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Developing a Concept to Visualize Object-based Weather Forecasting Ensembles

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Abstract

Operational weather forecasters face the challenge of having to process and interpret a large amount of available information. Therefore, condensation of extensive information is required. Research and development of forecasting techniques will on the one hand improve the forecast quality and on the other hand lead to an increased amount of data. A new extensive and valuable data set will emerge from the SINFONY project at Deutscher Wetterdienst (DWD). It aims at a seamless forecast of upcoming convective events from actual time up to some hours by combining observation-based nowcasting techniques and numerical weather prediction (NWP) ensembles into a single system. In this context, a group of products will comprise features ("cell objects") that were extracted from three-dimensional radar measurements and NWP ensemble simulations.
A user-oriented intuitive visualization of the new meteorological data is crucial for weather warning and forecasting. Before including new data into forecast operation, extensive tests and evaluations have to be performed. It therefore requires a careful iterative development process with continuous evaluation by the users.
To facilitate this process, an initial visualization mock-up is created, which will be used to prototype and refine visualization and data product concepts. The browser-based nature of the tool allows to quickly share an interactive design with the users which, in turn, will help to have in-depth discussions and to collect visualization requirements, before the final concept is implemented into the meteorological workstation.
This paper presents the first use-case for this approach: The development of a concept to visualize object-based severe convective events based on matching observed and simulated features.

CCS Concepts
•***Human-centered computing*** → ***Geographic visualization;*** •***Applied computing*** → ***Environmental sciences;***

1. Introduction

The uncertainties in the prediction of future atmospheric states can be assessed by using forecasting ensembles generated by numerical weather prediction (NWP) models. This technique utilizes the perturbations of input parameters and/or other uncertain model parameters to generate a number of simulations resulting in a probabilistic forecast of the future atmospheric state [GR05, WMO12]. It provides the likeliness of an event to occur at a certain location based, for instance, on the number of ensemble members predicting its appearance [KCKD12]. Experiments have shown that weather forecasts generated by ensemble prediction systems (EPS) outperform those relying on a single, deterministic prediction [GTPB11].

However, the state of the atmosphere at a certain point in time and very-short-term weather forecasts in the range of 0 – 2 hours ahead of this time are challenging for NWP-EPS systems. This is, amongst other reasons, due to model spin-up effects and the accurate assimilation of recent observations into the current physical state of the simulations [SXW*14]. For this very-short-term forecast, so-called nowcasting techniques (at DWD mostly based on remote-sensing observations) are used, which are based on image processing techniques to detect motions in timeseries of recent past and actual 2D observation maps (so-called "composites"). These motion vectors are used to linearly advect the observed features into the future. For short forecast lead times, this provides a high forecast skill at high spatial resolutions [SXW*14, KCKD12].

The project SINFONY (Seamless INtegrated FOrecastiNg sYstem) at DWD aims at combining both methods - nowcasting and NWP-EPS - into a single system to enable a seamless prediction of upcoming convective events in a time scale of several hours. This is especially critical to forecasting severe weather elements, such as thunderstorms or strong winds. In this context, information of high time and spatial resolution is key to be able to warn the general public well ahead of time.

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The data products developed in the course of this project are expected to be more complex and significantly more voluminous than most of the currently used operational data sets. For instance, it is planned that nowcasting techniques provide a probabilistic short-term forecast based on an ensemble system. Furthermore, the planned products aim at combining nowcasting-EPS with NWP-EPS to improve the forecast of deep convection events.

Conceptualizing visualization techniques for new data products requires a thorough and continuous evaluation by the forecasters, who use them in their daily routines. Therefore, to facilitate the iterative refinement of a visualization design, an initial visualization suggestion has been rapidly set-up in a web-browser. This allows to quickly share an interactive visualization mock-up to spawn goal-directed discussions, before the final evaluated visualization can be implemented into the operational meteorological workstation, called NinJo [HH09].

To showcase the initial implementation state of the mock-up, this paper presents a concept for a visual comparison of intense convection areas - referred hereafter as features - predicted by the deterministic nowcasting with those simulated by the NWP-EPS. This results in a visualization tool showing local ensemble spread, while simultaneously highlighting groups of members matching a nowcasting feature best.

The remainder of this paper is structured as follows: Section 2 illustrates related work in the visualization of uncertainties in the context of ensemble simulations. After that, we describe the characteristics of the data set, for which we aim to develop a visualization strategy. Section 4 describes an initial concept for the visualization of this data, which is discussed in Section 5. Finally, we draw a conclusion in Section 6.

2. Related work

According to Obermaier and Joy [OJ14], and as cited by Böttinger et al. [BPR*15], ensemble visualization techniques can be classified into feature-based and location-based approaches: While feature-based approaches are applied to objects found in each member, location-based approaches focus on analyses at "fixed locations" [OJ14]. The latter also corresponds to traditional techniques, where the results of an EPS are presented as a grid-based product. Here, each grid-cell is associated with a measure summarizing the results of all members, such as mean value, spread, or a probabilistic statement about how many members exceed a certain threshold [RKSW15].

This categorization can be applied to both ensemble visualization in climate and weather forecast. For instance, in the context of climate ensemble analysis, Böttinger et al. [BPR*15] make use of the location-based approach: They apply different visualization techniques to combine a predicted variable, skill and ensemble spread simultaneously in a single display for summarizing views upon the uncertainties. In contrast, Hüttenberger et al. [HFBG17] aim at showing the contribution of individual ensemble members to delineated areas of member disagreement, by combining a Pareto set analysis with a glyph-based region-summary.

The work described in this paper can be assigned to the group of feature-based ensemble visualization methods for weather forecasting applications. A classical example for a visualization technique in this category are so-called spaghetti plots: Here, isocontours of all involved ensemble members are plotted together on a single display to show their spatial divergence or correspondence [RKSW15, FKRW17]. This method is also used by Potter et al. [PWB*09] in their Ensemble-Vis framework, alongside with other views onto an ensemble data set. Also Sanyal et al. [SZD*10] make use of spaghetti plots, although they combine them with glyphs and ribbons that further illustrate uncertainties within the simulation domain or specifically along isocontours. Ferstl et al. [FKRW17] cluster the time series of isocontours in a spaghetti plot, and use the results to show the temporal development of uncertainties.

While the isocontours underlying these methods are frequently close to each other (or, at least, do not vary so much between single time steps), the features in the data set used in this paper might change a lot within short time spans, such that these techniques might be difficult to apply.

Not specifically related to ensemble visualization, but still relevant for the work described in this paper is the object-based comparison of precipitation forecasts with corresponding observations that was addressed by Wang et al. [WFZ*15]. Following a verification method described by Lakshmanan and Kain [LK10], Wang et al. approximate rain bands in both forecasts and observations using Gaussian Mixture Models and enable their simultaneous spatio-temporal analysis. However, they do not compare ensemble members to the observation, but they rather use a product averaging the available members.

3. Characteristics of the underlying data products

3.1. Nowcasting data

Nowcasting applications are developed to obtain the best possible forecasts for the coming minutes up to the next few hours. These are based on remote sensing observations at a high spatial and temporal resolution, with new forecasts generated in rapid succession (rapid update cycle). They are particularly valuable in meteorologically unstable situations that are often associated with severe weather events, such as thunderstorms.

The data provided by the DWD radar network is essential to detect deep convection. It is comprised of 17 polarimetric Doppler C-Band radars (Fig. 1) that deliver three dimensional data every five minutes. These data are used by the nowcasting techniques at DWD to detect, track and forecast deep convection, which are identifiable thanks to their high radar reflectivities. A reflectivity threshold is typically applied to identify the core of the thunderstorm or convective cell. The currently operational detection technique is called KONRAD (KONvektive Entwicklung in RADarprodukten, [Lan01]), which uses a single fixed reflectivity threshold of 46 dBz and takes into account only the two-dimensional near-ground radar reflectivity data. To take advantage of the three-dimensional character of the data, a new technique called KONRAD3D has been developed. Besides that, KONRAD3D applies an adaptive threshold scheme to detect the existence of a convective cell in the radar data. This method allows the detection of cells at individual thresholds, depending on their development phase [HMG*04]. Each detected cell can be considered a meteorological feature with its particular attributes like, e.g., geographical location (centroid), size, motion vector, maximum reflectivity, or vertical extent. In this paper, the convective cells detected based on radar data will be referred as observed features.

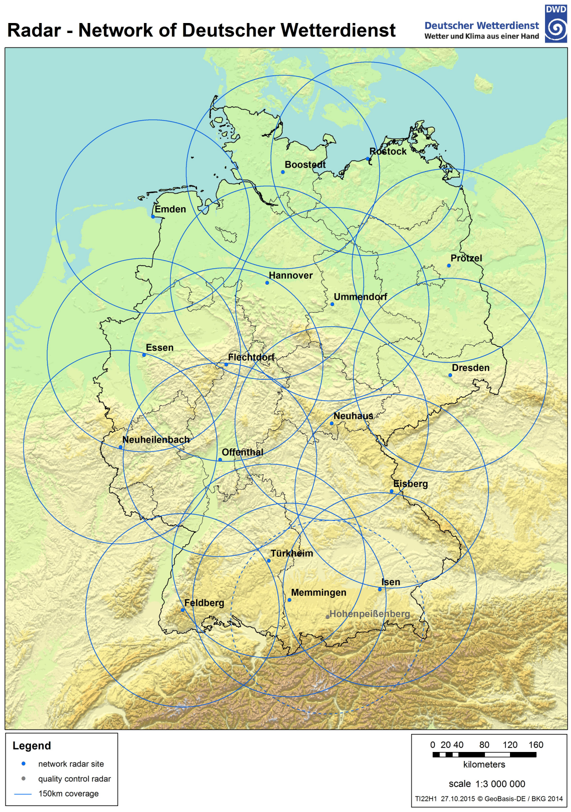

Figure 1: *Radar Network at DWD.*

3.2. NWP-ensemble data

At DWD, the ensemble forecasting system COSMO-DE-EPS [TGB17] is based on the numerical weather forecast model COSMO and currently includes 20 ensemble members, producing new forecasts every 3 h. Initial conditions for these forecast members are created by the KENDA-system (Kilometer-scale ENsemble Data Assimilation, [SRR*16]), which draws ensemble forecasts closer to the observations at hourly intervals by a sophisticated 4D Localized Ensemble Transform Kalman Filter (4D-LETKF) method. The grid spacing of COSMO-DE-EPS is 2.8 km and the domain covers whole Germany, Benelux, Switzerland, Austria and parts of the other neighboring countries.

For the SINFONY project, the COSMO-DE-EPS has been adapted to provide forecasts up to only +6 hours but providing new forecasts every hour. In addition, it provides simulated radar volume data with the same structure and time resolution as the actual radar observations (each 5 minutes), thanks to an efficient Modular VOlume scanning RADar Operator (EMVORADO) that is coupled to the COSMO model framework [ZBJ16]. This allows for the use of KONRAD3D to detect the convective cells simulated by the NWP-ensemble. These cells are referred hereafter as simulated features. The use of the same method for feature identification facilitates the comparison and further analysis of the identified features in both observation-based nowcasting and NWP.

3.3. Dataset

The SINFONY project focuses on severe summertime convective events. For the experimental phase, convective events that occurred between May 26 and June 26, 2016, are analyzed (see Fig. 2). Within this period, May 29, 2016, is of special interest due to the heavy rain registered during that day in several parts of Germany, including the well-known Braunsbach-flood in Southern Germany [BBC16].

This case has been selected for the first product mock-up presented here, choosing the 17:00 UTC forecast but showing the graphics at 17:15 UTC to mask out the unavoidable model spin-up time. This is also the time of day, at which the region around Braunsbach experienced heavy precipitation [ZJB16]. KONRAD3D has been applied to both radar observations and NWP-EPS simulations to retrieve the observed and simulated features, respectively. A total of 136 features were identified in the observed radar data.

In order to compare both simulated and observed convection features, a maximum distance threshold of 50 km around each observed feature was established to ensure that simulated cells are nearby the observed convective cells. Simulated objects beyond this threshold are removed from the dataset. After visualization requirements have been discussed, it could be possible that this threshold is modifiable by the user.

4. Visualization concept

4.1. Data analysis techniques

A clustering technique has been used as a first attempt for the comparison of simulated with observed features. Data clustering is a data exploration technique that allows objects with similar characteristics to be grouped together in order to facilitate their further processing [PDN04].

One of the most popular clustering algorithms is K-Means, a method first described by [Ste56]. Its popularity resides in the ease of implementation, simplicity, efficiency, and empirical success ([Jai10]). A limitation is, however, that the number of clusters (k) has to be pre-specified. As stated by [PDN04], to find the appropriate number of clusters for a given dataset is generally a trial-and-error process, which can become difficult due to the subjective nature of deciding what constitutes a "correct" clustering.

Despite this limitation, the K-Means algorithm was chosen for our case study as a first approach to group the simulated features based on their similarities to the observed objects. The parameters chosen to carry out the multivariate clustering analysis are: (a) maximum (radar) reflectivity, (b) minimum (radar) reflectivity, (c) geographical location (centroid) and (d) size of the feature (so-called matching parameters). In order to facilitate the interpretation of the product visualization, only three clusters will be taken into consideration ($k = 3$). The clustering has been done as follows:

1. Given an observed feature, the simulated features that are within a 50 km radius are selected for clustering.
2. The difference of the matching parameters from the simulated features compared to observed feature.
3. The K-Means method is then applied based on the difference values, which were previously scaled.

A new clustering is carried out to each group of simulated features that are around an observed feature (at a maximum distance of 50 km).

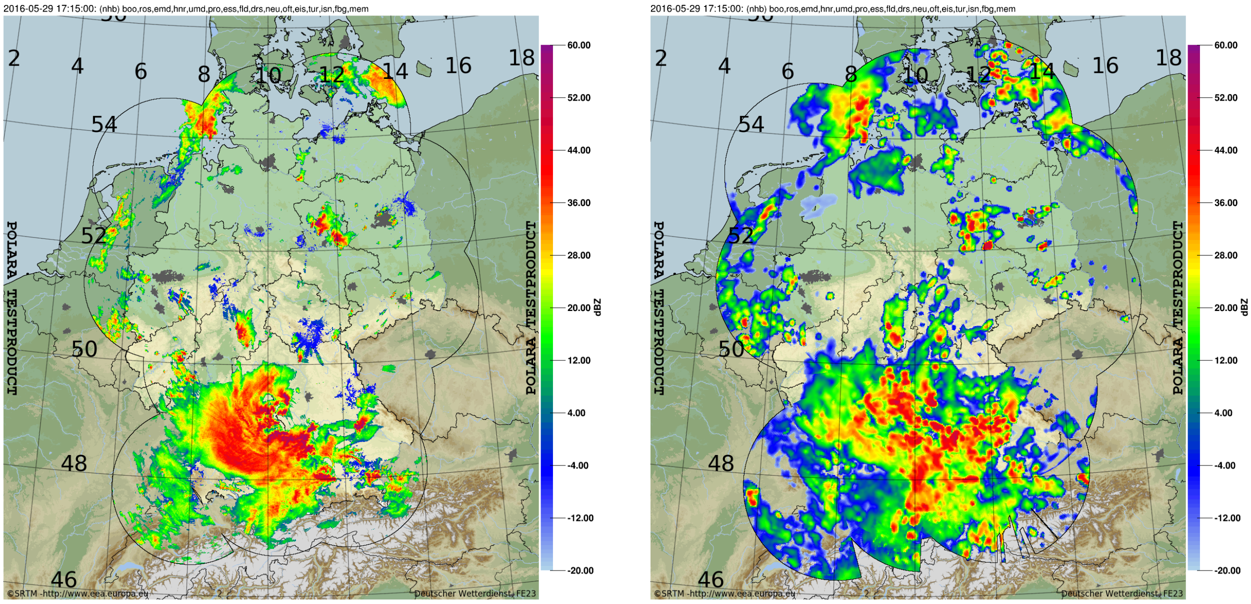

Figure 2: *Reflectivity composite based on observed radar measurement (left) and based on the simulated radar data from the deterministic forecast of the NWP-EPS (right) for May 29, 2016 at 17:15 UTC.*

4.2. Feature-based ensemble visualization

4.2.1. Mock-up overview

The ideas described in the following two subsections are implemented into an interactive browser-based mock-up that was created using Python 3.6 and Bokeh 0.12.14 [Bok14]. Bokeh was specifically designed to enable the quick generation of interactive plots, and was thus a suitable choice for the implementation of our initial visualization concept.

An overview over current state of the mock-up is shown in Figure 3. It comprises three panels, whereas the two plots on the right side are connected to the large map display. The connection is one-sided: When a user selects an observed feature on the map by click, the plots to the right are updated according to the data associated with that feature.

4.2.2. Visualizing ensemble spread

During the clustering process, the ensemble members are treated independently, i.e. the same ensemble member can have more than one simulated feature in the same cluster. As a result, each observed feature corresponds to a set of simulated features predicted by the ensemble. The distribution of these features around an observed convective cell then shows the local ensemble spread.

This concept is depicted in Figure 3(a). Here, the black feature corresponds to the observed feature, while the colored polygons in its surrounding show the location of its simulated counterparts. They are colored according to cluster membership, making use of a categorical color scheme taken from ColorBrewer [HB03]. Here, the blue cluster refers to the simulated features that match the selected observation best. The simulated features corresponding to the second-best match are shown in pink, while those belonging to the group of worst matches are colored green.

In addition to showing the cluster membership of an individual simulated feature by its color, its opacity reflects the mean of the four scaled differences with respect to the matching parameters. Hence, the lower the correspondence between simulated and observed feature is, the more transparent it will appear on the map – an additional visual cue that highlights the relative importance of a simulated feature within the entirety of the ensemble.

The mean opacity of all features belonging to one cluster is also plotted in a histogram to the right of the map display (Fig. 3b). This further depicts the employed classification, and thus, this plot simultaneously serves as a legend for the colors given to the polygons on the map.

Since the numerous features shown on the map partially overlap each other, their ordering is important. Occlusion of polygons cannot be avoided in the current setup, so we decided to plot the observed features on the very top. To visually distinguish them from the simulated features, they are filled in a dark-gray color, which changes to black once the feature was selected. These are followed by simulated features, which are again ordered according to their cluster membership – ordered from top to bottom following the global opacity value assigned to the corresponding cluster.

On the example shown in Figure 3, we focus on the area around Braunsbach, Baden-Württemberg, Germany. The simulated counterparts of the selected observed feature represent the high convective developments that were actually affecting this region (see also Fig. 2).

Figure 4 illustrates the distribution of the feature clusters dispersed around a selected observed feature near Magdeburg, Saxony-Anhalt, Germany (17:15 UTC). While the observations are approximated by the NWP-EPS, this example also shows the spread of the extracted KONRAD3D cells, as well as the distribution of the individual cluster members within a radius of 50 *km* around the selected cell.

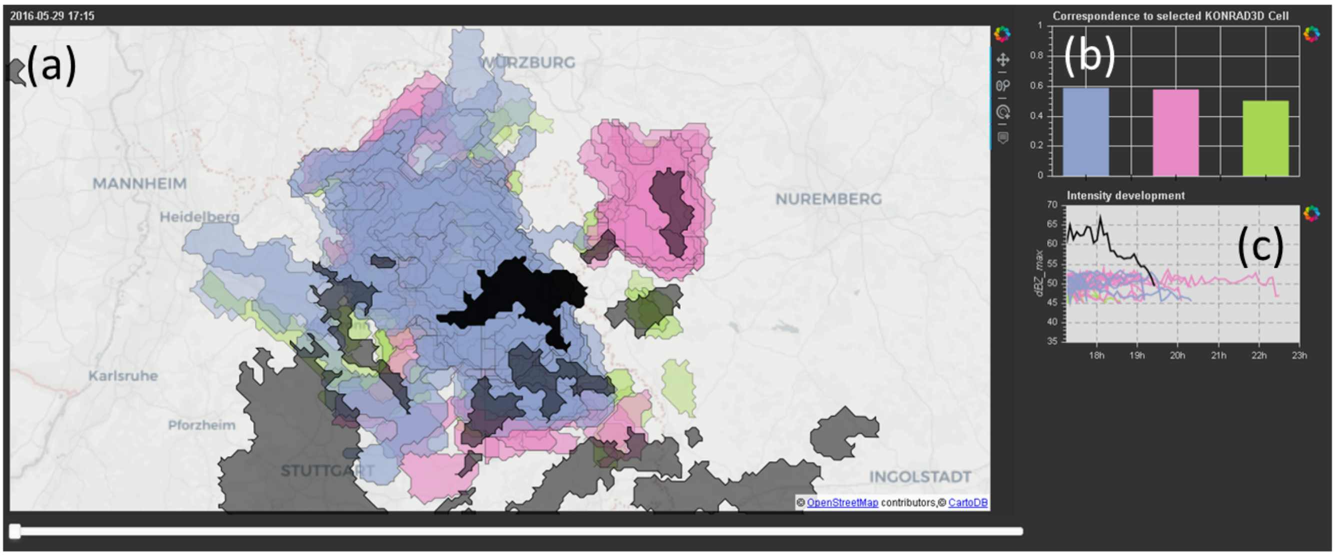

Figure 3: *The main map display (a) shows the distribution of simulated convective cells corresponding to an observed feature (in black), at 17:15 UTC. The different colors of the simulated features show their cluster affiliation. The plot in (b) provides a summary of the difference between the features affiliated with a specific cluster and the observed feature. The blue cluster shows the best correspondence to the observation, while the green cluster is the least similar. Finally, the temporal evolution of the features shown on the main map is plotted in (c). Each line corresponds to one of the polygons on the map. The black line depicts the development of the maximum intensity of the observed cell.*

4.2.3. Visualizing the temporal evolution of simulated features

In addition to showing the spatial distribution of the simulated features at a single point in time, the mock-up also provides the opportunity to follow their development over time, starting with the time step for which the clustering procedure was performed (in this case 17:15 UTC). The current concept provides two different views onto the temporal dimension of the data. The first view is connected to the polygons visualized on the map (Fig. 3(a)), whose temporal development can be followed through time by operating the time slider below the map. The second view is a time series plot, which is located to the right of the map: Here, the maximum intensity in dBZ over time is shown for each simulated feature visible on the map (Fig. 3(c)).

Besides showing the the maximum intensity associated with each feature around an observed feature on the map, the time series plot also gives the user an idea of the life cycle of each simulated cell, which can be compared to that of the observed cell. In this way, a first approach to forecasting the intensity can be carried out. In the example shown in Figure 3(c), it can be seen that the maximum intensity of the selected observed cell exceeds those of all simulated cells within the first two hours of simulation. However, the intensity of the observed cell falls below KONRAD3D's thresholding scheme earlier than some of the simulated cells.

5. Discussion and future work

In this short overview, a first approach to visualize object-based data from nowcasting and NWP-Ensemble is described. The features detected with KONRAD3D are plotted in an interactive map to allow the user the identification of areas with severe convection over Germany. Each observed feature is associated with a number of simulated features within a 50 km radius that are classified in three clusters using the K-Means multivariate clustering method. This classification simplifies the identification of features that best match a given observed feature. It also provides an estimation of the similarity between observed and simulated features, based on the matching parameters. Thus, the first cluster contains the features that are more similar to the observation, whereas the third cluster groups those features that differ the most from the observation. Once an observed feature is selected, the user can look at the evolution of the surrounding features over time and even compare their maximum reflectivities. This option can be seen as a good approach to visualize life cycle of the convective features. It has to be noticed, however, that the clustering method is only applied to the features available at a single reference time. This restricts the interpretation of the visualization, since it does not take into account new convective events that might have been forecast for later time steps, nor those forecast before the reference time.

It is expected to extend the clustering method to other time steps so that new convection events can be considered. Furthermore, ad-

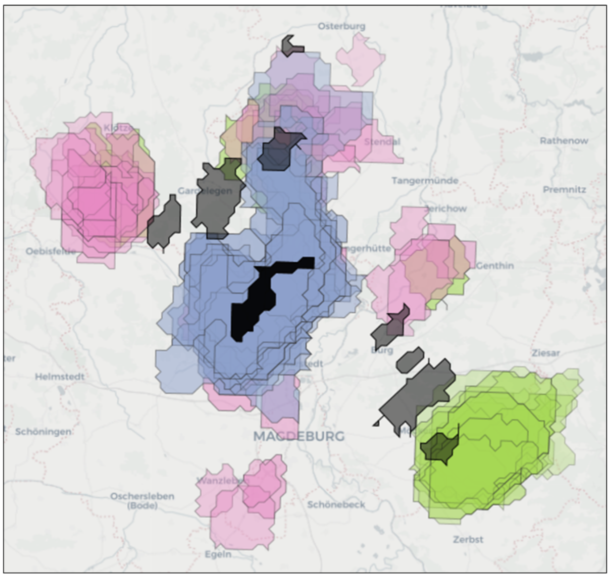

Figure 4: *A feature near Magdeburg, Saxony-Anhalt, Germany, was selected, which was also observed at 17:15 UTC. This example shows the ensemble spread around the surrounding observed cells, and also illustrates how the cluster membership of simulated features follows the distance to the feature in focus.*

ditional information that might be useful for potential users will be implemented in the mock-up tool, such as the number of features belonging to each cluster or the NWP-EPS member that forecast them. Additional parameters, e.g. lifetime of simulated cells, could also be included in the K-Means multivariate analysis to get a more accurate classification. It is also desired to explore alternative techniques to the K-Means method. For instance, the dbscan method introduced by [EKSX96] can be used to identify clusters of any shape, grouping together points that are closely packed together (points with many nearby neighbors). The points that lie alone in low-density regions are marked as outliers. An additional advantage of this method is that it does not require a pre-specified number of clusters.

6. Conclusion

The project SINFONY aims at combining probabilistic nowcasting methods and NWP-EPS into a single system to enable a seamless prediction of upcoming convective events in a time scale of several hours. The wealth of the dataset provided by the project has to be interpreted and adequately used to be of benefit for various applications. An effective use of these data will enhance our capabilities to predict convective features.

The experimental platform used here could be applied to conceptualize the data product and corresponding visualizations, before a thoroughly discussed and refined version is implemented into the meteorological workstation NinJo. The ability of the browser-based nature of the mock-up to be shared amongst a larger audience has the potential to help spawning these discussions.

This first approach takes advantage of the KONRAD3D nowcasting technique to detect convective features from radar data and the NWP ensembles. In order to easily interpret the ensemble of simulated features, a multivariate clustering analysis was carried out. It classifies the simulated features in three clusters based on their similarities with the observed features. Condensed additional information about these clusters are displayed adjacent to an interactive map of the feature locations.

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