Dear Georgy,

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

Major Comments:

Research Aim: The decision to predict individual storm characteristics, i.e., area, mean intensity, x and y components of velocity, and lifetime, instead of predicting the entire storm evolution as an integral object should be elaborated. In general, I understand the utility of predicting individual characteristics. However, in this way, we miss the detailed information about storm event spatiotemporal evolution and could not precisely estimate neither location nor intensity-related errors. For example, the spatial structure and distribution of rainfall intensities within the storm event are particularly relevant for urban applications. The example of the possible utilization of the predicted (individual) properties could help to clarify their choice.

> Yes of course, your concern is right and we will discuss it better in the updated version of the manuscript. In this paper we focus only on the storm characteristics to see, first if the k-NN application is suitable (either deterministic or probabilistic). Once the storm characteristics can be properly nowcasted, there are two options to deal with the spatial distribution of the rainfall intensities inside the storm region: 1. Increase/Reduce the area by the given nowcasted area (as target variable) for each lead time, scale the average intensity with the nowcasted intensity, and move the position of the storm in the future with the nowcasted velocity in x and y direction. 2. Take the spatial information of the selected neighbours (with the method we propose here), perform an optimisation in space (such that present storm and the neighbour’s storms locations match) and assign this spatial information to the present storm for each lead time. This will be done in a follow up paper. That is why we will check with the editor to see if the title can be changed to “Part I – Storm Characteristics”, to give the idea that this is only the first step, and the follow up paper will be “Part II – Rainfall Intensities at 1km^2”.

Database: The authors declare that the compiled dataset includes outliers (L198). That leads to the mixed-use of mean or probability-based (e.g., median) statistics. It is pretty hard to recognize and remember where and why the mean or median statistics are used. Moreover, the authors often describe the need to use mean/median for (not) accounting outliers but rarely communicate the obtained results based on that choice. Thus, it is interesting what is the proportion of outliers in the compiled database and could they be removed for the sake of consistency of mean/median statistics throughout the manuscript.

> 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: training and validation. Please refer to the updated Figures in the attached pdf.

The compiled database of storm events is based on the open data provided by the German Weather Service. Is it possible to share it? It would serve both manuscript's reproducibility and community interests in the field of storm tracking and prediction.

> Yes, the complied database of the storm events is based on the open data from the DWD. However, the tracking algorithm used as a basis for this study (HyRaTrac) is not open for public (or at least I have to ask the person who created it). But What I can make public is database of the storm characteristics and the application of the k-NN on these storm characteristics.

Baseline: The utilization of Lagrangian persistence as a baseline is reliable, and obtained results are interesting to compare. I recommend authors provide additional information about it (how nowcasted is computed etc.) to account for inexperienced readers.

> Following the comments of the other reviewers as well, we have updated the introduction to the topic to include more information for the inexperienced readers.

In Section 4.4., the authors compare the closest single neighbor and 30-member ensemble approach. Do the authors mind finding the single nearest neighbor as a more advanced baseline compared with four and 30-member ensemble solutions? It would then pose an additional research question (partially touched in Sect. 4.4) of an added value of ensemble approach compared to the single neighbor.

> In section 4.4 we do not compare the closest neighbour with the 30-member ensemble approach. The ensemble member is issued randomly based on the rank probability of the 30-closest neighbour. In this section, we assess the best possible outcome from the ensembles – which is the ensemble with the lowest error. This suggests that the predictors selected and their weights are not able to select the best single neighbour at the deterministic approach, that is why an ensemble approach is better (as it is not so dependent on the number of K to average, and the predictors weights). Following the comments of another reviewer, we have calculated the continuous rank probability score (CRPS) for the ensemble members, which is a generalization of the mean absolute error and ensures a direct comparison with the deterministic approach. The Figures 11 and 12 of the CRPS together with the mean absolute error (MAE) of the deterministic 4-NN for the two cases (storm- and target – based) are shown in the attached pdf. It is clear that the errors of the ensemble members are lower than the 4-NN approach, thus it is clear that the ensemble approach is more suitable.

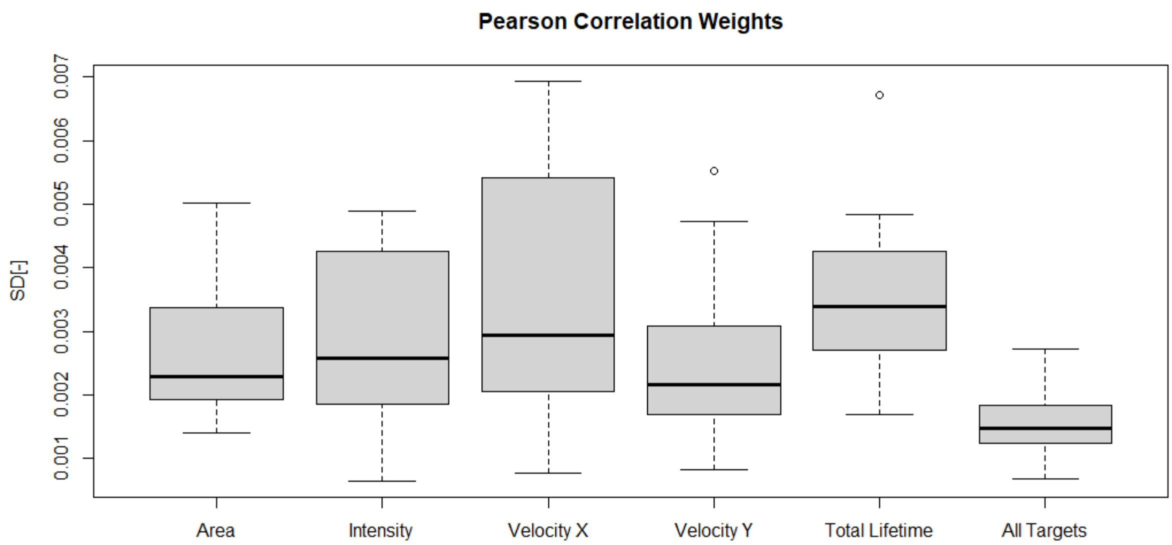
Information leakage: In modelling studies, it is particularly relevant to isolate calibration, validation, and test datasets to prevent so-called information leakage -- the situation when the information outside the calibration set is used for model calibration (training). In the presented study, I suspect four procedures that may lead to information leakage:

1. Normalization of events characteristics.
2. Importance analysis and weights calculation.
3. Optimization of the number of nearest neighbours.
4. Splitting into different event groups.

The authors state that normalization and importance analysis have been done "Before training and validating the k-NN method" (L191). In this way, there is an evident information leakage that connects calibration and validation datasets. Also, it is not clear how calibration and validation datasets have been isolated to find the optimal number of nearest neighbours. I do not think that addressing data leakage would change the results much, but it is vital to ensure methodological reliability.

> Regarding the importance analysis and weights calculations: In this application the information leakage may occur only at the important analysis and the weights calculations. Here all the

events are grouped together to check the relationship between predictors and target variables, and the importance weights are calculated. In the case of Pearson correlation, the weights are not changing drastically when one event is left out and the weights are calculated from the remaining events. This is not the case with the Partial Information Correlation, the weights are changing from one set to the other, that is why we also preferred the Pearson Correlation and the PIC. Since we have disregarded the use of the PIC for the weight calculations, here I would like to show you the results of the Pearson Correlation weights, how much they change when one event is left out (out at a time) and the weights are calculated from the remaining events. The following events indicate the standard deviation of the predictors' weights for each of the target variable computed from leaving one event out. The boxplot represents the standard deviation of the selected predictors. As you can see the deviation of the weights between the predictors and target variables is very low (lower than 0.01). This low variability of the predictors weights justifies our decision to estimate the weights from the whole database. While this is clear for the Pearson correlation, the same can not be said for the partial information correlation. Moreover, a sensitivity analysis like this can not be performed for the PIC because is extremely time consuming.



Regarding normalization of event characteristics: Here no information leakage is possible, because both pseudo-training and the validation of the k-NN is done on a "leave-one-out-event" approach. This means one event at a time is taken out of the database, and the past database that is used for the prediction has the remaining 109 events. The normalization of the event characteristics is then done only based on this past database, thus for the event nowcasted the values of the characteristics can be higher than 1 if they have higher values observed then in the past database. This procedure is done 110 times.

Regarding optimization of the number of nearest neighbours: As stated before this is also done is a "leave-one-out-event" approach. So, the optimum k for that event is found by the remaining past database. The optimum k is grouped then (only the results) according to the time when the nowcast is issued (nowcast time) to see how this value of K is changing with the lead time and with the nowcast time (see Figure 8 in the attached pdf). As it visible there is no clear best optimum k, and we selected the k=4 as a first attempt to reach this optimum. An information leakage would then be if we used the optimum k for each storm duration and lead time (results of this k-NN pseudo-training).

Regarding Splitting into different event groups: Im a bit confused about this. We do not use the information of different event groups prior, they are just used posterior. So the k-NN event is run with all durations together, and only later on the results are computed for different groups, so we can understand with groups are nowcasted better than the others.

We have included in Figure 3 were potential information leakage may occur and we will discuss it better in the paper.

Splitting the database into three groups according to their duration (L312-317, Table 2) was done before the modeling. In general (and in practice), we do not know a priori if the recently appeared storm will be sporadic or last for a couple of hours or more. So, in my opinion, in making predictions, we should use all the examples from the database to find closer candidates to be used for predictions, not only those from the group of a similar duration. That also would open the new directions of analysis, e.g., how would closest examples change with the storm's evolution. Is the more mature storm similar to storms with comparable duration, or is there some skew in characteristics similarity?

No, the database was not split into three groups before the modelling! Table 2 is just informative to see how many storms belong to each group, that can explain the effect of the database size on the results. K-NN doesn't know before that a storm is belongs at a particular duration, it just calculates based on the past database (all storm durations included) the most similar storms and take the response of the most similar storms. This is the case for instance of Figure 10, second row for nowcast time at 36th time step of storms existence. The k-NN is not able to find storms that have similar durations, but finds similar storms from the ones that have a long duration, and hence it overestimates the total lifetime of the storm and the rainfall area. So, to conclude, the storms durations (these three groups) are just use to summarize the results, to see which type can be simulated better, the k-NN is performed on the past database with all the storms grouped together.

We will try to clarify this better in the updated version of the manuscript. We have also included a new Figure (See Figure 3 in the attached pdf) that hopefully will make the work flow clearer.

The minor but also critical comment here is about the research code availability. For sure, open code would ensure research reproducibility and provide information on particular details of the computational workflow.

I hope Figure 3-C can make the workflow clearer. Due to time constrains at the moment we can not upload the R-codes, but we will soon do this.

Training, learning, and cross-validation:

The authors use terms of training and cross-validation, but, in my opinion, the presented manuscript does not involve both procedures. The nearest-neighbour model is not trained per se; it only uses a bag with historical examples to find one closer to the "storm-to-be-predicted" based on the similarity metric. In this way, the nearest-neighbour model also does not learn anything as it has no parameters to learn. The only parameter here is the number of the nearest neighbours to use for predictions. However, the choice of that number is entirely subjective (see comment above) and is independent of both the "storm-to-be-predicted" and the available examples and their characteristics. I would also question the use of the term cross-validation. There is no numerical model to validate as the nearest neighbour approach is instead a database search method than a "pure" numerical model.

Yes k-NN is a parsimonious model based on the past database, and is a lazy learner as it is entirely dependent on the past database. And yes, the k-value is the only parameter so to say that can be optimized or learned by having an optimization function. This is what we tried to do in the training/learning of this k-parameter, but the response we got was very dynamic in respect to the lead time and nowcast time. A proper learning of this k-values seems not to be possible for the nowcast application as there is not a single optimum reached and there are too many degrees of freedom (lead time and nowcast time) and instead we decided on a k-value. These are the disadvantages of the deterministic application of the k-NN (and we wanted to show actually that). We could also choose to show the deterministic application with the first neighbour, nevertheless that would have been criticized because it is always arguable that the value k-could have been optimized. Instead the probabilistic application of the k-NN doesn't have this problem because it doesn't need a training, and is taking the 30 closest neighbours (and it works better than the deterministic approach). However, I agree that this is not well discuss in the paper and we are trying to make it clearer in the updated version. We could refer to training also as pseudo-training and explain it to the reader that is not a proper training as for instance in the training of an artificial neural network.

Regarding the use of the cross-validation term, I do not agree fully with you. Even though this is not a numerical model, and even in the case it doesn't have parameters, the database search has still to be tested and to be validated that it works good enough. Cross-validation is a broader term not only for numerical models, and it refers to as out-of-sample testing of any model, regardless of what the model is made of (or what inside the model). As we want to check/test how well our past database can simulate a new event outside of our sample, and repeat this for N times, I think it lies within the definition of the cross-validation.

The authors explicitly communicate the aim of the study as "... to investigate if non-linear relationships learned from past observed storms can surpass the Lagrangian persistence and extend the predictability limit of different storms." However, as I mentioned above, the nearest neighbour model does not learn anything. It is also an open question if there are non-linear relationships (and what kind of relationships).

I think you might confuse the terms a little bit. Lagrangian persistence is a linear extrapolation in the future; constant area, intensity and movement. The "non-linear relationships" referred to here refers to the ability to included other non-linear extrapolations for the future: so the area, intensity and movement are changing with the lead time. More importantly that the storms can be dissipated because in the linear extrapolation of the Lagrangian persistence this is completely ignored. This is what we refer to with non-linear relationship – a non-linear extrapolation is time that can be learned or obtained from the past database. The phrase will is also now updated to:

"… to investigate if non-linear relationships estimated from past observed storms can surpass the Lagrangian persistence and extend the predictability limit of different storms…"

In the application of the kNN, it is clear that the storm dissipation can be captured better than the Lagrangian persistence, hence there is a non-linear behaviour of the storm that can be estimated based on a past database.

Minor comments:

● "Birth" → "initialization"? Noted and changed!

● "Death" → "dissipation"? Noted and changed!

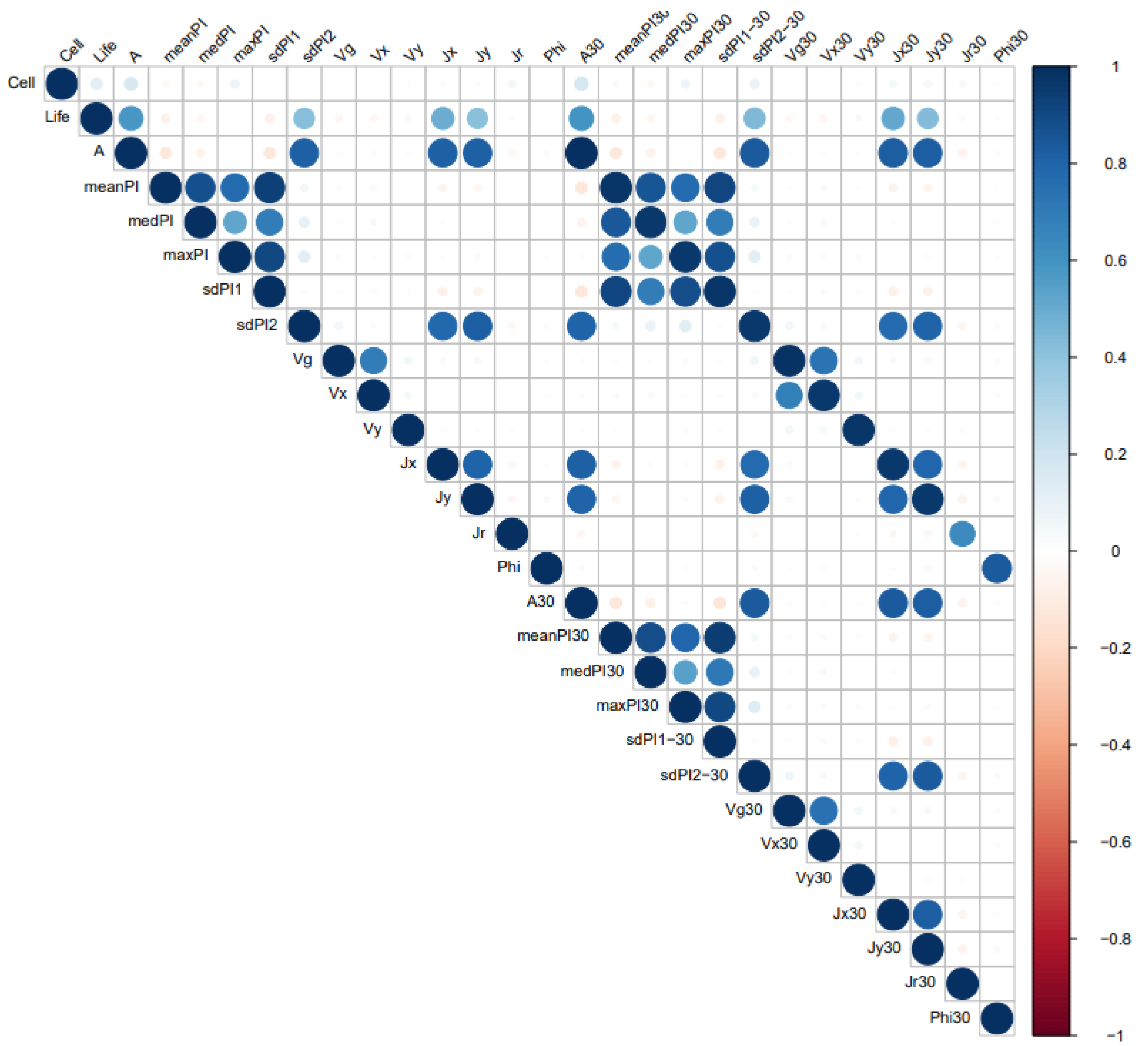
● L98: "k-NN." The first appearance needs transcription. Noted and changed!

● The orientation feature is in degrees. I wonder how the difference between 1 and 359 degrees is considered.

The orientation feature is expressed in degrees from 1 to 180 degrees with positive sign between 1 and 180 degrees and negative sign between 180 and 360 degrees (-180 to 0). So when considering the difference between 1° and 359° degrees (-1°), the difference will be 2 degrees.

● Interestingly, the area and number of storm cells do not show similar behaviour in importance analysis, but they are highly correlated.

I'm not sure I fully understand what you mean. The following figure shows the correlation between the predictors, and the number of storm cells are not highly correlated with the area, this is as well portrayed in the importance analysis. Please note that the number of the storm cells refers to the co-existence of storms in a split or merge situation, so there are two storms for instance but they are treated as one, and is not to be confused with the number of storms inside an event.



● L261-262: "Only neighbours that display a distance lower than 0.5 are selected for both single and ensemble nowcast in order to minimize the influence of non-similar storms." Any statistics of that?

The value 0.5 represents the 95% quantile of the calculated distances all the first 4 neighbours 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 distances.

● Figure 6: "The weights given here are averaged from the weights calculated at three different lead times and storm durations." However, the authors then mention (L341-342): "Contrary for Total Lifetime and Area, only for storms that last longer than 3 hours, the method is able to converge and give the most important predictors." However, we cannot see these results.

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 appendix. The tables for both target-based and storm-based approaches and for the two important analysis methods are given in the attached pdf (Appendix 8.1 and 8.2). 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.

● L348-349: "is not completely understood and is not investigated further on for the time being since it is outside the scope of this paper." But, from the abstract and introduction: "i) what features should be used to describe storms in order to check for similarity?" Thus, it is probably in the scope of the paper.

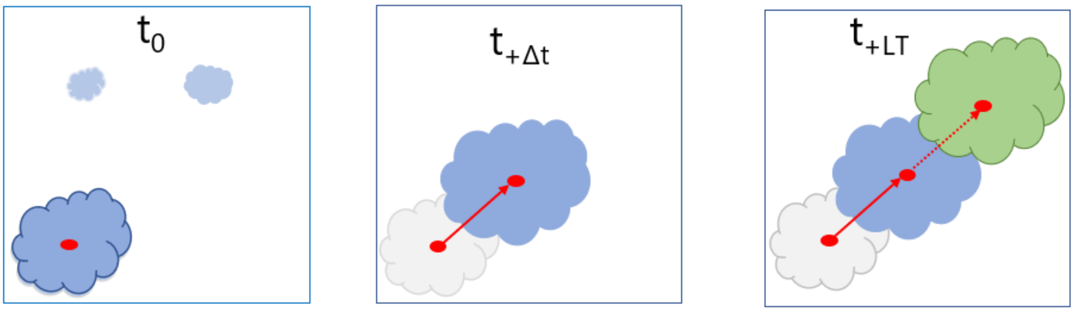
The PIC was built specifically for the k-NN application, nevertheless on our experience the PIC seems not so robust; as the values were changing depending on the database or if one randomly chose the events to be feed in the importance analysis. As mentioned in the paper, one of the main reasons why it works for the duration and not the other target variables are the presence of the zero values. When too many zero are present, the distribution is skewed and affected the calculation of the partial dependency. Also, when the data set is to big, based on personal experience the PIC is very time consuming and fails to converge. On the other side, the Pearson correlation seems to yield reasonable and stable results. Thus, we continue the k-NN application with Pearson correlation instead of with the PIC application, to identify the features that best describe similar storms. To understand fully why PIC specifically behaves like it does, was not the scope of the paper. What features should be used to describe storms to check for similarity is investigated with the Pearson correlation.

● L354-355: "Moreover, the important predictors do not change drastically from one lead time or storm group to the other, as seen in the PIC" Could we see it from any table or figure?

Please refer to the table above for the PIC weights.

● Figures: larger fonts and more vertical space between different types of events would be appreciated

Noted and implemented.



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)*

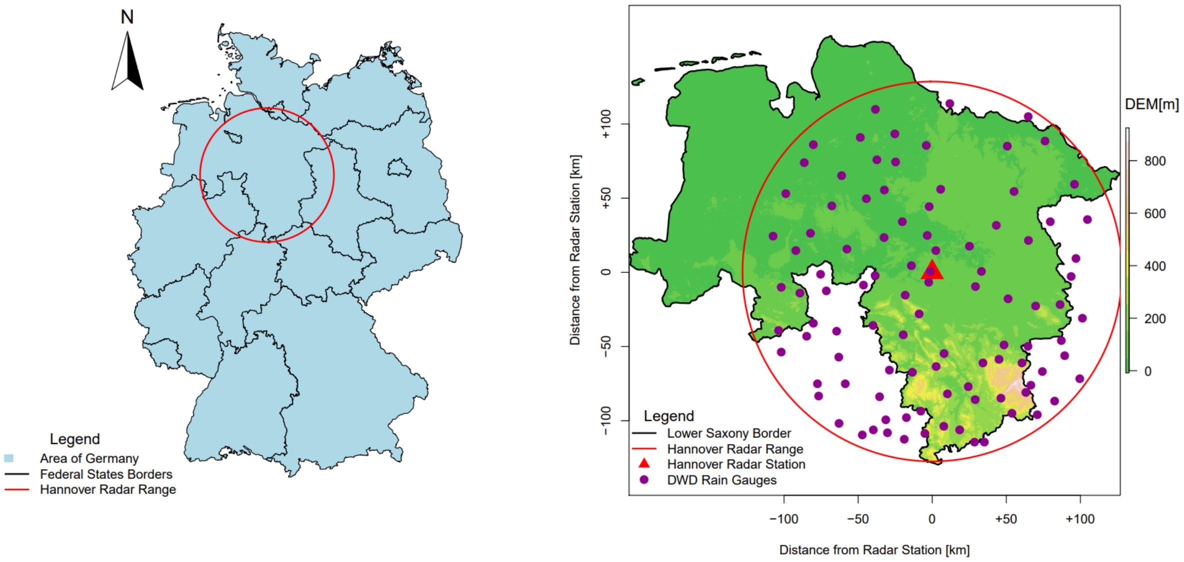


Figure 3 *The location of the study area left) within Germany and right) with the corresponding elevation and boundaries, and as well with the available recording rain gauges (purple) and radar (red) station. The DEM is short for Digital Elevation Model.*

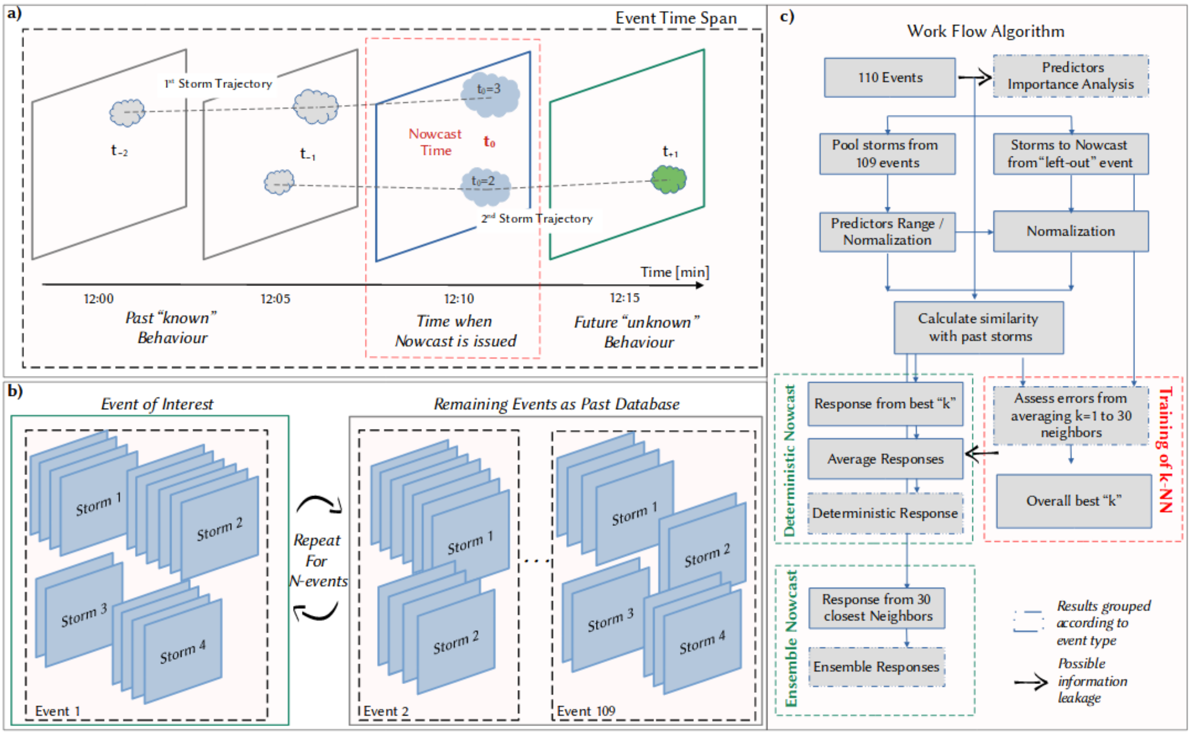


Figure 5 *Illustration of concepts and workflows in this study a) an event contains many rainfall storms inside the radar range which are tracked and nowcasted: the dashed grey lines indicate the movements of storms in space-time within the radar event and the event time span. b) The "leave-one-out-event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

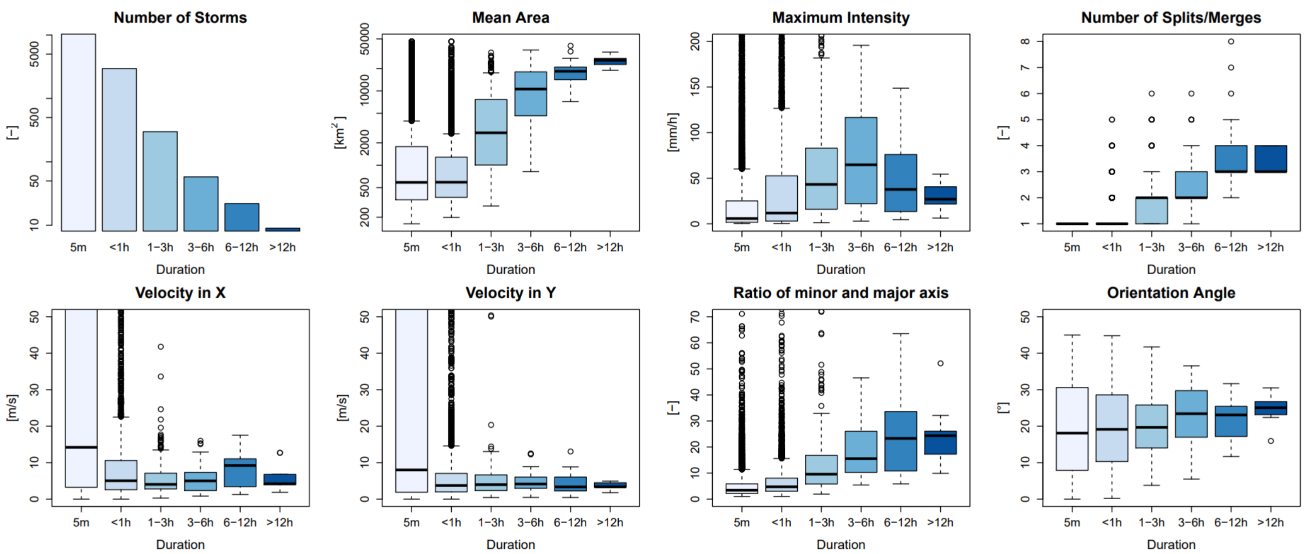


Figure 4 *Different properties of the storms recognized from 110 events separated into 6 groups according to their duration (shown in different shades of blue)*

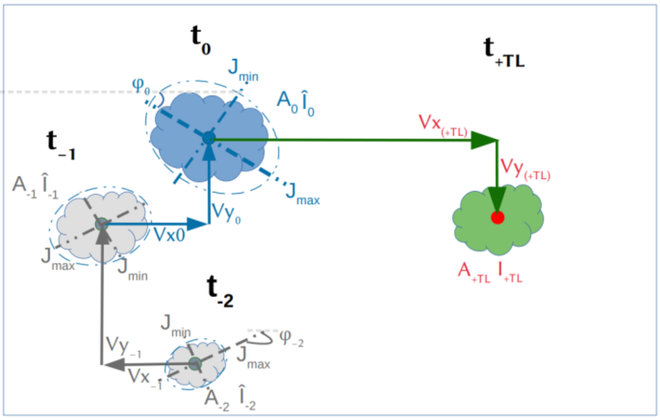


Figure 7 *The features describing the past (grey) and present (blue) states of the storm used as predictors to nowcast the future states of the storm (green) at a specific lead time (T_{+LT}) that is described by 4 target variables (in red). The nowcast is issued time t_0. A full description of these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

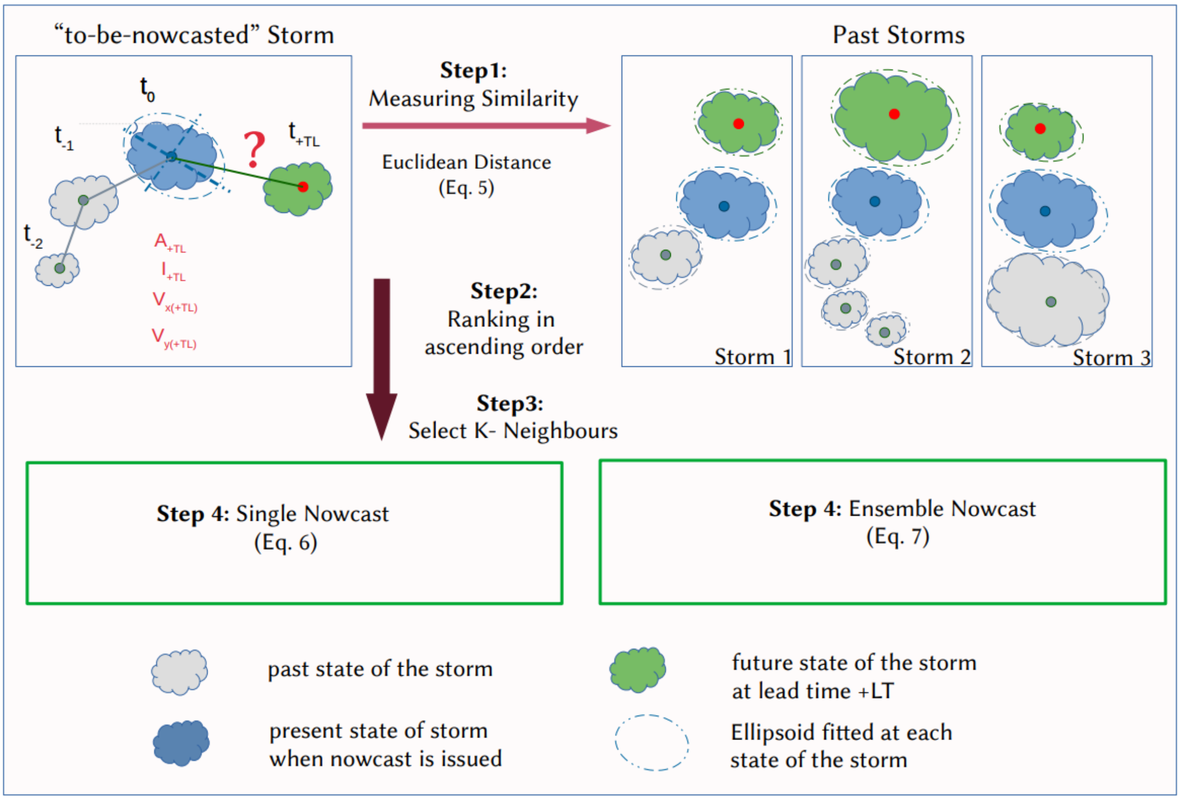


Figure 6 *The main steps involved in the k-NN based nowcast with the estimation of similar storms (Step 1 to 3) and assigning the future responses of past storm as the new response of the "to-be-nowcasted" storm either in a single nowcast (Step4-left) or in an ensemble nowcast (Step4-right).*

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

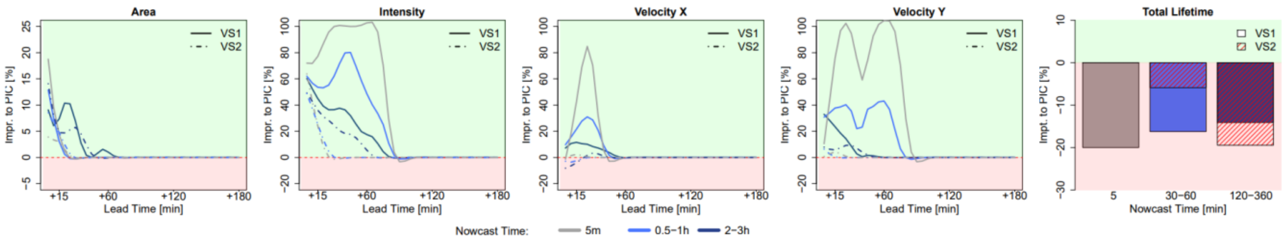


***Figure 8** The median Mean Absolute Error (MAE) improvement per lead time and target variable from applying the k-NN (VS1 target-based, VS2 storm-based) with the predictors and weights derived by the Pearson correlation instead of PIC. The improvements are averaged for different times of nowcast.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

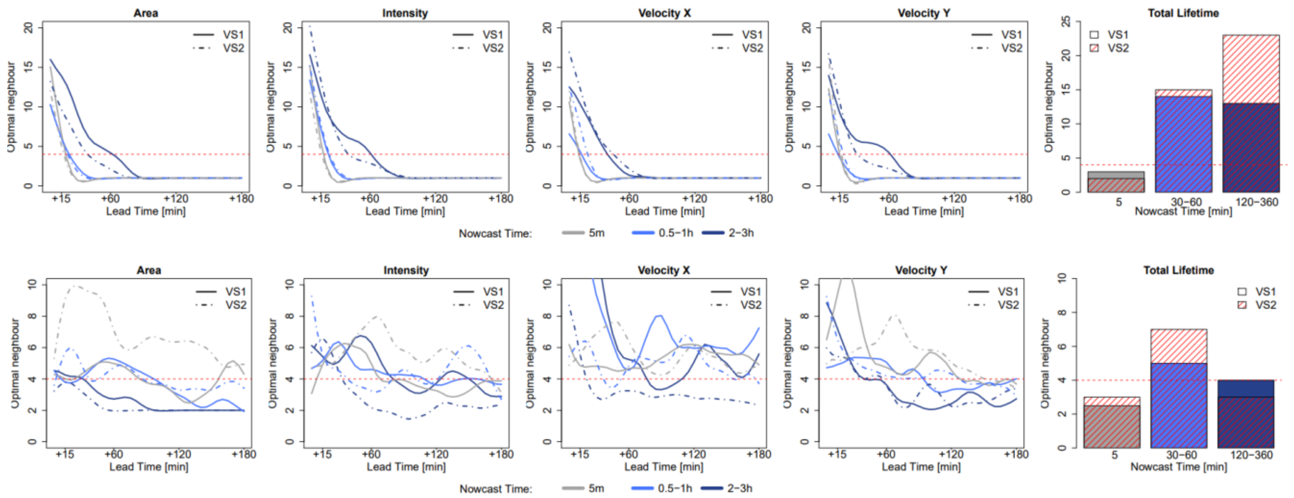


***Figure 9** The training of the k-NN per target variable based on predictors and weights derived from Pearson correlation analysis: the optimal selected "k" neighbours yielding the lowest absolute errors. Two k-NN applications are shown here – VS1 in solid line and VS2 in dashed line: First row – The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

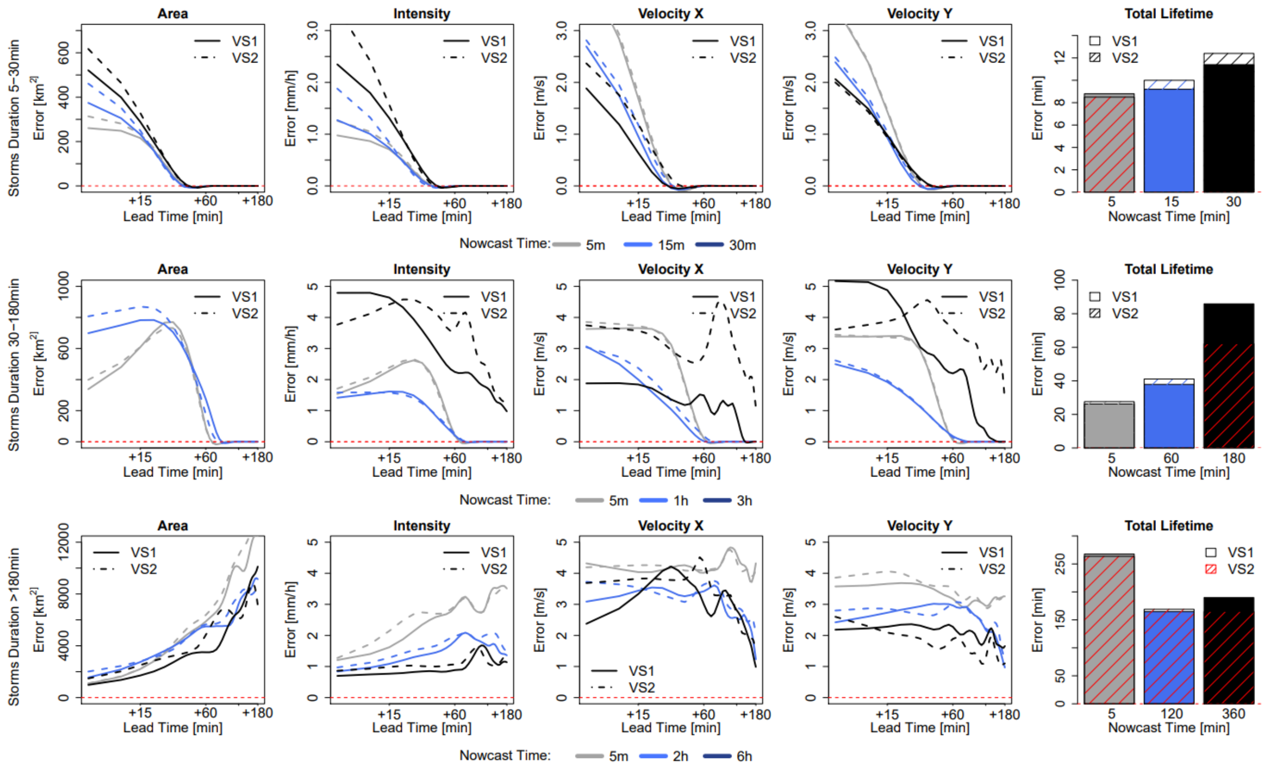


Figure 10 *The median absolute error for each target variable (Area, Intensity, Velocity in X and Y direction and Total Lifetime) based on two 4-NN applications: -VS1 in solid and VS2 in dashed lines. The median errors are computed over storms that are: shorter than 30 min (upper row), than 3 hours (middle 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 Duration	Nowcast Time	Area	Intensity	Velocity X	Velocity Y	Total Lifetime	Storm Duration	Nowcast Time	Area	Intensity	Velocity X	Velocity Y	Total Lifetime	Storm Duration	Nowcast Time	Area	Intensity	Velocity X	Velocity Y	Total Lifetime
5-30min	5min	-22%	-18%	2%	0%	0%	0.5-3h	5min	-15.91%	-9%	-2%	3%	0%	>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%

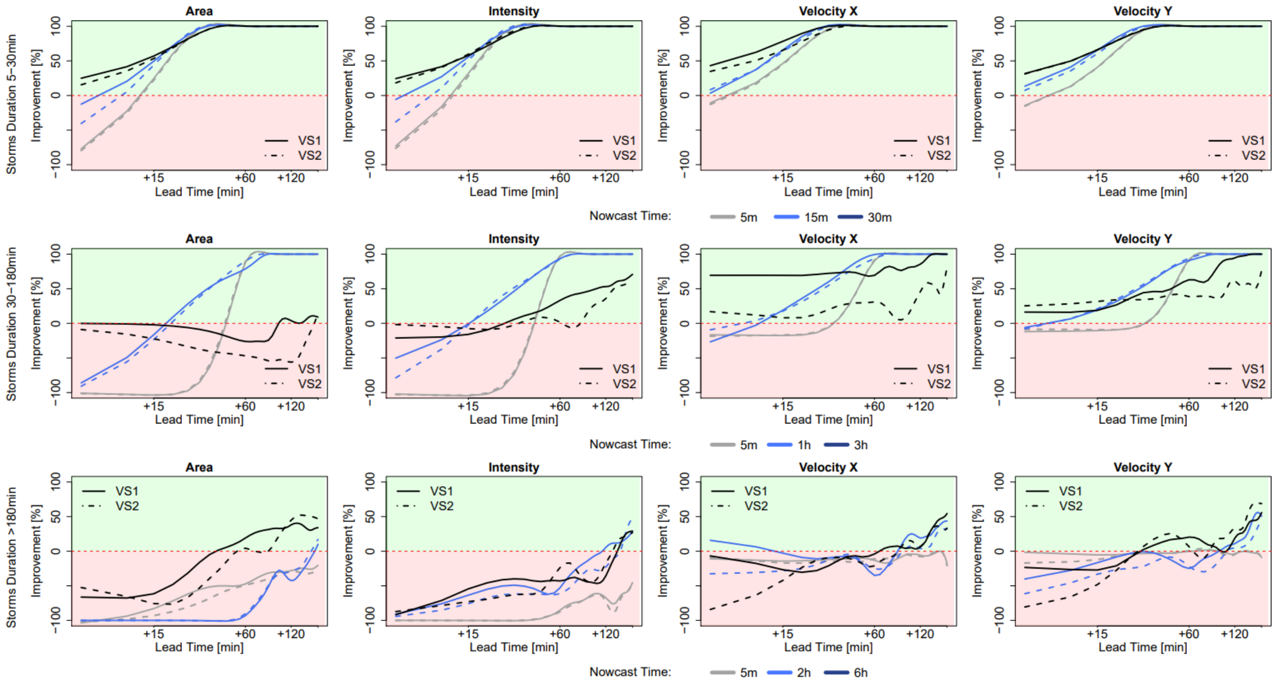


Figure 11 The median improvements that the single 4-NN nowcast can introduce in the nowcast of the target variables (Area, Intensity, Velocity in X and Y direction) in comparison to the Lagrangian persistence. The results are shown for each 4-NN application: VS1 in solid and VS2 in dashed lines and are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

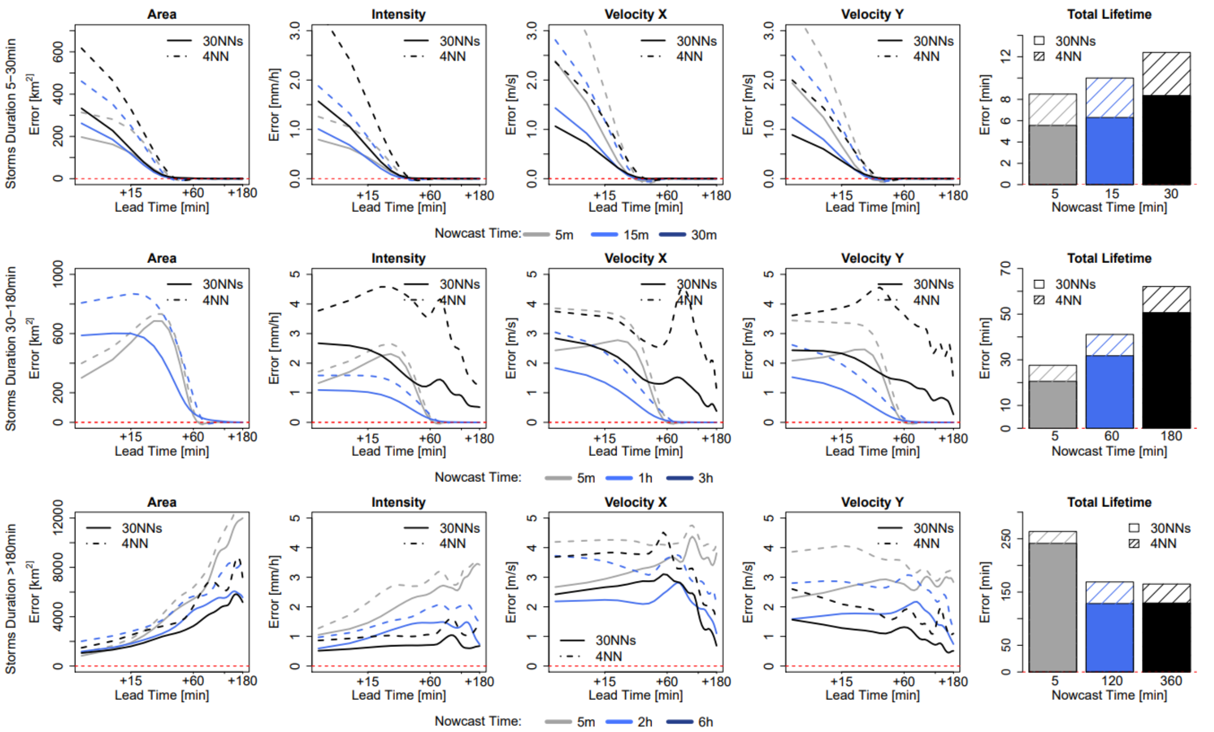


Figure 11. *The median absolute error for each target variable (Area, Intensity, Velocity in X and Y direction and Total Lifetime) on the storm-based applications: -4NN (deterministic) in solid and 30NNs (probabilistic) in dashed lines. The median errors are computed over storms that are: shorter than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

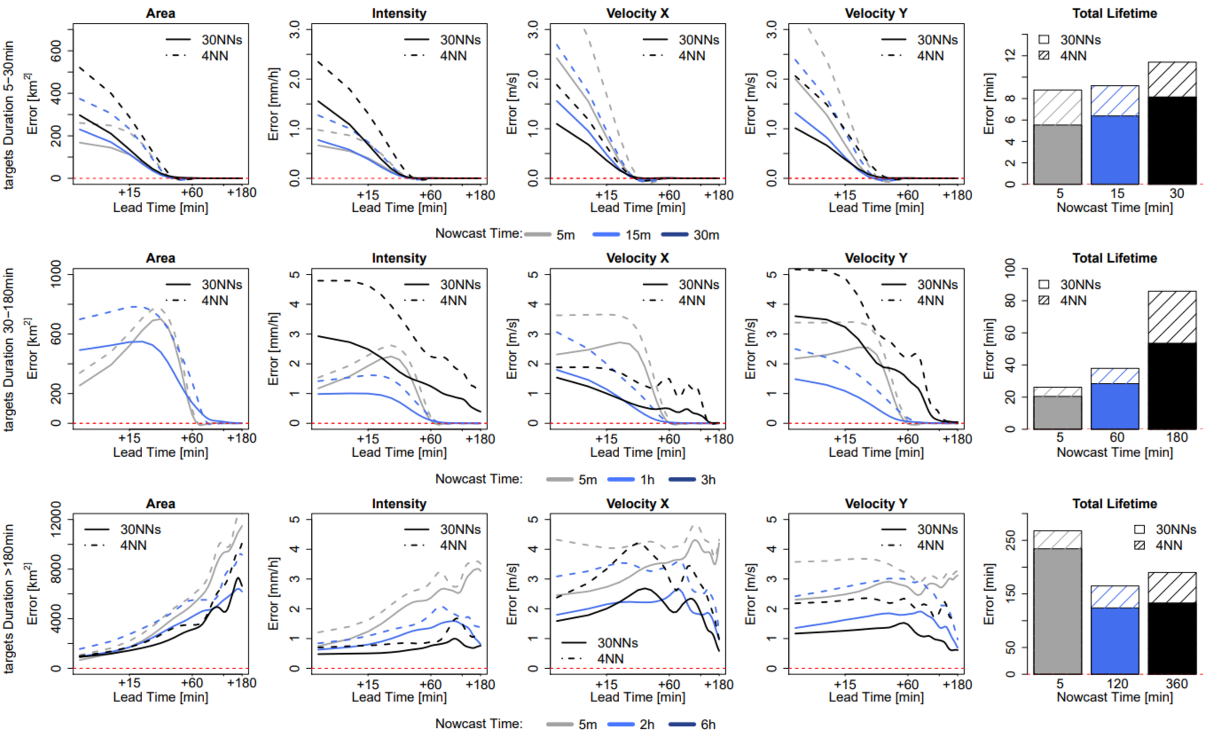


Figure 12 *The median absolute error for each target variable (Area, Intensity, Velocity in X and Y direction and Total Lifetime) on the target-based applications: -4NN (deterministic) in solid and 30NNs (probabilistic) in dashed lines. The median errors are computed over storms that are: shorter than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

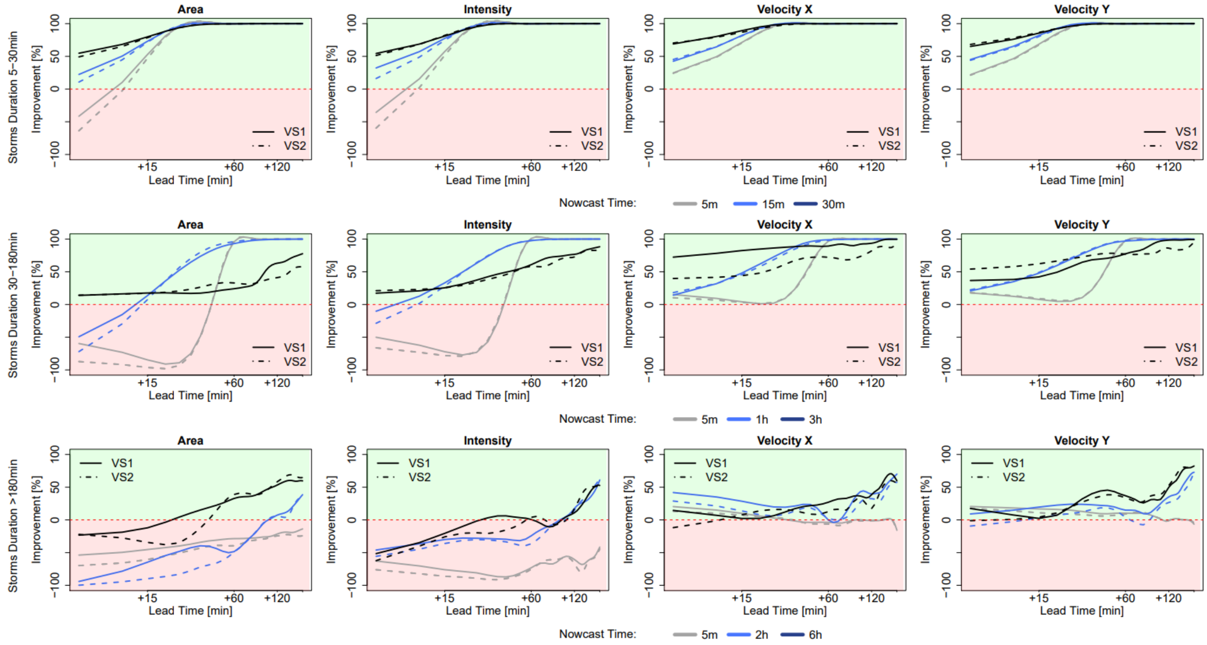


__Figure 13:__ The median improvements that the 30NNs nowcast can introduce in the nowcast of the target variables (Area, Intensity, Velocity in X and Y direction) in comparison to the Lagrangian persistence. The results are shown for each 30NNs application: VS1 in solid and VS2 in dashed lines and are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

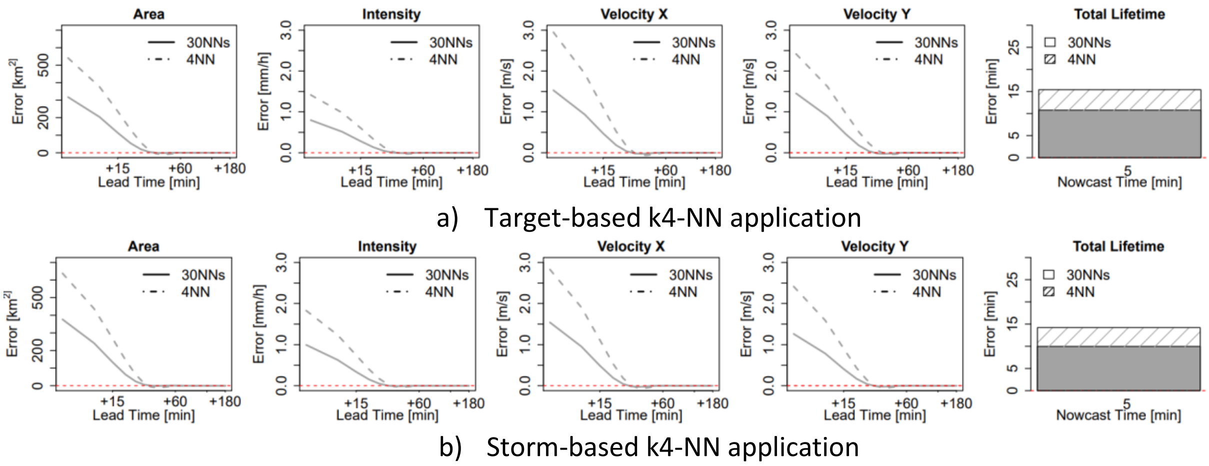


__Figure 14__ Median Error Performance for each of the target variables nowcasted from k4NN deterministic and 30NN probabilistic application for both target (upper row) and storm-based (lower row) kNN. The results shown here are only from the "unmatched storms" when the nowcast time is 5 min

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

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
<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

Intensity

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
<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

Velocity X

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
<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

Velocity Y

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
<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

Duration

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
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	0.00	0.33	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