12.6

SEVERE WEATHER PREDICTION USING THE GRAPHICAL FORECAST EDITOR

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1. Introduction

This paper describes a series of techniques to improve the severe weather recognition process using the National Weather Service's Graphical Forecast Editor (GFE). The GFE, developed by the NOAA Forecast Systems Laboratory is the cornerstone of the Interactive Forecast Preparation Systems (IFPS). It provides an integrated system to access, analyze, and graphically edit forecast model data. Scripting capability is built in to enable data manipulations and calculations for deriving gridded fields.

One of the more important and advantageous features of the GFE is the development of "Smart Tools" (Hansen, 2001). Smart Tools empower forecasters with a method to create scripts that integrate forecast techniques specific to the local forecast area (LeFebvre, 2001). A Smart Tool is a Python based computer program that converts complex meteorological equations and concepts into simplified grid data.

A detailed analysis of National Weather Service Tampa Bay Area, Ruskin, Florida WSR-88D radar and sounding data for severe weather events from1994 through 2000 provides many important correlations for severe weather recognition. The severe weather events were stratified by season, into hail, damaging wind, tornado, and waterspout categories. The GFE scripting capability is utilized to survey vertical model sounding data with the results from the severe weather and sounding correlations in an automated GFE environment. This provides a daily briefing of likely severe weather scenarios in areal graphic form. When thresholds are met, product specific color curves highlight threat levels. This GFE methodology of automated severe weather recognition has distinct time savings and enhanced viewing perspective advantages over manual analysis on a single sounding. The aforementioned radar analysis project also correlates changes in radar data from volume scan to volume scan to severe weather occurrence. With future access to WSR-88D radar data in GFE, automated scripts will check for temporal and spatial severe weather trends in radar data.

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2. Prediction Strategies

Through the years, methodologies were developed to help to diagnose the atmosphere's potential to produce severe convective weather. Miller (1972), related synoptic scale features to severe weather outbreaks. Composite charts identifying synoptic scale map features related to severe weather continue to be used at forecast centers. Many others have produced "rules of thumb" to help identify patterns associated with severe weather in localized areas. These techniques have traditionally been written checklists such as the comprehensive severe weather forecast checklist and reference guide by Gordon and Albert(2000). Many checklists require a modified morning sounding, time, and attention on the part of the forecaster. When incorporating model soundings through 24 or 48 hours, checklist completion becomes less likely. Many NWS offices have determined that the workload issue does not allow a checklist to be done at all, while other offices have a scaled-down version which saves time but may decrease the usefulness of the data obtained. GFE Smart Tools provide a method for integrating these rules of thumb into a severe weather potential identification process.

Several prediction strategies are being formulated and tested. The most basic method is to use a color table to highlight particular model parameter thresholds. Another simple method is based on calculating multiple grids of the most significant individual sounding indicators for a particular type of severe weather. Both these methods are awkward and cumbersome involving trying to correlate an excessive number of grids.

Another method is to consolidate parameters using a weighting system. This can be very effective. For example, hail development is well correlated with strong updrafts and cold mid-atmospheric temperatures (500-400 mb.) Thermodynamic instability and divergence are the basis for strong updrafts in this strategy. Table 1 shows the components for this strategy. Basically low, medium and high thresholds are identified for each parameter associated with a particular type of severe weather. Within the Smart Tool framework, a value (0,1,2,3) is assigned corresponding to a negligible, low, medium, or high potential for each parameter threshold, The results are then added to foresee an event that is low, moderate or high risk. Table 1 illustrates that method where the sum total of the values is less than 9 then expectations of hail are low, sums between 9 and 18 are moderate and values 18 to 27 are high. A Smart Tool easily extracts values from a model of choice and then sums parameter threshold values to determine the hazard category of that particular time frame. Output grids on the GFE analyze the threat for every 3 or 6 hours each day. This gives the forecaster additional flexibility to see atmospheric changes through the course of the day. By calculating the nine parameters listed in Table 1, and producing grids through GFE, time constraints are eased providing greatly enhanced severe weather recognition for the forecaster including how that severe threat will change throughout the day and saving time to view other severe weather parameters or complete other shift duties.

Table 1. Hail prediction checklist with parameters and corresponding Low, Moderate and High Thresholds. Values associated with thresholds are summed to determine category.

Hail				
Model Parameter	Units	Low Threshold	Moderate Threshold	High Threshold
Value		1	2	3
CAPE	JKg^{-1}	1000	2000	3000
T500	C	-7	-10	-13
T400	C	-18	-21	-24
Freezing level	m	4000	3500	3000
V850	ms^{-1}	15	20	25
V700	ms^{-1}	20	25	30
V500	ms^{-1}	35	40	45
V300	ms^{-1}	35	45	55
V200	ms^{-1}	40	50	60
Totals		9	18	27

3. West Central Florida Severe Weather Data Base

The underlying data in the development of the smart tools was derived from six years of archived data from the Tampa Bay Area - Ruskin WSR-88D radar accompanied by sounding data from the same site. The radar archive encompasses 118 cases with a variety of severe weather scenarios that were first separated into four major categories: damaging wind (19), hail (12), tornado (47), and waterspout (41).

Next the events were categorized by season. The cool season - December through April is categorized by convection coincident with mid-latitude troughs where instability is typically confined to narrow regions, shear is prevalent and organized convection is more likely. The early convective season - May and June, transitions tropical air in the lower levels with some remaining mid-latitude influence in the mid and upper levels. The summer season of July through September is dominated by tropical air and weak shear. The transition months of October and November are influenced by a mixture of mid latitude and tropical systems.

Events were then split into subsets of damaging wind, hail, tornado, and waterspout based primarily on convection configuration from radar reflectivity and velocity data. Some of the events produced more than one dominant type of severe weather. For example, bow echos typically produced damaging wind but some produced tornadoes and hail. Some bow “like” echoes were much smaller that others and those were often related to tropical cyclone banding. Some of the organized super cellular convection produced a combination of damaging wind, hail, and tornadoes. Waterspouts fit into three primary categories and occurred mainly during the warm season: strong convection moving offshore and intersecting low level boundaries, small but rapidly developing cells near the land breeze boundary, and weak cells embedded in westerly flow. Hail was primarily related to colder than normal mid level temperatures leading to more instability and faster hail growth.

Only 1200 UTC sounding data was used for this study. Some of the data were not necessarily representative of the atmosphere at the time of the weather but often 0000 UTC soundings are less representative from prior or existing convection. Table 2 shows the average and maximum (minium for negative) values for selected sounding parameters. For this study, the maximum and average values were used to capture the upper range of the severe events. These values were incorporated into smart tool thresholds.

4. Developing the Smart Tools

The data from Table 2 shows a contrast between season for damaging wind events. Although a regression analysis of all cases during this time frame may produce better results, for simplicity in this particular example, the maximum (or minimum for negative values) is considered the high threshold and the average is considered the low threshold. The median between the average and the maximum will be considered the moderate threshold. The Smart Tool gets values from the AWIPS D2D database using commands similar to this:

```
t500 = self.getValue("TBW_D2D_MESOETAU", "t",
       "MB500", x, y, GridTimeRange)
```

Next the calculations are made to compute those parameters that are not available directly from the model. The python math library may need to be imported for some of the calculations. The calculations may be made within one smart tool and applied to one final grid. A better method involves calculations made for several individual grids using a procedure that bundles several Smart Tool operations with a final Smart Tool calculation to infer the hazard category in a separate grid.

4. Conclusion

This paper describes a series of techniques that enhance the severe recognition process through the use of GFE and associated Smart Tools. The methodology described provides an easy to assemble consistent method for calculating the risk of severe weather using the GFE. These processes can be run from a separate

GFE server with a larger domain. Cron routines can automate the process of running GFE procedures that run bundles of these smart tools. For the sounding data presented in this case, only 12Z model grids are likely to produce favorable results but Smart Tools are easily updated to account for new findings at other periods. The GFE automates normally time-consuming forecaster tasks. While these methods have shown great promise for future operations, it is recognized that limitations with model grid data, Smart Tool calculations and underlying studies will keep forecaster attention paramount.

As these methods improve, the advances shown at the Tampa Bay Area NWS in the severe recognition process will prove to be important in other meteorological disciplines such as hydrology and winter weather. By being an open ended system with great flexibility, GFE shows great promise for future operations.

5. References

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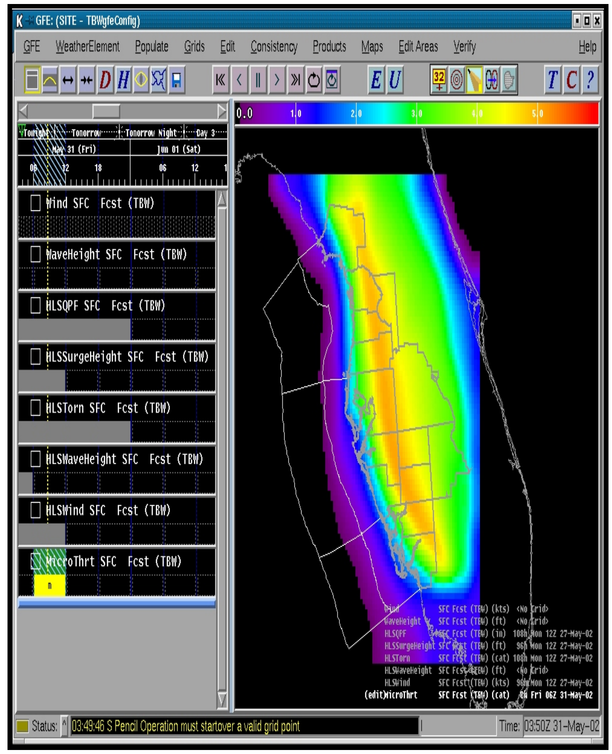

Figure 1. The GFE interface and associated 6 hour output grid for damaging wind prediction.

Table 2. 12Z Sounding parameters for damaging wind scenarios.

WIND	DEC-APR		MAY-JUN		JUL-SEP		OCT-NOV	
	AVG	MAX	AVG	MAX	AVG	MAX	AVG	MAX
Lifted Index	4.1	-0.8	-5.3	-6.5	-3.1	-8.5	-3.5	-7.1
SWEAT	202.7	254.3	169.5	187.0	181.6	252.8	223.5	283.7
K index	15.8	29.3	26.6	31.7	31.2	36.3	25.0	33.3
Cross totals	16.5	20.4	19.3	20.9	20.5	24.9	18.6	20.9
Vertical totals	22.8	24.3	26.8	26.9	25.2	27.9	24.6	26.9
Total-totals	39.3	44.5	46.1	47.8	45.7	50.8	43.1	47.8
CAPE	17.5	114.8	1959.9	2282.9	1070.6	3255.5	1267.5	2215.8
CIN	-16.7	-29.9	-23.6	-26.5	-99.8	-182.3	-10.1	-18.8
Equilibrium Level	39.3	866.7	184.9	193.1	259.1	518.7	242.7	378.5
Bulk Richardson #	0.3	959.5	523.7	671.7	384.9	1258.9	64.9	154.1
MML theta	291.5	294.5	299.5	300.1	299.1	301.0	296.3	298.2
MML mixing ratio	10.9	13.7	17.2	18.0	16.0	19.5	16.2	18.7
1000-500 mb thickness	5676.3	5684.0	5852.0	5867.0	5811.6	5897.0	5812.3	5857.0
Precipitable H2O(mm)	25.9	28.3	40.3	46.4	45.8	55.4	39.5	48.2