Atmospheric moisture's influence on fire behavior: surface moisture and plume dynamics

Brian E. Potter
US Forest Service, Pacific Wildland Fire Sciences Lab, 400 N 34th Street, Suite 201, Seattle, Washington, 98103, bpotter@fs.fed.us
Joseph J. Charney
US Forest Service, Northern Research Station, 1407 S. Harrison Road, Suite 220, East Lansing, Michigan 48823, jcharney@fs.fed.us
Lesley A. Fusina
US Forest Service, Northern Research Station, 1407 S. Harrison Road, Suite 220, East Lansing, Michigan 48823, lfusina@fs.fed.us

Abstract: Nine measures of atmospheric surface moisture are tested for statistical relationships with fire size and number of fires using data from the Great Lakes region of the United States. The measures include relative humidity, water vapor mixing ratio, mixing ratio deficit, vapor pressure, vapor pressure deficit, dew point temperature, dew point depression, wet bulb temperature and wet bulb depression. Two moisture-related measures of the vertical stability of the atmosphere (Convective available potential energy and a modified version of the same quantity) are also tested for the same fire data. Results suggest that measures that indicate the difference between equilibrium moisture content of the atmosphere and actual moisture content correlate more strongly with fire number in a region than do measures of actual moisture content. None of the moisture measures, including stability measures, appear to correlate with individual fire size.

Keywords: weather; humidity; fire danger

1. Introduction

Science and society have long recognized that atmospheric moisture influences fire behavior and fire danger. The energy (temperature) and abundance of water molecules in the air, in conjunction with the energy and abundance of water in dead tissue determine the rate of drying of fuels and the equilibrium moisture content of the fuels, which in turn exert a strong influence on the behavior of any fire that occurs. Relative humidity is the most common measure of atmospheric humidity used in the evaluation of fire behavior and fuel moisture (as a reflection of fire danger). Prior to 1930 however, researchers considered a variety of moisture measures including dew point depression (e.g., McCarthy 1923; Stickel 1931; Wallace 1936), wet bulb depression (Lloyd 1932), and vapor pressure (e.g., Munns 1921; Gisborne 1928.) Gisborne (1933) proposed the use of calibrated wooden sticks to measure fuel moisture, giving a direct measure of fuel moisture and reducing the need to find mathematical or physical relationships between weather and fuel moisture. As fire managers adopted Gisborne's wooden sticks, research on relationships between fuel moisture and atmospheric moisture decreased and relative humidity became the most commonly used measure of atmospheric moisture for finer fuels, despite the lack of consensus in the literature regarding which measure produces the best results. There is, in short, an unanswered question about which measure of atmospheric moisture corresponds most readily to fuel moisture and fire behavior.

There are at least nine quantities one can use to measure the presence or absence of moisture in the atmosphere (Table 1.) These include dew point temperature, dew point depression, wet bulb temperature, wet bulb depression, vapor pressure, vapor pressure deficit, mixing ratio, mixing ratio deficit, and relative humidity. In each case, deficit refers to a difference between the observed value of the moisture quantity and the equilibrium value of that quantity with respect to a plane surface of water. While vapor pressure and mixing ratio are very nearly proportional to one another, we include them both here to be thorough. Dew point temperature, wet bulb temperature, vapor pressure, and relative humidity are mathematically related, but not linearly. It is reasonable to expect statistical relations between the nine moisture variables and fire behavior will yield quite different correlation coefficients.

Table 1. Measures of surface atmospheric moisture (abundance) and dryness (or deficit) used in this study

Quantity	Symbol	Units	Moisture	Dryness	Both
Relative Humidity	RH	per cent			X
Water Vapor Mixing Ratio	q_v	g kg^{-1}	X		
Water Vapor Mixing Ratio Deficit	Dq_v	g kg^{-1}		X	
Vapor Pressure	e	Pa	X		
Vapor Pressure Deficit	De	Pa		X	
Dew point temperature	T_d	K	X		
Dew point depression	DT_d	K		X	
Wet bulb temperature	T_w	K	X		
Wet bulb depression	DT_w	K		X	

Historically, scientists and practitioners have focused on the moisture content of surface air in issues of fire behavior and fire danger. Brotak (1976) and Haines (1988) related atmospheric moisture at 850 hPa to the occurrence of large fires in the United States statistically, but at the time the physical mechanism that allows this air to influence fires at the ground was not quantified or documented in any detail. More recently, Potter (2005) considered the possible role of above-surface atmospheric moisture as it relates to stability and energetics, and the role of the moisture generated by combustion of woody fuels in convective plume dynamics. Stated briefly, the combined effects of combustion moisture in the fire's plume and dry air aloft's impact on virtual temperature and subsequently the buoyancy of air in the convective plume of the fire, when integrated over height, have the potential to make significant contributions to the energetics and dynamics of the fire environment and thus the fire's behavior. The energy of the fire's convective plume, measured in the form of convective available potential energy (CAPE), along with cloud microphysical processes, provides one possible framework for explaining the role of above-ground atmospheric moisture in fire behavior.

In this study, we consider 4 questions related to atmospheric moisture's influence on fire behavior through examination of relationships between atmospheric moisture and fire size or number for the states of Michigan, Minnesota, and Wisconsin in the Great Lakes region of the United States. The questions examined are (1) How well do the nine measures of atmospheric moisture correlate with individual fire sizes; (2) How well do the measures correlate with the number of fires within a region on a given day; (3) How well do the measures discriminate between "normal" conditions and "fire" conditions; (4) Do measures of plume energetics related to above-ground moisture show any relationship to fire size or number?

2. Methods

a. Data

For this study, we obtained the fire records for the states of Michigan, Minnesota, and Wisconsin from April 1 through May 7, 2005. Each state maintains records in a different format, but all include information on location, date, and size of the fire. Minnesota and Wisconsin report location as latitude and longitude, while Michigan reports Township-Range-Section. We converted these to latitude and longitude by placing each fire at the center of its reported section. This method leads to possible fire location errors up to 1.6 km (1 mile) for Michigan fires. Figure 1 shows the fire locations and Figure 2 shows the number of fires on each day.

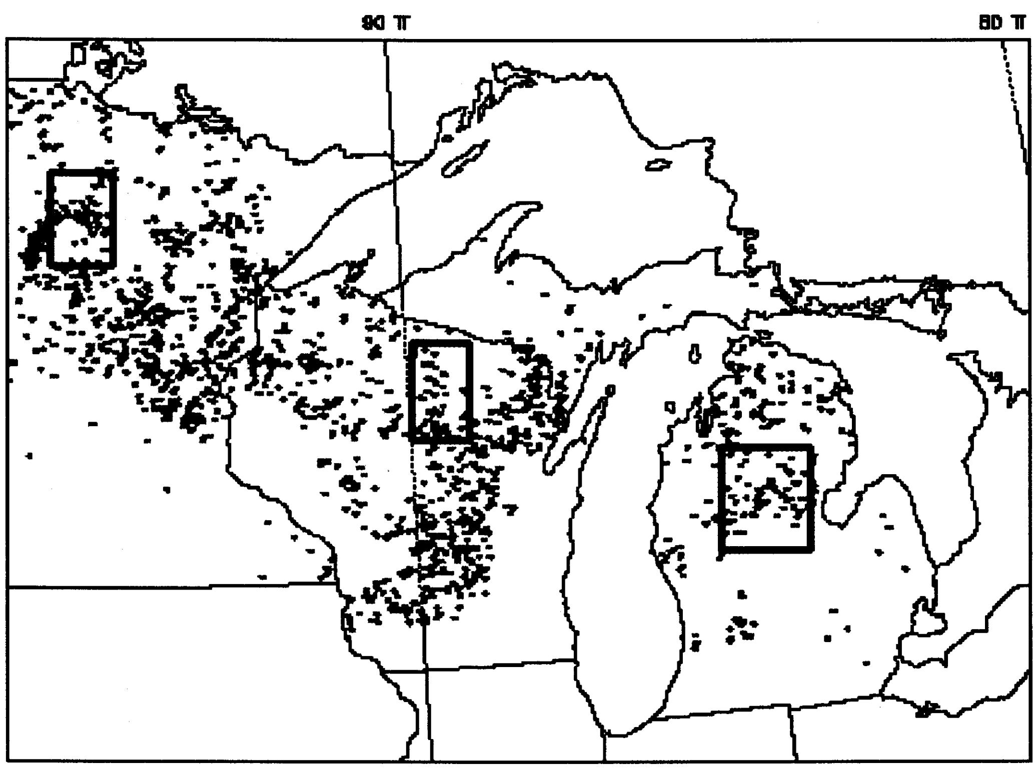


Figure 1. Dots indicate location of individual fires during the study period. Rectangular boxes indicate regions used for regional number, area, and distribution function analyses.

Michigan and Wisconsin both record observed weather data for fires, while Minnesota did not. For Michigan the observations come from the nearest weather station, usually within the same county (Michigan counties are approximately 38 km square.) For Wisconsin, these observations come from remote weather stations, and are never more than 16 kilometers from the fire.

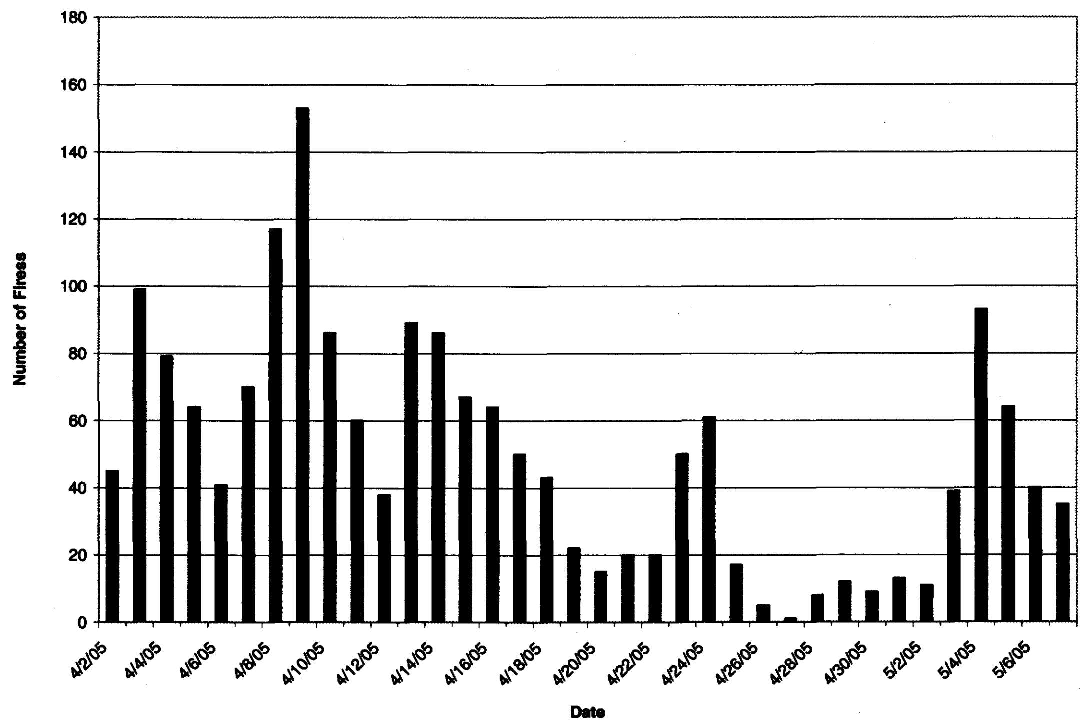


Figure 2. Number of fires on each day of the study period for Michigan, Minnesota, and Wisconsin combined

Observed weather data at or near the fires were insufficient for some of the analyses used in this study. Specifically, they were not suitable for calculations related to above-ground moisture, nor for comparison of weather on fire days and locations with regional data for the same time period, nor was it suitable for creation of distribution functions. To allow these types of comparisons, we used the Pennsylvania State/National Center for Atmospheric Research MM5 mesoscale atmospheric model (Grell et al, 1995) to generate gridded atmospheric data over the Lake States region. The MM5 used 0000 UTC 40km gridded analyses and boundary conditions from the United States' National Centers for Environmental Prediction (NCEP) to initialize the mesoscale model for a sequence of 48-hour simulations from April 2 through May 6, 2005. Hourly weather output at the ground and aloft from these simulations was saved for the entire period, and compared against the observed weather conditions and fire reports.

The convective available potential energy, or CAPE, was used to represent the above-ground impact of moisture on the updrafts produced by fires. Standard CAPE (Houze, 1993, p. 283-287) can indicate the role of stability, including the impact of moisture on stability, for the ambient environment. To evaluate the potential contribution of combustion to convective activity, we used a quantity we call CAPE2, which is simply the CAPE for a parcel of surface air that has 2 K added to its temperature and 2 g kg^{-1} added to its water vapor mixing ratio. These numbers are rough approximations of how combustion could heat and moisten plume air.

In addition to the previously mentioned weather information, Minnesota included the reported suppression cost on each fire. Suppression cost is certainly not physically related to atmospheric moisture, but since cost can be as important to fire management agencies as size or number of fires, we considered it a third possible measure of fire danger and included it in our study.

b. Statistical Analysis

The data for individual fire size and cost, and some of the moisture data, were not normally distributed. In comparing individual fire sizes with moisture variables, we nonetheless relied primarily on the coefficient of determination (i.e., the square of the Pearson correlation coefficient, r^2). We recognize that this approach is best suited to linearly related variables and assumes a normal distribution for each variable. We briefly examined Spearman rank correlations between fire and moisture data, but found the results were similar to those for the Pearson coefficient. Furthermore, we tried applying some simple, monotonic transformations to the data as tests of possible nonlinear relationships. Since rank correlations do not change with such transformations, they fail to show whether the transformed variable has a stronger linear relationship with the other variable under consideration.

We also considered the possibility that the relative importance of weather compared to human management efforts may be lower for smaller fires. To allow for this, we computed r^2 values for each moisture measure, considering only fires larger than thresholds of 0.4 hectares, 0.8 hectares, 2.0 hectares and 4.0 hectares (1 acre, 2 acres, 5 acres, and 10 acres, respectively.) Again, we limit our interpretation of the results to comparison of r^2 values for a given moisture measure with different fire size thresholds. We also consider relative r^2 values among moisture measures for a given size threshold, though we draw no conclusions based solely on these comparisons.

For questions about relationships between number of fires and atmospheric moisture, and questions about how well a given moisture variable discriminates between typical values and those associated with fire, we specified one region in each state for analysis, and examined the fire and model-generated data within those regions. For Michigan, the region extended from 43.5° N to 44.5° N and from 84° W to 85.5° W. This region contained 63 fires, with between 0 and 7 fires on a given day. For Minnesota the region boundaries were 47° N and 48° N, and 94.5° W and 95.5° W, and contained 67 fires total, with 0 to 6 on any day. For Wisconsin the boundaries were 45° N and 46° N, and 89° W and 90° W, with 102 fires total and between 0 and 16 fires on a given day (Figure 1).

We tested the 2 April through 6 May daily, regional totals (number, size or cost of fires) and averages (moisture variables) for normality using the D'Agostino-Pearson normality test (D'Agostino et al., 1990). Because this is a relatively stringent test of normality, we set the significance level for the normality test at p=0.95. (In other words, the probability of falsely rejecting the null hypothesis of normality is only 0.05.)

We then computed correlations between the regional moisture variables and the regional fire data. These correlations were tested for the null hypothesis that there is no significant correlation between a given moisture variable and the fire measure at the p=0.95 significance level. We considered several approaches to this portion of the analysis because we expected, and verified, that many of the variables show at least 1-day autocorrelations. In the end, based on Zwiers' (1990) observation that autocorrelation has only a minor effect on significance of cross correlations, we did nothing to adjust for the autocorrelations. We applied the Fisher Z-transformation (Wilks, 2006, p. 173) to the various correlation coefficients and used this in our significance tests.

To compare the frequency distribution of the moisture variables associated with fires to their background distributions, we computed cumulative distribution functions (CDFs) for the model data at each fire's location and day, and for all points and days in each box region. We then compared the fire and all-points CDFs for each state using the nonparametric Smirnov test with a significance level of p=0.95.

3. Results and Discussion

The coefficients of determination for fire size and observed surface moisture variables in Michigan and Wisconsin were all extremely low (Tables 2 and 3.) The r^2 values for comparison of model data and Minnesota fire data were similar (Table 4.) They were all so low, in fact, that we hesitate to suggest there is any significant physical relationship between moisture and individual fire size. As noted earlier, Spearman rank correlations were comparable to the Pearson correlations. Note that r^2 values are larger for measures of moisture deficit than for the corresponding measures of moisture content. Also, r^2 increases as the fire size threshold rises.

Table 2. Coefficients of determinaton, r^2, for Michigan fire size and observed moisture measures.

	All fires	>0.4 ha	>0.8 ha	>2.0 ha	>4.0 ha
Number of fires	253	151	97	51	31
RH	0.000	0.001	0.002	0.002	0.005
q_v	0.001	0.000	0.000	0.001	0.000
Dq_v	0.006	0.007	0.009	0.023	0.029
e	0.001	0.000	0.000	0.001	0.000
De	0.006	0.007	0.009	0.023	0.029
T_d	0.001	0.001	0.000	0.003	0.003
DT_d	0.000	0.001	0.002	0.002	0.004
T_w	0.002	0.002	0.001	0.007	0.008
DT_w	0.000	0.000	0.000	0.000	0.000
CAPE	0.000	0.000	0.000	0.000	0.004
CAPE2	0.000	0.000	0.000	0.000	0.003

Table 3. Coefficients of determinaton, r^2, for Wisconsin fire size and observed moisture measures.

	All fires	>0.4 ha	>0.8 ha	>2.0 ha	>4.0 ha
Number of fires	732	193	122	48	37
RH	0.002	0.006	0.011	0.026	0.026
q_v	0.000	0.001	0.002	0.007	0.009
Dq_v	0.005	0.017	0.026	0.055	0.062
e	0.000	0.001	0.002	0.007	0.009
De	0.005	0.017	0.026	0.055	0.062
T_d	0.000	0.001	0.002	0.005	0.006
DT_d	0.003	0.011	0.019	0.037	0.038
T_w	0.001	0.002	0.002	0.002	0.001
DT_w	0.002	0.007	0.012	0.023	0.023
CAPE	0.001	0.013	0.077	0.471	0.517
CAPE2	0.002	0.017	0.078	0.391	0.414

Table 4. Coefficients of determinaton, r^2, for Minnesota fire size and modeled moisture measures.

	All fires	>0.4 ha	>0.8 ha	>2.0 ha	>4.0 ha
Number of fires	777	345	259	169	120
RH	0.006	0.010	0.015	0.020	0.033
q_v	0.001	0.002	0.004	0.005	0.009
Dq_v	0.014	0.022	0.027	0.036	0.059
e	0.001	0.002	0.004	0.005	0.009
De	0.014	0.023	0.028	0.037	0.061
T_d	0.001	0.001	0.002	0.003	0.005
DT_d	0.008	0.014	0.018	0.025	0.044
T_w	0.000	0.001	0.000	0.001	0.001
DT_w	0.006	0.009	0.013	0.018	0.033
CAPE	0.000	0.003	0.005	0.015	0.035
CAPE2	0.000	0.001	0.000	0.016	0.037

To reduce the impact of the few extremely large fires on r^2 values, we calculated the natural log of size and recomputed r^2 values for the surface moisture variables. These r^2 values are shown for the Wisconsin data, for illustration purposes, in Table 5 (results for other states were similar.) Generally, the values in Table 5 are greater than the corresponding values in Table 3. Another similarity between these two tables is that r^2 values for measures of moisture deficit exceed those for moisture content. However, while r^2 values for a given moisture measure increased with increasing minimum fire size threshold in Table 3, there is no comparable trend in r^2 when natural log of size is used.

Table 5. Coefficients of determinaton, r^2, for Wisconsin natural log of fire size and observed moisture measures.

	All fires	>0.4 ha	>0.8 ha	>2.0 ha	>4.0 ha
Number of fires	732	193	122	48	37
RH	0.014	0.003	0.012	0.030	0.012
q_v	0.000	0.007	0.002	0.001	0.005
Dq_v	0.021	0.031	0.052	0.080	0.032
e	0.000	0.007	0.002	0.001	0.005
De	0.021	0.031	0.052	0.080	0.032
T_d	0.001	0.009	0.001	0.001	0.002
DT_d	0.012	0.007	0.027	0.048	0.020
T_w	0.012	0.029	0.026	0.018	0.001
DT_w	0.005	0.001	0.014	0.027	0.012
CAPE	0.005	0.002	0.005	0.305	0.349
CAPE2	0.005	0.001	0.008	0.265	0.276

The CAPE and CAPE2 results in Tables 2 through 5 vary in their implications. Michigan shows no correlation between either of these measures and fire size, but Minnesota shows a weak correlation that increases as the size threshold rises, and Wisconsin shows a much more substantial increase, to the point where CAPE's r^2 for fires over 4 ha is 0.517 (Table 3.) Closer examination indicates that r^2 falls to 0.007 for CAPE when one fire, with an area of 1360 ha, is removed from the data set. (All other fires are below 32 ha.)

Table 6. Coefficients of determinaton, r^2, for daily regional number of fires and average modeled moisture measures. Superscripts of 1, 2, and 3 on the variable names indicate that they passed the normality test for Michigan (1), Minnesota (2), or Wisconsin (3). A superscript "a" after a coefficient of determination indicates that the value is significant at the p=0.95 level.

	Number of fires			Total fire area		
	Michigan	Minnesota	Wisconsin	Michigan	Minnesota	Wisconsin
$RH^{1,2,3}$	0.20^a	0.04	0.09	0.03	0.00	0.00
q_v	0.00	0.03	0.00	0.01	0.01	0.00
$Dq_v^{1,2,3}$	0.25^a	0.12^a	0.18^a	0.11	0.02	0.01
e	0.01	0.02	0.00	0.01	0.01	0.00
$De^{1,2,3}$	0.26^a	0.12^a	0.18^a	0.11	0.02	0.01
$T_d^{1,2,3}$	0.00	0.04	0.00	0.01	0.02	0.01
$DT_d^{2,3}$	0.21^a	0.05	0.12^a	0.04	0.00	0.00
$T_w^{1,2,3}$	0.11^a	0.11	0.03	0.05	0.02	0.02
$DT_w^{1,2,3}$	0.14^a	0.02	0.07	0.01	0.00	0.00
$CAPE^2$	0.04	0.07	0.02	0.01	0.06	0.08
$CAPE2^2$	0.03	0.05	0.02	0.01	0.06	0.09

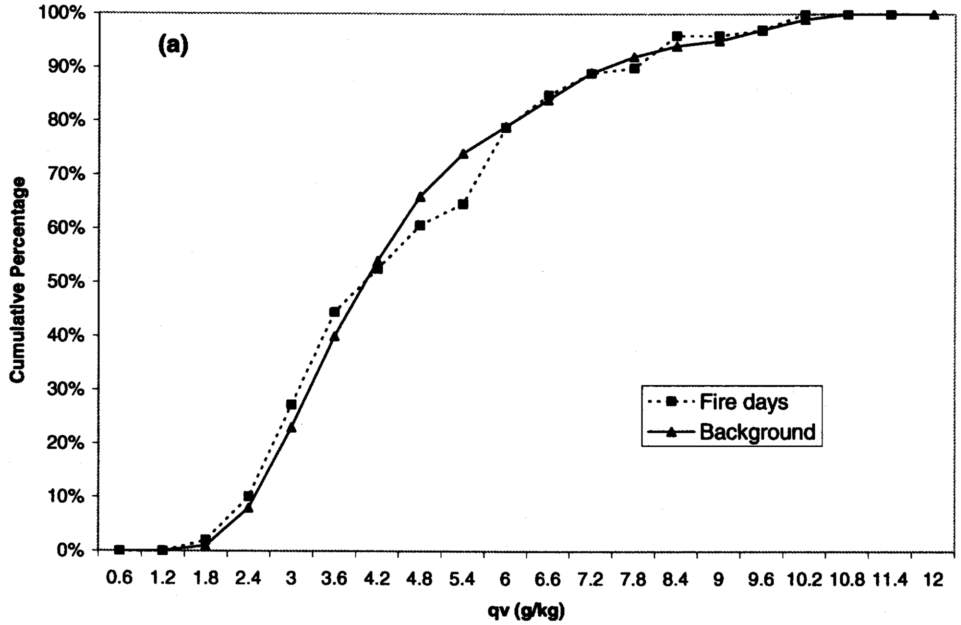
Table 6 shows results of the normality and correlation tests for daily regional number of fires and total fire area with daily regional average moisture measures for each state. None of the variables passed the correlation test when total fire area was considered, and hereafter we only discuss number of fires. Only two variables passed both the normality and correlation tests for number of fires for all three states, and those were mixing ratio deficit and vapor pressure deficit. While the correlations are all modest, these are the only two variables that appeared to show a "significant" correlation with number of fires. When we considered the correlations between moisture variables and daily, regional fire area, the only normal and significant variable was vapor pressure deficit, and only for Michigan. In Minnesota, none of the moisture variables showed significant correlation with daily, regional suppression cost. The correlation between daily number of fires on a given day and the next day was comparable to or greater than the strongest correlation between number of fires and any moisture variable.

The next step in our analysis was comparison of cumulative distribution functions for the fire day values of the moisture variables and the regional, background values of the variables. The results of the Smirnov tests (Table 7) indicate that the CDFs for measures of moisture deficit show more differences that are significant between fire and background than do measures of moisture presence. Of the surface moisture measures, only mixing ratio deficit showed significance for all three states. Figure 3 illustrates the CDFs for mixing ratio and mixing ratio deficit, for both fire days and background days for Wisconsin.

Table 7. Results of Smirnov test for comparison of variable distributions on fire days and on background, regional days. The values in the table are D_s values for the paired comparisons. Due to varying sizes of the regional boxes, $\alpha = 0.05$ significance thresholds vary among the states (D_s must exceed 0.17 for Michigan, 0.17 for Minnesota, or 0.14 for Wisconsin). Significant values have a superscript of "a."

Variable	Michigan	Minnesota	Wisconsin
RH	0.26[a]	0.13	0.15[a]
q_v	0.06	0.11	0.09
Dq_v	0.22[a]	0.18[a]	0.15[a]
e	0.19[a]	0.13	0.10
D*e*	0.20[a]	0.18[a]	0.14
T_d	0.09	0.12	0.07
DT_d	0.27[a]	0.14	0.17[a]
T_w	0.17	0.17	0.14
DT_w	0.24[a]	0.09	0.15[a]
CAPE	0.23[a]	0.19[a]	0.17[a]
CAPE2	0.23[a]	0.17	0.17[a]

When we examined the daily, regional fire and CAPE or CAPE2 data (Table 6) they only showed normality for the Minnesota data, and failed to pass the correlation test in all states. This was true for comparison against number, total size, and total cost. Examination of the CDFs for these variables suggested that CAPE and CAPE2 values from fire days and locations have a significantly different distribution than they do in the region over the whole period of study.



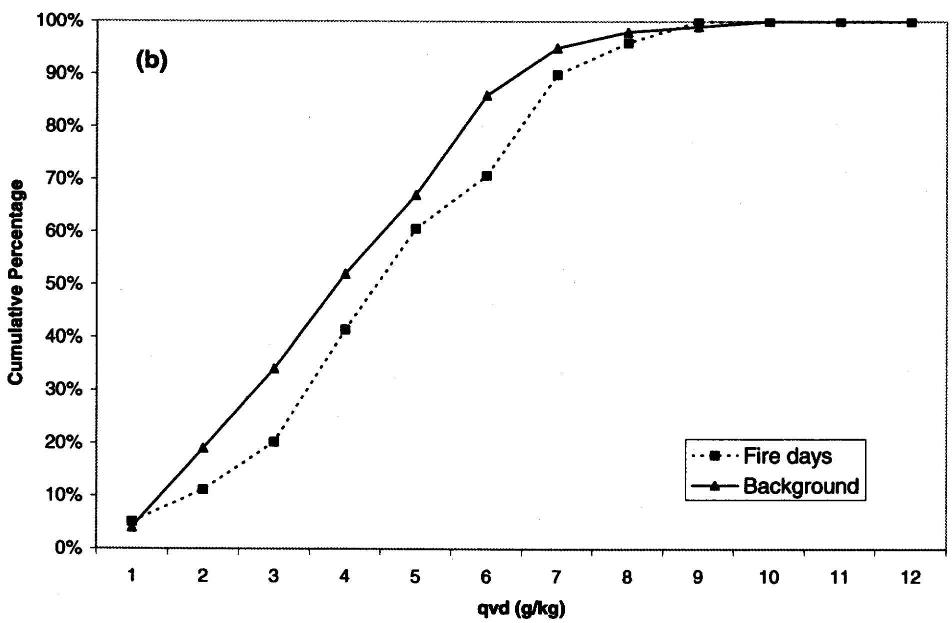


Figure 3. Cumulative percentage distributions for (a) mixing ratio and (b) mixing ratio deficit for Wisconsin data. Dashed lines with square symbols indicate distributions for fire days, solid lines with triangle symbols indicate background, regional distributions.

4. Summary and Conclusions

We examined nine measures of surface atmospheric moisture presence or deficit and their relationship to fire size, number, and total area in a region. While the data are far from ideal for classical parametric tests, cautious interpretation of the results does allow us to draw some conclusions. First, it appears there is no significant relationship between the moisture variables and individual fire size. Fire size is presumably affected by management efforts, terrain, and fuel load and it is possible that these factors obscure a real relationship between moisture and fire size. It is also possible that one or more of the moisture variables plays an important role in fire behavior, but that this role is not clearly reflected by final fire size. (For example, moisture could influence intensity or rate of spread more than it affects size.)

Our second conclusion is that regional number of fires corresponds more strongly to measures of moisture absence than to measures of moisture presence. The strongest measures in this respect were vapor pressure deficit and mixing ratio deficit. These correlations, however, were no greater than the 1-day lagged autocorrelation for number of fires – suggesting that the best predictor of fire activity in any of the states is not the expected, or even observed, atmospheric moisture, but the number of fires the day before. Total area in the region and cost for the region did not appear to correlate with any of the moisture measures.

Third, the data suggest that the distributions of moisture deficit measures may be different on fire days and "background" days, but that the distributions of moisture abundance measures are comparable on these days.

Taken individually, none of these three observations is strong enough to constitute a major finding. However, the persistent theme in the results, even in the extremely low correlation coefficients for individual fire sizes, is that measures of moisture deficit are more likely related to measures of fire size or number. Charney and Fusina (2006), looking at extreme fire behavior in the western United States during 2005 reached a similar conclusion, that high vapor pressure deficit at and above the surface appeared to correspond to periods of recorded extreme fire behavior.

From a thermodynamic perspective, this is reasonable. The importance of atmospheric moisture for fire, to first order, lies in its ability to dry fuels and this, in turn, is a function of the energy of water molecules in the cells and interstitial spaces of the fuel and of the difference between atmospheric moisture content and equilibrium moisture content. The vapor pressure deficit is a direct measure of the latter difference, and the mixing ratio deficit is nearly proportional to the vapor pressure deficit.

The last scientific observation we draw from our results is that CAPE may relate to individual fire size, but only for larger fires. Our data were not well suited to answering this question, and further study with a sample of much larger fires would be needed to address it.

The results do contain some information of value for daily, operational fire management. First among these is the suggestion that relative humidity, while a better indicator than some of the measures considered, is not the best. It falls short of the performance of measures of moisture deficit alone. Because relative humidity is a combination measure that includes some information on moisture presence and some on moisture absence, its value seems diluted by the moisture presence component.

The results also suggest that measuring atmospheric moisture on scales of 10 km or less for use in anticipating fire business needs may be unnecessarily precise. Our results yielded better correlations between moisture measures and regional number of fires than they did between moisture measures roughly 10 km away from fires and the size of those individual fires.

The general question of how to measure atmospheric moisture for fire science and fire management could bear further scrutiny, but this study represents a new step – after a nearly 70 year pause – towards answering the question. While science and management may serve different purposes, they may both be best served by the same measure, and if that is so, it would facilitate communication between the two groups and the development of better scientific tools for managers.

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