FUZZY INFERENCE WITH PROBABILISTIC RULE WEIGHTING TO ASSESS PARAGLIDING VIABILITY BASED ON WEATHER VARIABLES

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Abstract

Paragliding is an extreme sport and tourism activity influenced by unpredictable, dynamic weather conditions, requiring a method capable of systematically handling this uncertainty to assist tourists and novice pilots in making flight scheduling decisions. This study focuses on experimenting with the application of a fuzzy inference system with probabilistic rule weighting to evaluate the feasibility of paragliding in the Mount Banyak area, Batu City. The developed system combines the concept of fuzzification to model the uncertainty of meteorological parameters with a probabilistic approach at the inference stage to represent the level of confidence in each rule used. The experiment was conducted using actual weather data obtained through an Application Programming Interface (API) from open meteorological sources. The output of this method is a recommendation in three categories: “safe”, “caution,” and “dangerous.” Testing was conducted by comparing the system's predictions with actual data in the field and showed a Mean Absolute Percentage Error (MAPE) value of 9,30%. As a result, this system is capable of providing quick and accurate assessments that aid decision-making to improve the safety and operational efficiency of paragliding in the region. This approach shows broad application potential in other weather-based tourism fields, as well as supporting the development of environmentally friendly and sustainable technologies.

Keywords: decision support system, fuzzy inference, paragliding, probabilistic rule weighting, weather

1. Introduction

Indonesia is an island nation (archipelagic state) with more than 17,000 islands and a wide range of landscapes, from mountains to beaches (Pone et al., 2024). The natural conditions in Indonesia give the country a chance to grow its nature-based tourism sector, including extreme tourism. Paragliding is a form of tourism that combines the joy of exploring new places with the health benefits of physical and mental activity (Tobuhu et al., 2024). Mount Banyak, located in Batu City, East Java, is a natural tourist attraction that is used as a paragliding area with unique natural panoramas and serves as one of Batu City's leading tourist attractions (Warsaa & Kabelen, 2023).

There are several elements that can affect how well a pilot can paraglide, like the weather, the wind speed, and the direction of the wind. Changing weather might make flying less safe and less possible, especially for tourists or pilots who aren't very skilled (Lorensia & Sudarti, 2022). However, both visitors and novice pilots often find it difficult to recognize changes in weather, which makes them prone to errors when planning flights. A probabilistic fuzzy logic-based Decision Support System (DSS) can be a solution by automatically processing weather data and providing flight feasibility recommendations based on actual weather conditions in Batu City.

Previous studies have examined the use of artificial intelligence in meteorology and aviation, but each has its limitations. Research by Dagal and his team developed an adaptive fuzzy logic control system for aircraft landing gear automation. However, the focus was still on internal mechanical aspects without considering weather conditions (Dagal et al., 2025). Malolepsza and his team designed a fuzzy logic model that analyzes weather using temperature and wind parameters, but the model has not been used to assess the feasibility of an air activity (Małolepsza et al., 2025). Meanwhile, Fajaruddin and his team created a weather notification system for paragliding safety using a simple probabilistic approach, but the system still relies on local sensors and does not utilize real-time weather data (Akbar et al., 2019). This limitation is further compounded by the fact that conventional fuzzy inference approaches, such as Sugeno, generally rely only on membership values and firing strength during the inference process (Terenchuk et al., 2022).

This study proposes a new method that combines artificial intelligence with the real-world experience of experts to assess paragliding flight safety at Mount Banyak, consistent with probabilistic fuzzy approaches previously demonstrated in the risk classification context (Cardiel-Ortega & Baeza-Serrato, 2024). Unlike standard computer systems, this method utilizes a specialized weighting layer that assigns a "confidence value" to each safety rule based on its operational reliability in the field. Its primary advantage lies in its transparency and interpretability, as the system does not solely rely on complex statistical data but directly incorporates practical knowledge from experts. This makes the system remain accurate and adaptive even when historical weather data for the location is limited, allowing flight safety decisions to be made more confidently and measurably.

The system is designed to handle the uncertainty of weather conditions through the stages of fuzzification, probabilistic evaluation, and defuzzification to produce flight suitability recommendations in three categories, namely dangerous, cautious, and safe. Testing was focused on the Batu City area in East Java, considering key meteorological parameters without involving non-meteorological factors. The results of this study are expected to assist pilots and visitors in making safer, more efficient, and measurable flight decisions.

2. Methods

This research consists of several stages, including literature study, data collection, data processing, system design, and evaluation. In the literature study stage, understanding of the issues raised is strengthened by referring to various similar issues found in books, journals, or article. In addition, observations were made directly at the Mount Banyak paragliding site in Batu City to understand the environmental conditions and weather factors that affect paragliding activities. Several other things were also studied in this research, particularly related to the chosen method, namely the probabilistic fuzzy method.

The proposed method applies a fuzzy inference system with probabilistic rule weighting, which combines conventional fuzzy logic with probabilistic confidence weights assigned to each fuzzy rule. Fuzzy logic is used to handle ambiguity through membership degrees and linguistic variables (Hakim, 2024;Dwi Antoni & Findawati, 2024; Malasari Siregar et al., 2023). Probabilistic weighting mechanisms represent the confidence level of each rule during the inference process. This approach is integrated with probability theory, which measures uncertainty from two main perspectives: subjective and objective perspectives (Saki & Faghihi, 2022; Syaifudin & Choiruddin, 2021). The process is illustrated in the following diagram in Figure 1.

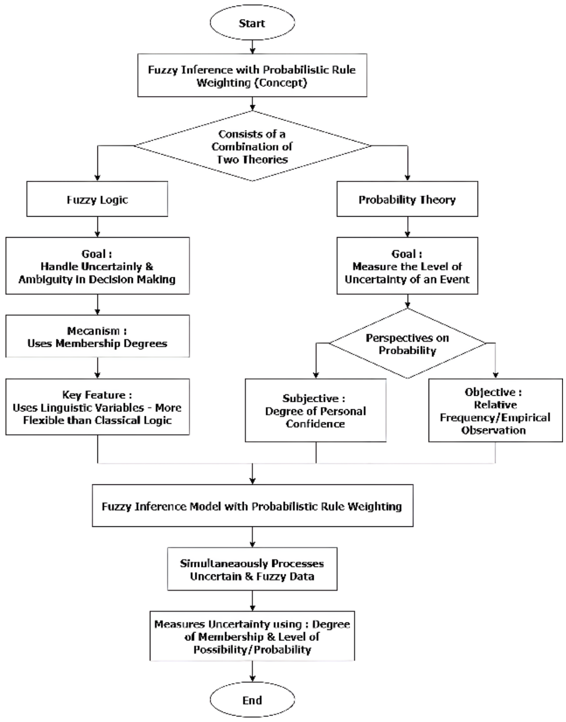

Figure 1. Probabilistic fuzzy logic theory

After conducting a literature study, the next step was data collection, which involved gathering data from Open-Meteo website and adjusting it for the required variables, such as time, wind speed, wind direction, visibility, and general weather conditions. The data was obtained directly from the weather API using the fetch_data() function. This function made a request to the API and collected actual weather data based on the geographical coordinates of Batu City, the research location. After the data were collected, they were processed using a fuzzy inference system with probabilistic rule weighting. The overall process consists of three main stages: fuzzification, weighted fuzzy inference, and defuzzification. (F. Li et al., 2025).

Fuzzification is the process of converting precise and definite input values into fuzzy linguistic labels as a qualitative representation of those values (Arifin et al., 2023). This process includes determining the best membership function to represent the input variables, so that ambiguous or uncertain information can be processed mathematically in a fuzzy model (Riali et al., 2025). The membership function is used to define fuzzy sets in the domain of each input variable, with the set boundaries determined based on the minimum and maximum values observed in the collected data (Saatchi, 2024). While there are various membership function forms available, the triangular and trapezoidal membership functions are the most widely adopted in applied fuzzy inference systems due to their computational simplicity and interpretability (Lima et al., 2025). Two of these three curves are used in this study, namely the triangular curve and the linear curve. According to (Yudha, 2021), fuzzy membership functions are curved, where the mapping of data input points has a membership degree value of 0 to 1. The next step is to process the data using fuzzy inference, as explained in Table 1.

Table 1. Probabilistic fuzzy logic process

Probabilistic fuzzy	
Input :	μ : degree of Membership of all inputs, generated from fuzzification. R_k : $IF\ x_1\ is\ I_{1,j}\ AND\ \ldots\ AND\ x_i\ is\ I_{i,j}\ AND\ \ldots\ AND\ x_n\ is\ I_{n,j}\ THEN\ y\ is\ O_j$ (Y. Li et al., 2022).
Output :	Ω : probabilistic support degree vector for each output category.

Step by step :	Ω : ∅ // Initialize the Probabilistic Support Degree for each output category
	FOR each Rule R_k in R DO:
	// Calculate the Trigger Strength (α)
	$\alpha_k = min(\mu_{A_k}, \mu_{B_k}, \ldots, \mu_{n_k})$
	// Calculate the Probabilistic Support (Ω)
	P_k= Probability of Rule R_k
	$\omega_k = \alpha_k \times P_k$
	Z_k= Output Category of Rule R_k
	// Aggregation (Using $\frac{MAX}{T-conorm}$)
	IF Ω[Z_k] does not exist then:
	$\Omega_{Z_k} = \omega_k$
	ELSE:
	$\Omega_{Z_k} = max(\Omega_{Z_k}, \omega_k)$
	END IF
	END FOR
	RETURN Ω

The inference process in this study applies a Fuzzy Inference System (FIS) with Probabilistic Rule Weighting, which extends conventional fuzzy logic by integrating confidence weights into each rule. In this approach, fuzzy rule weights were determined based on expert assessment scores collected through structured Likert-scale elicitation, following established practices in knowledge-intensive FIS design (Peralta et al., 2025). The process begins with the calculation of trigger strength (α_k) for each rule using the minimum operator based on the membership degrees of input variables (μ_{A_k}) obtained from the fuzzification stage. Unlike a standard fuzzy system, each rule is assigned a probabilistic confidence weight (P_k) determined through expert evaluation based on safety considerations and local weather characteristics. The weighted support value (ω_k) is then obtained by multiplying the trigger strength with the probabilistic weight to provide a more flexible representation of uncertainty. Next, the aggregation mechanism is applied to combine all weighted support values that belong to the same output category (Z_k) using the maximum operator. where the minimum operator is used as the t-norm for the AND connective between antecedents. The result of this stage is the aggregated support degree (Ω_Z), which represents the strongest support value for each output category.

The final stage is defuzzification, where the fuzzy-probabilistic inference results in the form of linguistic degrees or classifications are converted into clear outputs that can be used in decision making (Tang & Ahmad, 2024). In this process, fuzzy membership values and probability distributions are combined to produce a single numerical value that represents the final assessment so that conclusions can be drawn (Saki & Faghihi, 2022). In this study, defuzzification uses weighted average. The weighted average allows each active rule to contribute according to its degree of truth, so that the prediction results are more proportional and accurate (Firmansyah et al., 2025). This process is carried out by totaling the product of the Ω_{Z_k}value and the rule result value S_{Z_k} and then dividing it by the total Ω_{Z_k}value (Hadi et al., 2022). This calculation is denoted as in Formula (1).

$$Weighted\ Average = \frac{\sum_k (\Omega_{Z_k} \times S_{Z_k})}{\sum_k \Omega_{Z_k}} \quad (1)$$

After going through these processes, the output data then undergoes an evaluation process using the Mean Absolute Percentage Error (MAPE) method. The MAPE method was chosen because it is considered capable of describing the performance of each model in forecasting time series data by measuring the forecasting error relative to the actual value (Setyabudi et al., 2025). To calculate MAPE, Formula (2) is used as follows:

$$\text{MAPE} = \frac{100\%}{n} \sum_{t=1}^{n} \left| \frac{X_t - F_t}{X_t} \right| \quad (2)$$

where n is the number of prediction periods involved, Ft is the forecast in period t, and Xt is the actual data in period t (Afiyah et al., 2022). With performance details as listed in Table 2 (Aliniy et al., 2023).

Table 2. MAPE Performance

MAPE Score	Description
MAPE ≤ 10%	High
10% < MAPE ≤ 20%	Good
20% < MAPE ≤ 50%	Reasonable
MAPE ≥ 50%	Low

3. Results and Discussion

The process begins with collecting real-time weather data from the Open-Meteo API website for the location of Batu City. The data collected includes several variables such as time, wind speed, wind gust speed, wind direction, weather code, temperature, relative humidity, and visibility, which are then processed into two types, namely forward visibility and upward visibility. Next, several adjustments were made, such as calculating the wind gust factor, which is calculated as the ratio between wind speed and wind gust speed, while visibility on the upper horizontal axis is calculated based on the relationship between humidity and temperature.

The simplified data based on these required parameters is presented in tabular form that includes six parameters: WS (km/h) (wind speed), GF (%) (gust factor), WR (°) (wind direction), Weather (general condition), FV (m) (forward visibility), and VV (m) (vertical visibility) as shown in Table 3.

Next, the data undergoes the first step in the fuzzy logic process, in which the collected data is used to construct membership functions for the key weather variables used in the probabilistic fuzzy inference system. At this stage, each variable is presented by one or more membership functions to illustrate linguistic values relevant to flight feasibility analysis. In determining the membership functions, the opinions of professional pilots/paragliding instructors were taken into account. The resulting membership functions are shown in Table 4.

After the membership functions are defined, the next stage is the fuzzification process, which aims to extract fuzzy features from the input data. In this stage, crisp input values representing actual observation data are transformed into fuzzy values in the form of membership degrees within the predefined fuzzy sets. As an illustrative example, the input data were recorded on November 16, 2025, at 03:30 p.m. Western Indonesian Time, consisting of a wind speed of 1,80 km/h, a gust factor of 0%, a wind direction of 126.87°, overcast weather conditions (WMO code 3), a horizontal visibility of 9,580 meters, and a vertical visibility of 20 meters. The fuzzy feature values resulting from the fuzzification process are subsequently presented in Table 5.

Table 5. Table of Fuzzy Membership Functions

No	Feature	Degree	No	Feature	Degree
1	C_sunny	0	10	K_low	0,55
2	C_cloudy	1	11	K_suff	0,2
3	C_foggy	0	12	K_high	0
4	C_unsuit	0	13	VD_low	0
5	G_stabil	1	14	VD_med	0
6	G_dang	0	15	VD_high	1
7	A_head	1	16	VA_low	1
8	A_cross	0,1806	17	VA_med	0
9	A_tail	0	18	VA_high	0

In the fuzzy inference process, in addition to the membership values generated in the fuzzification stage, a set of rules that have been given probability weights are also needed for combination. Although the initial combination of seven variables produced 648 rules, this number was reduced to 7 rules that were more practical and efficient. Each rule has a probability weight that reflects its level of influence on the decision category, so that certain conditions can contribute more strongly to a particular category. The prior probability P_k assigned to each rule was determined through structured expert elicitation. A questionnaire was administered to 4 pilots, each with a minimum of 6 years of operational experience. Experts rated the reliability of each rule condition on a five-point Likert scale, representing the frequency with which that rule's antecedent correctly predicts the stated output category in real operational scenarios. The mean score across all respondents was normalized from the Likert scale range of 1–5 into a probabilistic weight interval of 0.1–0.9 using a linear transformation to obtain P_k are shown in Table 6.

Table 5. Fuzzy Rule Probability Weights

Rule	Consequence	Mean Likert	P_k
1	Dangerous	5/5	0.90
2	Dangerous	4.25/5	0.75
3	Dangerous	3/5	0.50
4	Caution	4.20/5	0.75
5	Caution	3.75/5	0.65
6	Safe	5/5	0.90
7	Safe	3/5	0.50

for example, of the rule:

[R1] IF (Wind Direction is Tailwind) OR (Weather Conditions are Not Flyable) THEN the status is Dangerous (P = 0.90);

[R4] IF (Wind Speed is Low) AND (Gust Factor is Stable) AND (Wind Direction is Crosswind), THEN the status is Caution (P = 0.75)

[R6] IF (Wind Direction is Headwind) AND (Wind Speed is Low OR Moderate) AND (Vertical Visibility is Moderate OR High) AND (Horizontal Visibility is Moderate OR High), THEN the status is Safe (P = 0.90)

At the inference stage, each rule's alpha value is calculated as the degree of input match to the rule premise, then multiplied by the probability weight (P) to produce a support value of α × P. This value indicates how much the rule contributes to a particular category. All α × P values that lead to the same category are then combined through an aggregation process by selecting the maximum value as a representation of the final support strength. The support values for these categories have been visualized in the graph in Figure 2.

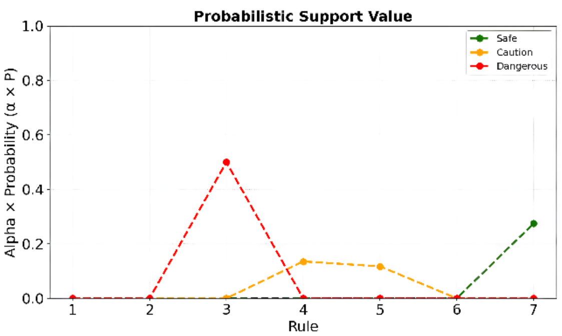

Figure 2. Probabilistic support value for all categories

The analysis results show that the probabilistic fuzzy inference stage successfully mapped weather conditions into complex risk distributions, producing the highest aggregated support (Ω) for the Safe category at 0,275, followed by Caution at 0,1355, and Dangerous at 0,5. This distribution indicates that although most weather conditions are in line with the eligibility criteria, moderate and high risk factors are still triggered with substantial collective support. This support pattern directly determines the Defuzzification result; using high Centroid (weight point) values for Safe (90) and low values for Caution (70) and Dangerous (30). The centroid values were assigned as Safe = 90, Caution = 70, and Dangerous = 30, representing the midpoints of equal sub-intervals within a normalized feasibility scale of 0–100, ensuring symmetric distance between consecutive categories. The Weighted Average calculation produces a probabilistic feasibility score of 54.07. This score indicates that the dominant support from the Hazardous category lowers the overall suitability. Based on the predetermined safety threshold, scores below 60 are classified as Dangerous. Therefore, with a final score of 54.07, the eligibility condition is strictly classified as Dangerous. This means that flight operations must be suspended because current weather conditions pose a serious risk that exceeds the safety tolerance limit.

The performance evaluation process of the proposed Fuzzy Inference System with Probabilistic Rule Weighting was carried out through external validation by comparing the weather feasibility prediction results (PKC Score) with real-time reference data. To ensure a high level of reliability and statistical significance, the evaluation utilized a large-scale dataset consisting of 5.184 data points, recorded continuously from November 14, 2025, at 00:00:00, until January 6, 2026, at 23:45:00. The evaluation method used in this study is the Mean Absolute Percentage Error (MAPE), which measures the average absolute difference between the predicted values and the reference values. Based on this comparison, the proposed fuzzy inference system with probabilistic weighting in its rules achieved a MAPE value of 9.30%. Additionally, the system demonstrated a high level of decision-making reliability with an Accuracy rate of 81.44%. These results, as represented in the graph in Figure 3.

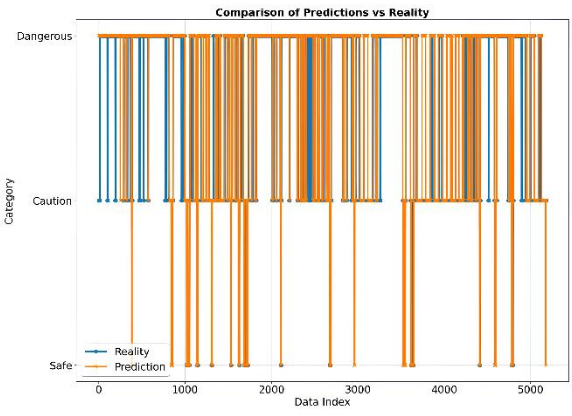

Figure 3. Comparison of System Predictions vs. Actual Labels

The evaluation results show that the PFL system obtained a MAPE value of 9.30%. Referring to the performance criteria in Table 2, a MAPE value below 10% is classified as High (Very Accurate Forecasting). This figure indicates that the system's average prediction error is only about 9.30% of the actual value. This level of accuracy demonstrates that the use of probabilistic fuzzy rules and well-defined membership functions is quite effective in representing the dynamic nature of weather patterns. The relatively small marginal error indicates that the probability weights set in the rule base and the determination of the support degree (Ω) have been well calibrated, enabling the system to provide reliable suitability scores on a large dataset with 5.184 observation points.

To further evaluate the effectiveness of the proposed method, a comparison was conducted with the Naive Bayes classification method. The comparison results show that the proposed Probabilistic Fuzzy approach produced more stable predictions and better interpretability than the Naive Bayes model, particularly in handling uncertainty and gradual transitions between weather conditions. While Naive Bayes assumes statistical independence among features, the proposed method is capable of representing expert knowledge through fuzzy rules and probabilistic support values.

To further validate the proposed method, a comparison was also conducted with the Naive Bayes method, which achieved an accuracy of 72.81% and exhibited several classification errors under weather conditions with overlapping characteristics. These results are further illustrated in Figure 4, which shows that the Naive Bayes predictions exhibit a larger deviation from the actual values.

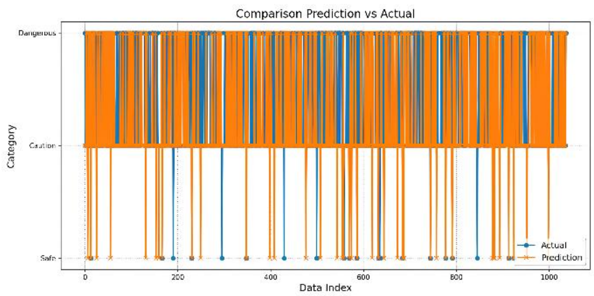

Figure 4. Naive Bayes Predictions

4. Conclusion

Research on the application of the Probabilistic Fuzzy Logic (PFL) method in assessing the feasibility of paragliding in the Mount Banyak area, Batu City, demonstrates strong capabilities in addressing uncertainties in meteorological data through the integration of fuzzy logic and probability during the inference stage. Based on testing of 5,184 data points (November 2025 – January 2026), the Mean Absolute Percentage Error (MAPE) was 9.30%, which falls within the high accuracy category, and classification accuracy reached 81.44%. These results indicate that the assignment of probability weights to the rule base and the determination of centroid values during the defuzzification stage were performed appropriately, enabling the system to consistently generate suitability classifications (safe, caution, and hazardous). In comparison, the Naive Bayes method produced a lower classification accuracy of 72.81% on the same dataset, indicating that the PFL approach provides better performance in handling uncertainty and capturing nonlinear relationships in meteorological conditions for paragliding feasibility assessment.

Nevertheless, several aspects can be further developed, such as refining the rule base and centroid values to enhance sensitivity to changes in weather conditions, adjusting membership functions when the system is applied to regions with different microclimatic characteristics, and integrating IoT sensor data as well as developing a real-time notification system. With these developments, the system is expected to become more adaptive and robust in supporting decision-making for weather-dependent paragliding activities.

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Attachment:

Table 3. Data Snippet

Time	WS(km/h)	GF (%)	WR(°)	Weather	FV(m)	VV(m)
2025-11-14 00:00:00	6.64	13.89	220.60	3	24140	236.49
2025-11-14 00:15:00	6.92	14.53	218.66	3	24140	259.64
2025-11-14 00:30:00	7.42	11.57	219.09	3	24140	259.83
2025-11-14 00:45:00	7.70	7.47	217.41	3	24140	283.07
2025-11-14 01:00:00	7.99	3.59	215.84	3	24140	306.82
:	:	:	:	:	:	:
2026-01-06 22:45:00	8.37	368.63	154.54	1	24140	478.93
2026-01-06 23:00:00	8.37	372.93	154.54	1	24140	479.83
2026-01-06 23:15:00	8.43	378.44	160.02	1	24140	481.44
2026-01-06 23:30:00	8.56	375.39	165.38	1	24140	509.14
2026-01-06 23:45:00	8.35	395.80	172.57	1	24140	537.35

Table 4. Table of Fuzzy Membership Functions

Variable	Range	Fuzzy Set	Domain (Parameters)	Function Shape
Wind Speed (km/h)	0 – 20	Low	[0, 4]	Linear (decreasing)
		Moderate	[0, 9, 18]	Triangular
		High	[15, 20]	Linear (increasing)
Gust Factor (%)	0 – 30	Stable	[0, 20]	Linear (decreasing)
		Dangerous	[15, 30]	Linear (increasing)
Wind Direction (°)	0 – 360	Headwind	[90, 110, 155, 180]	Trapezoidal
		Crosswind	[45, 90, 135] and [135, 180, 225]	Dual Triangular
		Tailwind	[0, 90] and [180, 360]	Constant
Weather Condition (WMO code)	0 – 99	Clear	{0,1}	Singleton
		Cloudy	{2, 3}	Singleton
		Foggy	{45, 48}	Singleton
		Not Flyable	{51, 53, 55, ... , 99}	Discrete
Forward Visibility (m)	0 – 15,000	Low	[2000, 3000]	Linear (decreasing)
		Medium	[2500, 5000, 6000]	Triangular
		High	[5000, 6000, 15,000]	Linear (increasing)
Vertical Visibility (m)	0 – 1,500	Low	[200, 300]	Linear (decreasing)
		Medium	[250, 500, 600]	Triangular
		High	[500, 600, 1,500]	Linear (increasing)