AUTOMATIC HAZARD LEVEL APPROXIMATION OF CONVECTIVE STORMS USING REAL TIME EMERGENCY DATA

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I. INTRODUCTION

Issuing warnings on severe convective weather is nowadays an essential part of operational weather services. Thanks to the development of real time accurate observations and numerical weather prediction, operative forecasters have access to numerous automatic severe weather nowcasting and warning tools that facilitate their work. However, these methods do not include reported damages that have already taken place due to severe weather.

This paper studies automatic real time hazard level determination of convective storms using a new information source: real time emergency reports. During severe convective storms, emergency call centers log a large number of reports, for example, due to flash floods, lightning damages and uprooted trees.

Since 2006, the Finnish Meteorological Institute (FMI) has received these reports from the emergency call centers in real time. This paper discusses attaching this information automatically to weather radar detected storms to characterize their hazardous properties.

The proposed method uses a weather radar based convective storm tracking algorithm in the background. Detected tracks of individual storms and incoming emergency reports are analyzed to determine the relationship between each report and a convective storm. Then, the method estimates the hazard level for each storm based on number of associated emergency reports. Finally, based on the hazard level, we can highlight potentially dangerous convective storms in nowcasting products.

This paper continues the work presented by Rossi et al. (2011).

II. OBJECT-ORIENTED CONVECTIVE CELL TRACKING

Object-oriented convective cell tracking algorithms are nowadays well-established methods for nowcasting and analysis of convective weather. These methods are able to capture motion and life-cycle of individual convective storms and enable spatially and temporally accurate analysis of individual convective cells. Various storm-related attributes, such as radar-based parameters or lightning data, can be attached to the tracked cells to characterize their properties. Here, we attach real time emergency calls to the tracked cells.

Individual convective cells can be tracked, for example, using consecutive weather radar images (e.g. Dixon and Wiener 1993), satellite images (e.g. Vila et al. 2008) or lightning location data (e.g. Tuomi and Larjavaara 1995). Further discussion on convective storm tracking is given for example by Wilson et al. (1998).

In this paper, the clustering based tracking method introduced by Rossi and Mäkelä (2008) is applied for detecting and tracking convective cells in composite weather radar data. The algorithm identifies cells from radar data by using a certain reflectivity threshold value and the morphological closing operation, after which the cell identification and tracking are performed with a density-based spatial clustering algorithm. However, the algorithm provides only background information for the hazard level estimation. Any other well-designed tracking method could be applied for similar purposes.

III. DATA SOURCES AND OBSERVATIONS

The radar data used in this study is obtained from FMI's eight Doppler C-band weather radar covering almost the whole Finland. The tracking algorithm uses constant altitude PPI images of 500 m altitude with 5 min temporal and 1 x 1 km spatial resolution.

The source of emergency reports is the real time emergency report data applied at the FMI. In addition to the location of the emergency, each report contains a coarse classification of the emergency type and a short verbal description of the incident for on-line use.

In this paper, we use emergency calls that are pre-classified by the rescue authorities as the loss prevention task. Majority of the calls that are caused by severe weather belong to this class. Still, this class may contain both meteorological and non-meteorological emergencies. For example, a broken water pipe and a storm-flooded cellar can be equally classified as the loss prevention task. However, during a convective situation, amount of "false alarms" with respect to true weather related events is small. It is also very unlikely that a non-meteorological loss prevention task falls under the path of a convective storm, and therefore the impact of these calls on our algorithm is usually negligible.

IV. ESTIMATING STORM HAZARD LEVEL WITH EMERGENCY CALL INFORMATION

The first step of our algorithm encompasses the minimum distance computation between each convective cell track and an emergency report. The distance $d(e_{i,t},m)$ between the ith emergency report $e_{i,t}$ at time t and convective cell m is defined as the minimum distance between the storm objects related to cell track history until the reporting time of the emergency and the report location.

The distance is transformed into the *relatedness* value, which describes how much an emergency report is related to a convective storm. The relatedness $r(e_{i,t},m) \in (0, 1)$ is obtained by mapping the distance $d(e_{i,t},m)$ through a Gaussian function with piecewise linear parts

$$r\left(e_{i,t},m\right)=\begin{cases}1, & \text{if } d\left(m,e_{i,t}\right)\leq d_0,\\ e^{-\left[d\left(e_{i,t},C_m^H(t)\right)-d_0\right]^2/s^2}, & \text{if } d\left(m,e_{i,t}\right)>d_0,\end{cases} \quad (1)$$

where d_0 is the threshold distance and s is the scaling distance. The threshold d_0 is used for compensating inaccuracies related to the locations of emergency calls and radar data. In this work, we set d_0 = 3 km and s = 20 km, corresponding to the relatedness 0.5 at an approximate distance of 10 km.

Since it is difficult to estimate which cell caused the event, we compute the relatedness values to all cells nearby. Moreover, an emergency may be caused by multiple storms, for example in a flooding case.

After the relatedness computation, we estimate the hazard levels of the storms using an autoregressive moving average model of relatedness values. For the *m*th convective cell track at time *t*, the *hazard level* $h(m,t)$ is computed recursively with

$$h(m,t)=\lambda h(m,t-1)+\sum_i \lambda^{\Delta t\left(e_{i,t},m\right)} w\left(e_{i,t}\right) r\left(e_{i,t},m\right), \quad (2)$$

where $\lambda \in (0, 1)$ is the user defined forgetting factor, w is the location weight and $\Delta t(e_{i,t},m)$ is the *hypothetical delay*, *i.e.* the delay between emergency report time and the time of the minimum distance of convective cell history. This parameter scales emergencies with varying delays properly. Otherwise, delayed emergency calls would have an exaggerated impact on the hazard level. The summation in (2) is taken over the emergency reports between the previous and current radar image times.

In (2), $w(e_{i,t})$ is the population dependent weight of the emergency event $e_{i,t}$. The population density weighting is necessary, since the flow of incoming emergency calls tend to increase in densely populated areas. In our study, the weight $w(e_{i,t})$ is computed with the following heuristic function

$$w\left(e_{i,t}\right)=\log_{10}\left(\tilde{\rho}\right)\Big/\log_{10}\left(\max\left\{\rho(e_{i,t}),\tilde{\rho}/5\right\}\right), \quad (3)$$

where $\rho(e_{i,t})$ is the population density of the emergency call location and $\tilde{\rho}$ is the median. In here, the population density is 2-2753 people/km^2 and the median density in southern Finland is 10.5 people/km^2. Hence in densely populated areas, the weight is approximately 10.7 times more than in sparsely populated areas. At the median population density point the weight is one.

One of the most important future improvements is to define population density weight (3) statistically, for example using conditional emergency probability given the population density. However, this is challenging as the current emergency data archive is not yet very extensive and the data is biased by individual intense storm cases.

V. CASE EXAMPLES OF THE AUTOMATIC HAZARD APPROXIMATION IN FINLAND

a. Intense convective storm, Jun 1 2011

On Jun 1 2011 an intense convective storm caused extensive damage in the western Finland, especially in the town of Parkano. The reasons for the reports were mainly fallen trees. Fig. 1 illustrates the hazard level algorithm in this case at 12:35 and 12:55 UTC.

The first emergency call that was related to the storm was recorded at 12:10. Later on, between 12:20-12:35 UTC, more emergency calls appeared in the vicinity of the storm, which increased the hazard level significantly. At this point, a warning could have been issued based on the high hazard level. A reasonable threshold for issuing warning could be, for example, the hazard level value of 2. At 12:55 UTC, the storm hit the town of Parkano, which started an intense inflow of emergency calls. The flow continued for two hours after the storm overpassed the town.

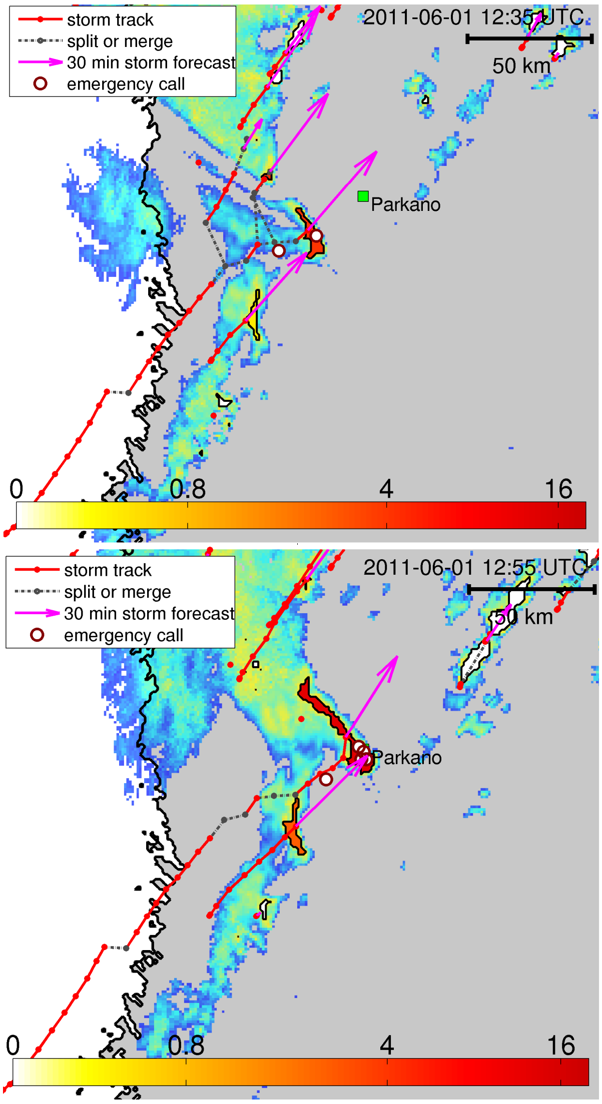

FIG. 1: Convective storm tracking and hazard level estimation on Jun 1 2011. Red and gray lines show storm tracks with split and mergers, red circles show past 5 min emergency calls and magenta arrows indicate 30 min nowcasts of the storms.

This example illustrates how hazard level information can be represented as time series information. Fig. 2 shows the time series of the storm that caused the damage in Parkano. Blue bars depict the sum of emergency relatedness values of the incoming emergency calls and the red line indicates the approximated hazard level. Between 12:30 and 13:00 UTC, the hazard level rises steeply, which reflects increasing cumulative sum of emergencies caused by the storm. Magenta bars in Fig. 2 illustrate the time-shifted summed relatedness, that is equivalent to the summed emergency relatedness, but instead of incoming emergency call time instants, the hypothetical delay $\Delta t(e_{i,t},m)$ is subtracted from the emergency call time. The graph gives an overview of estimated temporal distribution of the storm damage. In this case, a clear peak is experienced around 12:50 UTC, that is, the time when the storm hit the town.

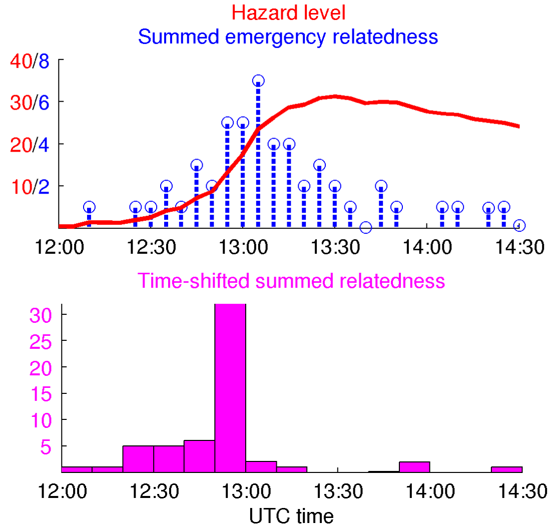

FIG. 2: Time series of storm emergency data based parameters on Jun 1 2011. For discussion, see text.

b. Mesoscale Convective System , Jul 29 2010

On Jul 29 2010 a severe mesoscale convective system (MCS) crossed the south-eastern border of Finland at 20:50 UTC, traversed through the central Finland and continued to west until Sweden, where it dissipated approximately nine hours later. A large number of emergencies were reported during the case, mainly due to uprooted trees by intense downbursts.

Immediately when the storm crossed the border, emergency calls started to pour in, and the hazard level of the storm increased despite the relatively sparsely populated location of the storm. The flow emergency calls remained persistent, which guaranteed increasing hazard level. Fig. 3 shows the output of the algorithm in this case at 22:20 UTC.

This case visualizes also how hazard level information could be represented in nowcasting tools in an easily understandable manner. A user can see at quick glance which of the storms have caused many emergencies (red color) and which ones have not (white color). In this case, the red MCS is obviously the most dangerous. In the meantime, the large storm further south does not cause any emergencies, which suggest that the storm is less hazardous. The information box in Fig. 3 provides also other useful features on the large red MCS.

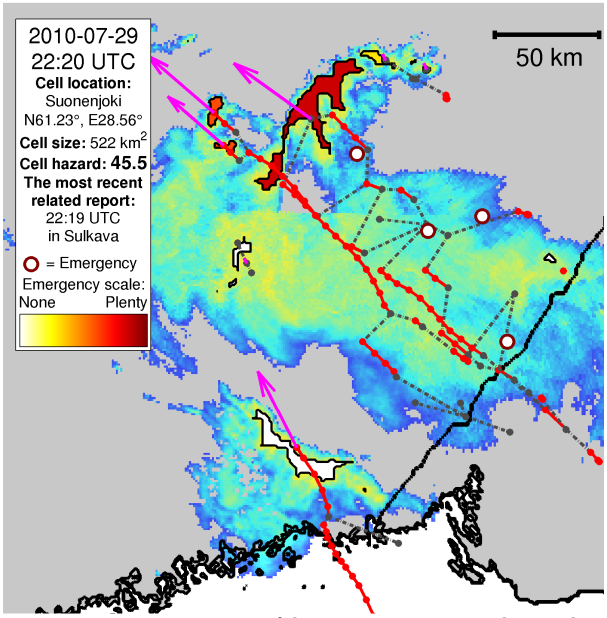

FIG. 3: Operative view vision of the convective storm tracking and hazard level estimation on Jul 29 2010. Map symbols as in Fig. 1.

VI. DISCUSSION

The presented hazard level approximation method exemplifies how real time emergency reports can be combined with weather radar data for automatic nowcasting of severe convective storms. The storms that have already caused damage can be highlighted in different nowcasting products based on the estimated hazard level. Thanks to the easily understandable output value, the algorithm could be applied by several end-user groups, such as operative weather forecasters or rescue authorities.

In addition to the real time nowcasting of potentially dangerous storms, the algorithm enables post analysis of the storms. By means of the algorithm, we can acquire better knowledge of the damage caused by the storms and illustrate hazard level evolution or temporal distribution of the damage caused by a certain storm cell.

The work presented in this paper provides a good platform for future developments. A future improvement is a statistically defined population density weighting method. Moreover, the algorithm could utilize forecasted locations of the storms; higher hazard level values could be given to storms threating weather sensitive targets, such as densely populated cities. Finally, the hazard level approximation could be combined with other algorithms that estimate severity of the storms using radar-derived attributes, lightning location data and other information sources.

VII. ACKNOWLEDGMENTS

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