Upward lightning at tall structures: Atmospheric drivers for trigger mechanisms and flash type

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Key Points:
- A substantial fraction of upward lightning initiated from tall structures such as wind turbines can only be detected at a few locations.
- A machine learning model reliably estimates even this fraction; the absence of nearby lightning is the most important factor.
- The closer the $-10^\circ$C isotherm is to the tower top, the higher the probability that upward lightning is self-triggered by the structure.

Abstract

Upward lightning is much rarer than downward lightning and requires tall (100+ m) structures to initiate it. While conventional lightning locations systems (LLS) reliably detect downward lightning they miss the substantial fraction of upward lightning flashes that consist only of a continuous current. Globally, only few specially equipped towers can detect them. The proliferation of wind turbines in combination with large damage from upward lightning necessitates a reliable estimate of upward lightning frequency and conditions under which they occur. These estimates are computed by combining direct measurements at the specially-equipped tower at Gaisberg mountain in Austria as target variable with covariates from LLS measurements and atmospheric reanalysis data (ERA5) in a conditional inference random forest machine learning model. The most important factor determining whether upward lightning will not be detectable by LLS is the absence of nearby (within 4 km) lightning activity. All atmospheric covariates combined are ten times less important. Atmospheric variables, on the other hand, reliably explain whether upward lightning is self-triggered by the tower or other-triggered by nearby lightning discharges. The most important factor is height of the $-10^\circ$C isotherm above the tall structure: the closer it is the higher is the probability of self-triggered flashes. Two-meter temperature and the amount of CAPE are also important. The results are an important step towards a comprehensive risk assessment of lightning damage to wind turbines and other tall structures.

Plain Language Summary

Upward lightning is much rarer than downward lightning. It needs tall structures of 100+ m to trigger it. A large fraction of upward lightning can only be detected by specially equipped towers. Since so many tall wind turbines are built to generate electricity, a reliable estimate of the frequency for upward lightning and the conditions under
which it occurs is needed to properly assess the risk of damage. Data from one of these specially equipped towers, from atmospheric conditions and measurements of downward lightning are combined in a machine learning model to get these estimates. Upward lightning will remain undetectable unless lightning strikes almost at the same time in vicinity of the towers. Meteorological conditions play a minor role. Meteorological conditions, on the other hand, determine, whether upward lightning is self-triggered by the tower or other-triggered by nearby lightning. The most important factor is the height at which \(-10\, ^\circ C\) are measured above the tower. The closer to the tower, the higher the chance that the tower itself triggers the lightning.

1 Introduction

Upward lightning initiated from the earth surface extending towards the clouds is much rarer than downward lightning initiated within the clouds extending towards the ground. Nevertheless, it poses a much larger damage potential as it is capable of transferring large amounts of charge up to hundreds of coulombs within a comparably long period of time (e.g., Diendorfer et al., 2015; Birkl et al., 2017). Tall structures (on the order of 100 m) are preferred starting locations for upward lightning (e.g., Rakov & Uman, 2003). Wind turbines typically exceed such heights and consequently lightning damages to them have gone up hand in hand with their ever-growing number in the quest for renewable energy sources (e.g., Rachidi et al., 2008; Montanyà Puig et al., 2016; Birkl et al., 2018; Pineda et al., 2018).

To make matters worse, more than half of upward lightning flashes might remain undetected by lightning location systems (LLS, Diendorfer et al., 2015). LLS require the fast rising current in the lightning channel to emit sufficiently large electromagnetic field pulses to be detected (Diendorfer et al., 2009). However, one particular subtype of upward lightning has only a relatively low-amplitude constant initial continuous current (ICC\textsubscript{only}, e.g., Birkl et al., 2018). Consequently, using only LLS observations substantially underestimates the risk of lightning damage (e.g., Rachidi et al., 2008; Smorgonskiy et al., 2011). Globally, only few specially instrumented towers exist that can measure ICC\textsubscript{only}. Finding widely available proxies from which their existence can be deduced would provide a better basis for proper risk assessment. While local, geographical and meteorological differences have been suspected (March, 2015; Birkl et al., 2018; Diendorfer et al., 2009), to our knowledge no systematic search has been conducted.

One of the instrumented towers with a height of 100 m is at Gaisberg in Austria. There, basically all lightning strikes are of the upward type (Diendorfer et al., 2015). Figure 1 (a) shows that the ICC\textsubscript{only} subtype exhibits no clear seasonal cycle. Additionally, it is undetectable by the regional LLS. Most of the other two subtypes (panel (b), with superimposed pulses ICC\textsubscript{P} or return strokes ICC\textsubscript{RS}), however can be detected. They do have a minimum during the summer months (JJA) and a maximum in spring and fall. Upward lightning at Gaisberg is thus in striking contrast to downward lightning where 95% of all flashes occur during the convective season (Diendorfer et al., 2011).

Upward flashes (i.e., initiated from the ground up) are so rare because of the extremely high field intensity required immediately above the ground or an object on it for a discharge to start (Rakov & Uman, 2003). Structures with an effective height of 500 m or more are assumed to deform the electric field sufficiently to experience only upward lightning. For shorter objects, nearby lightning activity can deform the electric field sufficiently to trigger a so-called “other-triggered” upward leader and flash. However, upward lightning can also be initiated from the tall structure itself (“self-triggered”).

Location, e.g., being situated on an isolated hill, and meteorological conditions, are assumed to be favorable ingredients for self-triggered upward lightning but details are not clear yet. Regional and seasonal differences are large. During six warm seasons at
Figure 1. Panel (a) and (b): Number of upward flashes observed at the Gaisberg Tower (2000 to 2015: total of 792 flashes) split into two categories. Upper panel (a): Initial continuous current only subtype (ICC\textsubscript{only}). Lower panel (b): Sum of flashes with initial continuous current superimposed by pulses and by return-stroke sequences, respectively (ICC\textsubscript{P} + ICC\textsubscript{RS}). Colors distinguish detection (green) by the EUCLID lightning location system (LLS) from non-detection (red). Panel (c): Number of flashes from Gaisberg Tower classified as self-triggered (yellow) and other-triggered (blue) following the classification scheme by Zhou et al. (2012). Based on 329 observations from 2000 to 2015.
tower locations in the USA and Brazil only other-triggered upward lightning occurred (Schumann et al., 2019). In other locations and for other studies the ratio between self-triggered and other-triggered upward flashes varies widely: 1 to 1 in Japan according to six winter seasons (Wang & Takagi, 2012). In the USA, T. Warner et al. (2012) show that the ratio is 1 to 4, whereas almost 80 % of self-triggered lightning and 15 % of other-triggered lightning occurred in the cold season. In Germany from measurements at the Peissenberg Tower, Manhardt et al. (2012) infer a ratio of 9 to 1, from which all self-triggered flashes occurred in the cold season. At the Gaisberg Tower, the ratio is 3 to 1 as shown in Figure 1 (c).

In addition to site-specific conditions (e.g., Smorgonskiy et al., 2015), differences in meteorological conditions have been proposed to explain variations in this ratio (e.g., Wang & Takagi, 2012; Jiang et al., 2014; Zhou et al., 2014; Smorgonskiy et al., 2015; Yuan et al., 2017; Mostajabi et al., 2018; Pineda et al., 2019). The results have been partly contradictory. For example, Zhou et al. (2014) and Smorgonskiy et al. (2015), found no significant relationship between the ambient wind speed and self-triggered flashes at Gaisberg, while Mostajabi et al. (2018) underline its importance both at Gaisberg and at Säntis (Switzerland). Temperature has a significant impact at the Gaisberg Tower (e.g., Zhou et al., 2014) and at the Säntis Tower (e.g., Smorgonskiy et al., 2015; Pineda et al., 2019), whereas wind speed is more crucial in studies conducted in Japan (Wang & Takagi, 2012), China (Yuan et al., 2017) or in the United States (T. A. Warner et al., 2014).

The goal of this study is to determine whether meteorological conditions can serve as a proxy for the upward lightning flash type and for the ratio of self-triggered to other-triggered flashes. If successful, the amount of upward lightning and the risk posed by it can be properly determined at locations other than the specially instrumented towers. Two recent advances have made this goal reachable: the availability of hourly reanalyses of atmospheric and microphysical conditions (ERA5, Hersbach et al., 2020) and powerful machine learning approaches with which to combine them with the lightning measurements.

This article is organized as follows: First, a brief overview of the data used is given including lightning observations and meteorological reanalysis data (section 2). Next, we introduce the statistical approaches for the two stated issues (section 3). The results on the atmospheric drivers for self-triggered over other-triggered upward flashes are presented and discussed in section 4. The results and a subsequent discussion on the atmospheric drivers for ICC only over ICCP + ICCRS upward flashes are addressed in (section 5 and section 6). Finally we summarize our findings in section 7.

2 Data

The study combines three different data sources. It uses upward lightning data measured directly at the Gaisberg Tower in Salzburg (Austria), lightning location system (LLS) data measured remotely by the European Cooperation for Lightning Detection (EUCLID, Schulz et al., 2016) and meteorological reanalysis data (ERA5, Hersbach et al., 2020).

2.1 Lightning observations

Since 1998 upward flashes have been directly measured at the Gaisberg Tower in Salzburg (Austria, Diendorfer et al., 2009). The 100 m radio tower is situated on top of the Gaisberg mountain 1 288 meters above mean sea level (47°48′ N, 13°60′ E). The study uses observations from 2000 to 2015. In total 819 upward flashes were recorded at the Gaisberg Tower during this period. Of these, 329 flashes could be unambiguously classified as self-triggered (246) or other-triggered (83), respectively. Further, 792 flash ob-
servations could be unambiguously assigned to a flash type. 373 flashes were classified as ICC\textsubscript{only} and 419 flashes were classified as ICC\textsubscript{P} + ICC\textsubscript{RS} type flashes.

For the identification of self-triggered and undetectable upward flashes by LLS, direct observations at the Gaisberg Tower are compared to remote observations provided by the LLS EUCLID. EUCLID measures downward lightning with a detection efficiency of more than 90\% (Schulz et al., 2005). The LLS measurements are used to determine whether an upward flash is other-triggered as described in Zhou et al. (2012).

2.2 Atmospheric reanalysis

ERA5 is ECMWF’s fifth generation of global climate reanalysis from 1950 onward. ERA5 has a spatial resolution of 31 km horizontally (available at a 0.25 ° × 0.25 ° latitude-longitude grid) and 137 levels vertically at hourly resolution. We consider the lowest 74 levels extending to approximately 15 km altitude, well into the stratosphere.

The meteorological data set used for modeling trigger mechanisms and the ICC\textsubscript{only} flash occurrence consists of 75 directly available and derived variables at the surface, on model levels and integrated vertically. Two temporal variables - day of year and time of day - complement the data set. Data are spatially and temporally bilinearly interpolated to each Gaisberg Tower flash observation.

The atmospheric variables fall into five broad categories: cloud physics, mass field, moisture field, surface exchange and wind field. A complete list of the variable groups and individual variables can be found in the supporting information file.

3 Methods

Investigating the drivers for trigger mechanisms and flash type both correspond to a binary classification problem. For the trigger mechanisms it is self-triggered versus other-triggered flashes; for the flash type, the response variable are ICC\textsubscript{only} versus ICC\textsubscript{P} + ICC\textsubscript{RS} type flashes. Seventy-seven variables (cf. section 2.2) are considered as potential drivers (or predictors).

To capture potential nonlinearities and interactions in the relationship between the two response variables and the predictors, we employ flexible regression methods based on ensembles of decision trees. More specifically, conditional inference random forests
are used (section 3.1) combined with permutation-based variable importance measures to assess the relative influence of the different atmospheric drivers (section 3.2).

3.1 Tree-structured ensembles based on conditional inference

Regression and classification trees (Breiman et al., 1984) are popular models due to their flexibility and intuitive interpretation. However, they are also rather unstable under small modifications of the learning data and often outperformed in terms of predictive performance. Using an ensemble of many trees on random subsamples of the full learning data overcomes both of these problems, leading to so-called random forests (Breiman, 2001) that are still extremely flexible and easy to set up while being more stable and typically with high predictive power.

Specifically, we employ conditional inference random forests (Hothorn et al., 2004) where the individual trees (Hothorn et al., 2006) are constructed in the following way. In each of the random subsample the association between the response variable and each of the driver variables is assessed using a permutation test (also known as conditional inference, Strasser & Weber, 1999). Then the driver with the strongest association (i.e., the lowest p-value) is selected and splits at the point with the highest contrast between the two response classes. The same driver and split point selection is then repeated recursively in each of the subgroups for all of the random subsamples. More details regarding the algorithm and corresponding implementation are provided in Hothorn et al. (2006) and Hothorn and Zeileis (2015).

3.2 Permutation variable importance

While random forests greatly stabilize the inferred regression relationship and improve the predictive performance, they lose the intuitive interpretation of single decision trees. Therefore, to gain insight which driver variables are mostly responsible for the predictions of the model so-called variable importance measures are typically used. Here we also follow that approach and employ the permutation variable importance (see Strobl et al., 2008). In short, the idea is to break up the relationship between the response variable and one driver variable by permuting the latter and then assessing how much the predictive performance deteriorates.

In more detail, we employ random forests based on 100 trees fitted on two thirds of the original learning data using the remaining out-of-bag observations as test data. Predictive performance on the test data is assessed using the area under the receiver operating characteristic curve (AUC, Wilks, 2011). For the variable importance either a single driver variable or a group of related variables is randomly permuted and the median AUC decrease is computed across all test data sets. The decrease of predictive performance when permuting the indicated variable is computed by

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\frac{100 \cdot (\text{original sample score} - \text{permuted sample score})}{\text{original sample score}}.
\]

The group of driver variable(s) leading to the strongest decrease are the most influential ones for the classification.

The idea for considering groups of drivers as opposed to single variables only is that many of them are highly correlated. This may lead to an underestimation of their individual importance as their influence might be spread among all variables in the group. Although different numbers of parameters represent the meteorological variable groups, it can be shown by principal component analysis, that the independent information content is comparable across the groups ensuring fair comparisons.
4 Atmospheric drivers for self-triggered flashes

Atmospheric conditions play a crucial role in determining whether the tall structure of Gaisberg Tower itself or a nearby discharge initiates an upward lightning flash. Figure 3 shows that the random forest models built from the pool of 77 predictor variables are both relatively reliable (a) and sharp (b) when tested on unseen data samples. The 100 test data samples always include one-third of the original number of observations not considered during the learning procedure of the ensembles. The value 1 is associated with a self-triggered flash and the value 0 is associated with an other-triggered flash. The error bars in (a) indicate the uncertainty of the predictions on the 100 test data samples by the 95% confidence interval. The shaded area indicates the 95% confidence interval of the average predicted probability. The refinement distribution in (b) is based on accumulated predictions. For each bin the difference between the average observed relative frequency and the predicted probabilities for of the test data samples (dots) are around zero and mainly fall into the 95% confidence interval of the predicted probabilities indicating a reliable performance. The larger deviation from zero in the lower close to a 0% probability of self-triggered flashes may attribute to the low number of predictions in this segment (see also in the refinement).

The predictions are not only reliable but also sharp as the concave like shape of the refinement curve in (b) and the maximum number of predictions close to the 100% probability of self-triggered flashes (value 1) indicate. The median AUC value of 0.93 based on the test data samples underlines the ability to reliably separate self-triggered from other-triggered flashes from atmospheric variables.
Figure 4. Left (a): Ranking of the variable group importance influencing whether an upward flash is self-triggered or other-triggered according to the permutation variable group importance procedure. The decrease of predictive performance is computed as described in section 3.2. Right (b): The ten most important variables influencing whether an upward flash is self-triggered or other-triggered according to the permutation variable importance. Colors indicate meteorological groups as in left panel.

The mass field is most influential to distinguish self-triggered from other-triggered flashes (see panel (a) of Figure 4). The bars indicate the medians of predictions on 100 test samples containing one third of 329 observations. Permuting all mass field variables decreases the median predictive performance more than the other five variable groups combined (about 7 percentage points). With a decrease in the predictive performance of about 3 percentage points, cloud physics is the second most important group according to the median of 100 test data samples. Minor contributors are the surface exchange, moisture field and the wind field with less than 0.5 percentage points, respectively.

The importance of the mass field is also reflected in Figure 4 (b) showing the permutation importance of individual variables. Four of the most important variables listed are part of the mass field group. Particularly the height of the $-10 \, ^\circ C$ isotherm has a large influence on the self initiation of upward flashes. Further the $-20 \, ^\circ C$ isotherm height, the $2 \, m$ temperature and CAPE have an impact.

The most influential variables from cloud physics are the total column water vapor, convective precipitation, the proportion of solid hydrometeors between $-20 \, ^\circ C$ and $-40 \, ^\circ C$ and ice crystals (total column). Two additional variables among the ten most influential ones are the skin temperature from the surface exchange group and the $2 \, m$ dewpoint temperature from the moisture field group.

The reason for including the height of isotherms is their importance for the electrification of thunderclouds (e.g., Rakov & Uman, 2003; Williams, 2018). The $-10 \, ^\circ C$ isotherm marks the main (negative) charge regime within the thundercloud where the majority of electrification processes are considered to take place (e.g., Saito et al., 2009; Heidler et al., 2013; Pineda et al., 2019).

The influence of a single variable in the random forests can be explained by varying it while other predictors are held constant at their mean value. Figure 5 (a) illustrates, albeit under artificial conditions that a higher $-10 \, ^\circ C$ isotherm decreases the prob-
ability of self-triggered upward flashes. The quantiles in the effect plots show the predicted effects from the ensembles based on 100 learning samples including two thirds of the original number of observations. We note a drop in the probability of self-triggered flashes associated with a $-10^\circ C$ isotherm between around 3 000 m and 3 500 m above ground. This drop makes about 7 percentage points in the probability of self-triggered flashes according to the median based on the 100 tree ensembles.

Similar to the isotherm height effect a higher amount of the total column water vapor decreases the probability of self-triggered over other-triggered flashes (panel (b) in Figure 5).

Further insights can be gained by examining the difference in the climatological distributions of the most influential variables identified by the random forest models. Figure 6 illustrates that driving variables for self-triggered flashes barely show an annual cycle, whereas other-triggered flashes clearly are above the daily median from 2000 to 2015. To demonstrate this, three representatives from the mass field (panel (a): $-10^\circ C$ isotherm height, (b): 2 m temperature and (c): CAPE and (d): one representative from cloud physics (total column water vapor) are explored. Shown are the interpolated daily median values of the four different variables and deviations from these at flash initiation time. We further distinguish between conditions marking self-triggered (yellow) and other-triggered (blue) flash initiation.

Self-triggered upward flashes occur preferentially with lower heights of the $-10^\circ C$ isotherm than the climatological median, especially during winter, spring and fall. Similarly, self-triggered flashes prefer a lower 2 m temperature throughout the year but especially in the transition season. Moreover, other-triggered flashes clearly favor high CAPE conditions and a high amount of water vapor.

Studies from different sites throughout the world have shown that the temperature plays a crucial role for self-triggered flashes which is in line with our findings (see e.g., Heidler et al., 2013; Zhou et al., 2014; Azadifar et al., 2016; Pineda et al., 2018; Pineda et al., 2019). Most frequently the importance of temperature is explained by its influence on the height of the thundercloud’s charge layer. Lower temperatures lower the cloud base and bring the main electrification region closer to the tall structure (e.g., Heidler et al., 2013). The reduced distance between the tall structure and the charged thundercloud then increases the electric field and eases the incidence of self-triggered lightning flashes (e.g., Heidler et al., 2013; Pineda et al., 2018; Pineda et al., 2019).

We note the dominance of temperature related variables ($-10^\circ C$ and $-20^\circ C$ isotherm height, 2 m temperature, skin temperature, 2 m dewpoint temperature) in Figure 4 all

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**Figure 5.** Left (a): Effect of the $-10^\circ C$ isotherm height above ground on probability of self-triggered flashes (value 1). Right (b): Effect of total column water vapor on probability of self-triggered flashes. Effects are predicted quantiles (0.1, 0.5, 0.9) based on the tree ensembles.
sharing relatively high mutual information values. Following the model fitting and the permutation variable importance process described in section 3, different variables may be selected as potential splitting variables at different stages. If in one stage the most important variable, i.e., the $-10 \, ^\circ\text{C}$ isotherm height is not selected, it might be replaced by a variable serving as proxy for it. From this we suggest that the random forest models require any information on the distance between the tall structure and the main electrification layer which is closely related and partly covered by temperature information.

Our findings concerning mass field related variables such as pressure, temperature or the isotherm height are in line with other studies introduced above. Additionally we showed that the wind field is unimportant for the trigger mechanism of upward flashes at Gaisberg. This supports the findings by Zhou et al. (2014) who noted that wind speed does not show an important effect on the trigger mechanism of upward flashes at the Gaisberg Tower.

5 Atmospheric drivers for ICC$_{\text{only}}$ flashes

Figure 7 depicts that the models are relatively well-calibrated and reliable up to predicted probabilities around 75 %. Both panels (a) and (b) can be interpreted analogously to Figure 3 from the previous section, whereas the value 1 is associated with ICC$_{\text{only}}$ flashes and the value 0 is associated with ICC$_{P} + \text{ICC}_{\text{RS}}$ flashes. The difference of the average observed relative frequency and the predictions according to the 100 test data samples including one-third of 792 observations lie within the 95 % confidence interval of the predictions below 75 %. However, both the refinement distribution (b) and the difference between observed and predicted probabilities (a) show that the models are not
sharp. They most frequently predict in a probability range between about 0.4 and 0.7 forming a hill shaped distribution. Further the models fail to correctly predict ICC\textsubscript{only} flashes reflected by the large deviation of the average observed from the predicted probabilities close to 1, i.e., 100 %. The median in the AUC based on 100 test samples is 0.66, which is, however, still better than the value of 0.5 for no explanatory power at all.

The lack of sharp predictions by the tree ensembles must not be misinterpreted as underperformance. The results rather reflect that in contrast to the trigger mechanism of upward flashes, meteorological information alone only constitutes one part explaining the occurrence of ICC\textsubscript{only} flashes over the occurrence of the other two subtypes of upward lightning. We suggest that conditions causing ICC\textsubscript{only} flashes requires additional information from other fields covering latent processes not included in the meteorological data.

Assessing the part explained by meteorology, Figure 8 (a) shows that of the six groups, cloud physics has the largest influence on the probability of ICC\textsubscript{only} flashes. Its influence is larger than the other five groups combined. Arbitrarily permuting all values enclosing this variable group decreases the AUC by more than 8 percentage points. With about 3 percentage points median decrease in predictive performance, the second most important group is the wind field. On rank three and four the variable group importance of the surface exchange and the mass field group yields a fractional decrease in the median AUC of about 1 percentage point.

Cloud physics variables also dominate the list of the ten most influential variables when they are individually randomly permuted (instead of groupwise). Eight out of the ten are cloud physics variables (see panel (b) in Figure 8). These eight involve key vari-

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**Figure 7.** Panel (a): Difference of the average observed relative frequency and predicted probability and refinement distribution (b) for ICC\textsubscript{only} versus ICC\textsubscript{P} + ICC\textsubscript{RS} flash type models based on test data samples. Median of AUC is 0.66. Shaded area and error bars indicate the 95 % confidence interval around the average predicted probabilities and average observed frequencies, respectively.
variables explaining the theory of charge separation (e.g., Williams, 2018). The charge separation process requires the presence of both supercooled liquid water and frozen hydrometeors (solid hydrometeors, supercooled liquid water (total column), between $-10 \degree C$ and $-40 \degree C$ and between $-20 \degree C$ and $-40 \degree C$). In the presence of supercooled liquid water differently large frozen hydrometeors collide receiving a different polarity. Gravity-driven motions then ensure the separation of differently charged particles resulting in a typical vertical charge structure. This charge structure is most often characterized by a dipole with a negative charge layer below a positive charge layer. This dipole structure is referred to as graupel dipole (see e.g., Williams, 2018). Further important cloud physics variables are the large scale precipitation, caused by non-convective processes and convective precipitation caused by rising motions due to less dense air below denser air in the lower atmosphere.

Permuting individual variables shows that the mean sea level pressure has the largest influence on the probability of ICC\textsubscript{only} flashes over ICC\textsubscript{P} + ICC\textsubscript{RS} flashes. Further, the pressure difference between North-East ($+1.4 \degree N, +1.4 \degree E$) and South-West ($-1.4 \degree N, -1.4 \degree E$) of the Gaisberg Tower, the surface latent heat flux and the day of the year have a comparable impact in magnitude on the probability of ICC\textsubscript{only} flashes. Even though permuting individual wind field variables do not show up in the top ten of the atmospheric drivers, significant information content is lost if no wind field variables were included (see panel (b) in Figure 8).

Predictions of 100 random forests on artificial data in which only the variable of interest varies show that a higher mean sea level pressure increases the probability of ICC\textsubscript{only} flashes (see panel (a) in Figure 9). According to the median predictions this probability increases from about 0.40 to 0.46 when the mean sea level pressure changes from 1 000 hPa to 1 030 hPa. This implies the hypothesis that ICC\textsubscript{only} flashes are not favored by intense low-pressure systems.
Solid hydrometeors (panel (b) in Figure 9) have the opposite effect on the probability of ICC\textsubscript{only} flashes. A lower proportion of solid hydrometeors increases the probability of ICC\textsubscript{only} over the other subtypes of upward flashes.

Explorative approaches using ERA5 data reveal that lower values in all of the four most important variables associated with cloud physics increase the probability of ICC\textsubscript{only} flashes (not shown here). The lower the proportion of solid hydrometeors, supercooled liquid water (total column and between −10 °C and −40 °C) and the lower the amount of large scale precipitation, the higher the probability for ICC\textsubscript{only} flashes according to the medians. The two important mass field variables are the mean sea level pressure and the North-East to South-West pressure difference. Exploring these, shows that higher values favor ICC\textsubscript{only} flashes at the Gaisberg Tower.

While the distributions of all six variables discussed above differ for the two flash type categories, their interquartile ranges overlap, highlighting that meteorological variables alone do not contain enough information to sharply separate the two categories of upward lightning flashes. Geographical and local topographical effects might have a significant influence on various flash parameters as emphasized by March (2015) and Birkl et al. (2018). We speculated that changes to the electric field surrounding the measurement site might provide additional valuable information, which the next section will explore in detail.

6 The influence of nearby lightning discharges on ICC\textsubscript{only} flashes

Since nearby lightning discharges often trigger upward lightning (e.g., Wang et al., 2008; Schumann et al., 2019) their occurrence might be also instructive in distinguishing between the different types of upward lightning. Consequently, three variables are added to the set of potential predictors: The spatial and the temporal distance of nearby discharges and the product of both. Exponential kernel functions with a normalization of spatial distance by 100 km, and temporal distance by 60 s are applied to them. Distances are computed to all these lightning discharges (cloud-to-ground and intra-cloud) from EUCLID within the defined spatial and temporal frame.

The improvement from including these predictors in the random forest is large (Figure 10). ICC\textsubscript{only} can now be more sharply separated from ICC\textsubscript{P} + ICC\textsubscript{RS} flashes. Most frequently the model identifies the upward flash to be ICC\textsubscript{only} with a probability of close to 90 % and 0 %, respectively. The difference between the average observed frequency and the predicted probabilities for each bin lie around zero and approach the zero line in the tails around 0 % and 90 %. The highest deviation from a zero difference is around
predictions of 60 % which the models predict more rarely compared to the tails as the refinement in (b) demonstrates. This is in stark contrast to Figure 7 without nearby discharge information showing the smallest difference for the intervals from close to 0 % to about 75 % and the largest differences approaching the right tail at 100 %. Note that to reduce noise and overfitting from unimportant variables in the predictive performance, only the ten most important atmospheric variables (see panel (b) in Figure 8) are used here to assess the predictive performance.

Nearby discharges are by far the most important variable group among all variable groups influencing whether flashes are of ICC\textsubscript{only} type or of ICC\textsubscript{P} + ICC\textsubscript{RS} type. Without them, as shown in Figure 11 by simultaneously permuting all three variables in this group, the AUC score is more than 35 percentage points lower. In comparison, permuting the most important meteorological variables group – cloud physics – is only one tenth as effective.

The farther away (in space and time) the nearby discharge is, the higher the probability that the upward lightning flash is of type ICC\textsubscript{only} (Figure 12). The probability does not change gradually but jumps step-like by about 10 percentage points at a discharge distance of about 4 km (a). The probability similarly steps up at a temporal distance of about 1.7 s (b). The product of spatial and temporal distance yields the biggest step of about 20 percentage points (c). Formulated differently, the results in Figure 12 show that lightning discharges close to location and time of upward lightning initiation favor the inception of ICC\textsubscript{P} + ICC\textsubscript{RS} flashes, whereas the absence of nearby lightning significantly increases the probability that an upward flash is of type ICC\textsubscript{only}.  

**Figure 10.** Panel (a): Difference of average observed relative frequency and predicted probability, (b): refinement distribution for ICC\textsubscript{only} versus ICC\textsubscript{P} + ICC\textsubscript{RS} flash type models when including the ten most important meteorological variables (see Figure 8) and information on nearby discharges (cloud-to-ground and intra-cloud). The performance is based on test data samples. Median of AUC is 0.9. Shaded area and error bars indicate the 95 % confidence interval around the average predicted probabilities and average observed frequencies, respectively.
Figure 11. Ranking of variable groups influencing whether an upward flash is of ICC\textsubscript{only} type according to the permutation variable group importance procedure described in section 3.2. Permutation variable important is based on models including all meteorological variables and the three additional predictors representing nearby discharges.

Figure 12. Left (a): Effect of discharge distance in space on probability of ICC\textsubscript{only} flashes (value 1). Center (b): Effect of nearby discharge distance in time. Right (c): Effect of product of discharge distance in space and time. Effects are predicted quantiles (0.1, 0.5, 0.9) based on the tree ensembles.
7 Conclusion

This study applied a machine learning method to a climatological dataset of atmospheric variables and lightning measurements to diagnose (i) when upward lightning initiated from a tall tower is triggered by nearby lightning ("other-triggered") and when by the tower itself ("self-triggered"), and (ii) of what particular subtype it is.

Measurements of upward lightning at Gaisberg Tower in Austria between 2000 and 2015 are combined with 75 atmospheric variables derived from the ERA5 reanalysis, time of day, day of year, and the occurrence of nearby lightning discharges detected by the EUCLID lightning location system. The atmospheric variables belong to five broad groups: cloud physics, mass field, moisture field, surface exchange and wind field. The probabilities for upward lightning to be self-triggered and of a particular type, respectively, are modeled with tree-structured ensembles in the form of conditional inference random forests.

Whether flashes are self-triggered can be reliably explained by atmospheric variables. The mass field is most important and has larger influence than the other four atmospheric variable groups combined. The most important variable from this group is the height of the $-10^\circ$C isotherm. As the distance to the tall structure decreases, the probability of upward flashes being self-triggered increases. Further important variables from this group are the $-20^\circ$C isotherm height, the 2 m temperature and CAPE.

Whether upward flashes are of the ICC\textsubscript{only} type has important consequences because that type cannot be spotted by lightning location systems but only by specially equipped towers so that no regionally detailed information of their occurrence exists. An ICC\textsubscript{only} type flash is characterized by initial continuous currents only, whereas the other types have superimposed pulses or return stroke(s).

For the occurrence of ICC\textsubscript{only} upward flashes, atmospheric conditions are far less influential than for the kind of trigger. The random forest results clearly indicate that meteorology constitutes only one part and cannot fully explain the occurrence of ICC\textsubscript{only} upward flashes. However, from the meteorological part, the most important group is cloud physics. It has a larger influence than all other four meteorological categories combined.

What is decisive for the type of upward lightning are nearby (in space and time) lightning discharges. Without them (or them being further away), ICC\textsubscript{only} flashes are more likely. “Nearby” translates to approximately 4 km, and within around 2 s, respectively. Above these thresholds, the probability of ICC\textsubscript{only} flashes jumps abruptly. Random forests are especially well-suited to capture such sharp boundaries (e.g., Hastie et al., 2009).

These random forest models can reliably estimate the probabilities whether upward lightning is self-triggered and of the ICC\textsubscript{only} type for new input data not used in their training – without needing the specialized tower measurements. Whether these models give reliable results also at different locations is an open question well worth investigating.

Acknowledgments

We acknowledge the funding of this work by the Austrian Research Promotion Agency (FFG), project no. 872656 and Austrian Science Fund (FWF) grant no. P 31836. We thank Siemens BLiDS for providing EUCLID data. The computational results presented here have been achieved in part using the LEO HPC infrastructure of the University of Innsbruck.
Author contribution

Isabell Stucke did the investigation, wrote software, visualized the results and wrote the paper. Deborah Morgernstern, Thorsten Simon and Isabell Stucke performed data curation, built the data set, and derived variables based on ERA5 data. Thorsten Simon contributed with coding concepts. Georg J. Mayr provided support on the meteorological analysis, data organization and funding acquisition. Achim Zeileis supervised the formal analysis and interpretation of the statistical methods. Achim Zeileis, Georg J. Mayr, and Thorsten Simon are the project administrators and supervisors. Gerhard Diendorfer, Wolfgang Schulz and Hannes Pichler made all lightning data available, this study relies on. Further they contributed to the interpretation of results from prior knowledge in lightning research. All authors contributed to the conceptualization of this paper, discussed on the methodology, evaluated the results, and commented on the paper.

Open Research

Data availability

ERA5 data are freely available at the Copernicus Climate Change Service (C3S) Climate Data Store (Hersbach et al., 2020). The results contain modified Copernicus Climate Change Service information (2020). Neither the European Commission nor ECMWF is responsible any use that may be made of the Copernicus information or data it contains. EUCLID data and direct observations from the Gaisberg Tower are available only on request. For more details contact Wolfgang Schulz or Siemens BLIDS.

Software

All calculations as well as setting up the final data sets, modeling and predicting were performed using R (R Core Team, 2021), using packages netCDF4 (Pierce, 2019), partykit (Hothorn & Zeileis, 2015), ggplot2 package (Wickham, 2016). Retrieving the raw data and deriving further variables from ERA5 required using Python3 (Van Rossum & Drake, 2009) and cdo (Schulzweida, 2019).

Competing interests

The authors declare that they have no conflict of interest.

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