



Measurement Methods and Applications of Atmospheric Refractivity Based on Raman Lidar

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Abstract. Atmospheric refractive index stratification significantly affects the propagation of electromagnetic waves. High-vertical-resolution atmospheric refractivity (N) data acquired within the near-surface layer can be used to effectively evaluate the operational effectiveness of electronic equipment. On the basis of the principle of Raman scattering, an N measuring instrument utilizing Raman lidar was designed. It achieves high-vertical-resolution detection of temperature and humidity profiles within the 2.4 to 120 m altitude range and calculates the N on the basis of these data via the hypsometric formula. A field comparison test was conducted in 10 to 26 January 2024 LT using layered observation data from a gradient tower. The overall root mean square error (RMSE) of the Raman lidar for air temperature (AT) and relative humidity (RH) detection were 0.50 °C and 3.11 %, respectively; the overall RMSE for N detection was 2.65 N-units. With respect to the altitude layer, the AT, RH, and N detection mean absolute error (MAE) ranged from 0.34 to 0.54 °C, 1.90 to 3.53%, and 1.87 to 2.35 N-units, respectively. This research provides an effective method for measuring the N.

1 Introduction

The atmospheric refractivity index is a key physical parameter that describes the changes in the propagation path of light or electromagnetic (EM) waves in the atmosphere as a result of the influence of the physical properties of the atmospheric medium, such as air temperature (AT), relative humidity (RH), and air pressure (AP) (Wei et al., 2025b; Su et al., 2026). It reflects the degree of curvature of the propagation path of EM waves when passing through atmospheres of different densities or compositions, which will have a direct impact on the energy efficiency of radio equipment, radar detection, and communication systems. The atmospheric refractive index, denoted as n , is fundamentally defined as the ratio of the speed of light in a vacuum (c) to the propagation velocity of EM waves in the atmosphere (v), expressed mathematically as $n = c/v$. Given that electromagnetic wave propagation in the atmosphere is marginally slower than in a vacuum, the atmospheric refractive index within the atmospheric boundary layer typically ranges between 1.00025 and 1.0004. To mitigate the inconvenience of handling such minute numerical values, the atmospheric refractivity (N) is conventionally adopted, calculated through the



relation $N = (n - 1) \times 10^6$ (Wei et al., 2025b). In the microwave and lower-frequency regimes, this N parameter can be quantitatively determined using AT and RH as primary variables. The following formula is adopted for the calculation:

$$N = \frac{77.6}{T} \times \left(P + \frac{4810e}{T} \right) \quad (1)$$

25 where T denotes AT (K), P represents AP (hPa), and e corresponds to water vapor pressure (hPa).

Currently, methods for determining the N include direct and indirect detection methods (Qiu et al., 2022). Direct detection methods use physical sensors to measure atmospheric parameters (AT , RH , AP , etc.) directly. The N is then calculated on the basis of formulas. Instrumentation for direct detection includes microwave refractometers, radiosondes, and microwave radiometers (Qiu et al., 2023). Indirect methods retrieve N profiles by analyzing the propagation effects of EM waves (e.g.,
30 global positioning system (GPS) signals and radar waves) in the atmosphere or changes in meteorological data. Examples include GPS sea surface scattering signal retrieval methods, refractivity from clutter (RFC) methods, satellite beacon remote sensing approaches, numerical weather prediction (NWP) technology, and lidar technology (Zhao, 2018; Li et al., 2025; Wang et al., 2011). In direct detection methods, the microwave refractive index meter is used to directly calculate the N by transmitting microwave signals and measuring their phase delay or frequency changes; this approach is often used for near-surface
35 monitoring of meteorological stations and the study of ocean evaporation ducts (Bull, 1966). Radiosondes carry temperature-humidity-pressure sensors aloft. They provide vertical profile data from the ground to the stratosphere (Doyle et al., 2025). This technique is a standard method in international meteorological observation networks. However, their operation is complex, they require manual timed releases, and their temporal resolution is low. Thus, radiosondes are typically used during comparison and validation experiments (Pham et al., 2021). Microwave radiometers passively receive microwave brightness
40 temperatures emitted by the atmosphere. They calculate AT and RH profiles through retrieval algorithms (Rose et al., 2005). Afterward, they derive the M . However, owing to their operation principles, they rely heavily on historical data (Sengupta and Glover, 2005). Among indirect methods, GPS sea surface scattering signal retrieval works by receiving delayed and Doppler-shifted GPS signals scattered by the sea surface. This technique uses bistatic radar equation modeling. It combines atmospheric propagation effects to retrieve sea surface roughness and N profiles, achieving global coverage retrieval at low cost using ex-
45 isting satellite data products (Yang et al., 2024). Radar clutter retrieval is based on the correlation between the radar sea clutter intensity and atmospheric propagation loss. This technique uses parabolic equation modeling to optimize the retrieval of N profiles. It has been successfully applied to optimize over-the-horizon detection for shipborne radar and offers the low-cost advantage of requiring no additional equipment (Douvenot et al., 2014). However, the retrieval accuracy depends on the sea surface scattering model. Errors are significant under high sea states (Ji et al., 2025; Zhao et al., 2017). Satellite beacon remote
50 sensing technology involves low Earth orbit (LEO) satellites receiving global navigation satellite system (GNSS) signals. This technology measures the bending angles or phase delays of satellites in the atmosphere, and it uses tomography techniques to retrieve the path-integrated N . It is suitable for large-scale coverage in global climate research and is currently used in joint global ionosphere and troposphere monitoring (Liu and Yi, 2014). However, its vertical resolution is low, and it is insensitive to near-surface changes (Lewis, 2025). NWP technology is based on atmospheric dynamics equations. This technology



55 assimilates multisource data (e.g., soundings and satellites) to forecast the future N, and it is used for over-the-horizon radar path planning. Moreover, NWP technology can be used to predict future N changes (Wei et al., 2025a). However, model errors accumulate with increasing forecast lead time, and real-time performance is poor (Hodur, 1997).

With advancements in precision laser technology, lidar has begun to play an increasingly important role in detecting meteorological elements. Atmospheric detection lidars actively measure atmospheric parameters using the interaction between laser light and the atmosphere. Thus, lidar has become increasingly important in atmospheric science research, environmental monitoring, weather forecasting, and other fields (Huige et al., 2021). In the application of Raman lidar, the N is obtained through the inversion of AT and RH and calculated of AP using the barometric formula, which as the core parameters driving the evolution of the climate system, profoundly shape weather processes and environmental quality through thermodynamic regulation and phase change energy transfer. The vertical distribution of AT in the troposphere directly determines the atmospheric stability and the diffusion efficiency of pollutants. The underlying AT inversion phenomenon is the core cause of haze formation (Neuberger, 1954); The boundary layer, as the main reservoir of near-Earth water vapor, its a rapidly changing humidity field not only affects the energy balance through latent heat release, but also participates in cloud microphysical processes as an aerosol activation medium (Zhao et al., 2023; Li and Pu, 2008). Therefore, it has become an important research object in multiple disciplines such as optics, meteorology, geophysics, and environmental science (Zhao et al., 2013). The ability of lidar to detect parameters such as upper atmospheric density, AT, and wind fields has gradually improved. This technology has acquired relatively abundant observational data with high temporal and spatial resolution. These data are used in atmospheric model development and near-space environment support and other related fields. lidars used for tropospheric AT detection include mainly pure rotational Raman lidar and high-spectral-resolution lidar. lidars used for water vapor detection include mainly differential absorption lidar and vibrational Raman lidar. Owing to its characteristics, water vapor vibration Raman lidar is technically very suitable for conventional observations of water vapor (Eichinger et al., 1999).

This paper addresses the need for high-vertical-resolution N measurements. Using the Raman scattering principle, a AT and RH profile of the Raman lidar system is designed and developed. In addition, the hypsometric formula is applied to calculate the N. This approach enabled high-precision retrieval of the N with a 1.5 m resolution within the 2.4 m to 120 m altitude range. A field comparison experiment was conducted in January 2024 using the flux gradient tower of the Institute of Atmospheric Physics, Chinese Academy of Sciences. This experiment verified the feasibility of using Raman lidar for N detection.

The remainder of this paper is structured as follows: Section 2 introduces the principles and methods for AT and RH retrieval and describes the hardware principles and operational process of the lidar. In addition, the dataset obtained using this equipment is explained. In Section 3, the lidar observation data are compared, validated, and analyzed against the tower-based measurement results. Section 4 summarizes the research conclusions of the entire paper.



85 2 Methods and Data

2.1 Raman Lidar Measurement Principle

2.1.1 AT Retrieval Method

AT can be measured by utilizing the difference in temperature dependence between the intensities of high- and low-quantum-number lines in the pure rotational Raman scattering spectrum of atmospheric molecules. Taking the nitrogen molecule as an example, the backscatter cross-sectional intensity of pure rotational Raman scattering for different rotational quantum numbers (Stokes branch lines $J=4, 6, 12$, and 15) at various temperatures is shown in Fig. 1.

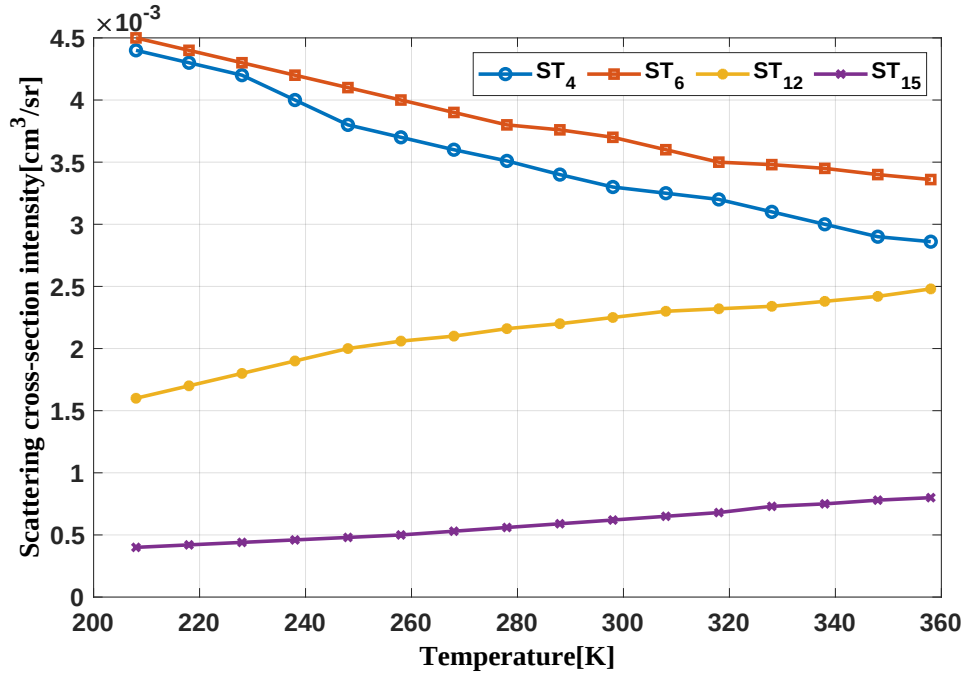


Figure 1. Intensity of pure rotational Raman scattering spectra at different temperatures.

As shown in Fig. 1, as the AT increases, the intensities of the low- and high-quantum-number rotational Raman lines of nitrogen increase and weaken, respectively. Therefore, a lidar can be designed to collect the intensities of the low- and high-quantum-number Raman scattering signals of nitrogen to retrieve AT (Liu and Yi, 2014). The ratio of the echo signal intensities from the low- and high-quantum-number channels is as follows:

$$Q = \frac{\sum_{J_{N_2}} H_1(\nu_{J_{N_2}}) \eta_{N_2} \beta_{N_2}(J_{N_2}, T) t(\nu_{J_{N_2}}) + \sum_{J_{O_2}} H_1(\nu_{J_{O_2}}) \eta_{O_2} \beta_{O_2}(J_{O_2}, T) t(\nu_{J_{O_2}})}{\sum_{J_{N_2}} H_2(\nu_{J_{N_2}}) \eta_{N_2} \beta_{N_2}(J_{N_2}, T) t(\nu_{J_{N_2}}) + \sum_{J_{O_2}} H_2(\nu_{J_{O_2}}) \eta_{O_2} \beta_{O_2}(J_{O_2}, T) t(\nu_{J_{O_2}})} \quad (2)$$



where $H(\nu_{J_{N_2}})$ is the reception efficiency of the lidar for light from pure rotational Raman scattering of nitrogen molecules with rotational quantum number J and frequency $\nu_{J_{N_2}}$; $H(\nu_{J_{O_2}})$ is the reception efficiency of the lidar for light from pure rotational Raman scattering of oxygen molecules with rotational quantum number J and frequency $\nu_{J_{O_2}}$; 1 represents the low-quantum-number channel, 2 represents the high-quantum-number channel; and $t(\nu_{J_{N_2}})$ and $t(\nu_{J_{O_2}})$ are the atmospheric transmittances for light of the corresponding frequencies. Since the wavelengths of the pure rotational Raman scattering lines are very close, they can be approximately considered equal; η_{N_2} and η_{O_2} are the proportions of nitrogen and oxygen molecules in the atmosphere, respectively; and $\beta_{N_2}(J_{N_2}, T)$ and $\beta_{O_2}(J_{O_2}, T)$ correspond to the atmospheric backscatter coefficients for the rotational Raman lines of nitrogen and oxygen, respectively.

The ratio of rotational Raman scattering echo signals of N_2 and O_2 molecules at high quantum numbers to that at low quantum numbers has an exponential relationship with AT, on the basis of which the AT can be retrieved (Martinsson et al., 1996).

Q is expressed in series form as follows:

$$Q = \exp\left(\sum_{i=0}^q \frac{\alpha_i}{T^i}\right) \quad (3)$$

In practical measurements, the value of q is finite. In general, it is considered that when $q = 2$ (during second-order calibration), the above formula is sufficiently accurate. At this point, the AT retrieval formula is expressed as follows:

$$T(z) = \frac{\beta + \sqrt{\beta^2 - 4\alpha\gamma + 4\alpha \ln Q(z)}}{2(\ln Q(z) - \gamma)} \quad (4)$$

where $T(z)$ is the AT at height z ; α , β , and γ are calibration constants; and $Q(z)$ is the intensity ratio of the low- to high-quantum-number spectral lines at height z .

2.1.2 RH Retrieval Method

The Raman lidar directly calculates the atmospheric water vapor mixing ratio (g/kg) by measuring the vibrational–rotational Raman scattering intensities from water vapor molecules and nitrogen molecules in the atmosphere. The formula is as follows:

$$D(z) = \kappa \frac{H_H(z)}{H_N(z)} \quad (5)$$

where κ is a calibration constant and $H_H(z)$ and $H_N(z)$ are the vibrational–rotational Raman scattering signal intensities of water vapor and nitrogen at height z , respectively. Based on the actual measurement results, the calibration yields $\kappa = 9$. RH can be calculated from the water vapor mixing ratio combined with the AT profile and the AP profile:

$$RH(z) = \frac{P(z)D(z)}{(A + BD(z)) \cdot 10^{\frac{aT(z)}{b+T(z)}}} \quad (6)$$



where $P(z)$ is the AP (hPa); A is constant at 3798.554; B is constant at 6.107; and for the water surface ($T(z) > 0$ °C), the coefficient $a = 7.5$, $b = 237.3$; for the ice surface ($T(z) \leq 0$ °C), the coefficient $a = 9.5$, $b = 265.5$.

125 The AP $P(z)$ at height z is calculated using the following hypsometric formula (Berberan-Santos et al., 1997):

$$P(z) = P_0 \left(1 - \frac{m_0 - 1}{m_0} \frac{\mu g z}{R} \right)^{\frac{m_0}{m_0 - 1}} \quad (7)$$

where P_0 is the surface AP; m_0 is the polytropic index, usually taken as 1.235; $\mu = 29.6 \cdot 10^{-3} \text{ kg/mol}$; $g = 9.801 \text{ m/s}^2$; and $R = 8.314 \text{ Pa} \cdot \text{m}^3 \cdot \text{mol}^{-1} \cdot \text{K}^{-1}$.

2.2 Raman Lidar Development

130 The structure of the Raman lidar system is shown in Fig. 2. It can be divided into a laser transmitter unit, telescope receiver unit, subsequent optical path unit, and a signal acquisition and processing unit.

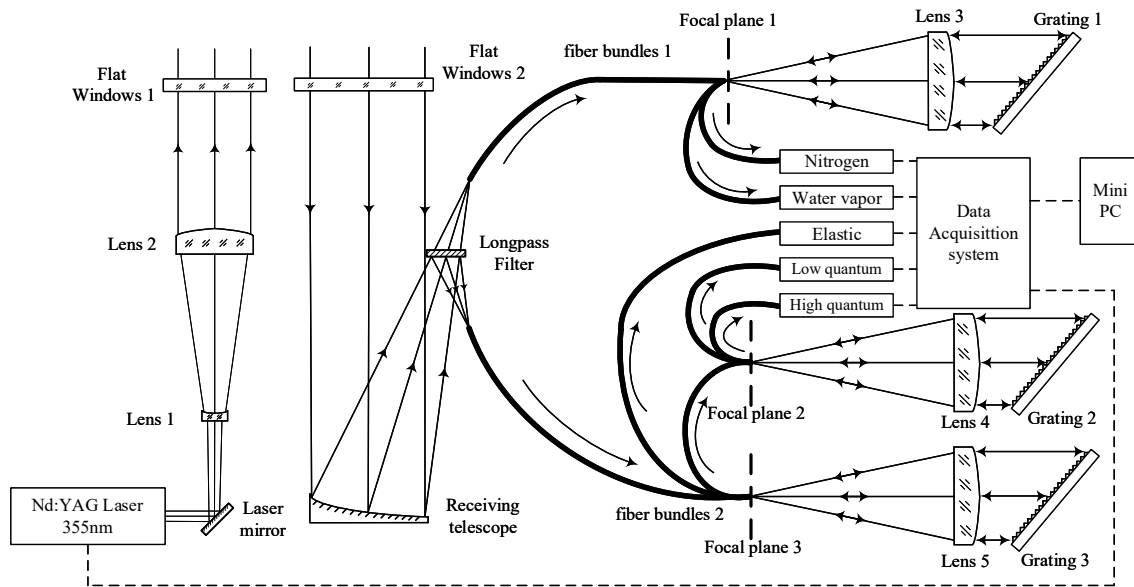


Figure 2. Schematic of the Raman lidar system.

In the laser transmission path, the laser is a Nd:YAG solid-state pulsed laser. After third-harmonic generation, it outputs laser light at a wavelength of 354.7 nm. Laser mirrors are used to fold the laser path. A Galilean beam expander achieves 8× beam expansion, further compressing the laser divergence angle.

135 In the signal reception path, the receiving mirror is an off-axis parabolic reflector. A long-pass edge filter achieves preliminary separation of the pure rotational Raman scattering signals and the elastic scattering signals from the vibrational–rotational Raman scattering signals. The pure rotational Raman scattering signals and the elastic scattering signals enter the temperature

spectroscopy system via fiber bundle 2. The vibrational–rotational Raman scattering signals enter the humidity spectroscopy system via fiber bundle 1.

140 The temperature spectroscopy system uses a double grating to extract elastic scattering signals (Rayleigh and Mie scattering), a low-rotational quantum number signal T_L , and a high-rotational quantum number signal T_H .

Compared with traditional double-grating spectroscopy systems, the self-developed system has two additional high-rotational-quantum-number channels (AST_{H2} and ST_{H2}), which can effectively increase the intensity of high-quantum-number signals. Taking the nitrogen molecule as an example, the pure rotational Raman spectra extracted by the temperature spectroscopy system are shown in Fig. 3.

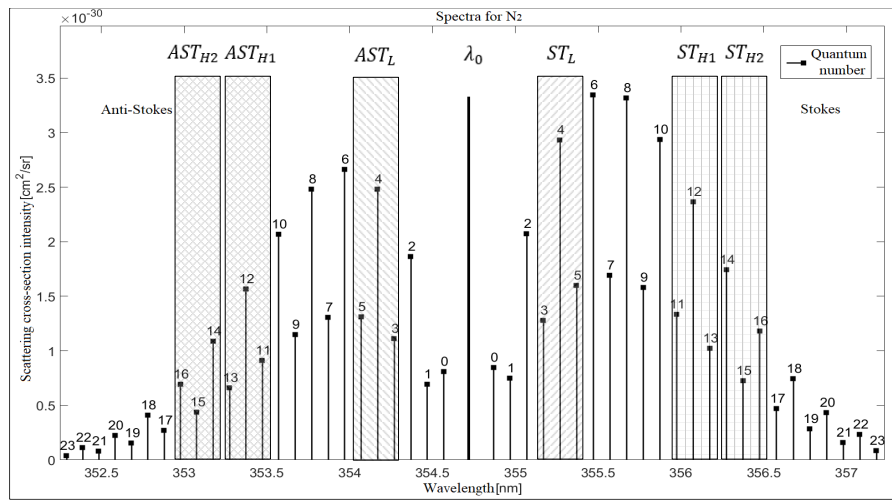


Figure 3. Spectra extracted by the temperature spectroscopy system.

145 The input and output in the humidity spectroscopy system are shown by the splitting at focal plane 1 in Fig. 4. A single grating is used to extract the vibrational–rotational Raman scattering signals of nitrogen S_N (386.7 nm) and water vapor S_H (407.5 nm). The input and output in the temperature spectroscopy system are shown by the splitting at focal planes 2 and 3 in Fig. 4. At focal plane 2, a single grating extracts 355 nm of elastic backscattered light. At focal plane 3, a double grating
 150 extracts the output from 4 high-quantum-number channel fiber bundles and 2 low-quantum-number channel fiber bundles.

Photomultiplier tubes (PMTs) are used as detectors. The data acquisition system operates in analog mode when strong signals are acquired from the temperature spectroscopy system; it operates in photon counting mode when weak signals are acquired from the humidity spectroscopy system.

The main parameters of the Raman lidar system are shown in Table. 1.

155 2.3 Raman Lidar Data Retrieval Process

The lidar data retrieval steps are as follows:

- a) Read measurement data

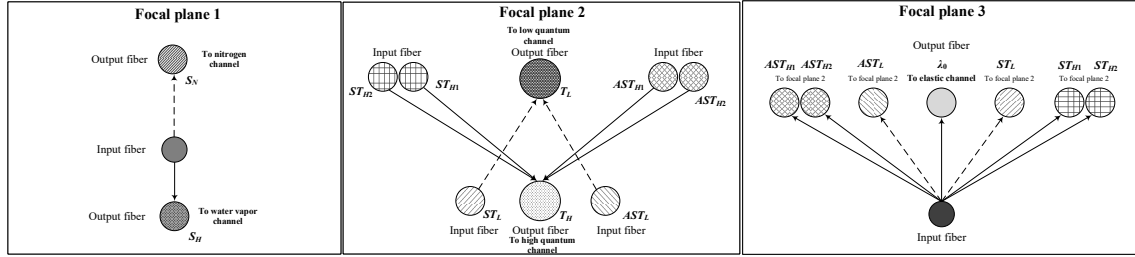


Figure 4. Input and output diagrams of temperature and humidity at different focal planes. (a) Input and output diagram of the humidity spectroscopic system at focal plane 1; (b) Input and output diagram of the temperature spectroscopic system at focal plane 2; (c) Input and output diagram of the temperature spectroscopic system at focal plane 3.

Read data from the 2 temperature measurement channels (operating in analog output mode), the 2 humidity measurement channels (operating in photon counting output mode), the intelligent weather sensor, and the internal temperature and humidity sensors.

b) Photomultiplier tube (PMT) temperature constant revision

PMTs are quite sensitive to temperature changes; their sensitivity varies at different temperatures. Even PMTs of the same model have certain differences in sensitivity. Therefore, the temperature constants for the PMTs in each channel must first be revised. The lidar uses PMTs with multialkali cathodes (BIALKALA). The measured results indicate that the revision coefficients for each channel's PMT are as follows:

TL: Temperature measurement channel, sensitivity revision coefficient $-0.4\%/^{\circ}\text{C}$;

TH: Temperature measurement channel, sensitivity revision coefficient $-0.34\%/^{\circ}\text{C}$;

H: Humidity measurement channel, sensitivity revision coefficient $-0.8\%/^{\circ}\text{C}$;

HN: Humidity measurement channel, sensitivity revision coefficient $-0.2\%/^{\circ}\text{C}$.

c) Photon counting correction

When the selected PMT operates in photon counting mode, the stronger the incident light intensity is, the higher the probability of pulse pile-up. This relationship leads to distorted photon counts under strong light, manifesting as a decrease in the saturation count. To increase the counting upper limit and broaden the linear working range of the PMT, a correction formula must be used to compensate for the counting loss. The photon counting correction formula is as follows:

$$N = \frac{P_0}{1 - \frac{P_0 \tau}{Q dt}} \quad (8)$$

where P is the corrected photon count; P_0 is the actual measured photon count; and τ is the correction coefficient, which should be 1.6 (the resolution limit of the PTM and its auxiliary counting circuit for the photon pulse pair is 1.6 ns); Q is the total number of measurement pulses (total frames); and dt is the sampling time corresponding to a single spatial resolution, taken as 8 ns (the sampling time corresponding to the original data's 1.2 m spatial resolution is 8 ns).



Table 1. Technical parameters of the Raman lidar system.

Name	Item	Parameter
Nd:YAG Laser	Wavelength	354.7 nm
	Pulse repetition rate	20 Hz
	Pulse energy	20 mJ
Beam expander	Type	Galilean Beam Expander
	Magnification	8×
Receiver	Mirror diameter	101.6 mm
	Focal length	304.8 mm
	Field of view	1 mrad
	Longpass filter	$T > 96\% @ 375 - 420 \text{ nm}$, $R > 99\% @ 340 - 365 \text{ nm}$
Fiber bundles	NA	0.22
	Input fiber diameter	0.3 mm
	Output fiber diameter	0.4 mm (aerosol), 0.6 mm (humidity), 1.0 mm (temperature)
Spectral separation system for pure rotational spectra	Reciprocal linear dispersion	0.75 nm/mm
	Groove density	2100/mm
	Working order	2
	Diffraction angle	48 °
	Efficiency	$\geq 17\% @ 350 \text{ } 360 \text{ nm}$
Spectral separation system for vibration–rotational spectra	Reciprocal linear dispersion	0.9 nm/mm
	Groove density	3600/mm
	Working order	1
	Diffraction angle	46 °
	Efficiency	$\geq 50\% @ 380 \text{ } 410 \text{ nm}$
Detectors	PMT	Hamamatsu H10720P-210
Data acquisition system	Analog mode	12 bit, 125 MHz
	Photon counting mode	500 MHz
	Range resolution	1.2 m



180 d) Preamplifier electronic noise and background noise removal

The first 500 data points are selected, summed, and averaged to calculate the preamplifier electronic noise and background noise level for each channel. The valid signal for each measurement channel is obtained by subtracting its corresponding channel's preamplifier electronic noise and background noise values from data points 534 to 1201.

e) Signal strength determination

185 A threshold is set to determine signal strength (typically set at 30% of the signal intensity under normal operating conditions, where normal conditions refer to visibility greater than 10 km, i.e., clear and cloudless weather). Signal strengths below this threshold may indicate the presence of cloud layers (fog layers) or system malfunction. Signal strength validation is performed using the TL and HN channel signals, assessed at altitudes of 360 m and 120 m, respectively. If the signal exceeds the threshold at 360 m, the valid data output extends to a 360 m altitude. If the signal is between the 360 m and 120 m thresholds, the valid
190 data output extends to a 120 m altitude. Otherwise, all outputs are marked as invalid.

f) Retrieval calculation of measurement results

Following the principles of Raman lidar measurement, the raw measurement results for AT and RH are calculated.

g) Data filtering

Data filtering is applied to the raw measurement results. The filtering methods employed in this study are, in sequence,
195 Butterworth low-pass filtering, empirical mode decomposition (EMD) filtering, and Kalman filtering. Butterworth low-pass filtering reduces random signal fluctuations; for Kalman filtering, the starting point for the filtering temperature results is the temperature value measured by the smart weather sensor plus a correction value, and the starting point for the filtering humidity results is the humidity value measured by the smart weather sensor plus a correction value.

h) Correction of the detection range factor

200 Signals from different altitudes enter the receiving optical fiber at different angles, resulting in variation in the equipment calibration constants at different heights. This variation introduces a consistent system error in the lidar that varies with altitude.

i) N calculation

On the basis of the measured results of the AT and RH, and combined with the hypsometric formula, the N is calculated.

j) Constant altitude point filtering

205 During continuous measurement, Kalman filtering can be applied to data from the same altitude point. This approach reduces fluctuations in the data at constant altitude points.

2.4 Data

To validate the performance of the self-developed Raman lidar, as show in in Fig. 5, a comparative experiment was conducted at the Tower Branch of the Institute of Atmospheric Physics in Haidian District, Beijing, from 10 to 26 January 2024. The AT,
210 RH, and N measured by the Raman lidar were compared and analyzed against data from the gradient observation tower.

During the experiment, the Raman lidar detection range varied from 2.4 m to 120 m with 2.4-m intervals, totaling 50 layers. The observational data were accumulated over 5-min intervals to generate a dataset with a temporal resolution of 5 minutes. The gradient observation tower is 320 m high and is equipped with temperature-humidity sensors at 15 altitude layers (320 m,

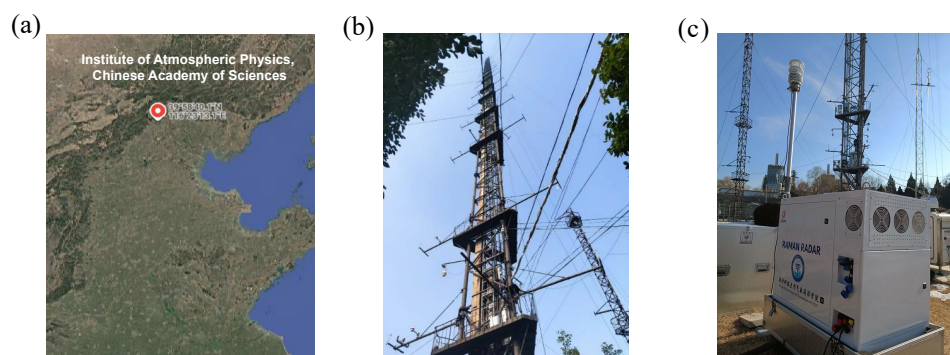


Figure 5. Raman lidar intercomparison environment. (a) experimental site; (b) gradient observation tower; (c) Self-developed Raman lidar. Maps data: © Google 2026.

280 m, 240 m, 200 m, 180 m, 160 m, 140 m, 120 m, 102 m, 80 m, 63 m, 47 m, 32 m, 15 m, and 8 m). These sensors collect
 215 AT and RH parameters at different heights with a data acquisition interval of 20 s, which serve as reference values for the
 Raman lidar. The time series curves of AT, RH, and N acquired by the gradient observation tower and the Raman lidar during
 the experiment are shown in Fig. 6. The data coverage ranges were as follows: AT of -11 to 11 °C, RH of 6 to 100%, and N of
 285 to 320 N-units. The data tended to stabilize throughout the experiment, with dispersion consistently within the allowable
 instrument measurement error range. No distortion was observed, confirming the high data reliability of this research.

220 3 Verification Results and Analysis

To compare the Raman lidar measurement data and the gradient observation tower data, temporal synchronization was per-
 formed on the basis of the lidar data, resulting in 4,001 sets of comparative observation data. Each set includes comparison
 points at 8 different heights, resulting in 32,008 data comparisons.

To analyze the accuracy of the Raman lidar observation data, full time series data of accumulated over 5 minutes from
 225 four altitude layers (8 m, 32 m, 80 m, and 120 m) were extracted for comparative analysis, with the results shown in Fig.
 7. The analysis indicates that the variation trends of AT, RH, and N at these four altitude layers are largely consistent over
 the same period. Among these parameters, AT shows the best consistency and accuracy; RH fluctuates more at lower ATs,
 primarily because of the combined effects of weaker laser output energy under low-temperature conditions, lower atmospheric
 water vapor content, and stronger environmental background noise. The accuracy of the N is closely related to the accuracy
 230 of the AT and RH, yet the overall performance trend is good. And from a height perspective, there is no obvious impact on
 the inversion accuracy due to height changes. In summary, the Raman lidar demonstrates high accuracy in lower atmospheric
 gradient retrieval and can effectively reflect the variation characteristics of atmospheric parameters.

To evaluate the accuracy of the observation data obtained by the Raman lidar under different integration times, observation
 data at the 63-m altitude layer with integration times of 5 min, 10 min, 15 min, and 60 min were extracted for comparative

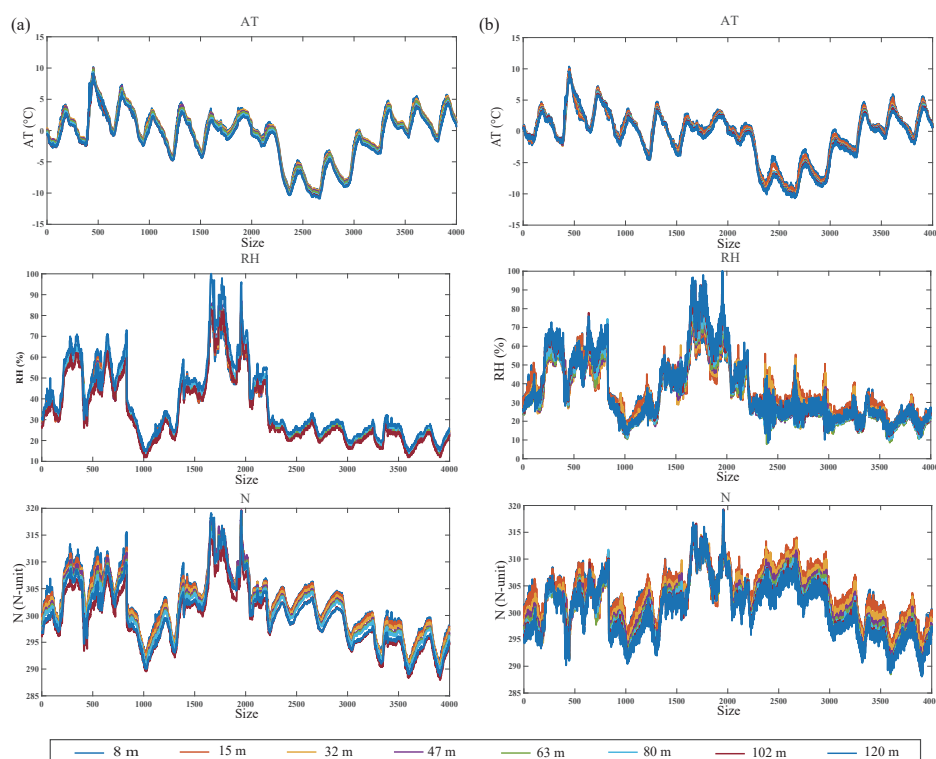


Figure 6. The value of AT, RH, and N at different heights obtained by gradient observation tower and Raman lidar. (a) respectively represent the AT, RH, and N at different altitudes measured by the gradient observation tower. (b) represent the AT, RH, and N at different altitudes measured by the Raman lidar.

analysis, and the results are shown in Fig. 8. The trends of AT, RH and N in the 5-minute accumulation time are basically consistent but the correlation is low. There are subtle high-frequency random glitches. Between Size 2000-3000, there are significant systematic deviations in AT, RH and N. The trend height of AT, RH and N in the 10-minute accumulation time in agreement, high-frequency random noise is weakened, severe random jitter in the medium and low AT areas is significantly suppressed, and the error is reduced. Even more so at 15-min. The curves of AR, RH, and N in the 60-min accumulation time are very smooth, random jitter is completely filtered, and random noise is greatly suppressed, but systematic deviations cannot be eliminated, and the error reduction is limited. At the 63-m altitude layer, the observation accuracy of the lidar significantly increases with increasing integration time. Specifically, the root mean square error (RMSE) and mean absolute error (MAE) decrease as the integration time increases. In particular, at the 60-min scale, the AT error is less than 0.5 °C, and the RH error is less than 2.5%. This finding indicates that appropriately extending the integration time can effectively increase the observation accuracy of the Raman lidar.

Figure 9 shows the comparative analysis of the correlation of observation data of 5-min, 10-min, 15-min, and 60-min accumulation time at a height of 63m. It can be concluded that changes in the accumulation time have little impact on the correlation

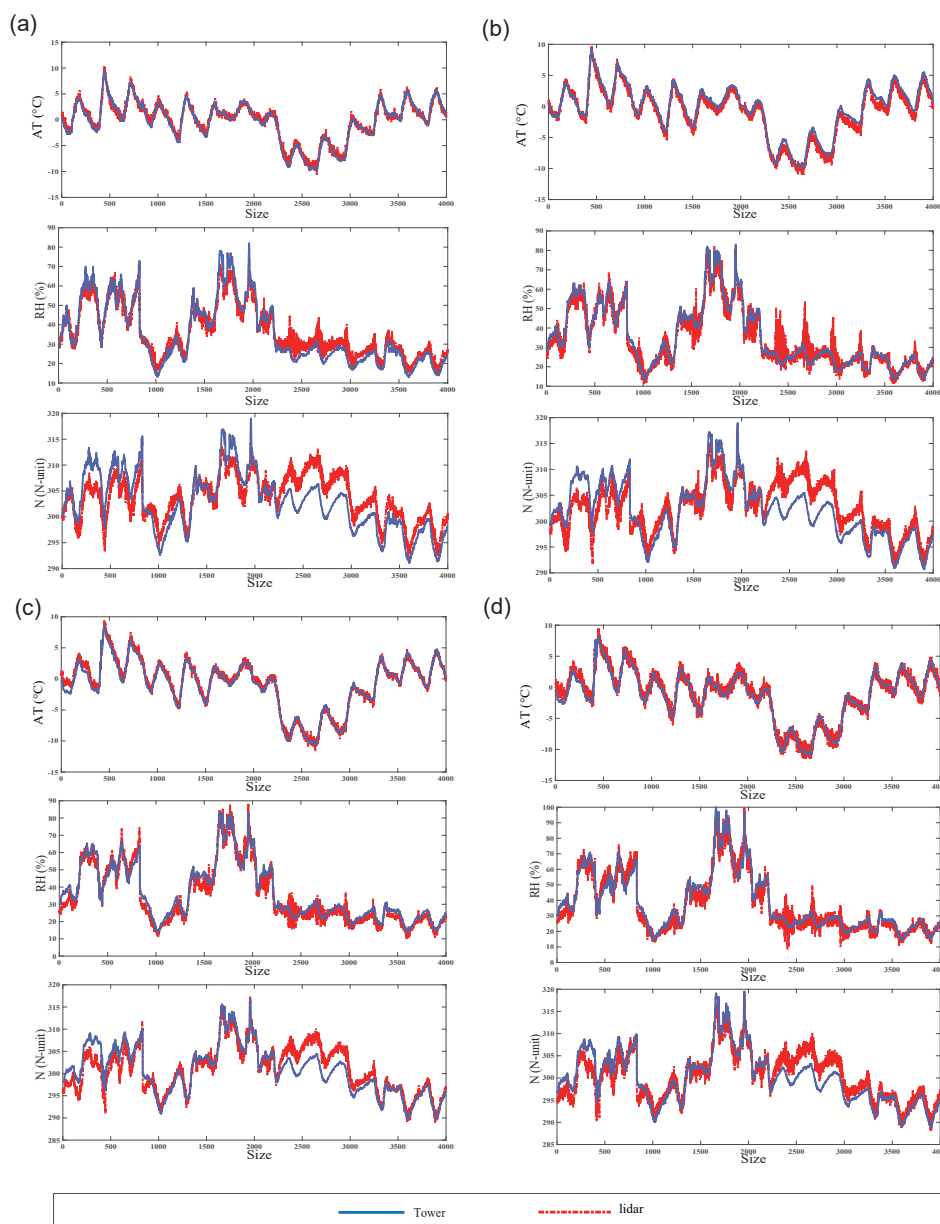


Figure 7. Comparative analysis of data variations in AT, RH, and N. Tower denotes the data from the gradient observation tower, while lidar represents the observation data from the Raman lidar. The observation height levels are (a) 8 m, (b) 32 m, (c) 80 m, and (d) 120 m, respectively.

of the inversion results, and the correlations are relatively high, even if the correlation of the N inversion value is not as good as that of AT and RH.

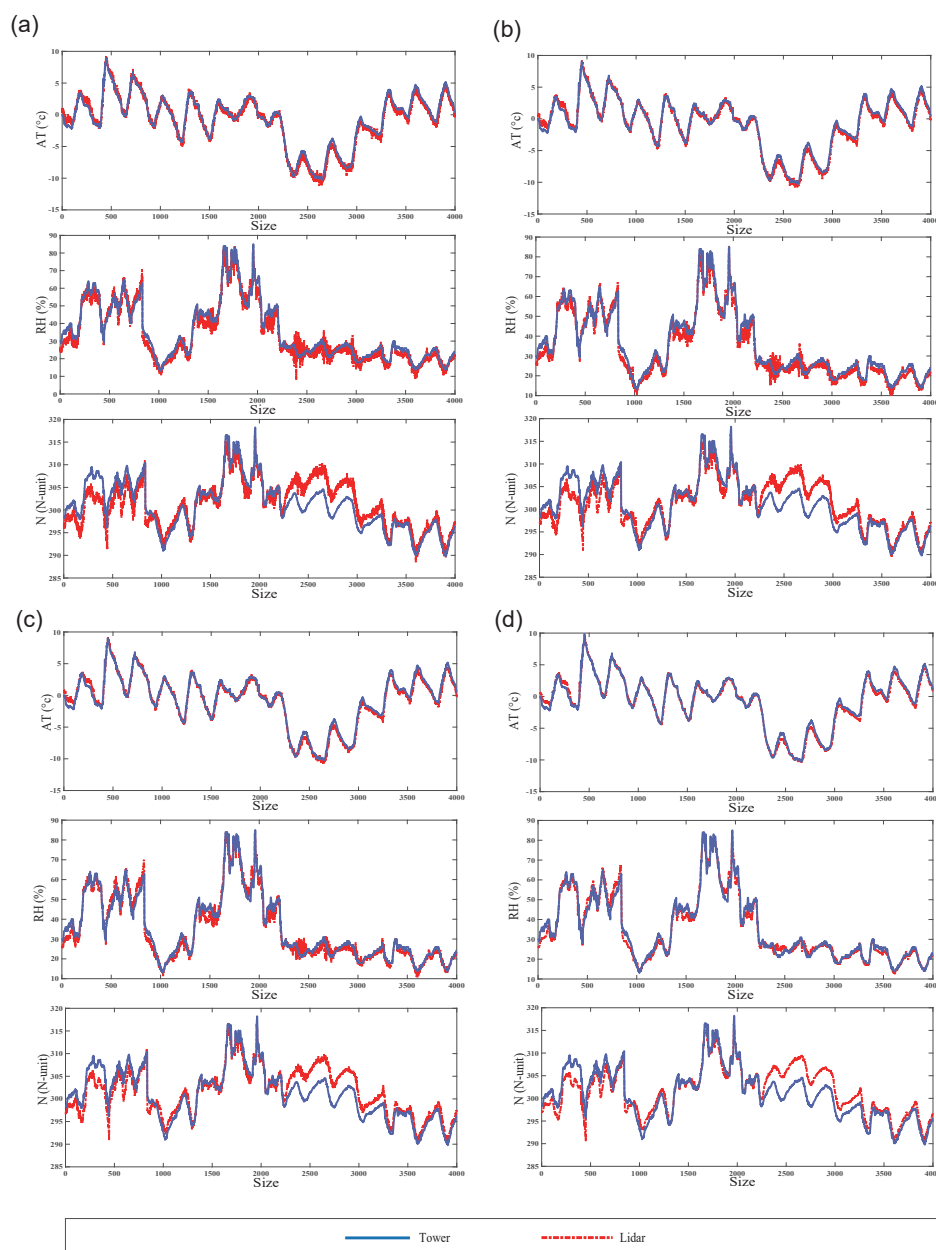


Figure 8. Comparative analysis of observation data at an altitude of 63 m with 5-min, 10-min, 15-min, and 60-min integration times. Tower denotes the gradient observation tower data, and lidar denotes the Raman lidar observation data. The integration times are (a) 5-min, (b) 10-min, (c) 15-min, and (d) 60-min, respectively.

250 Based on the observational data accumulated over a 60-minute integration period, a three-dimensional (3D) spatiotemporal scale analysis was performed to evaluate the reliability and precision of the self-developed lidar system. A comprehensive, full-

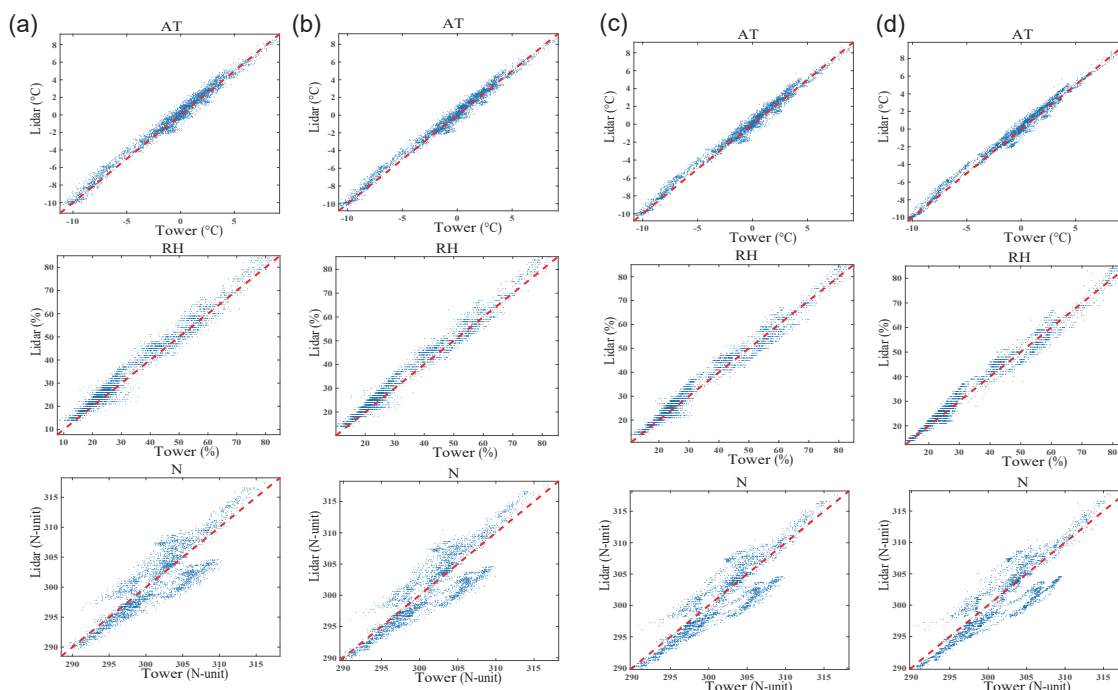


Figure 9. Comparative analysis of correlation analysis of observation data at 5-min, 10-min, 15-min, and 60-min accumulation time at a height of 63m. Tower is gradient observation tower data, and lidar is Raman lidar observation data. The integration times are (a) 5-min, (b) 10-min, (c) 15-min, and (d) 60-min, respectively.

dimensional comparison was conducted between the retrieval results of the Raman lidar and the meteorological tower across temporal, vertical, and physical magnitude dimensions. Fig. 10(a) and 10(b) illustrate the Raman lidar retrieved data and the gradient tower observations, respectively. Regarding AT, the Raman lidar retrievals exhibit high fidelity with the tower measurements, characterized by nearly identical morphological variations and spatial color distributions of the 3D surfaces. During the passage of a warm air mass (Time = 10–15 days), both instruments accurately captured a uniform, warm thermal stratification (5 °C to 10 °C, deep red region) extending from the near-surface to an altitude of 120 m. Throughout the subsequent cold period, they synchronously tracked the severe cooling process across the entire atmospheric layer, during which temperatures dropped uniformly to a range between -10 °C and -5 °C (deep blue region). Vertically, the subtle AT gradients with height are perfectly synchronized in both plots, demonstrating that the Raman lidar achieves a level of detection accuracy for vertical thermal stratification comparable to that of the meteorological tower. For RH, the spatiotemporal evolution of the Raman lidar retrievals is in excellent agreement with the tower observations, faithfully reconstructing the actual water vapor structure. During the high-humidity episode (Time = 15–18 days), both systems precisely resolved a strong humid structure where the mid-to-high altitude (Height > 40 m) RH exceeded 80%–90% (deep red region), clearly exhibiting a vertical stratification characterized by "upper-level moistening and lower-level drying". Conversely, during the hyper-arid period (Time = 22–30 days),



they concurrently reproduced the rapid desiccation of the atmosphere, with the mid-to-high altitude RH plunging to approximately 20%–30% (blue region). Furthermore, benefiting from the long 60-minute integration time, the 3D surface transitions of RH are exceptionally smooth; high-frequency random fluctuations are thoroughly suppressed, and the delicate fluctuations of the spatial field match the tower observations with high fidelity. In terms of the 3D spatiotemporal scale analysis of the N, the Raman lidar successfully and faithfully captures the pronounced negative gradient structure, where N decreases monotonically with height from approximately 310 N-units near the surface to about 290 N-units at higher altitudes. The two datasets demonstrate synchronous alignment regarding both the remarkable surge in N throughout the entire column (Time = 15–18 days) and the low-N troughs in the mid-to-upper atmosphere (Time = 22–28 days). Near the surface during Time = 11–18 days, the high-N zone retrieved by the Raman lidar extends slightly higher than that of the tower. This pattern substantiates the finding from the one-dimensional time-series analysis that the Raman lidar exhibits a slight, systematic positive bias in N. On a macro 3D structural level, however, this minor discrepancy does not materially affect the determination of the spatial field or the temporal evolutionary trends of the N. The aforementioned analysis demonstrates that the self-developed lidar system possesses outstanding spatial reproduction fidelity and temporal consistency on a 3D spatiotemporal scale for the atmospheric thermal structure (AT), the water vapor spatial field (RH), and the dielectric refractive index (N), thereby enabling highly reliable reconstructions of 3D spatiotemporal physical fields. The system exhibits sharp and sensitive boundary-capturing capabilities in both the vertical and temporal dimensions during transient weather processes (such as the cooling, drying, and refractive index abruptions induced by frontal passages), showing no observable lag or distortion relative to the tower measurements. Although the retrieved N exhibits a localized, slight overestimation at low altitudes, this deviation falls well within an acceptable margin from a full-dimensional evolutionary perspective and does not impede the scientific assessment of atmospheric stratification and its underlying dynamics. Consequently, having undergone full-dimensional validation, the self-developed Raman lidar system proves capable of replacing conventional meteorological towers for high-spatiotemporal-resolution 3D atmospheric observations.

To further evaluate the performance of the self-developed lidar system at various detection altitudes, a systematic statistical comparison and vertical profile analysis were conducted using the AT, RH, and N observations gathered across eight distinct height layers (8 m, 15 m, 32 m, 47 m, 63 m, 80 m, 102 m, and 120 m) under a 60-minute integration time; the statistical metrics are summarized in Table 2. Across all height layers from 8 to 120 m, the correlation coefficients (R) between the lidar measurements and the meteorological tower data remain consistently high, ranging from 0.99 to 1.00. This indicates that the lidar possesses a highly robust capability to track the fluctuation phases of temporal AT evolutions and periodic AT variations, a performance that remains virtually impervious to increasing detection altitude. Meanwhile, the RMSE of AT does not exhibit a monotonic trend with height, but rather fluctuates marginally between 0.42 °C and 0.63 °C. This non-monotonic, wavy vertical distribution is typically attributable to the local microclimate radiative interference caused by the physical structures of the meteorological tower at specific heights (such as the steel platforms), localized turbulence induced by bracket shielding, and variations in the signal-to-noise ratio (SNR) of the lidar beam at particular geometric distances. Nevertheless, the overall AT discrepancies remain strictly within 0.6 °C, satisfying high-precision meteorological observation standards. The vertical accuracy of RH peaks in the middle layers, with a localized pronounced anomaly manifested at the 102 m layer, followed by

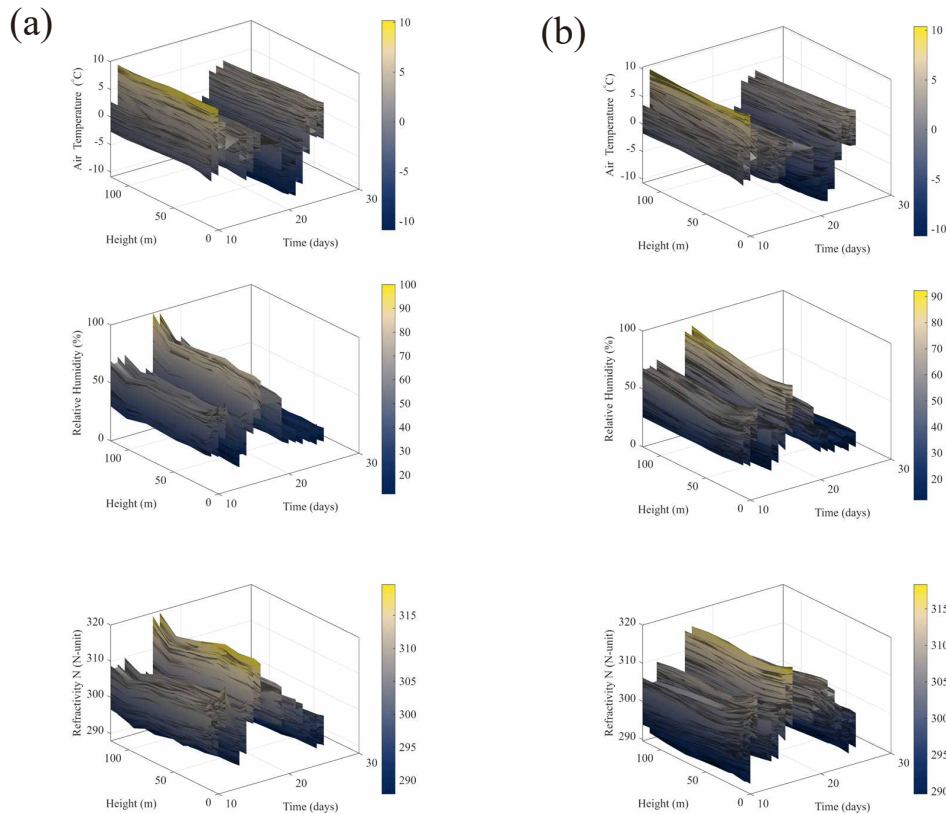


Figure 10. Comparative analysis of 60-minute integration periods data observations. (a) represent the AT, RH, and N at different altitudes measured by the Raman lidar. (b) represent the AT, RH, and N at different altitudes measured by the gradient observation tower.

a rapid retreat of the error back to normal levels at 120 m. This localized degradation is therefore not derived from long-range lidar signal attenuation; rather, it is more likely induced by the superposition of local microenvironmental anomalies at the 102 m tower sensor and localized inversion distortions of the lidar data at that specific height. For the N, the vertical accuracy in the mid-to-upper layers outperforms that in the lower layers. Below 47 m, the correlation coefficients for N are relatively lower ($R \approx 0.86$ to 0.88), accompanied by the maximum RMSE (2.62 to 2.84 N-units) and MAE across the entire profile. In contrast, the accuracy improves substantially in the mid-to-upper layers (63 to 120 m). Above 63 m, the correlation coefficient for N increases steadily, peaking at 0.93 at the 102 m level, while the RMSE drops to its minimum value of 2.41 N-units at 80 m. These vertical variations can be primarily explained by the fact that the surface layer (< 50 m) is heavily influenced by surface heat exchange, complex underlying surface perturbations, and intense mechanical turbulence, which generate highly violent and random fluctuations in the N; furthermore, near-surface clutter tends to contaminate the lidar return echoes. As the detection altitude increases, the system evades these intense near-surface perturbations and clutter interferences, where the atmospheric stratification becomes more stable, and the spatiotemporal distribution of N conforms better to actual observational

characteristics. Consequently, the Raman lidar demonstrates enhanced retrieval accuracy and higher correlation in the mid-to-upper layers, fully highlighting the unique technological advantages of active remote sensing instruments in upper-air boundary layer detection.

Table 2. Statistical analysis results of various meteorological variables at different altitudes

Height (m)	AT (°C)			RH (%)			N (N-units)		
	MEA	RMSE	R	MEA	RMSE	R	MEA	RMSE	R
8	0.37	0.46	1.00	2.43	3.16	0.98	2.12	2.62	0.89
15	0.34	0.42	0.99	2.41	3.08	0.98	2.28	2.78	0.88
32	0.54	0.63	0.99	2.12	2.72	0.99	2.33	2.84	0.86
47	0.44	0.53	0.99	2.02	2.72	0.99	2.35	2.84	0.88
63	0.39	0.49	0.99	1.90	2.47	0.99	2.05	2.58	0.89
80	0.34	0.4	0.99	2.21	2.87	0.99	1.87	2.41	0.90
102	0.42	0.54	0.99	3.53	4.55	0.99	2.25	2.66	0.93
120	0.37	0.47	0.99	2.47	3.28	0.99	1.95	2.44	0.91
Total	0.40	0.50	0.99	2.39	3.11	0.99	2.15	2.65	0.89

4 Conclusions

The N is a direct parameter that characterizes the propagation characteristics of light or EM waves in the atmosphere. It can directly affect the efficiency of radio equipment, radar detection, and communication systems. Therefore, studying the methods for obtaining the N has become one of the current research focuses. Currently, in order to measure the N, by obtaining AT, RH, and AP, and using the physical relationship between meteorological parameters and N to calculate and obtain the N has become a common method. To obtain the N profile, usually, methods such as balloon radiosondes, observation towers, and sounding rockets are adopted to obtain the AT, RH, and AP at different heights, calculate the N at different heights, and thereby obtain the N profile. However, these methods are relatively complex to operate, have high costs, require professional personnel to operate, and have limited observation ranges.

Variations in AT and RH induce interactions with laser photons in the air, generating Raman scattering—an inelastic scattering process where photons exchange energy with molecules, resulting in wavelength shifts between incident and scattered light. By establishing mathematical relationships between Raman scattering signal intensity and AT/RH characteristics, AT and RH profiles at different altitudes can be inverted through algorithms, enabling the retrieval of N profiles. Since Raman



scattering signals are molecule-specific, they allow precise identification of AT and RH parameters at varying heights without physical contact with the target gas, achieving long-range remote sensing while simultaneously retrieving AT, RH, and N data. This study designs and develops a Raman lidar-based N measurement system leveraging the temperature-dependent intensity of atmospheric rotational Raman spectral lines for AT inversion, derives RH from the lidar-measured water vapor mixing ratio, and calculates the N using physical relationships between AT, RH, and N. The paper details the Raman lidar hardware design and inversion methodology.

To verify the measurement accuracy of the Raman lidar, an experimental validation of a newly developed N profiler based on Raman lidar was conducted at the Institute of Atmospheric Physics, Chinese Academy of Sciences, from 10 to 26 January, 2024. Utilizing a stratified gradient observation tower, a comparative analysis was performed between the AT, RH, and N retrieved by the lidar and the corresponding measurements obtained from the tower. This paper established a comprehensive reliability validation across different accumulation times (5-min, 10-min, 15-min, and 60-min) and various altitude levels (from 8 m to 120 m), systematically comparing the results with the true values measured by the meteorological tower. Statistical results demonstrate that, with a 60-minute accumulation time, the overall RMSE of the system for AT, RH, and N are maintained at exceptionally low levels of 0.50 °C, 3.11 %, and 2.65 N-units, respectively, with mean R reaching 0.99, 0.99, and 0.89, respectively. As the detection altitude increases, the N measurements avoid interference from strong surface turbulence and near-ground clutter, exhibiting stronger correlation and lower errors in the middle-to-upper layers (63–120 m). This highlights the detection advantages of active remote sensing equipment. Consistent findings from both 3D spatiotemporal scale analysis and vertical profile statistical validation indicate that this lidar system can faithfully reproduce the macroscopic 3D spatial stratification and transient temporal evolution of the atmospheric thermodynamic, moisture, and dynamic medium fields. It demonstrates excellent reliability and possesses the potential to replace traditional meteorological towers for continuous boundary layer atmospheric observations with high spatiotemporal resolution.

This paper presents a novel and effective measurement approach for N observation, particularly suitable for mobile platforms, which enables real-time profiling of AT, RH, and N during underway navigation. This approach delivers large-scale N profile data to enhance radar and wireless communication systems. The self-developed Raman lidar system has successfully passed comprehensive reliability validation. Its outstanding detection performance and high spatial coverage demonstrate broad application prospects in atmospheric physics research, boundary layer micro-meteorological observations, and numerical weather prediction data assimilation. Moving forward, we plan to conduct long-term maritime experimental validations using offshore platforms such as sea gradient observation towers, research vessels, and buoys. These efforts aim to acquire more marine observation data to further verify our findings, optimize the measurement methods, and improve the accuracy of N measurements over the ocean. Addressing the limitations identified in this study—namely, the slightly restricted inversion accuracy of N in low-altitude strong turbulence zones and the susceptibility of specific altitude layers to local physical environmental interference from meteorological stations—future research will focus on developing low-level N filtering and correction algorithms that integrate adaptive underlying surface characteristics. Furthermore, in practical data assimilation applications, a dynamic weight adjustment mechanism will be introduced for altitude layers around 102 m, which are prone to micro-environmental interference from the tower structure. These advancements will further enhance the engineering appli-



365 cability and the upper limit of data inversion accuracy of this system in complex boundary layer environments, ultimately providing robust environmental data support for maritime radio detection and communication systems.

Data availability. The data presented in this study are available on request from the corresponding author.

Author contributions. YW and BW designed the experiments, and DL and MZ carried them out. YW and XZ developed the model code and ZZ performed the simulations. PY, KT and ZQ assisted the lidar data preprocessing and results analysis. ZQ prepared the manuscript with contributions from all co-authors.

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

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