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

Bora SHEHU¹, Uwe HABERLANDT¹

¹Institute for Hydrology and Water Resources Management, Leibniz University Hannover, Germany

5 Correspondence to: Bora Shehu (shehu@iww.uni-hannover.de)

6 Abstract.

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7 The nowcast of rainfall storms at fine temporal and spatial resolutions is quite challenging due to the erratic 8 unpredictable nature of rainfall at such scales. Typically, rainfall storms are recognized by weather radar, and extrapolated 9 in the future by the Lagrangian persistence. However, storm evolution is much more dynamic and complex than the 10 Lagrangian persistence, leading to short forecast horizons especially for convective events. Thus, the aim of this paper is 11 to investigate the improvement that past similar storms can introduce to the object-oriented radar based nowcast. Here we 12 propose a nearest neighbour approach that measures first the similarity between the "to-be-nowcasted" storm and past 13 observed storms, and later uses the behaviour of the past most similar storms to issue either a single nowcast (by averaging 14 the 4 most similar storm-responses) or an ensemble nowcast (by considering 30 most similar storm-responses). Three 15 questions are tackled here: i) what features should be used to describe storms in order to check for similarity? ii) how to 16 measure similarity between past storms? and iii) is this similarity useful for object-oriented nowcast? For this purpose, 17 individual storms from 110 events in the period 2000-2018 recognized within the Hannover Radar Range (R~115km²), 18 Germany, are used as a basis for investigation. A "leave-one-event-out" cross-validation is employed to test the nearest 19 neighbour approach for the prediction of the area, mean intensity, the x and y velocity components, and the total lifetime 20 of the "to-be-nowcasted" storm for lead times from +5min up to + 3 hours. Prior to the application, two importance 21 analyses methods (Pearson correlation and partial information correlation) are employed to identify the most important 22 predictors. The results indicate that most of storms behave similarly, and the knowledge obtained from such similar past 23 storms helps to capture better the storm dissipation, and improves the nowcast compared to the Lagrangian persistence 24 especially for convective events (storms shorter than 3 hours) and longer lead times (from 1 to 3 hours). The main 25 advantage of the nearest neighbour approach is seen when applied in a probabilistic way (with the 30 closest neighbours 26 as ensembles) rather than in a deterministic way (averaging the response from 4 closest neighbours). The probabilistic 27 approach seems promising, especially for convective storms, and it can be further improvement by either increasing the 28 sample size, employing more suitable methods for the predictor identification, or selecting physical predictors.

29 Keywords:

30 Rainfall nowcast, Lagrangian persistence, probabilistic nowcast, similar storms, nearest neighbour

31 1. Introduction

32 Urban pluvial floods are caused by short, local and intense rainfall convective storms, that overcome rapidly the 33 drainage capacity of the sewer network and lead to surface inundations. These types of floods are becoming more relevant 34 with time due to the expansion of urban areas worldwide (Jacobson, 2011; United, 2018), and the potential of such storms 35 getting more extreme under the changing global climate (Van Dijk et al., 2014). Because of the high economical, and 36 even human losses associated with these floods, modelling and forecasting becomes crucial for impact-based early 37 warnings (i.e. July 2008 in Dortmund Grünewald (2009), August 2008 in Tokyo, Kato & Maki (2009)). However, one of 38 the main challenges in the urban pluvial flood forecasting, remains the accurate estimation of rainfall intensities at very 39 fine scales. Since the urban area responds fast and locally to the rainfall (due to the sealed surfaces and the artificial 40 deviation of watercourse), the Quantitative Precipitation Forecasts (QPFs) fed into the urban models should be provided 41 at very fine temporal (1-5min) and spatial (100m² - 1km²) scales (Berne et al., 2004). The Numerical Weather Prediction 42 Models (NWP) are typically used in hydrology for weather forecast at to several days ahead, nevertheless they are not 43 suitable for urban modelling as they still cannot produce reliable and accurate intensities for spatial scales smaller than 44 10km² and temporal time steps shorter than an hour-(Kato et al., 2017; Surcel et al., 2015)(Golding, 2009; Surcel et al., 45 2015). Ground rainfall measurements (rain-gauges) are considered the true observation of rainfall but they are as well not 46 adequate for QPFs because, due to the sparsity of the existing rain-gauge networks, they cannot capture the spatial 47 structure of rainfall. Therefore, the only product useful in providing QPFs for urban pluvial floods remains the weather 48 radar. The weather radar can measure indirectly the rainfall intensities at high spatial (~1km²) and temporal (~5min) scales 49 resolutions by capturing the reflected energy from the water droplets in the atmosphere. The rainfall structures and their 50 evolution in time and space can be easily identified by the radar and hence serve as a basis for issuing QPFs at different 51 forecast horizons. One of the main drawbacks of radar-based forecast, is that a rainfall structure has to be first identified 52 in order to be extrapolated in the future. In other words, rainfall cannot be predicted before it has started anywhere in the 53 region, only the movement can be predicted. As already discussed in Bowler et al., (2006) and Jensen et al. (2015), these 54 initialization errors cause the radar forecast to be used only for short forecast horizons (up to 3 hours), and that is why are 55 typically referred to as nowcasts. For longer lead times a blending between NWP and radar based nowcasts should be 56 used instead (Codo & Rico-Ramirez, 2018; Foresti et al., 2016; Jasper-Tönnies et al., 2018). Nonetheless, for short 57 forecast horizons up to 2-3h, the radar nowcast remains the best product for pluvial flood simula-tions as it outperforms 58 the NWP one (Berenguer et al., 2012; Jensen et al., 2015; Lin et al., 2005; Zahraei et al., 2012).

59 Two approaches can be distinguished on the radar based QPFs depending on how the rainfall structures are 60 identified, tracked and extrapolated into the future: object-oriented nowcasting (herein as object-based to avoid the 61 confusion with the programming term) and field-based nowcasting. The object-based nowcast treats rainfall structures as 62 objects, each object is regarded as a storm and is defined as a set of radar grid cells that moves together as a unit (Dixon 63 & Wiener, 1993). The field-based approach considers the rainfall as an intermittent continuous field inside a given domain, 64 and through methods like optical flow, tracks and extrapolates how the intensity is moving from one pixel to the other 65 inside this domain (Ruzanski et al., 2011; Zahraei et al., 2012). Convective storms have been proven to have an unique 66 movement from nearby storms (Moseley et al., 2013), thus are thought to be better nowcasted with object-based approach (Kyznarová & Novák, 2009). On the other hand, the field-based approach with an optical flow solution, tracks and 67 68 extrapolates rainfall structures inside a region of size W together as a unit with a constant velocity (Lucas & Kanade, 69 1981) and are considered more suitable for major scale events, i.e. stratiform storms, as they are widespread in the radar 70 image and exhibit more uniform movements (Han et al., 2009). Even though the field-based approached has gained 71 popularity recently (Ayzel et al., 2020; Imhoff et al., 2020) they still have trouble nowcasting convective storms. Thus, 72 the focus in this study is on object-based nowcasts as they are more convenient for convective storms that typically cause 73 urban pluvial floods.

74 Figure 1 illustrates the three main steps performed in an object-based nowcast: a) first the storm is identified -a 75 group of grid cells with intensity higher than a threshold is recognized in the radar image at time t₀, b) the storm identified 76 is then tracked for the time $t_0+\Delta t$ (where Δt is the temporal resolution of the radar data) and velocities are assigned from 77 consecutive storm objects, and finally c) the storm as lastly observed at time t (when the nowcast is issued) is extrapolated 78 at a specific lead time (the time in the future when the forecast is needed) t_{+LT} , with the last observed velocity vector. This 79 is a linear extrapolation of the storm structure in the future, considering the spatial structure and the movement of the 80 storm as constant in time - also referred to as Lagrangian Persistence (Germann et al., 2006). Applications of such storm-81 based nowcast are common in literature like TITAN, HyRaTrac, Konrad etc. (Han et al., 2009; Hand, 1996; Krämer, 2008; 82 Lang, 2001; C. E. Pierce et al., 2004).



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_{0} +- Δt), and green indicates the future states of the storm (t_{0} + t_{1}) (Shehu, 2020)

83 Apart from the initialization errors mentioned before, other error sources in the object-based nowcast can be 84 attributed to storm identification, storm tracking and Lagrangian extrapolation (L. Foresti & Seed, 2015; C. Pierce et al., 85 2012; Rossi et al., 2015). Many works have been already conducted to investigate the role of different intensity thresholds 86 on the storm identification, or of different storm tracking algorithms on the nowcasting results (Goudenhoofdt & Delobbe, 2013; Han et al., 2009; Hou & Wang, 2017; Jung & Lee, 2015; Kober & Tafferner, 2009). Very high intensity thresholds 87 88 may be suitable for convective storms, however can cause false splitting of the storms and which can affect negatively 89 the tracking algorithm. Thus, one has to be careful in adjusting the intensity threshold dynamically over the radar field 90 and type of storm. Storm tracking algorithm can be improved if certain relationships are learned from past observed 91 dataset (like a Fuzzy approach in Jung & Lee (2015) or a tree-based structure in Hou & Wang (2017)), but there is still a 92 limit that the tracking improvement cannot surpass due to the implementation of the Lagrangian persistence (Hou & Wang, Formatted: Subscript Formatted: Subscript

93 2017). These errors due to the Lagrangian persistence are particularly high for convective events at longer lead times (past 94 1 hour) as the majority of convective storms dissipate within 60 minutes (Goudenhoofdt & Delobbe, 2013; Wilson et al., 95 1998). At these lead times, the persistence fails to predict the dissipation of these storm cells, while for shorter lead times 96 it fails to represent the growing/decaying rate and the changing movement of a storm cell (Germann et al., 2006). For 97 stratiform events, since they are more persistent in nature, Lagrangian persistence can give reliable results up to 2 or 3 98 hours lead time (Krämer, 2008). Nevertheless studies have found that for fine spatial (1km²) and temporal (5min) scales, the Lagrangian Persistence can yield reliable results up to 20-30 min lead time, which is also known in the literature as 99 100 the predictability limit of rainfall at such scales (Grecu & Krajewski, 2000; Kato et al., 2017; Ruzanski et al., 2011). In 101 object-based radar nowcast, this predictability limit can be extended up to 1 hour for stratiform events and up to 30-45min 102 for convective events if a better radar product (merged with rain gauge data) is fed into the nowcast model (Shehu & 103 Haberlandt, 2021). Past these lead times, the errors due to the growth/decay and dissipation of the storms governdominate. 104 The rainfall predictability of convective storms can be extended, if instead of the Lagrangian persistence, one 105 estimates these non-linear processes (growth/decay/dissipation) by consulting utilizing storm life characteristics analysed 106 from past observations (Goudenhoofdt & Delobbe, 2013; Zawadzki, 1973). For instance, Kyznarova and Novak (2009) 107 used the CellTrack algorithm to derive life cycle characteristics of convective storms and observed that there is a 108 dependency between storm area, maximum intensity, life phase and height of 0°C isotherm level. Similar results were 109 also found by (Moseley et al., 2013) which concluded that convective storms show a clear life cycle with the peak 110 occurring at 1/3 of total storm duration, a strong dependency on the temperature and increasing average intensity with 111 longer durations. In case of extreme convective storms, earlier peaks are more obvious causing a steeper increase to 112 maximum intensity. A later study by (Moseley et al., 2019) found that the longest and most intense storms were expected 113 in the late afternoon hours in Germany. Thus, it is to be expected that an extensive observation of past storm behaviours 114 can be very useful in creating and establishing new nowcasting rules (Wilson et al., 2010) that can outperform the 115 Lagrangian persistence. An implementation of such learning from previous observed storms (with focus only on the 116 object-based nowcast and not the field-based one) is for instance shown by Hou & Wang (2017) where a Fuzzy 117 classification scheme was implemented to improve the tracking and matching of storms which resulted in an improved 118 nowcast, and Zahraei et al. (2013) where a Self-Organizing-Maps (SOM) algorithm was used to predict the initialization 119 and dissipation of storms on coarse scales extending the predictability of storms by 20%. These studies suggest that past 120 observed relationships may be useful in extending the predictability limit of the convective storms. Under this context, a 121 nearest neighbour method (k-NN) may be developed at the storm scale and used to first recognize similar storms in the 122 past, and then assign their behaviours to the "to-be-nowcasted" storm. The nearest neighbour method has been used in 123 the field of hydrology mainly for classification, regression or resampling purposes (e.g. Lall & Sharma (1996)) but there 124 are some examples of prediction as well (Galeati, 1990). The assumption of this method is that similar events are described 125 by similar predictors, and if one identifies the predictors successfully, similar events that behave similarly can be identified. 126 For a new event, the respective response is then obtained by averaging the responses of past k - most similar storms. The 127 k-value can be optimized by minimizing a given cost function. Because of the averaging, the response obtained, will be a new one, satisfying thus the condition that nature doesn't repeat itself, but nevertheless it is confined within the limits

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129 of the observed events (therefore is unable to predict extreme behaviours outside of the observed range).

Similar approaches are implemented in field-based nowcast (referred to as analogue events), where past similar radar fields are selected based on weather conditions and radar characteristics i.e. in NORA nowcast by (Panziera et al., 2011) mainly for orographic rainfall, or in the multi-scaled analogues nowcast model by (Zou et al., 2020). Panziera et al. 2011 showed that there is a strong dependency between air-mass stability, wind speed and direction and the rainfall patterns observed from the radar data, and that the NORA nowcast can improve the hourly nowcasts of orographic rain 4

135 up to 1 hour when compared to Eulerian Persistence and up to 4 hours when compared with the COSMO2 NWP. 136 Improvement of predictability through a multi-scaled analogues nowcast was also reported by (Zou et al., 2020), which 137 identified neighbours first by accounting similar meteorological conditions and then the spatial information from radar 138 data. However, both of these studies show the applicability of the method on rainfall types that tend to repeat the rainfall 139 patterns; i.e. the orographic forcing in the case of Panziera et al. (2011) and winter stratiform events in the case of Zou et 140 al. (2020). So far, to the authors knowledge, such application of the k-NN has not been applied for convective events. 141 This application seems reasonable as an extension of the object-based radar nowcast, in order to treat each convective 142 storm independently. It can be used instead of the Lagrangian persistence in step 3 in Figure 1-c, for the extrapolation of 143 rainfall storms into the future. Moreover, the benefit of the k-NN application is that one can either give a single or an 144 ensemble nowcast; since k-neighbours can be selected as similar to a storm at hand, a probability based on the similarity 145 rank, can be issued at each of the past storm, providing so an ensemble of responses, which are more preferred compared 146 to the deterministic nowcast due to the high uncertainty associated with rainfall predictions at such fine scales (Germann 147 & Zawadzki, 2004). Thus, it is the aim of this study to investigate the suitability of the k-NN application to substitute the 148 Lagrangian Persistence in the nowcasting of mainly convective events that have the potential to cause urban pluvial floods. 149 We would like to achieve this by first investigating if a K-NN is able to nowcast successfully storm characteristics 150 like Area, Intensity, Movement and Total Lifetime at-for_different life cycles and lead times. Based on the observed 151 dependency of the storm characteristics on the life cycle, it would be interesting to see if the morphological features are 152 enough to describe the evolution of the convective storms. Therefore, the focus is here only of the features recognized by 153 the radar data, and further works will include as well the use of meteorological factors. To reach our aim, the suitability 154 of the k-NN approach is studied as an extension of the existing object-based nowcast algorithm HyRaTrac developed 155 from Krämer (2008). Before such an application, questions that arise are I) what features are more important when 156 describing a storm, II) how to evaluate similarity between storms and III) how to use their information for nowcasting the 157 storm at hand. The paper is organized as follows: first in Section 2 the study area is described, following with the structure 158 of the k-NN method in Section 3.1 where: the generation of the storm database is discussed in Section 3.1.1, the predictors 159 selected and target variables are given in in Section 3.1.2, the methods used for predictor identification in Section 3.1.3, 160 and different application of the k-NN in Section 3.1.4. The optimization and the performance criteria are shown in Section 161 3.2 followed by the results in Section 4 separated into predictors influence (Section 4.1), deterministic k-NN (Section 162 4.2), probabilistic k-NN performance (Section 4.3), and the nowcasting of unmatched storms (Section 4.4). Finally, the 163 study is closed by derived with conclusions and outlook in Section 5.

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164 2. Study Area and Data

165 The study area is located in northern Germany, and lies within the Hannover Radar Range as illustrated in Figure 166 2. The radar station is situated at the Hannover Airport, and it covers an area with a radius of 115 km. The Hannover radar 167 data are C-band data (single-pol) provided by German Weather Service (DWD), and measure the reflectivity at an azimuth 168 angle of 1º and at 5 min scans (Winterrath et al., 2012). The reflectivity is converted to intensity according to Marshall-169 Palmer relationship with the coefficients a=256 and b=1.42 (Bartels et al., 2004). The radar data are corrected from the 170 static clutters and erroneous beams and then converted to Cartesian Coordinate system (1 km² and 5 min) as described in 171 (Berndt et al., 2014), while the rain-gauges measure the rainfall intensities at 1 min temporal resolution but are aggregated 172 to 5min time steps.- Additionally, following the results from Shehu & Haberlandt (2021), a conditional merging between 173 the radar data and 100 rain-gauge recording (see Figure 2 -right) with the radar range at 5 min time steps is performed. 174 The conditional merging aims to improve the kriging interpolation of the gauge recordings by adding the spatial variability 175 and maintaining the storm structures as recognized by the radar data. In case a radar image is missing, the kriging



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Figure 2 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 (adapted from Shehu and Haberlandt, 2021).

176 interpolation of the gauge recordings is taken instead.

177 The period from 2000 to 2018 is used as a basis for this investigation, from which 110 events with different 178 characteristics were extracted (see Shehu & Haberlandt (2021) or Shehu (2020)). These events were selected for urban 179 flood purposes, and contain mainly convective events and few stratiform ones. Here, rainfall events are referred to a time 180 period when rainfall has been observed inside the radar range and at least at one rain gauge has registered an extreme 181 rainfall volume (return period higher than 5 years) for durations varying from 5 min to 1 day. The start and the end of the 182 rainfall event is determined when areal mean radar intensity is higher/lower than 0.05mm for more than 4 hours. Within 183 a rainfall event many rainfall storms, at different times and locations, can be recognized. Figure 3-a shows a simple 184 illustration to distinguish between the rainfall event and rainfall storm concepts employed in this study.

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Figure 3 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 optimization and application of the *k*-NN approach.

185 **3. Methods**

- 186 *3.1 Developing the k-NN model*
- 187 3.1.1 Generating the storm database

188 Each of the selected events contains many storms, whose identification and tracking was performed on the basis 189 of the HyRaTrac algorithm in the hindcast mode (Krämer, 2008; Schellart et al., 2014). A storm is initialized if a group 190 of spatially connected radar grid cells (> 64) has a reflectivity higher than Z=20dBz, while storms are recognized as 191 convective - if a group bigger than 16 radar grid cells has an intensity higher than 25 dBz, and as stratiform - if a group 192 bigger than 128 radar grid cells has an intensity higher than 20 dBz. Typically, higher values (40dBz) are used to identify 193 the core of convective storms (as in E-Titan), but to avoid false splitting of convective storms and to test the methodology 194 on all types of storms, these identification thresholds were kept low (following as well the studies from Moseley et al. 195 2013). Once storms at different time steps are recognized, they are matched as evolution of a single storm, if the centre 196 of intensity of storm at t=0 falls within the boundary box of the storm at t-5 min. The tracking of individual storms in 197 consecutive images is done by the cross-correlation optimization between the last 2 images (t=0 and t-5 min), and local 198 displacement vectors for each storm are calculated._-In case a storm is just recognized (the storm does not yet have 199 previous history), then global displacement vectors based on cross-correlation of the entire radar image are assigned to 7

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them <u>It is usually the case, that two storms merge together at a certain time, or a single storm splits between several</u>
 <u>daughter storms. The splitting and merging of the storms is considered here if two criteria are met; a) the minimum</u>
 distance between the storms that have splatted or merged is smaller than the perimeter of the merged or that-is-splitting
 storm, and b) the position of the centre of intensity of former/latter storms is within the boundaries of the latter/former,
 storm.

205 Thus, a dataset with several types of storms is built and saved. The storms are saved with an ID based on the 206 starting time and location, and for each time step of the storm evolution the spatial information is saved and various 207 features are calculated. Here the features computed from the spatial structure information of the rainfall inside the storm 208 boundaries at a given time step (in 5min) of the storms' life, is referred to as the "state" of the storm. A storm that has been 209 observed for 15 minutes, consists of three "states" each occurring at a 5 min time step. For each of the storm states an 210 ellipsoid is fitted to the intensities in order to calculate the major and minor axis and the orientation angle of the major 211 axis. This storm database is the basis for developing the k-NN method and for investigating the similarity between storms. 212 Some characteristics of the identified storms like duration (or also total lifetime of the storm), mean area, maximum 213 intensity, number of splits/merges, local velocity components, and ellipsoidal features, are shown in the Figure 4. These 214 storms characteristics were obtained by an hindcast analysis run of all 110 events with the HyRaTrac algorithm which 215 resulted in around 5200 storms. The local velocities in x and y direction are obtained by a cross-correlation optimization 216 within the storm boundary. The duration of the storm is then the lifetime of the radar pixels group as dictated by the 217 threshold used to recognize them and the tracking algorithm that decides if the same storm is observed at continuous time 218 steps. For more information about the tracking and identification and algorithm, reader is directed to Krämer (2008).

219 As seen from the number of storms for each duration in Figure 4, the unmatched storm cells make the majority 220 of the storms recognized. These are storms that last just 5 min (one-time step) as the algorithm fails to track them at 221 consecutive time steps. These "storms" can either be dynamic clutters from the radar measurement, as they are 222 characterized by small area, circular shapes (small ratio of minor and major axis) and by very high velocities, or artefacts 223 created by low intensity thresholds used for the storm identification, or finally produced by the unrepresentativeness of 224 the volume captured by the radar station. Another thing to keep in mind, is that merged radar are fed to the algorithm for 225 storm recognition, and this affect the storm structures particularly when the radar data is missing. In such case, the ordinary 226 kriging interpolation of rain gauges is given as input, which is well known to smoothen the spatial distribution of rainfall 227 and hence resulting in a short storm characterized by a very large area. Since the "not" matched storms can either be

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dynamic clutter or artefacts, they are left outside of the k-NN application. Nonetheless, they are treated shortly in section4.5.

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Apart from the unmatched storms, the majority of the remaining storms are of convective nature: storms with

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).

231 short duration (shorter than 6 hours), high intensity and low areal coverage. Here two types of convective storms are 232 distinguished: local convective with very low coverage (on average lower than 1000 km²) and low intensity (on average 233 \sim 5 mm/h), and mesoscale convective which are responsible for floods (with intensity up to 100 mm/h or more) and have 234 a larger coverage (on average lower than 5000 km²). The stratiform storms characterized by large area, long duration and 235 low intensities, as well as meso- γ scale convective events with duration up to 6 hours, are not very well represented by 236 the dataset as only a few of them are present in the selected events (respectively circa 20 and 50 storms). Therefore, it is 237 to be expected for the k-NN approach not to yield very good results for such storms due to the low representativeness. 238 From the characteristics of the storms illustrated in Figure 4, it can be seen that for stratiform storms that live longer than 239 twelve hours the variance of the characteristics is quite low (when compared to the rest of the storms) which can either 240 be attributed to the persistence of such storms or to the low representativeness in the database. Even though the data size 241 for stratiform is quite small, the k-NN may still deliver good results as characteristics of such storms are more similar. 242 Nevertheless, the stratiform storms are typically nowcasted well by the Lagrangian persistence (specially by a field-243 oriented approach) as they are wide-spread and persistent. Hence the value of the k-NN is primarily seen for convective 244 storms and not for stratiform ones.

245 3.1.2 Selecting features for similarity and target variables

246 At first storms are treated like objects that manifest certain features (predictors) like area, intensity, lifetime etc., 247 at each state of the storms' life until the storm dissipates (and the predictors are all set to zero). The features of the objects 248 are categorized into present and past features, as illustrated in Figure 5 (shown respectively in blue and grey). The present 249 features describe the current state of the storm at the time of nowcast (denoted with to in Figure 5), and are calculated 250 from one state of the storm. To compute certain features, an ellipsoid is fitted to each state of the storm. The past features, 251 on the other hand, describe the predictors of the past storm states (denoted with t.1, t.2 in Figure 5) and their change over 252 the past life of the storm. For example, the average area from time t_{-2} to t_{-1} is a past feature. A pre-analysis of important 253 predictors showed that the average features over the last 30 minutes are more suitable as past predictors than the averages over last 15 or 60 min or than the calculation of past changing rates. Therefore, averages over past 30 minutes are computed here:

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

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257 where P_i is the predictors value at time *i*, and P_{30} the average value of the predictor over last 30min. In case of missing 258 values, the remaining time steps are used for averaging. The selected features (both present and past) that are used here 259 to describe storms as objects, and hence tested as predictors, are shown in Table 1. Table 1. The present features help to 260 recognize storms that are similar at the given state when the nowcast is issued (blue storm in Figure 5) and the past ones 261 give additional information about the past evolution of the storm (average of grey storms in Figure 5). The aim of these 262 features is to recognize the states of previously observed storms that are most similar to the current one (shown in blue in 263 Figure 5) of the "to-be-nowcasted" storm. Once the most similar past storm states are recognized, their respective future 264 states at different lead times can be assigned as the future behaviour (shown in green in Figure 5) of the current state of 265 the "to-be-nowcasted" storms. Since the storms are regarded as objects with specific features, future behaviours at 266 different lead times are determined by four target variables: area (A+LT), mean intensity (I+LT) and velocity in X (Vx+LT) 267 and Y (Vy_{+LT}) direction. Additionally, the total lifetime of the storm is considered as a fifth target (L_{tot}) . Theoretically, the total lifetime is predicted indirectly when any of the first four targets is set to zero, however here it is considered as an 268 269 independent variable in order to investigate if similar storms have similar lifetime durations.

 t_{0} t_{1} t_{-1} $A_{0}I_{0}$ $V_{X_{(LT)}}$ $V_{Y_{(LT)}}$ $V_{Y_{(LT)}}$ $V_{Y_{(LT)}}$ $V_{Y_{(LT)}}$ $V_{X_{1}}$ $V_{X_{2}}$ $V_{X_{1}}$ $V_{X_{2}}$ $V_{X_{2}}$ $V_{X_{1}}$ $V_{X_{2}}$ $V_{X_{2}}$ $V_{X_{1}}$ $V_{X_{2}}$ $V_{X_{2}}$



For each state of each observed storm in the database, the past and present features of that state with its' respective, future states of the five target variables from +5min to +180min (every 5 min) lead times are saved together and form the

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272 predictor-target database that is used for the development of the k-NN nowcast model. A summary of the predictors and

target variables calculated per state is given in Table 1. Before optimizing and validating the k-NN method (advise Figure
3- c), an importance analysis is performed for each of the target variables in order to recognize the most important

predictors. As the predictors have different ranges, prior to the importance analysis and the k-NN application, they are normalized according to their median and range between the 0.05 and 0.95 quantiles:

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$$normP_i = \frac{P_i - Q_{P_i}^{0.5}}{Q_{P_i}^{0.95} - Q_{P_i}^{0.05}}$$

where *P* is the actual value, *normP* the normalized value, and $Q_{Pi}^{0.5}$, $Q_{Pi}^{0.95}$, $Q_{Pi}^{0.05}$ the quantiles 0.5, 0.05 and 0.95 of the *i*th predictors' vector. The reason why these quantiles were used for the normalization instead of the typical mean and maximum to minimum range, is that some outliers are present in the data. For instance, very high and unrealistic velocities are present in some convective storms where the tracking algorithm fails to capture adequate velocities (Han et al., 2009). Thus, to avoid the influence of these outliers, the given range is employed.

283 3.1.3 Selection of most relevant predictors

284 The application of the k-NN method can be relevant if there is a clear connection between the target variable and 285 the features describing this target variable. For instance, in the case of Galeati (1990), a physical background backed up 286 the connection between target variable (discharge) and the features (daily rainfall volume and mean temperature). In the 287 case of the storms at such fine temporal and spatial scales, due to the erratic nature of the rainfall itself, there are no 288 physical related information that can be extracted from radar data. Different features of the storm itself can be investigated 289 for their importance to the target variable. Nevertheless, the identification of such features (referred here as predictors) is 290 difficult because it is bounded to the set of the available data and the relationships considered. Commonly a strong Pearson 291 correlation between the predictors selected and the target variable is used as an indicator of a strong linear relationship 292 between them. Here, the Pearson correlation absolute values are used directly as predictors weights in the k-NN 293 application. However, the relationship between predictors and target variables may still be of non-linear nature, thus 294 another predictor importance analysis should be advised when selecting the predictors. Sharma & Mehrotra (2014) 295 proposed a new methodology, designed specifically for the k-NN approach, where no prior assumption about the system 296 type is required. The method is based on a metric called the Partial Information Correlation and is computed from the 297 Partial Information as:

298
$$PIC = \sqrt{(1 - \exp(-2PI))} \text{ with } PI = \int f_{X,P|Z}(x,p|z) \log \left[\frac{f_{X|Z,P|Z}(x,p|z)}{f_{X|Z}(X|Z)} \int_{FP|Z} dxdpdz \right] dxdpdz ,$$

299 where PIC is the Partial Information Correlation, PI is the Partial Information which represents the partial dependence of 300 X on P conditioned to the presence of a predictor Z. The Partial Information itself is a modification of the Mutual 301 Information in order to measure partial statistical dependency between the predictors (P) and the target variable (X), by 302 adding predictors one at a time (Z) (step-wise procedure). The evaluation of PIC needs a pre-existing identified predictor 803 from which the computation can start. If the pre-defined predictor is correctly selected, then through the Equation (3(3), (3(3)))304 the method is able to recognize and leave out the new predictors which are not related to the response and which don't 305 bring additional value to the existing relationship between the current predictors and target variable. Relative weights for 306 the k-NN regression application can be derived for each predictor, as a relationship between the PIC metric and the 307 associated partial correlation:

$$\alpha_{j} = PIC_{X,Zj|Z(-j)} \frac{S_{X|Z(-j)}}{S_{Z|Z(-j)}},$$
(4)

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), $S_{Z|Z(j)}$ the scaled conditional standard deviations between the additional predictor (*Z*_j) and the first predictor vector *Z*(-j), Formatted: Font: Bold

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(3)

312	and the a_j denotes the predictors weight. The R package NPRED was used for the investigation of the PIC derived
313	importance weights (Sharma et al., 2016).

814 Here in this study, these two importance analyses are used to determine the most important predictors and their 815 respective weights in the k-NN similarity calculation. For each target variable the most important predictor identified from 816 Pearson Correlation, is given to the PIC metric as the first predictor. The analysis is complex due to the presence of several 817 predictors, 38 states of future behaviour for each target variable (for each 5min between +5min to +180 min lead times), 818 and different nowcast times; the weights were calculated first for three lead times +15min, +60min and +180 min, and for 819 820 over these groups and lead times are calculated and used as a reference for each importance analysis. The k-NN errors 821 with these average weights are compared in Section 4.1.

Table 1 List of all the past and present features of the storms that are investigated for their importance as predictors,
and the respective target variables calculated for different lead times.

	Features	Symbol
	number of storm cells within the storm region	Cells [-]
	current storm lifetime at time of nowcast	L _{now} [min]
	area of the storm	A [km ²]
	mean spatial intensity	I _{ave} [mm/h]
	maximum spatial intensity	Imax [mm/h]
Present Features	standard deviation of the spatial intensities	Isd1 [-]
	standard deviation of intensities groups inside the storm	I _{sd2} [-]
	global velocity of the entire radar image	$V_{g}[m/s]$
	x and y component of the local velocity of the storm region	$V_x, V_y[m/s]$
	major and minor axis of the ellipsoid and their ratio	J _{max} , J _{min} [km], J _r [-]
	orientation angle of the major axis of the ellipsoid	Φ [°]
	average area over the last 30 min of storm existence	A ₃₀ [km ²]
	average mean intensity over the last 30 min of storm existence	Iave ₃₀ [mm/h]
	average maximum intensity over the last 30 min of storm existence	Imax ₃₀ [mm/h]
	average standard deviation of intensity over the last 30 min of storm existence	Isd1 ₃₀ [-]
Past Features	average standard deviation of intensity groups over the last 30 min of storm existence	Isd2 ₃₀ [-]
	average global velocity over the last 30 min of storm existence	Vg ₃₀ [m/s]
	average x and y component of the local velocity over the last 30 min of storm existence	Vx ₃₀ , Vy ₃₀ [m/s]
	average value of the major and minor axis of the ellipsoid and their ratio over the last 30 min of storm existence	Jmax _{30,} Jmin ₃₀ [km] Jr ₃₀ [-]
	average major axis orientation of the ellipsoid over the last 30 min of storm existence	Φ ₃₀ [°]
	Total lifetime of the storm	L _{tot} [min]
Target Variables	Estimated Area and Intensity at LT from +5min to +180min	A+LT [km ²], Iave+LT [mm/h],
	Estimated Velocity X and Y at LT from +5min to +180min	$Vx_{^{+\!LT}},Vy_{^{+\!LT}}[m/s]$

823 Here in this study, these two importance analyses are used to determine the most important predictors and their B24 respective weights in the k-NN similarity calculation. For each target variable the most important predictor identified from 825 Pearson Correlation, is given to the PIC metric as the first predictor. The analysis is complex due to the presence of several 826 predictors. 38 states of future behaviour for each target variable (for each $5 \min$ between $+5 \min$ to $+180 \min$ lead times). 827 and different nowcast times; the weights were calculated first for three lead times +15min, +60min and +180 min, and for 828 three storm groups separated according to their duration <60min, 60min-180min, and > 3 hours. Here the averages weights 829 over these groups and lead times are calculated and used as a reference for each importance analysis. The k-NN errors 830 with these average weights are compared in Section 4.1.

331 3.1.4 Developing the k-NN structure

332 The structure of the proposed k-NN approach at the storm scale is illustrated at Figure 6 - left) the current "to-333 be-nowcasted" storm is shown, while at - right) the past observed storms. First in Step 1, the Euclidean distance between 334 the most important predictors (either present or past predictors), of past storm states and the current one is calculated to 335 identify the most-similar states of the past storms (distance between the blue shapes at left and right side of Figure 6): 336 $E_d = \sqrt{\sum_{i=1}^N w_i \cdot (X_i - Y_i)^2},$ (5)337 where w is the weight of the respective i^{th} predictor as dictated by the importance analysis (results are shown in **Table** 838 <u>32</u>), X the predictor of the "to-be-nowcasted" storm, Y the predictor of a past observed storm, N the total number of 339 predictors used and E_d the Euclidian distance between the "to-be-nowcasted" and a past observed storm. The assumption 340 made here is that the smaller the distance, the higher the similarity of future behaviour between the selected storms and 341 the "to-be-nowcasted" storm. Therefore, in Step 2 these distances are ranked in an ascending order and 30 past storm 342 states with the smallest distance are selected (Step 3). Once the similar past storm states have been recognized (the blue-343 shape in Figure 6 - right), the future states of these storms (the green-shapes in Figure 6 - right, each for a specific lead 344 time from the occurrence of the selected similar blue-state), are treated as future states (the green-shape in Figure 6 - left) 345 of the "to-be-nowcasted" storm. In Step 4, either a single (deterministic) or an ensemble (probabilistic) nowcast is issued. 346 If a single nowcast is selected, then the green-instances of the k-neighbours are averaged with weights for each lead time: 347 (6) $R_{new} = \sum_{i=1}^k Pr_i \cdot R_i$, 848 where k is the number of neighbours obtained from optimization, R_i and Pr_i (from Equation 7) are respectively the 349 response and weight of the i^{th} neighbour and the R_{new} the response of the "to-be-nowcasted" storm as averaged from k

350 neighbours. The response R refers to each of the 5 target variables: Area, Intensity, Velocity in X and Y direction, and 351 Total Lifetime. Contrary, if a probabilistic nowcast is selected, 30- members ensembles are selected from the closest 30 352 storms where each member is assigned a probability according to the rank of the respective neighbour storm: 853

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

354 where k is the selected number of neighbours and Rank and Pr are respectively the rank and the probability weights of 355 the *i*th neighbour/ensemble member. An ensemble member is then selected randomly based on the given probability 356 weights. These probability weights calculated here are as well used for computation of the single nowcast in Equation (6).

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357 Since the performance of the single k-NN nowcast is highly dependent on the number of k – neighbours used for 358 the averaging, a prior optimization should be done in order to select the right k-neighbours that yield the best performance 359 (as illustrated in **Figure 3-**c). The application of the k-NN can either be done per each target variable independently, or 360 for all target variables grouped together. In the first approach, the dependency of the target variables between one another



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 deterministic nowcast (Step4-left) or in a probabilistic nowcast (Step4-right).

361 is not assured, they are predicted independently from one another. This is referred here as the target-based k-NN and is 362 denoted in the results as VS1. The main advantage of this application is that, since the relationship between the target 363 variables are not kept, new storms can be generated. Theoretically, the predicted variables should have a lower error since B64 the application is done specifically separately per each variable, nevertheless this approach doesn't say much if similar 365 storms behave similarly. Therefore, it is used here as a benchmark for best possible optimization that can be reached by 366 the k-NN with the current selected predictor set. In the second approach, the relationships between target variables as 367 exhibited by previous storms are kept. The storm structure and the relationship between features are maintained as 368 observed and thus the question if similar storms behave similarly can be answered. This is referred here as the storm-369 based k-NN and is denoted in the results as VS2. In this study the two approaches are used (respectively called VS1 and 370 VS2) to understand the potential and the actual improvement that the k-NN can bring to the storm nowcast.

371 3.2 Application of the k-NN and performance assessment

372 3.2.1 Optimizing the deterministic k-NN nowcast

373 The optimization of the k-NN is done based on the 5189 storms extracted from 110 events on a "leave-one-out" 374 cross-validation. Since the "not" matched storms can either be dynamic clutter or artefacts of the tracking algorithm, they 375 are left outside of the k-NN optimization and validation. The assumption is here that an improvement of the radar data or 376 tracking algorithm would eliminate the "not" matched storms, hence the focus is only on the improvement that the k-NN 377 can introduce to the matched storms. "Leave-one-event-out" cross-validation means here that the storms of each event 378 have to be nowcasted by considering as a past database the storms from the remaining 109 events (a detailed visualization B79 is given in Figure 3-b). The objective function is the minimization of the mean absolute error (Equation 8) and of the 880 absolute mean error (Equation 9) between predicted and observed target variables at lead times from +5min to +180 min: 881 $MAE_{target} = \sum_{i=1}^{N} (|Pred_{i,+LT}| - |Obs_{i,+LT}|)/N$ (88)

 $ME_{target} = |\sum_{i=1}^{N} (Pred_{i,+LT} - Obs_{i,+LT})/N|_{\perp}$

(<u>98</u>)

383 where the *Pred* is the predicted response, *Obs* the observed response for the i^{th} storm, +LT the lead time and N the number 884 of storms considered inside an event.- The results of the storms' nowcast are also dependent on the nowcast time in respect 385 to the storms' life (time step of the storm existence when the nowcast is issued - refer to Figure 3-a). If the nowcast time 386 is 5min, only the present predictors are used for the calculation of storm similarity, and as higher the nowcast time, as 387 more predictors are available for the similarity calculation. It is expected for the nowcast to perform worse at the first 388 5min of the storm existence, as the velocities are not assigned properly to the storm region and the past predictors are not 389 yet calculated. Therefore, the optimization is done separately for three different groups of nowcast times, in order to 390 achieve a proper application of the k-NN model: Group 1 - Nowcast issued at 1st timestep of storm recognition, Group 2 391 - Nowcast issued between 30min to 1 hour of storm evolution, and Group 3 - Nowcast issued between 2 and 3 hours of 392 storm evolution. The k-number with the lowest absolute error averaged over all the events for most of the lead times (as 893 median of MAE from Equation (9(8) and ME from Equation (9) over all events) is selected as a representative for the 394 deterministic nowcast.

395 3.2.2 Validating the k-NN deterministic and probabilistic nowcast

396 Once the important predictors are identified and the k-NN has been optimized, the performance of both 397 deterministic and probabilistic k-NN is assessed also in a "leave-one-event-out" cross-validation mode. Two performance 898 criteria are used to assess the performance:

i) absolute error per lead time and target variable <u>computed for each event and a specific selected nowcast time(as</u>
 in the optimization of the k-NN in Equation (8),

 $MAE_{target} = \sum_{i=1}^{N} (|Pred_{i,+LT} - Obs_{i,+LT}|) / N_{\perp}$

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402	where the <i>Pred</i> is the predicted response, Obs the observed response for the i^{th} storm, $+LT$ the lead time and N the number	
403	of storms considered inside an event.	
404	-and-ii) the improvement (%) per each lead time and target variable that the k-NN approach introduces to the	
405	nowcast (for a specific selected nowcast time) when compared to the Lagrangian persistence in object-based approach;	
406	$Error_{impr} [\%] = 100 \cdot \frac{(Error_{ref} - Error_{new})}{ Error_{ref} }, \qquad (\underline{119})$	
407	where the Error _{new} is the event error manifested by the k-NN, the Error _{ref} the event error manifested by the Lagrangian	
408	persistence and the Error _{impr} the improvement in reducing the error per each lead time. For improvements higher than	
409	100% or lower than -100%, the values are reassigned to the limits respectively 100% and -100%. Here the Lagrangian	
410	persistence refers to as persistence of the storm characteristics (Area, Intensity, Velocity in X and Y Direction) as last	
411	observed and constant for all lead times.	
412	For the probabilistic approach, the Continuous Rank Probability Score (CRPS) as shown in Equation (4129) is computed.	
413	$CRPS(F, y) = \int_{-\infty}^{\infty} (F(x) - 1\{y \le x\})^2 dx = E_F Y - y - \frac{1}{2} E_F Y - Y' $ (1240)	
414	where F is a probabilistic forecast, y the observed value, Y the and Y' independent random variables with CDF of F and	
415	Y' the finite first moment 2. (Gneiting and Katzfuss, 2014). The CRPS is a generalization of the mean absolute error, thus	_
416	if a single nowcast is given, it is reduced to the mean absolute error (Equation <u>\$10</u>). This enamables a direct comparison	-
417	between the probabilistic and deterministic nowcast and to investigate the advantages of the probabilistic one. As in	
418	Equation (8), the values obtained in Equation (10), (911) and (412 θ) are averaged per each of the 110 events.	
419	As stated earlier the results depend on the nowcast time and also storm duration (in regard to available storms).	
420	Therefore, the performance criteria for both k-NN nowcasts were computed separately for different storm durations and	
421	nowcast times as illustrated in Table 2. It is important to mention as well, that since one event may contain many storms	
422	of similar nature, when leaving one event out for the cross-validation, the number of available storms is actually lower	
423	than the numbers given in Table 2. This is particularly affecting the performance of the storms longer than 6 hours, as the	
424	"leave-one-event-out" cross-validation leaves fewer available storms for the similarity computation. Lastly, it is important	
425	to notice, that the performance criteria can be calculated even for nowcast times longer than the storm lifetime, if the	
426	nowcast fails to capture the dissipation of the storms. In this case, Area, Intensity, Velocity in X and Y Direction are	
427	compared against zero, while the Total Lifetime against the total observed lifetime of the storms.	

Table 2 The selected storm durations and nowcast times for the performance calculation of the deterministic and probabilistic nowcast and the respective number of storms for each case.

Storm living less	s than 30 min	Storms living with	in 0.5 - 3 hours	Storms living longer than 3 hours				
Nowcast Time	No. Storms	Nowcast Time	No. Storms	Nowcast Time	No. Storms			
5 min	4106	5 min	994	5min	89			
15 min	2265	1h	370	2h	89			
30 min	271	3h	6	6h	33			

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428 4. Results:

429 4.1 Predictors Importance Analysis

430 Table 3 illustrates the results of the two important analysis methods (Pearson correlation and partial information 431 correlations - PIC) for each of the target variable and their average over the 5 variables. The stronger the shade of the 432 green colour, the more important is the predictor for the target variable. The weights given here are averaged from the 433 weights calculated at three different lead times and storm durations (see Appendix 8.1 and 8.2 for more detailed 434 information about the calculated weights). First the Pearson Correlation weights are advised for the identification of the 435 most important predictors. From the results it is clear that the autocorrelation has a higher influence, as the target variables 436 are mostly correlated with their respective past and present values. This influence logically is higher for the shorter lead 437 times and smaller for the longer lead times. For longer lead times the importance of other predictors, that are not related 438 directly with the target variable, increases. Similar patterns can be observed among the Area, Intensity and Total Lifetime 439 target variables, indicating that these three variables may be dependent on each other, and on similar predictors like: 440 current lifetime, area, standard deviation of intensity, the major and minor ellipsoidal axis and the global velocity. This 441 conclusion agrees well with the life cycle characteristics of convective storms reported in the literature review. On the 442 other hand, are the velocity components, which seem to be highly dependent on the autocorrelation and slightly correlated 443 to area and ellipsoidal axes. It has to be mentioned that apart for the standard deviation intensities also the mean, median, 444 and maximum spatial intensities were investigated. Nevertheless, it was found that the Isd1 and Isd2 had the higher 445 correlation weights, and since there is a high collinearity between these intensity predictors, they were left out of the 446 predictor's importance analysis.

Table 3 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.

Mashaal	Tarret					Pres	sent P	redict	ors					Past Predictors - averaged from last 30 min									
Wethod	Target	Cells	Lnow	Α	lsd1	lsd2	Vg	Vx	Vy	Jmax	Jmin	Jr	Φ	A ₃₀	Isd1 ₃₀	Isd2 ₃₀	Vg ₃₀	Vx ₃₀	Vy ₃₀	Jmax ₃₀	Jmin ₃₀	Jr ₃₀	Φ_{30}
	Α	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
<u>د</u> 6	1	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
lati	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
Pea Dure	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
- 8	Ltot	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
	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
u u	1	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
-tial nati	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
orne Par	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
j <u>₹</u> 0	Ltot	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

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456 for Total Lifetime and Area, only for storms that last longer than 3 hours, the method is able to converge and give the 457 most important predictors; for Area - A, Vg, past Vy30 and the Lnow, while for Total Lifetime - A, Velg, Lnow and Jmin30. At 458 the moment it is unclear why the PIC method is unable to perform well for all of the target variables and storm groups. 459 One reason might be that only the Area and Total Lifetime are dependent on the chosen target variables. Another most 460 probable reason might be that for the other target variables the heavy-tail of the probability distribution and the high zero 461 sample size may influence the calculation of the joint and mutual probability distribution. The Total Lifetime is an easier 462 target to be analysed, which means the values are not zero and its distribution is not as heavy tailed as the distribution of 463 the other variables. The other variables, depending on the lead time, have more zeros included and have an asymptotic 464 density function. It seems that, whenever zeros are not present, like in the case of storms lasting longer than 3 hours, the 465 PIC is able to represent quite well the important predictors. However, Fthe reason why this method is performing poorly 466 for the application at hand, even though developed specifically for the k-NN application, is not completely understood 467 and is not investigated further on for the time being since it is outside the scope of this paper.

468 Overall, the results from the Pearson correlation seem more robust and stable (throughout the lead times and 469 storm groups) than the PIC method (refer to Appendix 8.1 and 8.2); the importance weights increase with the lifetime of 470 the storm and decrease with higher lead time. These behaviours are expected as with increasing lead time the uncertainty 471 becomes bigger and with increasing lifetime the storm dynamic becomes more persistent (due to the large scales and the 472 stratiform movements involved). Moreover, the important predictors do not change drastically from one lead time or 473 storm group to the other, as seen in the PIC. Therefore, the predictors estimated from the correlation with the given weights 474 in Table 3 are used as input to the k-NN application. In order to make sure that the predictor set from the Pearson 475 correlation was the right one, the improvement in the single k-NN training error of using these predictors instead of the 476 ones from PIC are shown in Figure 7. The results shown in this figure are computed according to the Equation (119) 477 (where "new" is k-NN with correlation weights, and "ref" is the k-NN with PIC weights) for the target-based k-NN 478 approach (solid lines) and storm-based k-NN approach (dashed lines) and are averaged for three groups of nowcast times 479 as indicated in the optimization of k-NN (Section 3.2.3) and as well in the legend of Figure 7.



Figure 7 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.

480 The results from Figure 7 indicate that for the Area, Intensity, and Velocity components, the Pearson correlation 481 weights improve the performance of target-based k-NN from 5 up to 100% compared to the PIC weights. This happens 482 mainly for the short lead times (LT<+60min) throughout the three groups of nowcast times. For longer lead times there 483 seems to be no significant difference between the predictors sets. The same cannot be said for the Total Lifetime as a 484 target variable, here the Pearson correlation weights do not give the best results for all the nowcast times. In fact, here the 485 k-NNs based on the PIC weights seem to be more appropriate and yielded better results. However, as the other 4 target 486 variables are better for the Pearson correlation, this predictor set was selected for all applications of the k-NN (with 487 different weights according to Table 3) to keep the results consistent with one another. A further analysis was done that Formatted: Font: (Default) Times New Roman, 10 pt, English (United Kingdom)

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488 proved that the application of the correlation weights produces lower errors than the non-weighted k-NN application (all 489 weights are assigned to 1 to the most important predictors from Pearson correlation).

490 Lastly, it should be emphasized that for the computation of predictors weights, all the events were grouped 491 together, and thus when applying the k-NN nowcast in the cross-validation mode, there is a potential that the information 492 leaks from the importancet analysis to the performance of the k-NN (also illustrated in Figure 3-c). In other words, the 493 performance of the k-NN will be better, because the weights were derived from all the events grouped together. Typically, 494 in modelling applications, the optimization dataset should be clearly separated by the validating one, in order to remove 495 the effect of such information leakage. For this purpose, the correlation weights were computed 110 times, on a "leave-496 one-event-out" cross-sampling, in order to investigate their dependence on the event database. The results of such cross-497 sampling are visualized in Appendix 8.3 and indicate a very low deviation of the predictors weights (lower than 0.01) 498 over all the target variables. The shown low variability of the Pearson Correlation weights justifies the decision to estimate 499 the weights from the whole database, as the potential information leakage is not likely affecting the results of the k-NN 500 performance. This is another reason favouring the calculation of the predictor's weights based on the Pearson Correlation. 501 On the other hand, the weights from the PIC analysis are changing very drastically depending on the dataset and hence 502 the effect of the information leakage would be much larger in the k-NN developed from PIC weights. Moreover, a 503 sensitivity analysis as done in Appendix 8.3 cannot be performed for the PIC analysis because it would be extremely 504 time consuming.

505 *4.2 Optimizing the deterministic k-NN nowcast*

506 Once the most important predictors and their weights are determined, the optimization of the single k-NN 507 nowcast for the two k-NN applications (storm-based and target-based) was performed. The optimal k-value obtained from 508 minimizing the mean absolute error (MAE) produced by k-NN are shown in **Figure 8-upper row**. The results are 509 computed for the given nowcast times, lead times and target variables for both k-NN applications (VS1 target-based and 510 VS2 storm-based). For the 4 target variables Area, Intensity and Velocity in X/Y direction, the number of optimal values 511 decreases quasi exponentially for lead time up to 1 hour. After these lead time, when the majority of the storms are



Figure 8 The optimization of the k-NN per target variable based on predictors and weights derived from Pearson correlation analysis: the median optimal selected "k" neighbours yielding the lowest absolute errors over the 110 events. Two k-NN applications are shown here – VS1 in solid line and VS2 in dashed line: *fEirst row* – The optimal neighbour is found from minimizing the MAE for given group of nowcast times per event, *Secondsecond* row – The optimal neighbour is found from minimizing the <u>absolute</u> mean error (ME) for the given group of nowcast times per event. The red dashed horizontal line indicates the k=4 that is chosen in this study for the deterministic k-NN application.

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512 dissipated, the optimal k-number converges at 1, meaning that the closest neighbour is enough to predict the dissipation 513 of the storms. Contrary, for the very short lead times, the closest identified neighbour is unable to capture the growth/decay 514 processes of the storms, thus the response has to be average from k-neighbours, with k depending strongly on target 515 variable, nowcast time, lead time, and total lifetime. This seems to be the case also for the Total Lifetime, where averages 516 between 3-15 neighbours are computed as K_{min} . Overall the k=1 seems to yield the lowest MAE for the majority of the 517 lead time, nowcast times and target variables, and therefore is selected to continue further on with the analyses. However, 518 selecting the first neighbour does not satisfy the requirement that the nature doesn't repeat itself, and ideally a k>1 should 519 be achieved such that the responses from similar neighbour can be averaged to create a new response. For this purpose, 520 the optimal K were additionally obtained by minimizing the absolute mean error (ME) and are shown in Figure 8 -lower 521 row. -Here the overestimation and underestimation of different storms balance one another, and the results seem to 522 converge when averaging 3-5 neighbours. A direct comparison of the MAE for k~2-5 and k=1 was performed in order to 523 understand if a higher k will benefit the application of both k-NN versions. The median improvements of using neighbours 524 from 2-5 instead of 1 (over the selected groups of nowcast times) are shown only for the Total Lifetime in Table 4. The 525 other target variables are left outside this analysis as the improvements averaged over all the lead times are very close to 526 zero, as the dissipation of storms is captured well by all the 5 closest neighbours. From the results of the Table 4 it is 527 visible that k=4 brings the most advantages and hence was selected for both applications as a better compromise. The 528 selection of k=4 is not an optimization per se, as it was not learned with artificial intelligence, instead was selected based 529 on human intuition, and it does not represent the best possible training of the Kmin. For a more complex optimization, the 530 machine learning can be employed in the future to learn the parameters of the exponential relationship between Kmin, lead 531 time, nowcast time and target variable. In that case a proper splitting of the database intro training and validation should 532 be done in order to avoid, information being leaked from the optimization to the validation of the k-NN. In our case, the 533 effect of the information leakage at this stage (also illustrated in Figure 3-c) is minimized by obtaining the K_{min} on a 534 cross-sampling of the events, and averaged over the events, lead times and nowcast times.

Table 4 The median improvement of the total lifetime MAE when using k=2-5 instead of k=1 over the three selected groups of nowcast times.

	k=2	k=3	k=4	k=5
Storm-based	9.09%	10.74%	13.09%	11.94%
Target-based	3.40%	5.89%	6.54%	6.02%

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536 4.3 Results of the deterministic 4-NN nowcast

537 The median MAE of the 4-NN determinist nowcast over all the events, run for both target- and storm-based 538 approaches are shown in Figure 9 for each lead time and target variable. The results are grouped according to the storm 539 duration; i) upper row - for storms that live 30min, ii) middle row - for storms that live up to 3 hours and iii) lower row 540 - for storms that live longer than 3 hours, and are averaged per nowcast times given in Table 2. As shown as well in the 541 optimization of the 4-NN, the target-based k-NN exhibits lower Area, Intensity and Velocity errors than the storm-based 542 4-NN. Table 5-a illustrates the median deterioration (-) or improvement (+) in percent (%) over all lead times that the 543 storm-based 4-NN can reach when compared to the target-based one.

Table 65 Median Deterioration (-) or Improvement (+) of k-NN storm-based (VS2) compared to target-based (VS1) over all lead times according to the storm duration and nowcast times (shown in %). Equation 9-11 is used here, where "ref" - is the target-based and "new" is the storm-based k-NN.

						a) determi	inistic comp	parison of r	nedian MA	E from sto	rm-based to	o target - ba	ised							
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	- 5min	-3%	8%	-8%	-27%	2%	Duration	5min	-0.21%	-2%	3%	-1%	-4%	Duration	5min	-9%	0%	2%	-1%	-1%
30min	15min	0%	7%	-14%	-38%	-7%	0.5-3h	60min	30.00%	2%	-5%	23%	-11%	>3h	120min	-10%	-7%	-3%	-10%	2%
	30min	0%	0%	0%	0%	13%		180min	-15%	-28%	-100%	-100%	28%		360min	-10%	-8%	-8%	21%	18%
	b) probabilistic comparison of median MAE from storm-based to target - based																			
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	5min	-19%	796	-12.75%	-50.00%	0.50%	Duration	5min	-3.00%	0.00%	-0.50%	-14.40%	-4.02%	Duration	5min	-9.30%	-4.24%	1.10%	-0.67%	-9.27%
John	15min	3%	4%	-6.95%	-58%	-9.61%	0.5-50	60min	11.58%	-0.23%	-11.60%	15.37%	3%	~31	120min	-5%	2%	-4%	-5%	4.79%
	Nowcast	Area	Intensity	c) determi Velocity X	inistic comp Velocity Y	arison of r Total Lifetime	nedian imp	Nowcast	owards La Area	ngrangear Intensity	Persistence Velocity X	e from stor Velocity Y	m-based to Total Lifetime	target-ba	Nowcast	Area	Intensity	Velocity X	Velocity Y	Total Lifetime
Duration 5	Smin	-196	0%	0%	-196		Duration	Smin	0.00%	056	195	096		Duration	Smin	-26%	096	6%	-8%	
30min	15min	0%	0%	0%	-1%		0.5-3h	60min	12.53%	196	-1%	3%		>3h	120min	-31%	-22%	.29%	.30%	
	30min	0%	0%	0%	0%			180min	0%	0%	1%	0%			360min	-5%	-21%	-8%	89%	
	d) probabilistic comparison of median improvement towards Langrangean Persistence from storm-based to target-based																			
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	5min	-1%	0%	0%	0%		Duration 0.5.3h	5min	-1.40%	0%	0%	-1%		Duration	5min	-44%	-11%	5%	-3%	
John	15min 20min	0%	0%	0%	0%		0.3-34	60min	2.50%	0%	0%	0%		-34	120min 360min	-20%	11%	-5%	-6%	
	Sound	078	076	0%	1/70			revinin	-170	170	076	-178			Joomin	-070	070	-2470	0%	

Table 55 Median Deterioration (-) or Improvement (+) of k-NN storm-based (VS2) compared to target-based (VS1) over all lead times according to the storm duration and nowcast times (shown in %). Equation 9 is used here, where "ref" is the target-based and "new" is the storm-based k-NN.

						a) determi	inistic comp	parison of r	nedian MA	E from sto	rm-based to	o target - ba	ised							
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	- 5min	-3%	8%	-8%	-27%	2%	Duration	5min	-0.21%	-2%	3%	-1%	-4%	Duration	5min	-9%	0%	2%	-1%	-1%
30min	15min	0%	7%	-14%	-38%	-7%	0.5-3h	60min	30.00%	2%	-5%	23%	-11%	>3h	120min	-10%	-7%	-3%	-10%	2%
	30min	0%	0%	0%	0%	13%		180min	-15%	-28%	-100%	-100%	28%		360min	-10%	-8%	-8%	21%	18%
	b) probabilistic comparison of median MAE from storm-based to target - based																			
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	5min	-19%	7%	-12.75%	-50.00%	0.50%	Duration	5min	-3.00%	0.00%	-0.50%	-14.40%	-4.02%	Duration	5min	-9.30%	-4.24%	1.10%	-0.67%	-9.27%
30min	15min	3%	4%	-6.95%	-58%	-9.61%	0.5-38	60min	11.58%	-0.23%	-11.60%	15.37%	3%	>3n	120min	-5%	2%	-4%	-5%	4.79%
	30min	30.23%	29.62%	35%	40.18%	3.45%		180min	-8%	-4%	-100%	-88%	5%		360min	-3.50%	-0.42%	-10%	11%	5.14%
				c) determi	nistic comp	arison of r	nedian imp	rovement t	owards La	ngrangear	Persistence	e from stor	m-based to	target-ba	ed					
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	5min	-1%	0%	0%	-1%		Duration	5min	0.00%	0%	1%	0%		Duration	5min	-26%	0%	6%	-8%	
30min	15min	0%	0%	0%	-1%		0.5-3h	60min	12.53%	1%	-1%	3%		>3h	120min	-31%	-22%	-29%	-39%	
	30min	0%	0%	0%	0%			180min	0%	0%	1%	0%			360min	-5%	-21%	-8%	89%	
	d) probabilistic comparison of median improvement towards Langrangean Persistence from storm-based to target-based																			
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	5min	-1%	0%	0%	0%		Duration	5min	-1.40%	0%	0%	-1%		Duration	5min	-44%	-11%	5%	-3%	
Jomm	15min	0%	0%	0%	0%		0.3-30	60min	2.50%	0%	0%	0%		-30	120min	-20%	11%	-5%	-6%	
	somm	0%	0%	0%	0%			raomin	-170	0%	0%	-1%			300min	-3%	0%	-2470	0%	

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For storm living less than 30 minutes, the MAE is decreasing with the lead time and past LT+30 min is mostly 545 zero, as the dissipations of the storms have been captured successfully. The Total Lifetime of the majority of the storms 546 can be captured with ~15 min over-/underestimation regardless of the nowcast time. The errors for the 4 target variables 547 (except Total Lifetime) are lower for the later nowcast times than for the earlier ones (as expected). The difference between

548 the storm- and target-based 4-NN is very small for Area, Intensity and Total Lifetime, but much higher for the velocity 549 components (with storm-based exhibiting up to 40% higher errors than the target-based). The biggest difference seems to 550 be for shorter lead times (LT < +1h). For the storms living up to three hours, the same behaviour is, more or less, observed. 551 The only difference is for nowcasts issued at 3rd hour of the storm existence (last moment the storm is observed). Here it 552 is clear that the 4-NN fails to capture the dissipation of the storms that live exactly three hours, however this is attributed 553 to the number of available storms with duration of 3 hours (median over 6 storms available). Since the Area, Intensity and 554 Total Lifetime are overestimated and not converging to zero for high lead times, it is clear that the nearest neighbours are 555 being selected from the longer storms that do not dissipate within the next 3 hours. The differences between the two 4-556 NN approaches are visible mainly for lead times up to 30 min (except the nowcast at 3rd hour of storms life), afterwards 557 the errors are relatively converging to each other. The storm-based 4-NN produces circa 10-20% higher errors than the 558 target-based one for the nowcast times lower than 3hours, while for nowcast time of 3 hours, the errors are up to 100% 559 higher than the target- based one. At these storms as well, the higher discrepancy between the two versions of 4-NN is 560 seen at the Velocity components.



Figure 9 The median mean absolute error (MAE) over all the events, 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 performance is shown for 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. <u>Nowcast time dictates when the nowcast is issued relative to storm initiation</u>

For the storms that live longer than 3 hours (under 100 storms available) the same problem, as in the nowcast time of 3 hours seen before, is present. The Total Lifetime is clearly underestimated (up to 100min) as due to database the information is taken from shorter storms. It is important to notice here, that although 70 storms are present, because of the "leave-one-event-out" validation, the storm database is actually smaller. Nevertheless, the error is manifested here differently: as the long storms are more persistent in their features: the Area, Intensity and Velocity components are captured better for the short lead times with the error increasing at higher lead times. Here as well the nowcast issued at



Figure <u>1144</u> The median improvements over all the events that the single 4-NN application 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),

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Figure <u>1044</u> The median improvements over all the events that the single 4-NN application 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. 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).

the earlier stages of the storm's life exhibit higher errors than in the later stages. Especially for the nowcast at the 6th hog

568 of the storm's existence, the errors are quite low for all 5 target variables due to the persistence of the stratiform storms. 569 For this group of long storms, the storm-based nowcast yields up to 10% higher errors than the target-based one, with 570 only few exceptions depending on the time of nowcast and variable. It is clear that the storm-based 4-NN is more 571 influenced by the number of available storms than the target-based approach.

572 Figure 10 shows the improvement that the 4-NN introduces to the nowcast when compared to the Lagrangian 573 persistence (either target- or storm-based) and are averaged per lead time for each of the three group of storms and the respective times of nowcast. Since the Lagrangian Persistence doesn't issue a Total Lifetime nowcast, only the four target 574 575 variables (Area, Intensity and Velocity components) are considered. The green area indicates the percent of improvement 576 from the application of the 4-NN approach, and the red area indicates the percent of deterioration from the 4-NN 577 application (Lagrangian persistence is better). Additionally, median improvements (+) or deterioration (-) over all lead 578 times of the storm-based compared to target-based 4-NN approach in respect to the Lagrangian Persistence are illustrated 579 in Table 5-c. For the 30min storms, the 4-NN approach (both target- and storm-based) are considerably better than the 580 Lagrangian persistence: improvement is higher than 50% from the LT+15min and up to 100% from LT+60min. The 581 improvement is greater for nowcast at the 15th min of storm existence (when the persistence predictors are considered). It 582 is clear than due to the autocorrelation, the Lagrangian persistence is more reliable for the short lead times and for earlier 583 nowcast times. However, after LT+15min and for nowcast times near to the dissipation of the storms, where the non-584 linear relationships govern, the improvements from the nearest neighbour are more significant. The target-based 4-NN 585 results in slightly higher improvements than the storm-based one only for lead time up to 30min, past this lead time the 586 improvements from both versions are converging. For the storms that live between 30 min to 3 hours, the improvements 587 are introduced first after LT+15 or +30 min depending on the nowcast time: with increasing nowcast time increases the 588 improvement as well. The only exception is for the nowcast of Area and Intensity on the 3rd hour of the storm existence, 589 where no clear improvement of the 4-NN approaches could be seen before LT+30min or LT+1h. This low improvement 590 for the nowcast time of 3 hours was expected following the poor performance of the 4-NN shown in Figure 9. It seems 591 like the Lagrangian persistence is particularly good for predicting the Area and Intensity at very short lead times (up to 592 LT+20min). Here, for nowcast times of 5min, the Lagrangian Persistence is 100% better than any of the 4-NN approaches. 593 But not the same is true for the Velocity Components, with the Lagrangian Persistence exhibiting very low advantages 594 against the 4-NN for the short lead times. Regarding the difference of the two 4-NN approaches, with few exceptions, the 595 storm-based nowcast exhibits similar improvements as the target-based. Another exception is the nowcast time of 3 hours, 596 where the storm-based improvements are clearly lower, especially for the higher lead times, than the target-based (up to 597 40%). For storms living longer than 3 hours, the improvements are present for lead times higher than 2 hours. Since the 598 features of the long storms (mostly of stratiform nature) are persistent in time, is understandable for the Lagrangian 599 Persistence to deliver better nowcast up to LT+2h. Past this lead time non-linear transformations should be considered. 600 Here, even though the storm database is small, the non-linear predictions based on the 4-NN capture better these 601 transformations than the persistence. The improvement introduceds by the storm-based are generally from 20-30% lower 602 than the improvements introduced from the target based.

603 To conclude, the 4-NN deterministic nowcast brings up to 100% improvements for lead times higher than the 604 predictability limit of the Lagrangian persistence and are dependentdepend mainly on the storm type and the size of 605 database. Overall, for all storms the improvement is mainly at the high lead times and later times of nowcast, as the 4-NN 606 is capturing particularly well the dissipation of the storms. The results from the long events are suffering the most from 607 the small size of the database. This was anticipated, as the events were mainly selected from convective events that have 608 the potential to cause urban floods. A bigger database, with more stratiform events included, can introduce a higher 609 improvement to the Lagrangian persistence. These improvements are expected to be higher for lead times longer than 2 24

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610 hours, but is yet to be seen if a larger database can as well behave better than the persistence even for lead times shorter 611 than the predictability limit. Regarding the two different 4-NN approaches, the storm-based performs 0-40% worse than 612 the target-based nowcast, introducing generally 40% lower improvements to the Lagrangian persistence. The main 613 differences between these two approaches lie between the growth/decay processes, which the target-based 4-NN can 614 capture better. Also, these differences are particularly larger for the Velocity Components and for the Total Lifetime, than 615 in the Area and Intensity as target variables. Furthermore, it seems that the storm-based 4-NN is more susceptible to the 616 size of the database than the target-based one. Nevertheless, there are some cases where the storm-based behaves better 617 than the target-based nowcast (as illustrated with green in Table 5 -a) even though the target-based approach should be 618 profiting more from the selected predictors and their respective weights. A better optimized K_{min} for each lead time and 619 nowcast time, may actually improve further on the results of both 4-NN versions, and give the advantages mainly to 620 target-based nowcast.

4.4 Results of the ensemble 30-NN nowcast

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623 The median CRPS over all the events for the probabilistic 30NNs (in solid lines) together with the 624 median MAE for the deterministic 4-NN (in dashed lines), are illustrated respectively for storm-based approach in Figure 625 11 and for target-based approach approaches in Figure 12. The results are shown as in the previous fFigures per each 626 lead time and target variable, for storms divided into 3 groups according to their duration and averaged depending on the 627 time of nowcast. Additionally, the median improvements (+) or deterioration (-) of storm-based CRPS values in 628 comparison with the target-based are given in Table 5-b. For the 30min long storms, the errors of the probabilistic nowcast 629 are typically lower than the single 4-NN nowcast for all the variables, lead times and nowcast times, independent of the 630 30NNs approach (either storm- or target-based). In contrast to the deterministic 4-NN, the probabilistic 30NNs 631 performance is very little dependent on the nowcast time (mainly for Area, Intensity and Total Lifetime). The storm-based 632 30NNs has up to 50% higher errors than the target-based, but on the other side can have up to 40% lower errors than the 633 target-based for nowcast times of 30min. This suggests that storms in this duration behave similarly and their dissipation 634 can be predicted adequately by the storm-based approach with more than 4 similar neighbours. For storms that live shorter 635 than 3 hours, the same performance is as well exhibited: the probabilistic 30NNs has lower errors than the deterministic 636 4-NN. The difference between the target- and storm-based nowcasts is within the range of the single 4-NN nowcast for 637 the first 4 target variables, with storm-based 30NNs having 15% higher errors in the first 30 min of the nowcast than the 638 target-based. For Intensity and the Total Lifetime, both of the 30NNs exhibit very similar errors for most of the nowcast 639 times. It is worth mentioning here, that for the nowcast at the 3rd hour of storms' existence the errors are much lower than 640 the single 4-NN nowcast. This proves that the most similar storms are within the 30 members, but not within the first 4 641 neighbours selected in the case of the single 4-NN nowcast. Due to the unrepresentativeness in the database, the errors of Formatted: Standard, Justified, Indent: First line: 1.25 cm

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Figure 1214 The median CRPS over all the events for each target variable (Area, Intensity, Velocity in X and Y direction and Total Lifetime) on the storm-based applications: 4-NN (deterministic) in *solid_dashed_and 30NNs* (probabilistic) in *dashed_solid_lines.* The performance is 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.



Figure 12, The median CRPS over all the events for each target variable (Area, Intensity, Velocity in X and Y direction and Total Lifetime) on the target-based applications: 4-NN (deterministic) in dashed and 30NNs (probabilistic) in solid 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.

row), and longer than 3 hours (lower row), and over the selected nowcast times. the longer storms are considerably higher than the other storm groups, and the errors of the first 4 target variables 27

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644 increasing with the lead time and decreasing with the nowcast time, as in the case of the deterministic 4-NN nowcasts.
645 However here unlike the other storm groups, the differences between the storm-based and target-based approach are
646 visible past 30 min lead time, with the storm-based errors being up to 15% higher than the target-based.
647

648Overall the ensemble results are clearly better than the single 4-NN nowcast, suggesting that the best responses649are obtained by singular neighbours (either the closest one or within the 30 neighbours) and not by averaging. Thus, there650is still room for improving the single 4-NN nowcast by selecting better the important predictors and their weights or651averaging differently the nearest neighbours. Nevertheless, the results from Figure 11 and Figure 12 emphasize that652similar storms do behave similarly, and that the developed k-NN on the given database with 30 ensembles gives653satisfactory results. Compared to the deterministic 4NNs it has the advantage that no k-optimization is needed, and the654two approaches (storm- and target-based) have less discrepancies with one another.

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Figure 13 The median improvements over all events, 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. 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 13 The median improvements over all events, 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. 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).

657

Figure 13 demonstrates the improvement of the probabilistic 30NNs when compared to the Lagrangia

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658 persistence (storm-based in dashed line, and target-based in solid line). As before the median improvement over the events 659 is computed and shown for each storm duration group, nowcast time, lead time and target variables (expect for the Total 660 Lifetime). For all the three groups it is visible that performance increases considerably with the lead time - suggesting 661 that the ensemble predictions are particularly useful for the longer lead times where the single nowcast is not able to 662 capture the storm evolution. For short storms (duration shorter than 30min) the Lagrangian persistence is only better for 663 the Area and Intensity at 5min nowcast time and for very short lead times (up to 10min). However, past this lead time, 664 the probabilistic 30NNs has the clear advantage with improvements up to 100%. Past LT+30min, which coincides with 665 the predictability limit of the Lagrangian persistence at such scales, there is no difference between the nowcast time and 666 30NNs approach (less than 1% for all target variables and nowcast times). For storms that live shorter than 3 hours, the 667 results are slightly worse than the very short storms., but still exhibit the same patterns. Here as well the main 668 improvements of the 30NNs probabilistic approach is seen between LT+15min to LT+30min for all the target variables. 669 Interesting in this storm group are the results from the nowcast time of 3 hours that exhibit different behaviours than the 670 deterministic approach. This is expected as the Lagrangian persistence performs particularly poorly because it cannot 671 model the storms dissipations. The difference between the two types of 30-NN is insignificant, although a bit higher than 672 for the very short storms (~2.5% difference). For the longer storms the benefit of the probabilistic 30NNs is seen mainly 673 for LT+60min to LT+120min, but still not as high as in the other storm groups. The worse performance is at nowcast time 674 of 5min, where the 30NNs fails to bring any advantage to the prediction of Area and Intensity when compared to the 675 Lagrangian Persistence. Interesting from these storms, is that the improvement is more significant at the Velocity 676 Components than in the Area and Intensity predictions. This suggest the velocity components are more persistent (see 677 Figure 4) and easier to be predicted from similar storms.

678 As a conclusion the probabilistic nowcasts are better than the Lagrangian Persistence mainly for convective 679 storms that last shorter than 3 hours and lead times higher than LT+15min. Of course, there is still room for improving 680 the 30NNs application by increasing the size of the past database. Overall, it seems that the velocity components can be 681 captured much better by the 30NNs application than the Lagrangian Persistence, while the Lagrangian Persistence is more 682 suitable for long persistent storms and for nowcast times of 5min where not enough information is available to select 683 similar storms. An increase in the database, with more stratiform storms, may improve the performance of the 30NNs and 684 its advantage towards over the Lagrangian Persistence. However, the value of the probabilistic 30NNs relies mainly in 685 the nowcasting of convective events. Moreover, the possibility of merging Lagrangian Persistence with a probabilistic 686 30NNs approach should be explored and further investigated; the Lagrangian Persistence should be implemented for very 687 short lead times (up to 30min) and for the first nowcast times where the predictors are not enough to select similar past 688 storms.

689 Improving the nowcasting of storm characteristics is the first step in improving rainfall nowcasting at fine 690 temporal and spatial scales. On a second step, the knowledge about the storm characteristics (as nowcasted by the 30NNs) 691 should be implemented on the spatial structure of the storms to estimate rainfall intensities at fine scales (1km² and 5min). 692 There are two options to deal with the spatial distribution of the rainfall intensities inside the storm region (which is so 693 far no treated in this study): 1. Increase/Reduce the area by the given nowcasted area (as target variable) for each lead 694 time, scale the average intensity with the nowcasted intensity, and move the position of the storm in the future with the 695 nowcasted velocity in x and y direction. 2. Take the spatial information of the selected neighbours, perform an 696 optimisation in space (such that present storm and the neighbour's storms locations match) and assign this spatial 697 information to the present storm for each lead time. The former is an extension of the target-based 30NNs, while the later 698 an extension of the storm-based 30NNs. So far, the comparison between these two versions, showed that the target-based 699 approach is better suited mainly to nowcast the velocity components, thus a merging of the two could also be reasonable: 30

700	the storm-based approach is used for nowcasting Area-Intensity-Total Lifetime (features that are co-dependent based on
701	the life cycle characteristics of convective storms), and the target-based approach for the nowcasting of the velocity
702	components. The suitability of the proposed combinations and the merging of the 30NNs with the Lagrangian persistence
703	for nowcasting rainfall intensities at fine scales, is currently under investigation and will be discussed in a follow up paper.
704	4.5 Nowcasting the unmatched storms
705	For the optimization and testing of the k-NN approaches, the unmatched storms from the tracking algorithm were
706	left outside of the database. Nevertheless, in an online application (operational nowcast), when the storm is recognized
707	for the first time, one can not cannot predict if the storm is an artefact, or it will not be matched by the tracking algorithm.
700	

Therefore, it is important to investigate how the developed k-NN deals with these unmatched storms. **Figure 14** illustrates the median performance over the 110 events of the developed target-based (upper row) and storm-based (lower row) k-NN when predicting the target variables of the unmatched storms from a past database of only matched storms (storms with duration equal or longer than 10min). As in the previous results, the 30NNs probabilistic application yields better errors than the deterministic one, causing an overestimation of these storms for the first 10-20min for the target-based approach and 15-30min for the storm-based one. A direct comparison of these errors with the Lagrangian Persistence is shown in **Figure 15**, with the deterministic 4-NN in the upper row and the probabilistic 30NNs in the lower row. As

expected the probabilistic 30NNs brings the most improvement when compared to the Lagrangian Persistence for all lead
 times and target variables. Thus, even though, most of these unmatched storms will be overestimated in their duration,

the 30NNs will capture their dissipation much better than either the deterministic 4-NN or the Lagrangian Persistence.





Figure 15414 Median CRPS error over the 110 events for each of the target variables nowcasted from 4-NN

deterministic (in dashed lines) and 30NNs probabilistic (in solid lines) applications for both target- (upper row) and storm-based (lower row) approaches. The results shown here are from the "unmatched storms" when the nowcast time is 5 min.



Figure 15 Median performance improvement over the 110 events for each of the target variables nowcasted from 4-NN deterministic (upper row) and 30NNs probabilistic (lower row) applications when compared to the Lagrangian Persistence, for both target- (solid lineupper row) and storm-based (lower rowdashed line) approaches. The results shown here are from the "unmatched storms" when nowcast time is 5min.

720 5. Conclusions

721 Accurate predictions of rainfall storms at fine temporal and spatial scales (5min, 1km²) based on radar data are 722 quite challenging to achieve. The errors associated with the radar measurements, identification and tracking of the storms, 723 and more importantly the extrapolation of the storms in the future based on the Lagrangian persistence, are limiting the 724 forecast horizons of such object-oriented radar based nowcasts to 30-45 min for convective storms and to 1 hour for 725 stratiform events (Shehu & Haberlandt, 2021). The focus of this paper was the improvement of the storm-oriented radar 726 based nowcasts by considering other non-linear behaviours for future extrapolation instead of the Lagrangian persistence. 727 For this purpose, a nearest neighbour approach was proposed that predicts future behaviours based on past observed 728 behaviours of similar storms. The method was developed and validated for the Hannover Radar Range where storms from 729 110 events were pooled together and used in a "leave-one-event-out" cross-validation. From 110 events a total of around 730 5200 storms with different morphology were identified and tracked with HyRaTrac in order to build up the database for 731 the k-NN implementation. The storms were treated as ellipses and for each state of the storms' evolution different features 732 (describing both present and past states) were computed. The k-NN approach was developed on these features to predict 733 the behaviour of the storms in the future (for lead times up to 3 hours) through 5 target variables (Area, Intensity, Velocity 734 in X and Y direction and Total Lifetime).

735 First an importance analysis was performed in order to recognize the most important predictors for each of the 736 target variable. Two different approaches were employed for this purpose: Pearson correlation, and Partial Information 737 Correlation (PIC). A comparison of these two methods revealed that for the application at hand the Pearson Correlation 738 is more reliable at determining important predictors, and delivers 5%-30% better results than the PIC method. However, 739 the PIC seems promising mainly for determining the most important predictors of the Area and Total Lifetime for storms 740 longer than 3 hours, and is still recommended for investigation in the future. The Area, Intensity and Total Lifetime of the 741 storms seem to be co-dependent on one another and on the features that describe their evolution. In particularly the 742 variance of the spatial intensity is an important predictor for the three of them. On the other hand, the velocity components 743 are dependent as well more on features that describe their evolution. Nevertheless, there is still a dependency of the area 744 and velocity components, and should be included when predicting each other mainly for high long lead times.

745 The weights derived from the Pearson correlation were used for the similarity estimation of different storms 746 based on the Euclidian distance. Two k-NN approaches were developed on two measurements of similarity metrics: a) 747 target-based approach - similarity was computed for each target independently and indicates the best performance 748 possible by the given predictors and weights, and b) storm-based approach - similarity was computed for each storm 749 keeping the relationship between the target variables. For the two approaches a deterministic (averaging the 4 closest 750 neighbours) and a probabilistic (with 30 nearest neighbours) nowcast were issued for all of the storms in "leave-one-751 event-out" cross-validation mode. In the deterministic nowcast the difference between the two remains mainly at short 752 lead times (up to 30 min) and at the Velocity Components, with the storm-based results yielding up to 40% higher errors 753 than the target-based ones. However, at higher lead times the difference between the two became insignificant, as the 754 dissipation processes were captured well for the majority of the storms. The same behaviours were observed as well in 755 the ensemble nowcast, with target-based ensembles being slightly better than the storm-based nowcast. Overall the storm-756 based approach seems reasonable for Area-Intensity and Total Lifetime, as they are co-dependent and their relationship 757 should be maintained for each storm, while target-based approach captures better the velocity components. A combination 758 of the both approaches, may results in better nowcasting of storms' characteristics.

To investigate what value each of the two k-NN approaches introduces to the nowcast, their errors (for both deterministic and probabilistic nowcast) were compared to the errors produced by the Lagrangian persistence. For both of the approaches the improvement was more than 50% for convective storms for lead times higher than 15 min, and for 33 762 mesoscale storms for lead times higher than 2 hours. The results were particularly good for the small convective storms 763 due to the high number of storms available in the database. For the mesoscale storms (with duration longer than 3 hours) 764 the improvements were not satisfactory due to the small sample size of such long storms. Increasing the sample size is 765 expected to improve the performance of the k-NN for these storms as well. However, when consulting the probabilistic 766 k-NN application it seems that, even for these storms and the given database, there are enough similar members in the 30 767 neighbours that are better than the Lagrangian persistence. This emphasizes that the probabilistic nowcast is less affected 768 by the sample size than the deterministic 4-NN. Moreover, the differences between the storm-based and target-based 769 approaches, become smaller in the probabilistic approach than the deterministic ones. Lastly, the optimization of the 770 adequate neighbours for the deterministic approach is far more complex than implemented here, but when issuing the 771 probabilistic nowcast there is no need to optimize the k-number. It is clear that the probabilistic application of the k-NN 772 outperforms the deterministic ones, and has more potential for future works.

773 Overall the results suggest that if the database is big enough, storms that behave similarly can be recognized by 774 their features, and their responses are useful in improving the nowcast up to 3 hours lead times. We recommend the use 775 of the nearest neighbour in a probabilistic application (30NNs) to capture better the storm characteristics at different lead 776 times. A merging with the Lagrangian Persistence for short lead times (up to 15min) and early nowcast times can be as 777 well implemented. Further improvements can be achieved if the predictors importance is estimated better (i.e. Monte 778 Carlo approach, or neural networks) or if additional predictors are included from other data sources like: cloud information 779 from satellite data, temperature, convective available potential energy (CAPE) and convective inhibition (CIN) from 780 Numerical Weather Prediction Models, lightening flash activity, additional measurements from Doppler or dual polarized 781 radar data (like phase shift, doppler velocity, vertical profile at different elevation angeles), various geographical 782 information (as distance from heavy urbanized areas, mountains or water bodies) and so on. The main benefit of the 783 probabilistic 30NNs is mainly seen for convective events and creating new nowcasting rules based on the predicted storm 784 characteristics. Future works include the integration of the developed 30NNs application in the object oriented radar 785 based nowcast to extend the rainfall predictability limit at fine spatial and temporal scales (1km² and 5min). In conclusion, 786 the results seem promising at the storms scale, nevertheless is still to be seen if the methodology applied here can introduce 787 improvements as well at the local scale, i.e. validation with the measurements from the rain gauge observations.

788 Improving the nowcasting of storm characteristics is the first step in improving rainfall nowcasting at fine 789 temporal and spatial scales. On a second step, the knowledge about the storm characteristics (as nowcasted by the 30NNs) 790 should be implemented on the spatial structure of the storms to estimate rainfall intensities at fine scales (1km² and 5min). 791 There are two options to deal with the spatial distribution of the rainfall intensities inside the storm region (which is so 792 far not treated in this study): 1. Increase/Reduce the area by the given nowcasted area (as target variable) for each lead 793 time, scale the average intensity with the nowcasted intensity, and move the position of the storm in the future with the 794 nowcasted velocity in x and y direction. 2. Take the spatial information of the selected neighbours, perform an 795 optimisation in space (such that present storm and the neighbour's storms locations match) and assign this spatial 796 information to the present storm for each lead time. The former is an extension of the target-based 30NNs, while the later 797 an extension of the storm-based 30NNs. So far, the comparison between these two versions, showed that the target-based 798 approach is better suited mainly to nowcast the velocity components, thus a merging of the two could also be reasonable: 799 the storm-based approach is used for nowcasting Area-Intensity-Total Lifetime (features that are co-dependent based on 800 the life cycle characteristics of convective storms), and the target-based approach for the nowcasting of the velocity 801 components. Future works (Part II - Local Intensities) will include the integration of the developed 30NNs application in 802 the object-oriented radar based nowcast to extend the rainfall predictability limit at fine spatial and temporal scales (1km² 803 and 5min). The main focus of the Part II is to investigate if the methodology applied here can introduce improvements as 34

804	well at the local scale, i.e. validation with the measurements from the rain gauge observations. The suitability of the
805	proposed combinations and the merging of the 30NNs with the Lagrangian persistence for nowcasting rainfall intensities
306	at fine scales, is currently under investigation and will be discussed in a follow up paper.
807	
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820 8. Appendix



Appendix₈-1₄Strength of relationship between the selected predictors and the target variables averaged for three lead⁴ times and storm duration groups based on correlation values. The green shade indicates the strength of the relationship: with 0 for no relationship at all, and 1 for highest dependency. The averaged computed values for each target variable

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(last row) are used as bases for **Table 3**. The correlation weights are absolute values of the correlation values between the predictors at specific lead times and target variables. Formatted: Font: Bold

823 824

8.2 Obtained predictors weights from the partial informational correlation importance analysis:



Appendix 8-2 Strength of relationship between the selected predictors and the target variables averaged for three lead⁴times and storm duration groups based on PIC method. The green shade indicates the strength of the relationship: with 0 for no relationship at all, and 1 for highest dependency. The averaged computed values for each target variable (last row) are used as bases for **Table 3**. For intensity, velocity in x and y direction, since the PIC recognized only one predictor as important, the average values is given as 1 for the selected respective predictor.

				Present Predictors								Average Past 30min Predictors																
	Durations	Lead Time	Cells	Lnow	Α	lave	Imax	lsd1	lsd2	Vg	Vx	Vy	Jmax	Jmin	Jr	Φ	A ₃₀	lave ₃₀	Imax ₃₀	lsd1 ₃₀	Isd2 ₃₀	Vg ₃₀	Vx30	Vy30	Jmax ₃₀	Jmin ₃₀	Jr ₃₀ (Φ ₃₀
1		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	J.00
	<1hr	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
		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	J.OO
8	1	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	1.00	0.00	0.00	0.00	0.00	0.00 0	J.OO
۲	<3hr	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	1.00	0.00	0.00	0.00	0.00	0.00 0	J.OO
	1	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	1.00	0.00	0.00	0.00	0.00	0.00 0	J.OO
	1	15min	0.00	0.10	0.25	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	J.OO
	>3hr	60min	0.00	0.29	0.67	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	0.33	0.00	0.00	0.00 0	J.OO
	1	180min	0.00	0.30	0.40	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	0.28	0.00	0.00	0.00 0	J.OO
		Average	0.00	0.08	0.15	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	0.33	0.00	0.07	0.00	0.00	0.33 0	0.00
	Durations	Lead Time	Cells	Lnow	A	lave	Imax	sd1	lsd2	Vg	Vx	Vy	Jmax	Jmin	Jr	Φ	A ₃₀	lave ₃₀	Imax ₃₀	Isd1 ₃₀	Isd2 ₃₀	V830	Vx30	Vy30	Jmax ₃₀	Jmin ₃₀	Jr ₃₀ (Φ30
		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
	<1hr	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	J. O O
₹		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	J.00
is is		15min	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	J.00
In te	<3hr	60min	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	J.00
	1	180min	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
		15min	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	J.00
	>3hr	60min	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	J.00
		180min	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	J.00
	Average				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	0.00
	Durations	Lead Time	Cells	Lnow	Α	lave	Imax	sd1	lsd2	Ve	Vx	Vv	Jmax	Jmin	Jr	θ	A ₃₀	lave ₃₀	Imax ₃₀	Isd1an	Isd230	Vgan	Vxao	Vya	Jmax ₁₀	Jmina	Jran (Φ
		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	0.00
	<1hr	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	0.00
×	1	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	J.00
A.		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	1.00	0.00	0.00	0.00	0.00 0	J.OO
ĕ	<3hr	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	1.00	0.00	0.00	0.00	0.00 0	J.OO
ž		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	1.00	0.00	0.00	0.00	0.00 0	J.00
		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	J.OO
	>3hr	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	J.OO
		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).0 0
		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	1.00	0.00	0.00	0.00	0.00 0).00
	Durations	Lond Time	Colle	Laser	•	laura	Inner	Lot	lun.	Ma	M.	M.	Inner	Inte	L.	•		laun.	Inner	last	Lun	Ma	N-	M.,	Inner	Inte	h (•
	Durations	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	*830 0.00	0.00	• • • • •	0.00	0.00	0.00 0	₩30 0.00
	<1br	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	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	0.00
E C		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	0.00
<u>o</u>	<3hr	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	0.00
Ň		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	0.00
1	1	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
	>3hr	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	0.00
1		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
-		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	0.00
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5	Durations	Lead Time	Cells	Lnow	Α	lave	Imax	sd1	lsd2	Vg	Vx	Vy	Jmax	Jmin	Jr	Φ	A ₃₀	lave ₃₀	Imax ₃₀	Isd1 ₃₀	Isd2 ₃₀	V ₈₃₀	Vx30	Vy30	Jmax ₃₀	Jmin ₃₀	Jr ₃₀ (Φ30
ati i	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	1.00 0	J.00
l la	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	1.00	0.00	0.00	0.00	0.00	0.00 0	J.00
<u> </u>	Dur >3hr		0.00	0.45	0.40	0.00	0.00	0.00	0.00	0.72	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.33	0.00 0	J.00
		Average	0.00	0.15	0.13	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	0.33	0.00	0.00	0.00	0.11	0.33 0).00

80 8.3 The standard deviation of the Pearson Correlation Weights from a cross-sampling of the events

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Appendix 8-3. The standard deviation of the Pearson Correlation Weights between predictors and target variables obtained from a cross-sampling of the events (leave one event at a time out). The boxplot for each target variable describes the spread of the standard deviation over all selected predictors.

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