



Vertical differences in liquid water content between warm and cold liquid-phase clouds over the North China Plain and their controlling factors: insights from in situ aircraft observations and ensemble learning models

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Abstract. Liquid water content (LWC) governs cloud radiative forcing and precipitation efficiency, and its contrast between
15 warm and supercooled liquid-phase clouds shapes cloud lifetime and the water cycle. Aircraft campaigns over the North China Plain have characterized droplet spectra, vertical structure, and aerosol responses, but LWC has mostly been diagnosed with single-factor or linear analyses, which cannot distinguish the individual contributions of different factors. It thus remains unclear which factors govern LWC in each regime, and whether any acts differently between them. Using in-situ observations from 13 K350 aircraft flights during 2019-2021, we compared the two cloud types and quantified predictor contributions and
20 interactions in an LWC prediction model with SHAP. An equal-weighted AdaBoost–LightGBM ensemble performed best. Adding further members provided no improvement, indicating that model complementarity outweighs ensemble size. Despite similar cloud-base distributions, cold clouds developed more deeply with stronger winds but lower LWC. The principal vertical contrast occurred at 1600-2300 m, where warm-cloud LWC temporarily exceeded cold-cloud LWC. Wind-related dynamical factors dominated LWC predictions in both cloud types (~41 % combined). From warm to cold clouds, the temperature contribution decreased from 15.5 % to 6.9 %, while aerosol-related contributions increased. The SHAP interaction between
25 temperature and vertical wind changed from positive to negative, indicating that the two regimes share a dynamic framework in which the temperature-wind coupling, not temperature itself, differs. By making these contributions directly comparable, the study identifies this interaction reversal as the key regime difference and provides an observational constraint for LWC parameterizations.



30 1 Introduction

Clouds are a key link in the Earth-atmosphere system, connecting atmospheric radiation (Slingo, 1990; Voigt et al., 2020), energy exchange (Stephens et al., 2012; von Schuckmann et al., 2020), and the atmospheric water cycle (Allan et al., 2020; Pierrehumbert, 2002). Among the various types of clouds, liquid-phase clouds are widely distributed and serve as major contributors to cloud radiative effects and cloud feedbacks (Myers et al., 2021; Zelinka et al., 2020), as well as an important
 35 subject for understanding aerosol-cloud interactions and precipitation formation (Bony et al., 2015; Li et al., 2025a; Mülmenstädt and Feingold, 2018; Rosenfeld et al., 2019). Extensive research on liquid-phase clouds has used satellite and ground-based remote sensing (Cadeddu et al., 2020; Khanal and Wang, 2018; Vishwakarma et al., 2023), aircraft observations (Li et al., 2025b; Liu et al., 2025; Sheng et al., 2022), and numerical simulations (Dziekan et al., 2019; Pathak et al., 2020) to analyze their macro-scale distribution, underlying processes, and in-cloud microphysical structures (Che et al., 2021; Luo et al., 2022; Wood, 2012; Zhang et al., 2022). These studies have advanced understanding of the macro- and microphysical characteristics of liquid-phase clouds across various scales and have shown that their evolution is jointly governed by thermodynamic and dynamic conditions (Chandrakar et al., 2021; Possner et al., 2020; Zhang et al., 2023).

Liquid-phase clouds are not confined to temperatures above 0 °C. When a cloud lies below the freezing level, its liquid water exists as supercooled water (Listowski et al., 2019; Yang et al., 2021), so liquid-phase clouds can be further divided into warm
 45 and cold clouds. Supercooled water is metastable and highly sensitive to ambient temperature, vertical motion, turbulent mixing, and aerosol conditions (Barrett et al., 2020; Fan et al., 2017; Murray et al., 2021). Nevertheless, it can persist within clouds and substantially influence their maintenance and development (Ricaud et al., 2020; Seiki and Roh, 2020). However, supercooled water is characterized by a short lifespan and sporadic spatiotemporal distribution (Yang et al., 2024; Yi et al., 2024), and it is difficult to effectively distinguish it from the ice phase using only a single remote sensing method (Aubry et al., 2024; Guyot et al., 2022). Consequently, current understanding of supercooled water remains limited (Kalesse-Los et al., 2022; Ricaud et al., 2024).

Microphysically, liquid water content (LWC) is jointly determined by the number concentration and volume of cloud droplets across the size spectrum. At the macrophysical level, it reflects the reservoir of condensed water within a cloud (Chen et al., 2025; Finstad et al., 1988). Since LWC is determined by the conversion of water vapor to the liquid phase and the consumption
 55 of liquid water (Igél, 2024; Yeom et al., 2023; Zhu et al., 2022), it is governed by both thermodynamic and dynamic conditions. Thermodynamic conditions control the direction and efficiency of condensation and evaporation through the saturation vapor pressure (Li et al., 2019; Prabhakaran et al., 2022), whereas dynamic conditions determine the liquid water budget through water vapor transport by vertical wind (Oh et al., 2023; Reutter et al., 2009) and mixing and dilution by horizontal wind (Chen et al., 2020; Lu et al., 2023).

60 Current understanding of LWC remains constrained by observational capabilities. While satellite and ground-based remote sensing offer broad spatial or temporal coverage (Kim et al., 2020), they lack vertical resolution and their results rely on retrieval algorithms (Billault-Roux and Berne, 2021; Lebsock et al., 2022), making it difficult to accurately characterize the



vertical structure within clouds. Numerical models, in turn, are constrained by cloud microphysics parameterizations and spatial resolution, preventing them from fully resolving small-scale dynamic variations (Berg et al., 2020; Bott, 2021; Pant et al., 2026). In contrast, by penetrating clouds, aircraft observations can directly yield high-temporal-resolution data of the cloud droplet size distribution, LWC, and meteorological variables. Despite their limited spatiotemporal coverage, in situ aircraft observations therefore remain an important means of evaluating remote-sensing retrievals and model parameterizations, as well as identifying in-cloud processes (Hou et al., 2021; Wu et al., 2020; Zhao et al., 2020).

Machine learning offers a new way to process the high-dimensional, nonlinear data obtained from aircraft observations (de Burgh-Day and Leeuwenburg, 2023; Reichstein et al., 2019). Unlike regression methods that require a predefined functional form, machine-learning models learn nonlinear mappings between inputs and outputs directly from the data, can accommodate multiple interrelated predictors simultaneously and remain robust to observational noise (Breiman, 2001; Jordan and Mitchell, 2015; Schulte et al., 2024). However, the performance of a single model is susceptible to factors such as sample size, hyperparameters, and model bias (Probst et al., 2019; Seifert and Rasp, 2020), which can lead to overfitting or poor generalization. Ensemble learning instead combines different base models (Dietterich, 2000; Sagi and Rokach, 2018) to reduce variance and improve generalization, raising predictive stability while preserving goodness of fit, and generally outperforms individual models (Ganaie et al., 2022; Li et al., 2026; Wang et al., 2026). Therefore, it is necessary to compare various types of base models and their different combinations to identify the optimal model.

However, complex machine learning models often exhibit strong "black-box" characteristics, making it difficult to intuitively reveal how individual variables contribute to predictions or how they act (Castelvecchi, 2016; Rudin, 2019), and to link the statistical relationships they identify to specific physical processes (Beucler et al., 2021; Camps-Valls et al., 2023). SHAP (SHapley Additive exPlanations), built on the Shapley value from cooperative game theory (Shapley, 1953), decomposes a model prediction into the additive marginal contributions of its input features, which provides local explanations for individual samples while remaining globally consistent, and thus quantifies the relative importance of each feature to the predicted value (Mosso et al., 2025; Tian et al., 2026; Wang et al., 2025).

Building on this, this study uses in situ K350 aircraft measurements over the North China Plain to compare the macro- and microphysical characteristics of warm and cold liquid-phase clouds. Then we construct and select ensemble learning models for LWC and apply the SHAP method to quantify the relative contributions of thermodynamic and dynamic factors in the two cloud types and to identify how their effects differ.

2 Methods and Data

2.1 Data sources and pre-processing

The data were obtained from King Air 350 (K350) in situ aircraft observations conducted by the Hebei Weather Modification Office over the North China Plain during 2019-2021. The airborne instrumentation included a Cloud Droplet Probe (CDP), a Cloud Imaging Probe (CIP), a Passive Cavity Aerosol Spectrometer Probe (PCASP), and a 20 Hz Aircraft-Integrated



95 Meteorological Measurement System (AIMMS-20). This study selected 16 cloud-containing flights that sampled liquid-phase, ice-phase and mixed-phase clouds. Detailed information regarding instrument specifications and flight information is provided by Liu et al. (2026).

Following aircraft observation experience and existing cloud-phase identification methods (Hobbs and Rangno, 1998; Lance et al., 2010; Liu et al., 2026), liquid-phase clouds were identified in this study (Fig. S1) from the number concentration of cloud droplets (N_c) and ice particles (N_i) larger than 125 μm (Korolev et al., 2011), using the criteria $N_c \geq 10 \text{ cm}^{-3}$ and $N_i \leq 1 \text{ L}^{-1}$ (Fu et al., 2022; McFarquhar and Heymsfield, 2001). To minimize the influence of probe noise and isolated particles, only segments consisting of at least 10 consecutive sampling points that satisfy the aforementioned criteria were retained as valid liquid-phase cloud samples.

After phase identification and continuity filtering, 13 flights contained valid liquid-phase cloud samples, and a total of 5584 samples were obtained for subsequent analysis. The liquid-phase clouds were further classified by temperature as warm ($T \geq 0 \text{ }^\circ\text{C}$) or supercooled ($T < 0 \text{ }^\circ\text{C}$) clouds (hereafter referred to as cold clouds), in which the cloud water exists as supercooled liquid droplets rather than ice (Fig. 1).

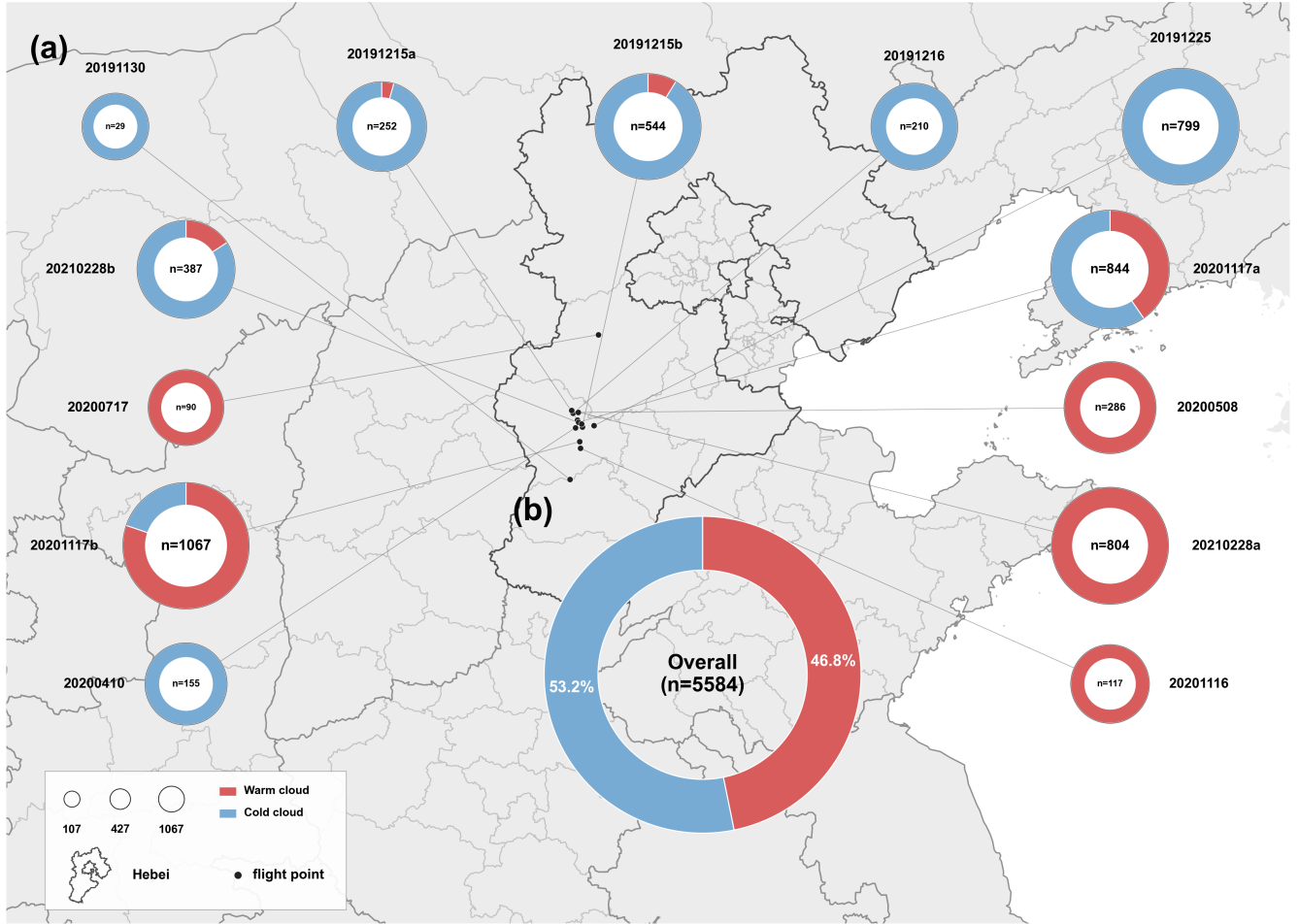


Figure 1: Spatial distribution and temperature-based classification of liquid-phase cloud samples observed by aircraft over the North China Plain during 2019-2021. (a) Flight-specific proportions of warm (red) and cold (blue) cloud samples. Donut size and the central n indicate the number of valid liquid-phase cloud samples. Black dots mark the corresponding takeoff locations. (b) Overall proportions of warm and cold cloud samples pooled across the 13 flights containing valid liquid-phase cloud samples.

2.2 Methods for calculation of cloud properties

The spectral density in the i -th bin measured by each probe is N_i ($\text{cm}^{-3} \cdot \mu\text{m}^{-1}$), and the number concentration of the i -th bin, n_i (cm^{-3}), is obtained by multiplying the spectral density by the bin width:

$$n_i = N_i \Delta D_i \quad (1)$$

where ΔD_i is the width of the size interval of the i -th bin (μm). The total number concentration N is obtained by summing over all bins:

$$N = \sum_i n_i \quad (2)$$



Specifically, the total cloud droplet number concentration (N_c) and the total aerosol number concentration (N_a) are obtained by summing the cloud droplet spectra (2-50 μm) observed by the CDP and the aerosol spectra (0.1-3 μm) observed by the PCASP, respectively.

Furthermore, to examine associations between particles in different size ranges and meteorological factors, and to provide size-resolved features for subsequent machine-learning modeling, the cloud droplets were further divided into 3 size ranges with reference to Wang et al. (2019) and Liu et al. (2026): N_{SCDNC} (2-12 μm), N_{MCDNC} (12-22 μm), and N_{BCDNC} (22-50 μm), and the aerosols into 2 ranges: N_{SANC} (0.1-1 μm) and N_{BANC} (1-3 μm), following the classical aerosol size classification (Whitby, 1978; Seinfeld and Pandis, 2016).

The effective radius of cloud droplets r_e was derived from the particle size distribution (Hansen and Travis, 1974):

$$r_e = \frac{\sum_i n_i r_i^3}{\sum_i n_i r_i^2} \quad (3)$$

where r_i is the particle radius in bin i and n_i is the corresponding particle number concentration.

The spectral relative dispersion ε describes the relative width of the particle size distribution (Pontikis and Hicks, 1992):

$$\varepsilon = \frac{1}{\bar{r}} \sqrt{\frac{\sum_i n_i (r_i - \bar{r})^2}{\sum_i n_i}} \quad (4)$$

where $\bar{r}$ is the mean particle radius:

$$\bar{r} = \frac{\sum_i n_i r_i}{\sum_i n_i} \quad (5)$$

Unlike the quantities above, the LWC used in this study was not derived from the droplet size distribution but measured directly by a hotwire liquid water content sensor, which provides a bulk measurement of LWC independent of the CDP spectra.

To investigate the vertical distribution characteristics within the cloud, this study defines the highest observation altitude of the aircraft within the cloud as the cloud top height z_t and the lowest as the cloud base height z_b , the relative height H corresponding to any observation altitude z within the cloud was calculated as:

$$H = \frac{z - z_b}{z_t - z_b} \quad (6)$$

2.3 Ensemble learning modeling

This study establishes an ensemble learning framework that encompasses data processing, model training and selection, and SHAP-based interpretation (Fig. 2). First, all observations at time points with any missing feature were excluded, followed by cloud-phase identification. Second, the base models and their ensembles were then compared individually to select the best model. Finally, by contrasting the macro- and microphysical properties of warm and cold clouds, we used the SHAP values and interactions to quantify predictor contributions to LWC, thereby revealing the differences in control mechanisms.

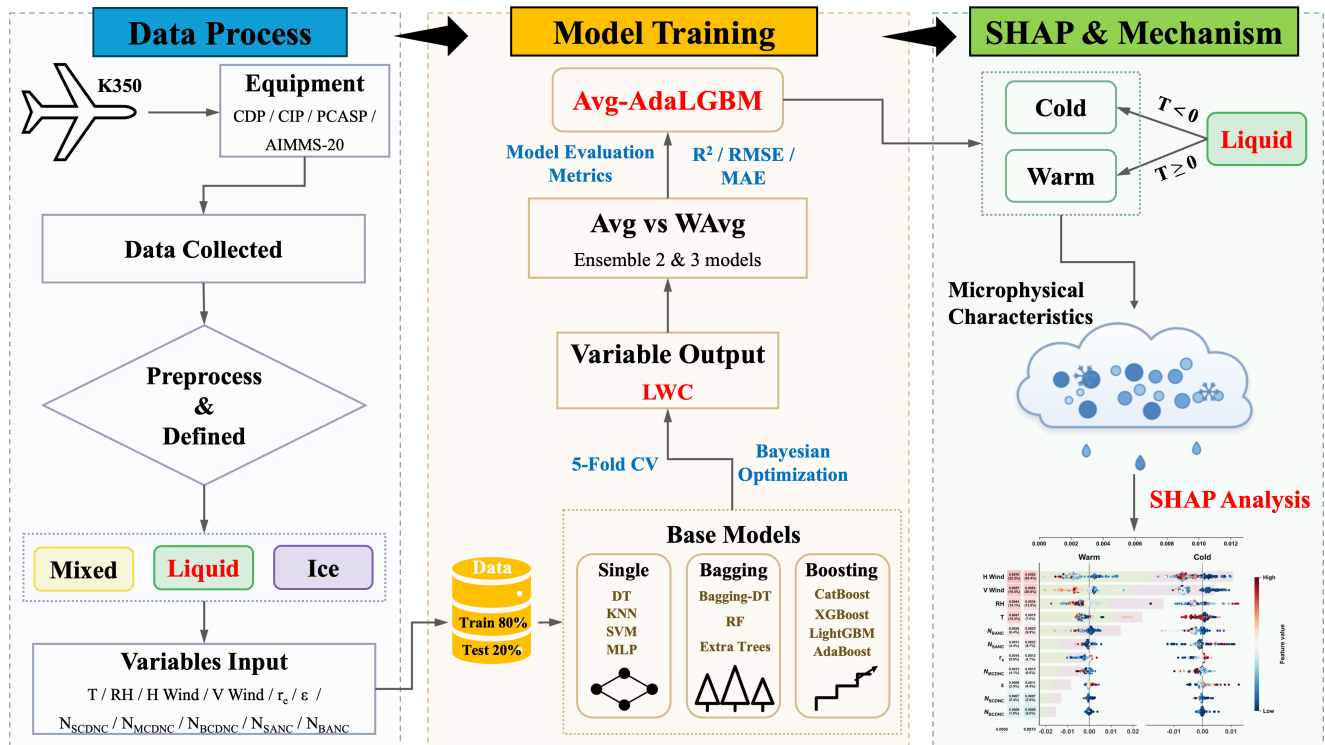


Figure 2: Workflow of the ensemble learning framework for cloud LWC. Three-stage pipeline: data processing, ensemble model training and selection, and SHAP-based mechanism analysis.

Eleven machine learning algorithms were selected as base models, covering Single (DT, KNN, SVM, MLP), Bagging (Bagging-DT, RF, ExtraTrees) and Boosting (CatBoost, XGBoost, LightGBM, AdaBoost), to ensure model diversity (see Text S1 for a description of each algorithm and Table 1 for a comparison of their strengths and limitations). The samples were randomly shuffled and split into a training set and an independent test set in a ratio of 8:2. Each base model was tuned separately by Bayesian optimisation (Snoek et al., 2012) combined with five-fold cross-validation (Kohavi, 1995) to determine its optimal hyperparameters (Table S1).

Model performance was evaluated using the correlation coefficient of determination (R^2), the root mean square error (RMSE) and the mean absolute error (MAE) (Willmott and Matsuura, 2005; Chai and Draxler, 2014; Hodson, 2022), which are defined in Text S2.

Table 1: Characteristics of the machine learning algorithms selected as base models.

Category	Model	Strengths	Limitations
Single	DT	Interpretable rule structure with low computational cost	Prone to overfitting and unstable to data perturbation
	KNN	Non-parametric and sensitive to local sample similarity	Depends on feature scaling and degrades in high dimensions



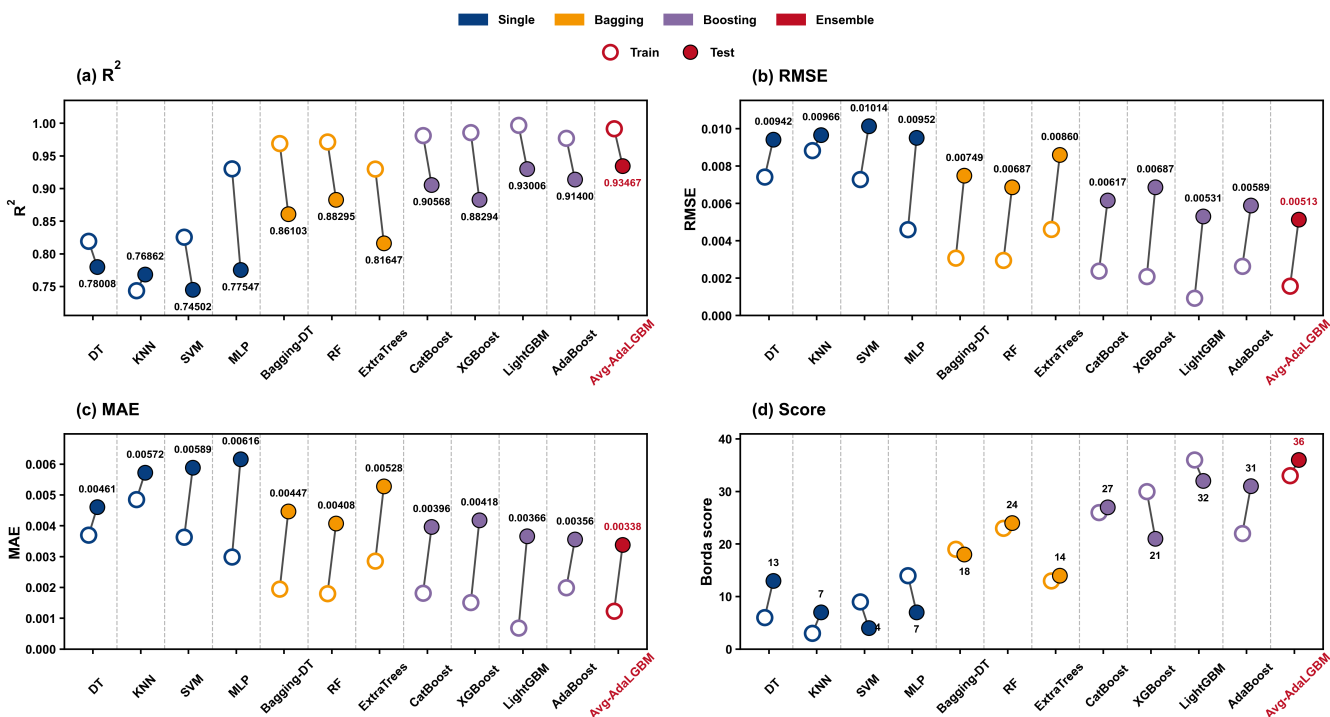
	SVM	Represents nonlinear relationships through kernel mappings	Sensitive to the choice of kernel and penalty parameters
	MLP	Flexible approximation of complex nonlinear	Requires large samples and offers low interpretability
Bagging	Bagging-DT	Reduces the variance of a single tree and trains in parallel	Correlated trees limit the ensemble gain
	RF	Decorrelates trees by feature subsampling and resists noise	Extrapolates poorly and smooths extreme values
	ExtraTrees	Random split thresholds further reduce variance and speed up training	Higher bias that may underfit weak signals
Boosting	CatBoost	Ordered boosting reduces prediction shift and stabilizes training	Slower training than other boosting frameworks
	XGBoost	Regularization and second-order optimization yield high accuracy	Sensitive to tuning and overfits noisy samples
	LightGBM	Leaf-wise growth gives strong fitting ability at low cost	Overfits small samples without depth constraints
	AdaBoost	Sequential reweighting of hard samples effectively reduces bias	Sensitive to outliers and cannot be parallelized

Building on this, all base models were combined in pairs to construct equal-weighted average (Avg) and weighted average (WAvG) ensembles. The equal-weighted AdaBoost-LightGBM ensemble (hereafter Avg-AdaLGBM) achieved the best performance across R^2 , RMSE and MAE (Fig. S2). A further exhaustive evaluation of all three-model ensembles revealed that no combination outperformed Avg-AdaLGBM on any of the three metrics (Fig. S3). The ensemble gain therefore arises mainly from the error cancellation between two models, whereas adding a third brings no consistent improvement and increases the computational cost.

To integrate the three metrics, we applied the Borda count to score all 12 models. All models were ranked separately by R^2 , RMSE and MAE, with the best assigned 12 points and the worst 1 point. The sum of the three ranks gives the Borda score. A higher score indicates better overall performance, and the training and test sets were ranked independently (Fig. 3d). On the test set, Avg-AdaLGBM scored 36, ranking first on all three metrics simultaneously. Compared to the base model that performed best on each individual metric, it achieved a 0.5% increase in R^2 (Fig. 3a) and reductions of 3.4% and 7.7% in RMSE and MAE, respectively (Fig. 3b, c). This indicates that the ensemble further reduces prediction errors while maintaining high fitting capability, resulting in more stable predictions. These improvements demonstrate that the ensemble reduced prediction errors while maintaining strong goodness of fit. We further assessed its predictive reliability using the fitted line



175 and residual distribution. The fitted line had a slope of 0.863, while the residuals were concentrated around zero, indicating no pronounced overall offset (Fig. S4a). Based on its overall performance and reliability, Avg-AdaLGBM was selected as the ensemble model for subsequent analyses.



180 **Figure 3: Dumbbell comparison of the training and test performance across the 11 base models and the selected ensemble model. (a) R^2 , (b) RMSE, (c) MAE and (d) Borda score of each model. The hollow and filled circles denote the training and test set values (a-c) and Borda scores (d), respectively. Circle color denotes the model category: Single (blue), Bagging (orange), Boosting (purple) and Ensemble (red).**

Next, the SHapley Additive exPlanations (SHAP) interpretability method (Lundberg and Lee, 2017; Lundberg et al., 2020) was applied to quantitatively assess the relative contribution of each feature (Shapley, 1953). We then used SHAP interaction values (Grabisch and Roubens, 1999) to analyze synergistic or inhibitory effects between features. For a detailed explanation of the algorithm, please refer to Text S3.

2.4 Backward trajectory analysis

The TrajStat plugin in Meteoinfo (Wang, 2014; Wang et al., 2009) was used to drive HYSPLIT (Stein et al., 2015) and calculate 24h air-mass backward trajectories. The driving meteorological fields were the GDAS1 global reanalysis ($1^\circ \times 1^\circ$, 3h) provided by the NOAA Air Resources Laboratory (<https://www.ready.noaa.gov/archives.php>). Trajectory starting points were selected for each cloud on each flight at cloud base ($H = 0$), cloud middle ($H = 0.5$), and cloud top ($H = 1$). Measurements that differed from the target relative height by more than 0.05 were excluded, as were level-flight cases. It should be noted that H was normalized using the highest and lowest observed altitudes within each cloud (Sect. 2.2), whereas trajectory starting



points were drawn from liquid-phase samples only. Consequently, a cloud contributed no starting point at a given level when
 195 no liquid-phase sample fell within ± 0.05 of that level, which is why the number of trajectories differs among the three levels
 (Fig. S8).

3 Results and Discussion

3.1 Observed macrophysical and microphysical characteristics of warm and cold liquid-phase clouds

Warm-cloud bases were located at approximately 300-3900 m, and cloud tops occurred at approximately 800-4200 m. Cold-
 200 cloud bases were located at approximately 600-3600 m, while cloud tops occurred at approximately 3000-5200 m (Fig. 4a).
 Warm-cloud thickness ranged from approximately 100 to 2400 m and was mostly below 500 m. Cold clouds reached
 approximately 3400 m in thickness and were mostly thicker than 1000 m (Fig. 4b). Cloud-base distributions were similar
 between the two cloud types, whereas the main differences occurred in cloud-top height and thickness. Thus, the difference
 between the two cloud types was not due to an overall vertical shift, but to the more extensive vertical development of cold
 205 clouds above the cloud base.

In-cloud observations show that temperature (T) ranged from 0 to 11 °C in warm clouds and was concentrated below 4 °C.
 Cold-cloud T ranged from -21 to 0 °C and showed modes near -20 and -5 °C (Fig. 4c). The relative humidity (RH) remained
 close to saturation in both cloud types, although cold clouds exhibited slightly lower values overall and a broader lower tail
 (Fig. 4d). Horizontal wind in clouds was mainly 8-18 m·s⁻¹, whereas cold clouds again showed a bimodal distribution, with
 210 modes near 10 and 40 m·s⁻¹ (Fig. 4e). Downdrafts (positive values) predominated in both cloud types, and the overall vertical
 wind ranges were similar, spanning approximately -8 to 10 m·s⁻¹. However, the downdraft distribution was broader in cold
 clouds (Fig. 4f). These dynamical differences, together with the more extensive vertical development of cold clouds, may help
 explain the broader low-RH tail (Fig. 4d). Clear cloud-type differences were also evident in the microphysical parameters.
 Compared with warm clouds, cold clouds exhibited lower values of cloud droplet number concentration (N_c), effective radius
 215 (r_e), and spectral dispersion (ϵ) (Fig. 4g-i). These microphysical differences, particularly the lower N_c and r_e , likely contributed
 to the lower LWC observed in cold clouds (Fig. 4j). Consequently, these macro- or microphysical parameters alone are
 insufficient to explain the LWC differences between cold and warm clouds. Further consideration is needed of the joint effects
 of size-distribution composition and dynamic and thermodynamic conditions.

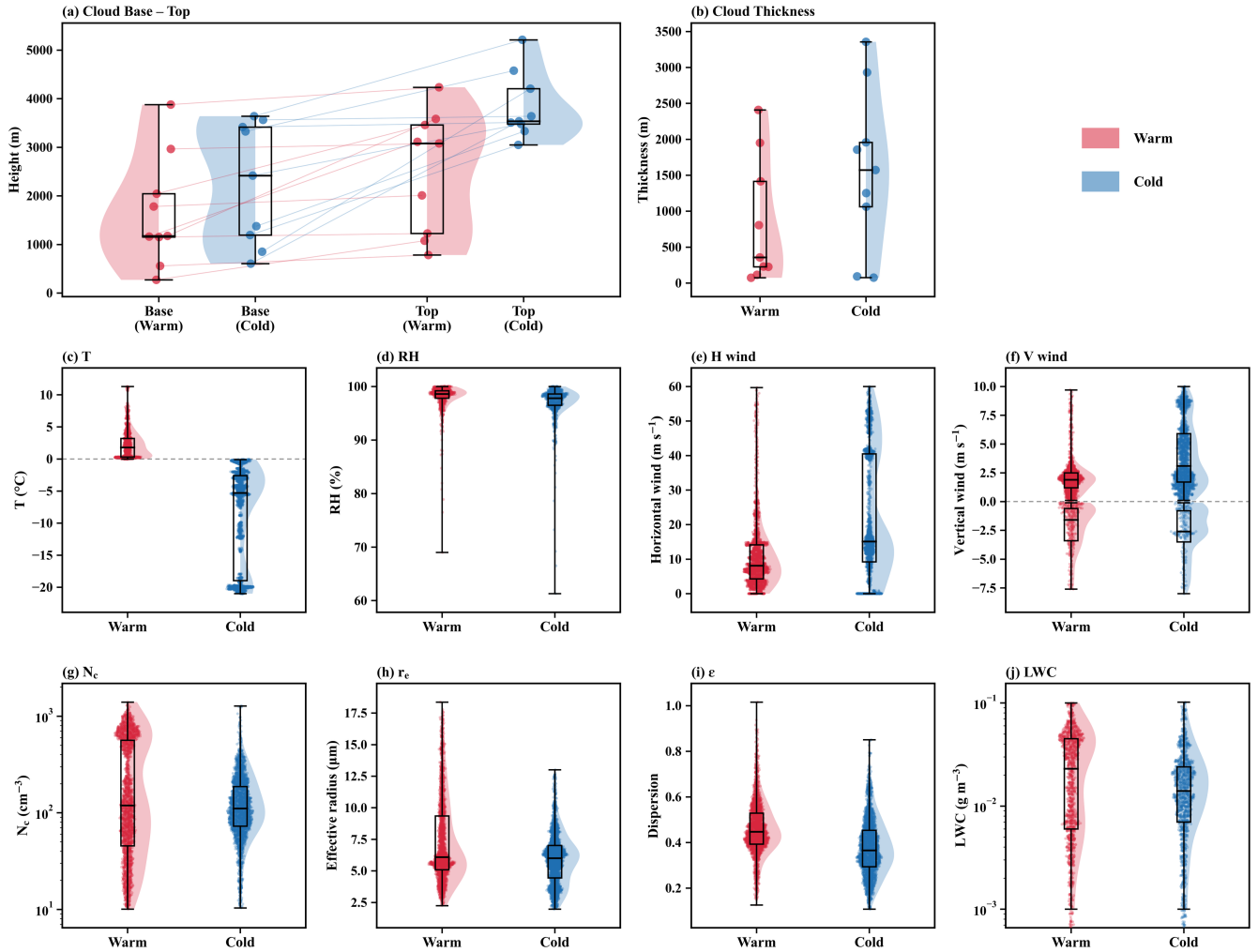


Figure 4: Comparison of the overall characteristics of warm and cold liquid-phase clouds. (a) Cloud-base and cloud-top heights, (b) cloud thickness, (c) T , (d) RH, (e) horizontal wind, (f) vertical wind, (g) N_c , (h) r_e , (i) ε and (j) LWC. Red and blue denote warm and cold clouds, respectively. Dots represent individual clouds in (a, b) and individual samples in (c-j); lines in (a) connect the cloud-base and cloud-top heights of the same cloud. Half-violin plots and boxplots show the distributions, medians and interquartile ranges.

To examine the vertical distribution of various characteristics within clouds, we binned the samples by altitude and connected the within-bin means to obtain average vertical profiles (Fig. 5; Fig. S5). LWC increased with altitude below 1000 m in both cloud types and then decreased gradually between 1000 and 1600 m (Fig. 5i). The lower portions of the relative-height profiles showed the same pattern (Fig. S5i). Within this layer, warm-cloud T increased with altitude, indicating a local temperature inversion, and was accompanied by downdrafts. In contrast, cold-cloud T continued to decrease with altitude throughout this layer (Fig. 5a, d). Correspondingly, warm-cloud r_e reached approximately 12 μm , compared with only approximately 4 μm in cold clouds (Fig. 5g). Despite its lower spectral number density, the warm-cloud droplet spectrum extended more clearly toward larger diameters (Fig. 5e), whereas the cold-cloud spectrum remained concentrated at smaller diameters (Fig. 5j).



Notably, both cloud types exhibited pronounced LWC minima within this downdraft layer (Fig. 5i). This pattern may reflect subsidence warming and associated entrainment mixing, both of which can suppress condensation and enhance droplet evaporation. Thus, at a given altitude, differences in cloud microphysics were generally associated with contrasts in vertical motion, temperature, and humidity.

Above 1600 m, LWC initially increased with altitude in both cloud types and peaked near 2300 m, where warm-cloud LWC exceeded cold-cloud LWC (Fig. 5i). At the same altitude, warm clouds had lower N_c but higher r_e and ε , and their spectra extended more prominently toward larger diameters (Fig. 5e–h). Warm-cloud RH also peaked, whereas cold-cloud RH remained relatively low (Fig. 5b). These contrasts were consistent with the observed difference in LWC. Above 2300 m, LWC generally decreased with altitude in both cloud types, while their microphysical profiles gradually converged. The corresponding droplet spectra also became similar, showing higher number densities at smaller diameters and decreasing number densities toward larger diameters (Fig. 5e, j). The relative-height profiles showed the same overall tendencies, although minor differences persisted at several levels (Fig. S5f–i).

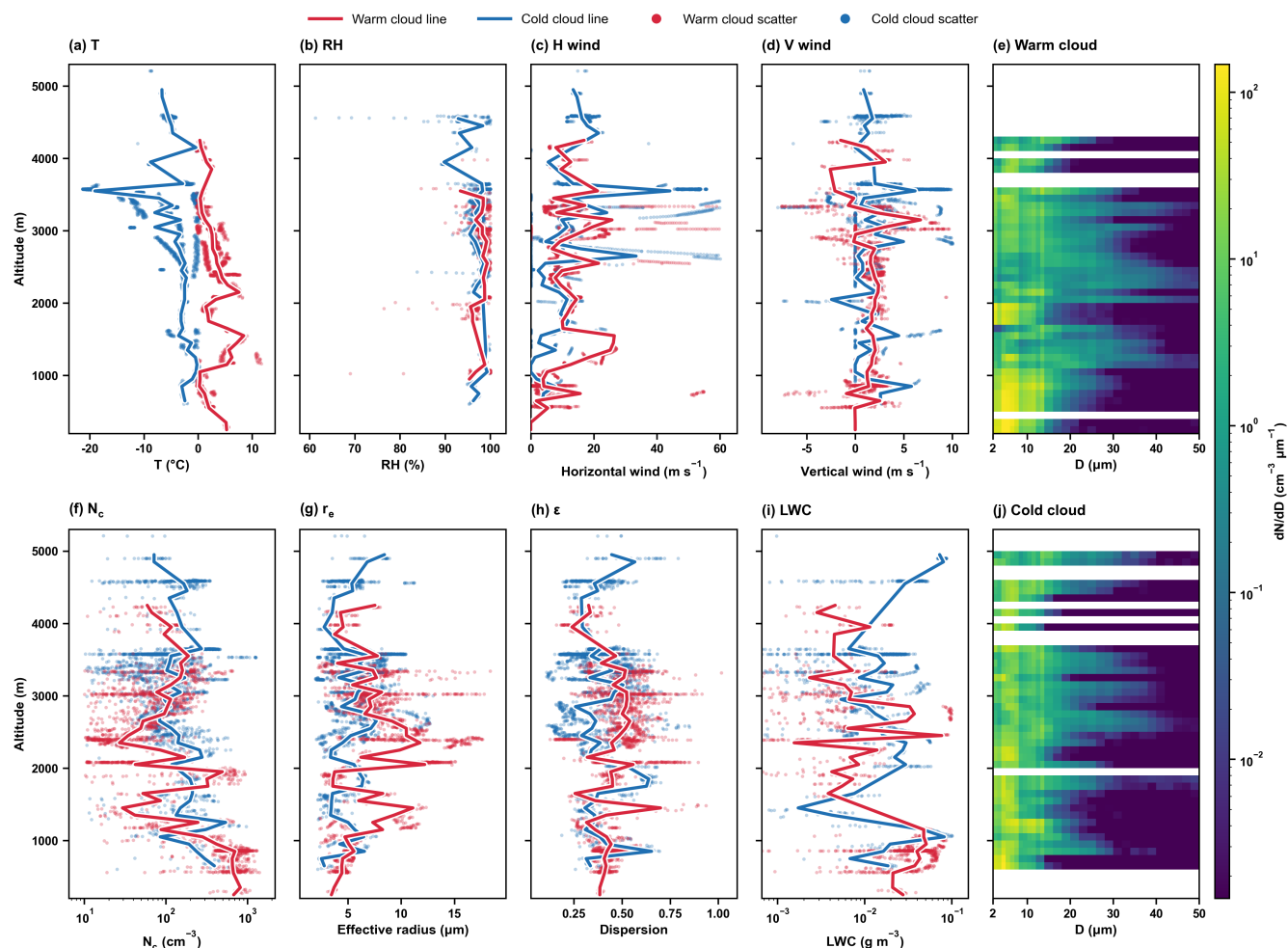
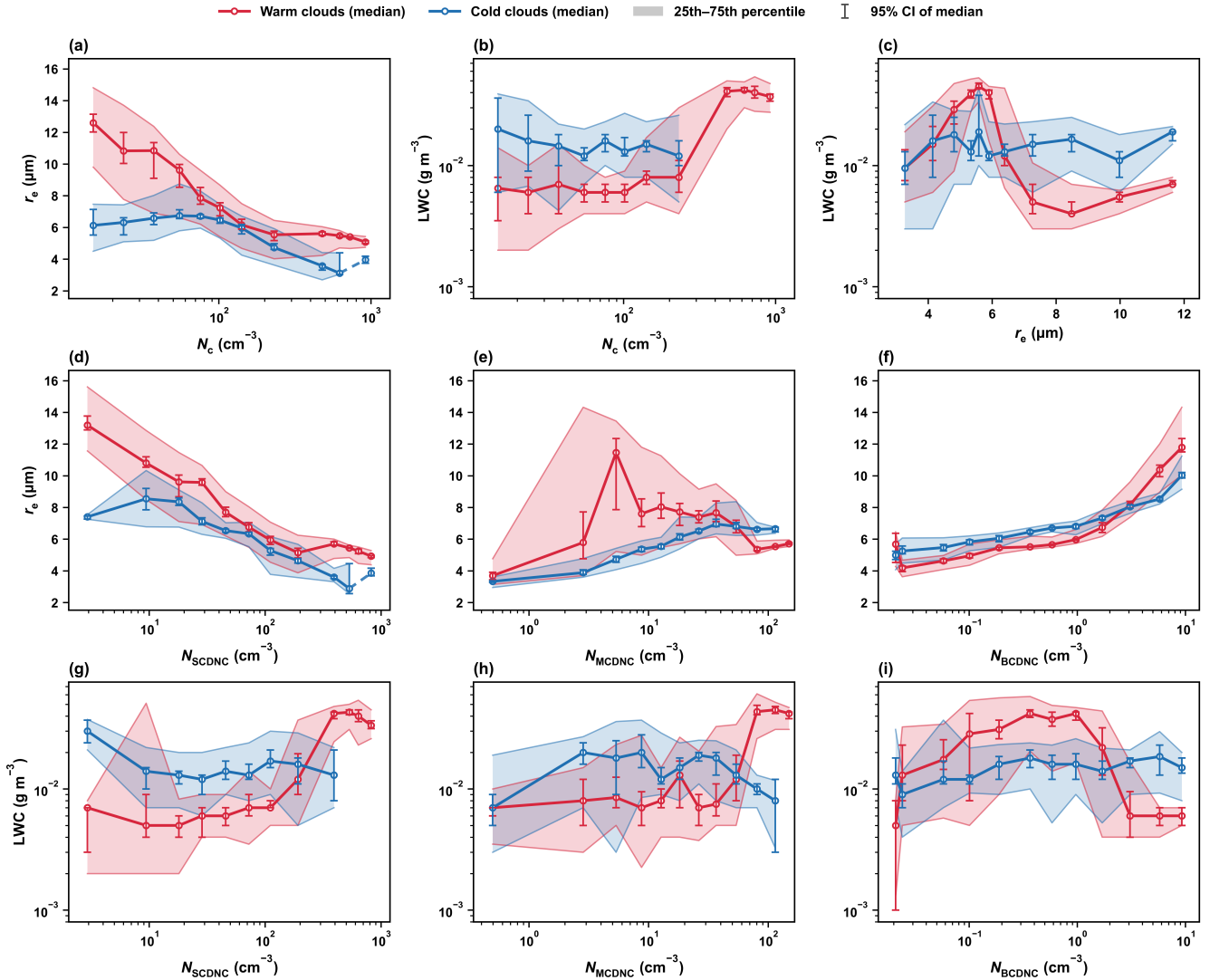


Figure 5: Vertical profiles of different environmental and cloud particle characteristics at absolute altitude for warm and cold liquid-phase clouds. (a) T , (b) RH , (c) horizontal wind, (d) vertical wind, (e) warm cloud droplet size distribution, (f) N_c , (g) r_e , (h) ϵ , (i) LWC and (j) cold cloud droplet size distribution. Dots are individual samples and solid lines are the binned mean profiles for warm (red) and cold (blue) clouds. Colors in (e) and (j) represent dN/dD .

The overall droplet spectra of warm and cold liquid-phase clouds were similar, with high spectral number densities below 15 μm followed by a general decline with increasing diameter. Warm-cloud number densities were higher across almost the entire diameter range, and the difference widened continuously toward larger diameters. This indicates that the primary distinction between the two cloud types involved large-droplet formation (Fig. S6). Temperature-stratified spectra varied non-monotonically with T . The spectrum at $0^\circ\text{C} \leq T < 5^\circ\text{C}$ nearly overlapped the overall warm-cloud spectrum and exceeded that at $5^\circ\text{C} \leq T < 10^\circ\text{C}$. In cold clouds, differences were concentrated at approximately 15–40 μm . Spectral number densities initially decreased with falling T , reached a minimum at $-15^\circ\text{C} \leq T < -10^\circ\text{C}$, and then recovered at lower temperatures.



Further analysis showed that r_e decreased with increasing N_{SCDC} and increased with N_{BCDC} in both cloud types, with substantially greater variations in warm clouds (Fig. 6d, f). At low number concentrations, warm-cloud r_e approached the threshold for efficient collision–coalescence (Freud and Rosenfeld, 2012). In contrast, cold-cloud r_e remained small, suggesting that collision–coalescence growth may be suppressed in cold clouds. The relative ordering of LWC between the two cloud types reversed twice. At low N_{SCDC} and N_{MCDNC} , cold-cloud LWC was higher than warm-cloud LWC. As both concentrations increased, warm-cloud LWC rose markedly and surpassed cold-cloud LWC (Fig. 6g, h), mainly reflecting cloud-water accumulation through condensational growth of small droplets. At high N_{BCDC} , however, warm-cloud LWC declined below cold-cloud LWC (Fig. 6i), possibly because of collision–coalescence loss following large-droplet enrichment. Cold-cloud LWC remained relatively stable across the component-concentration ranges. Thus, the LWC difference between warm and cold clouds was closely related to droplet-spectrum composition. The pronounced variation in warm-cloud LWC may reflect competition between condensational accumulation and collision–coalescence loss. In cold clouds, low temperatures may limit the supply of condensable water vapor and inhibit collision–coalescence initiation, thereby maintaining a relatively stable LWC.



270 **Figure 6: Relationships among cloud microphysical properties in warm and cold liquid-phase clouds. (a–c) Relationships of r_e with N_c , LWC with N_c , and LWC with r_e , respectively. (d–f) Relationships of r_e with N_{scDNC} , N_{mCDNC} and N_{bcDNC} , respectively. (g–i) Relationships of LWC with N_{scDNC} , N_{mCDNC} and N_{bcDNC} , respectively. Red and blue lines with open circles show the binned medians for warm and cold clouds, respectively; the shaded bands denote the 25th–75th percentiles of the data within each bin, and the error bars are the bootstrap 95 % confidence intervals of the medians. Bins containing fewer than 5 samples are not plotted, and the**
 275 **dashed line segments span the resulting gaps.**

3.2 Machine-learning-based analysis of the mechanisms controlling LWC in warm and cold liquid-phase clouds

Correlation analysis revealed clear differences between warm and cold liquid-phase clouds in the relationships between LWC and the other features (Fig. 7a). In warm clouds, LWC was negatively correlated with T, horizontal wind, and vertical wind. However, in cold clouds, these correlations weakened significantly, with the correlations involving T (0.03) and vertical wind
 280 (0.05) shifting to positive values. These differences may reflect the combined effects of thermodynamic and dynamical



processes on LWC. Additionally, T was strongly negatively correlated with horizontal and vertical wind in cold clouds, whereas the corresponding correlations were positive in warm clouds, suggesting that T does not act through an independent linear mechanism but is instead embedded within a coupled dynamic-thermodynamic relationship. Since conventional correlation analysis cannot distinguish the independent contributions of correlated features or adequately characterize nonlinear interactions (Dormann et al., 2013; McGovern et al., 2019), we employed ensemble learning for modeling and utilized the SHAP method to quantify the contribution of each feature to LWC prediction. VIF analysis revealed that most predictor VIFs were below 5, and all were below 10 (Fig. 7b). Therefore, no features were excluded solely because of collinearity.

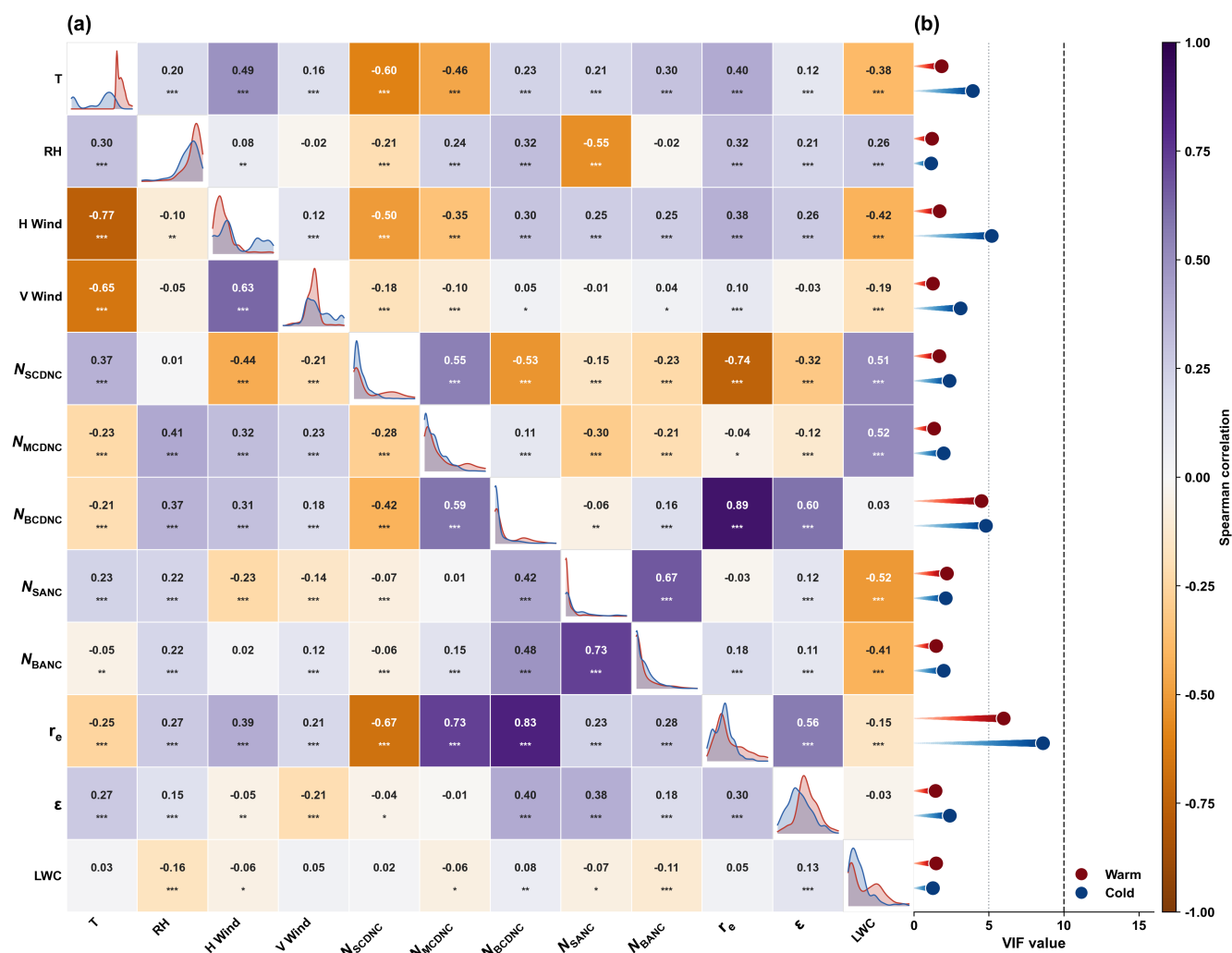


Figure 7: Correlation between different variables and multicollinearity diagnostics. (a) Pairwise Spearman correlation matrix, with the upper and lower triangles showing warm and cold liquid-phase clouds, respectively, and the diagonal showing the kernel density distribution of each variable for warm (red) and cold (blue) clouds. Cell shading follows the correlation coefficient (colour bar), and



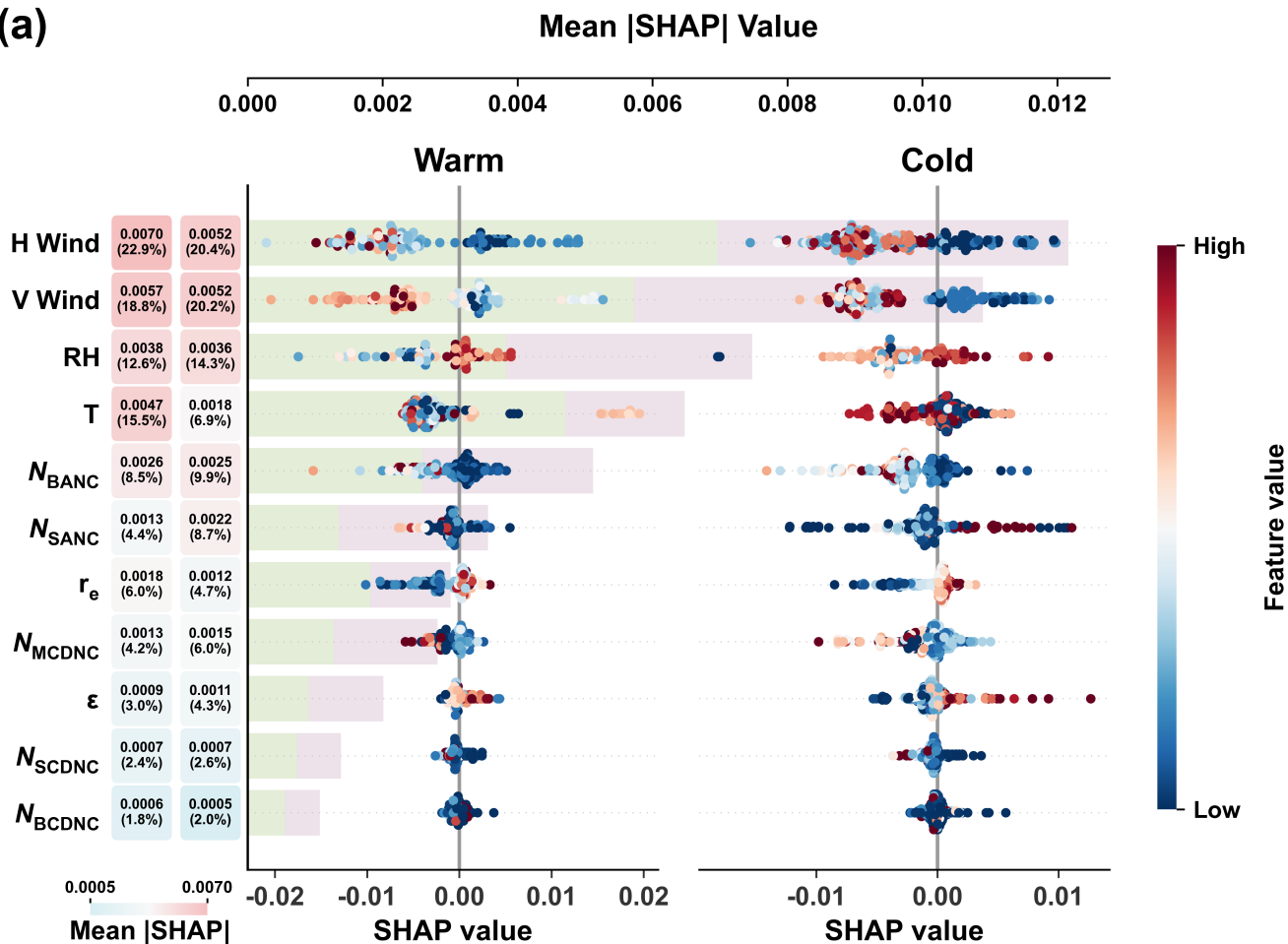
the asterisks beneath each coefficient denote its statistical significance (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$); coefficients shown without an asterisk are not significant at the 0.05 level. (b) Variance inflation factor (VIF) of each variable for warm (red) and cold (blue) clouds.

The trained Avg-AdaLGBM model (Sect. 2.3) was applied to the two cloud types to calculate SHAP values, thereby quantifying the marginal contribution of each feature. The ranking of importance (Fig. 8a) shows that for warm clouds, the five leading features were horizontal wind (22.9%), vertical wind (18.8%), T (15.5%), RH (12.6%), and N_{BANC} (8.5%). In cold clouds, they were horizontal wind (20.4%), vertical wind (20.2%), RH (14.3%), N_{BANC} (9.9%), and N_{SANC} (8.7%). T ranked sixth in cold clouds, with a contribution of 6.9%. Notably, the combined contribution of horizontal and vertical winds remained nearly constant in warm and cold clouds (41.7% vs. 40.6%). The contributions from RH were also similar (12.6% vs. 14.3%). Only the contribution from T decreased significantly, with the lost share primarily offset by aerosol predictors, as the combined contribution of N_{BANC} and N_{SANC} rose from 12.9% to 18.6%. These results suggest that the dynamic framework of warm and cold clouds was similar, and the difference in their LWC was associated mainly with a change in the thermodynamic regime, as characterized by temperature. To understand this difference, we must first clarify the dynamical effects.

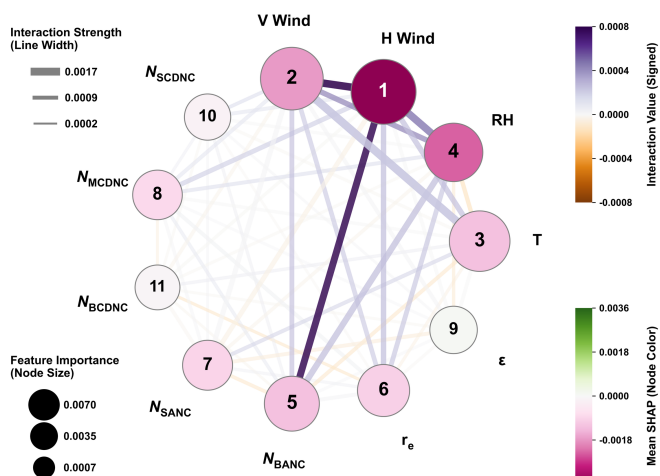
Horizontal wind was the feature with the highest contribution in both warm and cold clouds (Fig. 8a). Its response direction was similar in both cloud types. Low wind speeds produced positive SHAP contributions, which became negative above $10 \text{ m}\cdot\text{s}^{-1}$. The negative contributions at high wind speeds were stronger in warm clouds (Fig. S7a). This suggests that when wind speed surpassed a certain threshold, enhanced mixing and dilution effects may have hindered the maintenance of LWC (Blyth, 1993; Drueke et al., 2021). The 24 h backward trajectories overlapped at cloud middle and showed similar transport directions for both cloud types (Fig. S8b). At cloud base and cloud top, however, air mass origins differed markedly. Cold clouds were influenced mainly by northwestern or southwestern continental air masses, whereas warm clouds received more transport from the eastern ocean (Fig. S8a,c). Therefore, horizontal wind partly represented the air mass transport background.



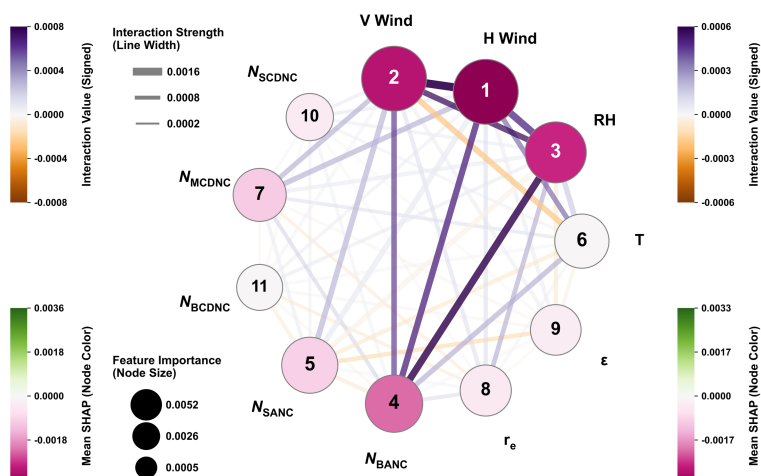
(a)



(b)



(c)





315 **Figure 8: SHAP analysis of LWC prediction. (a) SHAP beeswarm plots for warm and cold liquid-phase clouds, with features ranked by the sum of their mean absolute SHAP values. Heatmap shows mean absolute SHAP value and its relative contribution of each feature. (b, c) Feature interaction networks for warm (b) and cold (c) clouds. Node size and color represent feature importance and mean SHAP value, and the number within each node indicates its importance rank (1, highest). Edge width and color indicate interaction strength and direction.**

320 In contrast, vertical wind directly regulates vertical moisture transport within clouds and the production and loss of LWC (Korolev and Mazin, 2003; Pinsky et al., 2013). Its importance increased markedly in cold clouds and became nearly equal to that of horizontal wind (Fig. 8a). In both cloud types, updrafts (negative velocities) produced positive SHAP contributions, whereas downdrafts produced negative contributions. However, the overall decline in SHAP values from updrafts to
 325 approximately 0.002 in warm clouds (Fig. S7b). Consistently, $dLWC/dw$ became negative under strong updrafts in warm clouds but remained positive in cold clouds (Fig. 9d). This contrast indicates a stronger dependence of cold-cloud LWC on upward motion. Within the downdraft regime, warm-cloud LWC generally decreased, whereas cold-cloud LWC varied more strongly and remained relatively high under strong downdrafts (Fig. 9c).

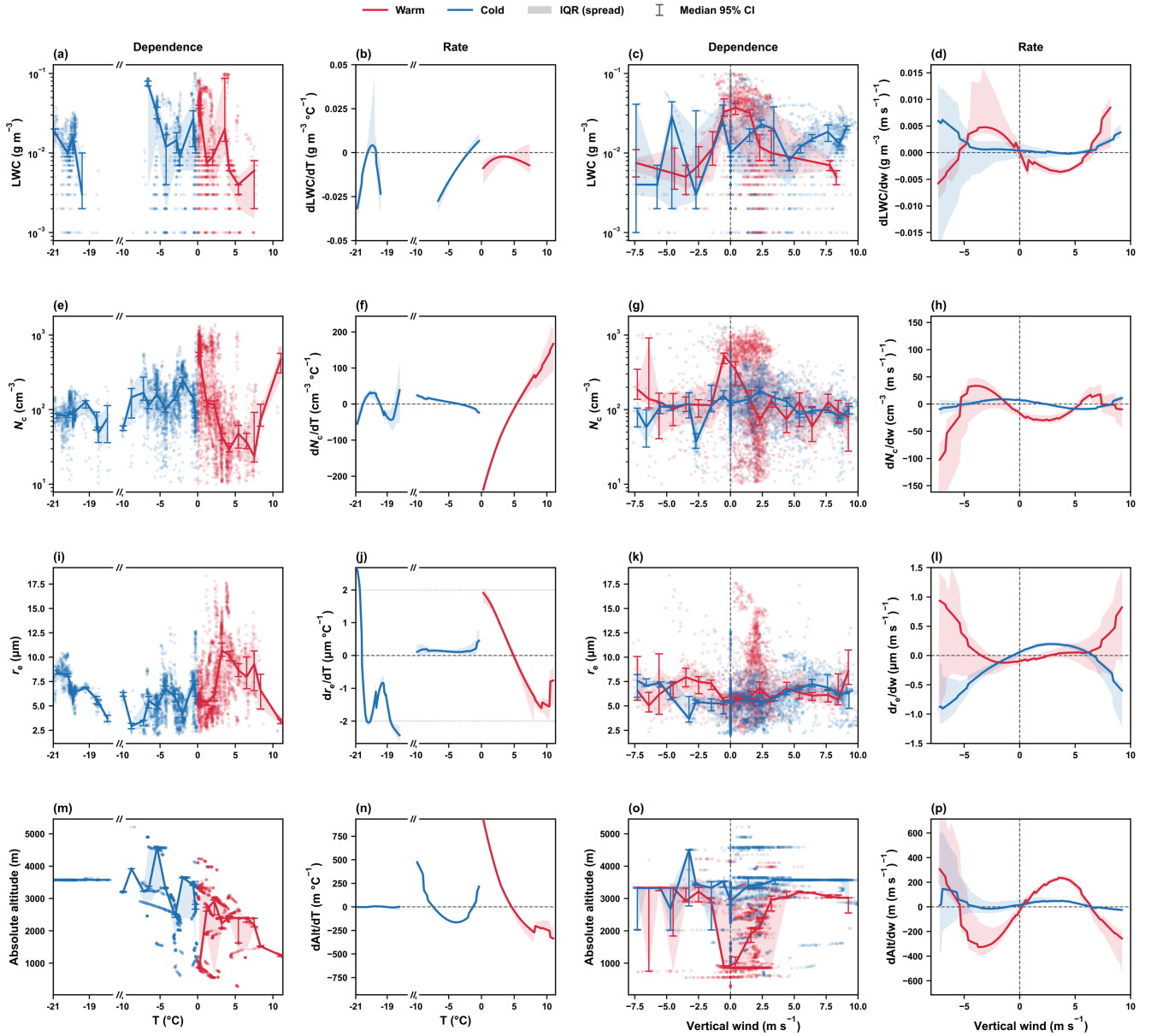
Moreover, across most of the downdraft regime, cold clouds experienced substantially stronger horizontal winds than warm
 330 clouds at comparable vertical wind speeds (Fig. S9e). Thus, even under similar vertical motion, differences in the horizontal-wind background may amplify or attenuate the corresponding LWC response. This interpretation is consistent with the strong positive interaction between vertical and horizontal winds in both cloud types (Fig. 8b,c), suggesting that the two wind components jointly regulate LWC rather than acting independently. Overall, their coupled effects provide the primary dynamical basis for both warm and cold liquid-phase clouds. Vertical wind determines the basic direction of LWC change,
 335 whereas horizontal wind modulates the response magnitude.

Wind field coupling defined the shared dynamic framework, whereas the LWC contrast between cold and warm clouds arose mainly from a change in the coupling between temperature and the wind field. The SHAP contribution of T decreased from 15.5% in warm clouds to 6.9% in cold clouds (Fig. 8a). More importantly, the direction of the SHAP interaction between temperature and vertical wind reversed. Warm-cloud LWC reached its highest values near 0 °C and generally decreased as T
 340 increased, with only a slight recovery at approximately 4–7 °C (Fig. 9a). However, the SHAP values of T remained predominantly negative across the entire warm-cloud temperature range (Fig. S7d). Thus, this recovery was unlikely to reflect warming itself and may instead result from the positive SHAP interaction between T and vertical wind (Fig. 8b). As the updraft strengthened, this positive SHAP interaction increasingly offset the negative contribution of T , thereby weakening the suppressive effect of temperature on LWC.

345 In cold clouds, the SHAP interaction between T and vertical wind changed from positive to negative (Fig. 8c), indicating a change in their joint contribution to LWC. As T decreased, its SHAP contribution shifted from negative to positive (Fig. S7d), suggesting that cooling itself favored LWC. At the low-temperature end, however, both horizontal wind and downdrafts strengthened markedly (Fig. S10c,e). Given the negative SHAP responses of the wind field described above, this unfavorable dynamical background may partially offset the beneficial effect of cooling. Consequently, LWC exhibited significant



350 fluctuations with T (Fig. 9a). Thus, temperature did not act on LWC independently. Dynamical processes determined the basic direction of liquid-water transport, whereas temperature modulated whether this transport was enhanced or weakened through its coupling with the wind field.



355 **Figure 9: T and vertical wind dependence of cloud microphysical properties in warm and cold liquid-phase clouds. (a, e, i, m)** Dependence of LWC, N_c , r_e and absolute altitude on T , respectively, with the corresponding rates of change, dY/dT , shown in (b, f, j, n). (c, g, k, o) Dependence of LWC, N_c , r_e and absolute altitude on vertical wind, respectively, with the corresponding rates of change, dY/dw , shown in (d, h, l, p). Negative and positive w denote updrafts and downdrafts, respectively, and the vertical dashed lines mark $w = 0$. The temperature axis is broken (//) between -17.5 and -10.0 °C because this interval contained too few samples for reliable



360 **binning. The two segments were binned and fitted independently and use different horizontal scales. In the dependence panels, dots show individual samples, lines show binned medians, shading shows interquartile ranges, and error bars show bootstrap 95% confidence intervals. Rate panels show local derivatives from sample-size-weighted local quadratic fits to the binned medians, with shading indicating bootstrap 95% confidence intervals. Rates are computed from untransformed values.**

365 Taken together, Fig. 10 summarizes the coupled dynamical-thermodynamic mechanisms governing LWC in warm and cold liquid-phase clouds. Air-mass transport establishes the background conditions for moisture supply and mixing, while horizontal and vertical winds jointly control the transport of water vapor and liquid water within clouds. Their combined contribution remains broadly consistent between the two cloud types. Temperature, as a state variable, does not constitute an independent control. By setting saturation vapor pressure, it defines the thermodynamic conditions for condensation and evaporation, while the resulting LWC response depends on concurrent moisture transport and mixing. Consistently, the SHAP interaction between temperature and vertical wind is positive in warm clouds but negative in cold clouds. Because both temperature and the wind
370 field are shaped by synoptic-scale circulation, this interaction likely also captures their covariance within the background flow rather than the isolated effect of temperature. Accordingly, the relative importance of temperature falls from third to sixth, with the corresponding increase occurring mainly among aerosol-related predictors. Thus, the differences between the two cloud types do not reflect a change in the overall controlling framework, but rather a shift in how thermodynamic processes couple with dynamical conditions.

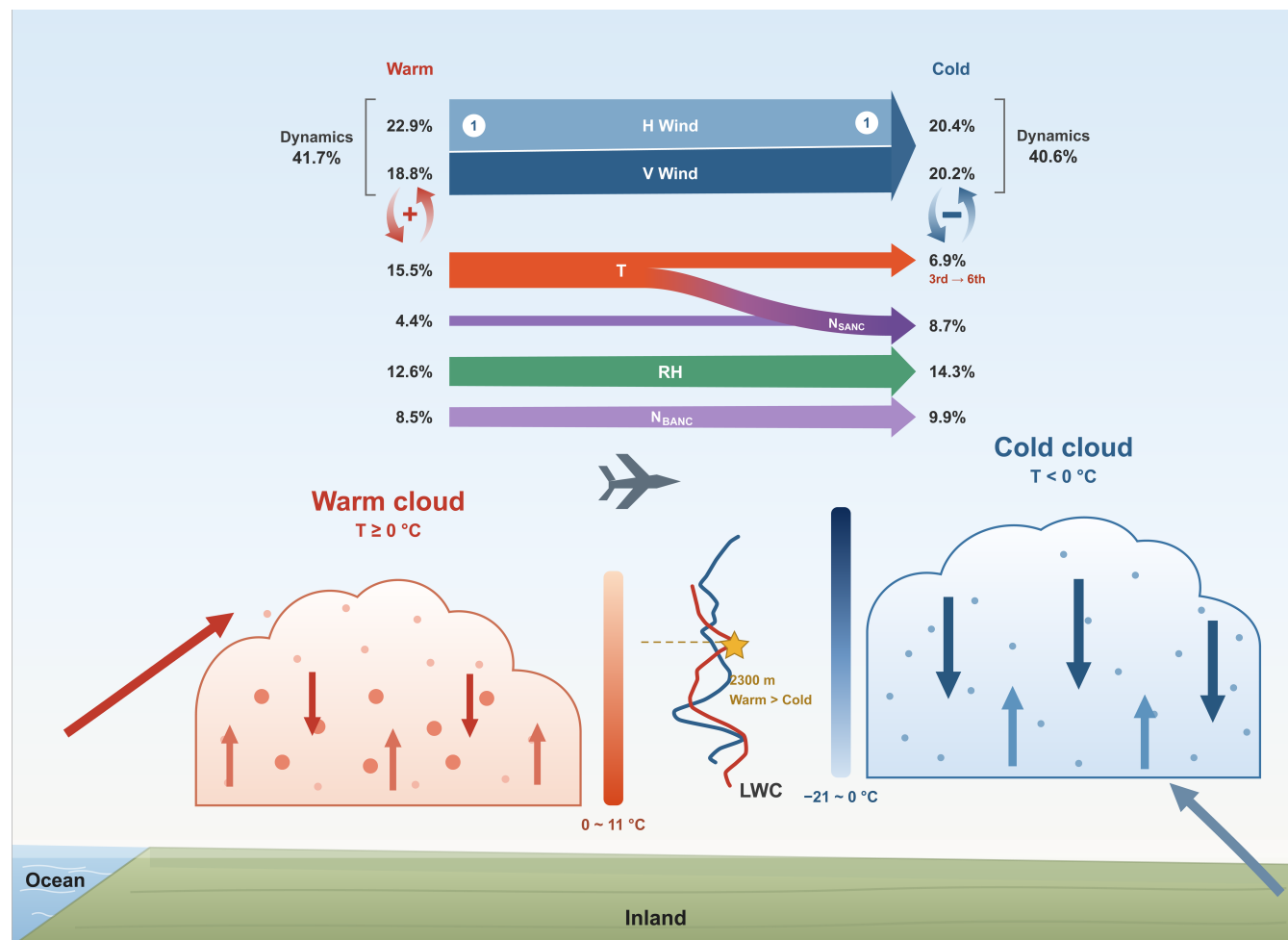


Figure 10: Conceptual illustration of the mechanisms controlling LWC in warm and cold liquid-phase clouds.

4 Conclusion

Liquid water content (LWC) is a key microphysical parameter governing cloud radiative forcing and precipitation efficiency, and its difference between warm and supercooled clouds directly affects cloud lifetime and the regional water cycle. For midlatitude stratiform clouds, aircraft observations have documented the droplet spectra and vertical structure of different cloud types (Cui et al., 2024; Ke et al., 2024; Yin et al., 2014), as well as the dependence of LWC on temperature (Gultepe and Isaac, 1997). These studies described how LWC behaves; what has remained unresolved is which factors set it, and whether those factors operate in the same way in warm and supercooled liquid-phase clouds. Our in situ aircraft observations showed that, given similar cloud-base distributions, cold clouds had higher tops and greater thickness. They also experienced stronger and more variable winds but exhibited lower LWC overall. Cloud droplet number concentration N_c , effective radius r_e , and relative spectral dispersion ε were all lower in cold clouds, consistent with their lower LWC.



However, these bulk properties alone could not fully explain the LWC differences between the two cloud types. Vertically, warm and cold liquid-phase clouds showed broadly similar LWC profiles, with minima between 1000 and 1600 m. Their main differences occurred between 1600 and 2300 m, where the warm-cloud droplet spectrum extended toward larger sizes and warm-cloud LWC temporarily exceeded that of cold clouds. This is consistent with the monotonic LWC–temperature relationship reported by Gultepe and Isaac (1997), although here the difference was confined to certain altitudes rather than present at all levels. Analyses of droplet spectra and size-binned number concentrations further linked the LWC contrast to droplet-size composition, particularly the formation of large droplets. The pronounced variability in warm-cloud LWC may reflect competition between condensational accumulation and collision-coalescence losses. By contrast, the relatively stable LWC in cold clouds may be associated with limited water-vapor availability and suppressed collision-coalescence initiation at low temperatures.

Because linear correlation analysis cannot represent nonlinear interactions between LWC and its predictors, we combined ensemble learning with SHAP-based attribution to quantify the contribution of each factor. The equal-weighted AdaBoost-LightGBM ensemble (Avg-AdaLGBM) performed best. Adding a third model provided no further improvement, indicating that model complementarity mattered more than ensemble size. The attribution results showed that wind-centred dynamic conditions dominated LWC in both cloud types. Their combined importance was nearly unchanged (41.7% in warm clouds vs. 40.6% in cold clouds). However, within cold clouds, the contribution of vertical wind increased markedly, reaching a level almost equal to that of horizontal wind. Horizontal wind partly represented the background effects of air-mass transport, mixing and dilution, with strong winds generally unfavorable for maintaining LWC. Vertical wind directly regulated in-cloud moisture transport and the LWC budget, and cold-cloud LWC depended more strongly on upward motion. The two wind components exhibited strong positive interactions in both cloud types. Vertical wind determined the basic direction of LWC change, whereas horizontal wind modulated the response magnitude, together forming a common dynamic framework for warm and cold clouds. What is new here is that the horizontal and vertical wind components, usually treated jointly as dynamic forcing, are separated and quantified.

The primary difference between the two cloud types was how the contribution of temperature (T) was conditioned by this dynamic framework. The relative contribution of T decreased from 15.5% to 6.9%, falling to sixth place, while the combined contribution of the aerosol-related predictors increased. The SHAP interaction between T and vertical wind also shifted from positive in warm clouds to negative in cold clouds. In warm clouds, upward motion weakened the negative contribution of T to LWC. In cold clouds, the marginal contribution of T shifted from negative to positive with decreasing temperature. However, this favorable effect was offset by stronger horizontal winds and more intense downdrafts at the low-temperature end, resulting in a pronounced non-monotonic LWC response to temperature. Such a sign reversal is not readily detectable with single-factor or linear diagnostics, which may be why it has received little attention in previous observational studies. Thus, the LWC difference between warm and cold liquid-phase clouds does not arise from an overall reorganization of the controlling framework, but from a change in how the temperature contribution is coupled to the dynamic field.



420 It should be noted that this study remains limited by the representativeness of the samples and by the interpretive scope of the
method. All observations were obtained from flights over the North China Plain, and operational flights are selective with
respect to weather conditions, so the applicability of the conclusions to other seasons and regions requires further examination.
Furthermore, SHAP provides a statistical attribution of contributions rather than a definitive causal relationship. Future work
could extend the sample coverage by combining aircraft observations across multiple regions and seasons, and could examine
425 the physical mechanism underlying the reversal of the temperature–vertical wind coupling using numerical models and related
approaches. In parallel, we will extend the observation–ensemble learning framework to ice-phase and mixed-phase clouds to
further characterize the liquid water budget under conditions of competition between ice and liquid phases.

Code and data availability

The aircraft observational data used in this study were collected during field campaigns conducted by staff of the Hebei
430 Provincial Weather Modification Office. Access to these data is subject to permission from the Hebei Provincial Weather
Modification Office. The authors are not authorized to redistribute these institution-owned data publicly; requests for access
should be directed to the Office and are subject to institutional review and approval.

The analysis code has not been publicly archived because its project-specific data-processing routines and file structures are
tightly coupled to these restricted observations. A documented version of the scripts used for data processing, machine-learning
435 model development, statistical analysis, and SHAP analysis, with restricted data paths and metadata removed, is available from
the corresponding author upon reasonable request.

Author contributions

YW carried out the data analysis, developed and evaluated the machine-learning models, performed the statistical and SHAP
analyses, prepared the figures, and wrote the original draft of the manuscript. YL and DL contributed to data preprocessing
440 and assisted with the analysis and interpretation of the results. HW and CL conceptualized and designed the study, supervised
the research, and revised the manuscript. SL and YY (Yang) provided the aircraft observations and contributed to data quality
control. ZL and YC assisted with data analysis and visualization. YY (Yin) and TZ provided scientific guidance and
contributed to the interpretation of the results. All authors discussed the results, reviewed the manuscript, and approved the
final version.

445 Competing interests

The contact author has declared that none of the authors has any competing interests.



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