Dear Ruben,

thank you for your comments and suggestions. Please find below the answers or our comments on the questions you have raised. Following your suggestions and those of another review, one of the main changes that I have done, was to update the results based on absolute error and computed the Continuous Rank Probability Score for the probabilistic nowcast. Thus, the results plots have changed accordingly, and are given in the response to this review. Please find below the answers and our comments on the questions/issues you have raised (given in blue below each point). Please note that some changes have been already done in the updated version of the manuscript (these are given in quotation) while other changes are yet to be done and thus I refer to as "will be included" in the updated version of the manuscript. The updated plots and tables are given in the attached document at the end of the response.

1. Methods:

- The unmatched storm cells are left out of the analyses. I do agree with this choice, but I wonder what the effect is on the algorithm performance once the 'normal' radar data, with these unmatched storm cells / artefacts, are fed into the algorithm. Can the authors comment on this?

  Yes, indeed the unmatched storm-cells affect the nowcast, especially when the nowcast in run with the Lagrangian Persistence, because they will be extrapolated in the future for the next 3 hours without change in area, intensity or movement. For the k-NN application, however, it seems that the dissipation of some unmatched storm-cells can be predicted based on their characteristics. We have run the proposed k-NN for unmatched storms with past database only from the matched storms, to see what is the error that we should expect at the nowcast time 5min (when the kNN doesn't now that they will dissipate in the next 5min). The results are shown for both target-and storm-based kNN in the Figure 14 in the attached pdf.

  Both applications of the kNN (as target based and storm based) nowcast that the storm will last 10 -15 min approximately on average, leading to overestimation of the 4 other target variables (Area, Intensity, Velocity in X and Y direction) for short lead times; up to 30 min for both deterministic and probabilistic nowcast. So, when running a nowcast online with normal nowcast data, one would expect an overestimation of the rainfall storms for the short lead times (up to 30 min). Alternatively, the "un-matched storms" can be part of the past-database, such that the kNN can predict their behaviour better. For both of kNN application (target-and storm-based) for both deterministic and ensemble nowcast, the median error for all storms lasting only 5 minute (and nowcast issue at nowcast time 5min) becomes zero independent of the lead time. This means that, they can be predicted well by the kNN, most probably because clutter is exhibited similarly from one event to the other (note that the kNN has the potential to also identify clutters). However, we do not suggest this as the presence of the "un-matched" storms in the past database can affect the nowcasting of the other storms, especially for long storms. The long storms are affected, because due to the merging techniques between the radar and the gauge, some "unmatched storms" have very large areas, thus causing the kNN to falsely choose the neighbours from these "unmatched storms". If the merging method is improved (for instance by an advection correction so it doesn't take the information only from gauge data when the radar data is missing), and a better tracking is implemented, the kNN can be then run on the full past database.

- What is the algorithm performance for extreme events or events that were not part of the training data? From both an operational and reproducibility perspective, this would be very relevant information.

  The performance shown in this paper is calculated leaving each event outside and predicting it with the rest of the dataset (so in cross-validation mode). So, each time the errors are calculated for a single event, that event has been taken out of the training data (hence was not part of the database). Regarding the extreme events, please keep in mind that the events selected here are already extreme events – events that have a return period higher than 5 years for durations varying from 1 hour to 1 day (based on Intensity-Duration-Frequency Curves). But we suppose you are referring to rare events of a very high return period – say 50 or 100 years? We will include an example of a single extreme event in the updated manuscript to discuss how the KNN behaves in such cases.

- In addition, can the authors say some more about the size (memory) of the training dataset, the computation times and how big the training set should be for adequate use?

  For the selected events the size of the characteristics that is save for all storms in all events is not very big (~20 MB). The computation time to extract the characteristics in hindcast mode is less than one day for all events and to train the k-NN (finding the best neighbour) based on 110 events takes in total less than 2 hours. While to issue nowcast for all 110 events once the number of K is selected is less than 3 min. Please note that this is the time of the kNN application only, an operational application together with radar data, merging with station data, tracking the storms and the nearest neighbour, has not been yet tested, thus we cannot say for sure how long are the computational times. The size of the available dataset plays an important role, but at the moment we can not conclude what is the adequate dataset for issuing reliable k-NN nowcast. This will be the subject of our future research. We will include this small discussion in the updated version of the manuscript.

- The authors often mention timestep of nowcast or nowcast time. Up to the end of the manuscript, I have found the terminology and meaning confusing (it may just be me..). Do the authors mean the issue time of the nowcast since the start/evolution of the storm with this? If so, I would recommend changing this for clarity.

  Thank you for the feedback. Apparently, it is also confusing to the other reviewers, so we will try to make it clearer. Yes, timestep of nowcast and nowcast time are referring to the same thing which is what you describe: the time (in 5min timesteps) when the nowcast is issued compared to the first identification of the storm. We have included a new figure in the manuscript to explain the nowcast time and we have used in the manuscript only the term "nowcast time". Please refer to the Figure 3 in the attached pdf.

- I appreciate the use of an adequate benchmark (another object-oriented nowcasting method using Lagrangian persistence for the movement of storm cells) in this study. However, can the authors comment on other works that take next to Lagrangian persistence also other processes into account, e.g. splits and mergers (e.g. Dixon & Wiener, 1993; Han et al., 2009), and the rate of growth and dissipation (e.g. Pulkkinen et al., 2020 – although not necessarily constructed for object-oriented nowcasts)? Thus, how would this work relate to or even improve such methods? An analysis comparing such a method to this method is of course outside the scope of this paper, but it would be great if the authors can at least comment on it.

  Yes, after following the comments of another referee (Seppo Pulkkinen) we will first improve the introduction to the rainfall nowcast and mention the work done recently on dissipation of the rainfall intensities (although on a different approach). Regarding the work done by Dixon& Wiener (1993) and Han et al. (2009), they have improved considerably the tracking of the storms – they recognize better if the storms are one unit (how they track them and how the velocities are assigned to them), however to our knowledge they still apply the Lagrangian persistence for the future extrapolation. It here that we see the value of our studies. Of course, it may be that the tracking algorithm is not working as good as in the reference studies, however it shows the potential of the kNN application to recognize the recognize the dissipation of the convective storms. The application of the kNN on their tracking algorithm may lead to better results. Regarding the work done by Pulkkinen (2020), a kNN application may be useful to maintain the storm properties of the convective storms.

2. Ensemble approach:

- The construction of the ensembles is interesting, but the description in the methodology was not always clear to me (see the comments mentioned later in this document). Can I ask the authors to describe a little more elaborately how the ensemble members are constructed and how different weights are applied for example?

  Yes of course. In theory the kNN for both deterministic and ensemble application is very similar. In both applications, first the 30 most similar neighbours are recognized, ranking them from the most similar (lowest Euclidian distance) to the least similar (largest Euclidian distance). In the case of the ensemble application, the probability of their occurrence will be given by their rank, so the first neighbour (the most similar and the first ensemble member) will have a higher probability than the last neighbour (the least similar and the 30th ensemble member). Then an ensemble member is issued randomly based on these rank probabilities.
  To make this clearer the following changes have been made in the text:

  "Contrary, if a probabilistic nowcast is selected, 30-member ensembles are selected from the closest 30 storms where each member is assigned a probability according to the rank of the respective neighbour storm with the "to-be-nowcasted" storm:

$$Pr_i = \frac{(1/Rank_i)}{\sum_{i=1}^{k}(1/R_{anki})}, \tag{1}$$

  where k is the selected number of neighbours and Rank and Pr are respectively the rank and the probability weights of the i^{th} neighbour/ensemble member. An ensemble member is then chosen randomly according to their probability weights. The probability weights calculated here are as well used for computation of the single nowcast in Equation (6)."

- The ensemble validation (e.g. lines 306 – 311) is useful and is clearly tailored toward showing that the target value is present in the training dataset. Besides the focus on separate ensemble members, it may be interesting to also plot the ensemble spread vs. the error to get a more statistical indication of whether the observation falls within the ensemble spread or not (for the full ensemble). Note that this is to a certain extent already present in e.g. Fig. 13. Hence, see this rather as a suggestion than a must. For inspiration, see for instance Fig. 9 in Foresti et al. (2016) or supplement Fig. S6 in Imhoff et al. (2020) as spread vs error examples for ensemble nowcasting.

  We followed the advice from Seppo Pulkkinen, to compute the Continuous Ranked Probability Score (CRPS) for the ensemble nowcast, and the mean absolute error for the deterministic nowcast. The Figures below show the ensemble and deterministic results for both k-NN approach; the storm based and target based. Please refer to Figure 11 and 12 in the attached pdf.

3. Results:

- Starting with the figures, I did like the analyses chosen by the authors, but the labels, legend and text in the figures was often hard to read. Zooming in is luckily possible, but can I ask the authors to make the font sizes of the figures bigger? Besides, the schematic figures describing the method are clear and are very nice figures (no changes needed there).

  Noted! We have increased the size of the labels, ticks and legends.

- One figure that I did miss at the start of the results, is an example nowcast for several lead times with the k-NN methods, the Lagrangian persistence and the observations (the radar images, I suppose). This can directly show what to expect and visualize why we see certain results in the subsequent figures. Can I ask the authors to make such a figure, possibly one for each class (duration), so likely a small-scale convective event, a mesoscale convective event and perhaps a stratiform event?

  Such a figure would be possible however it is misleading. So far, we have considered the storms as objects and we want to predict good their characteristics and not the spatial distribution of the storms (the image of the storm at different times as captured by the radar). As noted in the manuscript, another step should be implemented to transfer these predicted characteristics to the spatial distribution of the storm intensities: this can be done in two ways 1) consider the storm as an ellipse and increase/decrease the ellipse shape and intensity according to the Area and mean Intensity predicted (assumption about the internal distribution should be taken) and displace with the given velocity vector, or 2) get the information of the spatial intensity distribution from similar storms. However, in the latter case, one has to make sure that the storms have similar orientation and thus a space optimizer is needed. We would like to continue our work here with the second approach, and to publish a continuation paper with the space optimizer. But if you are interested about this, you can have a look at my phd thesis where these examples are given in the appendix (Shehu,2020). But nevertheless, I would like to avoid to show the figures that you mention because the method is not adequate for this yet.

4. Reproducibility:

- Are any of the data, scripts, etc. publicly available? That would increase the reproducibility, but also the impact of this very interesting work

  No so far, no data or scripts are made available. However, I can share the storms characteristics database, and part of the script that applies the nearest neighbour approach. However, the tracking algorithm I can not share because it is not developed by me, and the radar data is extremely memory consuming, so I would like to avoid that.

Specific comments:

- Title: Perhaps good to mention here radar-based rainfall nowcasts, to clarify the focus on rainfall forecasts

  Noted. We will discuss with the editor to see if the title can be changed as following to make clear that this is the application for the storm's characteristics, and that a second paper will follow to illustrate the suitability for the point scale.

  "Improving radar-based rainfall nowcast by a nearest neighbour approach: Part I – Storm Characteristics"

- Lines 33 – 43: Could you explain why the focus is on object-oriented nowcasting of primarily convective events here (so, why object-oriented and why convective events as focus)? I suppose this is because the authors focus on mostly convective events that can or have resulted in flooding.

  The focus was to improve the nowcasting of urban pluvial floods which are typically caused by convective events. Object-oriented can capture better the dynamics of these events because they treat them as independent objects rather, and can have independent movements from each other. The field-oriented approach, is more appropriate for wide spread events (stratiform events) because they have similar velocities at the whole radar image that can be captured well by the optical flow method. In optical flow methods, regions inside the radar image have different velocity fields, however may still not capture the convective storms uniqueness. A study done by Ruzanksi et al (2011) (also implemented by Pulkkinnen et al. 2020) shows that velocity can be captured by regions in the radar data through the DARTS methods, but one needs to select prior an empirical value. Thus, while the optical field is the most used approach recently, it requires specific parameters based on the region and expert knowledge, that the researcher may not be fully able to understand or capture well. That is why the objective oriented is used mainly in convective storms.

Following your suggestion, we will include a short explanation in the updated version of the manuscript about the overall aim and the use of object-oriented in general. Please note that the introduction will be updated, to introduce the motivation better (as suggested by another review).

Ruzanski, E., Chandrasekar, V., Yanting W. (2011). The CASA Nowcasting System. Journal of Atmospheric and Oceanic Technology,28(),640-655.

- Line 118: Is the C-band radar single or dual-pol?

  The radar is single pol C-band. We don’t have any phase shift (k) information, which would be interesting to use as an additional predictor to the k-NN application.

- Lines 122 – 123: Can I ask the authors to elaborate a bit on this merging method. It can be brief, the rest is mentioned in the paper of course.

  The following text was added in the manuscript:

  “The conditional merging aims to improve the kriging interpolation of the gauge recordings by adding the spatial variability and maintaining the storm structures as recognized by the radar data. In case a radar image is missing, the kriging interpolation of the gauge recordings is taken instead.”

- Line 124: “110 events”: What is the definition of an event in this study and did you systematically look for certain event characteristics? Seeing the following lines, the authors have chosen to focus on mostly convective events. How were those selected?

  An event is defined as time period where the radar recognizes continuous rainfall in the whole study area (so within the radar range). In an event many storms can be recognized within the radar range (also at different location and at different starting time). See Figure 3 below for a better explanation of the difference between event and storm. The events were selected based on two criteria a) on strong rainfall intensities captured by the rain gauges inside the radar range (for different durations the intensity exceeds the 2 years return period from the KOSTRA IDF relationship), b) a dry spell duration of 4 hours in the whole radar image is used to separate the events (so start and ending time). This work was done under the concern of pluvial floods in urban areas, so the focus is primarily at events that might cause such floods, thus very high intensities in a short duration. The following lines were added in the manuscript together with Figure 3 (see appendix).

  “Here, rainfall events are referred to a time period when rainfall has been observed inside the radar range and at least at one rain gauge has registered an extreme rainfall volume (return period higher than 5 years) for durations varying from 5minutes to 1day. The start and the end of the rainfall event is determined when areal mean radar intensity is lower than 0.1mm for more than 4 hours. Within a rainfall events many rainfall storms can be recognized at different times and locations inside the radar range. Figure 3-a shows a simple illustration to distinguish between the rainfall event and rainfall storm concepts employed in this study."

- Line 146 – "unmatched storm cells": What have you done with these unmatched storm cells? Are they left out of the method and analysis or not? I see the answer now in Sec. 3.2.3 Perhaps good to very briefly mention this (or point to Sec. 3.2.3) here

  The following changes were done in the text:

  "Since the "not" matched storms can either be dynamic clutter, they are left outside of the k-NN training and validation (see section 3.2.3). The section 4.4.4 discusses shortly the influence of the "unmatched storms" in the performance of k-NN approach."

- Lines 146 – 152: How is the storm duration defined?

  The storm is a group of radar pixels that have an intensity higher than a fixed threshold. The duration of the storm is then the lifetime of the radar pixels group as dictated by the threshold used to recognize them and the tracking algorithm that decides if the same storm is observed at continuous time steps.

  "Some characteristics of the identified storms like duration (or also total lifetime of the storm), mean area, maximum intensity, number of splits/merges, local velocity components, and ellipsoidal features, are shown in the Figure 4."

- Lines 158 – 161: I agree! Nowcasting, especially Lagrangian persistence, either in an object-oriented or intermittent field-based approach, works quite well for these stratiform events. It may be worth mentioning that this is not where the k-NN method will provide a lot of improvement (at least, that is what I expect) compared to already existing methods. Hence, it is no problem that the sample size is leaning more heavily on the convective events.

  The following lines were added in the text:

  "Nevertheless, the stratiform storms are typically nowcasted well by the Lagrangian persistence (specially by a field-oriented approach) as they are wide-spread and persistent. Hence the value of the k-NN is primarily seen for convective storms and not for stratiform ones."

- Line 164 / Eq. 1: What if one radar image is missing or another problem occurs for a certain time step? How will this be treated? In case of a missing radar image, would it be safer to divide by the number of used predictors in equation 1 (max. 6, but possibly less) instead of by 6? In addition, there are seven 5-min steps from t=0 to t=t-30, assuming that t=0 and t=t-30 are included. Should you divide by seven or is step t-30 not included?

  Here one should distinguish two different missing values: 1) when radar time steps are missing – then because of the merging between radar and station data, the ordinary kriging on station data will supply the spatial information that will be fed in the algorithm. This is not the optimal solution because will affect the tracking algorithm as the kriging information is usually smoothen in space and will result in very big areas with rainfall. This can be seen in the unmatched storms that have very big areas (this is the influence of missing radar and getting the information from the kriging interpolation on gauge data). This problem can either be fixed by implementing higher thresholds for the storm recognition, or by performing an interpolation in 1min of the information to ensure that the storm characteristics are maintained (As mentioned in Seo and Krajewski (2015) as advection correction). 2) The tracking algorithm fails to capture or associate values for the velocity or other characteristics, which means the predictor value for a specific time step is missing. In this case the predictors are calculated by excluding the missing value and calculating the mean accordingly. Regarding the Eq.1 thank you for noticing. Of course, we meant 7 so including the whole-time steps from t=0 to t-30.

The following lines were added in the text:

"Another thing to keep in mind, is that merged radar are fed to the algorithm for storm recognition, and this affect the storm structures particularly when the radar data is missing. In such case, the ordinary kriging interpolation of rain gauges is given as input, which is well known to smoothen the spatial distribution of rainfall and hence resulting in a short storm characterized by a very large area."

"$P_{30} = \sum_{i=t_0}^{t-30min} P_i/7$,

where Pi is the predictors value at time i, and P30 the average value of the predictor over last 30min. In case of missing values, the remaining time steps are used for averaging."

Line 242-243 and lines 253-255: we will follow your comment and refer to the equation here.

Lines 242 – 243 and lines 253 – 255: How are the weights determined? I see that the weight of eq. 5 is determined from the results (Fig. 6), perhaps good to refer to this

Regarding the predictors weight the following change was done to clarify this issue:

"$E_d = \sqrt{\sum_{i=1}^{N} w_i \cdot (X_i - Y_i)^2}$,

where w is the weight of the respective ith predictor as dictated by the importance analysis (results are shown in Figure 7), X the predictor of the "to-be-nowcasted" storm, Y the predictor of a past observed storm, N the total number of predictors used and Ed the Euclidian distance between the "to-be-nowcasted" and a past observed storm."

- Line 253 / Eq. 6: In the estimated response of the to-be-nowcasted storm, are the total lifetime, area and intensity simply the weighted average of the k nearest neighbours? What about the location, are VX+LT and VY+LT used to displace the location of the current state of the storm at t0? It may be clear for future readers to specify this a bit in more detail.

  Yes the area, total lifetime and the intensity are weighted averages from the 4 closest neighbours. So the first neighbour will have the 0.48, the second 0.24, the third 0.16 and the last 0.12 – these weights results from the ranking (1/(1:4))/sum(1/(1:4)). The same averaging is done also for the Vx and the Vy, which dictate in the displacement of the storm from the current state to the state at a specific lead times.

  The following line was added in the text:

  "The response R refers to each of the 4 target variables: Area, Intensity, Velocity in X and Y direction."

- Lines 255 – 261: I'm a bit lost with the way the ensemble nowcast is constructed. Are 30 individual members issued by taking every time a different selection of neighbors? Or just by one neighbor out the top 30?

Every time a nowcast is issued for a specific storm, based on the Euclidian distance the 30 most similar storms are selected. Each of these 30 most similar storms is than considered an ensemble member. The probability of each ensemble member (past similar storm) is calculated from the rank between the 30 members. One of these members is randomly selected based on their probability.

The following explanation was added in the text:

"Contrary, if a probabilistic nowcast is selected, 30- members ensembles are selected from the closest 30 storms where each member is assigned a probability according to the rank of the respective neighbour storm with the "to-be-nowcasted" storm:

$$Pr_i = \frac{(1/Rank_i)}{\sum_{i=1}^{k}(1/R_{anki})}, \quad (2)$$

where k is the selected number of neighbours and Rank and Pr are respectively the rank and the probability weights of the ith neighbour/ensemble member. An ensemble member is then selected randomly based on the given probability weights. These probability weights calculated here are as well used for computation of the single nowcast in Equation (6). "

- Lines 277 – 298: Is there a difference in the training between VS1 and VS2, mainly w.r.t. the error per target or for all targets together? Or is the training identical for both approaches?

The training procedure is the same for both approaches, but is done independently for both of them. In the end k=4 was implemented for both of them, to see if it is better to predict target independently or considering inter-dependency between them from the storm evolution.

- Line 304 – "Lagrangian persistence": Just to be sure, Lagrangian persistence in object-oriented nowcasting, right?

Noted, it has been changed to Lagrangian persistence in object oriented.

"ii) the improvement (%) per each lead time and target variable that the k-NN approach introduces to the nowcast when compared to the Lagrangian persistence in object-based approach;"

- Lines 314 – 316: Do you have an indication how much less this was (in the worst-case scenarios)?

This is particularly affecting the stratiform events (events longer than 6 hours) because there are not many events that fall in this category. So, in total there are 33 storms that have a lifetime longer than 6 hours, which come from 28 different events. The worst case here would be that for an event only 25 storms are available to choose the nearest neighbour.

- Lines 367 – 369: Do you have any idea why the result is different for the Total Lifetime?

My understanding, is that the duration is an easier target to be analysed, which means the values are not zero (because we consider here the total lifetime) and its distribution is not as heavy tailed as the distribution of the other variables. The other variables, depending on the lead time, have more zeros included and have an asymptotic density function. On personal experience, when zeros are not present (or at least not in the frequency of the 4 variables here) the PIC is able to represent quite well the important predictors.

- Lines 380 – 385 and Fig. 8: How large is the spread in the results (the optimal k-value) per class? I can imagine that this does not make the figure clearer when added (as IQR for example), but perhaps the authors have an indication of this.

    The IQR for each of the classes is quite high ~ 20 neighbours, sometimes up to 25 neighbours. This emphasizes again the complex relationship between predictors, time of nowcast and storm type.

- Lines 392 – 401: Is the decreasing error with increasing lead time (mainly visible in the top row of Fig. 9) a result of storms dissipating sooner than 30 min, which is then forecast well? Could the authors comment on that? It would otherwise be unexpected to see the performance improve with increasing lead time (you would expect the opposite).

    Yes, indeed one would expect the error to increase with the lead time as in the case on storms that live longer than 3 hours in Figure 9 for nowcast time 5 min. However, because the dissipation is captured well by the k4-NN, the errors are decreasing with the lead time. In the Lagrangian application, after the dissipation of the storm, the errors would be constant with the lead time.

- Lines 402 – 412: I agree with the reasoning for the 36th time step. However, the y-axis of Fig. 9 (middle row) is clearly scaled to this time step, which makes it hard to distinguish what happens for the other two lines. Could you change the axis scale and just describe why the 36th time step falls outside this scale (which is already described now)? Another question regarding the 36th time step, because I'm not sure I understand the times of nowcast well here: isn't the time of nowcasts the same as the issue time, so the nowcast starts 3h after the evolution of the storm. In the class here, you are only considering storms that last maximum 3h. Hence, aren't we looking at storms that should have died already?

    Yes we can use another range for the graph and mention that the 36th step is outside of this range. For the other case, the area errors of nowcast at 1st hour become zero after LT15min, with errors smaller than 100km2 for shorter lead times. While the area errors of nowcast at 5min become zero after LT50min. Regarding the nowcast at the 36th time step, yes the nowcast time is the issue time in respect to the initiation of the storm (when storm was first identified). The nowcast at the 36th time step, represent the nowcast issued at the last time step when the storm if observed, this means moment before complete dissipation (or how I call it death of the storm). At this point the viewer or the nowcast, has no information that the storm is going to stop is the next 5 minutes, and hence here the errors are the highest.

- Lines 452 – 453: I think this conclusion needs the nuance that this is the case for the shorter storm durations, whereas for longer durations this is not or only to a lesser extent the case.
  Line 492 – "Overall the ensemble results are better than the single 4-NN nowcast": Based on the results and the shown figure, I think you can only state that the best ensemble member performs better than the single 4-NN nowcast.
  Lines 574 – 576: There should be some nuance here. Although the results are very promising and often outcompete Lagrangian persistence, these high improvement numbers are generally reached for short-living storms, while the improvement is less (sometimes even worse) for longer-living storms

    Your comments are noted, and the lines will be changed accordingly.

- Line 586 – “additional predictors”: For the interested reader(s), can you say more about which predictors from those sources you think would be feasible for this?

  Some ideas that I think may be helpful in describing the storms better, are i) the phase shift “k” from dual polarized radars, the CAPE value from a numerical weather prediction NWP, the circulation patterns that are associated with certain events, the lightening activity that can be captured by remote sensing, or other mentioned by Seppo Pulkkinen in his comments: the convective inhibition (CN), geographical features for instance as terrain altitude and proximity to water bodies, or to dense urban areas. We have added the following lines in the manuscript:

  “Further improvements can be achieved if the predictors importance is estimated better (i.e. Monte Carlo approach, or neural networks) or if additional predictors are included from other data sources like: cloud information from satellite data, convective available potential energy (CAPE) and convective inhibition (CIN) from Numerical Weather Prediction Models, lightening flash activity, additional measurements from Doppler or dual polarized radar data (like phase shift, doppler velocity, vertical profile at different elevation angels), various geographical information (as distance from heavy urbanized areas, mountains or water bodies) etc.”
- Figure 4 caption: Perhaps refer to Table 1 for the meaning of the symbols (the predictors) in the figure

  Noted and updated!

Technical corrections

Regarding the technical correction, thank you for the feedback, they have been updated following your comments.

- Figure 2: As I hope that this interesting paper will be read by people from all over the world, it may be good to add a small subfigure indicating where this region is located in Germany or even in NWEurope. Besides, the indicated coordinates seem to be in a local coordinate system. Can I ask the authors to mention this in the caption or, perhaps even better, to place lat-lon coordinates on the map?

  Your suggestions were accepted, please refer to Figure 2 in the attached pdf.

- Figure 3: What is the last group (duration) on the x-axis?

  The last duration on the x-axis is storms longer than 12 hours. Following the comments of another reviewer the Figure has been updated below. Please note that the following changes were done to the Figure 4 (see attached pdf):

  The maximum intensity has been updated. Unfortunately, before the standard deviation was showing instead of the maximum intensity.

  The outliers of Maximum Intensity, Ratio of minor and major axis and the Orientation angle are included in the plot.

- Figures 7, 8 and 9: The light grey color for the 5-min class is not easy to distinguish (especially on a colored background). Could you make the grey a little darker or use a different color?

  Noted and implemented!

- Line 30 – “short-term rainfall nowcast”: perhaps say short-term rainfall forecasting?

  Noted and changed!

- Lines 32 – 33: A minor detail about the storm and intermittent field references: the list of references can be almost endless here. It is not necessary to cite all of them, but perhaps you could say (e.g. + references) to indicate that this is just a sample of all studies to these topics.

  Noted and will be implemented in the updated version of the manuscript. Following the comments of another review we will extend the introduction and the literature review on the topic.

- Line 84 – "show for instance Hou & Wang (2017)": is for instance shown by Hou & Wang (2017).

  Noted and changed!

- Line 211 – "predictor important analysis": should this be importance instead of important?

  Noted and changed!

- Line 391 – "event-based 4-NN": For consistency, did you mean storm-based 4-NN?

  Yes, we mean the storm-based 4-NN. Throughout the text, the event-based has been substituted to storm-based.

- Line 463 – "same results": similar results.

  Noted and changed!

- Line 561 – "Person": Pearson.

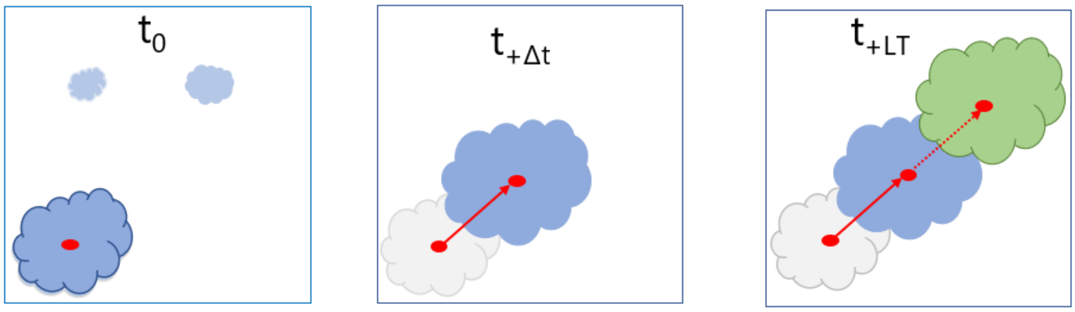
  Noted and changed!

- Line 562 – "two measurement": Two measurements.

  Noted and changed!

- Line 570 – "the death processes": Perhaps better to use dissipation processes of storms?

  Throughout the text, it has been changed accordingly.



a) Step1-Storm Identification b) Step2- Storm Tracking c) Step3- Storm Extrapolation

Figure 1 *The main steps of an object-based radar nowcast. Blue indicates the current state of the storm at any time t, grey indicates the past states of the storm (at t-Δt), and green indicates the future states of the storm (t_{+LT}) (Shehu, 2020)*

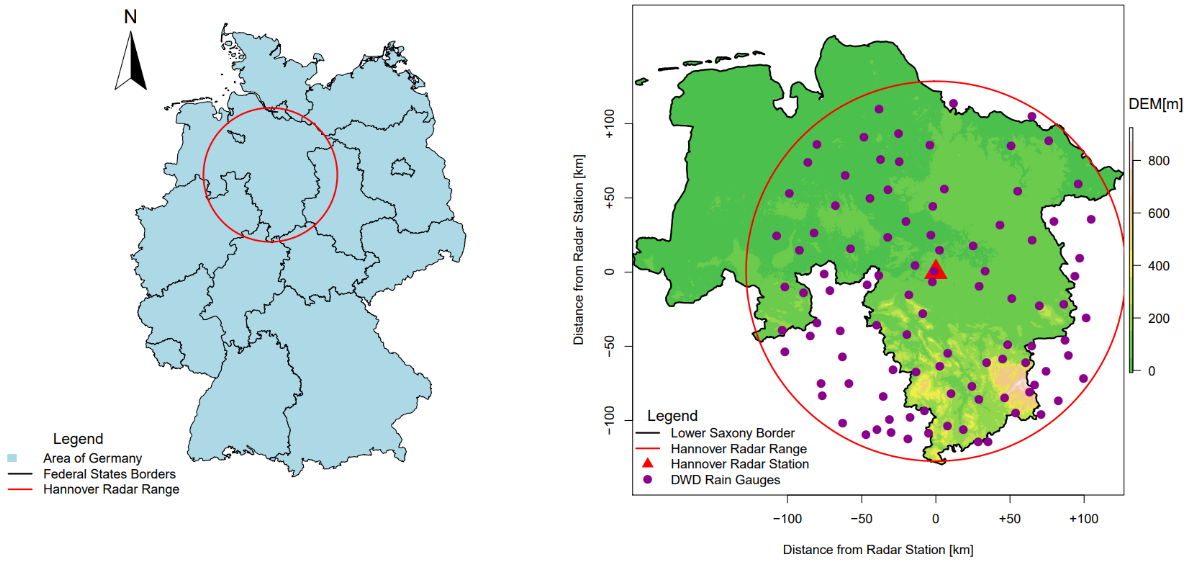


Figure 3 *The location of the study area left) within Germany and right) with the corresponding elevation and boundaries, and as well with the available recording rain gauges (purple) and radar (red) station. The DEM is short for Digital Elevation Model.*

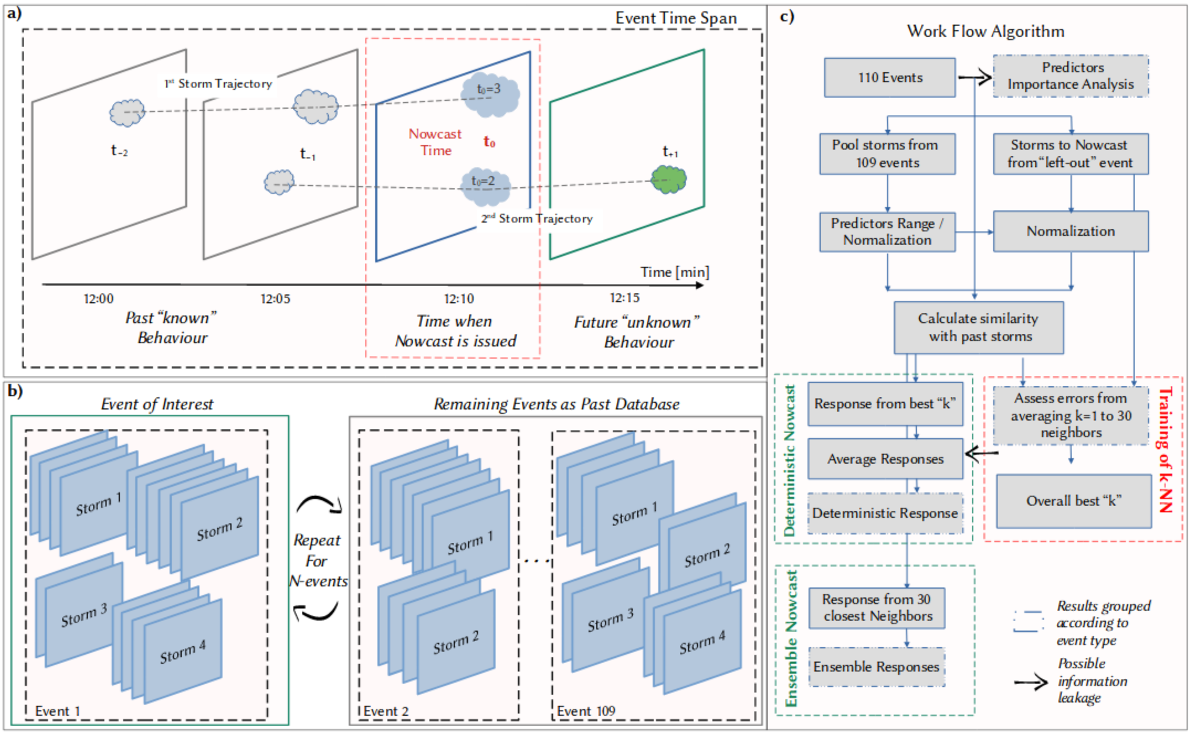


Figure 5 *Illustration of concepts and workflows in this study a) an event contains many rainfall storms inside the radar range which are tracked and nowcasted: the dashed grey lines indicate the movements of storms in space-time within the radar event and the event time span. b) The "leave-one-out-event cross-validation" – the storms of the event of interest are removed from the past database, and the nowcast of these storms is issued based on the past database. This process is repeated 110 times (once for each event). c) the workflow implemented here for the training at the application of the nearest neighbour approach.*

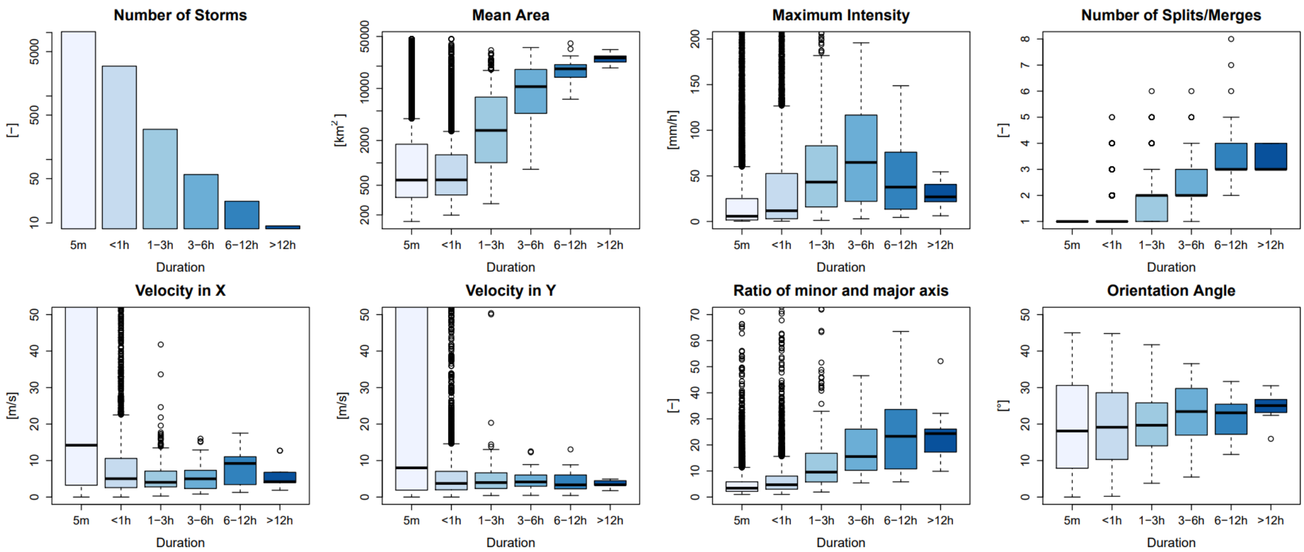


Figure 4 *Different properties of the storms recognized from 110 events separated into 6 groups according to their duration (shown in different shades of blue)*

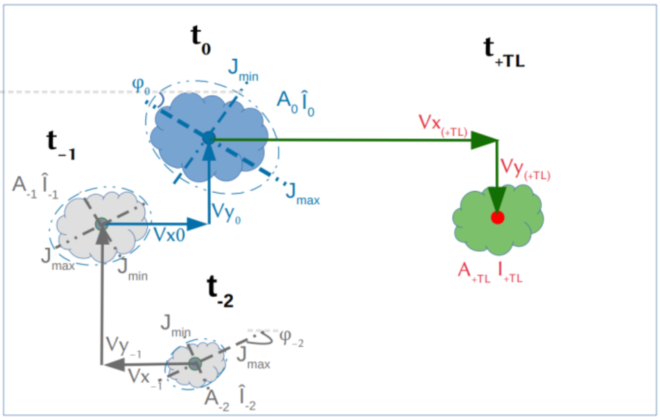


Figure 7 *The features describing the past (grey) and present (blue) states of the storm used as predictors to nowcast the future states of the storm (green) at a specific lead time (T_{+LT}) that is described by 4 target variables (in red). The nowcast is issued time t_0. A full description of these predictors and target variables is given in Table1.*

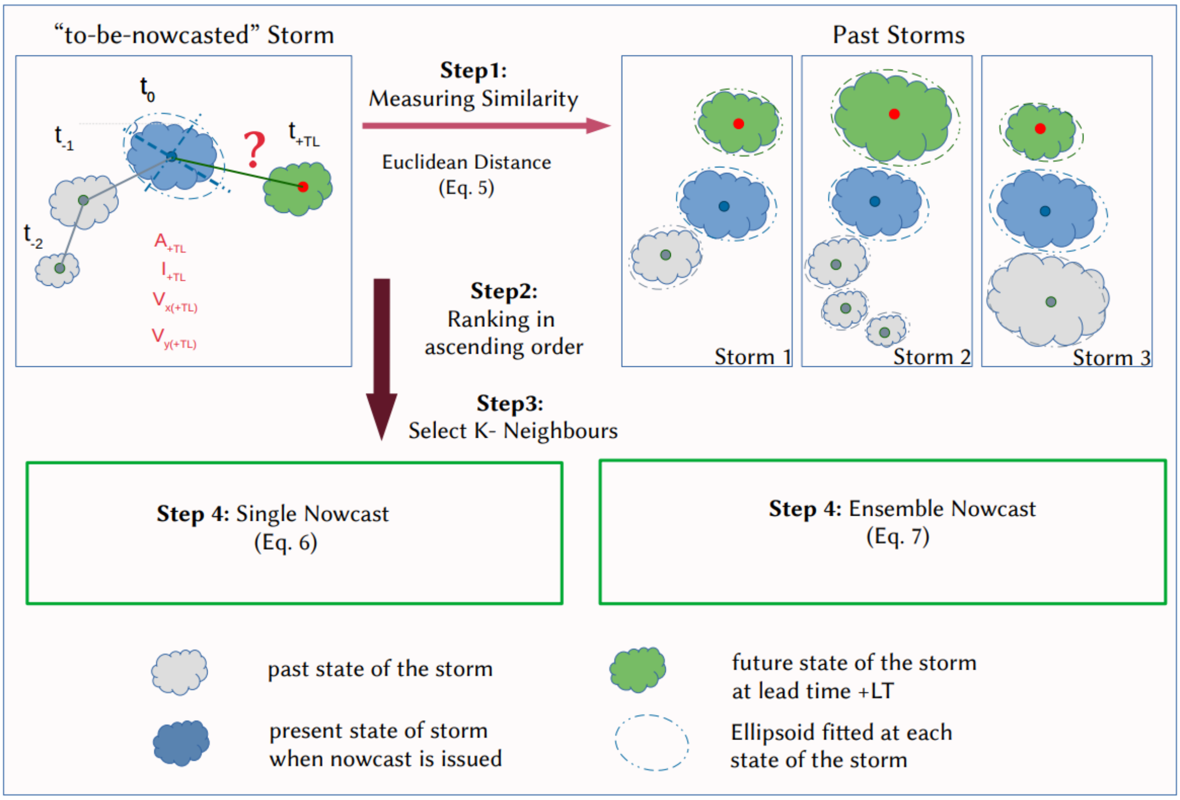


Figure 6 *The main steps involved in the k-NN based nowcast with the estimation of similar storms (Step 1 to 3) and assigning the future responses of past storm as the new response of the "to-be-nowcasted" storm either in a single nowcast (Step4-left) or in an ensemble nowcast (Step4-right).*

Table 1 Strength of relationship between the selected predictors and the target variables averaged for three lead times and storm duration groups (original weights can be seen in the Appendix 8.1 and 8.2) based on two predictors identification methods: upper –correlation, and lower –PIC weights. The green shade indicates the strength of the relationship: with 0 for no relationship at all, and 1 for highest dependency.

Method	Target	Present Predictors												Past Predictors - averaged from last 30 min									
		Cells	L_{now}	A	PI_{sd1}	PI_{sd2}	V_g	V_x	V_y	J_{max}	J_{min}	J_r	Φ	A	PI_{sd1}	PI_{sd2}	V_g	V_x	V_y	J_{max}	J_{min}	J_r	Φ
Pearson Correlation	A	0.09	0.18	0.67	0.15	0.48	0.05	0.00	0.00	0.50	0.49	0.09	0.00	0.65	0.17	0.00	0.07	0.00	0.06	0.51	0.49	0.12	0.00
	I	0.00	0.07	0.11	0.36	0.14	0.04	0.00	0.00	0.12	0.12	0.00	0.04	0.10	0.33	0.13	0.00	0.00	0.05	0.12	0.11	0.05	0.04
	Vx	0.00	0.00	0.10	0.02	0.04	0.16	0.21	0.00	0.08	0.00	0.00	0.03	0.09	0.00	0.00	0.18	0.28	0.00	0.09	0.00	0.00	0.00
	Vy	0.00	0.05	0.00	0.00	0.05	0.00	0.00	0.15	0.04	0.00	0.00	0.00	0.00	0.00	0.05	0.00	0.04	0.22	0.05	0.04	0.00	0.00
	L_{tot}	0.00	0.11	0.36	0.10	0.22	0.09	0.00	0.00	0.22	0.20	0.05	0.05	0.34	0.00	0.21	0.10	0.00	0.00	0.22	0.20	0.08	0.07
	Average	0.00	0.08	0.25	0.13	0.18	0.07	0.10	0.10	0.19	0.16	0.05	0.04	0.24	0.10	0.08	0.07	0.10	0.10	0.19	0.17	0.05	0.02
Partial Information Correlation	A	0.00	0.08	0.15	0.00	0.00	0.22	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.33	0.00	0.07	0.00	0.00	0.33	0.00
	I	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Vx	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00
	Vy	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00
	L_{tot}	0.00	0.15	0.13	0.00	0.00	0.24	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.33	0.00	0.00	0.00	0.11	0.33	0.00
	Average	0.00	0.05	0.06	0.00	0.00	0.09	0.00	0.00	0.20	0.00	0.00	0.00	0.00	0.00	0.00	0.13	0.20	0.01	0.20	0.02	0.13	0.00

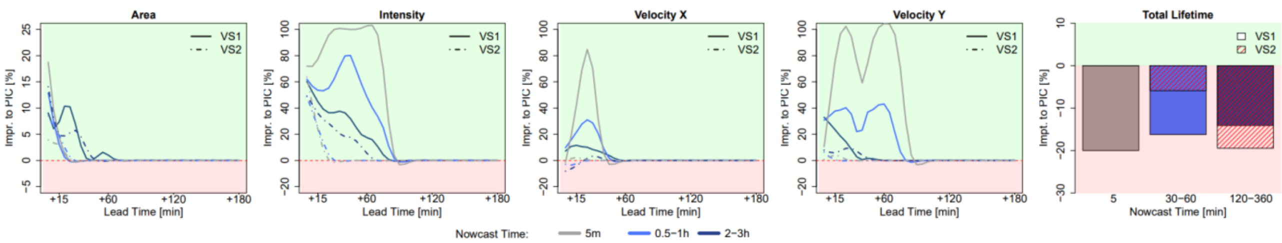


Figure 8 *The median Mean Absolute Error (MAE) improvement per lead time and target variable from applying the k-NN (VS1 target-based, VS2 storm-based) with the predictors and weights derived by the Pearson correlation instead of PIC. The improvements are averaged for different times of nowcast. The green plot region indicates a positive improvement of the correlation predictors in comparison to the PIC, and the red region indicates a deterioration.*

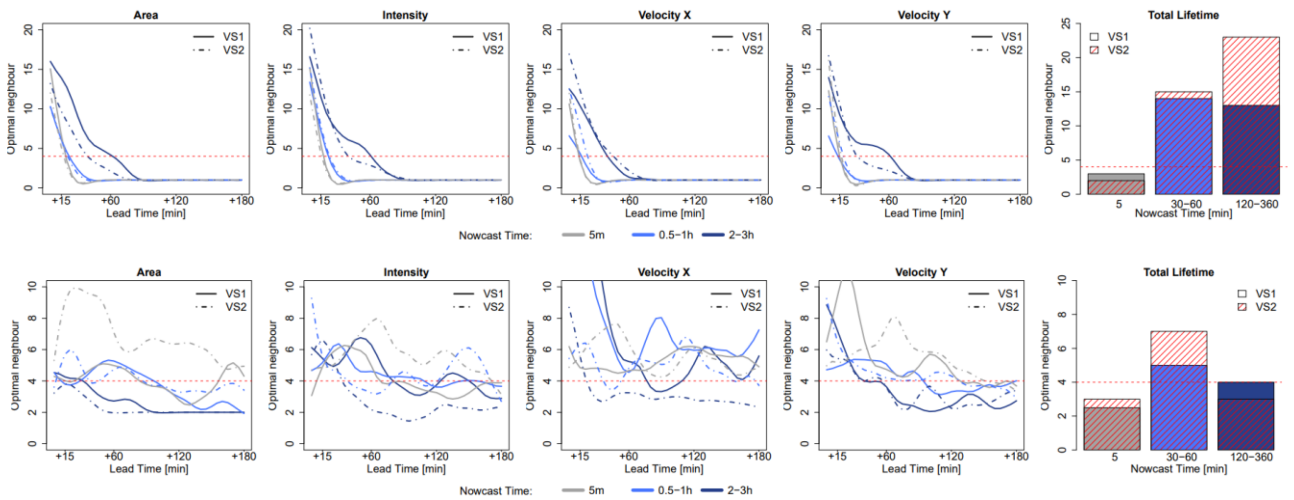


Figure 9 *The training of the k-NN per target variable based on predictors and weights derived from Pearson correlation analysis: the optimal selected "k" neighbours yielding the lowest absolute errors. Two k-NN applications are shown here – VS1 in solid line and VS2 in dashed line: First row – The optimal neighbour is found from minimizing the median absolute error for given group of nowcast times, Second row – The optimal neighbour is found from minimizing the mean absolute error for the given group of nowcast times. The red dashed horizontal line in the second row indicates the k=4 that is chosen in this study for the k-NN application.*

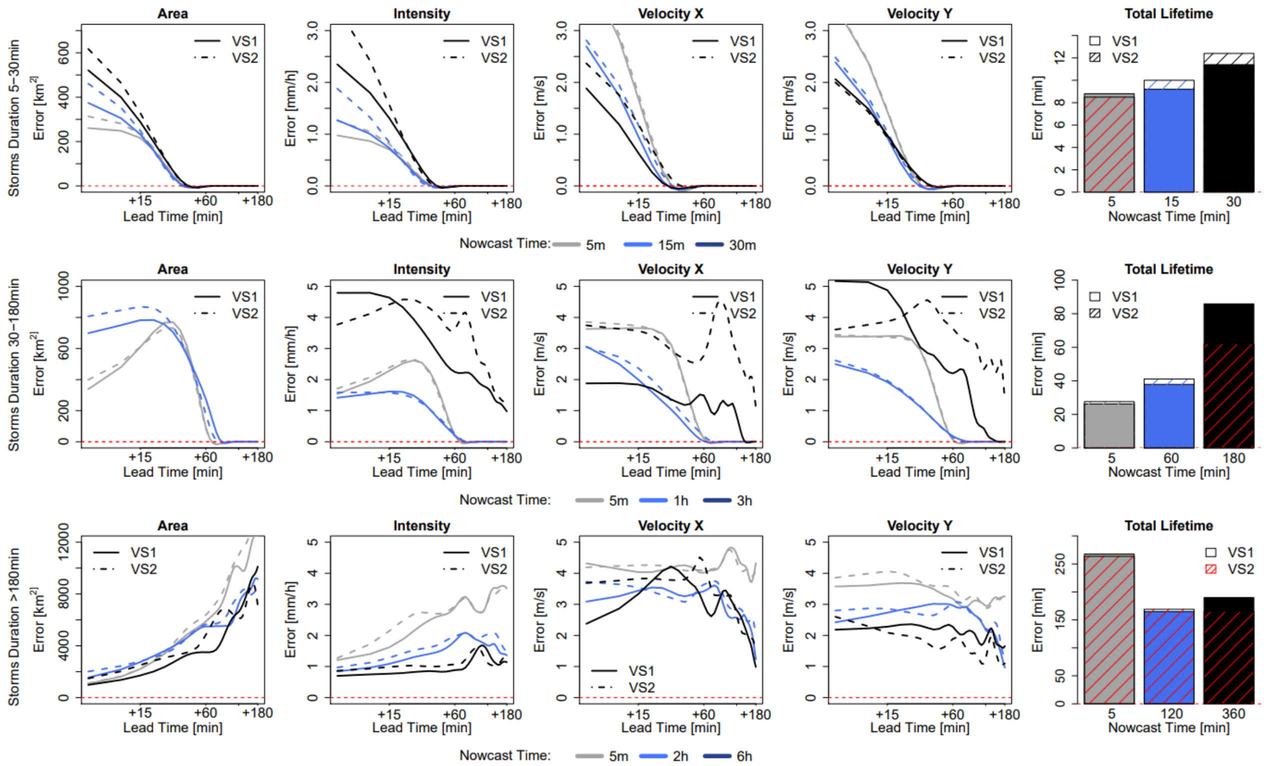


Figure 10 *The median absolute error for each target variable (Area, Intensity, Velocity in X and Y direction and Total Lifetime) based on two 4-NN applications: -VS1 in solid and VS2 in dashed lines. The median errors are computed over storms that are: shorter than 30 min (upper row), than 3 hours (middle row), and longer than 3 hours (lower row), and over the selected nowcast times. Nowcast time dictates when the nowcast is issued relative to storm initiation.*

Table 2 Maximum Deterioration (-) or Improvement (+) of k4NN-storm-based (VS2) compared to target-based (VS1) overall lead times according to the storm duration and nowcast times (shown in %).

Storm	Nowcast Time	Area	Intensity	Velocity X	Velocity Y	Total Lifetime	Storm	Nowcast Time	Area	Intensity	Velocity X	Velocity Y	Total Lifetime	Storm	Nowcast Time	Area	Intensity	Velocity X	Velocity Y	Total Lifetime
Duration 5-30min	5min	-22%	-18%	2%	0%	0%	Duration 0.5-3h	5min	-15.91%	-9%	-2%	3%	0%	Duration >3h	5min	-16%	-4%	-8%	-5%	-1%
	15min	-17%	-29%	-8%	-3%	-6%		60min	-7.30%	-3%	-13%	2%	-18%		120min	-12%	-14%	-45%	-18%	0%
	30min	-11%	-11%	-71%	5%	-3%		180min	-30%	-95%	-100%	-100%	14%		360min	-16%	-24%	-30%	25%	-3%

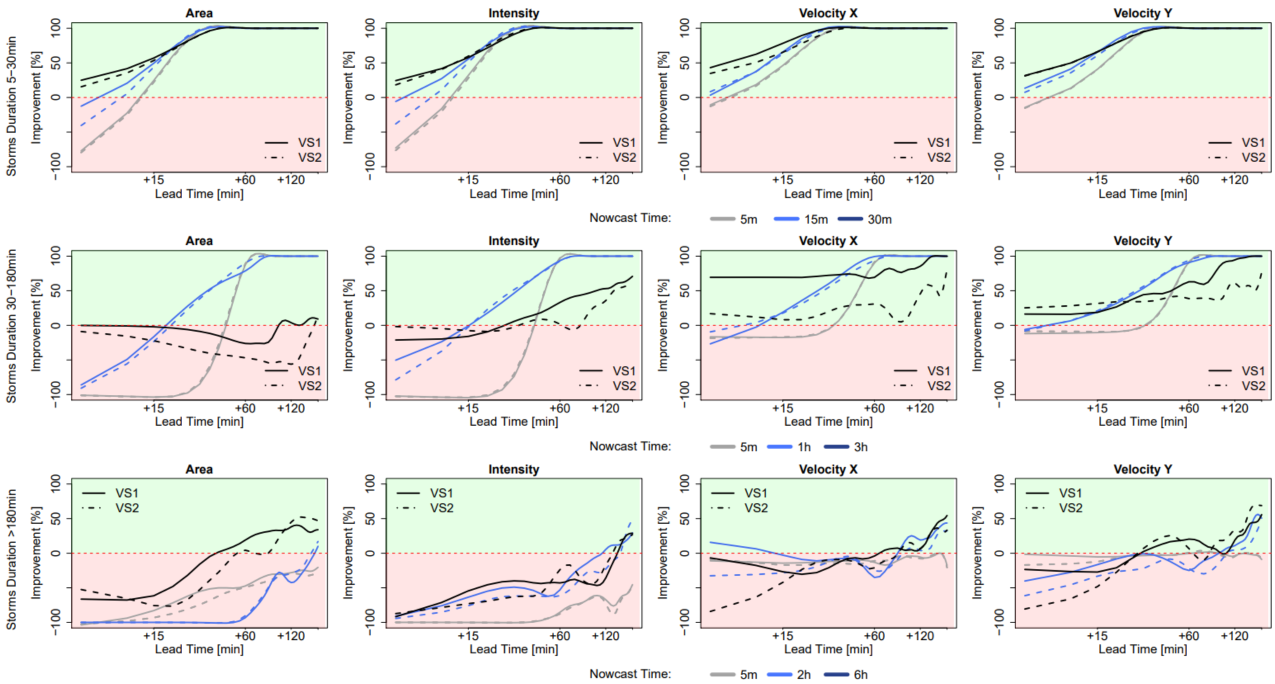


Figure 11 *The median improvements that the single 4-NN nowcast can introduce in the nowcast of the target variables (Area, Intensity, Velocity in X and Y direction) in comparison to the Lagrangian persistence. The results are shown for each 4-NN application: VS1 in solid and VS2 in dashed lines and are calculated separately for storms that live shorter than 30 min (upper row), shorter than 3 hours (middle row) and longer than 3 hours (lower row), and for the respective nowcast times. Nowcast time dictates when the nowcast is issued relative to storm initiation. The green region of the plot indicates a positive improvement (better nowcast by the 4-NN application) and the red region indicates a deterioration (better nowcast by the Lagrangian persistence).*

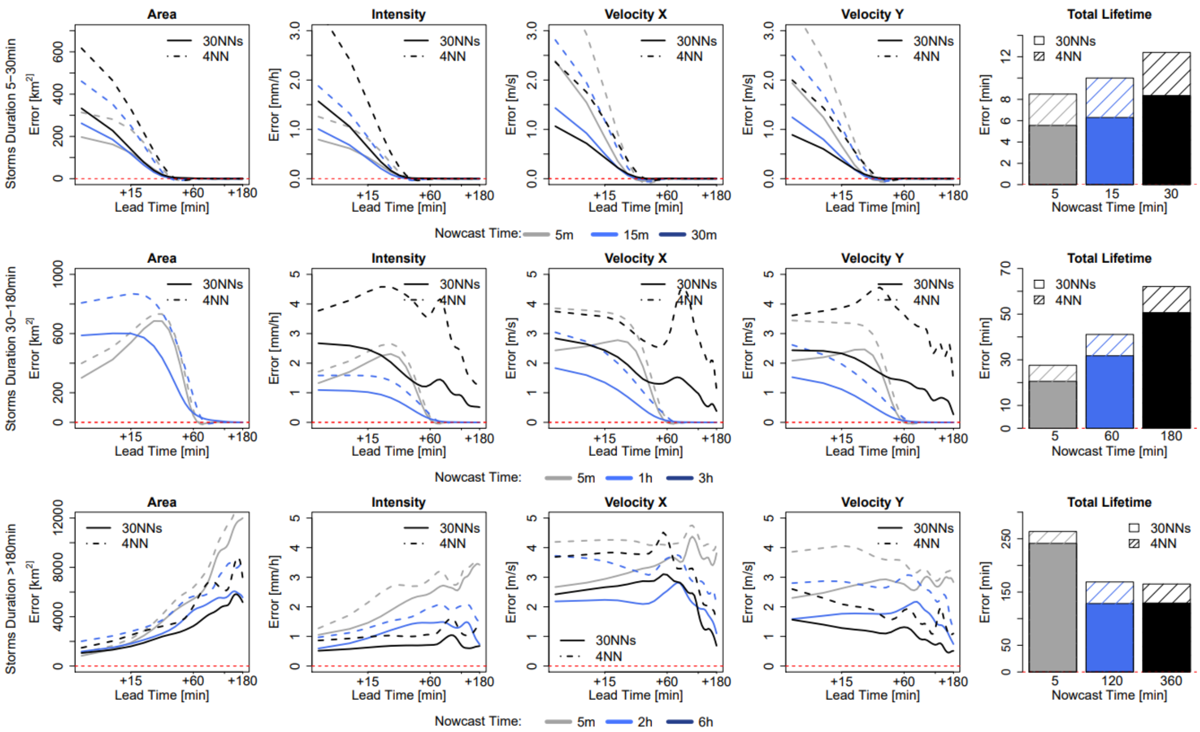


Figure 11. The median absolute error for each target variable (Area, Intensity, Velocity in X and Y direction and Total Lifetime) on the storm-based applications: -4NN (deterministic) in solid and 30NNs (probabilistic) in dashed lines. The median errors are computed over storms that are: shorter than 30 min (upper row), than 3 hours (middle row), and longer than 3 hours (lower row), and over the selected nowcast times. Nowcast time dictates when the nowcast is issued relative to storm initiation.

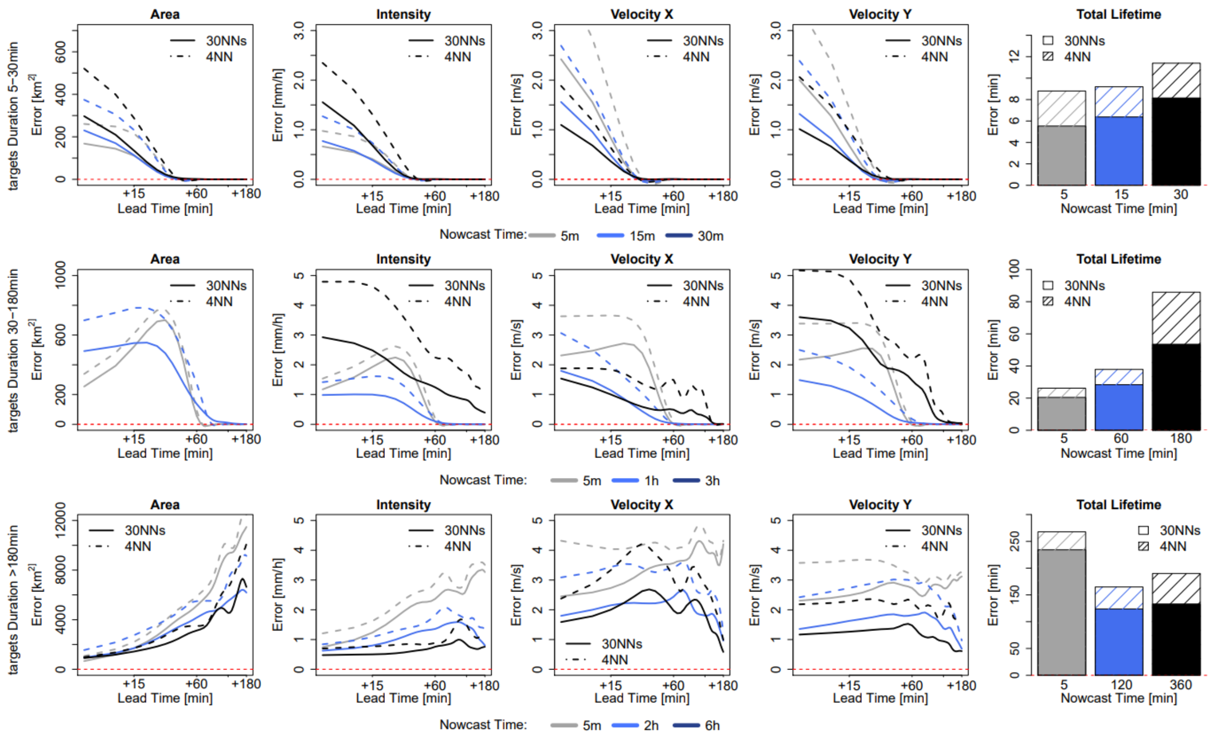


***Figure 12** The median absolute error for each target variable (Area, Intensity, Velocity in X and Y direction and Total Lifetime) on the target-based applications: -4NN (deterministic) in solid and 30NNs (probabilistic) in dashed lines. The median errors are computed over storms that are: shorter than 30 min (upper row), than 3 hours (middle row), and longer than 3 hours (lower row), and over the selected nowcast times. Nowcast time dictates when the nowcast is issued relative to storm initiation.*

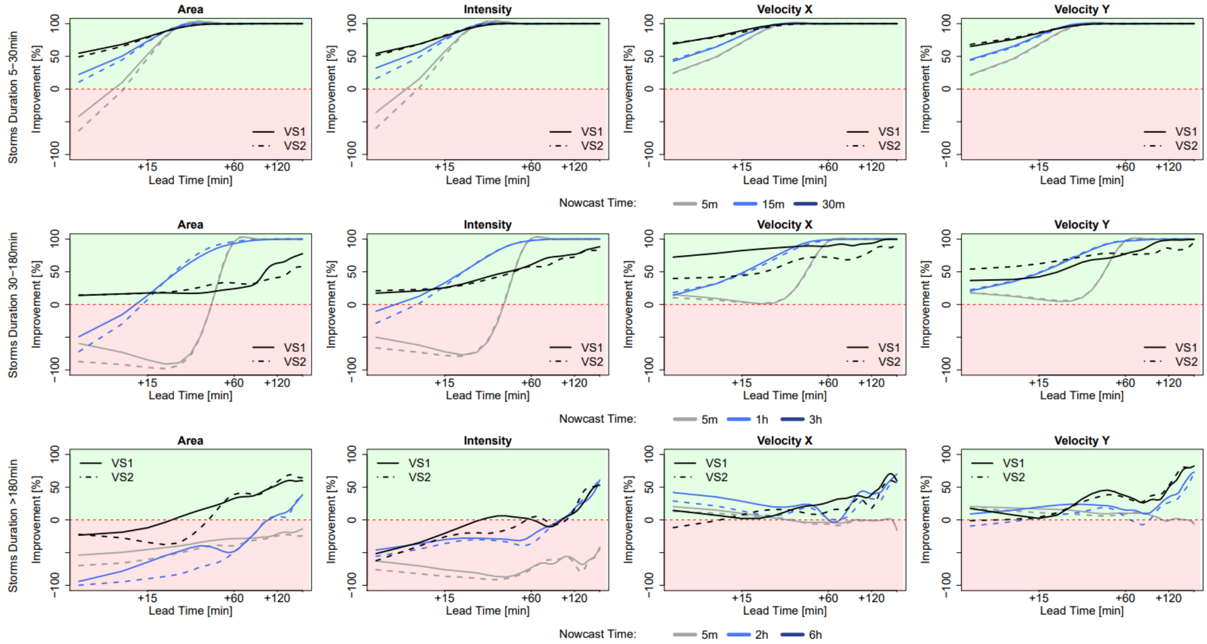


Figure 13: *The median improvements that the 30NNs nowcast can introduce in the nowcast of the target variables (Area, Intensity, Velocity in X and Y direction) in comparison to the Lagrangian persistence. The results are shown for each 30NNs application: VS1 in solid and VS2 in dashed lines and are calculated separately for storms that live shorter than 30 min (upper row), shorter than 3 hours (middle row) and longer than 3 hours (lower row), and for the respective nowcast times. Nowcast time dictates when the nowcast is issued relative to storm initiation. The green region of the plot indicates a positive improvement (better nowcast by the 4-NN application) and the red region indicates a deterioration (better nowcast by the Lagrangian persistence).*

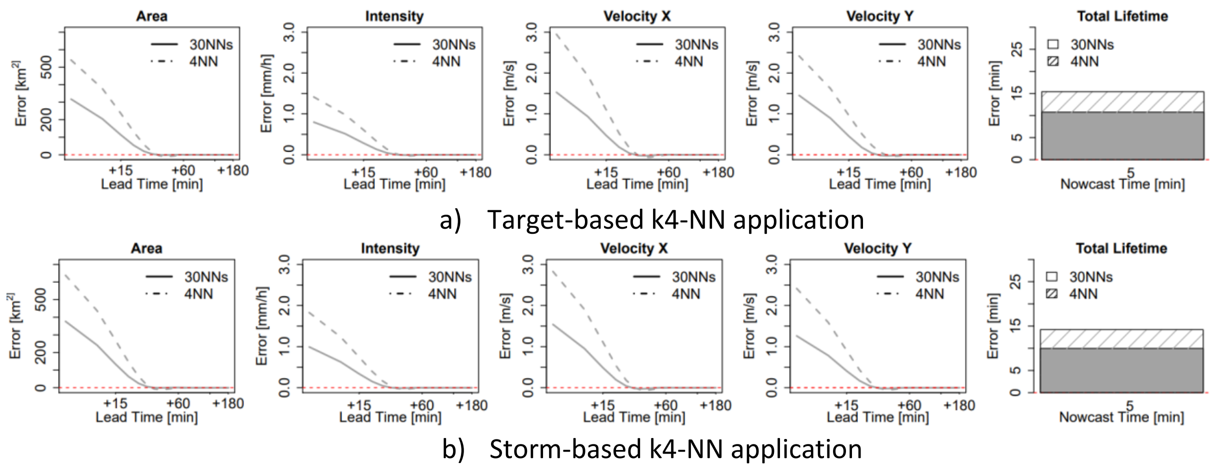


Figure 14 *Median Error Performance for each of the target variables nowcasted from k4NN deterministic and 30NN probabilistic application for both target (upper row) and storm-based (lower row) kNN. The results shown here are only from the "unmatched storms" when the nowcast time is 5 min*

Appendix 8.1 *Obtained Pearson Correlation predictors weight for each target variable, lead time and storm groups. The last row at each target variable (average values) are the predictors weights shown in Table 3*

	Area		Present Predictors															Average Past 30min Predictors														
	Durations	Lead Time	Cell	Life	A	avePI	medPI	maxPI	sdPI1	sdPI2	Vg	Vx	Vy	Jx	Jy	Jr	Φ	A	avePI	medPI	maxPI	sdPI1	sdPI2	Vg	Vx	Vy	Jx	Jy	Jr	Φ
Area	<1hr	15min	0.19	0.22	0.81	0.06	0.04	0.05	0.05	0.59	0.06	0.02	0.01	0.58	0.61	0.01	0.00	0.79	0.06	0.04	0.05	0.05	0.61	0.06	0.02	0.02	0.60	0.62	0.01	0.00
		60min	0.09	0.27	0.90	0.19	0.07	0.07	0.20	0.64	0.05	0.05	0.03	0.65	0.68	0.04	0.02	0.88	0.21	0.09	0.08	0.22	0.67	0.08	0.08	0.07	0.68	0.70	0.08	0.02
		180min	0.12	0.19	0.94	0.18	0.08	0.23	0.29	0.68	0.05	0.04	0.05	0.72	0.70	0.28	0.00	0.92	0.21	0.05	0.25	0.31	0.69	0.05	0.05	0.09	0.73	0.69	0.38	0.02
	<3hr	15min	0.12	0.19	0.61	0.04	0.03	0.03	0.04	0.45	0.00	0.01	0.00	0.43	0.49	0.01	0.01	0.60	0.05	0.03	0.02	0.04	0.46	0.00	0.02	0.02	0.45	0.50	0.01	0.01
		60min	0.04	0.25	0.72	0.13	0.05	0.01	0.13	0.48	0.01	0.03	0.03	0.55	0.55	0.03	0.01	0.69	0.15	0.07	0.03	0.15	0.51	0.02	0.05	0.05	0.56	0.55	0.07	0.02
		180min	0.09	0.13	0.80	0.16	0.06	0.20	0.25	0.58	0.10	0.01	0.05	0.63	0.57	0.24	0.00	0.77	0.20	0.02	0.23	0.28	0.57	0.11	0.00	0.09	0.61	0.55	0.32	0.02
	>3hr	15min	0.05	0.13	0.32	0.04	0.03	0.00	0.03	0.22	0.00	0.01	0.01	0.24	0.25	0.01	0.01	0.31	0.04	0.03	0.01	0.04	0.21	0.00	0.02	0.03	0.25	0.25	0.01	0.02
		60min	0.03	0.14	0.42	0.13	0.08	0.09	0.14	0.27	0.07	0.02	0.02	0.32	0.26	0.02	0.02	0.39	0.15	0.10	0.10	0.16	0.27	0.07	0.02	0.05	0.32	0.25	0.05	0.02
		180min	0.06	0.07	0.53	0.17	0.03	0.19	0.22	0.39	0.16	0.05	0.07	0.41	0.34	0.16	0.06	0.50	0.20	0.06	0.22	0.25	0.38	0.18	0.07	0.11	0.40	0.32	0.20	0.08
		Average	0.09	0.18	0.67	0.12	0.05	0.10	0.15	0.48	0.05	0.03	0.03	0.50	0.49	0.09	0.02	0.65	0.14	0.05	0.11	0.17	0.48	0.07	0.04	0.06	0.51	0.49	0.12	0.02

	Durations	Lead Time	No.Cells	Life.TS	Area	meanPI	medianPI	maxPI	sdPI1	sdPI2	GVel	VelX	VelY	Jx	Jy	J.ratio	Phi	Area	meanPi	medPI	maxPI	sdPI1	sdPI2	Velg	Velx	Vely	Jx	Jy	Jr	phi
Intensity	<1hr	15min	0.02	0.05	0.00	0.55	0.41	0.52	0.54	0.11	0.06	0.03	0.00	0.02	0.02	0.00	0.01	0.00	0.52	0.40	0.50	0.52	0.11	0.06	0.03	0.01	0.02	0.02	0.00	0.01
		60min	0.04	0.01	0.12	0.70	0.53	0.61	0.69	0.06	0.04	0.01	0.07	0.00	0.01	0.02	0.02	0.14	0.64	0.49	0.59	0.65	0.03	0.05	0.01	0.09	0.02	0.02	0.02	0.01
		180min	0.03	0.13	0.11	0.81	0.67	0.68	0.77	0.13	0.09	0.09	0.03	0.14	0.15	0.05	0.06	0.11	0.76	0.62	0.68	0.75	0.13	0.13	0.11	0.04	0.14	0.15	0.06	0.10
	<3hr	15min	0.02	0.10	0.11	0.15	0.08	0.22	0.17	0.14	0.04	0.02	0.01	0.08	0.10	0.01	0.00	0.10	0.14	0.07	0.20	0.16	0.13	0.04	0.02	0.01	0.08	0.09	0.02	0.01
		60min	0.01	0.06	0.01	0.31	0.18	0.45	0.37	0.10	0.02	0.02	0.03	0.07	0.07	0.02	0.05	0.01	0.28	0.16	0.43	0.34	0.09	0.03	0.02	0.06	0.06	0.05	0.04	0.05
		180min	0.01	0.06	0.10	0.43	0.40	0.50	0.47	0.20	0.08	0.06	0.01	0.25	0.22	0.09	0.09	0.08	0.42	0.37	0.47	0.44	0.19	0.10	0.08	0.01	0.24	0.21	0.12	0.10
	>3hr	15min	0.03	0.11	0.12	0.02	0.00	0.08	0.03	0.11	0.02	0.01	0.01	0.08	0.10	0.01	0.01	0.11	0.01	0.01	0.06	0.02	0.10	0.02	0.01	0.01	0.08	0.10	0.01	0.02
		60min	0.02	0.06	0.08	0.07	0.05	0.17	0.11	0.09	0.02	0.00	0.03	0.06	0.04	0.02	0.04	0.05	0.06	0.04	0.16	0.10	0.08	0.02	0.00	0.05	0.05	0.03	0.04	0.04
		180min	0.01	0.05	0.36	0.10	0.18	0.10	0.06	0.31	0.03	0.02	0.10	0.38	0.35	0.11	0.05	0.34	0.07	0.15	0.05	0.02	0.30	0.05	0.05	0.16	0.36	0.33	0.15	0.05
		Average	0.02	0.07	0.11	0.35	0.28	0.37	0.36	0.14	0.04	0.03	0.03	0.12	0.12	0.03	0.04	0.10	0.32	0.26	0.35	0.33	0.13	0.05	0.04	0.05	0.12	0.11	0.05	0.04

	Durations	Lead Time	No.Cells	Life.TS	Area	meanPI	medianPI	maxPI	sdPI1	sdPI2	GVel	VelX	VelY	Jx	Jy	J.ratio	Phi	Area	meanPi	medPI	maxPI	sdPI1	sdPI2	Velg	Velx	Vely	Jx	Jy	Jr	phi
Velocity X	<1hr	15min	0.04	0.02	0.09	0.01	0.01	0.01	0.00	0.06	0.14	0.17	0.02	0.06	0.05	0.01	0.02	0.08	0.01	0.01	0.01	0.00	0.08	0.13	0.18	0.02	0.14	0.07	0.02	0.02
		60min	0.03	0.03	0.12	0.03	0.04	0.02	0.02	0.04	0.31	0.37	0.06	0.10	0.03	0.01	0.03	0.11	0.04	0.04	0.02	0.03	0.04	0.33	0.52	0.09	0.15	0.04	0.00	0.03
		180min	0.04	0.01	0.06	0.05	0.06	0.04	0.05	0.00	0.27	0.32	0.05	0.12	0.06	0.01	0.06	0.07	0.04	0.05	0.03	0.04	0.00	0.35	0.42	0.05	0.16	0.07	0.01	0.05
	<3hr	15min	0.03	0.06	0.10	0.02	0.01	0.01	0.01	0.06	0.03	0.07	0.01	0.05	0.04	0.01	0.02	0.08	0.02	0.02	0.00	0.02	0.05	0.03	0.06	0.01	0.15	0.03	0.02	0.03
		60min	0.06	0.06	0.15	0.03	0.02	0.03	0.02	0.06	0.20	0.30	0.06	0.11	0.05	0.01	0.03	0.14	0.05	0.04	0.03	0.03	0.05	0.25	0.42	0.07	0.16	0.04	0.01	0.04
		180min	0.04	0.01	0.10	0.03	0.04	0.02	0.02	0.02	0.27	0.26	0.04	0.13	0.07	0.00	0.06	0.10	0.02	0.04	0.02	0.02	0.02	0.29	0.38	0.05	0.18	0.07	0.00	0.05
	>3hr	15min	0.04	0.06	0.10	0.02	0.02	0.01	0.01	0.04	0.02	0.05	0.02	0.04	0.01	0.01	0.02	0.09	0.02	0.02	0.00	0.02	0.04	0.02	0.05	0.01	0.15	0.01	0.01	0.02
		60min	0.04	0.04	0.05	0.04	0.04	0.03	0.04	0.04	0.07	0.16	0.05	0.00	0.04	0.00	0.02	0.04	0.05	0.04	0.03	0.04	0.05	0.08	0.23	0.07	0.15	0.05	0.02	0.02
		180min	0.03	0.02	0.10	0.00	0.03	0.02	0.02	0.03	0.15	0.17	0.03	0.11	0.04	0.01	0.03	0.10	0.01	0.02	0.02	0.02	0.03	0.16	0.24	0.03	0.15	0.05	0.01	0.04
		Average	0.04	0.03	0.10	0.03	0.03	0.02	0.02	0.04	0.16	0.21	0.04	0.08	0.04	0.01	0.03	0.09	0.03	0.03	0.02	0.02	0.04	0.18	0.28	0.04	0.15	0.05	0.01	0.03

	Durations	Lead Time	No.Cells	Life.TS	Area	meanPI	medianPI	maxPI	sdPI1	sdPI2	GVel	VelX	VelY	Jx	Jy	J.ratio	Phi	Area	meanPi	medPI	maxPI	sdPI1	sdPI2	Velg	Velx	Vely	Jx	Jy	Jr	phi
Velocity Y	<1hr	15min	0.04	0.04	0.04	0.02	0.00	0.05	0.03	0.06	0.03	0.02	0.15	0.03	0.03	0.01	0.00	0.04	0.02	0.00	0.04	0.03	0.07	0.04	0.03	0.17	0.04	0.03	0.01	0.00
		60min	0.00	0.04	0.02	0.08	0.07	0.09	0.08	0.00	0.03	0.05	0.22	0.00	0.00	0.01	0.02	0.03	0.08	0.07	0.09	0.08	0.00	0.01	0.06	0.33	0.01	0.00	0.02	0.02
		180min	0.03	0.08	0.05	0.02	0.01	0.03	0.03	0.05	0.00	0.04	0.27	0.07	0.01	0.02	0.00	0.06	0.02	0.01	0.03	0.03	0.06	0.01	0.05	0.41	0.08	0.02	0.01	0.02
	<3hr	15min	0.01	0.06	0.06	0.03	0.02	0.07	0.04	0.07	0.01	0.01	0.05	0.03	0.05	0.00	0.01	0.05	0.03	0.01	0.06	0.04	0.06	0.02	0.00	0.04	0.02	0.04	0.00	0.00
		60min	0.01	0.06	0.02	0.04	0.03	0.10	0.06	0.03	0.01	0.06	0.18	0.02	0.05	0.01	0.01	0.00	0.04	0.03	0.11	0.06	0.03	0.00	0.07	0.26	0.01	0.04	0.01	0.01
		180min	0.00	0.06	0.03	0.00	0.00	0.00	0.00	0.06	0.01	0.03	0.22	0.07	0.04	0.01	0.01	0.04	0.01	0.01	0.00	0.00	0.07	0.00	0.04	0.33	0.07	0.05	0.01	0.01
	>3hr	15min	0.01	0.07	0.03	0.00	0.01	0.03	0.01	0.03	0.01	0.01	0.04	0.00	0.01	0.01	0.02	0.02	0.00	0.01	0.02	0.00	0.02	0.01	0.01	0.03	0.00	0.00	0.01	0.03
		60min	0.03	0.02	0.02	0.01	0.01	0.03	0.01	0.07	0.00	0.04	0.09	0.09	0.08	0.01	0.01	0.04	0.01	0.01	0.03	0.00	0.09	0.01	0.07	0.16	0.10	0.10	0.01	0.00
		180min	0.00	0.01	0.01	0.05	0.04	0.04	0.04	0.04	0.01	0.02	0.14	0.09	0.08	0.01	0.01	0.02	0.05	0.05	0.04	0.04	0.05	0.02	0.01	0.22	0.10	0.08	0.00	0.00
		Average	0.01	0.05	0.03	0.03	0.02	0.05	0.03	0.05	0.01	0.03	0.15	0.04	0.04	0.01	0.01	0.03	0.03	0.02	0.05	0.03	0.05	0.01	0.04	0.22	0.05	0.04	0.01	0.01

	Durations	Lead Time	No.Cells	Life.TS	Area	meanPI	medianPI	maxPI	sdPI1	sdPI2	GVel	VelX	VelY	Jx	Jy	J.ratio	Phi	Area	meanPi	medPI	maxPI	sdPI1	sdPI2	Velg	Velx	Vely	Jx	Jy	Jr	phi
Duration	Dur <1hr		0.06	0.16	0.31	0.02	0.02	0.04	0.00	0.22	0.03	0.03	0.00	0.19	0.24	0.00	0.03	0.30	0.02	0.03	0.03	0.01	0.21	0.03	0.03	0.01	0.19	0.25	0.01	0.04
	Dur <3hr		0.00	0.16	0.35	0.10	0.05	0.04	0.10	0.22	0.08	0.02	0.04	0.23	0.21	0.02	0.11	0.32	0.12	0.07	0.05	0.11	0.22	0.08	0.03	0.07	0.23	0.21	0.05	0.15
	Dur >3hr		0.07	0.02	0.43	0.20	0.11	0.18	0.21	0.21	0.15	0.04	0.04	0.25	0.16	0.14	0.01	0.40	0.22	0.14	0.20	0.23	0.20	0.18	0.07	0.07	0.23	0.14	0.18	0.01
		Average	0.04	0.11	0.36	0.11	0.06	0.09	0.10	0.22	0.09	0.03	0.03	0.22	0.20	0.05	0.05	0.34	0.12	0.08	0.09	0.12	0.21	0.10	0.04	0.05	0.22	0.20	0.08	0.07

Appendix 8.2 *Obtained PIC predictors weight for each target variable, lead time and storm groups. The last row at each target variable (average values) are the predictors weights shown in Table 3.*

	Area		Present Predictors															Average Past 30min Predictors												
	Durations	Lead Time	Cell	Life	A	avePI	medPI	maxPI	sdPI1	sdPI2	Vg	Vx	Vy	Jx	Jy	Jr	Φ	A	avePI	medPI	maxPI	sdPI1	sdPI2	Vg	Vx	Vy	Jx	Jy	Jr	phi
Area	<1hr	15min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00
		60min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00
		180min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00
	<3hr	15min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00
		60min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00
		180min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00
	>3hr	15min	0.00	0.10	0.25	0.00	0.00	0.00	0.00	0.00	0.57	0.00	0.00	0.00	0.00	0.00	0.00	0.08	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
		60min	0.00	0.29	0.67	0.00	0.00	0.00	0.00	0.00	0.66	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.33	0.00	0.00	0.00	0.00
		180min	0.00	0.30	0.40	0.00	0.00	0.00	0.00	0.00	0.72	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.28	0.00	0.00	0.00	0.00
		Average	0.00	0.08	0.15	0.00	0.00	0.00	0.00	0.00	0.22	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.33	0.00	0.07	0.00	0.00	0.33	0.00

	Durations	Lead Time	No.Cells	Life.TS	Area	meanPI	medianPI	maxPI	sdPI1	sdPI2	GVel	VelX	VelY	Jx	Jy	J.ratio	Phi	Area	meanPi	medPI	maxPI	sdPI1	sdPI2	Velg	Velx	Vely	Jx	Jy	Jr	phi
Intensity	<1hr	15min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
		60min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
		180min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	<3hr	15min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
		60min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
		180min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	>3hr	15min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
		60min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
		180min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
		Average	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

	Durations	Lead Time	No.Cells	Life.TS	Area	meanPI	medianPI	maxPI	sdPI1	sdPI2	GVel	VelX	VelY	Jx	Jy	J.ratio	Phi	Area	meanPi	medPI	maxPI	sdPI1	sdPI2	Velg	Velx	Vely	Jx	Jy	Jr	phi
Velocity X	<1hr	15min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
		60min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
		180min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	<3hr	15min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00
		60min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00
		180min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00
	>3hr	15min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
		60min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
		180min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
		Average	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00

	Durations	Lead Time	No.Cells	Life.TS	Area	meanPI	medianPI	maxPI	sdPI1	sdPI2	GVel	VelX	VelY	Jx	Jy	J.ratio	Phi	Area	meanPi	medPI	maxPI	sdPI1	sdPI2	Velg	Velx	Vely	Jx	Jy	Jr	phi
Velocity Y	<1hr	15min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
		60min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
		180min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	<3hr	15min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
		60min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
		180min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	>3hr	15min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00
		60min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00
		180min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00
		Average	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00

	Durations	Lead Time	No.Cells	Life.TS	Area	meanPI	medianPI	maxPI	sdPI1	sdPI2	GVel	VelX	VelY	Jx	Jy	J.ratio	Phi	Area	meanPi	medPI	maxPI	sdPI1	sdPI2	Velg	Velx	Vely	Jx	Jy	Jr	phi
Duration	Dur <1hr		0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00
	Dur <3hr		0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00
	Dur >3hr		0.00	0.45	0.40	0.00	0.00	0.00	0.00	0.00	0.72	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.33	0.00	0.00	0.00
		Average	0.00	0.15	0.13	0.00	0.00	0.00	0.00	0.00	0.24	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.33	0.00	0.00	0.00	0.11	0.33	0.00