Postprint of the Aircraft Cold Cloud Precipitation Enhancement Potential Forecast Model for the Greater Khingan Range, Inner Mongolia

Authors: Yi Nana, Bilige, Shi Jinli, Cai Min, Xu Zhili, Zheng Fengjie, Lina

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Abstract

The Daxing' anling region is of immeasurable significance for maintaining regional ecological balance and ecological security, yet it also constitutes one of the key fire-risk areas. Establishing an aircraft cold-cloud precipitation enhancement potential forecast model for the Daxing' anling region provides important technical support for precise precipitation enhancement operations for fire prevention and suppression. This study utilizes observations of small and large cloud particle number concentrations from weather modification aircraft during 2017–2020 and 2023 to classify precipitation enhancement potential into three categories: strongly seedable, seedable, and non-seedable. Based on ERA5 reanalysis data, environmental parameters of the three categories of precipitation enhancement potential samples are investigated. The results indicate that the threshold values for relative humidity at 750 hPa are 79.1% and 95.6%, meaning that non-seedable samples have relative humidity below 79.1%, strongly seedable samples have relative humidity above 95.6%, and seedable samples have relative humidity values between these two thresholds. The threshold values for temperature-dewpoint difference at 700 hPa are 0.3 °C and 2.4 °C, vertical velocity at 650 hPa are 0.7 $Pa \cdot s^{-1}$ and -0.06 $Pa \cdot s^{-1}$, liquid water content at 650 hPa and 700 hPa are 0.01 $g \cdot kg^{-1}$ and 0.08 $g \cdot kg^{-1}$, rainwater mixing ratio at 850 hPa are 0.01 $g \cdot kg^{-1}$ and 0.07 $g \cdot kg^{-1}$, and vertically integrated supercooled liquid water are 0.5 mm and 2.2 mm. The discrimination accuracy of these environmental parameter threshold values for the three categories of precipitation enhancement potential samples all exceeds 60%. Considering comprehensively the discrimination accuracy of environmental parameter threshold values for the three categories of samples and the collinearity relationships among the parameters, four environmental parameters were ultimately selected to establish two precipitation enhancement potential forecast models using Fisher and Bayes methods. The two models achieve average recognition rates of 88.6% for the training set and 98.6% for the test set, providing strong technical support for scientific and precise weather modification operations.

Full Text

Abstract

The Da Xing' anling Mountains are of immeasurable significance in maintaining regional ecological balance and ecological security, yet they also represent one of China' s key fire-risk zones. Establishing an aircraft cold-cloud precipitation enhancement potential forecast model for this region provides crucial technical support for precise artificial rain enhancement operations for fire prevention and suppression. This study utilizes airborne observations of small and large cloud particle number concentrations collected during weather modification flights from 2017-2020 and 2023 to classify precipitation enhancement potential into three categories: strongly seedable, seedable, and not seedable. Based on ERA5 reanalysis data, we investigate the environmental parameters characterizing these three categories of enhancement potential. The results indicate threshold values at 750 hPa relative humidity of 79.1% and 95.6% (relative humidity below 79.1% indicates not seedable, above 95.6% indicates strongly seedable, with seedable samples falling between these values). At 700 hPa, dew point temperature difference thresholds are 0.3°C and 2.4°C. At 650 hPa, vertical velocity thresholds are 0.7 $\mathrm{Pa \cdot s^{-1}}$ and -0.06 $\mathrm{Pa \cdot s^{-1}}$. At 650-700 hPa, liquid water content thresholds are 0.01 $\mathrm{g \cdot kg^{-1}}$ and 0.08 $\mathrm{g \cdot kg^{-1}}$. At 850 hPa, rainwater mixing ratio thresholds are 0.01 $\mathrm{g \cdot kg^{-1}}$ and 0.07 $\mathrm{g \cdot kg^{-1}}$. Vertical cumulative supercooled water thresholds are 0.5 mm and 2.2 mm. The discrimination accuracy for all these environmental parameter thresholds exceeds 80.0% for classifying the three enhancement potential categories. Considering both the discrimination accuracy and collinearity relationships among parameters, four environmental parameters were ultimately selected to establish two precipitation enhancement potential forecast models using Fisher and Bayes discriminant methods. Both models achieved average recognition rates of 88.6% for the training set and 98.6% for the test set, providing robust technical support for scientific and precise weather modification operations.

Keywords: weather modification; Da Xing' anling Mountains in Inner Mongolia; environmental parameters; forecasting models

Introduction

Forests constitute a critical component of terrestrial ecosystems, playing an irreplaceable role in maintaining regional carbon balance, regulating climate change, and protecting biodiversity [?]. They also represent one of the regions most sensitive to climate change [?]. Climate warming and drying have significantly increased the frequency and intensity of forest fires [?], which destroy vegetation and organisms, disrupt forest ecosystem balance, and cause severe losses to human life, property, and the national economy [?]. With ongoing climate warming and intensified human disturbances, forest fires have become the greatest threat to China' s ecological civilization construction and forest resource security [?].

Forest fire occurrence is closely related to meteorological conditions, with adverse weather phenomena such as low precipitation, continuous drought, high temperatures, and strong winds often preceding fires [?]. Artificial precipitation enhancement can increase rainfall and alleviate drought, serving as an effective means of preventing and suppressing forest fires [?]. Many provinces and municipalities in China have conducted artificial precipitation enhancement operations for forest fire suppression [?]. However, practice demonstrates that incorrect timing of operations not only wastes seeding materials but may also reduce precipitation [?]. Therefore, accurately judging and grasping the conditions for artificial precipitation enhancement is a prerequisite for scientific operations.

Current research on precipitation enhancement potential primarily relies on comprehensive analysis of multi-source data including reanalysis data, radar observations, satellite data, sounding data, automatic weather station records, and numerical simulations to derive comprehensive enhancement potential indicators. However, most of these studies are limited to statistical analysis of one or more specific cases [?], resulting in limited representativeness and lacking validation from actual aircraft detection data. In China, routine weather modification operations primarily focus on drought relief and rain enhancement, with few operations conducted in the Da Xing' anling region. Moreover, meteorological observation stations are sparse in this area with limited equipment variety, resulting in scarce research on precipitation enhancement potential for the Da Xing' anling Mountains.

Located in the mid-high latitudes of the Northern Hemisphere, the Da Xing' anling Mountains represent China' s largest and most ecologically strategically important state-owned forest region. While vital for maintaining regional ecological balance and security, it is also one of China' s key fire-risk zones. In 2023 alone, 75 forest fires occurred in the Da Xing' anling region, with burned areas reaching 75.2$\times$10^{3}$ hm^2 [?]. Consequently, implementing precise artificial precipitation enhancement for fire prevention and suppression is critically important. This study utilizes long-term aircraft observation data to classify precipitation enhancement potential, analyzes differences in environmental parameters among different potential categories based on reanalysis data, and establishes an aircraft cold-cloud precipitation enhancement potential forecast model for the Da Xing' anling Mountains using statistical methods. This provides a scientific basis for designing flight routes and implementing precise artificial precipitation enhancement operations, enabling weather modification to better serve forest fire risk prevention, control, and ecological protection and restoration.

Data and Methods

1.1 Aircraft Observation Data

The weather modification aircraft is equipped with an airborne cloud particle detection system that continuously observes and records cloud microphysical particle number concentrations (cloud droplets, raindrops, etc.) along the flight trajectory, with a temporal resolution of 1 s. Each data group includes latitude, longitude, and flight altitude information. This study utilizes observations of small cloud particle (Cloud and Aerosol Spectrometer) and large cloud particle (Cloud Imaging Probe) number concentrations collected during flights over the Da Xing' anling region (43°–54°N, 117°–126°E) from 2017–2020 and 2023. Based on the discrimination criteria (Table), three categories of precipitation enhancement potential samples were selected (Table). Samples from 2017–2020 and 2022 were used as the training set for model development, while 2023 samples served as the test set for model validation.

1.2 Reanalysis Data

The European Centre for Medium-Range Weather Forecasts (ECMWF) fifth-generation global reanalysis dataset (ERA5) is the latest atmospheric reanalysis product from ECMWF, with a spatial range of 0°–60°N, 70°–140°E, spatial resolution of 0.25°$\times$0.25°, temporal resolution of 1 h, and vertical levels from 100–1000 hPa at 50 hPa intervals. This dataset demonstrates good reproducibility of actual soil moisture and precipitation in Inner Mongolia [**?**].

1.3 CMA-CPEFS v2.0

The China Meteorological Administration Weather Modification Center's Cloud-Precipitation Enhancement Forecast System (CMA-CPEFS) v2.0 releases products twice daily (at 08:00 and 20:00 BJT) (http://10.1.64.139:8080/ryzhxx/). The cloud model includes forecast variables such as vertical cumulative supercooled water and relative humidity, with a forecast lead time of 72 h, temporal resolution of 1 h, and spatial resolution of 0.03°. The vertical range spans 150–1000 hPa at 50 hPa intervals, providing input data for the precipitation enhancement potential forecast model.

1.4 Methods

Grid data processing primarily follows the "nearest neighbor" principle: temporally selecting the reanalysis data closest to the seedable, not seedable, and strongly seedable sample points, and spatially selecting the grid data nearest to the sample points. Formulas for calculating pseudo-equivalent potential temperature ($_{se}$), ice-surface saturated vapor pressure (e_{si}), vertical cumulative supercooled water (SL), precipitable water vapor (PWV), and divergence (DIV) are as follows:

$$_{se} = \quad \times \exp[(L_v \times q) / (c_p \times T_{LCL})]$$

e_{si} = 6.11 × exp[21.87 × (T - 273.16) / (T - 7.66)]
SL = (1/) {p{top}}^{p_{bottom}} Q_L × dp
PWV = (1/ g) {p{surface}}^{p_{top}} q × dp
DIV = u/ x + v/ y

where is equivalent potential temperature (K), q is specific humidity at the initial pressure level ($kg \cdot kg^{-1}$), T_{LCL} is temperature at the lifting condensation level (K), e_{si} is ice-surface saturated vapor pressure (hPa), T is temperature (K), Q_L is cloud liquid water mixing ratio ($kg \cdot kg^{-1}$), is liquid water density ($kg \cdot m^{-3}$), SL is vertical cumulative supercooled water (mm), PWV is precipitable water vapor (mm), v is meridional wind speed ($m \cdot s^{-1}$), u is zonal wind speed ($m \cdot s^{-1}$), and DIV is divergence (s^{-1}).

Two statistical methods were employed to establish the precipitation enhancement potential forecast model: Fisher discriminant analysis and Bayes discriminant analysis. Fisher discriminant analysis utilizes variance analysis concepts, constructing a linear discriminant function from multiple observations of known samples to determine coefficients that maximize between-group variance while minimizing within-group variance. Bayes discriminant analysis is a classification method based on Bayes' theorem, assuming n samples divided into k classes. For a new sample x, classification follows the maximum posterior probability criterion, assigning x to the class with the highest posterior probability P. Detailed prior probability settings and posterior probability equations can be implemented using statistical analysis software (https://www.ibm.com/).

Results

2.1 Environmental Parameters

2.1.1 Moisture Content Precipitation requires adequate moisture. Vertical distributions of relative humidity and dew point temperature difference for the three sample categories show that seedable and strongly seedable samples have relative humidity greater than 72.2% below 600 hPa, while not seedable samples have relative humidity below 66.5%. Dew point temperature difference decreases with height, with seedable and strongly seedable samples showing values less than 2.0°C at 600-800 hPa, while not seedable samples exceed 2.0°C. Specific humidity decreases with height for all three categories, with strongly seedable and seedable samples showing values greater than 7 $g \cdot kg^{-1}$ in the lower layers, while not seedable samples are below 7 $g \cdot kg^{-1}$. Previous research indicates that clouds with precipitation enhancement potential should have lower-layer specific humidity exceeding 7.5 $g \cdot kg^{-1}$ [**?**].

Box plots reveal the most significant differences among the three categories at 750 hPa for relative humidity and at 700 hPa for dew point temperature difference (Figure [Figure 2: see original paper]). The method for calculating discrimination thresholds follows Yi et al. [**?**]. The 700 hPa dew point temperature difference threshold of 0.3°C can identify 72.2% of strongly seedable samples, 79.1% of seedable samples, and 80.6% of not seedable samples. The 750 hPa relative humidity threshold of 79.1% and 95.6% can identify 66.5% of strongly seedable samples, 75.1% of seedable samples, and 68.6% of not seedable samples, which is consistent with Ding et al. [?] who reported maximum relative humidity values for precipitation enhancement operations in Hunan Province. Both relative humidity and dew point temperature difference thresholds achieve discrimination accuracy exceeding 80.0% for the three categories. Although precipitable water vapor distributions show overlapping box plots among the three categories, with discrimination accuracy below 80.0%, these parameters cannot effectively distinguish the three sample types.

2.1.2 Stratification Stability Stratification can indirectly reflect vertical motion within clouds. Pseudo-equivalent potential temperature increases with height for strongly seedable samples, indicating they typically occur in stably stratified clouds. Not seedable and seedable samples show weak convective instability in the 700–900 hPa layer. Box plots for pseudo-equivalent potential temperature differences between 700 hPa and 500 hPa, and between 850 hPa and 500 hPa, show overlapping ranges (Figure [Figure 3: see original paper]), making them unsuitable for discriminating enhancement potential. Temperature difference thresholds cannot simultaneously exceed 60.0% accuracy for strongly seedable, seedable, and not seedable samples, limiting their utility for discrimination. Unlike severe convective weather such as hail [?], stratification provides limited guidance for precipitation enhancement operations.

2.1.3 Upward Motion Upward motion is a necessary condition for scientific precipitation enhancement operations [?]. Significant differences exist in vertical distributions of divergence and vertical velocity among the three categories. Convergence layers for strongly seedable samples are primarily located at 700–900 hPa, while seedable samples show convergence throughout 500–1000 hPa, albeit with weaker intensity. Not seedable samples exhibit divergence below 850 hPa and sinking motion below 650 hPa (Figure [Figure 4: see original paper]). Both strongly seedable and seedable samples show obvious upward motion in the lower atmosphere, with maximum upward velocity for strongly seedable samples at 400–650 hPa and for seedable samples at 450–650 hPa. Not seedable samples show sinking motion below 650 hPa.

Box plot differences are most pronounced for vertical velocity at 650 hPa and 750 hPa (Figure [Figure 4: see original paper]). The threshold values of -0.7 $\mathrm{Pa \cdot s^{-1}}$ and -0.06 $\mathrm{Pa \cdot s^{-1}}$ at 650 hPa achieve discrimination accuracy of 65.9% for strongly seedable samples, 67.8% for seedable samples, and 66.1% for not seedable samples. Divergence at 750 hPa cannot effectively distinguish the three categories due to overlapping box plots.

2.2 Precipitation Enhancement Factors

Five precipitation enhancement environmental parameters generally increase with height before decreasing. Ice water mixing ratio and snow water mixing ratio show unimodal vertical distributions for not seedable and seedable samples, while strongly seedable samples exhibit bimodal distributions (Figure [Figure 5: see original paper]). Liquid water mixing ratio and rainwater mixing ratio show significant differences among categories, with seedable sample values falling between those of strongly seedable and not seedable samples (Figure [Figure 5: see original paper]).

Box plot analysis reveals that ice water mixing ratio box plots overlap significantly across all three categories, preventing threshold calculation (Figure [Figure 6: see original paper]). Snow water mixing ratio also cannot be used for discrimination due to overlapping ranges. However, liquid water mixing ratio at 650 hPa shows non-overlapping box plots, enabling threshold calculation. The threshold of 0.1$×10^{-3}$ kg · kg^{-1} and 0.8$×10^{-3}$ kg · kg^{-1} at 650 hPa achieves discrimination accuracy exceeding 60.5% for all three categories. Rainwater mixing ratio at 700 hPa shows a threshold of 0.01$×10^{-3}$ kg · kg^{-1} and 0.7$×10^{-3}$ kg · kg^{-1}, with discrimination accuracy exceeding 63.3% for all categories. Vertical cumulative supercooled water, a key technical indicator for weather modification, shows non-overlapping box plots across categories (Figure [Figure 6: see original paper]). The threshold of 0.5 mm and 2.2 mm achieves discrimination accuracy exceeding 65.0% for all three categories.

Model Development

3.1 Model Establishment

Based on the above results, relative humidity at 750 hPa, vertical velocity at 650 hPa, rainwater mixing ratio at 850 hPa, and vertical cumulative supercooled water all achieve discrimination accuracy $ $80.0% for classifying seedable, strongly seedable, and not seedable samples, outperforming other environmental parameters. These four parameters were selected as core modeling variables. Collinearity analysis indicates no significant correlations among the four parameters, while equality of means tests confirm significant differences among the three categories. Fisher and Bayes discriminant methods were used to develop classification models.

Fisher discriminant equations (formula group) were established, and F-function value distributions were analyzed using box plots (Figure [Figure 7: see original paper]). Not seedable and strongly seedable samples show completely overlapping F-function value ranges, indicating limited discriminatory power. Based on the distribution characteristics, Bayes discriminant threshold values were determined: $F_1 \geq 2.9$ identifies 73.0% of strongly seedable samples; $-2.9 < F_1 < 2.9$ identifies 97.9% of seedable samples; and $F_1 \leq -2.9$ identifies 75.3% of not seedable samples.

Relative humidity serves as a cloud discrimination indicator [?]. Vertical profiles show that thicker clouds exhibit stronger seedability (Figure [Figure 1: see original paper]): not seedable samples are primarily outside clouds (cloud samples account for only 24.7%), seedable samples are mostly within clouds (91.4%), and strongly seedable samples are almost entirely within clouds (96.6%). Therefore, RH shows positive correlation with F. Supercooled water, vertical upward motion, and ice nuclei deficiency are necessary conditions for cold-cloud precipitation enhancement. Vertical cumulative supercooled water (VIL) positively correlates with F, while vertical velocity (W) negatively correlates with F (since negative values represent upward motion). The cold-cloud seeding principle involves dispersing appropriate amounts of glaciogenic catalysts into supercooled water regions within clouds, where ice crystals consume supercooled droplets to grow rapidly while droplets evaporate, thereby increasing precipitation efficiency. Thus, more abundant supercooled water indicates stronger seedability. Vertical upward motion, as a primary precipitation condition, also transports catalysts into supercooled water regions to trigger the Bergeron process. Vertical velocity profiles show that stronger and deeper updrafts within clouds indicate greater seedability (Figure [Figure 4: see original paper]).

Rainwater mixing ratio reflects whether raindrops exist in the lower layers (indicating natural precipitation potential). The purpose of weather modification is to increase precipitation in clouds with low natural precipitation efficiency. Therefore, clouds must possess inherent precipitation capability. If lower-layer raindrops are scarce or the lower atmosphere is dry, raindrops cannot grow or will evaporate before reaching the surface, preventing effective precipitation and artificial enhancement.

The Fisher discriminant equation for the training set achieves an average recognition accuracy of 82.1%:

F_1 = -4.408 + 0.013 × RH_{750} + 1.726 × W_{650} + 10.195 × Q_R_{850} - 0.586 × VIL
F_2 = -6.986 + 0.097 × RH_{750} - 0.349 × W_{650} + 4.630 × Q_R_{850} + 1.248 × VIL
F_3 = -5.378 + 0.084 × RH_{750} + 0.177 × W_{650} + 2.765 × Q_R_{850} + 0.338 × VIL

Each sample yields three F values, and the sample is classified into the category with the maximum function value. If F_1 is maximum, the sample is strongly seedable; if F_2 is maximum, seedable; if F_3 is maximum, not seedable. Among the three discriminant equations, F_1 has the largest constant term, with RH and Q_R weight coefficients being similar, while VIL weight coefficients vary significantly. Q_R is positively correlated with F_1, while W is negatively correlated. The Q_R magnitude is relatively small, generally requiring larger VIL values to maximize F_1, which is constrained by actual VIL values in practical applications.

The Bayes discriminant equation achieves an average recognition accuracy of 95.1% for the training set:

F_1 = -25.834 + 0.724 × RH_{750} - 0.964 × W_{650} + 66.879 × Q_R_{850} + 3.105 × VIL
F_2 = -59.554 + 0.822 × RH_{750} + 4.241 × W_{650} - 0.914 × Q_R_{850} + 11.109 ×

VIL
F_3 = -41.334 + 0.865 × RH_{750} + 3.668 × W_{650} + 42.280 × Q_R_{850} + 2.746 × VIL

3.2 Model Validation

The 2023 aircraft observation data were used to validate model accuracy. The Fisher discriminant model identified all seedable and not seedable samples, with an average recognition rate of 88.6%. The Bayes discriminant model identified all not seedable samples and 99.6% of seedable samples, with an average recognition rate of 97.6% (Table).

In practical applications, model accuracy depends on the accuracy of input forecast data. A case study of an aircraft artificial precipitation enhancement operation for forest fire suppression in Hulunbuir City, northern Inner Mongolia, on August 12, 2024, was used to test model applicability. Fires occurred in Arongshan Town and Mangui Town of Genhe City, Hulunbuir (Figure [Figure 8: see original paper]). Due to high temperatures and strong winds, the fire spread continuously with multiple concentrated ignition points. On the afternoon of August 12, under favorable seeding conditions, ground operations and aircraft coordination resulted in light rain around the fire area, successfully completing the forest fire suppression mission.

The precipitation system was a cold vortex with spiral cloud bands. Clouds contained multiple convective cells with uneven distribution. The model forecasted seedable and strongly seedable enhancement potential zones around the fire area, primarily located in regions with high vertical cumulative supercooled water and 850 hPa rainwater mixing ratio values (relative humidity $\geq$ 75.0% at 750 hPa) (Figure [Figure 9: see original paper]). Actual flight operations were affected by airspace restrictions and wind conditions at seeding levels, but overall, the forecasted enhancement potential zones from the Fisher model were consistent with actual aircraft operation areas.

The CMA-CPEFS v2.0 model forecasted vertical cumulative supercooled water values less than 1.0 mm at all times with uneven spatial distribution. Grid points with vertical cumulative supercooled water >0.5 mm were discontinuous or had limited coverage, preventing the model from forecasting enhancement potential zones. Therefore, practical application of the aircraft cold-cloud precipitation enhancement potential forecast model requires careful attention to the accuracy of input vertical cumulative supercooled water values and unit consistency.

Conclusion

Precipitation enhancement potential within cloud systems is extremely complex, and studying potential using any single physical parameter has inherent limitations. This study utilizes long-term aircraft observation data from 2017-2023 to analyze environmental parameters for three categories of precipitation enhancement potential samples in the Da Xing' anling region. Threshold values for relative humidity at 750 hPa, vertical velocity at 650 hPa, rainwater mixing ratio at 850 hPa, and vertical cumulative supercooled water achieve discrimination accuracy exceeding 80.0% for the three sample categories, outperforming other environmental parameters. Based on Fisher and Bayes methods, aircraft cold-cloud precipitation enhancement potential forecast models for the Da Xing' anling Mountains were established using these four parameters. Both models achieved average recognition rates exceeding 88.6% for the training set and 98.6% for the test set, providing robust technical support for scientific and precise weather modification operations.

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Note: Figure translations are in progress. See original paper for figures.