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## A Quantitative Approach to Flash Flood Prediction in Southern Utah

**M.M. Hurwitz[1, 2], C.V. Gibson[1], M. Jackson[1, 3] and B. McInerney[1]**

(1) NWS Weather Forecast Office, Salt Lake City, Utah
(2) Now at: Centre for Atmospheric Science, University of Cambridge, UK
(3) Now at: NWS Weather Forecast Office, Los Angeles/Oxnard, California

Flash floods are a dangerous, but common, summertime occurrence in southern Utah. A record of historical flash flooding was compiled to determine the frequency of events from 1959 to 2003. A complete data set, consisting of both historical flash flooding days and non-event days, was assembled; a trial of the 2003 flash flood season assessed which variables and which data source to use in studying the eight flash flood seasons between 1996 and 2003. Neural networks were employed to determine the relationship between the atmospheric state and a particular day's flash flood severity. The final neural network found precipitable water, low-level relative humidity, convective available potential energy (CAPE), the 500hPa height change between 12Z and 0Z, and the previous day's flash flood severity to be the important determinants of flash flooding in southern Utah. Verification of the final neural network algorithm was completed using the flash flood record of 2004 and 2005. Improvements in flash flood prediction, based on the results of this study, will soon be implemented by weather forecasters at the NWSFO in Salt Lake City.

## Introduction

Flash flooding is a natural hazard in southern Utah. The terrain of the lower elevations in this region is characterized by slick-rock topography. Due to lack of vegetation and soil, rainfall quickly runs off this nearly impermeable, rocky terrain and collects to form flash floods. Erosion processes have formed very narrow 'slot' canyons; rain can fill these narrow recesses quickly, resulting in severe flash floods. Due to the rapid runoff, rain from distant mountains can cause flooding of desert canyons as far as 20 to 30 miles from the rainfall.

In 2003, 23 reported flash flood events, all of which occurred in the southern half of Utah, caused more than $1.7 million in property damage[1] and put visitors to the region's five National Parks and numerous state parks and monuments[2] at risk. State and federal land managers must therefore inform visitors of the significant threat posed by flash floods, and must decide whether to close dangerous canyon hiking areas when thunderstorms threaten. With this in mind, the National Weather Service Forecast Office (NWSFO) in Salt Lake City has provided a daily Flash Flood Potential Rating (FFPR) for southern Utah since the mid-1990s. The FFPR is read on the NOAA All Hazards Radio and is disseminated as a text product via the internet[3]. The FFPR provides land managers with forecasts of the flash flood potential for a given day, with a lead time of 12 to 48 hours. Unfortunately,

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[1] http://www.ncdc.noaa.gov
[2] Utah Division of Travel Development
[3] http://www.wrh.noaa.gov/saltlake/projects/ifp/html/ffp.php

the FFPR is quite subjective; classifications rely on a mixture of forecaster experience, an evaluation of the air mass properties based on forecast model data, and the previous day's flash flood activity. The goal of this study was to improve forecasting skill and develop a more quantitative flash flood prediction tool to replace the FFPR.

## Flash Flood Event Record

Though the incidence of flash flooding in Utah has been well-documented since the 1950s, until this study, no single document contained the complete record of flash flood events. Thus, the first objective was to compile such a record. Two data sources were used. Monthly issues of Storm Data were used from 1959 to 1992. The National Climatic Data Center (NCDC) U.S. Storm Events database[4] yielded information for all flash flood events in the state of Utah, from 1993 to 2003. Since most flash flooding occurs during the summer, the search for historical flash flood events was narrowed to the six months of each year between May 1st and October 31st. Following Maddox et al (1980), each flash flood record contained the date, time, city and county (or where appropriate, a general location such as Zion National Park). Approximate coordinates were assigned to each flash flood event. Events were assigned a 'region' based on these coordinates: 'Southwest Utah' (SW) was defined as the rectangle between 39.18ºN, 111.46ºW and 37.00ºN, 114.00ºW; 'southeast Utah' (SE) was defined as the rectangle between 39.34ºN, 109.00ºW and 37.00ºN, 111.46ºW. Figure 1 shows the two regions geographically. Events that affected south-central Utah were assigned to one of the regions based on the area of predominant flooding.

The complete record consisted of 290 flash flood events between 1959 and 2003. As expected, most of the events occurred in southern Utah. However, there were 32 reported flash flood events in Salt Lake County, perhaps because of the influence of the dense population of the Salt Lake City area (see figure 2). Urbanization contributes to rapid runoff and flash flooding and the dense population contributes to the reporting frequency of these events. Another notable feature of the flash flood record was that the number of reported events increased with time (see figure 3). This trend may result from the fact that, as the population of and number of visitors to Utah has grown; so has the probability that flash flood events are witnessed.

A continuous record of days, spanning multiple years, was compiled. In the past, the 93-day period between June 15th and September 15th defined the season of flash flood monitoring at the Salt Lake City NWSFO. The same period has been used to delimit the flash flood 'seasons' throughout this study. Days on which no flash flood events were reported in Utah were assigned a regional flash flood severity index (RFFSI) of '0' in both the SW and SE regions. Days during which at least one event was reported (between 12PM and 2AM local time) were assigned two severity indexes, one in SW and the other in SE Utah. Event-day RFFSI values ranged from 1 to 4, and depended on the geographical extent of the flooding. '1' was assigned to days without any events in that region but at least one event elsewhere in Utah; '2' was assigned to days when a single event was reported in that region; '3' was assigned to days with two reported events, or, with flooding affecting much of a county; '4' was assigned to days with severe flash flooding, affecting two or more of the counties in that region. It should be noted that days on which events occurred in northern Utah were counted as 'event' days, such that the RFFSI = 1; however, flash flooding in southern Utah remained the subject of interest throughout the study.

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[4] http://www.ncdc.noaa.gov

The authors' method of assigning two RFFSI values to each study day was somewhat subjective. In some cases, it was unclear how many 'events' had occurred on a particular day, and in others the location of the flash flooding was hard to pinpoint. However, it was encouraging that, as the severity index increased, the number of days in each severity category decreased exponentially. Specifically, in 45 years of flash flood data, there were 112 days with a SW Utah RFFSI of '1', 52 days of '2', 31 days of '3' and 8 days of '4'.

Conducting an analysis of the atmospheric influence on flash flooding required access to meteorological data. Two data sets were chosen as candidates for this study. Flagstaff, Arizona upper-air soundings provided a set of data and data-derived instability indexes (such as convective available potential energy (CAPE)) twice daily. Flagstaff is located in northern Arizona but satisfies the criteria for "proximity soundings" (Brooks et al, 1994; Rasmussen and Blanchard, 1998) given that the city is within 400km of all points in southern Utah and that, during the summertime, the low-level winds in this region tend to have a southerly component. In other words, it is assumed that Flagstaff soundings have sampled the same air mass as that in the study area. The University of Wyoming's Department of Atmospheric Science website[5] provided access to the sounding data. NCEP/NCAR global reanalysis data[6] met the criterion of having sampled the air mass above southern Utah with more certainty, as its data points at 37.5ºN, 112.5ºW and 37.5ºN, 110.0ºW, were located in SW and SE Utah, respectively. The availability of distinct values at the two grid points was an especially convenient feature of the reanalysis data set.

Meteorological variables were chosen based on previous studies of flash floods in the southwestern U.S. Li et al (2001) found that the severe Las Vegas flash floods of 1999 were correlated with very high values of precipitable water (PW) and CAPE. Maddox et al (1980) noted the importance of high PW, high atmospheric instability values, low wind speeds and short-wave troughs; similarly, Doswell et al (1996) concluded that flash flood-producing storms tended to be associated with deep, moist and slow-moving convection. Until the present study, forecasters at the Salt Lake City NWSFO had primarily based their daily FFPR classifications on the presence of high values of PW, weak mid-tropospheric winds and approaching short-wave troughs. Table 1 lists the variables that were chosen at this initial stage; note that the zonal (u) and meridional (v) wind components were converted to wind speed and direction, in the case of the reanalysis data. With the exception of the 12-hour height change at 500hPa (where 12Z values were subtracted from 0Z values) all of the variables were examined at 0Z the following day (that is, 6PM local time on the forecast day) in order to coincide with the time of peak flash flooding. In addition, Julian (or calendar) day and the previous day's RFFSI were included in this list of variables.

It is likely that some of the variables listed in table 1 are not physically independent. For instance, the low-level relative humidity undoubtedly relates to precipitable water values. CAPE and LI, by definition, are negatively correlated to some degree. However, the above variables are assumed to be statistically independent enough to provide meaningful information about their relationships to flash flood severity.

## Neural Network Analysis

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[5] http://weather.uwyo.edu/upperair/sounding.html
[6] http://www.cdc.noaa.gov/cdc/reanalysis

A trial study of the 2003 flash flood season directly compared the two data sets so as to assess which was the more reliable, and determined which variables could be eliminated from future study. Neural network techniques were chosen to analyze the sounding and reanalysis data, because of their ability to capture non-linearity in input-output relationships. Though non-traditional, neural networks are not new to meteorology. In particular, a recent study used a neural network to predict severe hail size, given the occurrence of severe hail (Marzban and Witt, 2001). Not only did the authors find that their neural network statistically outperformed an existent weather radar hail size prediction algorithm, they also obtained high correlation coefficients for both their training and validation data sets. These results encouraged the study of flash flooding via neural networks.

The neural network software used in this study was the AI Trilogy package by Ward Systems Group[7]. In this case, the input-output relationship was that of the atmospheric state to flash flood severity in southern Utah. The NeuroShell Predictor program was chosen when continuous output was desired; the NeuroShell Classifier program was employed when discretized output was desired. Genetic learning, that ‘breeds’ the data set to optimize the network’s solution, was used to train the neural network. In general, the network ran for several hundred ‘generations’ in order to achieve the best result. Upon completion, the software returned the relative importance of each of the variables involved. Depending on the type of output selected, the software displayed the overall correlation of the timeseries of actual flash flood severity to that predicted by the neural network, or, the proportion of data rows that had been classified correctly.

At this stage, NeuroShell Predictor was used to relate the meteorological variables to flash flood severity. Training a neural network with the sounding data set yielded an overall correlation coefficient of approximately 0.7. The 500hPa wind direction, CAPE and Julian day were found to be the most important predictors of flash flood severity, while LI, LFC and a weighted version of the Julian day (sin(JD/2)) were found to be of little importance. 500hPa winds were found to be more important than 700hPa winds. Since a measure of instability could not be easily retrieved from the reanalysis data, sounding-derived CAPE was added to the reanalysis data set to make it easier to compare to the sounding data set. The reanalysis-plus-sounding-CAPE data set yielded the rather high correlation coefficient of 0.83. Unfortunately, there was a lot of day to day and SW to SE variation in the reanalysis 500hPa wind data. This led to doubts about the quality of these data, which were confirmed by the poor performance of both 500hPa wind speed and direction in the neural network.

Based on the findings of the 2003 flash flood season trial, it was concluded that the Flagstaff, Arizona soundings would likely provide more reliable and insightful information about the relationship between the atmospheric state and flash flood severity than would the reanalysis data. Furthermore, the 700hPa wind speed and direction, LI and LFC were eliminated from any further study due to their apparently weak influence on flash flooding in southern Utah.

It should be noted that the authors refer to flash flood severity as the output variable rather than ‘incidence’ (a binary option, with ‘0’ denoting non-event days and ‘1’ denoting days on which at least one event occurred). The choice of severity over incidence was made because of initial trials of the neural network, in which the most important variables related to flash flood severity were those predicted by past

[7] http://www.wardsystems.com

forecasting experience (CAPE and 500hPa wind speed), whereas those related to flash flood incidence (Julian day and the 500hPa temperature) were not.

Seven years of atmospheric data, from 1996 to 2002, were added to the existing matrix of 2003 flash flood-related data. This larger study was restricted to eight years because Flagstaff, Arizona soundings only became available in time for the 1996 flash flood season. With two data rows per day, 93 days per year and eight years, there were thus 1488 rows of data available for analysis with the neural network. The neural network was trained with all nine variables listed in table 2. Precipitable water was obtained as the most important variable (see figure 4). At 0.44, the overall correlation coefficient was much lower than it had been for the 2003 trial (0.70). The low correlation coefficient may be related to the random nature of flash flooding; events may occur over a range of atmospheric conditions. Another possibility is that two rows containing the same sounding data and yet, on some days, two different RFFSIs, may have confused the neural network. For example, on July 28th 2003, the RFFSI was '3' in SW Utah but '1' in SE Utah.

To avoid this possible confusion, the data were split into two groups. Both groups contained the same set of meteorological data. The first group used the daily SW RFFSI as the output variable; the second group used the SE RFFSI. Figure 5 shows that training the neural network with the SW and SE groupings does not yield the same result. Furthermore, neither of the sets of results of figure 5 is similar to the results of figure 4, where the complete dataset was used to train the neural network.

Problems with the RFFSI motivated the creation of a 'combined' severity index (CFFSI), categorizing each day's flash flooding throughout southern Utah. CFFSI was defined as follows: '0' was assigned to days when no flash flood events occurred in southern Utah; '1' was assigned to days when a single event was reported anywhere in southern Utah; '2' was assigned to days when two events were reported, or, when flash flooding affected much of a county; '3' was assigned to days when severe flash flooding, affecting two or more counties, occurred. Of the 744 days studied, there were 676 days rated as '0', 49 rated as '1', 15 rated as '2', and 4 rated as '3'.

The unexpected results of training the neural network with the Predictor software are shown in figure 6. The temperature at 500hPa was found to be the most important parameter, overwhelming even the combination of the eight remaining variables. The correlation coefficient of 0.31 was quite low. When the same data matrix was applied to the Classifier program, however, 71% of the days studied were classified correctly (see figure 7). PW, the 700hPa RH, the previous day's CFFSI and CAPE were found to be the most important of the nine variables.

Several subsets of the nine variables were tested with NeuroShell Classifier. The objective of this testing was to maximize the proportion of days classified correctly by the software, while minimizing the number of variables needed to do so. Figure 8 shows the set of variables that met the above criteria. The numerical performance of the neural network is summarized in table 3. This 'best result' neural network algorithm correctly identified 79% of the '0' days, 47% of the '1' days, 40% of the '2' days and none of the '3' days; overall, 76% of days studied were classified correctly. Note that the presence of the 500mb wind speed makes virtually no difference to the neural network. The wind speed has been included only to make the point that its importance in determining flash flood severity, as determined by the neural network, is much less than was previously thought.

## Verification of Neural Network Algorithm

The 2004 flash flood season was examined with the goal of testing the 'best result' algorithm discussed in the previous section. This verification dataset consisted of Flagstaff sounding data for the 2004 flash flood season; sufficient data were available to run the neural network algorithm (with NeuroShell Run-Time) for 83 days.

Flash flood activity was monitored throughout the 2004 flash flood season. Each of 93 days was assigned a flash flood severity index describing the activity in southern Utah. In total, there were 8 event days and 85 non-event days. Of the 83 days when sounding data, and thus neural network-derived CFFSIs, were available, 75 were non-event days, while 5 were assigned an actual flash flood severity of '1' and 3 were assigned a severity of '2'.

Table 4 shows the actual flash flood severity versus that calculated by the neural network algorithm. 60 of the 75 days in the '0' category were classified correctly, while none of the eight events in categories '1' and '2' was correctly predicted by the algorithm. There were no severe flash flood days in 2004, defined as category '3', either in actuality or as classified by the neural network. Thus, 60 of the 83 days, approximately 73%, were modeled correctly by the algorithm.

The procedure used for the 2004 flash flood season was repeated with data from the following year. Table 5 compares the actual and neural network-calculated daily flash flood severities for the 2005 flash flood season. There were 89 days for which sounding data were available; these included 7 days classified as '1', 3 days classified as '2' and one severe event day classified as '3'. 82% of non-event days and 18% of event days were classified correctly by the neural network algorithm; overall, 74% of study days were classified correctly.

## Algorithm Implementation and Future Work

During the 2006 flash flood season, forecasters in Salt Lake City will have access to the 'best result' neural network algorithm. The input data necessary to run the algorithm will be gathered from the highest resolution forecast model available, at the grid point closest to Flagstaff, Arizona. Use of model data will allow for assessment of the current day's flash flood severity in southern Utah and for the prediction of this severity one to three days in advance. If the additional information provided by the neural network algorithm is deemed useful to forecasters, running the algorithm will become part of daily operations in subsequent flash flood seasons and the FFPR will be revised so as to reflect the classification system developed in this study.

Meanwhile, both the monitoring of flash flood activity and the collection of Flagstaff sounding data will continue through the 2006 flash flood season and beyond. Expanding the verification dataset will be insightful in determining whether concerns about the algorithm's accuracy noted in the 2004 and 2005 data, namely the slight bias toward overprediction and large number of missed events, are recurrent problems or simply result from too small a sample of event days.

While 76% of days in the training dataset and 73% of days in the two-year validation dataset were classified correctly by the 'best result' neural network algorithm, the following alterations to the training dataset are likely to improve this performance: First, 500hPa wind speed should be removed from the list of input variables; its unimportance in determining flash flood severity has been illustrated above. Second, the training dataset should be expanded to 10 years, so as to include data from the 2004 and 2005 flash flood seasons. A final modification would further expand the training dataset by using sounding data prior to 1996. Data both from Winslow, Arizona and from Desert Rock, Nevada are available, though these locations are further from southern Utah than is Flagstaff and thus may not reflect atmospheric conditions in the study area as well.

Expansion of both the training and validation datasets will hopefully result in a neural network-based flash flood prediction tool that is adequately accurate for the needs of forecasters. Although such an algorithm would provide input relevant to the 'watch' phase of flash flood forecasting (lead times of 12-24 hours), it would not be able to pinpoint the location of predicted flash flooding. Additional detail about the location of flash floods could be obtained by repeating this study on a smaller scale. NCEP/NCAR regional reanalysis data could be used to link atmospheric conditions in various flash flood-prone regions, including Washington county, with flash flood severity in this same region.

## Discussion

Meteorological data were examined with a neural network to determine the quantitative relationship between the atmospheric state and daily flash flood severity in southern Utah. The results of this analysis should reassure forecasters that their experience is indeed valuable. The final neural network confirmed the importance of moist air (PW and RH at 700mb), unstable air (CAPE) and approaching short-wave troughs (12-hour 500mb height change) in flash flood severity. Nevertheless, there were two surprises as to the conditions that have significant impact on a coming day's flash flood activity. Despite southern Utah's rocky terrain and thus short memory for rainfall, the previous day's flash flood severity was found to relate to the current day's flooding. Also surprising was the nonexistence of a relationship between low wind speeds and flash flood severity. The authors have observed two mechanisms for the occurrence of flash floods in windy conditions. Storms can form repeatedly and inundate a given area with rainfall even though individual storms quickly advect downwind. Also, when cool air outflow boundaries from storm complexes become nearly stationary, storms will continually develop over the boundary as environmental flow is lifted by the boundary.

The 'best result' neural network algorithm correctly identified the flash flood severity for a large proportion of the study days. However, it should be noted that the network performed much better for the less severe days than for the days when severe flash flooding occurred. That is, the neural network underclassified days in the '2' or '3' CFFSI categories. Nevertheless, the neural network outperformed a linear regression model. The linear regression coefficients were computed using the same six variables as in the 'best result' algorithm. The regression model severely underclassified the meteorological dataset; all but two days were classified as non-event days (see table 6). This result supports the use of neural networks in predicting flash floods, as well as the notion that flash flooding is a non-linear process.

If the neural network algorithm presented earlier is deemed a success, it will likely become an additional dynamic layer in the Colorado Basin River Forecast Center's Flash Flood Potential Index (FFPI; Jackson et al, 2005). Furthermore, neural network-based analyses of sounding and reanalysis data, similar to that for southern Utah discussed in this report, could be conducted for northern Utah, northern Arizona and beyond. Making the process of flash flood prediction more quantitative will surely give more meaning to flash flood warnings and reduce the number of unpredicted flash flood events.

## Acknowledgements

The authors would like to thank Dr. L. Dunn, Meteorologist-In-Charge, and the staff of the Salt Lake City NWSFO for their support with this project. Meteorologist C. Young helped produce graphics of the study areas.

## Figures

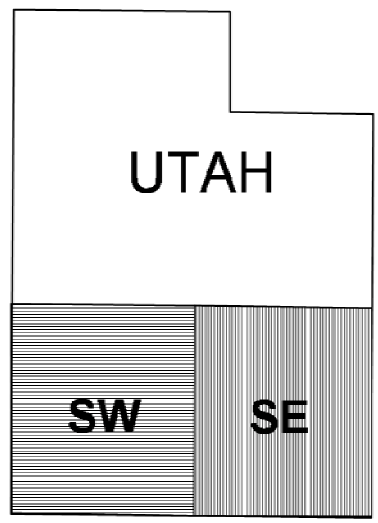



**Figure 1:** Study areas: southwest (SW) and southeast (SE) Utah.

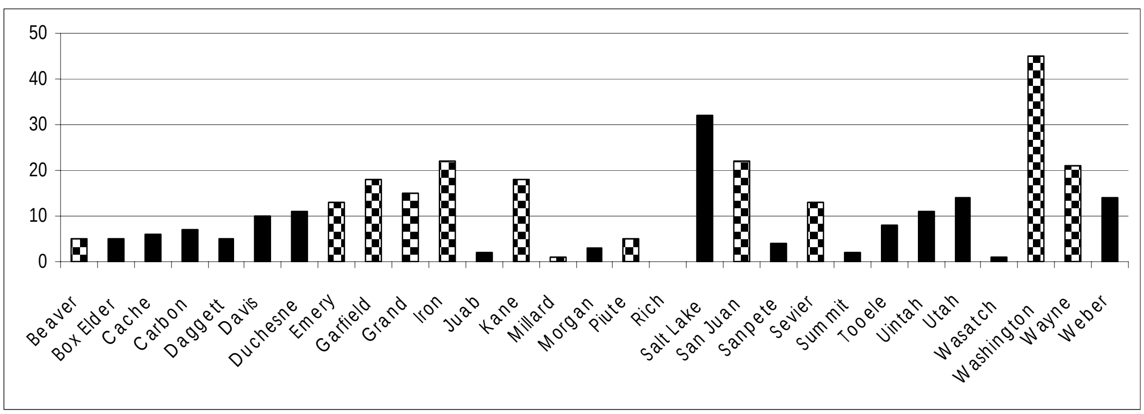



**Figure 2**: Reported number of flash flood events per county, 1959-2003. Counties in southern Utah are shown as patterned bars.

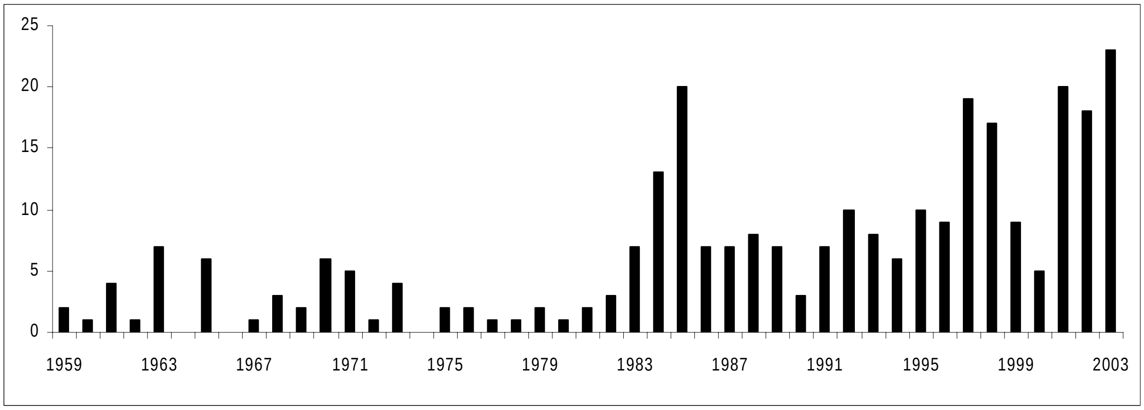



**Figure 3**: Reported number of flash floods per May-October season, 1959-2003.

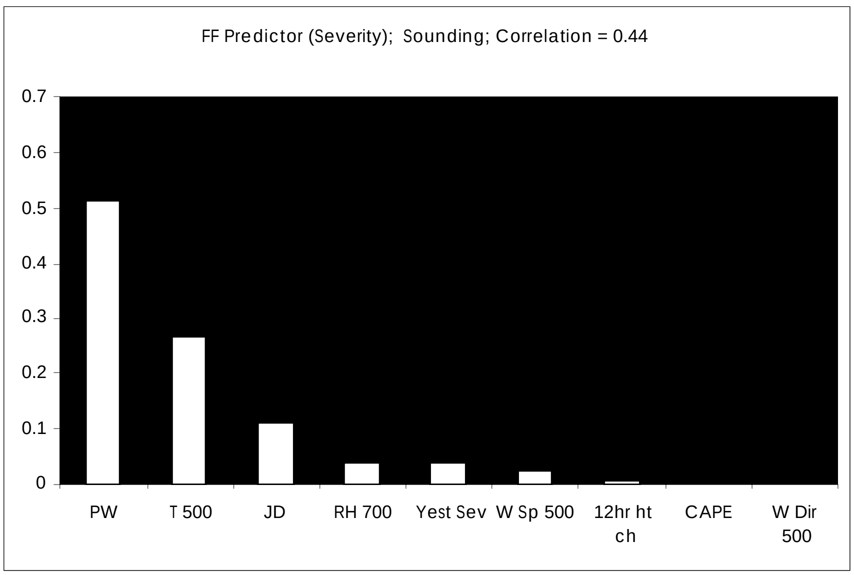
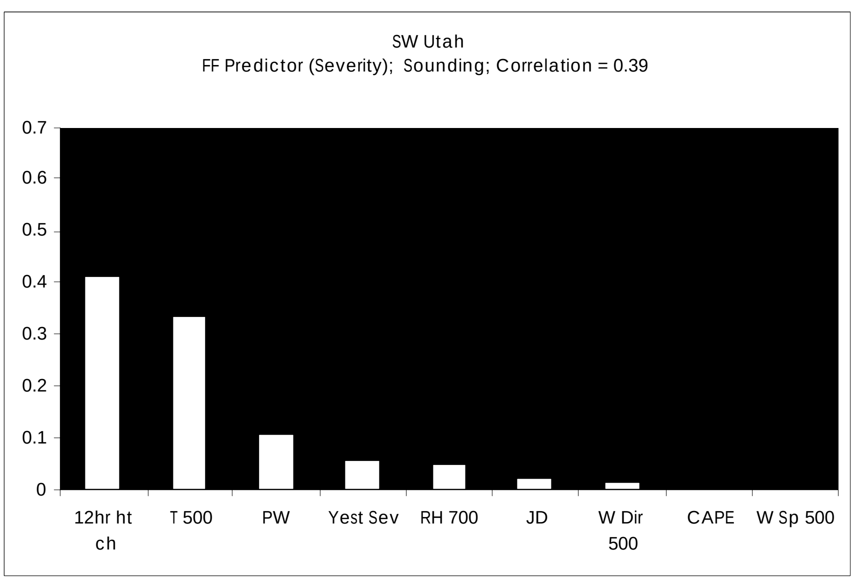



**Figure 4**: NeuroShell Predictor results using RFFSI and sounding dataset.

*a*



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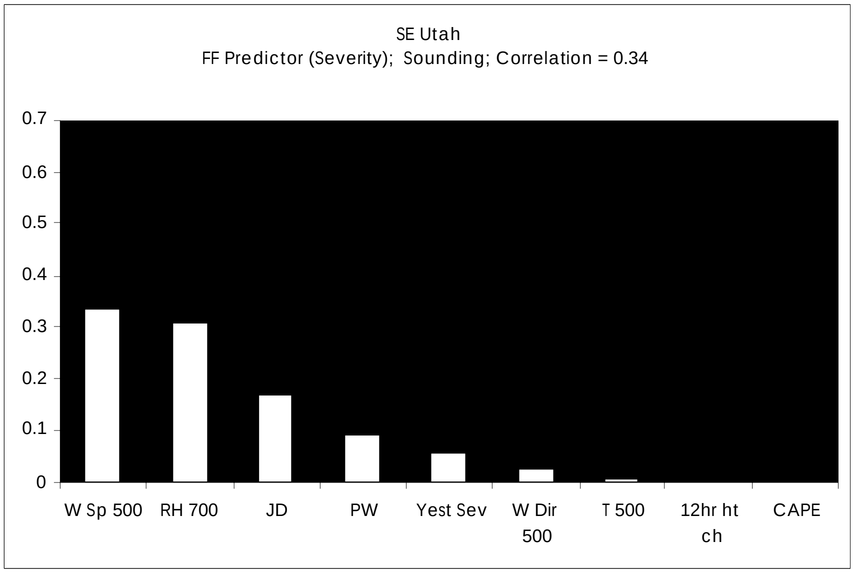


**Figure 5**: NeuroShell Predictor results with two groupings of RFFSI (a: SW Utah; b: SE Utah).

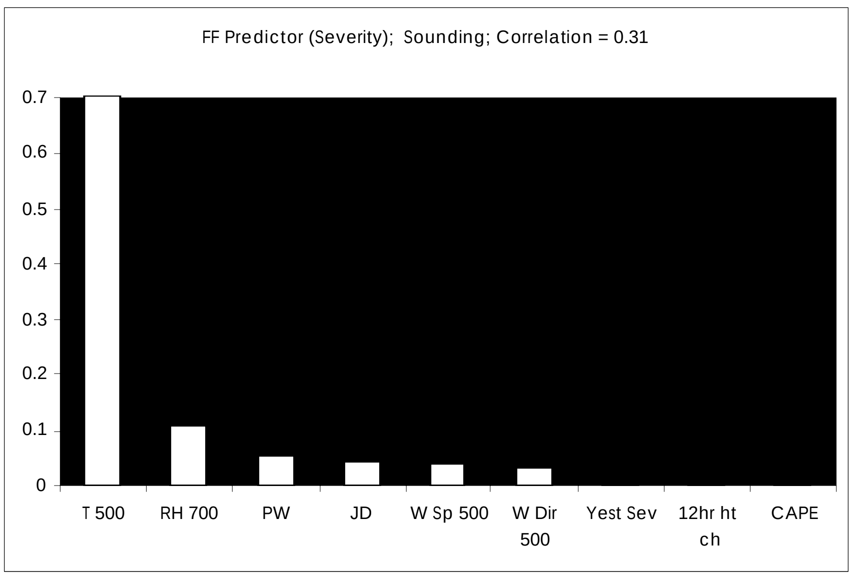


**Figure 6**: NeuroShell Predictor results using CFFSI.

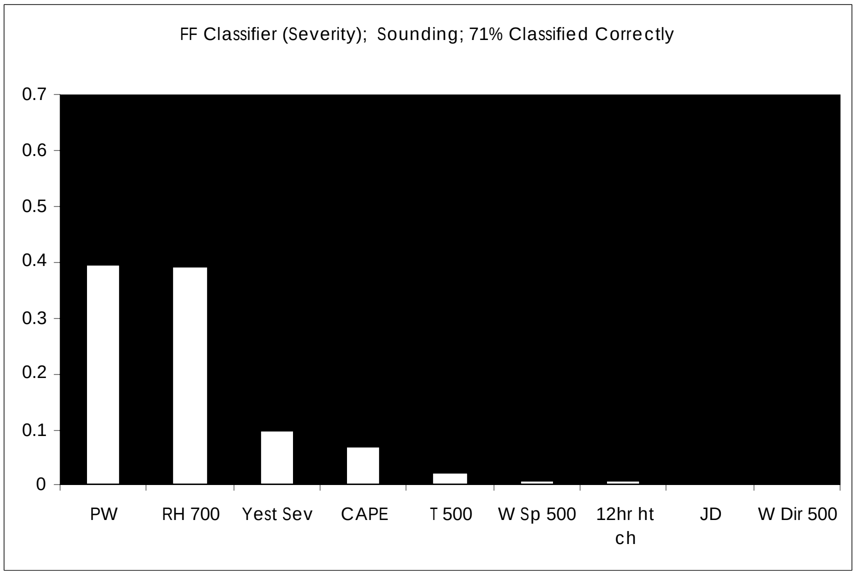


**Figure 7**: NeuroShell Classifier results using CFFSI.

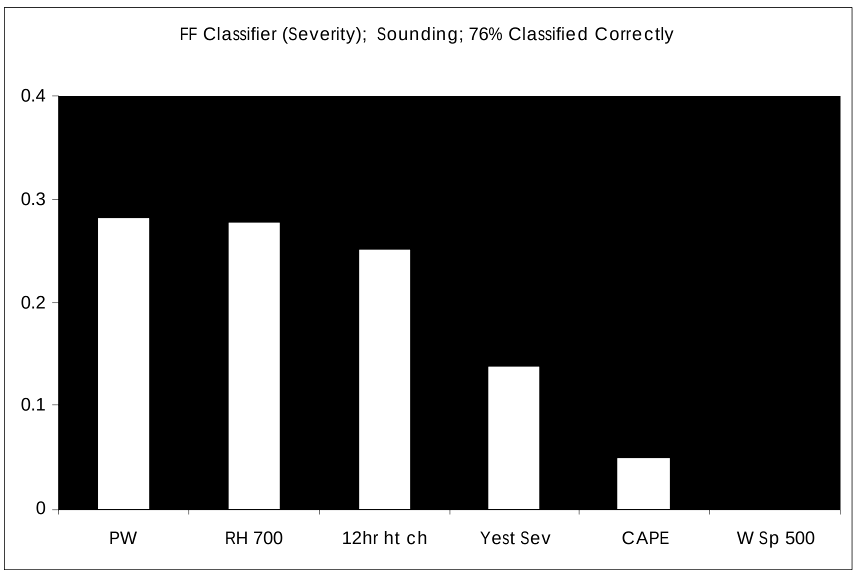


**Figure 8**: NeuroShell Classifier 'best result' algorithm, using CFFSI.

<table>
<tr><th>Flagstaff, AZ Soundings</th><th>NCEP/NCAR Reanalysis</th></tr>
<tr><td colspan="2">700hPa Relative Humidity (RH; %)</td></tr>
<tr><td>700hPa Wind Speed (kts)</td><td></td></tr>
<tr><td>700hPa Wind Direction (º)</td><td></td></tr>
<tr><td colspan="2">500hPa Wind Speed (kts)</td></tr>
<tr><td colspan="2">500hPa Wind Direction (º)</td></tr>
<tr><td colspan="2">500hPa Temperature (ºC)</td></tr>
<tr><td colspan="2">12-hour 500hPa Height Change (m)</td></tr>
<tr><td colspan="2">Precipitable Water (PW; mm)</td></tr>
<tr><td>Convective Available Potential Energy (CAPE; J/kg)</td><td></td></tr>
<tr><td>Lifted Index (LI)</td><td></td></tr>
<tr><td>Level of Free Convection (LFC; m)</td><td></td></tr>
<tr><td colspan="2">Julian Day (JD)</td></tr>
<tr><td colspan="2">Previous Day’s Flash Flood Severity Indexes (FFSI) in SW and SE Utah</td></tr>
</table>

**Table 1**: List of variables used in the preliminary neural network analysis, using data from the 2003 flash flood season.

| Flagstaff, AZ Soundings |
|---|
| 700hPa Relative Humidity (RH; %) |
| 500hPa Wind Speed (kts) |
| 500hPa Wind Direction (º) |
| 500hPa Temperature (ºC) |
| 12-hour 500hPa Height Change (m) |
| Precipitable Water (PW; mm) |
| Convective Available Potential Energy (CAPE; J/kg) |
| Julian Day (JD) |
| Previous Day’s Flash Flood Severity Indexes (FFSI) |

**Table 2**: List of variables used in the neural network analysis.

| | | Actual CFFSI | | | | |
|---|---|---|---|---|---|---|
| | | **0** | **1** | **2** | **3** | **Total** |
| **Computed CFFSI** | **0** | 533 | 22 | 7 | 2 | 564 |
| | **1** | 89 | 23 | 1 | 1 | 114 |
| | **2** | 45 | 4 | 6 | 1 | 56 |
| | **3** | 9 | 0 | 1 | 0 | 10 |
| | **Total** | 676 | 49 | 15 | 4 | 744 |

**Table 3**: Contingency table for the ‘best result’ neural network algorithm. Shaded boxes indicate the number of days that were correctly classified by the algorithm.

| | | Actual CFFSI | | | | |
|---|---|---|---|---|---|---|
| | | **0** | **1** | **2** | **3** | **Total** |
| **Computed CFFSI** | **0** | 60 | 5 | 3 | 0 | 68 |
| | **1** | 11 | 0 | 0 | 0 | 11 |
| | **2** | 4 | 0 | 0 | 0 | 4 |
| | **3** | 0 | 0 | 0 | 0 | 0 |
| | **Total** | 75 | 5 | 3 | 0 | 83 |

**Table 4**: Contingency table for the verification of the ‘best result’ algorithm using sounding data from the 2004 flash flood season.

| | | Actual CFFSI | | | | |
|---|---|---|---|---|---|---|
| | | **0** | **1** | **2** | **3** | **Total** |
| **Computed CFFSI** | **0** | 64 | 4 | 3 | 0 | 71 |
| | **1** | 9 | 2 | 0 | 1 | 12 |
| | **2** | 4 | 1 | 0 | 0 | 5 |
| | **3** | 1 | 0 | 0 | 0 | 1 |
| | **Total** | 78 | 7 | 3 | 1 | 89 |

**Table 5**: Contingency table for the verification of the 'best result' algorithm using sounding data from the 2005 flash flood season.

| | | Actual CFFSI | | | | |
|---|---|---|---|---|---|---|
| | | **0** | **1** | **2** | **3** | **Total** |
| **Computed CFFSI** | **0** | 675 | 49 | 14 | 4 | 742 |
| | **1** | 1 | 0 | 1 | 0 | 2 |
| | **2** | 0 | 0 | 0 | 0 | 0 |
| | **3** | 0 | 0 | 0 | 0 | 0 |
| | **Total** | 676 | 49 | 15 | 4 | 744 |

**Table 6**: Contingency table of the performance of the multiple linear regression model, using the sounding dataset.

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