Response to the Comments RC1 on Manuscript Predicting power outages caused by extratropical storms

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We thank the reviewer for taking the time to read our paper and for giving us insightful, constructive, and extremely valuable comments and improvement suggestions. We have addressed all the comments as accurately and precisely as possible and made the improvements in the manuscript.

In the following, we respond to the comments item-by-item. The referee's comments are indented and with italic typesetting. The authors' comments are with normal typesetting. Direct quotes from the manuscripts are marked with double-quotes.

Responds to the general remarks

General remarks

The article investigates windstorm impacts on the power grid in Finland. The authors present a methodology to identify storm objects as polygons and combine them with meteorological and non-meteorological data to predict power outages. They use ERA5 reanalysis data, a national forest inventory and a dataset with information about time and location of power outages in Finland. Storm objects are identified using a fixed wind speed threshold of 15 m/s are tracked in time and space. A large set of meteorological and non-meteorological parameters is gathered for each storm object. From these parameters the most relevant are selected and five different methods are used to classify the storm objects with respect to the damage they caused to the power grid using three damage classes. It is tested how well the different methods are able to predict the class of a storm object using cross-validation. Finally, the best performing classification method is applied to three test cases of severe storms.

In general, the article addresses the very interesting and relevant topic of predicting the impacts of extreme weather events. The authors use state-of-the-art data and methodology. However, there are some issues in the manuscript and there are some parts that need more detailed explanation and discussion. These issues should be addressed before the manuscript is accepted.

The authors use sophisticated methods for classification of storm objects with a large set of parameters. What is missing in the study is ***an analysis of the relevance of the individual parameters for the classification task.*** *It remains unclear* ***which of the parameters play an important role****. It might be, for example, that it is mainly the size of the storm object or the number of transformers under the object that is relevant for the damage, while the standard deviation of wind direction plays a minor role. It would be beneficial* ***to include an***

analysis of the importance of the parameters, at least for the best performing method, to add more scientific insight to the rather technical aspects of classification task.

We conducted a permutation feature importance analysis using the Gaussian processes (GP) model and a randomly selected test set of the national dataset. The same model and data are used to produce the case examples.

The manuscript is appended with the following chapters (page 17 in the updated manuscript):

“The relevance of the individual predictive features can be explored by using the permutation test, as done by Breiman (2001). First, the baseline score of the fitted model is calculated using the test set. Then each feature is randomly permuted, and the difference in the scoring function is calculated. The random permutation is repeated 30 times for each parameter, and the average of the results is used. The procedure offers information on how important the feature, the individual parameter, is to obtain good results. It should be mentioned that highly correlated features may get low importance as other features work as a proxy to the permuted feature. Using completely independent features is not, however, possible in weather data since weather parameters are often dependent on each other, and eliminating even the most apparent pairs from used features impaired the results in our experiments.

We used the macro average of F1 defined in Equation 7 as a scoring function and randomly selected test set from the national data. The relevance is shown in Figure 7. Most features show at least little relevance for the results. The first twelve features are more significant than the rest. The most important features contain at least one representative of all meteorological parameters used in training. In other words, all employed meteorological parameters are important for the prediction, while different aggregations are contributing to the "fine-tuning" of the model.

As Figure 7 shows, the most significant parameter regarding our model performance is the average wind speed. Numerous studies support our result of wind being the most important damaging factor (Virot et al., 2016; Valta et al., 2019; Jokinen et al., 2015) that are, however rather highlighting the importance of maximum wind gusts. Surprisingly, in our analysis, the wind gust speed does not belong to the most critical parameters. Instead, maximum mixed layer height, related to the wind gustiness, contributes crucially to the model performance. The dependencies between predictive features might be one reason for some parameters to have lower rank in the results.

The stand mean diameter and height are the most important features regarding the forest parameters, which corresponds to our expectations. Previous studies also state these features to influence the wind damage in forests (Pellikka and Järvenpää,2003) and hence indirectly electricity grids. As Pellikka and Järvenpää (2003) and Suvanto et al. (2016) discuss, also the age of the forest has an impact on storm damages. However, in the feature importance test, forest age does not seem to contribute significantly to the prediction outcome.

The most important object feature is the size of the object. Object movement speed and direction did not contribute to the results much. However, previous studies indicate that besides the size of the impacted area, the duration of strong winds – i.e., the movement speed of the system – influences also the amount of damage (Lamb and Knud, 1991)."

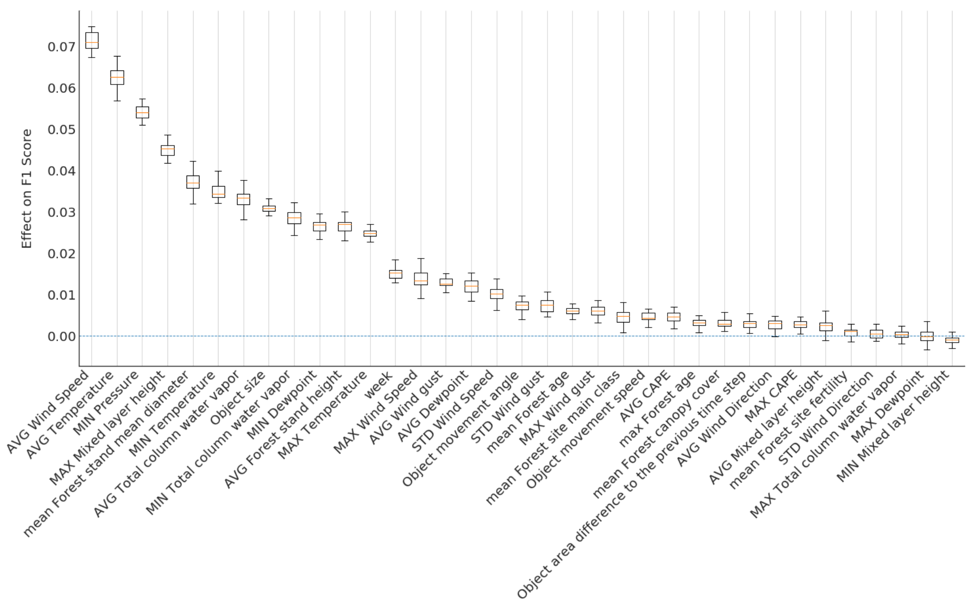


Figure7. Permutation feature importances using GP classification method trained with the randomly selected national dataset. The higher effect on the F1 score is (y-axis), the bigger is the significance.

The authors should discuss what is ***the benefit of using storm objects, rather than directly relating wind speeds and other parameters to power outages in a certain area, for example in a grid-based approach.*** *Following the approach in the manuscript, one is able to assign a damage class to the whole area of the storm object.* ***However, this does not provide any information about the specific location of the outage. I would suggest to discuss in more detail what could be the use of such large-scale damage information for an energy provider (see also my specific comment further below).***

Using storm-objects instead of fitting the models with gridded data is a fundamental design choice of the work. Its benefits and downsides will definitely be an interesting subject to cover. We added the following discussion into the manuscript (page 22, 415-430 in the updated manuscript):

"The presented object-based approach has both advantages and disadvantages. Extracting storm objects in advance, preprocesses the data for machine-learning techniques, such as RFC, which do not perform feature learning. It enables machine-learning methods to focus only on the relevant parts of the data. Methods not containing feature learning, such as RFC and logistic regression, have been found to outperform neural networks for forest (Hart et al., 2019) and weather data (Tervo et al., 2019). It also leads to significantly faster training times. Processing objects instead of the grid makes it also easier to track and use object attributes such as age, speed, and movement. Moreover, objects are easy to visualize, and user interfaces may be enriched with related actions such as tracking and alarms.

On the other hand, storm objects use only aggregated attributes, which may decrease the classification accuracy when predictive features vary significantly under the storm object area. Several machine-learning methods, i.e., deep neural networks, could be trained to employ those local features to gain better accuracy. Such methods could also utilize three-dimensional data.

Extracting storm objects requires a fixed threshold of wind gust and pressure, which may vary depending on the characteristics of geospatial locations. Nevertheless, the previous studies indicate the critical threshold for wind gust speed to be the same for the almost whole geospatial domain of this work (Gardiner et al., 2013). Moreover, the correct threshold may vary depending on the data source. When extending the geospatial domain or changing the data source, this would become a more serious issue, and different thresholds might be needed. One possibility to determine the optimal threshold might be to use specific quantiles of the parameter values, but this would need further studies."

In many figures the labels are hardly readable.

We went carefully through all figures and enlarged the labels.

The manuscript needs to be checked for English language.

We carefully checked the language and made corrections to the manuscript.

Respond to the specific remarks

Page 3, line 81: What is the spatial resolution of the forest inventory?

This information has now been added to the manuscript on page 4, lines 98-101.

"The original geospatial resolution of the data is 16 meters, which is reduced to approximately 1.6 km resolution to speed up the processing. Taking into account the size of extratropical cyclones (diameter ~1000 km) and the wide areas where wind damages typically occur, e.g., near to the cold front, we consider resolution of 1.6 km being sufficiently high for modelling wind storm damages."

Page 3, line 84-88: It could be useful to introduce Figure 1 already here in the data section. This would be helpful for the reader to understand the extraction of storm object feature in *section 3.2. You should also go into more detail about the spatial accuracy of the local and national data set.*

We have improved Figure 1 and moved it in the data section and made it more easily understandable and to have it in a more logical place. Firstly, we separated Figures 1a and 1b from 1c and 1d and improved the figures (pages 5 and page 9 in the updated manuscript). We have also added more information about the structure of the local and national dataset and on the spatial accuracy to the data section (page 4, lines 102-115):

“Power outage data are obtained from two complementary sources. *The national dataset* is acquired from Finnish Energy (Finnish Energy, 2010-2018) who aggregates the data from power distribution companies in Finland. The national data is provided only for research purposes and for areas containing a minimum of six grid companies; this is, for example, to ensure energy users’ anonymity. Therefore, the national dataset does not include exact locations of the faults. We have also obtained some parts of the data with better spatial accuracy from two individual power distribution companies. In this paper, we name this data to the local dataset. In the local dataset, the fault locations are reported in relation to transformers, i.e, the spatial resolution of the outages vary between few meters to kilometers.

Figure 1 illustrates the geographical coverage of the power outage data. The local dataset contains all outages from 2010 to 2018 from the northern area (Loiste) and outages related to major storms in the southern area (JSE), shown in Figure 1a. The national dataset contains all outages in Finland from 2010 to 2018 divided into five regions, shown in Figure 1b. The national dataset contains in total 6 140 434 outages with relatively low geographical accuracy. On the other hand, the local dataset represents a substantially smaller geographical area with a good geographical accuracy but contains only 22 028 outages in total. We train our classification models, described in more detail in Chapter 3.4, with both datasets to evaluate their performance for different types of data.”

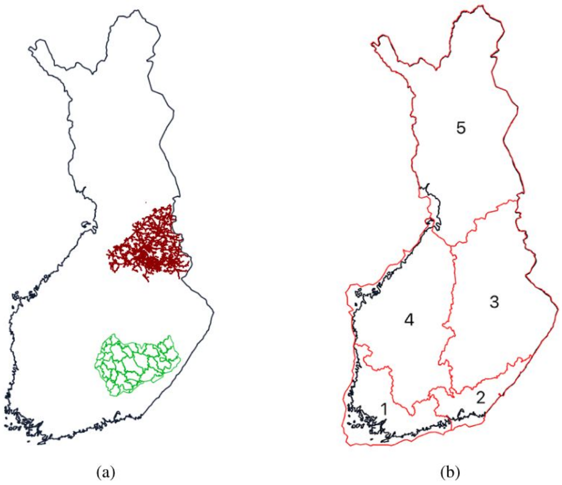


Figure 1. (a) Geographical coverage of the outage data (local dataset). The red lines represent the power grid of Loiste (northern grid company) and the green lines the operative areas of JSE (southern grid company). Outages of the local dataset are collected from both of these areas. (b) Regions in the national outage dataset. Outages are gathered from the whole Finland and aggregated to the regions shown in the figure.

Page 4, line 97: Can the storm polygons have "holes", if within the area of a polygon areas with winds below 15 m/s exist?

The contouring algorithm is capable of finding interior rings of the polygons. The used wind gust fields did not, however, contain any such cases. Thus one storm object represents a solid area (polygon).

This information has been added to the updated manuscript on page 5, lines 125-126.

page 4, line 103: Here you mention pressure objects for the first time. Are they defined by the 1000 hPa threshold? Please describe in more detail. Also, when you use the word "object" on its own, it is not clear if you refer to a "storm object" or "pressure object". Therefore you should only use "storm object" and "pressure object". Later you also use the term "wind object".

We clarified these paragraphs on page 5, lines 124-138, and revised the use of the word “object”. In particular, we describe the object identification and tracking method following:

“Storm objects are identified by finding contour lines of wind gust fields using 15 ms^{-1} thresholds from the ERA5 surface level grid with a time step of 1 hour. The contouring algorithm is capable of finding interior rings of the polygons. The used wind gust fields did not, however, contain any such cases. Thus one storm object represents a solid area (polygon) where hourly maximum wind gust exceeds 15 ms^{-1} during one particular hour. The threshold of 15 ms^{-1} is selected as different sources indicate Finland being vulnerable to windstorms and rather moderate winds (from 15 ms−1) causing damages to forests (Valta et al., 2019; Gardiner et al., 2013). Valta et al. (2019) developed a method to estimate the windstorm impacts on forests by combining the recorded forest damages from the nine most intense storms and their observed maximum inland wind gusts. According to the formula developed in the study, the inland wind gusts of 15 ms^{-1} alone result in forest damages of 1800 m^3.

We also identify pressure objects by finding contour lines using a 1000 hPa threshold to connect potentially distant wind objects around the low-pressure center to the same storm event.

After identification, storm objects are connected to other storm objects around the common low-pressure objects and to the storm and pressure objects in preceding timesteps using Algorithm 1. Each object having pressure objects or preceding objects within the threshold is assigned to the same storm event and gets the same storm ID. Single storm objects without nearby pressure objects or preceding objects are left without ID as they are not assumed to be part of any storm."

page5, algorithm1: What is the"previous pressure object"? Is it previous in time? Or is there another for-loop that cycles through the pressure objects, which is not mentioned in the algorithm? What is"other object"? You mention "object", without specifying if it is a storm or pressure object. Please revise the algorithm, so that it is easy to understand for the reader.

The algorithm description has been updated to be more explicit. The readability may have been affected a little bit, but we believe this is a better and more precise way to describe the tracking algorithm. Meritoriously notified questions about previous objects and object types are addressed as well.

The updated algorithm is listed below and updated to the manuscript.

Algorithm 1 Storm tracking

Input

Wind and pressure objects S_o arranged by time

$pressure\ distance\ threshold$

$wind\ distance\ threshold$

$speed\ threshold$

$time\ step$

Output

Connected wind and pressure objects with storm ID

for all wind and pressure object $O_{w|p} \in S_o$ **do**

$current\ time \leftarrow$ time of the object $O_{w|p}$

$previous\ time \leftarrow current\ time - time\ step$

Current time pressure objects $S_p^c \leftarrow$ pressure objects having centroid within $pressure\ distance\ threshold$ from object $O_{w|p}$ centroid and time stamp $current\ time$

Previous time pressure objects $S_p^p \leftarrow$ pressure objects having centroid within $speed\ threshold$ from object $O_{w|p}$ centroid and time stamp $previous\ time$

Current time wind objects $S_w^c \leftarrow$ wind objects having centroid within $wind\ distance\ threshold$ from object $O_{w|p}$ centroid and time stamp $current\ time$

Previous time wind objects $S_w^p \leftarrow$ wind objects having centroid within $speed\ threshold$ from object $O_{w|p}$ centroid and time stamp $previous\ time$

if pressure object $O_p^c \in S_p^c$ exists with ID **then**

Use pressure object O_p^c ID

else if pressure object $O_p^p \in S_p^p$ exists with ID **then**

Use previous time pressure object O_p^p ID

else if wind object $O_w^c \in S_w^c$ exists with ID **then**

Use wind object O_w^c ID

else if wind object $O_w^p \in S_w^p$ exists with ID **then**

Use previous time wind object O_w^p ID

else if wind or pressure object $O_{w|p}^p \in S_w^p \cup S_p^p$ exists without ID **then**

Give new ID to the previous object $O_{w|p}^p$ and current object $O_{w|p}$

else

Leave object $O_{w|p}^p$ without ID

end if

end for

page5, line123-128: From your description it is not clear how you selected the relevant parameters. You write about a fitted Gaussian distribution. How do you fit it, to which data and with which purpose? What is class one and two? What is the criterion for selecting the 35 relevant parameters?

We clarified the description as follows in the updated manuscript on pages 6-8, lines 156-173:

“We selected the 35 parameters based on two main factors: First, we prepared a list of potential parameters detected in related studies e.g. Suvanto et al. (2016); Peltola et al. (1999); Valta et al. (2019), or identified through the empirical experience of duty forecasters (Weather and of Finnish Meteorological Institute Duty forecasters, 05/2020). Second, we selected the relevant parameters, which were available to us or accessible with reasonable effort. However, some possibly important parameters, like soil temperature from ERA5 reanalysis were left out because of the slow downloading process.

After the preliminary selection of the parameters, we conducted dozens of light experiments using different combinations of parameters and models to find the best possible setup. To this end, we fitted Gaussian distribution to each parameter using at first all samples, then samples with few outages, and finally with many outages (classes 1 and 2 specified in Section 3.3). While many other distributions are known to suit better modelling particular parameters, such as Gamma in precipitation, Weibull in wind speed, and Lognormal in cloud properties (Wilks, 2011), Gaussian distribution is a sufficient simplification to help in selecting relevant parameters. We inspected visually the differences between fitted Gaussian distributions to deduce the potential relevance of the parameter. Supposedly the distribution of one parameter is different for all samples and samples with many outages. In this case, the classification method may exploit the parameter to predict the damage potential of the storm object. Distribution of some selected parameters is shown in Appendix A. In total, 35 parameters, shown as bolded in Table 1, were chosen for the final classification. "

page 7, line 130-131: At this point it is not clear how you define the three classes. To make it easier for the reader, I would suggest to spend some words on how the classes are defined here, or to move this part to page 8, line 155, where the classes are actually introduced.

We restructured the text to introduce classes on page 10, line 202 (originally on page 8, line 155), as you suggested.

page 7, line 136-138: You write "the local dataset contains 24,542 storm objects". Would it be more precise to say that "24,542 storm objects are related to outages in the local outage dataset"? It would be very informative to know how many outages are in the dataset in total and how many of them are NOT related to a storm object. Maybe you can add that information here.

Using only storm objects related to outages would result in overestimating predictions as the classification model would not see any "harmless" class 0 samples in the training process and assume every sample to cause damage. Thus, we also consider storm objects which are not related to any outage.

The local dataset contains 24 542 storm objects and 5 837 outages connected to 2 363 storm objects. Thus 22 179 storm objects in the local dataset have not caused any outages. The local power outage data contains 16 191 outages, which can not be connected to any storm object. The national dataset contains 142 873 storm objects and 5 965 324 outages connected to 33 796 storm objects. 109 077 storm objects are not connected to any outages, and 175 110 outages can not be connected to any storm object.

We added this information to the manuscript on page 9, lines 174-179.

page 7, figure 1a: Can you explain why the network topologies look so different in the northern and southern area? In the north it looks like branches that end some where, in the south it rather looks like district boundaries. Figures 1 c and d: What is shown here in red color? Number of outages per area? Please add a legend. I would recommend to plot the grid topology with a darker color on top of the shading to increase its visibility.

The differences between the network topologies are simply explained by the data we have received from the two individual companies. From the northern company (Loiste), we received a shapefile of their grid. The southern company (JSE) provided their operational areas instead of the grid topology. Therefore, these two topologies look so different, even though in reality also JSE's grid looks similar compared to Loiste.

We have now separated Figures 1a and 1b from 1c and 1d and improved the figures based on the suggestions (Pages 5 and 9 in the updated manuscript). See also the reply to the second comment about the spatial accuracy of datasets.

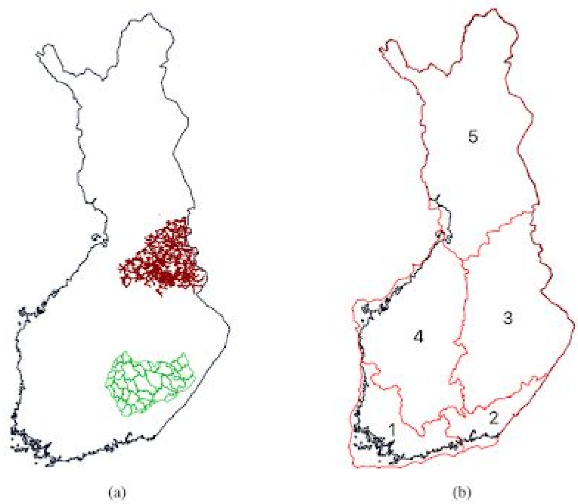


Figure 1. (a) Geographical coverage of the outage data (local dataset). The red lines represent the power grid of Loiste (northern grid company) district and the green lines the operative areas of JSE (southern grid company). Outages of the local dataset are collected from both of these areas. (b) Regions in the national outage dataset. Outages are gathered from the whole Finland but aggregated to the regions shown in the figure.

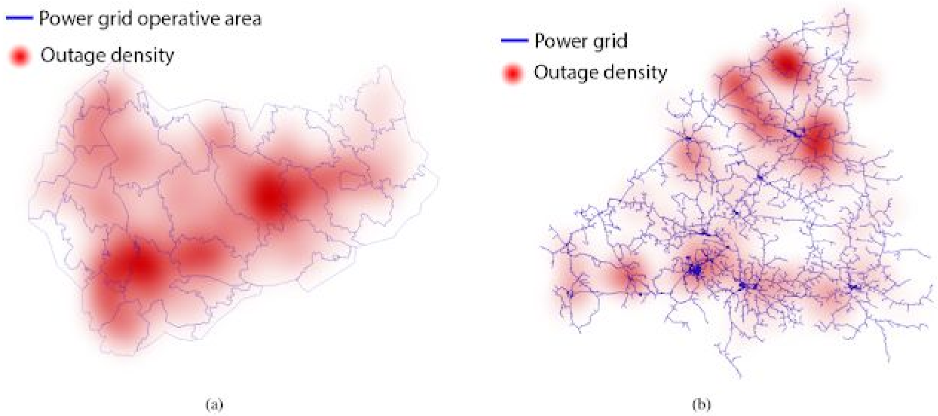


Figure 2. (a) Spatial distribution of the outages in the JSE network (southern area), data gathered between 2010 and 2018. (b) Spatial distribution of the outages in the Loiste network (northern area), data gathered between 2010 and 2018.

page8, line153-154: Please explain in more detail what is shown in figure 4. Does one dot represent the outages and affected customers related to a specific storm object? Is the line a linear regression?

One dot indeed represents the outages, but it may not be related to any specific storm. The line is trendline (linear regression). We also added a legend to the figure and extended the description in the manuscript on page 10, lines 196-201 following:

“Figure 5 renders how many customers are typically affected by one outage. The figure contains all outages in the dataset, whether they are related to a storm or not. In the local dataset, usually, 20-30 customers lose electricity in one outage. In the national dataset, only six customers usually lose electricity in one outage. We assume that this roots to different network topologies in other areas.”

The original manuscript also contained an error. The original manuscript stated that 200-300 would be typically affected, which is wrong. One outage usually affects from 6 to 30 outages depending on the dataset. We corrected this.

page 10, table 2: The caption say "Classes for local dataset", but shown are also classes for the national dataset.

We compliment, and corrected this on page 12, table 2.

page 10, line 153-154: Is "model" the correct term here? Isn’t it rather "classification algorithm"?

We assume that this refers to page 10, lines 163-164. The “model” is normally used in this context in machine-learning literature. We see the word “algorithm” to refer more to heuristic algorithms instead of models that are fitted to the data. Another option would also be “method”, but it may be confused with the overall method, including storm identification and tracking.

We see that the word “model” is the best term in this context.

page 11, equations 1, 2, 3: If you use equations, you need to define the individual variables. Also, the equations are not easily understood without further explanation.

The definitions of the variables are fundamental for equations, and we added them to the manuscript. They should help to understand the equations. We also added references for all kernels used in this work. As the used kernels are widely used standard kernels, we prefer to omit a more detailed explanation to keep the text concise and readable.

page 14, section 4.1: As far as I can see it is not mentioned in the text which classification algorithm was used for the case examples.

Gaussian processes (GP) was used in case examples. Thus, we also analyzed feature importances using GP.

This information is added to the manuscript on page 19, line 354. We also changed a conclusion slightly on page 22, lines 409 to form:

“Both Gaussian Processes and Support Vector Classifiers provided good results. [...]”

The original statement in the conclusion honoured only SVC, which is inconsistent with results. SVC and GP provided almost similar performance.

page 15, figure 5: The figures should be as self-explanatory as possible. Please explain in the caption what the numbers represent.

We added the following information to the manuscript on page 19:

“Each cell of the confusion matrices represents a share of predictions having a corresponding combination of predicted and true class. For example, the middle right cell tells the share of samples belonging to class 1 but predicted to have class 2.”

page 16, line 305: The term "cell" is usually used for convective thunderstorms, but not for large-scale winter storms. I would suggest to simply use the word "storm".

Good point, this has been changed to “storm object”.

page 17, line 307: The authors state that "the model is able to provide a more specific and geospatially accurate prediction of caused damage to the power grid than for example weather warning." I do not think that this statement is true. If I understand the model correctly, it assigns a damage class to the whole area of a storm object. This area can be quite large, as figure 6a and 6b show. Furthermore, the model provides no geospatial *information about where inside this area the damages are expected. I suppose that weather warnings are available for Finland at a much higher spatial resolution. Additionally, weather warnings are released in advance of an event. In this manuscript the authors do not take into account forecast uncertainty. Therefore, a comparison to weather warnings difficult.*

We acknowledge that the comparison with weather warnings can be challenging. As the referee mentions, the model's ability to provide more specific and geospatially accurate information than weather warnings is not a straightforward issue. We mention the geospatial accuracy because, in some cases, the storm object areas are not as big as in 6a and 6b (8a and b in updated manuscript), which are two examples of extremely strong storms. This was the case, for instance, with the extratropical storm, Pauliina where the yellow level of wind warnings was issued to wide areas in central and southern Finland and orange level of wind warnings to the south (see attached figure). This broad wind warning likely leads to all power companies in southern and central Finland being alert and possibly overpreparing for the event. Another important aspect of this work compared to weather warnings is an analysis of inflicted power outages, which can give an insight to power grid operators and duty forecasters about the impacts of forecasted warnings.

Nevertheless, because of the problematic task to indeed take into account the uncertainty of the forecast, we decided to modify the paragraph and update the manuscript (page 21, line 398-402) with a comment about the forecast uncertainty:

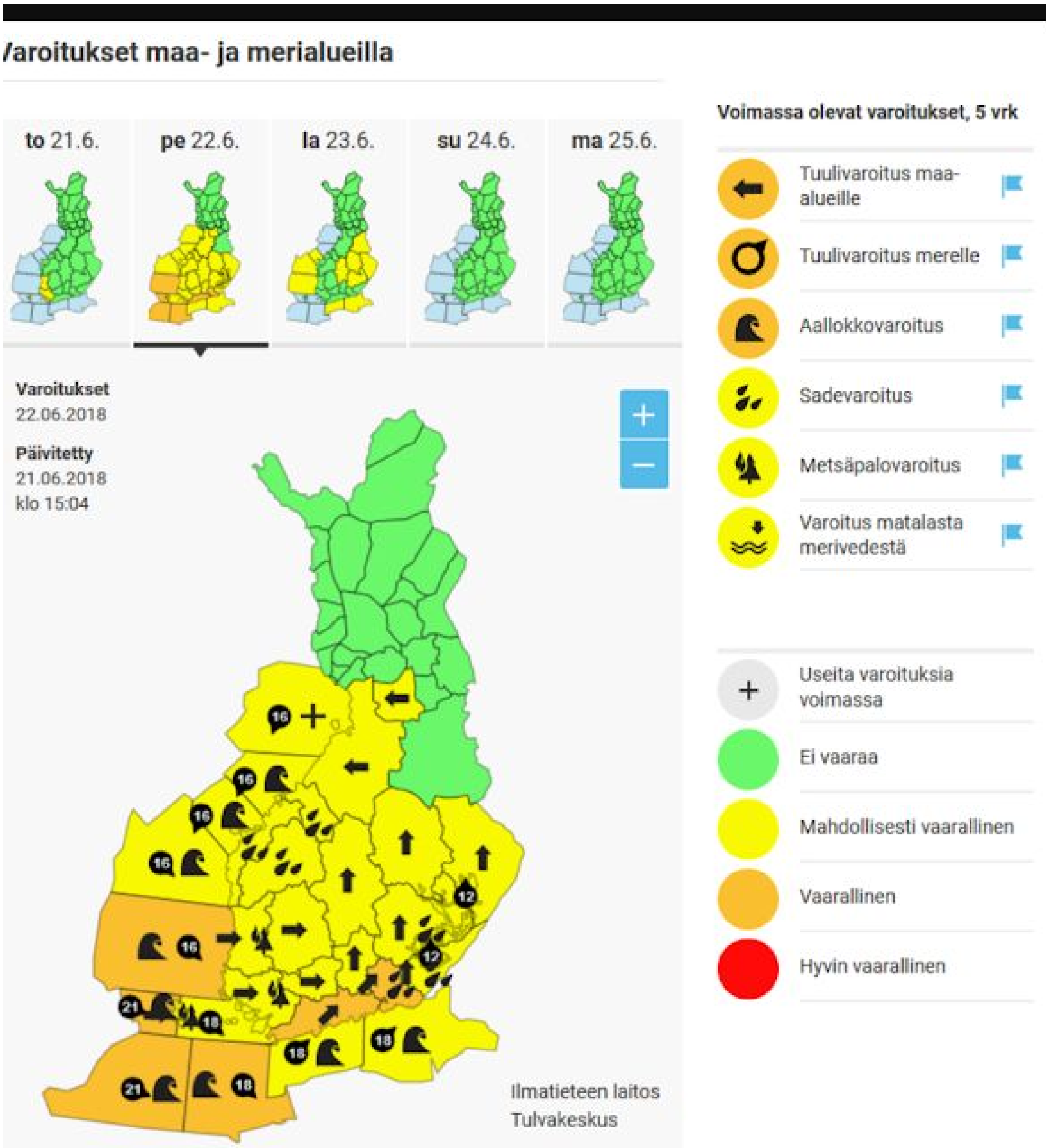
"While weather warnings were issued to large areas in southern and middle parts of Finland (Myrskyvaroitus, 2018), predicted and true damage to the power grid occurred in a relatively small geographical area. This example shows the potential added value of impact estimation for power grid operators. However, in this example, we do not take into account the uncertainty of the weather forecasts before the event. Therefore, it is challenging to compare issued warnings with the model performance purely."

We also added the following clarification to the introduction (page 3, lines 70-74):

""[...] The ERA5 atmospheric reanalysis (European Centre for Medium-Range Weather Forecasts, 2017) provides the primary meteorological input data for this study, while the national forest inventory provided by The Natural Resources Institute Finland (Luke) is used to represent the forest conditions in the prediction. Finally, historically occurred power outages from two sources are used to train the model. However, the operational use of the model would require the use of weather prediction data instead of reanalysis."

And following clarification to the conclusion (page 22, line 412-414):

"The evaluation was, however, based on the ERA5 reanalysis data. Using the method in operations would require weather prediction data, which introduces additional uncertainty to the outage prediction."



Figures A1 and A2: The figure labels are hardly readable and the figure caption is not self-explanatory. There are abbreviations used in the figure titles which are not defined. Please spend some more words on what is shown on the figures. Can you explain the peak at -1000 in the figure titled "speed_self" and "angle_self"? It appears to be completely detached from the rest of the distribution. Why is there no blue line in the figures titled "AVG Wind gust"?

We reduced the number of shown parameters to enlarge label size. We also replaced “speed_self”, “angle_self”, “area_m2”, and “area diff” with corresponding feature names listed in Table 1. We added the following caption to the figures so that the figures should be self-explanatory:

“Histogram of and fitted Gaussian distribution of selected predictive parameters in the local dataset. The Gaussian distribution is fitted separately to all samples and samples with little outages and many outages (classes 1 and 2 specified in Section 3.3).”

Peaks at -1000 represent missing values. We dropped samples with missing values, which changed the fitted distributions a little. In particular, the differences between the mean values of the distributions reduce, which makes the deduction a little more challenging. Nevertheless, the same parameters still stand out in the analysis.

Fitted Gaussian distributions marked with the blue line have been missing in the original Figures A1 and A2 because of missing values. After dropping all samples with missing values (technically all rows having values -1000 and np.nan), the fit is successful also to AVG Wind gust, MAX Wind gust, and STD Wind gust, and mean Forest stand mean height.

Figures are updated in the manuscript and shown below.

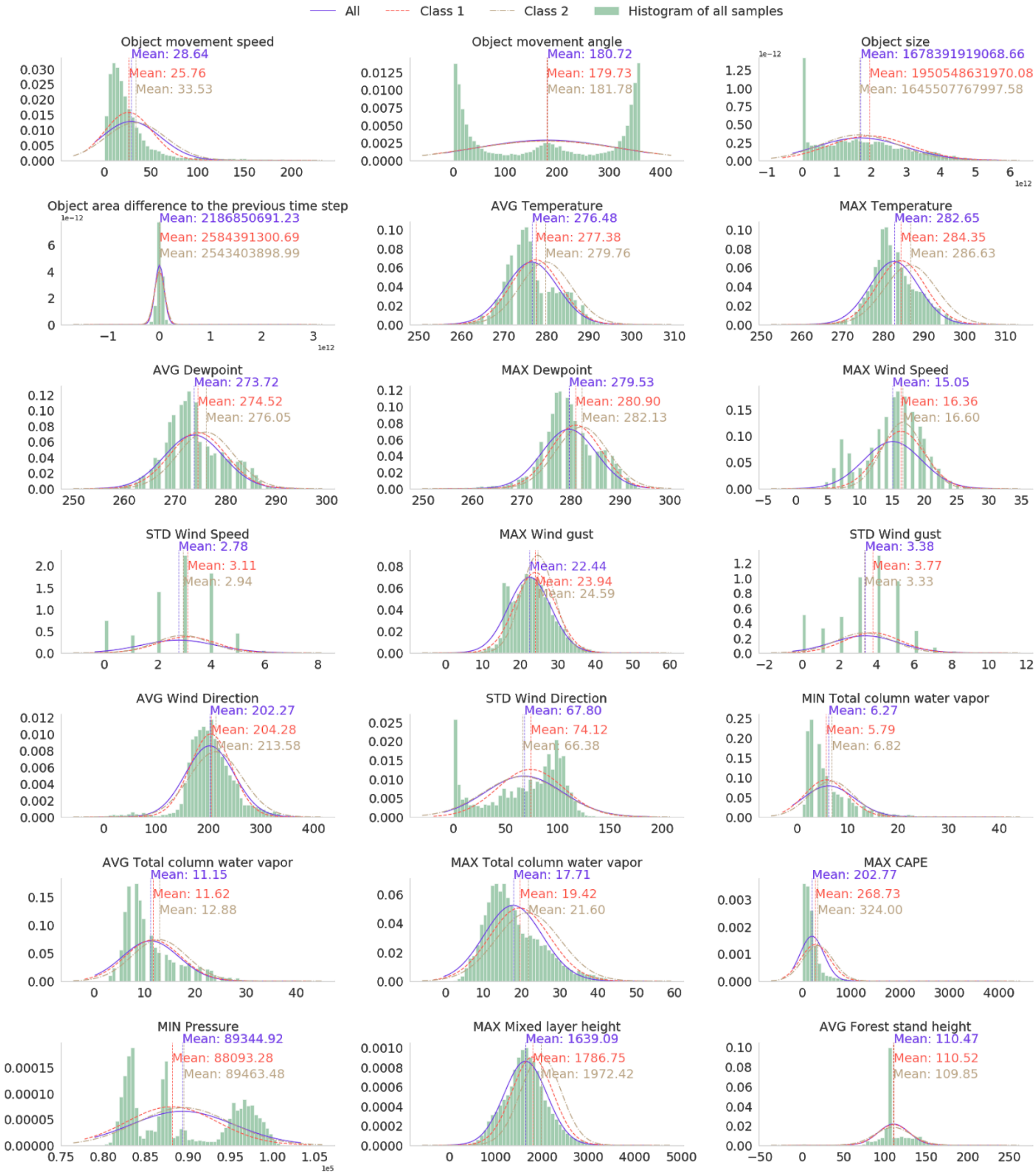


Figure A1. Histogram of and fitted Gaussian distribution of selected predictive parameters in the local dataset. The Gaussian distribution is fitted separately to all samples and samples with little outages and many outages (classes 1 and 2 specified in Section 3.3).

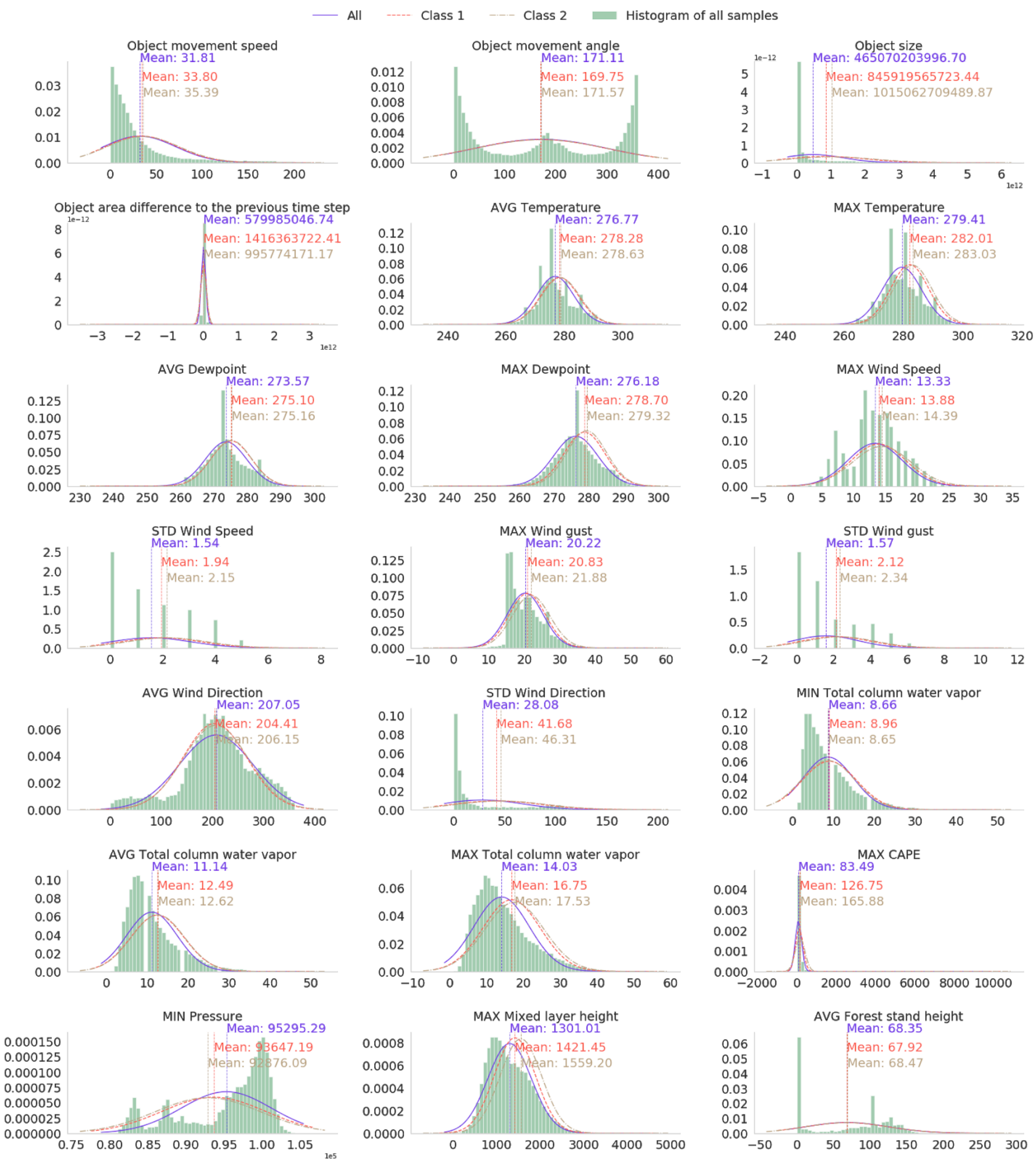


Figure A2. Histogram of and fitted Gaussian distribution of selected predictive parameters in the national dataset. The Gaussian distribution is fitted separately to all samples and samples with little outages and many outages (classes 1 and 2 specified in Section 3.3).

Technical comments:

page 2, line 50 "showed that" instead of "showed at"

We did this correction with compliments.

page 3, lines 63-66: Please check the description of the paper organization. There are missing words and incomplete sentences.

We changed and modified the paragraph as follows (Page 3, lines 75-79):

“This paper is organized as follows: Chapter 2 presents the used data, which is followed by a step-by-step method description in Chapter 3. Chapter 3.1 discusses identifying storm objects and explains the storm tracking algorithm. Chapter 3.2 considers predictive features containing both storm and forest characteristics. Chapter 3.3 discusses how to define labels of storm objects based on the outage data. Chapter 3.4 describes the used machine learning methods. In Chapter 4, we discuss the performance of the method. Finally, Chapter 5 includes discussion and conclusion."

page 7, line 136: Do not use blank spaces to separate numbers in order to prevent line breaks.

We prevented line breaks in the middle of numbers using the latex \mbox command but preferred to keep spaces for clarity.