1. Introduction

Severe convective weather causes hazardous situations throughout the world. However, the concept of convective cell severity is not easily defined and it can be measured in several ways. As an example, in the United States, a severe thunderstorm is defined as a storm producing lightning and large hail exceeding 1 inch (2.5 cm), and strong gusts exceeding 50 kts (26 m s\(^{-1}\)), and/or a tornado (Galway 1989). Thunderstorm intensity might also be expressed by the incurred damages. Still, the damage depends on where the storm occurred and the full extent of the damage may not always be known.

Nowadays, spatially and temporally accurate remote sensing instruments, such as weather radars and lightning location networks, provide real time information on these rapidly changing but disastrous phenomena. Still, even though we are able to identify and track convective storms through remote sensing data, a single and easily understandable objective measure on storm severity is rarely available. An automatic, real time severity measure would assist several end users, such as operational forecasters, which are usually overloaded in case of a severe and extensive convective event (Punkka and Teittinen, 2007).

Some automatic real time methods for evaluating storm severity have been implemented even for operational purposes. For example, Bally (2004) introduces the Thunderstorm Interactive Forecast System (TIFS), which creates automatic radar data based warnings for forecasters. Another example is a severity ranking method included in TRT thunderstorm nowcasting system that is employed operationally in Switzerland (Hering et al. 2006). The method includes a straightforward severity ranking algorithm for a tracked storm using three radar based cell attributes VIL, mean 45 dBZ EchoTop altitude and maximum reflectivity.

In here, we propose a new classification scheme for the severity of a convective cell. The method employs several weather radar parameters and cloud-to-ground lightning location data. The starting point of the classification is statistical analysis of the cell intensity parameters. A statistical study on the properties of cell attributes is an important prerequisite to evaluate extremity of the convective events. A convective cell tracking algorithm is used for extracting extensive cell life cycle data sets of several radar and lightning data based severity attributes. Statistical extremities of cell intensity attributes are used as an initial guess of the cell severity.

Statistical analysis is not the only source of the classification. Although statistically extreme convective cells usually coincide with severe convective cells, also expert’s view is incorporated to improve the severity classification. We propose a fuzzy logic based methodology to add important expert knowledge to fine-tune the decision boundaries of the algorithm. The fuzzy logic algorithm mimics expert’s view of convective cell severity. In addition, it is a powerful tool to add rather subjective expert knowledge and linguistic expressions to the classification system and to combine multiple information sources into single parameter. When combined with the convective cell tracking, the classification algorithm considers not only current stage of cell attributes, but also past attribute values. Furthermore, the fuzzy logic algorithm can be customized to correspond user-specific needs of different end user groups.

2. Data and methods

2.1 Radar and lightning data

The radar data used in this study is obtained from eight Finnish Meteorological Institute’s (FMI) Doppler C-band weather radars, which cover the whole Finland. The main radar derived product in this study is the composite pseudo CAPPI 500 m image with 5 min temporal and 1 km \(\times\) 1 km spatial resolution, as it is widely used in operational meteorology in Finland. Fig. 1.a shows an example of the used radar composite. In addition to CAPPI 500 m, other radar derived products included in the study are composite EchoTop 20 dBZ, EchoTop 45 dBZ and rainfall accumulated during a short period, e.g. 30 min.

The source of the lightning data is the FMI’s Lightning Location System (FMI LLS). The network comprises of two types of sensors: three total lightning (cloud plus ground lightning) sensors of SAFIR-type covering the SW part of Finland, and 29 IMPACT type-sensors distributed all over the Nordic countries (NORDLIS cooperation) for the detection of ground lightning. Due to the small effective cloud-to-cloud lightning detection range covered by SAFIR-sensors, cloud-to-cloud lightning data is not included in our study.
2.2. Tracking method

Object oriented convective cell tracking algorithms are nowadays well-established methods for nowcasting and analysis of convective cells. These methods capture different cell parameters as time series and enable spatially and temporally accurate analysis of convective cells. Individual convective cells can be tracked, for example, using consecutive weather radar images.

In this study, we apply the clustering based tracking method introduced by Rossi and Mäkelä (2008) for the detection and tracking of convective cells in the weather radar composite data. However, the used tracking algorithm is only used for demonstrating the proposed severity classification methods and any convective cell tracking algorithm could be applied with similar severity classification.

2.3 Applied severity attributes

As mentioned above, severity of a convective cell can be measured in several ways. Our approach includes severity parameters that are usually available in operational weather radar and lightning location data. Therefore, for example an objective measure for wind gust severity is not considered in our study, as it difficult to observe accurately from operational remote sensing data. In our approach, the following severity attributes are calculated in each individual tracked cell and used for severity classification.

- **Cell dBZ values** - Large radar reflectivity factor values within the cell area imply general severity of the cell. Heavy rainfall, hail and intense lightning correlate with high cell maximum reflectivity values. Here, dBZ values in composite pseudo CAPPI 500 m images are applied.

- **EchoTop 20 dBZ** - A number of severe phenomena, such as severe gusts, lightning and hail, are associated with deep convection, which can be implicitly measured with radar EchoTop. Here, EchoTop 20 dBZ is applied, because it still has a proper measurement quality with FMI's operational radar tasks.

- **EchoTop 45 dBZ** - Like EchoTop 20 dBZ, high EchoTop 45 dBZ values anticipate several severe convective related phenomena, but especially hail risk is obtained from this parameter. However, a more sophisticated hail indicator should include also the melting layer height information. For example, Probability Of Hail (Holleman, 2001) would be a good option.

- **Radar derived rainfall accumulation** - High rainfall accumulation reflects the hydrological severity of a convective cell. If an intense convective cell is stagnant, it may quickly pour a tremendous amount of water in a fixed place and cause a flash flood in the worst case. As floods inflicted by severe convective cells usually occur suddenly, a rather short accumulation period, for example 30 minutes, is preferred.

- **Cell area** - Also an indicator of general intensity of convection. Quite often weather related emergency reports result from large convective systems, such as MCSs. In here, cells are identified as polygon objects in composite pseudo CAPPI 500 m images using a dBZ threshold and morphological image processing (Rossi and Mäkelä, 2008).

- **Lightning density** - Lightning density is used for indicating the severity of lightning. Dense lightning is also quite often associated with other severity parameters, such as hail and heavy rainfall. Located cloud-to-ground flashes are averaged to lightning density maps with a suitable window. For instance, past 15 minutes cloud-to-ground flashes within 10 km radius can be used to represent lightning density in a fixed place. Thereafter, for example the maximum lightning density value within the cell area is used to measure the lightning severity.

2.4 Statistical approach for defining severity boundaries

The cell tracking algorithm is used for extracting extensive datasets of the severity attributes introduced in Subsection 2.3. In each tracked convective cell, maximum values of severity attributes during the cell lifetime are recorded. After that, empirical cumulative distributions of these parameters are calculated.

Suitable percentile values of each distribution are used as an initial guess of the cell severity class boundaries in the fuzzy logic model, which is briefly described in Subsection 2.5. As an example, for each severity parameter an appropriative boundary can be chosen such that percentile values of 99.9%, 99 %, 95 %, 90 % correspond boundaries of the severity classes “extreme”, “severe”, “moderate” and “weak”.

Such an approach is naturally climate dependant and therefore the same boundaries may not be applicable in two different places. In addition, one should note that the applied methodology depends on the selected tracking algorithm, definitions and parameters. For example, if the tracked cells are identified with the reflectivity thresholds 35 dBZ and 40 dBZ, the results are naturally different. Additionally, the approach requires an extensive dataset in order to achieve statistically significant distributions. Suitable boundaries can be also drawn from climatological distributions estimated with other methodologies, for example those given by Zipser et al. (2006).
Fig. 1: An example of the applied radar data composite data and convective cell tracking on July 1, 2010, 0945 UTC. The images depict a) radar data only, b) radar data and tracked cells, c) a close-up of the tracked cells within the area indicated by the dashed rectangle in b). White polygons denote identified convective cells and red lines past two hour cell tracks.

2.5 Fuzzy logic based severity classification

Fuzzy logic is a tempting tool when data can be expressed with linguistic variables such as “hot”, “cold” or “warm”. Quite often these terms can be further described with rather subjective terms such as “not at all”, “more or less” or “very”. As noted by Zadeh (1965), most of the objects in the real world are of fuzzy, not sharply defined, type. This is also the case when describing convective cell severity and therefore fuzzy logic is a well-justified tool for our purposes.
The implemented fuzzy logic model encompasses a conventional three-step procedure: Firstly, severity attribute values are mapped to fuzzy sets using the model membership functions in the fuzzification stage. After that, the fuzzy inference is carried out, which mimics the inference procedure performed by a human expert. The fuzzy inference of the model produces a fuzzy model state, which itself is rarely a suitable output for an end-user. Therefore, in the final defuzzification phase, we map the resulting fuzzy set to a crisp continuous value \( I(t) \), which describes the cell severity at time step \( t \). The output can be scaled, for example, to continuous range 0-1, where 0 stand for a weak cell and 1 for a severe convective cell. The model output can be also weighted such that it emphasizes different end user needs, such as hydrological severity or lightning severity.

The model membership functions and fuzzy inference rules are primarily defined by the statistical percentile values of different severity parameters, as noted in Subsection 2.3. However, an expert can also modify these \textit{a priori} decision boundaries to correspond his/her view better.

After the severity index \( I(t) \) is calculated, the final severity value \( S(t) \) is obtained by filtering the severity index with the tracking information (see Subsection 2.6). Fig. 2 represents schematically the whole procedure from the severity attribute calculation until the final severity value \( S \). An example of the severity classification is given in Fig. 3.

2.6 Filtering severity by means of the tracking information

One of the main advantages of the convective cell tracking is that it enables the use of history information. Tracking methods capture time series of different parameter values in individual convective cells, which can be used to estimate cell state parameters better. Also severity classification can be improved by means of the convective cell tracking. Without the tracking information, the severity information is lost immediately, for example, if the lightning activity of a cell ceases temporarily. In order to exploit the severity information from the past time steps, the severity \( S(t) \) of the \( i \)th cell at time step \( t \) can be estimated with the following recursive filter

\[
S_i(t) = \lambda \cdot I_i(t) + (1 - \lambda) \cdot S_i(t-1), \text{ if } I_i(t) \geq S_i(t-1) \\
S_i(t) = \gamma \cdot I_i(t) + (1 - \gamma) \cdot S_i(t-1), \text{ if } I_i(t) < S_i(t-1).
\]

In Equation 1, \( I \) is the intensity classification inferred from the current cell severity attributes only, \( S \) is the filtered final severity classification result and user defined parameters \( \lambda \) and \( \gamma \) are the forgetting factors in the interval 0,...,1. Two different forgetting factors are required to treat cases where cell intensity attributes increase or decrease differently. Generally, we would like to emphasize increases in cell severity parameters. On the other hand, we would certainly like to retain some degree of severity, if the cell intensity parameters are decreasing. As an example, if cell attributes imply that the cell is severe at time instant \( t \) but the less severe at time instant \( t+1 \), the severity decays with respect to the forgetting factor \( \gamma \). A reasonable value for \( \gamma \) should be close to zero, say \( \gamma = 0.1 \), in order to retain severity. This means that the system remembers for some time that the cell is still potentially dangerous. However, in case of rapid increase in cell severity attribute values we would like to mark the cell immediately as severe. Therefore, a practical forgetting factor \( \lambda \) should be close to one, for example 0.9.

![Fig. 2:Schematic illustration of the severity estimation at time instant t. After the cell severity attribute calculation, current severity value I(t) is estimated by the fuzzy logic model. This is followed by filtering procedure, which results the final severity estimate S(t).](image-url)
Fig. 3: An example of the severity classification on August 14, 2007, 1420 UTC and 1445 UTC. Several severe thunderstorms occurred during that day. Red lines denote cell tracks and colored polygons identified convective cells. The color scale of the cells denote the severity index 0-5, where 5 stand for severe and 0 for weak. The severe storm in the centre of the figure caused several emergency calls, which are marked as red stars in the images.

3. Discussion

A new real time severity classification method for convective storms has been developed. The procedure is based on a fuzzy logic scheme that ingests real time weather radar and lightning data and results a value that classifies storm’s severity. Real time severity classification of a storm provides a single easily understandable measure, which is valued for example by operational forecasters. In addition, the method can be weighted such that it evaluates the storm severity emphasizing different end-user needs, for instance hydrological severity, lightning severity or hail severity. This way, individual end user specific severity measures can be generated.

Future improvements of the method include the integration of new severity attributes to the system. In order to measure severity of the cell objectively, it is essential to incorporate all the available real time information into the procedure. As an example, enhancing severity classification with real time emergency report data would provide a great additional input for the severity classification. For this purpose, e.g. the algorithm developed by Halmevaara et al. (2010) could be integrated with the proposed severity classification scheme.

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