ α	$a^*(t)$ β
u	A	2.08	0.04	2.44	0.0005	2.00	0.08	2.44	0.002	2.14	0.07
		(0.06)	(0.007)	(0.06)	(0.007)	(0.05)	(0.008)	(0.05)	(0.01)	(0.05)	(0.009)
	B	2.00	0.07	2.46	0.02	2.15	0.08	2.33	0.06	2.10	0.09
		(0.06)	(0.007)	(0.06)	(0.007)	(0.05)	(0.008)	(0.05)	(0.01)	(0.05)	(0.009)
	All	2.03	0.06	2.45	0.009	2.08	0.08	2.37	0.04	2.11	0.08
		(0.04)	(0.005)	(0.04)	(0.005)	(0.04)	(0.006)	(0.03)	(0.008)	(0.04)	(0.006)
v	A	2.07	0.06	2.47	0.02	2.48	0.02	2.51	0.01	2.20	0.06
		(0.06)	(0.007)	(0.05)	(0.007)	(0.05)	(0.008)	(0.05)	(0.008)	(0.05)	(0.007)
	B	2.13	0.05	2.47	0.006	2.22	0.06	2.52	-0.004	2.29	0.04
		(0.06)	(0.007)	(0.06)	(0.008)	(0.05)	(0.008)	(0.05)	(0.008)	(0.05)	(0.008)
	All	2.10	0.05	2.47	0.01	2.35	0.04	2.51	0.005	2.24	0.05
		(0.04)	(0.005)	(0.04)	(0.005)	(0.03)	(0.005)	(0.03)	(0.006)	(0.04)	(0.005)

$$r(f;t) = \left[\left(U(f;t) - U(f;t-1)\right)^2 + \left(V(f;t) - V(f;t-1)\right)^2 \right]^{1/2}$$

$$a(f;t) = \left|U(f;t) - U(f;t-1)\right|$$

$$r^*(t) = \left[\left(U(f;t) - U(o;t-1)\right)^2 + \left(V(f;t) - V(o;t-1)\right)^2 \right]$$

$$a(o;t) = \left|U(o;t) - U(o;t-1)\right|, \quad a^*(t) = \left|U(f;t) - U(o;t-1)\right|$$

TABLE 4A
Two-Variate Models
Parameter Estimates
(Standard Errors)
850 mb. February Data

Wind Comp	Data Set	$\log MSE = \alpha + \beta_1 r^*(t) + \beta_2 a(o;t)$			$\log MSE = \alpha + \beta_1 r_f(t) + \beta_2 a(f;t)$			$\log MSE = \alpha + \beta_1 r^*(t) + \beta_2 a^*(t)$		
		α	β_1	β_2	α	β_1	β_2	α	β_1	β_2
u	A	1.75 (0.07)	0.04 (0.007)	0.08 (0.008)	2.13 (0.06)	0.05 (0.008)	-0.03 (0.012)	2.08 (0.06)	0.02 (0.01)	0.05 (0.01)
	B	1.65 (0.07)	0.06 (0.007)	0.07 (0.008)	1.98 (0.06)	0.06 (0.008)	0.02 (0.01)	1.99 (0.06)	0.03 (0.009)	0.07 (0.01)
	All	1.70 (0.05)	0.05 (0.005)	0.08 (0.006)	2.04 (0.05)	0.06 (0.006)	-0.004 (0.008)	2.03 (0.04)	0.02 (0.007)	0.06 (0.009)
v	A	2.08 (0.07)	0.06 (0.007)	-0.002 (0.009)	2.47 (0.06)	0.02 (0.01)	-0.009 (0.02)	2.09 (0.06)	0.04 (0.01)	0.03 (0.01)
	B	2.04 (0.07)	0.03 (0.008)	0.04 (0.009)	2.45 (0.06)	0.03 (0.02)	-0.03 (0.02)	2.13 (0.06)	0.05 (0.01)	-0.007 (0.01)
	All	2.05 (0.05)	0.05 (0.005)	0.02 (0.006)	2.46 (0.04)	0.03 (0.01)	-0.02 (0.01)	2.10 (0.04)	0.05 (0.009)	0.01 (0.01)

$$r(f;t) = \left[\left(U(f;t) - U(f;t-1)\right)^2 + \left(V(f;t) - V(f;t-1)\right)^2 \right]^{1/2}$$

$$a(f;t) = \left|U(f;t) - U(f;t-1)\right|$$

$$r^*(t) = \left[\left(U(f;t) - U(o;t-1)\right)^2 + \left(V(f;t) - V(o;t-1)\right)^2 \right]$$

$$a(o;t) = \left|U(o;t) - U(o;t-1)\right|, \quad a^*(t) = \left|U(f;t) - U(o;t-1)\right|$$

TABLE 1B
Log-Likelihood
500 mb. Height/February Data

One-Variate Models

Wind Comp	Data	Model	Const	$r^*(t)$	$r(f;t)$	$a(o;t)$	$a(f;t)$	$a^*(t)$	$r(t)$	$w(o;t)$	$w(f;t)$	$m(f;t)$
u	A	A	-7894.4	-7865.0	-7877.6	-7699.3	-7876.1	-7866.0	-7732.5	-7846.3	-7866.9	-7860.5
	B	B	-7965.1	-7816.5	-7928.9	-7711.9	-7963.0	-7854.9	-7780.2	-7890.7	-7936.8	-7923.2
	B	A	-7966.4	-7854.2	-7933.2	-7714.0	-7973.1	-7871.6	-7780.7	-7893.5	-7937.9	-7925.4
	A	B	-7895.6	-7897.9	-7881.8	-7701.0	-7885.5	-7878.3	-7732.9	-7848.9	-7868.0	-7862.9
v	A	A	-7720.5	-7702.4	-7716.8	-7624.9	-7709.3	-7695.9	-7616.2	-7683.2	-7696.0	-7706.7
	B	B	-7849.7	-7841.9	-7847.6	-7723.5	-7845.6	-7842.2	-7740.4	-7780.6	-7827.2	-7828.2
	B	A	-7853.8	-7849.2	-7852.2	-7727.3	-7853.3	-7854.3	-7744.2	-7787.3	-7830.9	-7832.9
	A	B	-7724.5	-7709.1	-7721.2	-7628.3	-7715.9	-7706.3	-7619.8	-7689.3	-7699.5	-7711.2

$$r(f;t) = \left[\left(U(f;t) - U(f;t-1)\right)^2 + \left(V(f;t) - V(f;t-1)\right)^2\right]^{1/2}$$

$$a(f;t) = \left|U(f;t) - U(f;t-1)\right|$$

$$r^*(t) = \left[\left(U(f;t) - U(o;t-1)\right)^2 + \left(V(f;t) - V(o;t-1)\right)^2\right]$$

$$a(o;t) = \left|U(o;t) - U(o;t-1)\right| \quad \text{for } u \text{ - wind component error}$$

$$a(o;t) = \left|V(o;t) - V(o;t-1)\right| \quad \text{for } v \text{ - wind component error}$$

$$a^*(t) = \left|U(f;t) - U(o;t-1)\right| \quad \text{for } u \text{ - wind component error}$$

$$a^*(t) = \left|V(f;t) - V(o;t-1)\right| \quad \text{for } v \text{ - wind component error}$$

$$r(t) = \left[\left(U(o;t) - U(o;t-1)\right)^2 + \left(V(o;t) - V(o;t-1)\right)^2\right]^{1/2}$$

$$w(o;t) = \left[U(o;t)^2 + V(o;t)^2\right]^{1/2}$$

$$w(f;t) = \left[U(f;t)^2 + V(f;t)^2\right]^{1/2}$$

$$m(f;t) = \max\left(U(f;t), V(f;t)\right)$$

TABLE 2B
Log-Likelihood
500 mb. Height
February Data

Two-Variate Models

Wind Comp	Data	Model	Const	$r^*(t), a(o;t)$	$r(f;t), a(f;t)$	$r^*(t), a^*(t)$	$r^*(t), a(f;t)$	$r(t), w(o;t)$	$r(t), w(f;t)$
u	A	A	-7894.4	-7693.4	-7873.2	-7860.2	-7860.3	-7718.3	-7724.1
	B	B	-7965.1	-7676.8	-7923.7	-7807.4	-7813.6	-7762.7	-7772.2
	B	A	-7966.4	-7689.2	-7950.9	-7843.4	-7873.3	-7763.1	-7772.6
	A	B	-7895.6	-7704.0	-7893.6	-7891.5	-7905.7	-7718.7	-7724.5
v	A	A	-7720.5	-7622.3	-7706.6	-7695.7	-7701.5	-7601.9	-7609.0
	B	B	-7849.7	-7722.0	-7845.0	-7841.3	-7841.9	-7711.0	-7730.8
	B	A	-7853.8	-7733.8	-7853.9	-7853.6	-7850.4	-7716.5	-7734.6
	A	B	-7724.5	-7633.9	-7714.1	-7706.2	-7708.9	-7607.0	-7612.6

$$r(f;t) = \left[(U(f;t) - U(f;t-1))^2 + (V(f;t) - V(f;t-1))^2\right]^{1/2}$$

$$a(f;t) = |U(f;t) - U(f;t-1)|$$

$$r^*(t) = \left[(U(f;t) - U(o;t-1))^2 + (V(f;t) - V(o;t-1))^2\right]$$

$a(o;t) = |U(o;t) - U(o;t-1)|$ for u - wind component error

$a(o;t) = |V(o;t) - V(o;t-1)|$ for v - wind component error

$a^*(t) = |U(f;t) - U(o;t-1)|$ for u - wind component error

$a^*(t) = |V(f;t) - V(o;t-1)|$ for v - wind component error

$$r(t) = \left[(U(o;t) - U(o;t-1))^2 + (V(o;t) - V(o;t-1))^2\right]^{1/2}$$

$$w(o;t) = \left[U(o;t)^2 + V(o;t)^2\right]^{1/2}$$

$$w(f;t) = \left[U(f;t)^2 + V(f;t)^2\right]^{1/2}$$

TABLE 3B
One-Variate Models
Parameter Estimates
(Standard Errors)
500 mb. February Data

Wind Comp	Data Set	$r^*(t)$ α	$r^*(t)$ β	$r(f;t)$ α	$r(f;t)$ β	$a(o;t)$ α	$a(o;t)$ β	$a(f;t)$ α	$a(f;t)$ β	$a^*(t)$ α	$a^*(t)$ β	$m(f;t)$ α	$m(f;t)$ β
u	A	2.56	0.03	2.63	0.02	2.31	0.07	2.68	0.03	2.64	0.03	2.55	0.02
		(0.06)	(0.005)	(0.06)	(0.006)	(0.05)	(0.006)	(0.05)	(0.008)	(0.05)	(0.007)	(0.06)	(0.003)
	B	2.25	0.06	2.60	0.02	2.28	0.08	2.83	0.01	2.50	0.06	2.53	0.02
		(0.06)	(0.005)	(0.06)	(0.006)	(0.05)	(0.006)	(0.05)	(0.008)	(0.05)	(0.006)	(0.06)	(0.003)
	All	2.40	(0.04)	2.60	0.03	2.29	0.08	2.75	0.02	2.56	0.05	2.54	0.02
		(0.04)	(0.004)	(0.04)	(0.004)	(0.03)	(0.004)	(0.03)	(0.006)	(0.03)	(0.005)	(0.04)	(0.002)
v	A	2.54	0.02	2.66	0.01	2.41	0.04	2.63	0.02	2.56	0.03	2.57	0.01
		(0.06)	(0.005)	(0.06)	(0.006)	(0.05)	(0.005)	(0.05)	(0.007)	(0.05)	(0.006)	(0.06)	(0.003)
	B	2.69	0.01	2.75	0.008	2.40	0.05	2.75	0.01	2.72	0.01	2.58	0.01
		(0.06)	(0.005)	(0.06)	(0.006)	(0.05)	(0.005)	(0.05)	(0.006)	(0.05)	(0.005)	(0.06)	(0.003)
	All	2.62	0.02	2.71	0.01	2.40	0.05	2.69	0.02	2.65	0.02	2.57	0.01
		(0.04)	(0.004)	(0.04)	(0.004)	(0.03)	(0.003)	(0.03)	(0.004)	(0.03)	(0.004)	(0.04)	(0.002)

$$r(f;t) = \left[\left(U(f;t) - U(f;t-1)\right)^2 + \left(V(f;t) - V(f;t-1)\right)^2\right]^{1/2}$$

$$a(f;t) = \left|U(f;t) - U(f;t-1)\right|$$

$$r^*(t) = \left[\left(U(f;t) - U(o;t-1)\right)^2 + \left(V(f;t) - V(o;t-1)\right)^2\right]$$

$$a(o;t) = \left|U(o;t) - U(o;t-1)\right|, \quad a^*(t) = \left|U(f;t) - U(o;t-1)\right|$$

TABLE 4B
Two-Variate Models
Parameter Estimates
(Standard Errors)
500 mb. February Data

Wind Comp	Data Set	$\log MSE = \alpha + \beta_1 r^*(t) + \beta_2 a(o;t)$			$\log MSE = \alpha + \beta_1 r_f(t) + \beta_2 a(f;t)$			$\log MSE = \alpha + \beta_1 r^*(t) + \beta_2 a^*(t)$		
		α	β_1	β_2	α	β_1	β_2	α	β_1	β_2
u	A	2.20	0.01	0.07	2.62	0.01	0.02	2.55	0.02	0.02
		(0.07)	(0.005)	(0.006)	(0.06)	(0.008)	(0.01)	(0.06)	(0.007)	(0.009)
	B	2.02	0.03	0.07	2.58	0.05	-0.02	2.24	0.04	0.02
		(0.06)	(0.005)	(0.006)	(0.06)	(0.008)	(0.01)	(0.06)	(0.007)	(0.008)
	All	2.10	0.02	0.07	2.60	0.03	-0.002	2.39	0.03	-0.02
		(0.05)	(0.004)	(0.004)	(0.04)	(0.005)	(0.007)	(0.04)	(0.005)	(0.006)
v	A	2.33	0.009	0.04	2.68	-0.02	0.04	2.55	0.004	0.02
		(0.06)	(0.006)	(0.005)	(0.06)	(0.01)	(0.01)	(0.06)	(0.008)	(0.009)
	B	2.45	-0.007	0.05	2.78	-0.009	0.02	2.69	0.008	0.007
		(0.06)	(0.006)	(0.005)	(0.06)	(0.01)	(0.01)	(0.06)	(0.009)	(0.009)
	All	2.39	0.001	0.05	2.73	-0.01	0.03	2.62	0.006	0.01
		(0.05)	(0.004)	(0.004)	(0.04)	(0.008)	(0.008)	(0.04)	(0.006)	(0.006)

$$r(f;t) = \left[\left(U(f;t) - U(f;t-1)\right)^2 + \left(V(f;t) - V(f;t-1)\right)^2 \right]^{1/2}$$

$$a(f;t) = \left| U(f;t) - U(f;t-1) \right|$$

$$r^*(t) = \left[\left(U(f;t) - U(o;t-1)\right)^2 + \left(V(f;t) - V(o;t-1)\right)^2 \right]$$

$$a(o;t) = \left| U(o;t) - U(o;t-1) \right|, \quad a^*(t) = \left| U(f;t) - U(o;t-1) \right|$$

TABLE 1C
Log-Likelihood
250 mb. Height/February Data

One-Variate Models

Wind Comp	Data	Model	Const	$r^*(t)$	$r(f;t)$	$a(o;t)$	$a(f;t)$	$a^*(t)$	$r(t)$	$w(o;t)$	$w(f;t)$	$m(f;t)$	$U(f;t)$ $V(f;t)$
u	A	A	-9376.4	-9253.8	-9365.4	-8609.8	-9362.6	-9289.9	-8705.7	-8614.6	-9137.6	-8962.3	-9074.1
	B	B	-8957.8	-8897.4	-8927.6	-8559.6	-8950.7	-8946.3	-8637.6	-8600.3	-8890.9	-8795.1	-8911.9
	B	A	-9001.3	-8931.4	-8977.3	-8562.1	-9024.6	-8989.3	-8641.4	-8611.9	-8923.2	-8816.7	-8991.9
	A	B	-9426.8	-9292.8	-9423.7	-8612.3	-9463.7	-9351.3	-8710.3	-8629.4	-9188.4	-8994.9	-9186.6
v	A	A	-8803.2	-8669.4	-8801.6	-8477.6	-8782.9	-8621.7	-8435.0	-8355.6	-8692.4	-8693.1	-8786.2
	B	B	-8916.9	-8835.6	-8864.4	-8566.5	-8833.5	-8829.6	-8565.4	-8507.1	-8886.9	-8877.3	-8913.0
	B	A	-8920.4	-8843.7	-8898.1	-8575.9	-8843.0	-8860.6	-8571.7	-8516.4	-8907.8	-8890.4	-8922.6
	A	B	-8806.6	-8677.3	-8820.1	-8486.7	-8788.3	-8647.8	-8440.6	-8364.2	-8714.4	-8706.5	-8794.8

$$r(f;t) = \left[(U(f;t)-U(f;t-1))^2 + (V(f;t)-V(f;t-1))^2\right]^{1/2}$$

$$a(f;t) = |U(f;t)-U(f;t-1)|$$

$$r^*(t) = \left[(U(f;t)-U(o;t-1))^2 + (V(f;t)-V(o;t-1))^2\right]$$

$$a(o;t) = |U(o;t)-U(o;t-1)| \quad \text{for } u \text{ - wind component error}$$

$$a(o;t) = |V(o;t)-V(o;t-1)| \quad \text{for } v \text{ - wind component error}$$

$$a^*(t) = |U(f;t)-U(o;t-1)| \quad \text{for } u \text{ - wind component error}$$

$$a^*(t) = |V(f;t)-V(o;t-1)| \quad \text{for } v \text{ - wind component error}$$

$$r(t) = \left[(U(o;t)-U(o;t-1))^2 + (V(o;t)-V(o;t-1))^2\right]^{1/2}$$

$$w(o;t) = \left[U(o;t)^2 + V(o;t)^2\right]^{1/2}$$

$$w(f;t) = \left[U(f;t)^2 + V(f;t)^2\right]^{1/2}$$

$$m(f;t) = \max(U(f;t), V(f;t))$$

TABLE 2C
Log-Likelihood
250 mb. Height
February Data

Two-Variate Models

Wind Comp	Data	Model	Const	$r^*(t), a(o;t)$	$r(f;t), a(f;t)$	$r^*(t), a^*(t)$	$r^*(t), a(f;t)$	$r(t), w(o;t)$	$r(t), w(f;t)$
u	A	A	-9376.4	-8537.9	-9361.5	-9252.4	-9231.0	-8504.0	-8685.4
	B	B	-8957.8	-8553.5	-8900.9	-8896.2	-8864.2	-8502.1	-8581.6
	B	A	-9001.3	-8572.7	-9004.9	-8934.7	-8981.0	-8507.2	-8594.4
	A	B	-9426.8	-8567.0	-9479.4	-9297.6	-9465.5	-8509.3	-8698.6
v	A	A	-8803.2	-8417.8	-8756.1	-8621.6	-8660.9	-8288.9	-8426.5
	B	B	-8916.9	-8565.9	-8828.3	-8821.9	-8818.3	-8415.8	-8541.6
	B	A	-8920.4	-8598.2	-8854.5	-8858.3	-8894.1	-8424.4	-8553.3
	A	B	-8806.6	-8469.7	-8772.4	-8646.8	-8710.8	-8296.5	-8437.9

$$r(f;t) = \left[(U(f;t)-U(f;t-1))^2 + (V(f;t)-V(f;t-1))^2\right]^{1/2}$$

$$a(f;t) = |U(f;t)-U(f;t-1)|$$

$$r^*(t) = \left[(U(f;t)-U(o;t-1))^2 + (V(f;t)-V(o;t-1))^2\right]$$

$$a(o;t) = |U(o;t)-U(o;t-1)| \quad \text{for } u \text{ - wind component error}$$

$$a(o;t) = |V(o;t)-V(o;t-1)| \quad \text{for } v \text{ - wind component error}$$

$$a^*(t) = |U(f;t)-U(o;t-1)| \quad \text{for } u \text{ - wind component error}$$

$$a^*(t) = |V(f;t)-V(o;t-1)| \quad \text{for } v \text{ - wind component error}$$

$$r(t) = \left[(U(o;t)-U(o;t-1))^2 + (V(o;t)-V(o;t-1))^2\right]^{1/2}$$

$$w(o;t) = \left[U(o;t)^2 + V(o;t)^2\right]^{1/2}$$

$$w(f;t) = \left[U(f;t)^2 + V(f;t)^2\right]^{1/2}$$

TABLE 3C
One-Variate Models
Parameter Estimates
(Standard Errors)
250 mb. February Data

Wind Comp	Data Set	$r^*(t)$		$r(f;t)$		$a(o;t)$		$a(f;t)$		$a^*(t)$		$m(f;t)$	
		α	β	α	β	α	β	α	β	α	β	α	β
u	A	3.50	0.03	3.81	0.02	3.10	0.06	3.88	0.02	3.72	0.03	3.00	0.03
		(0.06)	(0.003)	(0.07)	(0.005)	(0.05)	(0.004)	(0.05)	(0.005)	(0.04)	(0.003)	(0.06)	(0.002)
	B	3.34	0.03	3.52	0.02	3.07	0.05	3.88	-0.01	3.66	0.01	3.16	0.02
		(0.06)	(0.004)	(0.06)	(0.004)	(0.05)	(0.004)	(0.05)	(0.005)	(0.05)	(0.004)	(0.07)	(0.002)
	All	3.42	0.03	3.67	0.02	3.08	0.05	3.87	0.005	3.68	0.02	3.05	0.03
		(0.04)	(0.002)	(0.04)	(0.003)	(0.03)	(0.003)	(0.03)	(0.004)	(0.03)	(0.003)	(0.05)	(0.001)
v	A	3.07	0.04	3.63	0.005	3.13	0.04	3.50	0.02	3.10	0.05	3.14	0.02
		(0.06)	(0.005)	(0.06)	(0.004)	(0.04)	(0.003)	(0.05)	(0.005)	(0.05)	(0.004)	(0.06)	(0.002)
	B	3.22	0.03	3.42	0.02	3.10	0.04	3.44	0.03	3.37	0.03	3.34	0.01
		(0.07)	(0.004)	(0.06)	(0.004)	(0.05)	(0.002)	(0.05)	(0.004)	(0.05)	(0.004)	(0.07)	(0.002)
	All	3.15	0.03	3.46	0.03	3.12	0.04	3.46	0.03	3.25	0.04	3.23	0.02
		(0.05)	(0.003)	(0.03)	(0.003)	(0.03)	(0.002)	(0.03)	(0.003)	(0.04)	(0.003)	(0.05)	(0.001)

$$r(f;t) = \left[\left(U(f;t) - U(f;t-1)\right)^2 + \left(V(f;t) - V(f;t-1)\right)^2\right]^{1/2}$$

$$a(f;t) = \left|U(f;t) - U(f;t-1)\right|$$

$$r^*(t) = \left[\left(U(f;t) - U(o;t-1)\right)^2 + \left(V(f;t) - V(o;t-1)\right)^2\right]$$

$$a(o;t) = \left|U(o;t) - U(o;t-1)\right|, \quad a^*(t) = \left|U(f;t) - U(o;t-1)\right|$$

$$m(f;t) = \max\left(U(f;t), V(f;t)\right)$$

TABLE 4C
Two-Variate Models
Parameter Estimates
(Standard Errors)
250 mb. February Data

Wind Comp	Data Set	$\log MSE=\alpha+\beta_1 r^*(t)+\beta_2 a(o;t)$			$\log MSE=\alpha+\beta_1 r_f(t)+\beta_2 a(f;t)$			$\log MSE=\alpha+\beta_1 r^*(t)+\beta_2 a^*(t)$		
		α	β_1	β_2	α	β_1	β_2	α	β_1	β_2
u	A	2.73	0.03	0.05	3.83	0.007	0.01	3.50	0.03	0.006
		(0.06)	(0.003)	(0.003)	(0.07)	(0.006)	(0.007)	(0.06)	(0.004)	(0.005)
	B	2.93	0.009	0.05	3.61	0.03	-0.03	3.35	0.03	-0.006
		(0.07)	(0.004)	(0.004)	(0.06)	(0.004)	(0.006)	(0.06)	(0.004)	(0.005)
	All	2.80	0.02	0.05	3.68	0.02	-0.01	3.42	0.03	0.007
		(0.05)	(0.002)	(0.003)	(0.04)	(0.004)	(0.004)	(0.04)	(0.003)	(0.004)
v	A	2.80	0.02	0.03	3.69	-0.04	0.06	3.09	0.001	0.05
		(0.06)	(0.003)	(0.003)	(0.07)	(0.008)	(0.008)	(0.06)	(0.005)	(0.006)
	B	3.06	0.003	0.04	3.52	-0.02	0.05	3.25	0.02	0.02
		(0.07)	(0.004)	(0.003)	(0.06)	(0.007)	(0.007)	(0.07)	(0.006)	(0.006)
	All	2.90	0.02	0.04	3.58	-0.03	0.05	3.18	0.01	0.03
		(0.04)	(0.002)	(0.002)	(0.04)	(0.005)	(0.005)	(0.04)	(0.004)	(0.004)

$$r(f;t)=\left[\left(U(f;t)-U(f;t-1)\right)^2+\left(V(f;t)-V(f;t-1)\right)^2\right]^{1/2}$$

$$a(f;t)=\left|U(f;t)-U(f;t-1)\right|$$

$$r^*(t)=\left[\left(U(f;t)-U(o;t-1)\right)^2+\left(V(f;t)-V(o;t-1)\right)^2\right]$$

$$a(o;t)=\left|U(o;t)-U(o;t-1)\right|,\quad a^*(t)=\left|U(f;t)-U(o;t-1)\right|$$

TABLE 5
Percent of Increase
$(\tilde{\ell}-\tilde{\ell}_c)/|\tilde{\ell}_c|$

Pressure Level mb	Wind Comp	Data Set	Model	One-Variate Models r	$w(o)$	$a(o)$	r^*	a^*	$w(f)$	$m(f)$
850	u	B	A	0.8	1.6	1.5	1.4	1.9	0.2	-0.2
		A	B	0.8	0.5	1.7	0.5	0.8	-0.03	-0.1
	v	B	A	0.7	2.2	0.4	0.7	0.3	0.2	0.1
		A	B	0.4	2.6	-0.3	1.3	1.1	0.08	-0.09
500	u	B	A	2.3	0.9	3.2	1.4	1.2	0.3	0.03
		A	B	2.0	0.6	2.4	-0.04	0.2	0.3	0.4
	v	B	A	1.3	0.8	1.6	0.006	-0.005	0.2	0.2
		A	B	1.3	0.4	1.2	0.1	0.2	0.3	0.1
250	u	B	A	3.5	3.9	4.4	0.3	-0.4	0.4	3.0
		A	B	7.1	8.0	8.1	0.8	0.3	2.0	4.0
	v	B	A	3.9	4.5	3.8	0.8	0.6	0.1	0.3
		A	B	4.1	5.0	3.6	1.4	1.7	1.0	0.1

TABLE 6

Sample Moments of
First-Guess Wind Speed Errors Divided by Predicted Standard Deviations

Wind Comp	Covariates	Est. Method	Mean	Std.Dev.	Skewness	Kurtosis
u	none	–	0.11	7.04	-1.28	51.1
	constant	MLE	0.02	1.01	-1.24	57.4
	$w(f)$	MLE	0.02	1.01	-0.73	32.9
	$w(f)$	2 bins	0.02	1.01	-0.59	34.4
		3 bins	0.02	1.02	-0.98	42.9
	$m(f)$	MLE	0.01	1.01	1.01	27.6
	$m(f)$	2 bins	0.02	1.01	-0.63	34.1
		3 bins	0.01	1.03	-1.11	41.0
	$a(o)$	MLE	0.02	1.00	0.24	6.0
	$r(o)$	MLE	0.02	1.00	0.17	7.7
	$a(f)$	MLE	0.02	1.02	-0.92	57.6
	a^*	MLE	0.01	1.00	-1.42	64.5
v	none	–	-0.11	6.47	-1.98	35.5
	constant	MLE	-0.02	1.00	-1.98	35.3
	$w(f)$	MLE	-0.00	1.01	-1.49	28.6
	$w(f)$	2 bins	-0.00	1.00	-1.28	23.9
		3 bins	-0.01	1.03	-2.04	37.8
	$m(f)$	MLE	-0.00	1.00	-1.33	24.8
	$m(f)$	2 bins	-0.02	1.00	-2.00	36.2
		3 bins	-0.01	1.04	-2.14	40.9
	$a(o)$	MLE	-0.02	1.00	2.08	36.1

$$m(f;t) = \max\left(U(f;t), V(f;t)\right)$$

$$w(f;t) = \left[U(f;t)^2 + V(f;t)^2\right]^{1/2}$$

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