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EVALUATION OF A METHOD FOR SHORT-RANGE FORECASTING OF EVAPORATION DUCT HEIGHTS

Wayne A. Sweet

Naval Environmental Prediction Research Facility

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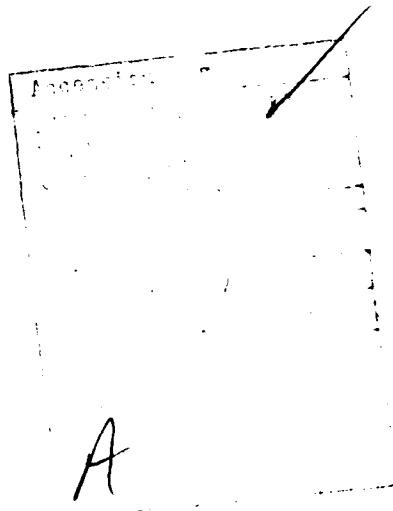
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1. INTRODUCTION

This study evaluates the skill of a forecasting method* that utilizes surface-observed meteorological variables to develop short range (3-12 hr) predictions of evaporation duct heights. Although this method was developed for use in short range statistical terminal forecasting, its adaptation to duct height prediction required only the selection of appropriate predictors and individual internal transformations.

Data from two ocean weather stations (OWS) in the North Atlantic Ocean, OWS Charlie and OWS Echo, were used in the evaluation, the former to represent the higher latitudes and the latter to represent the midlatitudes. For purposes of this evaluation, skill and threat scores derived from these data were compared to persistence scores.

The forecast method, the OWS data samples, and the evaluation procedure are described in Section 2. Results are discussed in Section 3. Threat and skill scores are defined in the Appendix.

*Developed by Dr. R. G. Miller, Techniques Development Laboratory, NOAA, Silver Spring, MD 20910.

2. FORECAST METHOD

2.1 INTRODUCTION

Forecasters presently use a combination of climatology, persistence, and data on the existing synoptic situation, to develop short range (1-12 hr) weather predictions. Indications of the existing synoptic situation, in turn, can be found in certain meteorological variables observed at the surface every one to three hours.

Using this premise that surface observables can provide valid synoptic predictors, Miller (1979) designed a conditional climatological prediction method for short range forecasting based on a technique called regression estimate of event probability (REEP).^{*} Applying the basic Markovian process to the REEP, Miller expanded the technique to develop hourly forecasts for one to twenty-four hours; these forecasts are the event probabilities determined by the regression equations, converted to categorical forecasts by a set of threshold probabilities.

It was reasonable to extend this method to the prediction of evaporation duct heights, insofar as these ducts are surface layer phenomena.

2.2 DISCUSSION

As an example, consider attempting to forecast winds and pressure using only these same variables as predictors. Wind speed (WS), wind direction (WD) and sea level pressure (P) are transformed into (0,1) dummy variables where the value is set equal to 1 if the observation falls within the dummy's prescribed interval, and to 0 otherwise. A possible transformation would be the following:

^{*} See Miller, 1964.

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Variable

P (mb)	P ₁ (50-990), P ₂ (990-1000), P ₃ (1000-1010) P ₄ (1010-1015), P ₅ (1015-1020), P ₆ (1020-1100)
WS (kt)	WS ₁ (0-4), WS ₂ (4-8), WS ₃ (8-12) WS ₄ (12-20), WS ₅ (20-30), WS ₆ (30-100)
WD	WD ₁ (N-E), WD ₂ (E-S), WD ₃ (S-W), WD ₄ (W-N)

These three variables are then transformed into 16 (0,1) dummy variables; if the observed P is 1013, then P₄=1, and for all other i's, P_i=0. Wind speed and direction are set in like manner. A regression equation is then calculated for each of the dummy variables.

Using all 16 dummies as predictors, Miller (1979) has shown that this method gives probabilities directly from the regression equation, such that

$$P[P_1=1] = a_0 + \sum_{i=1}^{16} a_i z_i \quad (2-1)$$

P[P₁=1] is the probability that P₁ (i.e., pressure is between 950 and 990) equals one; a_i are the regression coefficients, and Z = (0010 0) is a vector whose components are 1 if the observed P, WS, and WD occur with the given range and are 0 if not.

There are 16 such regression equations,

$$\begin{aligned} P[P_1=1] &= a_{0,1} + \sum_i a_{i,1} z_i \\ &\vdots \\ &\vdots \\ &\vdots \\ P[P_{16}=1] &= a_{0,16} + \sum_i a_{i,16} z_i \end{aligned}$$

The coefficients can be represented by a 16x16 matrix \underline{Q} .

$$\underline{Q} = \begin{pmatrix} a_{0,1} & a_{1,1} & a_{1,2} & \dots & a_{1,16} \\ a_{0,2} & a_{1,2} & a_{2,2} & \dots & a_{2,16} \\ \cdot & & & & \cdot \\ \cdot & & & & \cdot \\ \cdot & & & & \cdot \\ a_{0,16} & a_{1,16} & \dots & \dots & a_{16,16} \end{pmatrix}$$

so that

$$\underline{P} = \underline{Z} \cdot \underline{Q}, \quad \text{where} \quad (2-4)$$

$$\underline{P} = (P_0 P_1 \dots P_{16}) \quad (2-5)$$

$P_0 = 1$, since it is simply a constant needed for regression; P_i ($i=1, \dots, 16$) are the probabilities that the respective dummy variables will be 1. If the regression coefficients are determined from hourly observations, the predicted values will be for one hour later. To generate a n-hour forecast, the first order Markov process is assumed, and one has $\underline{P}(n) = \underline{Z} \underline{Q}^n$.

A true first order Markov process is one in which the next event depends only on the preceding event and not on the earlier chain of events. Whether a Markov first order process is applicable to meteorological phenomena depends on the extent to which the real world violates the simple model. This model has been shown to hold fairly well (Miller, 1979). Empirical tests such as the one reported here are the only way to examine, indirectly, the validity of the Markov assumption.

The advantages and disadvantages of transforming continuous variables such as temperature into discrete variables (the (0,1) dummies)* are summarized as follows:

Advantages

- (1) Probabilities computed directly from regression equations.
- (2) Facilitate computations
- (3) Probabilities sum to zero.
- (4) Probabilities essentially minimize the Brier-Allen P score.

*See Miller, 1964.

Disadvantages

- (1) Probabilities are not bounded by 0 and 1.
- (2) Transformation from a continuous variable to a discrete variable discards some information.

The first disadvantage can be corrected by normalizing those forecast probabilities that do exceed the (0,1) interval.*

The second disadvantage is accepted as a reasonable trade-off in order to handle the Markov process by simple matrix algebra. This is accomplished by using the vectors of dummy variables, rather than the "true state" vector. In this sense the process is an "equivalent Markov method." It would be impractical, even on large computers, to attempt to compute the true Markov transition matrix for all states, using even a small number of predictors (see Whiton, 1978).

Once the forecast probabilities for each dummy variable are computed, the question arises of how best to use these probabilities to generate a forecast. Miller and Best (1979) have developed a method to determine statistically appropriate threshold probabilities, P^* , so that a set of categorical forecasts \underline{C} can be found by

$$\underline{C} = \underline{P} \cdot \underline{P}^* \quad (2-6)$$

The C's are either zero or one, indicating which dummy is categorically forecasted.

2.3 EVAPORATION DUCT HEIGHT FORECASTING

The adaptation of the "equivalent Markov method" to the problem of forecasting evaporation duct heights requires first the selection of appropriate meteorological variables from those recorded in the marine surface observations data file. Duct height is calculated from the air, sea and dew point temperatures, and wind speed (Jeske, 1971; Hitney, 1975). The calculated duct height is then added to the selected meteorological variables to form the data base from which the regression coefficients are calculated.

* See Miller, 1964.

The variables selected to form the predictor set for this present study are listed in Table 1. The weather types are simply the occurrences or non-occurrences of the variable. These 19 variables were then transformed through interval transformation to the 111 dummy variables listed in Table 2 for ocean weather station Echo.

Table 1. Variables in the predictor set.

1. Month
2. Time
3. Wind direction
4. Wind speed
5. Air temperature
6. Dew point
7. Sea surface temperature
8. Air-sea temperature difference
9. Sea level pressure
10. Pressure change (3 m)
11. Total cloud amount
12. Lower cloud amount
13. Duct height - present weather
14. Rain, drizzle, snow
15. Rain showers, snow showers
16. Fog - past weather
17. Rain, drizzle, snow
18. Rain showers, snow showers
19. Fog

Table 2

<u>Month</u>	<u>Time</u>	<u>Wind Direction</u>	<u>Wind Speed</u>
Jan (1)	2000-0900 (13)	N-NE (16)	0-8 (24)
Feb (2)	0900-1300 (14)	NE-E (17)	9-11 (25)
Mar (3)	1300-2000 (15)	E-SE (18)	12-14 (26)
Apr (4)		SE-S (19)	15-17 (27)
May (5)		S-SW (20)	18-20 (28)
Jun (6)		SW-W (21)	21-23 (29)
Jul (7)		W-NW (22)	24-27 (30)
Aug (8)		NW-N (23)	28-30 (31)
Sep (9)			31-99 (32)
Oct (10)			
Nov (11)			
Dec (12)			

<u>Air Temperature</u>		<u>Dew Point</u>	<u>Sea Surface Temperature</u>
-30. -15.6 (33)		-30. -8.5 (43)	- .1-17.0 (54)
15.7 -16.7 (34)		8.6-11.0 (44)	17.1-17.8 (55)
16.8 -17.8 (35)		11.1-12.5 (45)	17.9-18.3 (56)
17.9 -18.5 (36)		12.6-13.5 (46)	18.4-19.5 (57)
18.6 -19.2 (37)		13.6-15.5 (47)	19.6-21.0 (58)
19.3 -20.0 (38)		15.6-16.5 (48)	21.1-22.7 (59)
20.1 -21.7 (39)		16.6-17.5 (49)	22.8-23.9 (60)
21.8 -24.0 (40)		17.6-18.5 (50)	24.0-25.6 (61)
24.1 -25.5 (41)		18.6-20.5 (51)	25.6-99 (62)
25.6 - 9.9 (42)		20.6-21.5 (52)	
		21.6-99 (53)	

Table 2 (continued)

<u>TA-TS</u>	<u>Sea Level Pressure</u>	<u>Pressure Change</u>
-30.-4.5 (63)	800-1012 (71)	- 90-1.5 (78)
-4.4-2.8 (64)	1012-1017 (72)	-1.4-1.2 (79)
-2.7-1.6 (65)	1017-1020 (73)	-1.1-0.9 (80)
-1.5-1.0 (66)	1020-1022 (74)	-0.8-0.5 (81)
-0.9-0.5 (67)	1022-1024 (75)	-0.4-0.2 (82)
-0.4-0.0 (68)	1024-1027 (76)	-0.1-0.0 (83)
0.1-0.8 (69)	1027-1100 (77)	0.1-0.3 (84)
0.8-99 (70)		0.4-0.8 (85)
		0.9-1.5 (86)
		1.6-99 (87)

<u>Total Cloud Amount</u>	<u>Lower Cloud Amount</u>	<u>Duct Height</u>
Clear (88)	Clear (92)	0-8 (96)
Scattered (89)	Scattered (93)	9-12 (97)
Broken (90)	Broken (94)	13-20 (98)
Overcast (91)	Overcast (95)	21-90 (99)

<u>Present Weather</u>	<u>Past Weather</u>
R,L,S (100)	R,L,S (106)
No R,L,S (101)	No R,L,S (107)
RW,SW (102)	RW,SW (108)
No RW,SW (103)	No RW,SW (109)
Fog (104)	Fog (110)
No Fog (105)	No Fog (111)

The intervals chosen were such that the relative frequencies of occurrence were roughly the same (within a factor of 2), with the exception of duct height intervals which were selected on the basis of operational factors. Those intervals for variables such as temperature are latitude-longitude dependent; OWS Charlie therefore has intervals somewhat different than those listed in Table 2 for OWS Echo. The total number of dummies in each case is the same.

The regression coefficients for the equations for each of these dummy variables were calculated using a 10-year data base with observations at three-hour intervals. The probabilities and categorical forecasts were then obtained by matrix multiplication, as shown in Eqs. 2-4 and 2-6.

2.4 DATA BASE

Surface observations for OWS Charlie (52°N, 35°W) and OWS Echo (35°N, 48°W) were used to evaluate the forecast procedure. Ten-year data samples for each OWS were used to calculate the regression coefficients. Independent data samples of about three years for each station were also processed to be used to produce forecasts and skill scores. Each meteorological variable was screened for reasonable values, and observations with any missing variables were discarded.

2.5 EVALUATION PROCEDURE

Evaporation duct height forecasts for three, six, nine, and twelve hours were produced, and then compared to the observed duct heights. Heidke skill scores, threat scores and total percent correct were computed. Since persistence is the best objective forecast technique currently available, it was also tabulated and skill scores computed.

The scores were subjected to a one-way analysis of variance to determine statistically significant differences in the equivalent Markov method and persistence forecast skills.

3. RESULTS

Contingency tables were constructed so that the columns contain the forecasts and the rows contain the observed values of duct heights. Tables 3 through 18 give the cell counts and scores for both ocean weather stations. The "a" tables are the various forecasts using the equivalent Markov forecast procedure; the "b" tables are those for persistence. Both dependent and independent sample results are shown.

The threat score for each diagonal cell and the weighted average for the threat scores were computed (see Appendix); Heidke skill scores for each contingency table also were computed.

3.1 OWS CHARLIE

The Heidke scores for both independent and dependent data samples in Table 19a show that the forecast procedure (F) appears better overall than persistence (P). The averages over all four forecast periods are also larger for F than for P, for both data samples. An analysis of variance* was performed on both samples; the F-values and probabilities are given in Tables 19a and 19b.

The analysis answers the question of whether the forecast average scores really are higher than the persistence average scores. For OWS Charlie, statistically there is a 32% (61%) chance for the "no" answer for the independent (dependent) sample (see Table 19a). Therefore one must reject that answer and accept that the average scores for the forecast procedure and simple persistence are not statistically different. Hence the forecast procedure is no better than persistence, based on the Heidke scores.

Threat scores were also subjected to an analysis of variance. Table 19a shows that the average threat score for the independent sample are .579 and .547 for F and P, respectively. The analysis shows no statistical difference between these averages (44% chance of being wrong if one assumes they are different). The dependent sample shows even stronger evidence that the forecast procedure is no better than persistence.

*The necessary assumption of similar sample variances is clearly satisfied (see Table 17).

3.2 OWS ECHO

Heidke scores are shown in Table 19b for both data samples for OWS Echo. An analysis of variance strongly indicated that the forecast procedure was no better than persistence. The threat scores shown in Table 19b also reveal small F-test values, and high probabilities that these two set of scores are indeed similar.

3.3 DISCUSSION OF RESULTS

The forecast method was compared to persistence via Heidke skill scores and threat scores. Comparisons were made for both the dependent data sample (the data used to generate the forecast equations) and an independent data sample. Data from OWS Charlie (a northern latitude location) and OWS Echo (a midlatitude location) were used to examine the forecast skills for different evaporation duct height distribution (see Sweet, 1979; and Tables 1-16 of this report).

The northern latitude station, Charlie, had a duct height distribution skewed toward the lowest duct height cell (0-8 m). The Heidke skill scores were higher for this station than for Echo, whose distribution was centered about the 12-20 m cell. The same difference was noted for the threat scores (see Tables 19a and 19b). Since the higher duct heights affect more fleet radar systems, Echo's duct height distribution was representative of a more operationally significant distribution type. Therefore, lessor skills of Echo as compared to Charlie is discouraging. This trend was also revealed in the total percent of correct forecasts shown in Tables 20a and 20b.

An analysis of variance comparing the forecast method's skills to the persistence skills revealed that the forecast method was not statistically better than simple persistence. Some forecast-valid periods (i.e., Echo's Heidke skill for the six hour forecast) taken singularly appeared to show that the forecast method was measureably better than persistence. However, when both Heidke and threat scores were considered, no forecast-valid period consistently had higher scores than persistence.

It is concluded that the forecast algorithm as a predictive method is no better than simply forecasting the continuation of current observed duct heights. It appears that further study or development of the forecast method evaluated here would be unproductive unless new developments of the method promise greater skill.

Table 3. OWS Charlie Independent Sample.

3 HR FORECAST
FORECAST

OBSERVED	Ht. (m)	0-8	8-12	12-20	>20	TOTAL	CORRECT = 77%	SKILL = .507
	0-8	2958	506	21	10	3495		
8-12	312	849	80	7	1248	(0-8) = .762		
12-20	29	134	50	6	219	(8-12) = .446		
>20	13	13	4	8	38	(12-20) = .154		
TOTAL	3312	1502	155	31	5000	(>20) = .131		
						Average = .652		

a

3 HR PERSISTENCE
FORECAST

OBSERVATION	Ht. (m)	0-8	8-12	12-20	>20	TOTAL	CORRECT = 75%	SKILL = .423
	0-8	2865	384	41	11	3301		
8-12	421	690	152	6	1269	(0-8) = .758		
12-20	44	156	158	10	368	(8-12) = .378		
>20	12	16	13	21	62	(12-20) = .275		
TOTAL	3342	1246	364	48	5000	(>20) = .235		
						Average = .621		

b

Table 4. OWS Charlie Independent Sample.

		6 HR FORECAST					
		FORECAST					
OBSERVED	Ht. (m)	0-8	8-12	12-20	>20	TOTAL	
	0-8	947	291	12	0	1250	CORRECT = 70%
	8-12	151	451	41	1	644	SKILL = .429
	12-20	18	69	12	0	99	THREAT
	>20	6	1	0	0	7	(0-8) = .664
	TOTAL	1122	812	65	1	2000	(8-12) = .448
						(12-20) = .078	
						(>20) = .0	
						Average = .560	

a

		6 HR PERSISTENCE					
		FORECAST					
OBSERVATION	Ht. (m)	0-8	8-12	12-20	>20	TOTAL	
	0-8	1569	258	37	8	1872	CORRECT = 69%
	8-12	306	327	85	0	718	SKILL = .369
	12-20	51	91	81	4	227	THREAT
	>20	18	7	6	0	31	(0-8) = .712
	TOTAL	1944	683	209	12	2848	(8-12) = .304
						(12-20) = .228	
						(>20) = .0	
						Average = .569	

b

Table 5. OWS Charlie Independent Sample.

9 HR FORECAST

FORECAST

OBSERVED	Ht. (m)	0-8	8-12	12-20	>20	TOTAL
	0-8	999	297	4	0	1300
8-12	173	388	21	0	582	
12-20	30	66	8	0	104	
>20	10	4	0	0	14	
TOTAL	1212	755	33	0	2000	

CORRECT = 70%

SKILL = .389

THREAT

(0-8) = .660

(8-12) = .408

(12-20) = .062

(>20) = .000

Average = .553

a

9 HR PERSISTENCE

FORECAST

OBSERVATION	Ht. (m)	0-8	8-12	12-20	>20	TOTAL
	0-8	779	144	26	0	949
8-12	177	160	48	2	387	
12-20	43	47	31	0	121	
>20	12	4	3	1	20	
TOTAL	1011	355	108	3	1477	

CORRECT = 66%

SKILL = .303

THREAT

(0-8) = .659

(8-12) = .274

(12-20) = .156

(>20) = .045

Average = .518

b

Table 6. OWS Charlie Independent Sample.

		12 HR FORECAST					
		FORECAST					
OBSERVED	Ht. (m)	0-8	8-12	12-20	>20	TOTAL	
	0-8	1066	250	5	0	1321	CORRECT = 69%
	8-12	208	314	20	0	542	SKILL = .343
	12-20	51	59	2	0	112	THREAT
	>20	17	8	0	0	25	(0-8) = .667
	TOTAL	1342	631	27	0	2000	(8-12) = .365
						(12-20) = .014	
						(>20) = .000	
						Average = .552	

a

		12 HR PERSISTENCE					
		FORECAST					
OBSERVATION	Ht. (m)	0-8	8-12	12-20	>20	TOTAL	
	0-8	2491	603	119	33	3246	CORRECT = 62%
	8-12	589	546	178	5	1318	SKILL = .254
	12-20	142	158	89	3	392	THREAT
	>20	30	11	2	1	44	(0-8) = .621
	TOTAL	3252	1318	388	42	5000	(8-12) = .261
						(12-20) = .123	
						(>20) = .011	
						Average = .482	

b

Table 7. OWS Charlie Dependent Sample.

		3 HR FORECAST				
		FORECAST				
		0-8	8-12	12-20	>20	TOTAL
OBSERVED	Ht. (m)					
	0-8	861	292	9	5	1167
	8-12	125	484	54	2	665
	12-20	16	93	46	2	157
	>20	4	3	2	2	11
TOTAL	1006	872	111	11	2000	

CORRECT = 70%

SKILL = .455

THREAT

(0-8) = .656

(8-12) = .459

(12-20) = .207

(>20) = .100

Average = .547

a

		3 HR PERSISTENCE				
		FORECAST				
		0-8	8-12	12-20	>20	TOTAL
OBSERVATION	Ht. (m)					
	0-8	1043	164	26	6	1239
	8-12	168	291	78	4	541
	12-20	24	82	84	7	197
	>20	7	4	6	6	23
TOTAL	1242	541	194	23	2000	

CORRECT = 71%

SKILL = .459

THREAT

(0-8) = .725

(8-12) = .368

(12-20) = .274

(>20) = .150

Average = .577

b

Table 8. OWS Charlie Dependent Sample.

		6 HR FORECAST						
		FORECAST						
OBSERVED		Ht. (m)	0-8	8-12	12-20	>20	TOTAL	
0-8			848	307	16	1	1172	CORRECT = 67%
8-12			152	464	41	2	659	SKILL = .403
12-20			21	105	31	0	157	THREAT
>20			9	3	0	0	12	(0-8) = .626
TOTAL			1030	879	88	3	2000	(8-12) = .432
								(12-20) = .145
								(>20) = .000
								Average = .519

a

		6 HR PERSISTENCE						
		FORECAST						
OBSERVATION		Ht. (m)	0-8	8-12	12-20	>20	TOTAL	
0-8			965	188	48	11	1212	CORRECT = 65%
8-12			188	250	88	8	534	SKILL = .350
12-20			54	82	77	7	220	THREAT
>20			10	16	5	3	34	(0-8) = .659
TOTAL			1217	536	218	29	2000	(8-12) = .304
								(12-20) = .213
								(>20) = .050
								Average = .505

b

Table 9. OWS Charlie Dependent Sample.

9 HR FORECAST
FORECAST

OBSERVED	Ht. (m)	0-8	8-12	12-20	>20	TOTAL	CORRECT = 65%	SKILL = .342
	0-8	819	329	8	0	1156		
8-12	197	461	24	0	682	THREAT		
12-20	33	107	10	0	150	(0-8) = .587		
>20	9	3	0	0	12	(8-12) = .411		
TOTAL	1058	900	42	0	2000	(12-20) = .055		
						(>20) = .000		
						Average = .490		

a

9 HR PERSISTENCE
FORECAST

OBSERVATION	Ht. (m)	0-8	8-12	12-20	>20	TOTAL	CORRECT = 61%	SKILL = .300
	0-8	918	199	62	11	1190		
8-12	186	220	111	9	526	THREAT		
12-20	81	95	75	4	255	(0-8) = .625		
>20	11	11	3	4	29	(8-12) = .265		
TOTAL	1196	525	251	28	2000	(12-20) = .174		
						(>20) = .075		
						Average = .465		

b

Table 10. OWS Charlie Dependent Sample.

		12 HR FORECAST					
		FORECAST					
OBSERVED	Ht. (m)	0-8	8-12	12-20	>20	TOTAL	
	0-8	832	322	5	0	1159	CORRECT = 63%
	8-12	234	420	9	0	663	SKILL = .299
	12-20	50	106	4	0	160	THREAT
	>20	13	5	0	0	18	(0-8) = .571
	TOTAL	1129	853	18	0	2000	(8-12) = .383
						(12-20) = .022	
						(>20) = .000	
						Average = .472	

a

		12 HR PERSISTENCE					
		FORECAST					
OBSERVATION	Ht. (m)	0-8	8-12	12-20	>20	TOTAL	
	0-8	901	223	66	11	1201	CORRECT = 60%
	8-12	209	225	99	4	537	SKILL = .267
	12-20	75	98	64	3	240	THREAT
	>20	11	7	4	0	22	(0-8) = .602
	TOTAL	1196	553	233	18	2000	(8-12) = .200
						(12-20) = .156	
						(>20) = .000	
						Average = .450	

b

Table 11. OWS Echo Independent Sample.

		3 HR FORECAST					
		FORECAST					
OBSERVED	Ht. (m)	0-8	8-12	12-20	>20	TOTAL	
	0-8	167	60	15	1	243	CORRECT = 63%
	8-12	49	134	135	8	326	SKILL = .447
	12-20	14	75	680	178	947	THREAT
	>20	4	14	183	283	484	(0-8) = .538
	TOTAL	234	283	1013	470	2000	(8-12) = .282
						(12-20) = .531	
						(>20) = .421	
						Average = .403	

a

		3 HR PERSISTENCE					
		FORECAST					
OBSERVATION	Ht. (m)	0-8	8-12	12-20	>20	TOTAL	
	0-8	159	63	17	4	243	CORRECT = 62%
	8-12	58	140	111	17	326	SKILL = .443
	12-20	18	106	656	167	947	THREAT
	>20	5	19	167	293	484	(0-8) = .490
	TOTAL	240	328	951	481	2000	(8-12) = .272
						(12-20) = .528	
						(>20) = .436	
						Average = .459	

b

Table 12. OWS Echo Independent Sample.

		6 HR FORECAST						
		FORECAST						
OBSERVED		Ht. (m)	0-8	8-12	12-20	>20	TOTAL	
	0-8		157	66	23	0	246	CORRECT = 54%
	8-12		60	109	141	22	332	SKILL = .330
	12-20		33	88	500	294	915	THREAT
	>20		10	28	162	307	507	(0-8) = .449
	TOTAL		260	291	826	623	2000	(8-12) = .212
								(12-20) = .402
								(>20) = .373
								Average = .370

a

		6 HR PERSISTENCE						
		FORECAST						
OBSERVATION		Ht. (m)	0-8	8-12	12-20	>20	TOTAL	
	0-8		145	58	34	3	240	CORRECT = 52%
	8-12		46	110	127	38	321	SKILL = .295
	12-20		33	115	549	227	924	THREAT
	>20		5	34	235	241	515	(0-8) = .447
	TOTAL		229	317	945	509	2000	(8-12) = .208
								(12-20) = .415
								(>20) = .307
								Average = .358

b

Table 13. OWS Echo Independent Sample.

		9 HR FORECAST						
		FORECAST						
		Ht. (m)	0-8	8-12	12-20	>20	TOTAL	
OBSERVED	0-8	166	60	33	1	260		CORRECT = 48%
	8-12	86	98	117	39	340		SKILL = .261
	12-20	48	106	394	337	885		THREAT
	>20	20	32	170	293	515		(0-8) = .400
	TOTAL	320	296	714	670	2000		(8-12) = .182
								(12-20) = .596
								(>20) = .328
								Average = .422

a

		9 HR PERSISTENCE						
		FORECAST						
		Ht. (m)	0-8	8-12	12-20	>20	TOTAL	
OBSERVATION	0-8	85	48	22	6	161		CORRECT = 49%
	8-12	28	68	87	31	214		SKILL = .235
	12-20	36	65	375	177	653		THREAT
	>20	7	23	198	161	389		(0-8) = .366
	TOTAL	156	204	682	375	1417		(8-12) = .194
								(12-20) = .390
								(>20) = .266
								Average = .325

b

Table 14. OWS Echo Independent Sample.

		12 HR FORECAST					
		FORECAST					
OBSERVED	Ht. (m)	0-8	8-12	12-20	>20	TOTAL	
	0-8	156	57	37	2	252	CORRECT = 45%
	8-12	106	80	103	40	329	SKILL = .222
	12-20	52	134	387	326	899	THREAT
	>20	23	41	184	272	520	(0-8) = .360
	TOTAL	337	312	711	640	2000	(8-12) = .142
						(12-20) = .316	
						(>20) = .305	
						Average = .291	

a

		12 HR PERSISTENCE					
		FORECAST					
OBSERVATION	Ht. (m)	0-8	8-12	12-20	>20	TOTAL	
	0-8	67	36	19	6	128	CORRECT = 47%
	8-12	23	45	63	25	156	SKILL = .230
	12-20	14	59	259	127	459	THREAT
	>20	11	24	126	111	272	(0-8) = .380
	TOTAL	115	164	467	269	1015	(8-12) = .163
						(12-20) = .388	
						(>20) = .258	
						Average = .317	

b

Table 15. OWS Echo Dependent Sample.

3 HR FORECAST
FORECAST

OBSERVED	Ht. (m)	0-8	8-12	12-20	>20	TOTAL	CORRECT = 58%	SKILL = .383
	0-8	120	89	26	1	236		
8-12	57	165	159	11	392	THREAT		
12-20	20	94	639	133	886	(0-8) = .369		
>20	12	22	209	243	486	(8-12) = .276		
TOTAL	209	370	1033	388	2000	(12-20) = .497		
						(>20) = .385		
						Average = .417		

a

3 HR PERSISTENCE
FORECAST

OBSERVATION	Ht. (m)	0-8	8-12	12-20	>20	TOTAL	CORRECT = 56%	SKILL = .359
	0-8	124	84	18	10	236		
8-12	66	170	130	26	392	THREAT		
12-20	27	118	561	180	886	(0-8) = .362		
>20	13	23	190	260	486	(8-12) = .275		
TOTAL	230	395	899	476	2000	(12-20) = .458		
						(>20) = .370		
						Average = .390		

b

Table 16. OWS Echo Dependent Sample.

6 HR FORECAST
FORECAST

OBSERVED	Ht. (m)	FORECAST				TOTAL	
		0-8	8-12	12-20	>20		
0-8		116	85	43	1	245	CORRECT = 52%
8-12		79	173	150	22	424	SKILL = .303
12-20		35	117	533	184	869	THREAT
>20		16	35	198	213	462	(0-8) = .309
TOTAL		246	410	924	420	2000	(8-12) = .262
							(12-20) = .423
							(>20) = .318
							Average = .352

a

6 HR PERSISTENCE
FORECAST

OBSERVATION	Ht. (m)	FORECAST				TOTAL	
		0-8	8-12	12-20	>20		
0-8		136	78	48	11	273	CORRECT = 50%
8-12		66	168	151	38	423	SKILL = .291
12-20		49	138	485	181	853	THREAT
>20		17	37	182	215	451	(0-8) = .336
TOTAL		268	421	866	445	2000	(8-12) = .248
							(12-20) = .393
							(>20) = .316
							Average = .337

b

Table 17. OWS Echo Dependent Sample.

		9 HR FORECAST					
		FORECAST					
OBSERVED	Ht. (m)	0-8	8-12	12-20	>20	TOTAL	
	0-8	110	84	44	2	240	CORRECT = 47%
	8-12	106	148	150	28	432	SKILL = .239
	12-20	45	138	484	223	890	THREAT
	>20	22	27	192	197	438	(0-8) = .286
	TOTAL	283	397	870	450	2000	(8-12) = .217
						(12-20) = .379	
						(>20) = .285	
						Average = .307	

a

		9 HR PERSISTENCE					
		FORECAST					
OBSERVATION	Ht. (m)	0-8	8-12	12-20	>20	TOTAL	
	0-8	147	72	46	17	282	CORRECT = 47%
	8-12	64	140	155	39	398	SKILL = .236
	12-20	49	144	475	215	883	THREAT
	>20	13	44	205	175	437	(0-8) = .360
	TOTAL	273	400	881	446	2000	(8-12) = .213
						(12-20) = .368	
						(>20) = .247	
						Average = .309	

b

Table 18. OWS Echo Dependent Sample.

		12 HR FORECAST						
		FORECAST						
OBSERVED		Ht. (m)	0-8	8-12	12-20	>20	TOTAL	
0-8			111	71	44	7	233	CORRECT = 48%
8-12			109	136	151	26	422	SKILL = .246
12-20			56	134	521	202	913	THREAT
>20			26	27	189	190	432	(0-8) = .262
TOTAL			302	368	905	425	2000	(8-12) = .208
								(12-20) = .402
								(>20) = .285
								Average = .320

a

		12 HR PERSISTENCE						
		FORECAST						
OBSERVATION		Ht. (m)	0-8	8-12	12-20	>20	TOTAL	
0-8			126	68	61	15	270	CORRECT = 45%
8-12			70	134	154	42	400	SKILL = .219
12-20			39	139	452	221	851	THREAT
>20			28	46	211	194	479	(0-8) = .309
TOTAL			263	387	878	472	2000	(8-12) = .205
								(12-20) = .354
								(>20) = .256
								Average = .295

b

Table 19. Ocean Weather Station Charlie.

HEIDKE SCORES

<u>INDEPENDENT</u>			<u>DEPENDENT</u>	
<u>F</u>	<u>P</u>	<u>HR</u>	<u>F</u>	<u>P</u>
. 507	. 483	3	. 455	. 459
. 429	. 369	6	. 403	. 356
. 389	. 303	9	. 342	. 300
. 343	. 254	12	. 299	. 267
. 417	. 352	Average	. 374	. 345
.0036	.0074	σ^2	.0035	.0053
1.144		F-Value		.291
.32		Probability		.61

THREAT SCORES

<u>INDEPENDENT</u>			<u>DEPENDENT</u>	
<u>F</u>	<u>P</u>	<u>HR</u>	<u>F</u>	<u>P</u>
. 652	. 621	3	. 547	. 577
. 560	. 569	6	. 519	. 505
. 553	. 518	9	. 490	. 465
. 552	. 482	12	. 472	. 450
. 579	. 547	Average	. 507	. 499
.0018	.0027	σ^2	.0008	.0024
.667		F-Value		.055
.44		Probability		.82

a

Table 19. Ocean Weather Station Echo.

HEIDKE SCORES

<u>INDEPENDENT</u>			<u>DEPENDENT</u>	
<u>F</u>	<u>P</u>	<u>HR</u>	<u>F</u>	<u>P</u>
. 447	. 443	3	. 383	. 359
. 330	. 295	6	. 303	. 291
. 261	. 235	9	. 239	. 238
. 222	. 230	12	. 246	. 219
. 315	. 300	Average	. 292	. 276
.0073	.0074	σ^2	.0033	.0029
.0414		F-Value	.1222	
.84		Probability	.74	

THREAT SCORES

<u>INDEPENDENT</u>			<u>DEPENDENT</u>	
<u>F</u>	<u>P</u>	<u>HR</u>	<u>F</u>	<u>P</u>
. 403	. 459	3	. 417	. 390
. 370	. 358	6	. 352	. 337
. 422	. 325	9	. 309	. 309
. 291	. 317	12	. 320	. 295
. 371	.364	Average	. 349	. 332
.0025	.0032	σ^2	.0017	.0013
.0239		F-Value	.2724	
.88		Probability	.62	

b

Table 20

Ocean Weather Station Charlie

PERCENT CORRECT

<u>INDEPENDENT</u>			<u>DEPENDENT</u>	
<u>F</u>	<u>P</u>	<u>HR</u>	<u>F</u>	<u>P</u>
77	75	3	70	71
70	69	6	67	65
70	66	9	65	61
69	62	12	63	60

a

Ocean Weather Station Echo

<u>INDEPENDENT</u>			<u>DEPENDENT</u>	
<u>F</u>	<u>P</u>	<u>HR</u>	<u>F</u>	<u>P</u>
63	62	3	58	56
54	52	6	52	50
48	49	9	47	47
45	47	12	48	45

b

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APPENDIX
THREAT AND SKILL SCORES DEFINITIONS

THREAT SCORES

Consider a 2x2 contingency table.

		Forecast		Totals
		F ₁	F ₂	
Observed	O ₁	d ₁	b	R ₁
	O ₂	c	d ₂	R ₂
Totals		c ₁	c ₂	T

The threat score is defined as

$$TS = \frac{d_1}{d_1 + b + c} .$$

This score examines the ratio of correct forecasts (d_1) to the sum of correct and incorrect ($d+b+c$). If $b=c=0$, then $TS=1$. Therefore $0 \leq TS \leq 1$.

Notice that since $R_1 = d_1 + b$ and $c_1 = d_1 + c$,

$$TS = \frac{d_1}{R_1 + c_1 - d_1} .$$

Using this formula, threat scores for $n \times n$ contingency tables can be computed for each diagonal element ($d_i, i=1, \dots, n$). For a ($n \times n$) contingency table, n threat scores are computed.

To compare threat scores for two contingency tables, a weighted average is computed.

$$(TS)_1 = \frac{d_1}{R_1 + c_1 - d_1}$$

$$(TS)_2 = \frac{d_2}{R_2 + c_2 - d_2}$$

Then $(TS)_A$, the weighted average, is defined by

$$(TS)_A = \left(\frac{R_1 + c_1}{2}\right) (TS)_1 + \left(\frac{R_2 + c_2}{2}\right) (TS)_2.$$

SKILL SCORES

Heidke skill scores are defined for (2×2) contingency tables as follows.

	F ₁	F ₂	Total
Observations O ₁	d ₁	d	R ₁
O ₂	c	d ₂	R ₂
Total	c ₁	c ₂	T

$$S = \frac{X - C}{T - C}$$

where

$$X = d_1 + d_2$$

$$C = \frac{(R_1 C_1)}{T} + \frac{(R_2 C_2)}{T}$$

For a $(n \times n)$ contingency table the generalized formula is

$$S = \frac{X - C}{T - C}$$

$$X = \sum_{i=1}^n d_i$$

and

$$C = \frac{1}{T} \sum_{i=1}^n (R_i C_i).$$

The Heidke skill score compares total correct forecasts with the expected total correct forecasts, as determined from a chance selection procedure.

For example, the chance that any single forecast event will fall in the first column is $(\frac{C_1}{T})$. The chance that any single observed event will fall in the first row is $(\frac{R_1}{T})$. Therefore, the chance that any single forecast-observation event will fall in the first diagonal cell (cell d_1) is $(\frac{C_1}{T})(\frac{R_1}{T})$, and the expected number of events to fall in cell d_1 is the

$$(\frac{C_1}{T}) \times (\frac{R_1}{T}) (T) = (\frac{C_1 R_1}{T}) .$$

Therefore

$$C = \frac{1}{T} \sum_{i=1}^n (C_i R_i),$$

is simply the total expected number of events to fall on the diagonal elements.

The skill score then is the ratio of actual minus expected to total minus expected.

If $x=c$, then $s=0$, and thus the forecast method shows no skill better than random chance. If $X=T$, $S=1$; the forecast is perfect. (Notice it is possible to get negative skills (i.e., $X < C$), which means that chance beats the forecast method.)

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