Abstract: The current methods for lightning risk warnings that are based on atmospheric electric field (AEF) data have a tendency to rely on single features, which results in low robustness and efficiency. Additionally, there is a lack of research on canceling warning signals, contributing to the high false alarm rate (FAR) of these methods. To overcome these limitations, this study proposes a lightning risk warning method that incorporates enhanced empirical Wavelet transform-Adaptive Savitzky–Golay filter (EEWT-ASG) and one-dimensional morphology, using time-frequency domain features obtained through the Wavelet transform (WT). The proposed method achieved a probability of detection (POD) of 77.11%, miss alarm rate (MAR) of 22.89%, FAR of 40.19%, and critical success index (CSI) of 0.51, as evaluated on 83 lightning events. This method can issue a warning signal up to 22 min in advance for lightning processes.

Keywords: atmospheric electric field (AEF); lightning risk warning; enhanced empirical wavelet transform-adaptive Savitzky–Golay filter (EEWT-ASG); one-dimensional morphology; wavelet transform (WT)

1. Introduction

Lightning disasters pose a significant threat to humanity and have been listed as “one of the ten most severe natural disasters” by the United Nations. In southern China, lightning disasters account for 82.98% of total disasters, and casualties constitute 82.94% of the total number of casualties [1,2]. The atmospheric electric field (AEF) is a fundamental parameter in atmospheric physics and atmospheric electricity [3,4]. Lightning activities are often accompanied by changes in AEF, which can be utilized for lightning warnings.

In recent years, research on lightning risk warnings based on AEF has rapidly progressed. Warning methods can be broadly divided into two categories: time-domain and frequency-domain. Time-domain methods typically employ the simple AEF threshold method for lightning risk warnings. However, these methods exhibit a low probability of detection (POD) and neglect the inherent physical characteristics of AEF. Furthermore, they fail to thoroughly explore the relationship between AEF characteristics and lightning [5,6].

In 2008, Murphy conducted a preliminary investigation of lightning warning using the threshold judgment method for AEF data [7]. In 2009, Aranguren compared and analyzed the threshold method and the polarity reversal method, discovering that the first polarity reversal of AEF data was more effective in predicting lightning occurrence, with 47% accuracy [8]; in 2015, Srivastava combined AEF data with the Markov model to achieve a POD of 66.45%, but the false alarm rate (FAR) reached 59.7%, rendering it unsuitable for practical application [9].
Frequency-domain methods first employ spectral transform methods, such as Fourier transform, Hilbert–Huang transform (HHT), and short-time Fourier transform (STFT), to obtain features. Lightning warnings are then achieved by setting thresholds for these features. Although the warning effect has improved compared to time-domain methods, the application of AEF data remains insufficient [10,11]. In 2014, Kang demonstrated that AEF energy could be used as a characteristic of lightning risk warning via STFT [12]; in 2016, Lu utilized HHT and observed that the high-frequency energy of AEF gradually increased during lightning events. A method for using energy for lightning risk warnings was also proposed [13]. However, previous studies have failed to account for the impact of noise on the AEF [14].

In this study, we address the noise of AEF and the low POD of existing methods by proposing a lightning risk warning method based on EEWT-ASG and Morpho. This method initially decomposes the AEF signal using EEWT-ASG to minimize the noise component, then extracts time-domain and frequency-domain features employing wavelet transform (WT), and ultimately achieves lightning risk warning by setting thresholds for the features and Morpho-based trend calculation. Compared to using time-domain or frequency-domain features, the POD of warning is improved, and both MAR and FAR are reduced.

The remainder of this paper is organized as follows. Section 2 describes the EEWT-ASG and global trend calculations based on Morpho. Section 3 analyzes the time-frequency spectrum of the AEF for both lightning and non-lightning events. Section 4 presents our lightning risk warning method and introduces the corresponding evaluation metrics. Finally, Section 5 concludes this study by summarizing and discussing its findings, while also outlining future work. This includes the consideration of incorporating meteorological radar data and employing data fusion techniques to enhance the performance of lightning risk warnings.

2. Method

In this section, we introduce two approaches for lightning warning scenarios, aimed at mitigating the impact of noise and augmenting the generalizability of the lightning risk warning methodology.

2.1. EEWT-ASG

In 2021, Yang emphasized the importance of denoising for the study of AEFs and proposed a complementary ensemble empirical mode decomposition with adaptive noise and a Savitzky–Golay filter (CEEMDAN-SG) for AEF noise reduction [14]. However, CEEMDAN, being an iterative signal decomposition method, demands a considerable amount of time to process intricate signals [15], rendering it unsuitable for real-time warning requirements. In 2013, Gilles presented an empirical wavelet transform (EWT) [16], which offers faster processing than empirical mode decomposition (EMD). Nevertheless, the challenge with EWT lies in executing spectrum segmentation. Although Gilles proposed several solutions to this issue [17], these methods still led to excessive spectrum segmentation, resulting in redundancy in the decomposition outcomes. In 2017, Hu investigated Gilles’ spectrum segmentation methods and introduced an enhanced empirical wavelet transform [18].

In this study, we employed EEWT to carry out the decomposition of AEF signals, with the decomposition outcomes displayed in Figure 1. It is evident that the original AEF signal is partitioned into four modes, each displaying a progressively increasing frequency. We designated the AEF signal and the decomposed $k$ component signals as $D(n)$ and $D_i(n)$, $i \in [1,k]$, respectively, which maintain the following relationship:

$$D(n) = \sum_{i=1}^{k} D_i(n).$$  (1)
Indeed, the value of $k$ is dictated by the inherent complexity of the processed AEF signal, which stems from the adaptive spectral analysis performed by the EEWT. The more intricate the frequency components of the AEF signal, the greater the number of decomposed modes. In order to ascertain whether each component contained noise, we employed an autocorrelation analysis, inspired by Yang, to make this determination [14]. We computed the normalized autocorrelation function of $D_i(n)$ as follows:

$$R_{D_i}(m) = \frac{\sum_{n=-\infty}^{\infty} D_i(n)D_i(n+m)}{\sum_{n=-\infty}^{\infty} D_i(n)D_i(n)}.$$ (2)

At this time, the normalized autocorrelation function for all components can be obtained as:

$$R_D \approx [R_{D_1} \ R_{D_2} \ldots \ R_{D_k}].$$ (3)

Furthermore, the normalized autocorrelation function of the ideal Gaussian white noise was computed and denoted as $R_{Noise}$. Subsequently, the Pearson correlation coefficient [19] was employed to gauge the similarity between $R_{D_i}$ and $R_{Noise}$, as follows:

$$Pearson = \frac{COV(R_{D_i}, R_{Noise})}{\sigma_{R_{D_i}}\sigma_{R_{Noise}}} = [Pearson_1 \ Pearson_2 \ldots \ Pearson_k].$$ (4)
Among them, COV and σ denote the covariance and standard deviation, respectively. The range of Pearson_i is between −1 and 1. Pearson_i closer to 1 means that the correlation between R_D and R_Noise is better, then it is more probable that R_D contains noise. In this study, the component signal D_Noise(n) that contains noise is defined as follows:

\[
D_{\text{Noise}}(n) = \begin{cases} 
D_i(n), & \text{if } \text{Pearson}_i > 0.75 \\
0, & \text{if } \text{Pearson}_i \leq 0.75
\end{cases}
\]  

(5)

An Adaptive Savitzky–Golay (ASG) filter is employed for D_Noise(n) to smooth it [20]. The ASG filter addresses the issue of selecting two key parameters in the SG filter: the size of the data window and the polynomial degree. If the data window is excessively wide, it may result in the loss of valuable information in the signal. Conversely, if the data window is too narrow to effectively filter the signal, opting for a large polynomial degree might introduce new noise, while selecting a small polynomial degree could cause distortion due to oversmoothing of the signal [14,21]. Given that the AEF signal is non-stationary, fixing both the data window size and the polynomial degree in signal smoothing could lead to the loss of original information in the signal. In [14], Xu utilized an SG filter to address the noise in AEF and set the polynomial degree and data window size to 3 and 7, respectively. Building on Xu’s work, we adopted a polynomial degree of 3 and employed the G-FL scheme to dynamically adjust the data window size [20]. The denoising results are depicted in Figure 2.

![Figure 2](image-url)

Figure 2. The denoising results of EEWT-ASG are presented, with (a) representing the original signal, (b) illustrating the denoised signal, (c) depicting the dynamic adjustment of the data window size using the G-FL scheme, and (d) showcasing the noisy signal.
2.2. Calculation of Global Trend Based on Morpho

To delineate the global trend of the signal over time, drawing inspiration from Hu and Gilles’ trend computation [18,22], we put forth the following method to acquire the global trend based on morphology.

\[
Dilate(n) = \text{MAX}_{k \in A_s}(X(k))
\]

(6)

\[
Erode(n) = \text{MIN}_{k \in A_s}(X(k))
\]

(7)

where \( X \) is the data sequence and \( A_s \) is a sliding window of size \( s \). Euclidean distances between the local maxima of the data are calculated and denoted as \( X_{\text{Localmax}} \).

\[
s = \text{MAX}(X_{\text{Localmax}})
\]

(8)

\[
Cl(n) = Erode(Dilate(n))
\]

(9)

\[
Op(n) = Dilate(Erode(n))
\]

(10)

\[
morpho(n) = \frac{Cl(n) + Op(n)}{2}
\]

(11)

Prior to the Dilate and Erode calculations, data must undergo preprocessing using the mirror expansion method to ensure consistent data size [18]. The results of Morpho are rectified through the following steps. Firstly, the first-order backward differentiation of \( morpho(n) \) is calculated and denoted as \( \Delta morpho(n) \). Subsequently, the upward and downward regions in \( morpho(n) \) are identified as:

\[
\text{Trend} = \begin{cases} 
\text{Upward Region}, & \text{if } \Delta morpho > 0 \\
\text{Flat Top}, & \text{if } \Delta morpho = 0 \\
\text{Downward Region}, & \text{if } \Delta morpho < 0
\end{cases}
\]

(12)

Ultimately, the flat top is rectified based on the following three criteria:

- The flat top is classified as the upward region if both the left and right sides of the flat top are within the upward region;
- The flat top is designated as the downward region if both the left and right sides of the flat top are within the downward region;
- The remaining flat tops, identified as the complex region, have their trends disregarded.

Here, we calculate the global trend using Equation (13).

\[
\text{GlobalTrend} = \begin{cases} 
\text{Upward}, & \frac{\text{Length(Upward Region)}}{\text{Length(Upward Region+Downward Region)}} > 0.60 \\
\text{Downward}, & \frac{\text{Length(Downward Region)}}{\text{Length(Upward Region+Downward Region)}} > 0.60 \\
\text{Unclear}, & \text{Others}
\end{cases}
\]

(13)

In Equation (13), the global trend is represented as a ratio, which is subsequently assessed by establishing a threshold value. The selection of this threshold bears a direct influence on the efficacy of the global trend determination. We used the 22 days of lightning weather data analyzed statistically in the next section and set the threshold to 0.6 by the 95th percentile method. The outcomes of the trend computations are illustrated in Figure 3. The corrected upward (downward) trend range is depicted in green (red). By employing Equation (13), the signal in Figure 3 is characterized as a global uptrend. This methodology provides a more holistic examination of the signal trend, as opposed to solely relying on slope for the determination of the global trend. Furthermore, the presence of a data window
of size $s$ (Equation (8)) imparts partial resistance to interference, ensuring that substantial local signal fluctuations do not compromise the global trend determination.

![Graph](image)

**Figure 3.** Global trend of the Morpho with rectification.

### 3. Time-Frequency Spectrum Feature Statistics

The AEF represents the magnitude of the electric field in the atmosphere at any given location and time. AEF changes are intimately connected to lightning activity, and lightning may occur when the AEF potential gradient reaches a breakdown value. Consequently, analyzing the AEF characteristics of a specific region is not only beneficial for understanding the AEF characteristics of lightning weather, but also plays a crucial role in lightning warning systems.

In this study, AEF data were obtained from a novel Microelectromechanical Systems (MEMS) Atmospheric Electric Field Meter (AEFM) [23]. This device employs highly sensitive, low-power MEMS electric field sensor chip technology, fulfilling the requirements for real-time monitoring of lightning weather events [24]. The AEFM was positioned atop the Guangzhou Tower at an elevation of 500 m (113°19′9″ E, 23°6′33″ N). Considering the AEFM’s resolution for AEF measurements, we selected a total of 62 days of AEF data for statistical analysis, which included 22 days with lightning weather events and 40 days with non-lightning weather events. In the lightning weather cases, the initial cloud-to-ground (CG) flash locations were all within a 10 km radius of the AEFM. In order to facilitate the subsequent statistical analysis, it is ensured that the risk warning duration for all selected lightning weather events is greater than 25 min.

The variations in AEF and frequency spectrum during the lightning event are depicted in Figures 4 and 5, respectively. The red and green dashed lines represent the warning time and de-warning time as determined by the Guangdong–Hong Kong–Macau Lightning Location System (GHMLLS), respectively. In 2022, data from artificially triggered lightning experiments conducted by Yue were employed to assess the performance of the GHMLLS utilized in this study. The outcomes revealed that the detection efficiencies for artificially triggered lightning and strokes were 96% and 88%, respectively. The arithmetic mean, geometric mean, and median values of location error amounted to 279 m, 193 m, and 202 m, respectively [25].
Integrating Figures 4 and 5, it is evident that the AEF data exhibited significant fluctuations around the warning time (indicated by the red dashed line), accompanied by a substantial increase in the spectral bandwidth. Consequently, we employed the manually determined warning information as the benchmark and computed the spectral bandwidth $B(n)$, energy difference $\text{Diff}$, and standard deviation $\text{STD}$ of the AEF data, as presented in Tables 1 and 2, respectively.

In Table 1, the first-order backward differentiation of $B(n)$ is calculated and represented as $\Delta B(n)$. Using 10 min of AEF data as the statistical length, we evaluated $|\Delta B_{\text{avg}}|$, $|\Delta B_{\text{max}}|$, $|\Delta B_{\text{min}}|$ and $\text{STD}$ under lightning and non-lightning conditions. $|\Delta B_{\text{avg}}|$, $|\Delta B_{\text{max}}|$, and $|\Delta B_{\text{min}}|$ represent the average, maximum, and minimum values of $|\Delta B(n)|$, respectively. The lightning event was divided into four stages based on the warning information from the time flow: before the warning, after the warning, before the de-warning, and after the de-warning. In Table 1, it can be observed that after the warning, $|\Delta B_{\text{avg}}|$ shows a significant increase. Similarly, after the de-warning, $|\Delta B_{\text{avg}}|$ decreases rapidly. Additionally, after the warning, there is a notable increase in $\text{STD}$. Comparing the values of $|\Delta B_{\text{avg}}|$ and $\text{STD}$ between the lightning and non-lightning events, significant differences
can be observed. Therefore, we consider $|\Delta B_{\text{avg}}|$ and $\text{STD}$ as the features for lightning risk warning.

**Table 1.** Spectral bandwidth (mHz) and STD (kV/m) statistical results of lightning and non-lightning events.

<table>
<thead>
<tr>
<th>Category</th>
<th>Phase</th>
<th>Period</th>
<th>Index</th>
<th>Average</th>
<th>Range</th>
</tr>
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<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>$</td>
<td>\Delta B_{\text{avg}}</td>
<td>$</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>$</td>
<td>\Delta B_{\max}</td>
<td>$</td>
</tr>
<tr>
<td>Lightning</td>
<td>Before</td>
<td></td>
<td>$</td>
<td>\Delta B_{\min}</td>
<td>$</td>
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<tr>
<td></td>
<td></td>
<td></td>
<td>STD</td>
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<td>0.21</td>
</tr>
<tr>
<td></td>
<td>After</td>
<td></td>
<td>$</td>
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<td></td>
<td></td>
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<td>$</td>
<td>\Delta B_{\max}</td>
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<td>$</td>
<td>\Delta B_{\min}</td>
<td>$</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>STD</td>
<td>5.73</td>
<td>0.22</td>
</tr>
<tr>
<td>De-warning</td>
<td>Before</td>
<td></td>
<td>$</td>
<td>\Delta B_{\text{avg}}</td>
<td>$</td>
</tr>
<tr>
<td></td>
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<td></td>
<td>$</td>
<td>\Delta B_{\max}</td>
<td>$</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>$</td>
<td>\Delta B_{\min}</td>
<td>$</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>STD</td>
<td>1.55</td>
<td>0.22</td>
</tr>
<tr>
<td></td>
<td>After</td>
<td></td>
<td>$</td>
<td>\Delta B_{\text{avg}}</td>
<td>$</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>$</td>
<td>\Delta B_{\max}</td>
<td>$</td>
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<td></td>
<td></td>
<td></td>
<td>$</td>
<td>\Delta B_{\min}</td>
<td>$</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>STD</td>
<td>1.59</td>
<td>0.18</td>
</tr>
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</table>

**Non-lightning**

<table>
<thead>
<tr>
<th>Category</th>
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<th>Period</th>
<th>Index</th>
<th>Average</th>
<th>Range</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>$</td>
<td>\Delta B_{\text{avg}}</td>
<td>$</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>$</td>
<td>\Delta B_{\max}</td>
<td>$</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>$</td>
<td>\Delta B_{\min}</td>
<td>$</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>STD</td>
<td>0.06</td>
<td>0.01</td>
</tr>
</tbody>
</table>

**Table 2.** Statistical results of energy differences (dB) between warning and de-warning of the original AEF data, CEEMDAN-SG denoised data, and EEWT-ASG denoised data.

<table>
<thead>
<tr>
<th>Filter</th>
<th>No Filter</th>
<th>CEEMDAN-SG</th>
<th>EEWT-ASG</th>
</tr>
</thead>
<tbody>
<tr>
<td>Index</td>
<td>Average</td>
<td>Range</td>
<td>Average</td>
</tr>
<tr>
<td>$\text{Diff}_{\text{avg}}$</td>
<td>12.96</td>
<td>5.33</td>
<td>38.08</td>
</tr>
<tr>
<td>$\text{Diff}_{\max}$</td>
<td>27.89</td>
<td>17.01</td>
<td>57.07</td>
</tr>
<tr>
<td>$\text{Diff}_{\min}$</td>
<td>1.91</td>
<td>0</td>
<td>16.72</td>
</tr>
<tr>
<td>$\text{Diff}'_{\text{avg}}$</td>
<td>13.54</td>
<td>5.89</td>
<td>30.82</td>
</tr>
<tr>
<td>$\text{Diff}'_{\max}$</td>
<td>34.36</td>
<td>20.98</td>
<td>59.54</td>
</tr>
<tr>
<td>$\text{Diff}'_{\min}$</td>
<td>0.75</td>
<td>0</td>
<td>5.68</td>
</tr>
</tbody>
</table>

In Table 2, we denote the energy of the original AEF signal as $E(n)$ and the energy of the AEF signal with low-frequency components removed as $E'(n)$. Furthermore, we represent the warning and de-warning moments as $n_{w}$ and $n_{daw}$, respectively. The energy difference $\text{Diff}$ is given by Equation (15). Similarly, we calculate the energy difference for $E(n)$, denoted by $\text{Diff}'$. For both $\text{Diff}$ and $\text{Diff}'$, we also calculate the average, maxi-
mum, and minimum values, which are denoted as $\text{Diff}_{\text{avg}}$, $\text{Diff}_{\text{max}}$, and $\text{Diff}_{\text{min}}$, respectively.

$$E_d(m,n) = |E(m) - E(n)|$$  \hspace{1cm} (14)

$$\text{Diff} = \begin{bmatrix} E_d(n_w - 300, n_{dw} - 300) & \cdots & E_d(n_w - 300, n_{dw} + 300) \\ E_d(n_w - 299, n_{dw} - 300) & \cdots & E_d(n_w - 299, n_{dw} + 300) \\ \vdots & \cdots & \vdots \\ E_d(n_w + 300, n_{dw} - 300) & \cdots & E_d(n_w + 300, n_{dw} + 300) \end{bmatrix}$$  \hspace{1cm} (15)

Combining Table 2 and Figure 6, it can be observed that the energy difference between $n_w$ and $n_{dw}$ is very small. Meanwhile, owing to the slow fluctuation of the AEF (i.e., low-frequency signal) during the non-lightning process, we consider it as a disturbance in the lightning warning. After excluding the signal energy near the zero frequency, $\text{Diff}_{\text{min}}$ was only approximately 1 dB; therefore, we chose $E'(n)$ as the main feature for de-warning. Comparing the energy difference between the original and denoised signals, the ranges of $\text{Diff}_{\text{avg}}$ and $\text{Diff}_{\text{max}}$ after denoising were reduced to different degrees. This indicates that the denoised AEF signal has a better energy correspondence between $n_w$ and $n_{dw}$, which has positive implications for lightning risk warning. The denoising effects of CEEMDAN-SG and EEWT-ASG were similar. In terms of time consumption, EEWT-ASG requires less time than CEEMDAN-SG.

![Figure 6.](image_url) The AEF energy changes during a lightning event. The red and green dashed lines represent the warning time and de-warning time, respectively.

4. Lightning Risk Warning Method and Evaluation

Building upon the time-frequency spectrum statistics for lightning and non-lightning events presented in Section 3, we merge the two techniques from Section 2 to develop a lightning risk warning method. Moreover, an evaluation of this risk warning method is provided to demonstrate its effectiveness.

4.1. Lightning Risk Warning Method Based on AEF Signal

The lightning risk warning method proposed in this paper consists of two components: warning and de-warning. The “global trend” referenced here is computed using the method detailed in Section 2.2. The criteria for warning and de-warning are outlined below.

**Warning conditions:**
- $B(n)$ and $E'(n)$ of the AEF signal show a global upward trend over 20 min;
- $|\Delta B_{\text{avg}}| > 0.5 \text{ mHz}$, $E'_{\text{avg}} > -20 \text{ dB}$, and $\text{STD} > 0.5 \text{ kV/m}$ in 10 min;
During the design of de-warning conditions, we found that relying solely on AEF energy at the moments of warning and de-warning led to inaccuracies in identifying the conclusion of a minor fraction of lightning events. To guarantee the smooth operation of the entire method, we devised an alternative Scheme II as a supplementary measure for the lightning risk warning method in cases where the de-warning signal is unable to be issued properly.

De-warning conditions:

Scheme I
- \( B(n) \) and \( E'(n) \) of the AEF signal show a global downward trend over 20 min;
- \(|E'_{\text{avg}} - E'_{w}| \leq 1 \text{ dB} \) and \( \text{STD} \leq 1 \text{ kV/m} \) in 10 min;

Scheme II
- The sum of the 10 judgments for \( |\Delta B_{\text{avg}}| \) was less than 0.1 mHz;
- \( \text{STD} \leq 1 \text{ kV/m} \) in 10 min;

In the Scheme I, \( E'_{w} \) is the minimum value of \( E'_{\text{avg}} \) among the 10 judgments before the lightning risk warning method is judged as a warning. \( E'_{w} \) changed with the value of \( E'_{\text{avg}} \) each time the lightning risk warning method was judged to be a warning state. A flowchart of the lightning warning method is presented in Figure 7.

![Flowchart of the lightning risk warning method.](Figure 7)

4.2. Evaluation Metrics

In accordance with the scholarly definitions of the Area of Concern (AOC) and Warning Area (WA) within the “Two Area Method” [7,26,27], we establish the AOC and WA as illustrated in Figure 8. Here, the circle’s center represents the location of the AEFM, while the AOC encompasses the area surrounding the AEFM that requires protection from lightning hazards. Additionally, the WA constitutes the outer region encircling the AOC.

To assess the performance of the warning behavior, we utilized five metrics: Probability of Detection (POD), Miss Alarm Rate (MAR), False Alarm Rate (FAR), Critical Success...
Index (CSI), and Mean Warning Lead Time (WLT). These metrics are represented by Equations (16)–(20), respectively.

\[
POD = \frac{EA}{EA + FTW} \tag{16}
\]

\[
MAR = \frac{FTW}{EA + FTW} = 1 - POD \tag{17}
\]

\[
FAR = \frac{FA}{FA + EA} \tag{18}
\]

\[
CSI = \frac{EA}{FA + EA + FTW} \tag{19}
\]

\[
WLT = \frac{\sum_{i=1}^{EA} (time'_{i} - time_{i})}{EA} \tag{20}
\]

In these metrics, \( EA \) represents the number of effective alarms, referring to warnings issued prior to the first cloud-to-ground (CG) flash within a warning cycle. Conversely, \( FTW \) denotes the number of failures to warn, which occur when warnings are either issued or absent after the first CG flash within a warning cycle. Additionally, \( FA \) signifies the number of false alarms, indicating the absence of a CG flash during a warning cycle. Lastly, \( time'_{i} \) and \( time_{i} \) correspond to the time of the first CG flash as detected by the Guangdong–Hong Kong–Macau Lightning Location System (GHMLLS), and the warning time provided by the AEF-based lightning risk warning method, respectively.

![AOC and WA](image)

**Figure 8.** Configuration of AOC and WA.

### 4.3. Results and Analysis

We evaluated the lightning risk warning method proposed in this paper using AEF data with 83 lightning events, employing the evaluation metrics in Section 4.2. In addition, using 123 days of AEF data for non-lightning events, we employed POD to evaluate the performance of the lightning risk warning method for non-lightning events. The statistical results are presented in Table 3.

<table>
<thead>
<tr>
<th>Method</th>
<th>Lightning</th>
<th>Non-Lightning</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>POD</td>
<td>MAR</td>
</tr>
<tr>
<td>EFAI [28]</td>
<td>18.07%</td>
<td>81.93%</td>
</tr>
<tr>
<td>EFDI [28]</td>
<td>91.57%</td>
<td>8.43%</td>
</tr>
<tr>
<td>Lu [13]</td>
<td>18.07%</td>
<td>81.93%</td>
</tr>
<tr>
<td>We proposed</td>
<td>77.11%</td>
<td>22.89%</td>
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</tbody>
</table>
In Table 3, we compare our proposed method with previous studies in the literature [13, 28]. It was found that the EFDI method had the highest Probability of Detection (POD) during lightning events, but its False Alarm Rate (FAR) reached 60.00%, indicating low reliability [29]. Lu’s method had the highest POD of 98.26% during non-lightning events, but it performed poorly with a POD of 18.07% during lightning events and failed to meet the warning goal. Our proposed method achieved the lowest FAR (40.19%) and highest Critical Success Index (CSI) (0.51) among the four methods during lightning events, while maintaining a reasonable POD. Additionally, our method also had a high POD (90.24%) during non-lightning events, although it was lower than that of Lu’s method. We also visualized the warning lead time of the warning methods in this paper (Figure 9), and it can be seen that the warning lead times are mostly within the range of 0 to 20 min.

![Figure 9. The distribution of warning lead time.](image)

5. Discussions and Conclusions

Lightning risk warnings play a crucial role in safeguarding critical infrastructure, sensitive equipment, and various facilities from the impact of lightning strikes. In this paper, we propose a lightning risk warning method specifically tailored for the Guangzhou Tower in China, which is capable of automatically deactivating for a set period following a lightning event. The key contributions of this study can be summarized as follows:

1. We introduced the EEWT-ASG and morpho-based global trend calculation methods, specifically designed for lightning warning scenarios.
2. Employing Wavelet Transform (WT), we conducted a statistical analysis of the time-frequency spectral characteristics for both lightning and non-lightning events.
3. We proposed a lightning risk warning method that utilizes features from both time and frequency domains.

In this paper, we analyze the time-frequency spectral characteristics of lightning and non-lightning events in Section 3. Building on the results from Section 3, we create a lightning risk warning method in Section 4, using both techniques described in Section 2. Additionally, we provide an evaluation of this risk warning method. Table 1 demonstrates that $|\Delta B_{avg}|$ and STD can effectively distinguish between lightning and non-lightning events, making them suitable for use as warning features.

For de-warning, we observe similar energy magnitudes in the AEF signal at both warning and de-warning moments (Figure 6), which is supported by the energy difference statistics presented in Table 2. This finding reinforces our hypothesis that, as lightning develops, the AEF signal energy progressively concentrates in the high-frequency band and eventually returns to its pre-lightning value when the lightning process concludes.

Moreover, when calculating the AEF signal energy, we exclude the low-frequency components due to the presence of slow fluctuations (i.e., low-frequency signals) in the AEF during non-lightning events, which are considered as interference. To enhance the
universality of the method, we also incorporated the calculation of one-dimensional morphological global trends into the warning method, reducing the reliance on thresholds. From Table 2, we can observe that the ranges of $\text{Diff}_{\text{avg}}$ and $\text{Diff}_{\text{max}}$ decrease after denoising. This reduction in range enables the threshold to be triggered more efficiently for de-warning, indicating that denoising has a positive impact on lightning warning. When comparing the performance of CEEMDAN-SG and EEW-T-ASG in terms of energy features, we can see that both methods yield similar results (Table 2). However, their theoretical foundations differ: CEEMDAN is based on an iterative approach, while EEWT relies on mathematical spectrum segmentation. Consequently, EEW-T-ASG achieves a faster processing speed than CEEMDAN-SG.

We evaluated the time required to process a 20 min AEF signal using the two filters mentioned above, and the results demonstrated that EEW-T-ASG can complete the smoothing operation more quickly (121.1 s for CEEMDAN-SG and 5.8 s for EEW-T-ASG). Thus, EEW-T-ASG is more suitable for lightning warning scenarios.

However, the proposed method has certain limitations that must be addressed. Firstly, it does not incorporate a function for classifying lightning risks and issuing warnings. Secondly, it is necessary to reduce the false alarm rate (FAR) further. Finally, as the AEFM is a passive detection device, it lacks positional information, which can result in some errors in the warnings issued. To overcome these limitations, we are considering incorporating radar information or multiple AEFM networks into the current setup to obtain the location information of thunderstorm cloud clusters, which can be used for their localization and lightning risk warning. Additionally, we plan to conduct a thorough study of the thresholds that have been set (Equations (5) and (13)), based on the AEF data collected in this paper, in order to further improve the proposed method.

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