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A Joint Program for Agriculture and Resources Inventory Surveys Through Aerospace Remote Sensing

November 1981

APPLICATION OF THERMAL MODEL FOR PAN EVAPORATION TO THE HYDROLOGY OF A DEFINED MEDIUM, THE SPONGE

M. H. Trenchard and J. A. Artley

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16. Abstract

Many crop and soil moisture models require evaporation values. Unfortunately, evaporation data are unavailable in many areas and thereby restrict the selection of models for use in large area estimation such as those conducted in the AgRISTARS program. In this document a technique is presented which estimates pan evaporation from the commonly observed values of daily maximum and minimum air temperatures. These two variables are transformed to saturation vapor pressure equivalents which are used in a simple linear regression model. The model provides reasonably accurate estimates of pan evaporation rates over a large geographic area.

The derived evaporation algorithm is combined with precipitation to obtain a simple moisture variable. A hypothetical medium with a capacity of 8 inches of water is initialized at 4 inches. The medium behaves like a sponge: it absorbs all incident precipitation, with runoff or drainage occurring only after it is saturated.

Water is lost from this simple system through evaporation just as from a Class A pan, but at a rate proportional to its degree of saturation. The contents of the sponge is a moisture index calculated from only the maximum and minimum temperatures and precipitation.

17. Key Words (Suggested by Author(s))

AgRISTARS, methodology, crop moisture index, moisture index, evaporation model, sponge

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APPLICATION OF THERMAL MODEL FOR PAN EVAPORATION TO THE HYDROLOGY OF A DEFINED MEDIUM, THE SPONGE

Job Order 72-452

This report describes weather analysis activities of the Foreign Commodity Production Forecasting project of the AgRISTARS program.

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LOCKHEED ENGINEERING AND MANAGEMENT SERVICES COMPANY, INC.

Under Contract NAS 9-15800

For

Earth Resources Applications Division
Space and Life Sciences Directorate
NATIONAL AERONAUTICS AND SPACE ADMINISTRATION
LYNDON B. JOHNSON SPACE CENTER
HOUSTON, TEXAS

November 1981

LEMSCO-16935

PREFACE

The Agriculture and Resources Inventory Surveys Through Aerospace Remote Sensing is a multiyear program of research, development, evaluation, and application of aerospace remote sensing for agricultural resources, which began in fiscal year 1980. This program is a cooperative effort of the U.S. Department of Agriculture, the National Aeronautics and Space Administration, the National Oceanic and Atmospheric Administration (U.S. Department of Commerce), the Agency for International Development (U.S. Department of State), and the U.S. Department of the Interior.

The work which is the subject of this document was performed by the Earth Resources Applications Division, Space and Life Sciences Directorate, Lyndon B. Johnson Space Center, National Aeronautics and Space Administration and Lockheed Engineering and Management Services Company, Inc. The tasks performed by Lockheed Engineering and Management Services Company, Inc., were accomplished under Contract NAS 9-15800. Funding for this study was provided by the National Oceanic and Atmospheric Administration under the Foreign Commodity Production Forecasting (FCPF) project of the AgRISTARS program.

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1. INTRODUCTION

The Agriculture and Resources Inventory Surveys Through Aerospace Remote Sensing (AgRISTARS) program is a multiyear program of research, development, evaluation, and application of aerospace remote sensing. The goal of the program is to determine the usefulness, cost, and extent to which remotely sensed data can be integrated into existing or projected U.S. Department of Agriculture (USDA) systems to improve the objectivity, reliability, timeliness, and adequacy of information required to carry out USDA missions.

Major efforts in the AgRISTARS Foreign Commodity Production Forecasting (FCPF) project and its historical predecessors have been directed toward the estimation of crop acreages from spectral data obtained by the Landsat multispectral scanner. Over time, a number of cultural and environmental parameters have been identified which cause difficulty in the interpretive process. One such parameter is the crop moisture condition at the time the spectral data are collected.

A number of approaches to the monitoring of crop moisture conditions are being developed and evaluated in the context of the AgRISTARS program. Unfortunately, a common feature of these relatively sophisticated technologies is the requirement for data which are currently available only in a research mode. The FCPF project is particularly constrained by the need to use widely available data that are at least potentially available in real time. In this paper, an interim solution to the problem of estimation of crop moisture conditions is presented. This solution is the form of an indicator of relative agricultural moisture conditions and is designed for international application within the realistic expectations for availability of meteorological data obtained from group observations.

The index is based upon a moisture balance between precipitation (gains) and evaporation (loss) for a uniform medium. A key element of this index is the estimation of evaporation from maximum and minimum air temperatures.

The following section contains a brief review of the technical literature on evaporation and evapotranspiration estimation. Details of the development of the evaporation model are given in section 3. The moisture index is presented in section 4.

2. BACKGROUND AND REVIEW OF THE LITERATURE

Evapotranspiration is crucial in the life cycle of a plant. Its primary function is to maintain a favorable daylight temperature in the plant, that is, to keep the leaves a few degrees cooler than the environment under adequate moisture conditions. The consequences of low moisture are complex: photosynthesis decreases due to the higher leaf temperatures caused by the decrease in transpiration as well as the lower supply of raw materials (water and carbon dioxide).

The crop modeler finds that evapotranspiration measurements are even scarcer than those of evaporation. They may take some consolation from Chang (ref. 1) who states that "a relationship — good enough for many agricultural purposes usually exists between evaporation and evapotranspiration for a period of a day or longer." He goes on to cite numerous examples of the superiority of Class A pan evaporation data over other methods of estimating evapotranspiration.

However, one is still left with the lack of Class A pan data. Since both evaporation and evapotranspiration are controlled by the atmospheric demand for moisture (air temperature, vapor pressure deficit, windspeed, and net radiation), many estimation techniques use combinations of these elements.

In 1948, Penman (ref. 2) derived a semi-empirical equation to estimate evaporation from a free water surface. His technique required daily mean air temperature, dew point temperature, mean windspeed, and net radiation. The air and dew point temperatures were transformed to their corresponding saturation vapor pressures to approximate the atmospheric demand.

The modified Jensen-Haise method (ref. 3) estimates potential evapotranspiration from daily mean temperature, net radiation, and station-specific constants. One of the constants, the air temperature coefficient, is derived from the saturation vapor pressures associated with the normal maximum and minimum temperatures during the month with the greatest mean air temperature.

Simpler methods have also been devised which require only air temperature measurements. One such evapotranspiration method is that of Thornthwaite (ref. 4) which uses mean monthly temperatures and an empirical annual heat index. More recently, several techniques to estimate pan evaporation from air temperatures alone have been developed. Griffiths (ref. 5) and his colleagues Moe (ref. 6) and Miller (ref. 7) tested and expanded a technique of estimating pan evaporation rates from air temperature. Their equation was of the form

$$EP = a_0 + a_1 TX \quad (1)$$

where

EP = the amount of monthly total evaporation from the pan in inches
TX = the monthly mean of daily maximum temperatures in degrees Fahrenheit
a_0 and a_1 are linear regression coefficients with a_0 in inches and a_1 in inches per degrees Fahrenheit

Their approach determined the two coefficients for each station in a network. Next, the coefficients were plotted on maps which were analyzed for isolines of these coefficients. Such maps could be used to estimate the coefficients for a hypothetical pan at any station observing TX. Moe (ref. 6) created such maps for Texas, and Miller (ref. 7) expanded the area to include most of the southern United States.

The patterns of the isolines on these maps have a reasonable physical and areal interpretation. The theoretical basis for the formula, the special characteristics of the maps, and the sources of errors in the model were first interpreted and analyzed by Trenchard (ref. 8). He found that much of the error in the maps for Texas was due to the seasonal variability of windspeeds and that this could be reduced with a simple correction term based upon the month of the year. Again, maps of the coefficients were generated for interpolation.

The models previously listed rely on the high correlation of pan evaporation with air temperature. This correlation varies with location primarily because of the geographic dependence of the relationships between temperature and the active factors governing evaporation. In addition, while a station's temperature may represent a region the size of a crop reporting district, the station's evaporation measurements may not be due to advection effects. However, evaporation models based on solely air temperature are still somewhat station-specific and not entirely satisfactory for large area crop modeling. It is believed that the station dependency of such models may be decreased by using the saturation vapor pressures associated with maximum and minimum temperatures instead of the temperatures themselves. The use of vapor pressure equivalents of the temperatures helps to account for the nonlinearity of the vapor pressure function in the evaporation process, the variability of atmospheric moisture, and a portion of the influence of advection and ventilation. Thus, they are included in the model which is derived in the following section.

3. MODEL DEVELOPMENT

3.1 DATA

The data for the development and test of this model consist of 1104 monthly mean maximum and minimum temperatures (degrees Fahrenheit), windspeeds (miles per hour), and monthly total evaporation (inches) collected at 26 weather stations throughout the Great Plains. The locations of these stations are given in table 1 and figure 1. The stations are part of the cooperative network maintained by the Environmental Data Information Services of the National Oceanic and Atmospheric Administration (EDIS/NOAA).

The saturation vapor pressure in millibars corresponding to each temperature was calculated with the following formula.

$$\text{Vapor} = 6.11 \times \exp \frac{-176204.2621 + 5597.607915 \times T - 2.850772636 \times T^2}{125416.2 + 273 \times T}$$

where T is the temperature in degrees Fahrenheit.

TABLE 1.- DEVELOPMENT DATA SET

Station number	State	Name	Latitude, N	Longitude, W	Elevation, ft.	Observations		Years of data recorded, no.
						Number[a]	Percentage[b]	
050834	Colo.	Bonny Dam	39°38'	102°11'	3647	30	5.43	10
053592	Colo.	Green Mountain	39°53'	106°20'	7740	21	3.80	10
057866	Colo.	Springfield 7 WSW	37°23'	102°44'	4575	34	6.16	10
058582	Colo.	Vallecito Dam	37°22'	107°35'	7650	36	6.52	10
141383	Kan.	Cedar Bluff Dam	38°48'	99°43'	2135	3	.54	1
141699	Kan.	Colby 1 SW	39°23'	101°04'	3170	29	5.25	10
142686	Kan.	Fall River Dam	37°39'	96°05'	1020	55	9.96	13
142980	Kan.	Garden City Experimental Station	37°59'	100°49'	2840	32	5.80	10
143527	Kan.	Hays 1	38°52'	99°20'	2000	2	.36	1
144104	Kan.	John Redmont Dam	38°15'	95°45'	1091	2	.36	1
144178	Kan.	Kanopolis Dam	38°36'	97°57'	1492	43	7.79	13
144357	Kan.	Kirwin	39°40'	99°07'	1697	2	.36	1
144857	Kan.	Lovewell Dam	39°54'	98°02'	1602	4	.72	1
144977	Kan.	Manhattan Agronomy Farm	39°12'	96°35'	1106	3	.54	1
147073	Kan.	Sabetha Lake	39°54'	95°54'	1250	40	7.25	11
148191	Kan.	Toronto Dam	37°45'	95°56'	961	4	.72	1
148235	Kan.	Tribune 1 W	38°28'	101°46'	3620	7	1.27	3
148259	Kan.	Tuttle Creek Dam	39°15'	96°36'	1057	4	.72	1
148648	Kan.	Webster Dam	39°25'	99°25'	1863	2	.36	1
322188	N. Dak.	Dickinson Experimental Station	46°53'	102°48'	2585	22	3.99	9

TABLE 1.- Concluded.

Station number	State	Name	Latitude, N	Longitude, W	Elevation, ft.	Observations		Years of data recorded, no.
						Number[a]	Percentage[b]	
322859	N. Dak.	Fargo Weather Service Office	46°54'	96°48'	895	25	4.52	10
327585	N. Dak.	Riverdale	47°30'	101°21'	1950	26	4.71	10
329430	N. Dak.	Williston Experimental Farm	48°08'	103°45'	2105	22	3.99	10
340184	Okla.	Altus Dam	34°53'	99°18'	1525	35	6.34	10
343628	Okla.	Goodwell Research Station	36°36'	101°37'	3310	28	5.07	10
343740	Okla.	Great Salt Plains Dam	36°45'	98°08'	1195	41	7.43	10
Total						552	100	

[a]Number of years for which observations have been made at the station.

[b]Percentage of total observations in data set.

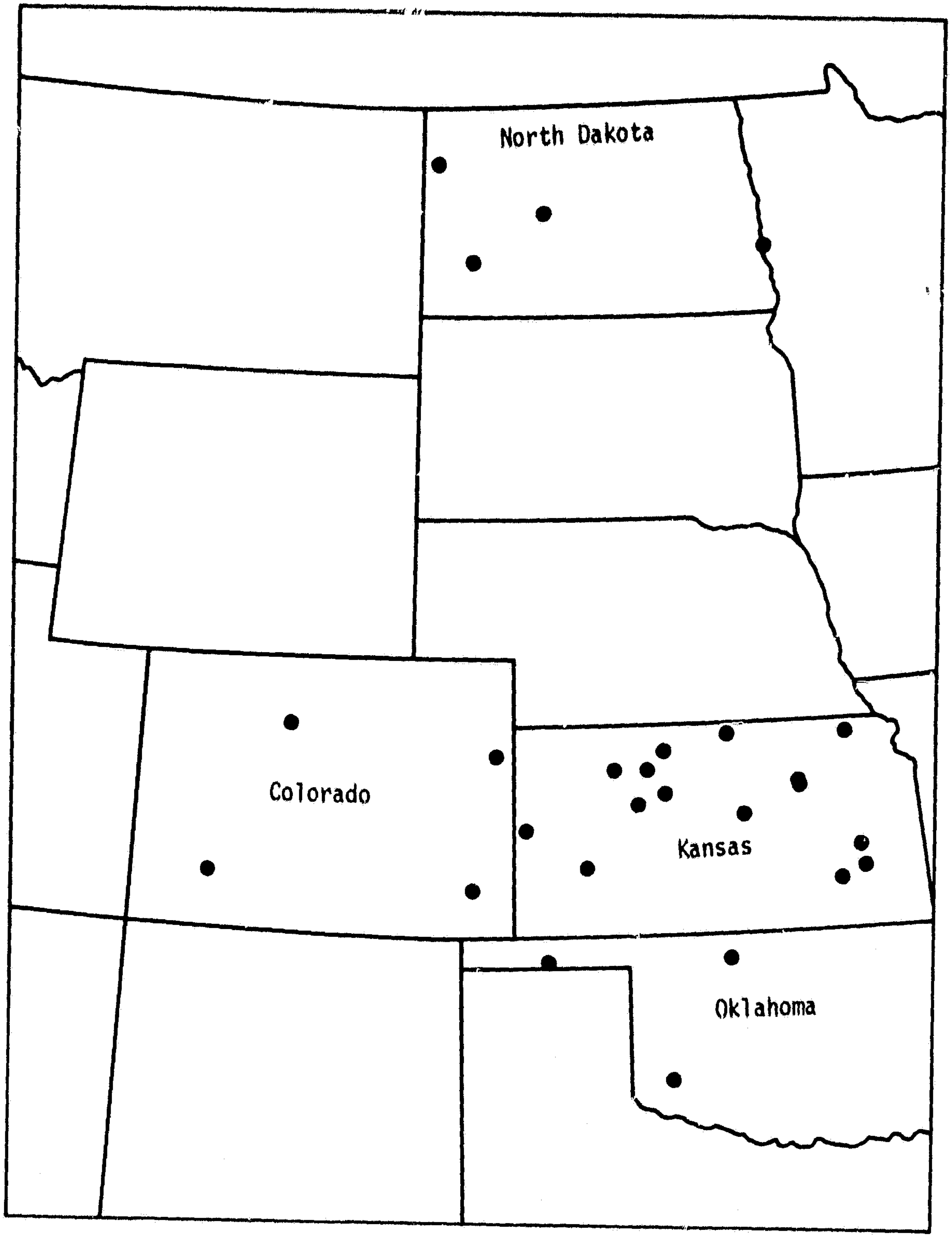

Figure 1.- Map showing station locations in the U.S. Great Plains.

Half (552) of the observations for each year at each station were placed in the development data set. The remaining observations were reserved for testing.

3.2 PROCEDURE

The evaporation model was derived through regression analysis. Much of the statistical computations were performed with procedures available in the Statistical Analysis System (SAS) computer system (ref. 9) installed on the Laboratory for Applications of Remote Sensing (LARS) IBM 370 computer.

The first step in model development was to study the correlation table of the weather variables (table 2). Pan evaporation is most highly correlated with the vapor-pressure corresponding to maximum temperature, then with maximum temperature, minimum temperature, and minimum vapor pressure. It is least correlated with wind.

As expected, the temperatures are extremely well correlated with their corresponding vapor pressures [correlation coefficient (r) = 0.98]. This suggests that, in a linear regression model, only one variable from each temperature-vapor pressure pair needs to be included. For example, maximum temperature and maximum vapor pressure provide similar information to a model. To include both of these variables would be redundant.

The correlations between maximum and minimum air temperatures and maximum and minimum water temperatures are also great ($r > 0.90$). These four variables are similar, while the wind variable differs from them. In modeling terms, just one of the first four should be sufficient before adding wind.

To obtain the model, we used forward selection of variables in the stepwise regression procedure available on the SAS. Through this process, the model is built one variable at a time. The next variable which enters the model offers a significant F-statistic. After each iteration, the F-statistics for all variables in the model are checked for significance. A variable is deleted from the model if its F-statistic is not significant. The procedure continues until either all variables have been included or the next variable selected for entry is deleted at the previous iteration.

TABLE 2.- CORRELATION MATRIX FOR THE VARIABLES IN THE DATA SET

Variables	Coefficient of variation for —							
	Year	Month	Daily pan evaporation	Daily wind (m.p.h.)	Maximum air temperature (F)	Minimum air temperature (F)	Maximum temperature vapor pressure	Minimum temperature vapor pressure
Year	1.00000	0.03050	0.06532	-0.12497	0.02249	-0.06004	-0.02174	-0.06205
Month	0.03050	1.00000	-0.22527	-0.29054	0.08695	0.08509	0.08679	0.08333
Daily pan evaporation	0.06532	-0.22527	1.00000	0.38167	0.79305	0.68303	0.80520	0.67417
Daily wind (m.p.h.)	-0.12497	-0.29054	0.38167	1.00000	-0.01445	0.04654	-0.00724	0.01918
Maximum air temperature (F)	0.02249	0.08696	0.79305	-0.01445	1.00000	0.92289	0.98672	0.90430
Minimum air temperature (F)	0.06004	0.08509	0.68303	0.04654	0.92289	1.00000	0.91471	0.98318
Maximum temperature vapor pressure	0.02174	0.08679	0.80520	-0.00724	0.98672	0.91471	1.00000	0.92050
Minimum temperature vapor pressure	-0.06205	0.08333	0.57417	0.01918	0.90430	0.98318	0.92050	1.00000

When all variables were submitted to stepwise regression, the best model included the following three variables: maximum vapor pressure, wind, and minimum vapor pressure. (Statistics and parameter estimates are given in figure 2.) Because wind speed data are less widely available than temperature data, the wind variable is excluded and the stepwise fitting is recalculated. This time all four of the remaining variables were included in the following order: maximum vapor pressure, minimum vapor pressure, maximum temperature, and minimum temperature (figure 3). It is interesting to note that the last two variables improve the model only slightly, possibly due to their high correlation with the first two variables.

The comparison of the results of the stepwise regression suggests that minimum vapor pressure should be included in a model without the wind variable, although it does not improve the second model as much as the addition of the wind variable improves the first model. The coefficient of determination (R^2) improved, and the F-value remained significant at the 0.001 level. Also, the root mean squared error (RMSE) decreased and the bias improved. For these reasons and theoretical reasons to be discussed in the next section, it was believed that minimum vapor pressure should be retained as a model variable.

3.3 RESULTS

The final model estimates monthly total evaporation EP in inches from vapor pressures corresponding to the mean monthly maximum and minimum temperatures (TX and TN, respectively).

$$EP = 0.2163 + 0.3473\ \text{Vapor}(TX) - 0.2644\ \text{Vapor}(TN) \qquad (3)$$

where Vapor is the vapor pressure function given in equation (2). With the development set, equation (3) predicts pan evaporation with a RMSE of 1.72, a bias of 0.0012, and a correlation coefficient of 0.8232. The model performs equally well with the test data set and given as the RMSE of 1.71, shows a bias of 0.08 and an r of 0.8228.

The use of the saturation vapor pressure function over water as a transformation of the air temperature values is merely an effort to make the model

STEP 1 VARIABLE VAPOR_MX ENTERED (9) R SQUARE = 0.64834375 C(P) = 639.69898781

	DF (4)	(5) SUM OF SQUARES	(6) MEAN SQUARE	(7) F	(8) PROB>F
REGRESSION (1)	1	3269.22452123	3269.22452123	1014.03	0.0001
ERROR (2)	550	1773.20012443	3.[illegible]400023		
TOTAL (3)	551	5042.42464565			

(10)	(11) B VALUE	STD ERROR	(12) TYPE II SS	F	(13) PROB>F
INTERCEPT	0.54378790				
VAPOR_MX	0.23129227	0.00726334	3269.22452123	1014.03	0.0001

STEP 2 VARIABLE WIND ENTERED R SQUARE = 0.79851082 C(P) = 134.51824867

	DF	SUM OF SQUARES	MEAN SQUARE	F	PROB>F
REGRESSION	2	4026.43064751	2013.21532375	1087.86	0.0001
ERROR	549	1015.99399815	1.85062659		
TOTAL	551	5042.42464565			

	B VALUE	STD ERROR	TYPE II SS	F	PROB>F
INTERCEPT	-2.15054364				
WIND	0.70244802	0.03472694	757.20612628	409.16	0.0001
VAPOR_MX	0.23209855	0.00550313	3291.88425949	1778.79	0.0001

STEP 3 VARIABLE VAPOR_MN ENTERED R SQUARE = 0.83754321 C(P) = 4.68856184

	DF	SUM OF SQUARES	MEAN SQUARE	F	PROB>F
REGRESSION	3	4223.24854454	1407.74951485	941.73	0.0001
ERROR	548	819.17610111	1.49484690		
TOTAL	551	5042.42464565			

	B VALUE	STD ERROR	TYPE II SS	F	PROB>F
INTERCEPT	-2.62007347				
WIND	0.72618887	0.03127935	805.71337806	538.99	0.0001
VAPOR_MX	0.36611145	0.01268329	1245.54608434	833.23	0.0001
VAPOR_MN	-0.30529916	0.02660674	196.81789704	131.66	0.0001

STEP 4 VARIABLE MIN ENTERED R SQUARE = 0.83787259 C(P) = 5.57612152

	DF	SUM OF SQUARES	MEAN SQUARE	F	PROB>F
REGRESSION	4	4224.90938567	1056.22734642	706.72	0.0001
ERROR	547	817.51525998	1.49454344		
TOTAL	551	5042.42464565			

	B VALUE	STD ERROR	TYPE II SS	F	PROB>F
INTERCEPT	-2.01893700				
WIND	0.73160485	0.03169534	796.28925392	532.80	0.0001
MIN	-0.02845177	0.02698979	1.66086112	1.11	0.2923
VAPOR_MX	0.36810379	0.01282205	1231.78233915	824.19	0.0001
VAPOR_MN	-0.24897050	0.05969081	26.00095913	17.40	0.0001

STEP 5 VARIABLE MIN REMOVED R SQUARE = 0.83754321 C(P) = 4.68856184

	DF	SUM OF SQUARES	MEAN SQUARE	F	PROB>F
REGRESSION	3	4223.24854454	1407.74951485	941.73	0.0001
ERROR	548	819.17610111	1.49484690		
TOTAL	551	5042.42464565			

	B VALUE	STD ERROR	TYPE II SS	F	PROB>F
INTERCEPT	-2.62007347				
WIND	0.72618887	0.03127935	805.71337806	538.99	0.0001
VAPOR_MX	0.36611145	0.01268329	1245.54608434	833.23	0.0001
VAPOR_MN	-0.30529916	0.02660674	196.81789704	131.66	0.0001

NO OTHER VARIABLES MET THE 0.5000 SIGNIFICANCE LEVEL FOR ENTRY INTO THE MODEL.

Code:

1. The source of variation regression.
2. The source of variation error.
3. The source of variation total.
4. Degrees of freedom.
5. Sums of squares.
6. Mean squares.
7. F-value, which is the ratio of the regression mean square to the error mean square.
8. The significance probability of the F-value.
9. R^2, the square of the multiple correlation coefficient.
10. The names of the independent variables included in the model.
11. The corresponding estimated regression coefficients.
12. The Type II sum of squares for each variable.
13. F-values and significance probabilities associated with the Type II sums of squares.

Figure 2.- Stepwise regression procedure for dependent variable Pan with all independent variables.

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STEP 1    VARIABLE VAPOR_MX ENTERED  (9)R SQUARE = 0.64834375      C(P) =    72.94339247
                  DF(4)          (5)SUM OF SQUARES      (6)MEAN SQUARE         (7)F   (8)PROB>F

REGRESSION(1)       1             3269.22452123          3269.22452123       1014.03     0.0001
ERROR (2)         550             1773.20012443             3.22400023
TOTAL (3)         551             5042.42464565

(10)              (11)B VALUE         STD ERROR         (12)TYPE II SS            F   (13)PROB>F

INTERCEPT         0.54378790
VAPOR_MX          0.23129227         0.00726334          3269.22452123       1014.03     0.0001
-----------------------------------------------------------------------------------------------
STEP 2    VARIABLE VAPOR_MN ENTERED     R SQUARE = 0.67775632      C(P) =    23.00762169
                  DF              SUM OF SQUARES          MEAN SQUARE            F      PROB>F

REGRESSION          2             3417.53516649          1708.76758324        577.34     0.0001
ERROR             549             1624.88947916             2.95972583
TOTAL             551             5042.42464565

                     B VALUE          STD ERROR            TYPE II SS            F      PROB>F

INTERCEPT         0.21597080
VAPOR_MX          0.34734624         0.01781047          1125.70800252        380.34     0.0001
VAPOR_MN         -0.26444009         0.03735656           148.31064526         50.11     0.0001
-----------------------------------------------------------------------------------------------
STEP 3    VARIABLE MIN ENTERED          R SQUARE = 0.67995466      C(P) =    21.12586247
                  DF              SUM OF SQUARES          MEAN SQUARE            F      PROB>F

REGRESSION          3             3428.62013175          1142.87337725        388.09     0.0001
ERROR             548             1613.80451390             2.94489875
TOTAL             551             5042.42464565

                     B VALUE          STD ERROR            TYPE II SS            F      PROB>F

INTERCEPT        -1.37042901
VAPOR_MX          0.34262394         0.01793177          1075.12667259        365.08     0.0001
VAPOR_MN         -0.40881570         0.08322349            71.06139171         24.13     0.0001
MIN               0.07253216         0.03738511            11.08496526          3.76     0.0529
-----------------------------------------------------------------------------------------------
STEP 4    VARIABLE MAX ENTERED          R SQUARE = 0.69021980      C(P) =     5.00000000
                  DF              SUM OF SQUARES          MEAN SQUARE            F      PROB>F

REGRESSION          4             3480.38134215           870.09533554        304.69     0.0001
ERROR             547             1562.04330350             2.85565503
TOTAL             551             5042.42464565

                     B VALUE          STD ERROR            TYPE II SS            F      PROB>F

INTERCEPT         8.00019248
VAPOR_MX          0.64426638         0.07301782           222.32023452         77.85     0.0001
VAPOR_MN         -0.87104788         0.13602850           117.09273634         41.00     0.0001
MAX              -0.31570950         0.07415464            51.76121040         18.13     0.0001
MIN               0.29614809         0.06414092            60.87776460         21.32     0.0001
-----------------------------------------------------------------------------------------------
NO OTHER VARIABLES MET THE 0.5000 SIGNIFICANCE LEVEL FOR ENTRY INTO THE MODEL.
```

Code:

1. The source of variation regression.
2. The source of variation error.
3. The source of variation total.
4. Degrees of freedom.
5. Sums of squares.
6. Mean squares.
7. F-value, which is the ratio of the regression mean square to the error mean square.
8. The significance probability of the F-value.
9. R^2, the square of the multiple correlation coefficient.
10. The names of the independent variables included in the model.
11. The corresponding estimated regression coefficients.
12. The Type II sum of squares for each variable.
13. F-values and significance probabilities associated with the Type II sums of squares.

Figure 3.- Stepwise regression procedure for dependent variable Pan without the wind variable.

variables similar to those used in more sophisticated models requiring both saturation vapor pressure values for air and vapor pressure values for the water surface. An example of this use is given by Penman (ref. 2). The function itself is nonlinear over the normal temperature range of agricultural activity, a property which should not be ignored in the evaporation process.

The inclusion of minimum vapor pressure is based upon the empirical relationship of minimum temperature with dew point. With reduced advection in the hours before dawn, minimum air temperature is usually limited by the dew point. If we assume this to be true, minimum temperature becomes significant in the application of the evaporation model to both moist and dry climatic regimes, where maximum temperature alone may not be a distinguishing factor. The negative sign for the regression coefficient of this variable in the model is probably more than coincidence and agrees well with other models which use the vapor pressure at the dew point, e.g., the modified Jensen-Haise method (ref. 3).

The omission of any ventilation or advection term from the model is a significant source of error. Wind confounds the relationship of minimum temperature and dew point, usually producing a positive difference between the two and a serious overestimate of atmospheric moisture. On the other hand, advective effects are frequently reflected in higher daily maximum temperatures (the positive component of the model) so that some compensation is possible under windy conditions.

4. SPONGE, A GENERALIZED MOISTURE INDICATOR

In part, the evaporation algorithm was developed in order to assess crop moisture status. In a general sense, crop moisture is the balance of precipitation and evapotranspiration over time.

The crop moisture index (CMI) (refs. 10 and 11) is currently used in many AgRISTARS projects to assess moisture conditions. It includes a 2-layer soil water model and potential evapotranspiration calculated with Thornthwaite's method. Some of its requirements restrict its use to regions for which long-term average data as well as current precipitation and temperature data are available. An additional restriction inherent in the CMI is that it is an indicator of regional moisture for periods of at least a week and may give unreliable results when applied to a single station on a daily basis.

The evaporation algorithm of equation (3) allowed us to develop a simple moisture indicator with a sound physical basis that used common meteorological variables, was suitable over a broad range of climates, and was applicable to a single station. The result was named "sponge." Figure 4 shows a conceptual illustration of sponge.

Sponge is described as a simple medium with 8 inches of water-holding capacity which is initialized half-full of water on January 1*. Each day, in accordance with the hydrologic cycle, water is added to the medium from precipitation and lost through evaporation. Precipitation (both liquid and frozen) is added at the full amount until the layer is saturated. It is this sponge-like behavior which gives the variable its name. Any additional precipitation is assumed to be lost as run-off or drainage. Evaporation occurs at a fraction of the Class A pan rate, the exact proportion being the ratio of the current contents to the total capacity of the sponge. Either actual or estimated evaporation pan values may be used. The daily contents of the sponge are defined as

$$S_i = S_{i-1} + P_i - (E_i \times S_{i-1}/CAP) \quad (4)$$

where

S_i = sponge contents on day i, in inches

P_i = precipitation on day i, in inches

E_i = actual or estimated pan evaporation in inches on day i

CAP = sponge capacity in inches

and $0 < S_i < CAP$.

*Alternatively, the final value of the previous year may be used as an initial value, and the capacity may be varied for a particular region.

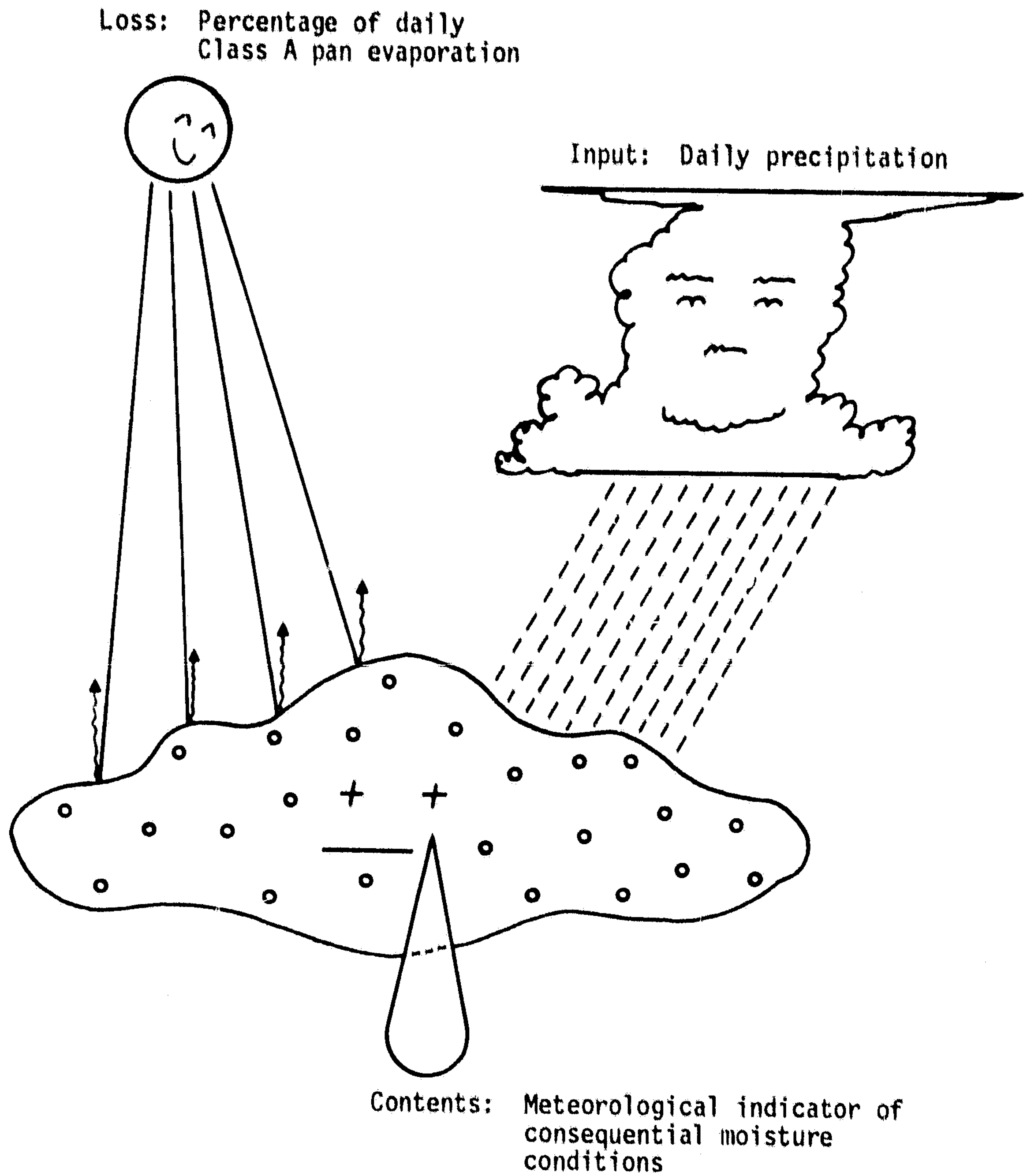

Figure 4.- The sponge moisture variable.

When evaporation pan measurements are not available, they may be estimated with equation (3), with a divisor of 30 days to convert the evaporation function to a daily value.

$$S_i = S_{i-1} + P_i - (EP(TX_i, TN_i) \times S_{i-1}/CAP \times 30) \qquad (5)$$

where

EP = pan evaporation function (equation 3)

TX_i = maximum temperature on day i

TN_i = minimum temperature on day i

Because of its simple data requirements (daily precipitation and evaporation estimated from maximum and minimum temperatures), the sponge can be calculated at any temperature-precipitation observation station.

5. SUMMARY

An attempt has been made to align meteorological observations with crop conditions by developing a method of estimating Class A pan evaporation (a surrogate for evapotranspiration) from air temperatures. A regression model of monthly evaporation totals from 26 Class A pans in the U.S. Great Plains accounted for two-thirds of the variance of this variable. Ventilation (wind) accounted for most of the remaining variance but was not included so that the model could have more general application.

The first suggested use for these evaporation estimates has been to define a hypothetical medium (sponge) and to propose a simple budget of precipitation and evaporation as an indicator of meteorological moisture stress. The simple form and minimal data requirements for this new variable make it an ideal candidate for investigation and application to various AgRISTARS projects which use meteorological data.

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