

Dear Seppo,

thank you for your comments and suggestions, that have contributed in improving the manuscript and the idea after the nearest neighbour application. Following your suggestions, 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 pdf at the end of this response.

General Comments:

- To make the title better reflect the content, you could add the word "rainfall" because the paper is about rainfall nowcasting

Following your suggestion and that of another review, the title has been changed accordingly. We will ask the editor if the title can be change to the following, to give the idea that this is only a first step in implementing the nearest neighbour method.

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

Please note that we have added "Part I – Storm Characteristics", as this paper is focusing only on 5 characteristics (Area, intensity, velocity x and y and duration). The plan is to follow this paper with a second one "Part II – Point scale Intensities" where the focus is the predictability of rainfall intensities at point scales (1km²) for urban flood application.

- Before going directly to the matter, it could be worthwhile to add one general paragraph about nowcasting. Like why nowcasting is done, its societal need and what kind of hazards can be prevented with reliable rainfall nowcasts. In the beginning of the introduction, the authors should make a clearer distinction between the two nowcasting approaches (field- and object-based) and add more description about what purposes they are used for. For instance, mention that field-based methods are well-suited for predicting large-scale stratiform precipitation systems but cell-based methods are best-suited for predicting the motion of intense convective cells.

The introduction to the rainfall nowcast topic and the literature review will be updated according to your suggestions and those of the first reviewer.

- To put their work into a broader context, the authors could mention in the introduction that the proposed approach is conceptually similar to the so-called analogue-based nowcasting. The idea of this approach is to look for similar events from a large sample of archived radar data. See, for instance: L. Panziera, U. Germann, M. Gabella and P. Mandapaka: NORA–Nowcasting of Orographic Rainfall by means of Analogues, Quarterly Journal of the Royal Meteorological Society, 137(661), 2106-2123, 2011. There are a number of others, so I recommend the authors to do a literature review. However, all the previous studies I know attempt to find analogs from full radar images, not from individual cells or their features. This is a novel aspect, which should be clearly pointed out in the manuscript.

Thank you for your suggestion. Of course, we will take your advice and mention the analogue-approach from Panziera et al and relate with the nearest neighbour application.

- I have concerns about the choice of the predictors. The proposed methodology opens the possibility to use a large number of different predictors (and targets). However, the set chosen in the study is in my opinion quite limited and the capability of the model is thus not fully utilized. In addition, they are more or less correlated with each other, and also with the target variables, which the authors

admit. I think that using the following additional predictors could reveal the full potential of the model: ◦ convective available potential energy (CAPE) ◦ convective inhibition (CIN) ◦ signatures from radar-measured Doppler and polarimetric parameters, as well as vertical profile information obtained by using all elevation angles ◦ lightning flash density ◦ geographical features like terrain altitude or proximity of water bodies These are probably beyond the scope of this study, but I encourage the authors to include them in a follow-up paper. In addition, the authors could replace the generic description of additional predictors in the last paragraph of Section 5 by specifically mentioning some of the above. Note that a relationship between CAPE and CIN and the life cycle of convective cells is suggested in: C. Moseley, O. Henneberg and J. O. Harter: A Statistical Model for Isolated Convective Precipitation Events, *Journal of Advances in Modeling Earth Systems*, 11(1), 360-375, 2019.

Regarding the choice of the predictors, I agree with your concerns, however the main idea here was to investigate if only the storm's characteristics derived from the radar data are able to give some extra information in improving the radar-based nowcast. Of course, in the future we plan to extend the methodology in conjunction with numerical weather prediction models (based on CAPE or CIN) and geographical features (although for the case study it is a bit difficult because the terrain is mainly flat). Extra information from Doppler or Dual-polarized radar data is quite promising to my opinion, because storms type could be distinguished better, but may be limited to the data availability in the study region. Lightning flash density is also another good idea and it has been proven to be correlated with rainfall intensity, but mainly for high lightning activity. For this manuscript, we have updated the possible predictors text in Section 5 with this and more possible predictors that can be used in the future works as follows:

“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, lightning 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.”

- A fundamental reason why similar storm cells behave similarly is that their life cycles follow characteristic patterns. For instance, the areal extent and intensity of storm cells are related to each other and the storm lifetime. In particular, the future behavior of cells depends on what stage they are in their life cycle. I think this aspect needs to be discussed more in the paper with literature references to put the research in a broader context. To this end, the authors could study the following papers: H. Kyznarova and P. Novak: CELLTRACK-Convective cell tracking algorithm and its use for deriving life cycle characteristics, *Atmospheric Research*, 93(1-3), 317- 327, 2009 C. Moseley, P. Berg and J. O. Haerter: Probing the precipitation life cycle by iterative rain cell tracking, *JGR: Atmospheres*, 118(24), 361-370, 2013 There is also a large amount of meteorological literature, where the life cycles of convective storms are discussed.

We are aware that convective storms have life cycles that have some characteristic pattern – that's why the idea of the nearest neighbourhood originated. Following your comments, we will discuss it more in the paper and include some more meteorological literature.

- A major limitation of the k-neighbors approach is that it cannot generalize beyond the training data. How would the proposed method perform for extreme events that have a very limited number or no training samples? Please add more discussion or analysis about this.

The events that have been selected as part of the database and are investigated are so to say extreme events; where the measured rainfall at different durations (1 hour and 1 day) exceed

the return period of 5 years. So, this is already assessing the suitability of k-NN for predicting extreme events from a given database of extreme events. But of course, if there is a very extreme event with high intensity (exceeding previous observations), the k-NN will fail to capture the high intensity, but may still associate to it, the largest intensity observed so far. The results depend highly on the nowcast time; nowcasting before the peak or after peak. To discuss this more, we will include an example of an extreme event, and the response of the k-NN in comparison to the Lagrangian persistence.

- In many places, the authors are describing results that are not shown anywhere, so the reader cannot verify the validity of the claims. An example of this can be seen at lines 362-374. Could you include some of the not shown results that are discussed in the text in an appendix or in supplementary material?

Yes sure, the results are the average improvements obtained from the Figures. To make these results clearer we will include a table with the information.

Specific comments

- Line 101: What does "step 3" refer to? Storm extrapolation in Figure 1?

Yes, the step 3 is referring to the storm extrapolation Figure 1-c. The explanation has been added to the text as following:

“The application of the k-NN seems reasonable as an extension of the object-based radar nowcast. It can be used instead of the Lagrangian persistence in step 3 in Figure 1-c, for the extrapolation of rainfall storms into the future.”

- Figure 2: ◦ What do the numbers represent in the x- and y-tick labels? I think it would be more informative to show the distance from the radar in kilometers.

The x- and y- tick labels show the coordinates in meters of the study area in UTM-Zone 32N. We would prefer to leave the UTM coordinates, so the reader can have an idea about the location of the study area. However, following the comments of reviewer one we have included a map of Germany to explain where the study area is located, and we have updated the x-y tick labels with the distance from radar centre in meter. Please refer to Figure 2 in the attached pdf.

- Does DEM mean altitude obtained from a digital elevation model?

Yes, DEM refers to the Digital Elevation model. This is now included in the Figure caption (see Figure 2 in the attached pdf).

- Lines 131-137: What is the justification for these threshold choices?

Typically, larger thresholds are used for the identification of convective storms, but however may lead to false splitting of the storms, which then might be treated independently in the k-NN. Thus, we lowered the threshold to 20dBz and 25dBz (light rain) so we could have a better overview of similar storms. Nevertheless, this is only a starting point, and more work will be done to see how a change in threshold affects the application of the kNN.

- Lines 139-140: What is the "spatial rainfall intensity of a storm". Is it some kind of average or maximum value taken inside the storm object?

The spatial rainfall intensity of a storm- refers here to the spatial distribution of the rainfall intensities within the boundaries of the storm object at a specific time step. We have changed it to “Here the spatial distribution of rainfall intensities inside the storm boundaries at a given time step (in 5min) of the storms’ life...”

- Line 142: I'm curious how the ellipsoid is fitted. Please provide a more detailed explanation (though no need to include this in the paper).

The ellipsoid fitting is done by the existing algorithm (HyRaTrac) that we use as a base for nowcast. More information is provided in the full description (although in German) of the methodology in Kraemer 2008. The ellipsoid is fitting to taking into consideration the mass centroid of the storm and the areal moments of inertia. So first the mass centroid of the storm is found (X_s, Y_s) and the areal moments of inertia in respect to the x and y coordinates of the centroid (J_x and J_y) and the centrifugal moments (J_{xy}) are computed as shown in Eqn. 1. The axes of the ellipsoid are referred to as J_{min} and J_{max} and calculated as shown in Eqn. 2.

$$J_y = \int (y - Y_s)^2 dA, \quad J_x = \int (x - X_s)^2 dA \quad \text{and} \quad J_{xy} = J_{yx} = - \int (y - Y_s) \times (x - X_s) dA \quad (1)$$

$$J_{max} = \frac{J_x + J_y}{2} + \sqrt{\left(\frac{J_y - J_x}{2}\right)^2 + J_{xy}^2} \quad \text{and} \quad J_{min} = \frac{J_x + J_y}{2} - \sqrt{\left(\frac{J_y - J_x}{2}\right)^2 + J_{xy}^2} \quad \text{and} \quad \tan 2\Phi = \frac{2J_{xy}}{J_y - J_x} \quad (2)$$

- Line 145: Please give a more detailed description about how the storm velocities are estimated?

The following lines were added in the text:

“These storms characteristics were obtained by an hindcast analysis run with the HyRaTrac algorithm. The local velocities in x and y direction are obtained by a cross-correlation optimization within the storm boundaries.”

- Line 145 and Figure 3: The merges are mentioned in the text but not shown in the figure.

The figure refers to both the number of merges and splits and has been updated accordingly. The updated Figure is shown below. Please note that the maximum intensity has been updated as well. 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.

- Figure 3: The very high velocities of 5-minute storms look suspicious to me. How can you even estimate the velocity of a storm if its duration is only 5 minutes (i.e. one-time step)?

The velocities of 5min storms are explained shortly in the text as:

“In case a storm is just recognized, then global displacement vectors based on cross-correlation of the entire radar image are assigned to them.”

For the very high velocities please check the following point.

- Is there a reason for specifying the duration intervals in inclusive way? I would use separate intervals (i.e. 0-1h, 1-3h, 3-6h, 6-12h).

We have separated the duration intervals in the following groups: a) only 5 min, b) 5min – 1h, c) 1-3h, d) 3-6 h, e) 6-12h and f) longer than 12 h. The 5min we have included to illustrate the problem with the unmatched storms, and the longer than 12 hours to demonstrate very persistent storms (see updated Figure 4 in the attached pdf).

- I'm very surprised to see how the 5-minute storms have such a large area. I would expect all storms having area over 500 km² to have lifetime longer than 5 minutes. Can you explain this?

I understand your concern, but please remember that here merged data are fed to the algorithm and not raw radar data. In the merged data, a merging between the stations and the

radar is performed. This is affecting the structure of the storms mainly when the radar data is missing, because the information is taken from interpolating rain gauge information with ordinary kriging – which is known to smoothen the distribution of the rainfall and leading to very large areas above a threshold. This explains why these large areas are shortly lived (only 5 min) with low intensities and very high velocities. The following explanation was given 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 short storms characterized by a very large area.”

- Line 152: Please give numbers describing "high intensity" and "low areal coverage".

The following changes where done in the text:

“Here two types of convective storms are distinguished: local convective with very low coverage (on average lower than 1000 km²) and low intensity (on average ~ 5 mm/h), and mesoscale convective which are responsible for floods (with spatial mean intensity up to 25 mm/h) and have a larger coverage (on average lower than 1000 km²).”

- Lines 153-154: What is the evidence for making this conclusion? At least this cannot be seen from Figure 3.

I’m a bit confused to which conclusion you refer: that the meso-scale convective are the main cause for generating flooding? Yes, this cannot be seen directly from Figure 4 (see attached pdf), but it is known that the meso-scale convective storms are the main cause of the flooding and they are characterized by higher coverage, high intensity and durations lower than 6 hours. We will add citations to back this statement up. Please note that I have updated Figure 4 (the maximum Intensity) because before mistakenly I was showing the standard deviation of the intensity instead of the maximum value.

- Line 210 onwards: It is not obvious to me how the partial information correlation is better able to capture non-linear behaviour than the Pearson correlation coefficient. Can you add more discussion about this?

Yes sure, the Pearson correlation is computed based on the linear regression between two variables; so, the main assumption is that the two variables are linearly dependable. The partial information correlation is based on mutual information which describes the statistical dependency of the variables on each other. Here the conditional probability distributions of the values are considered, and no previous assumption in the linearity is considered. Moreover, as explained in the text the PIC is a stepwise procedure, considering the interaction between more than two predictors, which is not the case for the Pearson correlation (as it considers only the dependencies between two variables). We will update the manuscript by writing clearly how the PIC captures the non-linear behaviour and what is the main difference with the Pearson correlation.

- Equation (3): How is PI defined?

The following changes were done in the text to address this question:

$$PIC = \sqrt{(1 - \exp(-2PI))} \text{ with } PI = \int f_{X,P|Z}(x, p|z) \log \left[\frac{f_{X|Z,P|Z}(x, p|z)}{f_{X|Z}(x|z) f_{P|Z}(p|z)} \right] dx dp dz , \quad (1)$$

“where PIC is the Partial Information Correlation, PI is the Partial Information which represents the partial dependence of X on P conditioned to the presence of a predictor Z. The Partial Information itself is a modification of the Mutual Information in order to measure partial statistical dependency between the predictors (P) and the target variable (X), by adding predictors one at a time (Z) (step-wise procedure).”

- Equation (4): The notation is confusing. What does X(-j) mean? Maybe you should use subscripts for j and -j instead.

We have done the following changes in the text to match as well the annotations from Eqn (3):

$$\alpha_j = PIC_{X,Z_j|Z(-j)} \frac{S_{X|Z(-j)}}{S_{Z_j|Z(-j)}},$$

“where X is the target response, Z_j is the added predictor from the step-wise procedure, Z(-j) previous predictor vector excluding the predictor Z_j, S_{X|Z(-j)} the scaled conditional standard deviations between target (x) and predictor vector Z(-j), S_{Z_j|Z(-j)} the scaled conditional standard deviations between the additional predictor (Z_j) and the first predictor vector Z(-j), and the α_j the predictors weight.”

As explained in the paragraph before the PIC is a step-wise procedure. One needs to have a starting predictor (a known important predictor), and then add the other predictors one at a time and see if they provide more information to the dependency or not. The Z_j expresses the predictor being added in this procedure and Z(-j) is the previous predictor vector. When the procedure has just started the Z(-j) is the pre-identified predictor.

- Table 1: I would not use the word "predicted" for the target variables. I thought that they are obtained from observations, not predictions. For the velocities, I would use the word "estimated" since they are not directly observed but estimated by using some method.

Noted! We have changed from predicted to estimated.

- Table 1: You could attempt to eliminate the dependency of the standard deviation on the mean value by using the coefficient of variation instead (i.e. standard deviation divided by the mean).

Thanks for the suggestion, we will consider this in the future. Nevertheless, I am not sure if there will be a big difference, because the predictor set is already normalized according to the median the range between Q95% and Q5% (see Eqn. 2 in the manuscript).

- Lines 255-262: The actual procedure for generating the ensemble is not well described. Are the ensemble members somehow randomly assigned based on their probabilities?

Yes, the ensemble members are randomly assigned by on their rank probabilities. The following description is added in the text:

“Contrary, if a probabilistic nowcast is selected, 30-ensemble members 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:

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

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 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).”

- Line 261: What is the justification for choosing the value 0.5? Is the model sensitive to this value?

The value 0.5 represents the 95% quantile of the calculated distances of the 4th neighbour for all storms/events. Actually, the model is not very sensitive to this value, but to avoid confusion and to make a fair comparison with Lagrangian persistence (not to exclude the time steps where the neighbours have a higher distance than 0.5) we have excluded this limitation and show the results for all neighbours. However, the idea in the future is that when the kNN method is not able to recognize a similar neighbour (with distance below this threshold), the Lagrangian persistence should be used instead.

- Equations (6) and (7): To me it appears that the same symbol R is used for two different purposes: response and rank. Could you use different symbols?

Noted! In Equation (7) we refer to it as *Rank* instead of *R*.

- Equation (8): Should the summation terms be taken their absolute values? To me summation over the differences does not make much sense if it's used as the objective function.

The absolute values were not considered in order to balance the over and under-estimation. However, we have changed the error calculation for the absolute values and updated the results of the deterministic nowcast. We have done so because we have calculated as well the Continuous Rank Probability Score for the ensemble nowcast, and thus we can provide a direct comparison between the deterministic and probabilistic approaches. The following change has been done in text:

$$Error_{target} = \sum_{i=1}^N (|Pred_{i,+LT}| - |Obs_{i,+LT}|) / N, \quad (8)$$

Please note that because we have changed the objective functions, the results of the training have been updated as well. Please refer to Figure 7 and 8 in the attached pdf.

- Line 304: Please define precisely the concept of Lagrangian persistence in this context. It can be defined in many different ways depending on the type of the nowcast (i.e. grid- or object-based). Here it means that all storm attributes (not only the shape) are taken from the most recent values and they remain constant for all lead times. Right?

Yes, you are right. The following changes have been done in the text:

“where the $Error_{new}$ is the error manifested by the k-NN, the $Error_{ref}$ the error manifested by the Lagrangian persistence and the $Error_{impr}$ the improvement in reducing the error per each lead time. Here the Lagrangian persistence refers to as persistence of the storm characteristics (Area, Intensity, Velocity in X and Y Direction) as last observed and constant for all lead times.”

- Figure 6: ◦ In Table 1, the target variables A, I, V_x and V_y have the subscript denoting lead time. However, these are omitted in Figure 6. Thus, it is not clear to me what lead times do the correlations shown in Figure 6 represent. The text is just saying that the values are averaged from three different lead times. ◦ The correlations depend on the lead time. Would it make sense to show the correlations separately for each of the chosen lead times instead of averaging over different lead times?

At the end of section 3.1.3 the averaging of the three lead times was explained:

“Here in this study, these two importance analyses are used to determine the most important predictors and their respective weights in the k-NN similarity calculation. For each target variable the most important predictor identified from Pearson Correlation, is given to the PIC metric as the first predictor. The analysis is complex due to the presence of several predictors, 38 states of future behaviour for each target variable (for each 5min between +5min to +180

min lead times), and different times of nowcast; the weights were calculated first for three lead times +15min, +60min and +180 min, and for three storm groups separated according to their duration <60min, 60min-180min, and > 3 hours. Here the averages weights over these groups and lead times are calculated and used as a reference for each importance analysis. The k-NN errors with these average weights are compared in Section 4.1.”

We have added the correlations for each of the selected lead times in the Appendixes 8.1 and 8.2 (see tables in the pdf attached). The tables for both target-based and storm-based approaches and for the two important analysis methods are given here. The reason why we took the average from these three lead times is because we wanted to have only one set of weights independent of the lead times and storm types as a starting point for the nearest neighbour approach.

- Lines 365-366: This is difficult to follow. It is confusing that the authors mention both mean and median but are not showing the latter anywhere. In addition, you should clearly state in the caption of Figure 7 that it shows the mean.

In the first manuscript draft, the mean is used only for the training of the k-NN, because it is a typically used target optimization statistics. The median is used when validating the k-NN, because we were interested to see the error if the k-NN on the majority of the cases. However, in the new updated manuscript we are showing the median for all the results (both training) and validation (see Figure 7 and 8 in the attached pdf).

- Lines 391 and 397: The authors are using a confusing term "event-based" that is not defined previously. Does this mean storm-based?

Yes we meant “storm-based” and we have changed it accordingly throughout the text.

- Figure 7: The interpretation of the Total Lifetime figure on the right was not immediately clear to me. In particular, the connection of the black and red lines labelled as VS1 and VS2 to the boxes shown in the figure could be clearer.

We have updated the legend in all the Figures to make it clearer for the reader.

- Figure 9: ◦ What is the "Timestep of nowcast"? This should be clearly explained in the caption text. Now I found it from line 403 only after reading through the main text. ◦ As in Figure 7, it was not immediately obvious to me how to interpret the right pane.

Following the confusion reported by another reviewer and we have the term to Nowcast Time throughout the text and in the figures. The nowcast time is also explained on a new figure that we have included to explain the main terms. Please refer to Figure 3 in the attached pdf.

- Figure 10: ◦ Again, clarify the meaning of the "Timestep of nowcast". Please explain it in the figure caption.

The captions of all figures were updated accordingly. Please refer to the attached pdf.

- To me it is striking that in the worst case the 4-NN nowcast can perform more than 100% worse than the Lagrangian persistence. This is lacking discussion in the text that focuses mainly on the improvement from the Lagrangian persistence. ◦ My advice here is to explore, or at least mention the possibility of blending the Lagrangian persistence and the 4-NN nowcast by using weights that depend on the lead time. This would combine the strengths of both approaches.

The 4-NN nowcast can perform more than 100% worse than the Lagrangian Persistence mainly for the area as target variable, for short lead times ($LT < 30\text{min}$ so within the predictability limit of the Lagrangian Persistence) and for storms living more than 0.5 hour. For the storms living between 30min and 3 hours, for nowcast times 5min the area errors of the KNN are more than 100% bigger than the Lagrangian Persistence error for lead times up to 15min, while for the storms living longer than 3 hours they are higher than the persistence for lead up to 1 hour. This is expected at a certain extent, that for very low lead times, the autocorrelation governs and thus Lagrangian Persistence has very low errors. Since the errors are low and the improvement is obtained by diving with low error, the lower the error of Lagrangian the higher will be the deterioration on %. So, in my opinion, important is here than up to this lead time the given kNN cannot surpass the Lagrangian persistence, and persistence is behaving much better.

So to summarize, you are right one should merge the two models. As shown in Germann et al. 2002, for short lead times Lagrangian should be used (up to 20-30min) and after that a more complex model should be applied. The same is true here: the deterministic kNN can be employed for lead times past 30min. These results were of the deterministic nowcast, and we have included a new Figure that compares the CRPS of the ensemble with the MAE of the Lagrangian to see for what lead times the probabilistic nowcast are better (see Figure 13 in the attached pdf). The result of the ensemble follows same patterns of the deterministic 4-NN, but please pay attention that the deteriorations are not lower than 100%. This suggests that the probabilistic approach, i.e. single neighbours may be more useful than averaging through most similar neighbours (the case of the 4NNs).

- Figure 12: It could be more informative to compute instead the fraction of verifying observations within (or outside) the ensemble and average this statistic over the events. The "% of timesteps" statistic gives no information about this fraction.

The % of time steps is showing the fraction of the verifying observations within the ensemble range, but averaged for each nowcast time and storm duration groups. Do you mean to average this value for each event first and then for nowcast time and storm duration group? If so, we will update this Figure by showing the event average fraction of verifying observations that fall within the range of the ensemble members, shown for each lead time, nowcast time and storm duration group.

- Sections 4.2 and 4.3: The authors use the terms lead time and timestep interchangeably. When reading the text, their correspondence is not immediately clear to the reader (until the reader goes to Section 2 to recall that the time step is 5 minutes). Could you use only one of them?

Yes of course, we have updated the manuscript and tried to keep only the term lead time.

- Section 4.4: I have some doubts whether the "best ensemble member" or "% of ensemble members better than Lagrangian persistence" verification approach is meaningful. These are not standard verification metrics. In practice, one does not know a priori which ensemble members to choose to obtain the best forecast skill. There are more elaborate ways of showing the advantages of ensemble-based predictions over deterministic ones. For instance, you can compute the continuous ranked probability score (CRPS), which is a generalization of mean absolute error (MAE) for deterministic nowcasts. The CRPS of the ensemble nowcast should be lower than the MAE, which indicates the added value of the ensemble nowcast.

We have now computed only the Continuous rank probability score (CRPS) for the ensemble predictions, and the MAE for the deterministic nowcast. The Figures 11 and 12 in the attached pdf show the ensemble and deterministic results for both k-NN approach; the storm based and

target based. These Figures are included in the new updated version of the manuscript. As you see for both storm-based and target-based approach, the errors of the ensemble nowcast are lower than the deterministic nowcast for all nowcast times, storms groups and target variable – hence the added value of the ensemble nowcast. This suggests that the nearest neighbour approach should be better implemented in an ensemble approach and not by averaging the closest neighbours. As seen in the training of the kNN, a proper converging of the K-number was not possible (as the number of k to average is depending on the nowcast and lead time). This problem of training can be avoided on the ensemble nowcast and the result show that the errors are lower than in the case of the deterministic approach.

- Line 511 onwards: I guess that the authors mean individual ensemble members, not whole ensembles?

Yes, we were referring to individual ensemble members.

- Lines 538-539: Can you give some numbers to describe what are the fine spatial and temporal scales?

The following changes have been done in the text:

“Accurate predictions of rainfall storms at fine temporal and spatial scales (5min, 1km²) based on radar data are quite challenging to achieve.”

- Line 546: Where does the number 5200 come from? It is mentioned for the first time in the conclusions. Perhaps it should be mentioned in Section 2 as well.

The following description was mentioned in Section 3.1.1:

“These storms characteristics were obtained by an hindcast analysis run of all 110 events with the HyRaTrac algorithm which resulted in around 5200 storms.”

Technical corrections

- I'm not sure if it's proper to use the word "object-oriented". It refers to programming terminology. Could you use object-based instead?

I agree with your concern and it can also be changed to object-based. However, in some literature that we cite (Hand 1996; Rossi et al., 2015), it is already mentioned as “object-oriented”, while in others as object-based (Zahrei et al., 2013). For this reason, we mention as “object-oriented” the first time in the introduction, but we clarify that in order to avoid confusion with the programming term we refer as the object-based nowcast.

Hand, W. H. (1996). An object-oriented technique for nowcasting heavy showers and thunderstorms. *Meteorological Applications*, 3, 31–41.

<https://doi.org/10.1002/met.5060030104>

Rossi, P. J., Chandrasekar, V., Hasu, V., & Moisseev, D. (2015). Kalman filtering-based probabilistic nowcasting of object-oriented tracked convective storms. *Journal of Atmospheric and Oceanic Technology*, 32(3), 461–477. <https://doi.org/10.1175/JTECH-D-14-00184.1>

Zahraei, A., Hsu, K. lin, Sorooshian, S., Gourley, J. J., Hong, Y., & Behrangi, A. (2013). Short-term quantitative precipitation forecasting using an object-based approach. *Journal of Hydrology*,

- Figure 2: Should the legend read "Lower Saxony border"?

Noted and changed!

- Line 211: important ← importance?

Noted and changed!

- Lines 226-227: "the α_j the predictors weight" ← " α_j denote the predictors weight"?

Noted and changed!

- Line 256: 30-ensembles ← 30-member ensembles?

Noted and changed!

- Line 447: persistence ← persistent?

Noted and changed!

- Line 544: behaviours ← behaviour

Noted and changed!

- Line 578: An increment in the sample size ← Increase in the sample size?

Noted and changed!

- Figure 6: Should this be titled as a figure or a table?

We changed it to a table title.

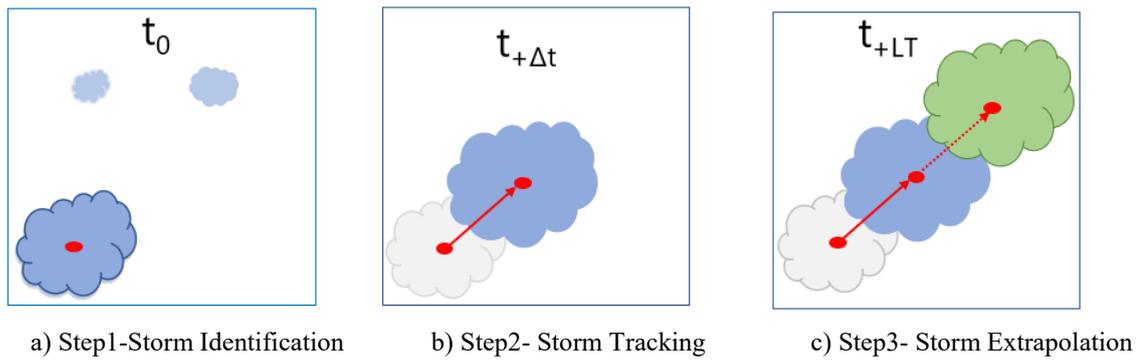


Figure 1 The main steps of an object-based radar nowcast. Blue indicates the current state of the storm at any time t , grey indicates the past states of the storm (at $t-\Delta t$), and green indicates the future states of the storm ($t+LT$) (Shehu, 2020)

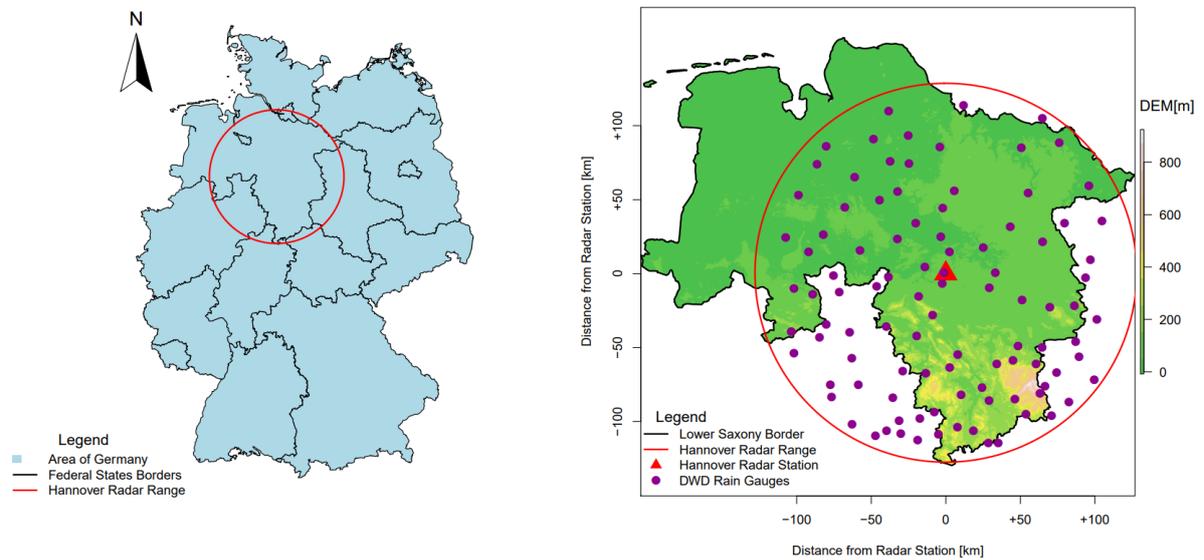


Figure 3 The location of the study area left) within Germany and right) with the corresponding elevation and boundaries, and as well with the available recording rain gauges (purple) and radar (red) station. The DEM is short for Digital Elevation Model.

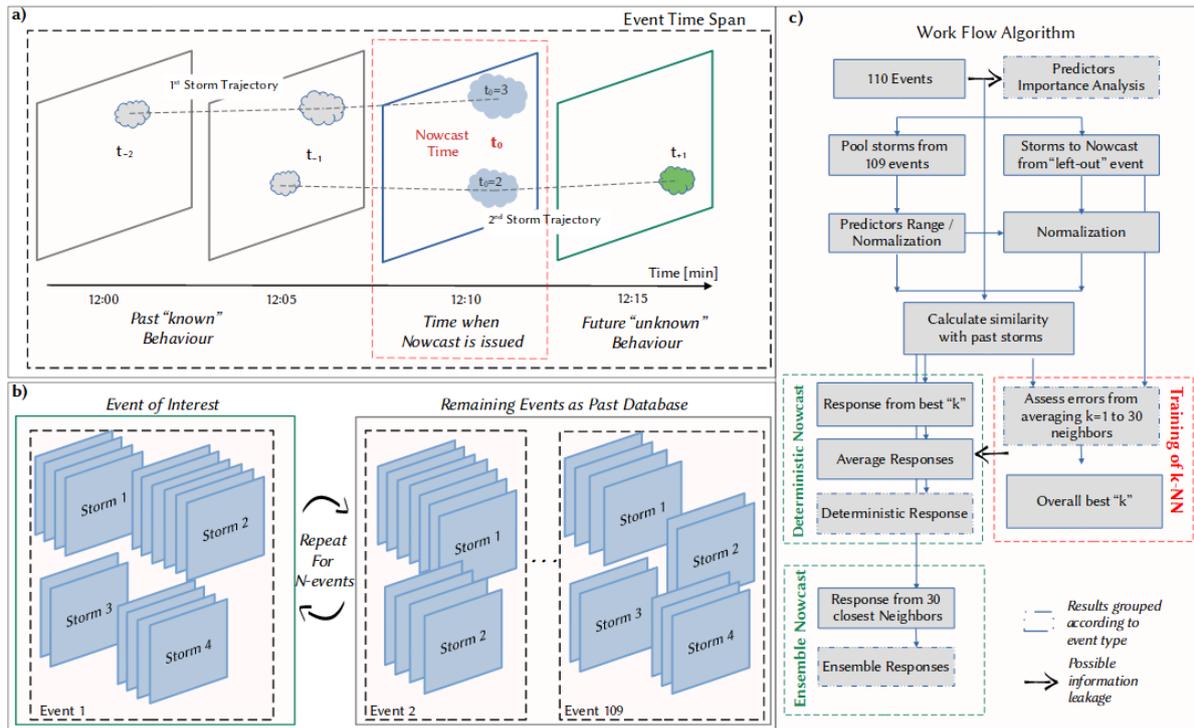


Figure 5 Illustration of concepts and workflows in this study a) an event contains many rainfall storms inside the radar range which are tracked and nowcasted: the dashed grey lines indicate the movements of storms in space-time within the radar event and the event time span. b) The “leave-one-out-event 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.

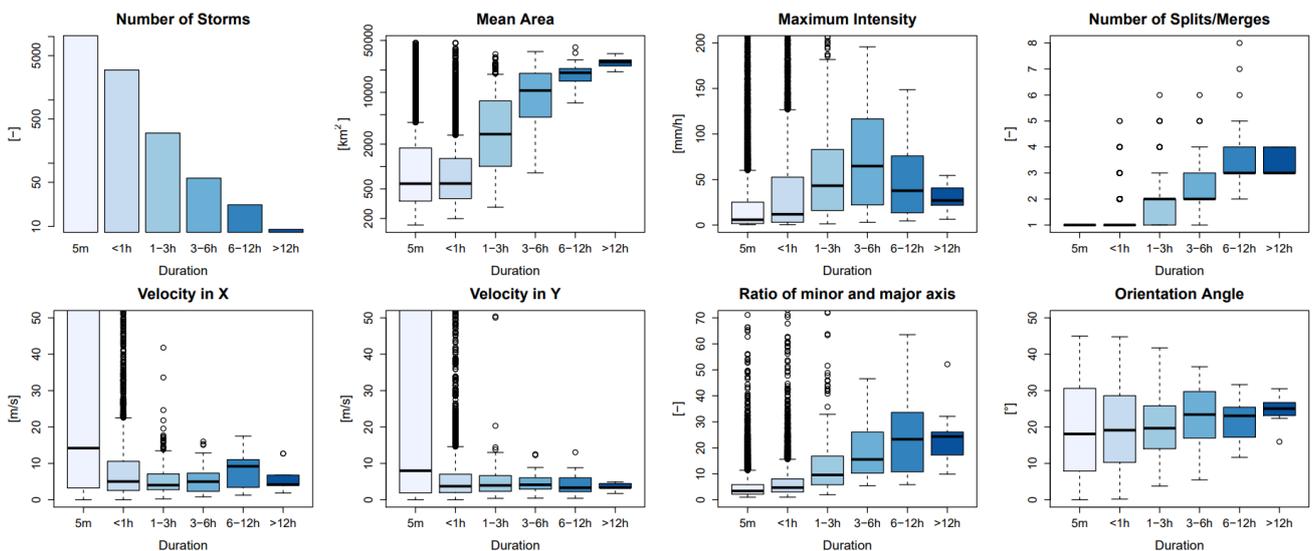


Figure 4 Different properties of the storms recognized from 110 events separated into 6 groups according to their duration (shown in different shades of blue)

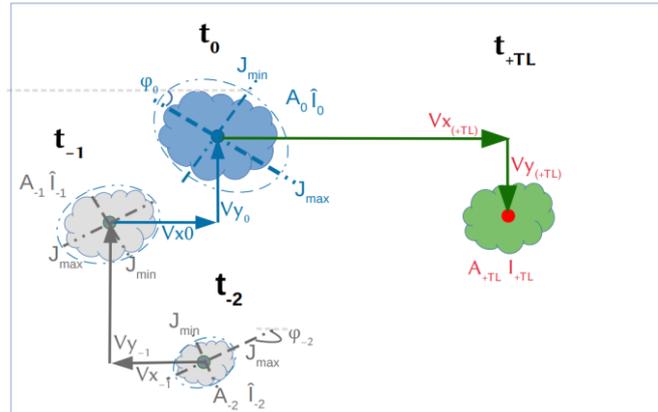


Figure 7 The features describing the past (grey) and present (blue) states of the storm used as predictors to nowcast the future states of the storm (green) at a specific lead time (T_{+LT}) that is described by 4 target variables (in red). The nowcast is issued time t_0 . A full description of these predictors and target variables is given in Table 1.

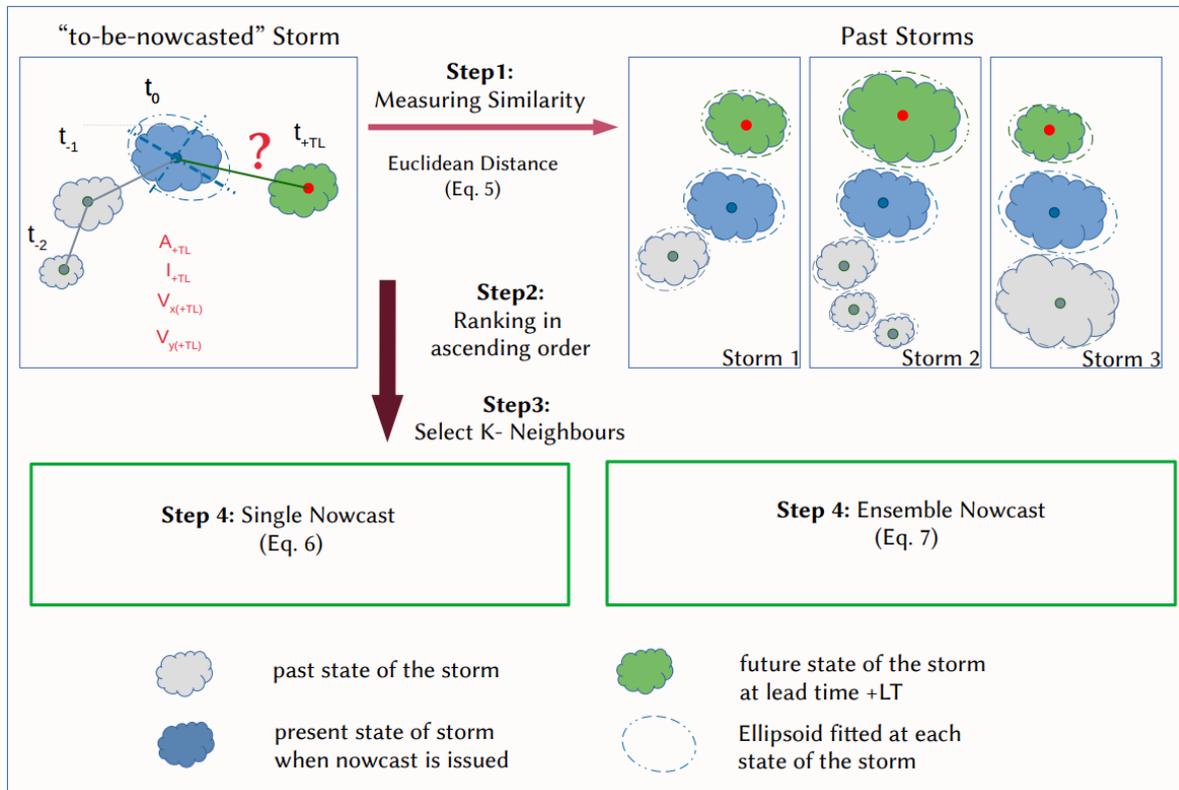


Figure 6 The main steps involved in the k -NN based nowcast with the estimation of similar storms (Step 1 to 3) and assigning the future responses of past storm as the new response of the “to-be-nowcasted” storm either in a single nowcast (Step4-left) or in an ensemble nowcast (Step4-right).

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
	V _x	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
	V _y	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	0.01	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	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	
	V _x	0.00	0.00	0.00	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	
	V _y	0.00	0.00	0.00	0.00	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	
	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	0.33	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

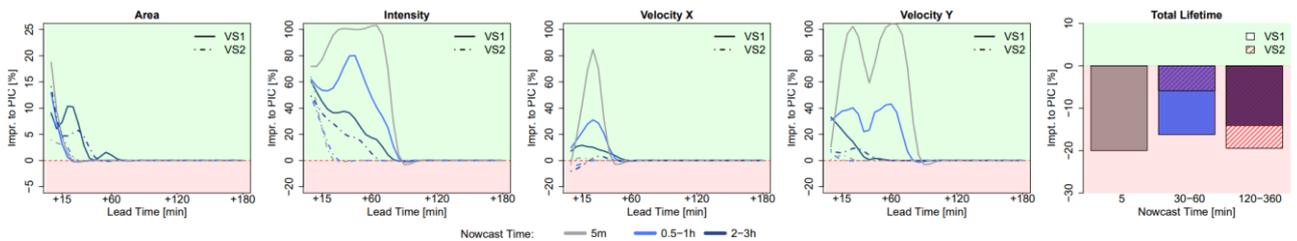


Figure 8 The median Mean Absolute Error (MAE) improvement per lead time and target variable from applying the k -NN (VS1 target-based, VS2 storm-based) with the predictors and weights derived by the Pearson correlation instead of PIC. The improvements are averaged for different times of nowcast. The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

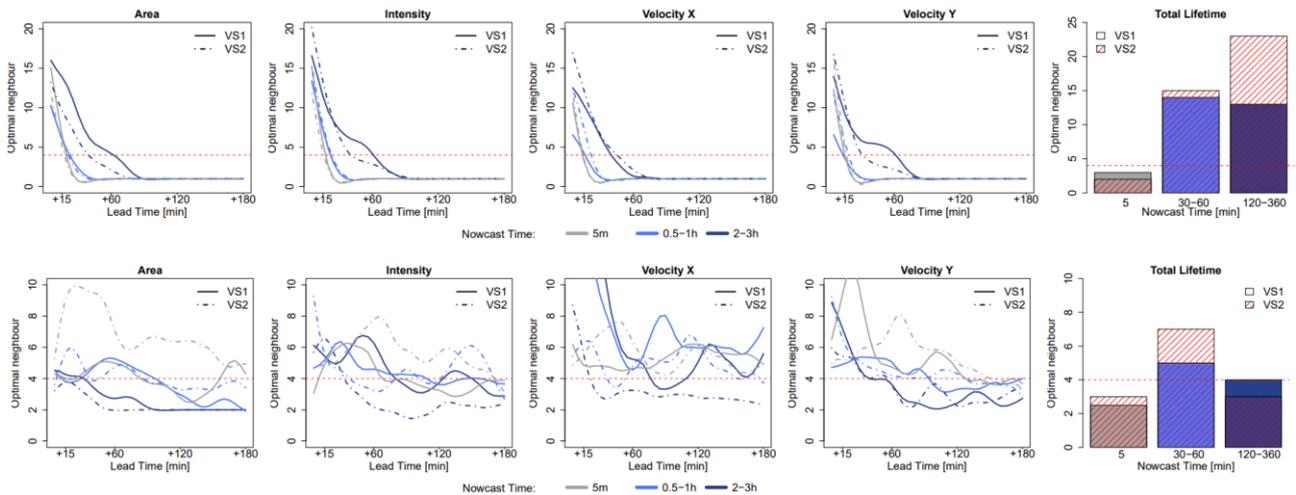


Figure 9 The training of the k -NN per target variable based on predictors and weights derived from Pearson correlation analysis: the optimal selected “ k ” neighbours yielding the lowest absolute errors. Two k -NN applications are shown here – VS1 in solid line and VS2 in dashed line: First row – The 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.

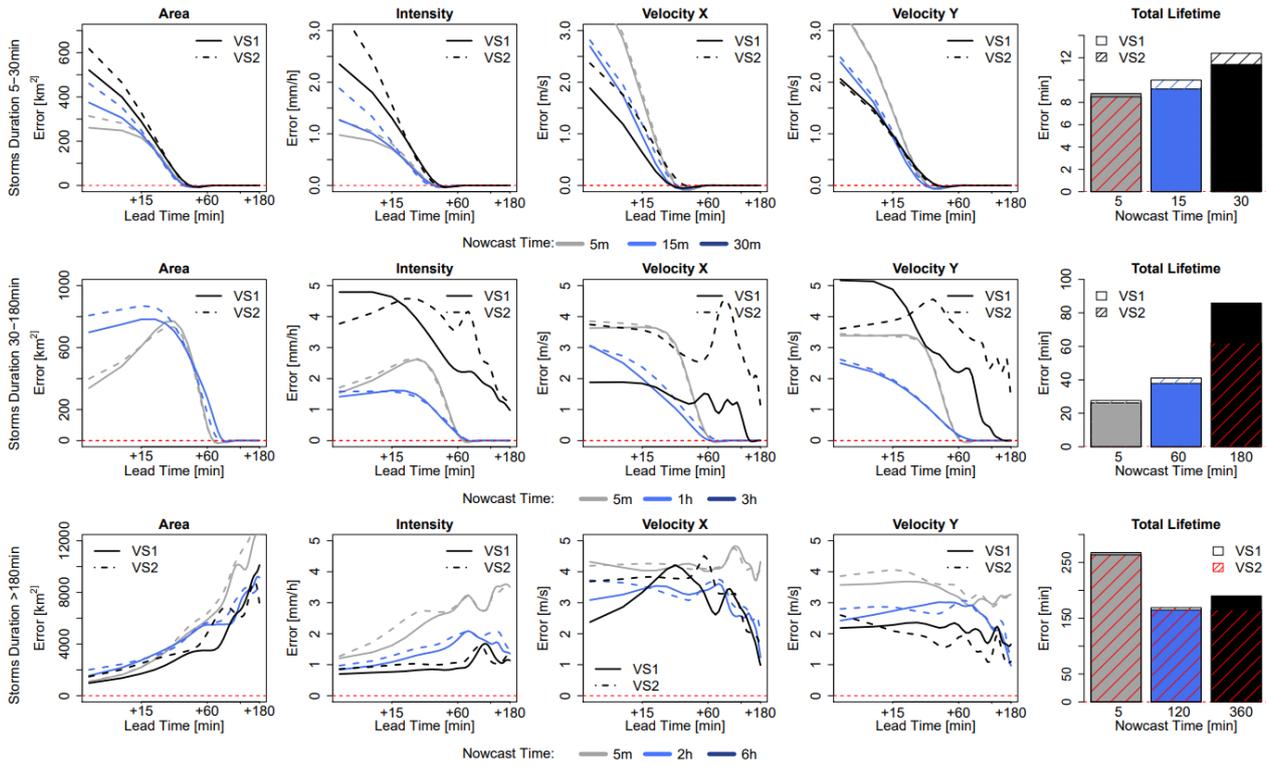


Figure 10 The median absolute error for each target variable (Area, Intensity, Velocity in X and Y direction and Total Lifetime) based on two 4-NN applications: -VS1 in solid and VS2 in dashed lines. The median errors are computed over storms that are: shorter than 30 min (upper row), than 3 hours (middle 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%

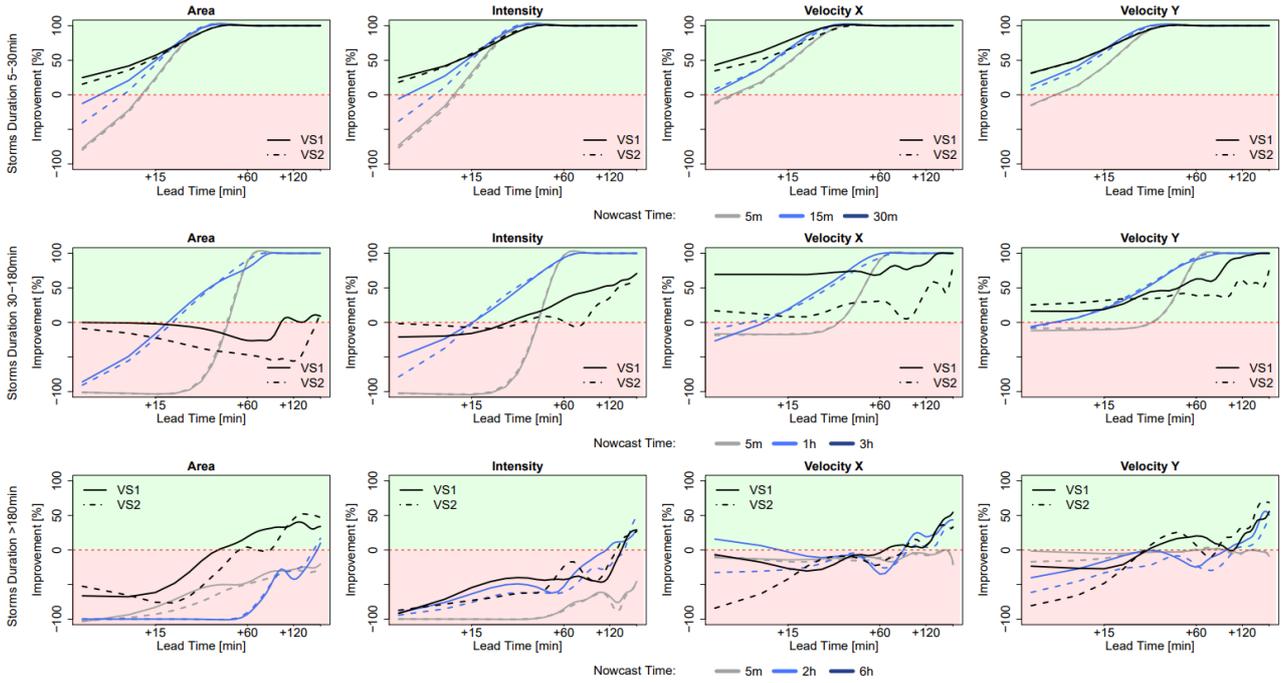


Figure 11 The median improvements that the single 4-NN nowcast can introduce in the nowcast of the target variables (Area, Intensity, Velocity in X and Y direction) in comparison to the Lagrangian persistence. The results are shown for each 4-NN application: VS1 in solid and VS2 in dashed lines and are 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).

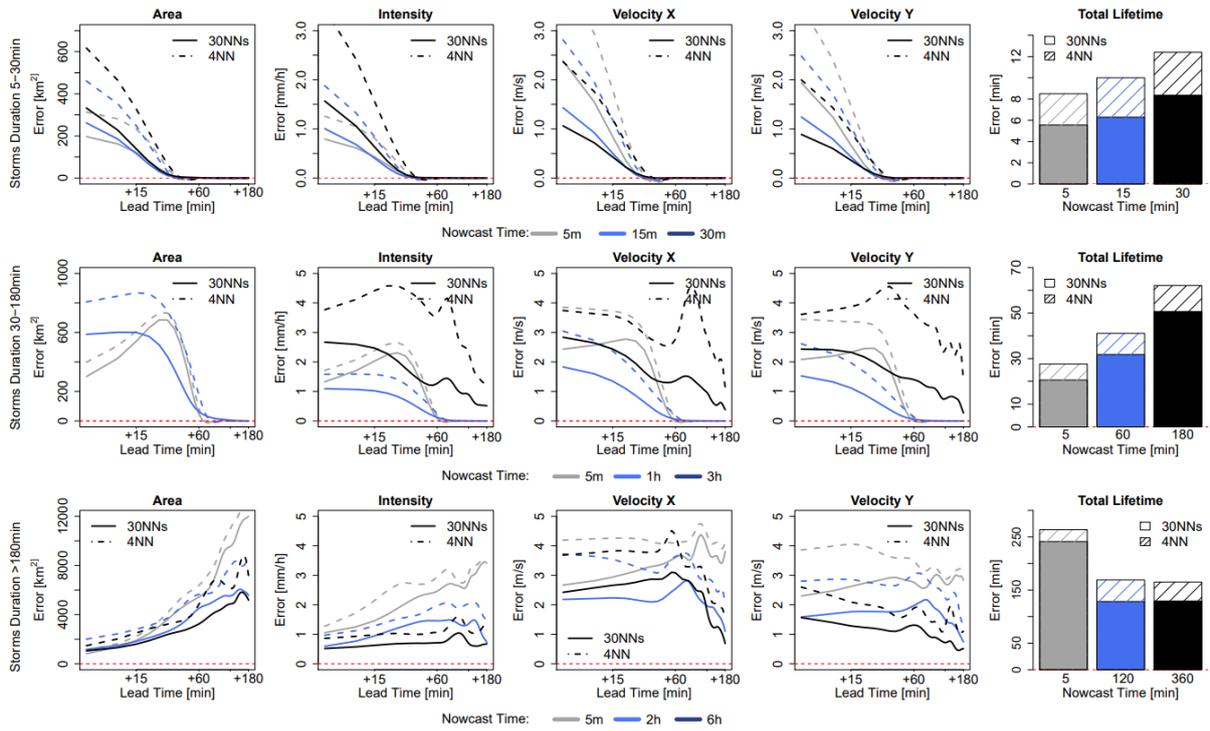


Figure 11. The median absolute error for each target variable (Area, Intensity, Velocity in X and Y direction and Total Lifetime) on the storm-based applications: -4NN (deterministic) in solid and 30NNs (probabilistic) in dashed lines. The median errors are computed over storms that are: shorter than 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.

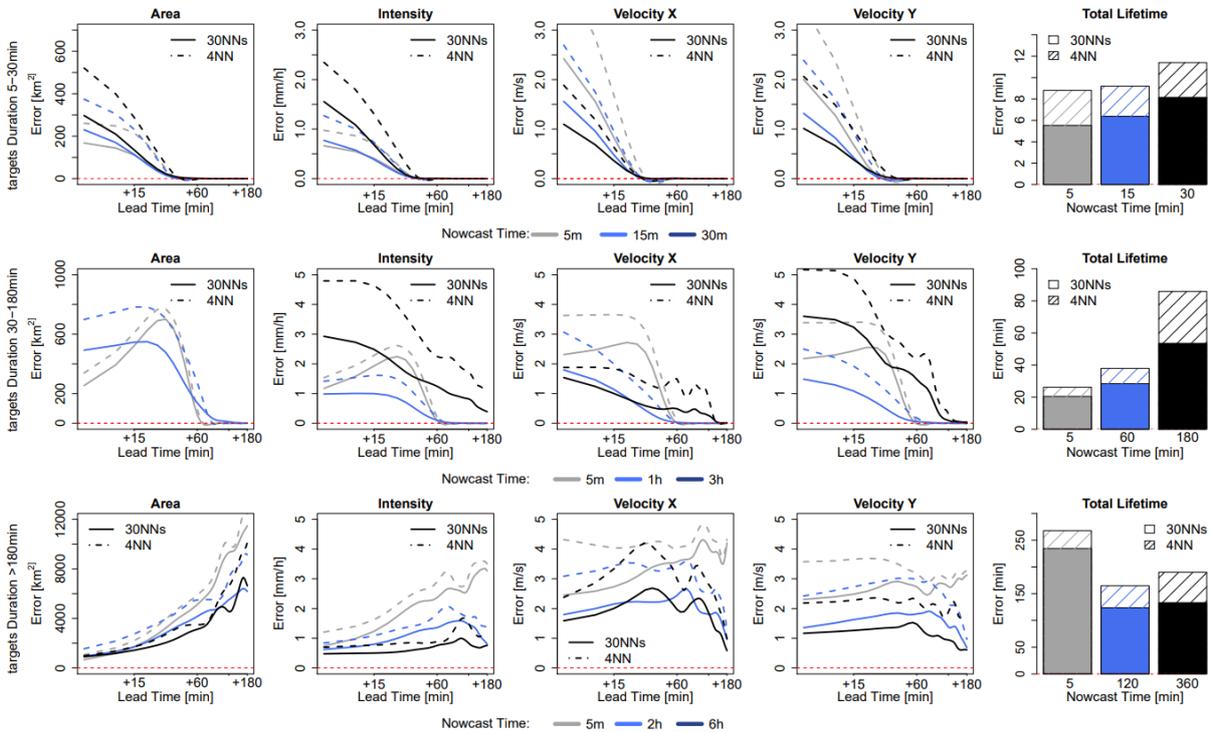


Figure 12 The median absolute error for each target variable (Area, Intensity, Velocity in X and Y direction and Total Lifetime) on the target-based applications: -4NN (deterministic) in solid and 30NNs (probabilistic) in dashed lines. The median errors are computed over storms that are: shorter than 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.

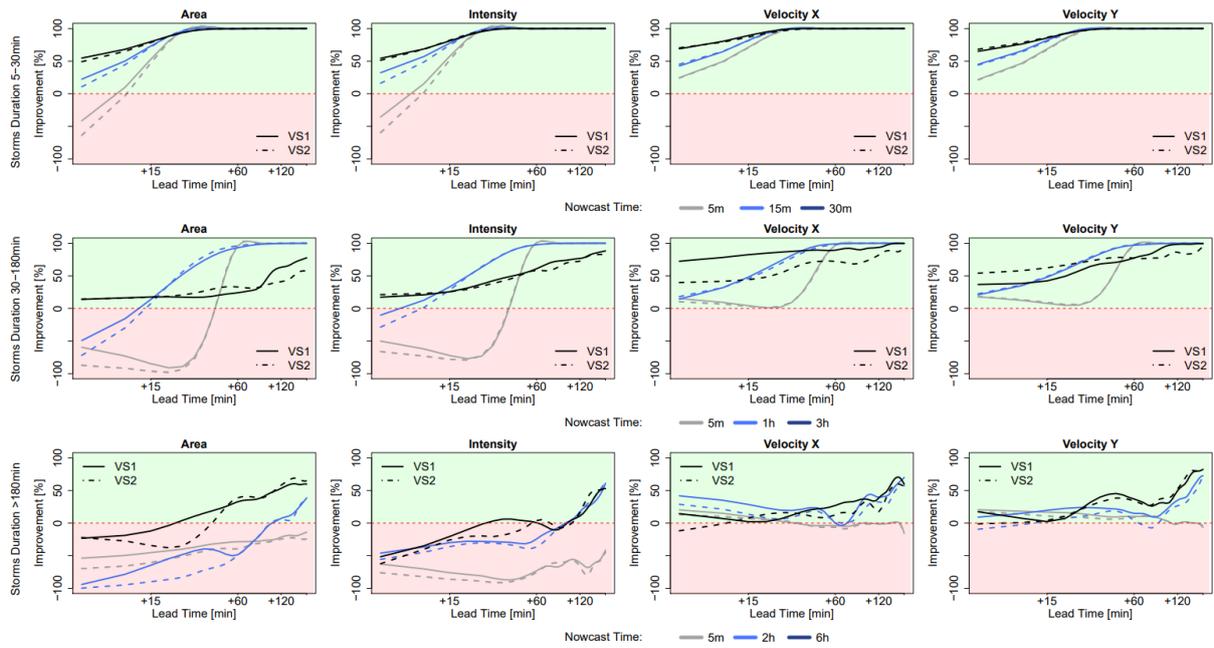


Figure 13: The median improvements that the 30NNs nowcast can introduce in the nowcast of the target variables (Area, Intensity, Velocity in X and Y direction) in comparison to the Lagrangian persistence. The results are shown for each 30NNs application: VS1 in solid and VS2 in dashed lines and are calculated 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).

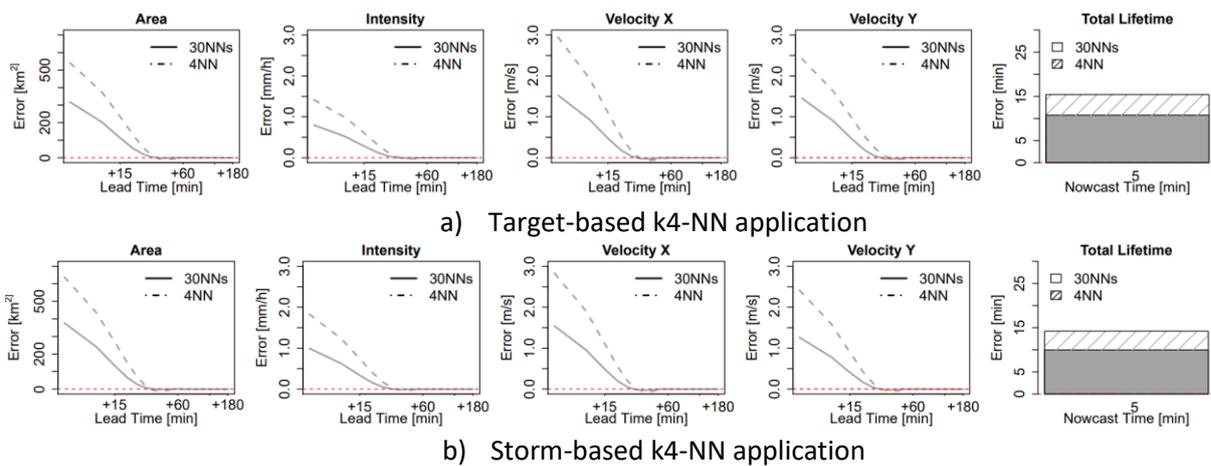


Figure 14 Median Error Performance for each of the target variables nowcasted from k4NN deterministic and 30NN probabilistic application for both target (upper row) and storm-based (lower row) kNN. The results shown here are only from the “unmatched storms” when the nowcast time is 5 min

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	GVel	Vx	Vy	Jx	Jy	Jr	Phi	A	avePI	medPI	maxPI	sdPI1	sdPI2	Vg	Vx	Vy	Jx	Jy	Jr	Phi	
Area	15min	0.19	0.22	0.31	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	
	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	
	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
	Intensity	15min	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
		60min	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
180min		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	
15min		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	
60min		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	
180min		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	
15min		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	
60min		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	
180min		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	
60min		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
Velocity X		15min	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
	60min	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	
	180min	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	
	15min	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	0.04	0.00	0.35	0.42	0.05	0.16	0.07	0.01	0.05		
	60min	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	
	180min	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	
	15min	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	
	60min	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	
	180min	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	
	60min	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	0.02	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
	Velocity Y	15min	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
60min		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	
180min		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	
15min		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	
60min		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	
180min		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	
15min		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	
60min		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	
180min		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	
60min		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
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	0.2			

