

JGR Space Physics



METHOD

10.1029/2026JA035345

Key Points:

- Measurements with the IAP potassium resonance lidar are uniquely sensitive to nonlinear scattering effects (i.e., saturation)
- These measurements provide validation for a newly developed method for simulating saturation effects, both in magnitude and spectral form
- Saturation effects can cause biases in line-of-sight wind and temperature measurements of 10s of m/s and 10s of K, respectively

Supporting Information:

Supporting Information may be found in the online version of this article.

Correspondence to:

C. Geach,
christopher.geach@dlr.de

Citation:

Geach, C., Kaifler, B., Höffner, J., & Baumgarten, G. (2026). Saturation effects in narrowband resonance lidar measurements, Part 2: Potassium lidar systems and experimental results. *Journal of Geophysical Research: Space Physics*, 131, e2026JA035345. <https://doi.org/10.1029/2026JA035345>

Received 18 MAR 2026

Accepted 18 JUN 2026

Author Contributions:

Conceptualization: C. Geach, B. Kaifler

Data curation: Josef Höffner

Formal analysis: C. Geach, B. Kaifler

Investigation: Josef Höffner

Methodology: C. Geach, B. Kaifler

Resources: Josef Höffner

Software: C. Geach

Validation: G. Baumgarten

Visualization: C. Geach

Writing – original draft: C. Geach

© 2026 Deutsches Zentrum fuer Luft- und Raumfahrt e.V. and The Author(s). Journal of Geophysical Research: Space Physics published by Wiley Periodicals LLC on behalf of American Geophysical Union. This is an open access article under the terms of the [Creative Commons Attribution License](https://creativecommons.org/licenses/by/4.0/), which permits use, distribution and reproduction in any medium, provided the original work is properly cited.

Saturation Effects in Narrowband Resonance Lidar Measurements, Part 2: Potassium Lidar Systems and Experimental Results

C. Geach¹ , B. Kaifler² , Josef Höffner³, and G. Baumgarten³

¹Deutsches Zentrum für Luft- und Raumfahrt, Institut für Solar-Terrestrische Physik, Neustrelitz, Germany, ²Deutsches Zentrum für Luft- und Raumfahrt, Institut für Physik der Atmosphäre, Oberpfaffenhofen, Germany, ³Leibniz-Institute of Atmospheric Physics at University Rostock, Kühlungsborn, Germany

Abstract Resonance lidars targeting the D_1 resonance line of potassium at 770 nm have been employed over the past 5 decades to yield numerous insights into the dynamics of the middle and upper atmosphere. It has long been recognized that these measurements can be severely affected by nonlinear behavior in the scattering process, that is, saturation effects, particularly when high pulse energies, narrow beam divergences, and narrow laser linewidths are employed. The measurements by the potassium resonance lidars developed at the Leibniz Institute of Atmospheric Physics are in this respect unique—these are the only systems for which saturation effects have been detected. However, the observed degree of saturation is inconsistent with theoretical estimations thus far. A new method of calculating the degree of saturation, previously applied only to the D_2 line of sodium, is described in a companion paper (Geach & Kaifler, 2026, <https://doi.org/10.1029/2026JA035269>); here, we apply the method to the D_1 resonance line of potassium. We show that the observed degree of saturation, approximately 70%, is consistent with the model; we show that a spectral signature of saturation effects, predicted by the model, is consistent with the observations; we present the saturation-induced biases on temperature and wind measurements; and we discuss the implications of saturation on ideal instrument design.

Plain Language Summary For over 50 years, atmospheric resonance lidars have been used to study the composition and dynamics of the middle and upper atmosphere. More recently, lidar systems targeting a resonance line of potassium have observed that the backscatter signal is no longer proportional to the laser pulse energy—these systems have entered a saturated regime. However, the observed degree of saturation is not consistent with attempts thus far to approximate it. Here, we show that a new approach to estimating saturation effects is consistent with observations, both in its overall severity and in its spectrum; further, we discuss the resulting biases on temperature and wind measurements.

1. Introduction

Atmospheric resonance lidars have been used since the pioneering measurements by Bowman et al. (1969) to probe the structure and dynamics of the middle atmosphere. These first measurements relied on the D_2 resonance line of sodium at 589 nm, but the technique was soon expanded to the D_1 line of potassium at 770 nm by Felix et al. (1973). Megie et al. (1978) made a series of measurements of both the sodium and the potassium lines over almost 1 year, leading to inferences as to the sources of the respective layers. The authors also highlighted a potential systematic effect in resonance lidar measurements: at high laser energy concentrations (whether in the space, time, or frequency domain), nonlinear effects in the scattering process begin to play a role, as the target atoms are driven into a saturated regime. This is due to the finite lifetime of the excited state. When a significant fraction of the target atoms are simultaneously excited, the probability of back-scattering for later-arriving photons is reduced, resulting in a detected signal that no longer scales linearly with the laser pulse energy.

The next advancement in potassium resonance lidars was the introduction of a narrow-band, solid-state Alexandrite laser as part of a compact, transportable lidar system by von Zahn and Höffner (1996). This system was also capable of measuring at multiple frequencies across the potassium D_1 line, enabling a retrieval of vertical profiles of temperatures. The authors also addressed the issue of saturation, concluding that for their instrument, a saturation of just 0.2% was to be expected (i.e., the observed signal was reduced by 0.2% relative to what it would have been in the absence of saturation effects) and that due to the relative strength of the individual hyperfine

Writing – review & editing: B. Kaifler,
G. Baumgarten

transitions, the effect of saturation on temperature was small in any case: for a saturation of 10%, the authors calculated a temperature bias of 0.2 K.

This instrument was subsequently modified to enable daylight temperature measurements; this modification entailed the introduction of a narrow-band Faraday anomalous-dispersion optical filter (FADOF; Höffner & Fricke-Begemann, 2005) and a reduction in the divergence of the laser beam and the field-of-view of the telescope (Lautenbach et al., 2017). This reduction in the laser beam divergence led to a higher energy concentration at the potassium layer, leading in turn to measurable losses due to saturation. The authors estimated the effect of saturation on the retrieved potassium densities by comparing measurements made at different laser beam divergences; the authors increased the retrieved potassium densities by a factor of 3 to account for losses due to saturation, corresponding to a saturation of 67%.

To our knowledge, no satisfactory explanation for the observed degree of saturation has been given. The approximation offered by Megie et al. (1978) is valid only for lidar systems that employ lasers with linewidths significantly wider than the Doppler-broadened resonance line of the target species (on the order of 600 MHz full-width at half-maximum (FWHM) for potassium); hence, it is no surprise that this approximation predicts a significantly lower degree of saturation for the IAP lidar systems. von der Gathen (1991) described a more sophisticated method of calculating saturation in the case of sodium lidars, using a set of differential equations to numerically solve for the evolution of the populations of each of the ground and excited states separately, but the method was not extended to potassium lidars. Papen, Gardner, and Pfenninger (1995) used a similar numerical approach to derive saturation predictions for a simulated potassium lidar, based on the formalism laid out and applied to the sodium D_2 line in Papen, Pfenninger, and Simonich (1995). However, this approach assumes transition-specific excited state lifetimes for each transition within the line, which is not physical, and the resulting estimates of saturation are therefore unreliable.

The measurements described in Lautenbach et al. (2017) are among the only resonance lidar measurements for which a significant degree of saturation has been observed. Thus, the measurements represent a unique opportunity for empirical validation of a newly developed model of saturation. In a companion publication (Geach & Kaifler, 2026), we have described such a model, which can be applied generally to resonance lidars and represents an extension of the work by von der Gathen (1991) (which only treated sodium resonance lidars and contained a subtle but important error in the weighting of individual hyperfine transitions). In this paper, we summarize the model and highlight the aspects that are of particular importance for potassium resonance lidars; we compare the simulated degree and spectrum of saturation with the measurements by Lautenbach et al. (2017); and we investigate the saturation-induced biases on wind and temperature measurements that can arise for potassium lidar systems.

2. Saturation Model

The saturation model used here is described in detail in Geach and Kaifler (2026) and is largely based on the model developed by von der Gathen (1991); here, we present a brief overview, as applied to the potassium D_1 resonance line. The model consists of a system of differential equations for the relative number densities of atoms in each ground state and excited state in terms of their velocity-dependent Doppler shift. The evolution of these number densities is solved for, tracking the excitation of atoms from the ground states to the excited states and the spontaneous or stimulated relaxation of atoms from the excited states into the ground states. The total number of spontaneous relaxations corresponds to the number of spontaneously emitted photons and is therefore proportional to the detected lidar signal. We perform two simulations, one accounting for saturation effects, in which the ground states are depleted as the excited states are populated, and one where saturation effects are excluded, in which the ground states (non-physically) remain fully populated despite the increased population of the excited states. By comparing the number of spontaneous relaxations in each simulation, the degree of saturation can be retrieved.

The potassium D_1 line consists of four transitions between two ground and two excited states. Furthermore, there are two naturally occurring isotopes of potassium (^{39}K , with a relative abundance of 93.3%, and ^{41}K , with a relative abundance of 6.7% (Tiecke, 2019)); thus, the D_1 line consists of 8 distinct resonance lines, designated by $^n\alpha_j^k$, with n designating the isotope, j the ground state of the transition, and k the excited state. The intrinsic

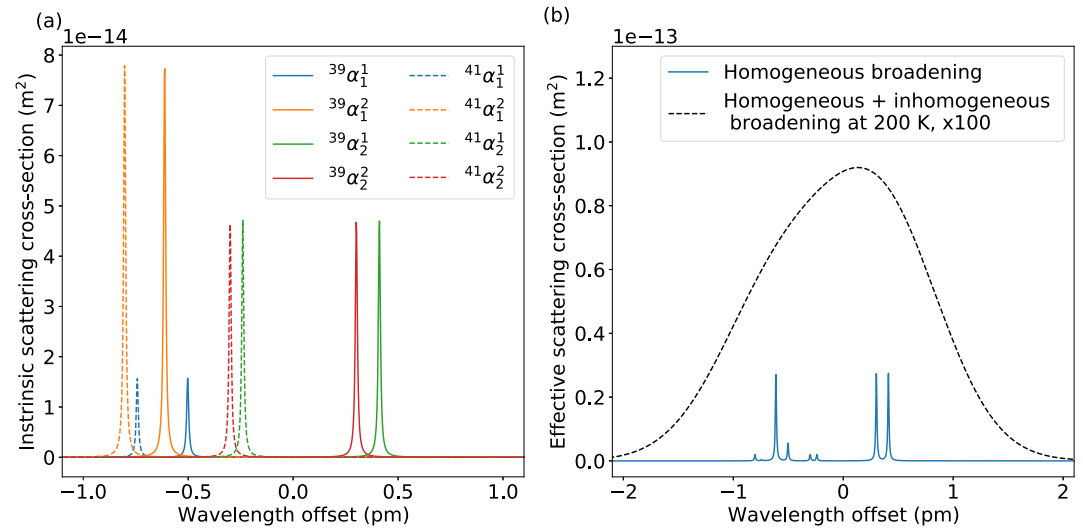


Figure 1. (a) Spectra of total intrinsic scattering cross-section $^n\alpha_j^k$ for each of the 4 hyperfine transitions of ^{39}K (solid lines) and ^{41}K (dashed lines), plotted as a function of wavelength offset relative to the center of the transition, showing only homogeneous broadening. (b) Combined total effective scattering cross-section spectra of the 8 transitions of the potassium D_1 line, weighted by the relative abundance of the corresponding ground state and isotope, in the case of homogeneous broadening (blue solid line) and homogeneous and inhomogeneous broadening assuming a potassium layer temperature of 200 K (dashed black line). Note that the dashed black line is scaled by a factor of 100 for the purposes of visibility.

scattering cross-section spectra are shown in Figure 1a. The relative line strengths g_j^k and isotope-dependent frequency shifts $\Delta\nu_j^k$ for each of the hyperfine transitions are given in Table 1. The other necessary parameters for the D_1 line are the wavelength of the transition (770.108 nm in vacuum), the Einstein A coefficient (37.34 MHz), and the oscillator strength of the transition (0.332) (Kramida et al., 2024).

There is an important distinction to be made in regards to the relative strengths of these transitions: for the purposes of calculating saturation, only the intrinsic scattering cross-section plays a role, that is, the scattering cross-section for a particular atom, regardless of the relative population of atoms of that particular isotope and in that particular ground state. For the purposes of calculating an effective, Doppler-broadened scattering cross-section, on the other hand, the relative populations of the individual isotopes and ground states must be considered. The corresponding total effective scattering cross-section spectrum, showing the line strengths of the 8 transitions weighted by the relative abundance of the respective ground state and isotope, is shown in the blue solid line in Figure 1b for the case of homogeneous broadening, and in the dashed black line for the case of inhomogeneous (Doppler) broadening, assuming a potassium layer temperature of 200 K. As discussed in Geach and Kaifler (2026), this has been a frequent source of misunderstanding, particularly the relative strength of individual hyperfine transitions. The relative strength of the individual transitions are often weighted by the term $g_j^k / \sum_{l,m} g_m^l$ (e.g., in von der

Gathen (1991)) where they should in fact be weighted by $g_j^k / \sum_l g_j^l$. Note that the effective relative line strengths, as given by von der Gathen (1991), are recovered by multiplying the relative line strengths by the relative abundance of each ground state, which is given by the factor $\sum_l g_j^l / \sum_{l,m} g_m^l$.

Table 1
Frequency Offsets and Line Strengths g_j^k for the Potassium D_1 Line
(Tiecke, 2019)

$S_{1/2}$	$P_{1/2}$	$^{39}\text{K } \Delta\nu_j^k$ (MHz)	$^{41}\text{K } \Delta\nu_j^k$ (MHz)	g_j^k	Relative line strengths
$j = 1$	$k = 1$	253.9	375.2	1	1/6
	$k = 2$	309.4	405.7	5	5/6
$j = 2$	$k = 1$	-207.8	121.1	5	1/2
	$k = 2$	-152.3	151.6	5	1/2

Though the distinction here is subtle, it has significant implications for calculating saturation. For example, von Zahn and Höffner (1996) argue that saturation has a minor effect on retrieved temperatures for a potassium lidar because the potassium resonance line consists of three transitions of equal strength and a fourth that is considerably weaker. In fact, the relative strengths of the transitions, as given in the rightmost column of Table 1, lead to an asymmetric spectrum of saturation, as shown in Figure 2a, as opposed to the much more symmetrical spectrum that arises when the effective relative line strengths are used; see Figure S1a in Supporting Information S1. As a result,

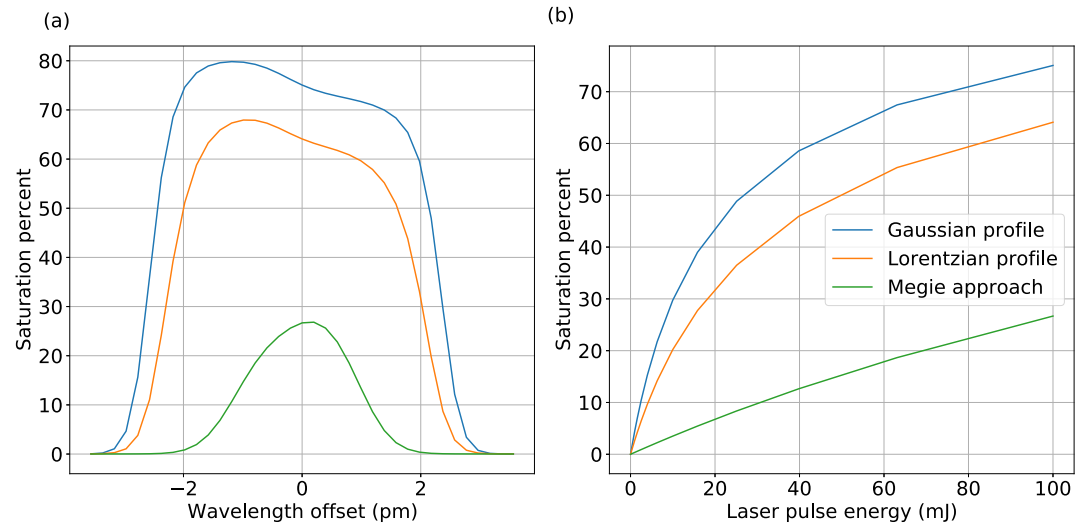


Figure 2. (a) Theoretical saturation percentages plotted as a function of laser wavelength offset for the D_1 resonance line of potassium assuming either a Gaussian profile for the laser line shape (blue curve) or a Lorentzian profile (orange curve). For reference, the saturation obtained using the approach by Megie et al. (1978) is also shown (green curve). Lidar system parameters are modeled after the potassium lidar described in von Zahn and Höffner (1996) and Lautenbach et al. (2017); see Table 2. (b) Theoretical saturation percentages as a function of laser pulse energy. Lidar system parameters other than laser pulse energy are the same as in panel (a).

the effect of saturation on retrieved temperatures is significantly larger than has been so far assumed; see Section 4 and Figure S2 in Supporting Information S1.

To compute the spectrum of saturation for a potassium lidar, we used system parameters taken from von Zahn and Höffner (1996) and Lautenbach et al. (2017); see Table 2. Here, we use a pulse energy of 100 mJ and a beam divergence of 133 μ rad. Note that the laser linewidth could not be measured due to the limited resolution of the spectral analyzer; the value given in Table 2 represents an upper-limit. Also, we assume that the laser line shape is constant for the duration of the pulse; though significant chirp is likely to have been present, no measurement of it was made. As in von der Gathen (1991), we assume a laser pulse shape given by:

$$N(t) = N_t t^2 e^{-at} \frac{a^3}{2} \quad (1)$$

where N_t is the total number of photons emitted per pulse, $a = 3.4/t_L$, with t_L the FWHM pulse length, and the factor of $\frac{a^3}{2}$ is used for normalization.

Table 2
Potassium Lidar Parameters from von Zahn and Höffner (1996) and Lautenbach et al. (2017)

Parameter	Value
Pulse energy ^a	100/50 mJ
Pulse length	275 ns
Laser linewidth (FWHM)	20 MHz
Beam divergence ^a	133/270 μ rad
Telescope field-of-view	186 μ rad

^aThe value of this parameter changed over time; the value used for each simulation is given in the text.

We further assumed a potassium layer with an average altitude of 92.5 km with a temperature of 200 K and a one-way atmospheric transmission at 770 nm of 70%. The resulting spectra of saturation are shown in Figure 2a for a Gaussian (blue curve) and a Lorentzian (orange curve) laser line shape. The saturation spectrum obtained using the approach by Megie et al. (1978) is also shown (green curve). Similarly, we computed the degree of saturation for the same system parameters but for a range of laser pulse energies up to 100 mJ; the results are shown in Figure 2b. As can be seen, the resulting degree of saturation depends significantly on the laser line shape, but in either case, the expected saturation is consistent with the observed value of 67% given the quoted confidence interval of 50%–75% (Lautenbach et al., 2017). The curves shown here are reproduced in Figure S1 of Supporting Information S1, except that the effective relative line strengths are used instead of the intrinsic relative line strengths, resulting in a more symmetric saturation spectrum.

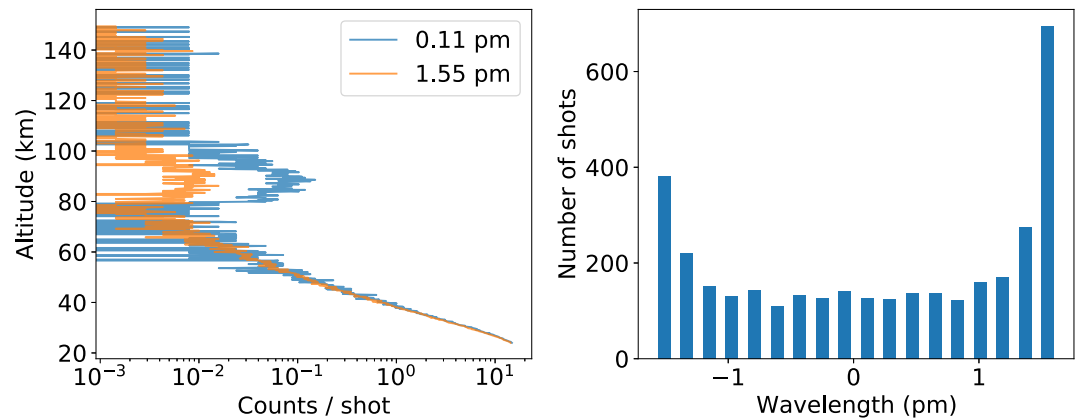


Figure 3. (Left) lidar count profiles, normalized for the number of shots, for a wavelength at the center of the potassium spectrum (blue curve) and one at the edge of the spectrum (orange curve). (Right) Distribution of shots per wavelength bin for a typical scan period.

3. Comparison With Observation

Given the form of the saturation spectrum shown in Figure 2a, saturation is expected to result not only in a substantial reduction of the signal detected by a potassium resonance lidar, but also a deformation of the spectrum. In order to investigate this hypothesis, we performed the following analysis, explained in more detail below: for the experimental data, we calculated the measured scattering cross-section spectra at a range of altitudes and for a range of observation periods. We determined the best-fit spectra based on the theoretical model of the scattering cross-section (which depends on the temperature and line-of-sight velocity of the potassium layer), without accounting for saturation effects in this fit. We then computed the resulting residuals between the measured spectrum and the fit. Similarly, we simulated a measurement at the same laser wavelengths for the given instrument parameters, accounting for saturation effects; we determined the best-fit spectra for these simulated measurements, again neglecting the effects of saturation in the fit; and we computed the resulting residuals. As shown below, the residuals predicted by the model are in general consistent with the experimental residuals.

3.1. Lidar Observations

We have analyzed data from 5 nights of observation made between January 2010 and February 2011 by the instrument described in Lautenbach et al. (2017). The data consist of measured profiles of collected photons, with a vertical resolution of 200 m, a temporal resolution of approximately 120 s, and a spectral resolution of 0.18 pm, with 18 wavelength bins over ± 1.5 pm. For each time step, the data contain the number of photons per altitude and wavelength bin, $N[t, z, \lambda]$, as well as the number of laser pulses (or shots) emitted within each wavelength bin, $S[t, \lambda]$, where the square brackets indicate that these quantities are discrete functions of the given variables. A representative example of $N[t, z, \lambda]/S[t, \lambda]$ for a single temporal bin is shown in the left panel in Figure 3 for a wavelength at the center of the potassium spectrum (blue curve) and at the edge of the spectrum (orange curve). The strong, rapidly decreasing signal at low altitudes is due to Rayleigh scattering in the lower atmosphere; the “bump” at 80–105 km is the resonance signal from the potassium layer. The wavelength scan strategy is depicted in the right panel of Figure 3, showing the number of shots recorded in this temporal bin within each wavelength bin. More data were recorded at the wavelengths at the edges of the scan than at the center, resulting in lower noise at those wavelengths; this reduced noise is evident in the left panel, where less noise is present in the orange curve than in the blue curve.

Resonance lidars are typically calibrated using the Rayleigh signal from the lower atmosphere to correct for fluctuations in laser output power (see, e.g., Chu & Papen, 2005). However, as argued in Höffner and Fricke-Begemann (2005), the power stability of the alexandrite laser obviated the need for this calibration. Therefore, we assume that $S[t, \lambda]$ is proportional to the emitted laser energy within the corresponding time and wavelength bin. Thus, neglecting saturation effects, we can write the lidar equation as:

$$N[t, z, \lambda] \propto S[t, \lambda] (\rho[z] \sigma[\lambda] + B[t, \lambda]) \quad (2)$$

where $\rho[z]$ is the number density of potassium atoms, $\sigma[\lambda]$ is the total Doppler-broadened scattering cross-section (see e.g., Geach & Kaifler, 2026), and $B[t, \lambda]$ is the altitude-independent background. $B[t, \lambda]$ depends on λ as well as t because detected photons are only attributed to a given wavelength bin when they correspond to laser pulses within the given wavelength bin. Note that, in principle, the FADOF causes a wavelength dependent detection efficiency, but we estimate this effect to be less than 0.3%, based on the FADOF transmission curve presented in Höffner and Fricke-Begemann (2005). Though ρ and σ are continuous functions of z and λ , respectively, the square brackets indicate that they are evaluated at the center of their respective altitude or wavelength bins. Note that Equation 2 does not include either Rayleigh or Mie scattering—given the altitude and measurement season, these contribute negligibly to the observed signal.

We estimated the altitude-independent background by assuming that no potassium is present at altitudes above 125 km, so that any detected photons at those heights are attributable to the background; that is,

$$B[t, \lambda] = \sum_{z > 125 \text{ km}} N[t, z, \lambda] \quad (3)$$

We then filtered the data based on the total background noise, summed over all wavelengths, and on the signal level of the data, as assessed by the total background-subtracted Rayleigh signal between 40 and 50 km. These are given by

$$B_{\text{tot}}[t] = \sum_{\lambda} B[t, \lambda] \quad (4)$$

and

$$R_{\text{tot}}[t] = \sum_{\lambda} \sum_{40 \text{ km} < z < 50 \text{ km}} N[t, z, \lambda] - \frac{10}{25} B_{\text{tot}} \quad (5)$$

respectively, where the factor of $\frac{10}{25}$ accounts for the fact that the background is determined over an altitude range of 25 km whereas the Rayleigh signal is determined over a range of 10 km. We filter out data for which B_{tot} is more than twice its median value or for which R_{tot} is less than half its median value.

For each observation period, we integrated the remaining data in time and in a series of fifteen 1 km bins in altitude between 85 and 100 km, subtracting the background and normalizing for the total number of shots in each wavelength bin to obtain 15 measured spectra $N_K^i[\lambda]$:

$$N_K^i[\lambda] = \frac{\sum_t \sum_{z_i} N[t, z_i, \lambda] - \frac{1}{25} \sum_t B[t, \lambda]}{\sum_t S[t, \lambda]} \quad (6)$$

where z_i designates the i th altitude bin, and as before the factor $\frac{1}{25}$ accounts for the difference in size between the signal bin and the background bin. The corresponding uncertainties are propagated based on photon counting statistics.

Next, for each N_K^i , we performed a three-parameter fit in terms of the potassium temperature T , line-of-sight wind speed v_{av} , and overall amplitude A , using a Levenberg-Marquardt optimization and the definition of $\sigma(\lambda)$ given in Geach and Kaifler (2026). Note that this fit is weighted based on the measurement uncertainties and neglects the effects of saturation. Also, $\sigma(\lambda)$ depends on the linewidth and line shape of the laser; we assumed either a Lorentzian or a Gaussian profile with a FWHM linewidth of 20 MHz. We define T_{av} , the temperature retrieved from the fits averaged over the entire potassium layer, to be used in the next section. We designate these best-fit spectra as $N_{\text{fit}}^i[\lambda]$, and compute the relative residuals of the fits $Res_{\text{obs}}^i[\lambda]$:

$$Res_{\text{obs}}^i = \frac{N_K^i[\lambda] - N_{\text{fit}}^i[\lambda]}{N_K^i[\lambda]} \quad (7)$$

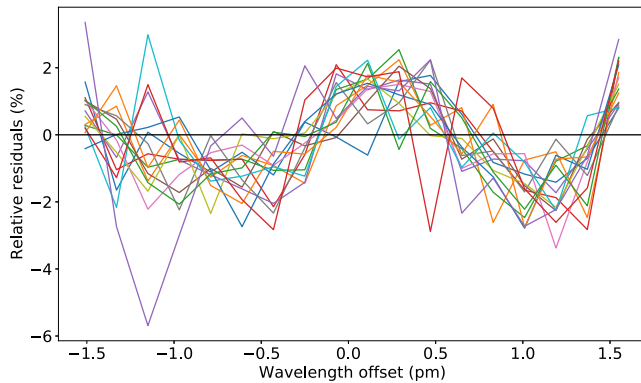


Figure 4. Relative residuals for the potassium spectra measured on 24–25 February 2011, representing 10.3 hr of data. Each color represents a different 1 km altitude bin between 85 and 100 km altitude, averaged over the entire observation period. The best-fit spectra were found assuming a laser beam with a Lorentzian profile and a 20 MHz FWHM linewidth. The uncertainties (not shown) have a median value of 1.4%.

The resulting relative residuals for the observation period with the highest signal are shown in Figure 4, showing a persistent and distinctive “W” pattern.

3.2. Model Residuals

To compare these relative residuals to our saturation model, we used the simulated number of spontaneous relaxations while accounting for saturation effects as a proxy for simulated lidar observations, up to scaling by an overall constant. We performed the simulation at the same measurement wavelengths used in the previous section. We used the system parameters given in Table 2 with two changes: we assumed that the laser pulse energy had decreased from 100 to 50 mJ since the measurements of the saturation factor given in Lautenbach et al. (2017), and we assumed a laser beam divergence of 270 μ rad. Though the estimate of 67% saturation was made for a divergence of 133 μ rad, the divergence was later increased to maximize the signal. No measurement of the divergence was made subsequent to this change, but simulations (not shown here) suggest that the signal is maximized for a laser beam divergence of approximately 270 μ rad. For each observation period, we

assumed the corresponding potassium layer temperature T_{av} from the previous section. We denote the simulated measurement spectrum as $\tilde{N}[\lambda]$.

For each simulated profile $\tilde{N}[\lambda]$, we performed a three-parameter fit as in the case of the observational data, again neglecting saturation effects for the fit and weighting the fit using uncertainties scaled from those retrieved from the data. This choice of weighting is an important factor: due to the scan strategy, the relative uncertainties are approximately constant across the scan range, meaning that the absolute uncertainties are appreciably larger in the center of the scan range than at the extremes. This gives the measurements at the extremes more importance in the fit. By keeping the same weighting as in the analysis of the observational data, we achieve the most apt comparison. We denote the resulting best-fit spectrum as $\tilde{N}_{fit}[\lambda]$ and define the relative residuals $Res_{model}[\lambda]$:

$$Res_{model}[\lambda] = \frac{\tilde{N}[\lambda] - \tilde{N}_{fit}[\lambda]}{\tilde{N}[\lambda]} \quad (8)$$

Thus, for each observation period (and corresponding average temperature), we can compare the observed relative residuals to the expected relative residuals based on the saturation model. The results are shown in Figure 5: the black solid lines show the average of the fifteen $Res_{obs}^i[\lambda]$, the dashed black lines show the standard deviation of the $Res_{obs}^i[\lambda]$, and the red solid lines show the corresponding $Res_{model}[\lambda]$.

As can be seen, the “W” pattern in the relative residuals is a persistent feature for both the observed and simulated spectra. The amplitude of the residuals is slightly over-estimated in the first two nights of observation—this could be due, for example, to an over-estimate of either the laser power or the atmospheric transmission for these observations or to imperfect modeling of the laser line shape. The assumption of a Lorentzian profile results in better agreement between model and observation than the assumption of Gaussian profile, but presumably neither of these is a perfect approximation to the true line shape. The sensitivity of saturation effects to the laser line shape, also seen in Figure 1, highlights a difficulty in accurate characterization of these effects.

4. Saturation-Induced Temperature and Wind Biases

The spectral dependence of saturation results in a bias on temperatures inferred from resonance lidar measurements. Similarly, for a hypothetical instrument that also retrieves line-of-sight wind speeds, a saturation-induced bias on the wind speeds would also be expected. In order to investigate the magnitude of these biases, we followed the procedure laid out in Geach and Kaifler (2026), briefly summarized here: from the saturation model, we obtained simulated spectra for the scattering cross-section with and without saturation effects at the same measurement wavelengths as those used in the previous section. We then performed a three-parameter fit on both spectra. To illustrate the importance of the scan strategy, we performed this fit in two ways: we assumed a scan

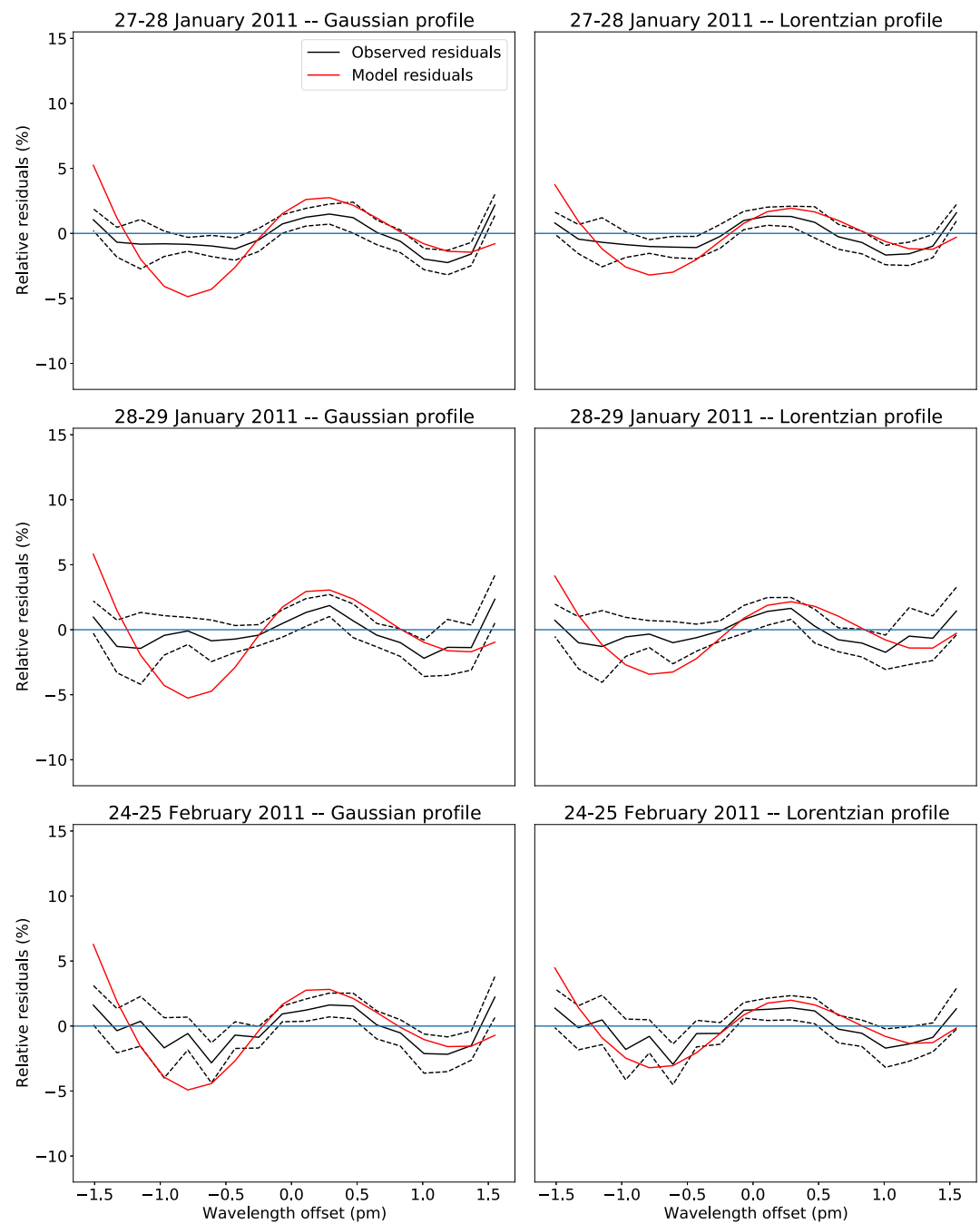


Figure 5. Average relative residuals (solid black lines), 1σ ranges (black dashed lines) and model residuals (red lines) for 27–28 January 2011 (top row, 11.5 hr of data), 28–29 January 2011 (middle row, 6.9 hr of data) and 24–25 February 2011 (bottom row, 10.3 hr of data). For the saturation simulation and analysis of the observations, a laser with a FWHM linewidth of 20 MHz was assumed, either with a Gaussian profile (left column) or a Lorentzian profile (right column).

strategy that resulted in equal absolute uncertainties at each wavelength bin, resulting in a uniform weighting, and we assumed a scan strategy that resulted in equal relative uncertainties, resulting in higher weighting of the wavelength bins at the edge of the scan range. This latter scan strategy is similar to the one employed by Lautenbach et al. (2017), discussed above. In each case, we retrieved best-fit estimates of the temperature, line-of-sight wind speed, and amplitude of the spectrum. In the case of the “no saturation” simulation, this process reliably recovers the input temperature and wind speed; therefore, the saturation-induced biases are given by the difference between the parameters retrieved from the two spectra, that is:

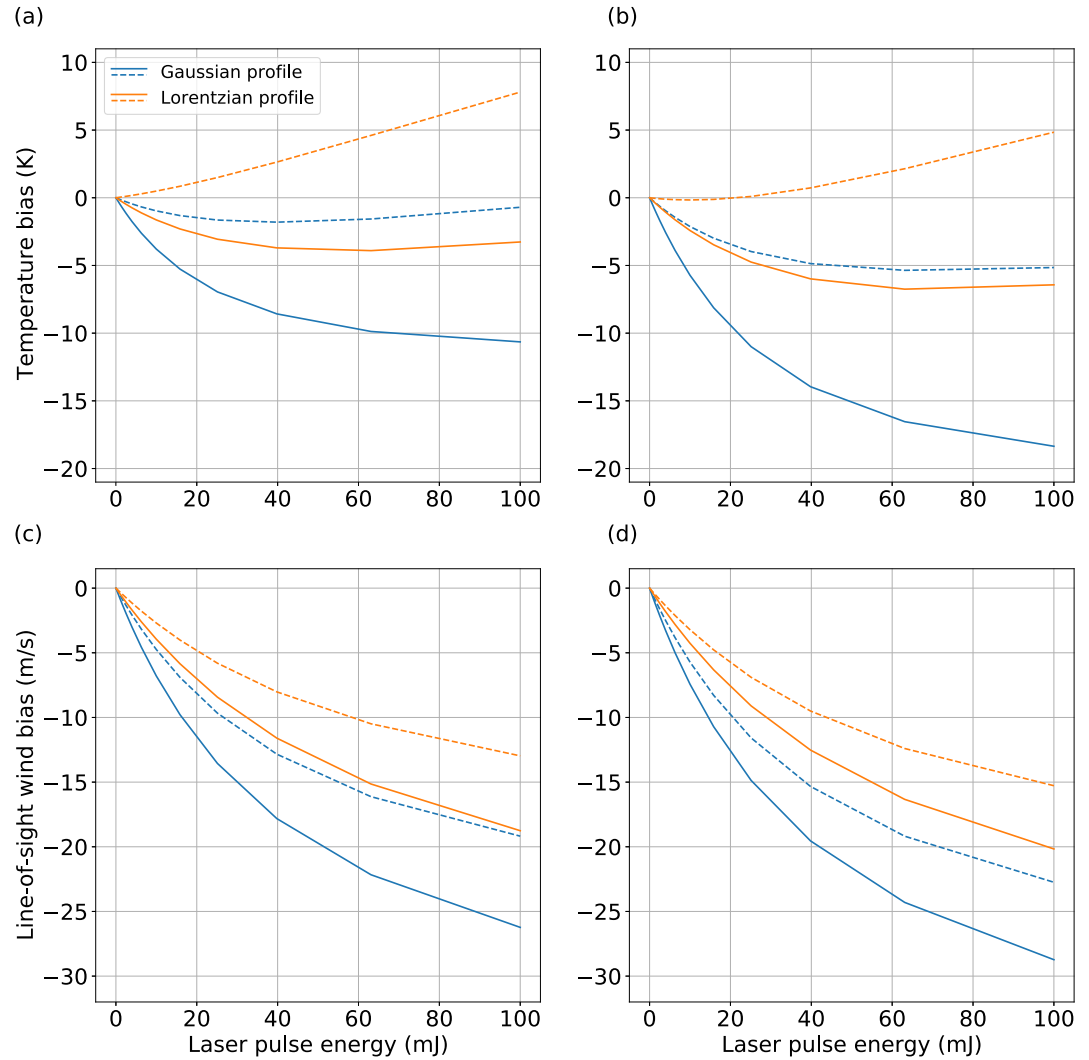


Figure 6. (a) Saturation-induced temperature biases as a function of laser pulse energy, for a Lorentzian laser profile (blue curve) or Gaussian laser profile (orange curve), assuming a potassium temperature of 150 K. Weighting of the fits was based either on an “equal absolute uncertainties” scan strategy (solid curves) or an “equal relative uncertainties” scan strategy (dashed curves). System parameters other than laser pulse energy are modeled after the potassium lidar described in von Zahn and Höffner (1996) and Lautenbach et al. (2017); see text for details. (b) Same as panel (a), but for a potassium layer temperature of 200 K. (c, d) Same as (a, b), but for line-of-sight wind biases.

$$\Delta T = T_s - T_{ns} \quad (9)$$

$$\Delta v_{av} = v_{av,s} - v_{av,ns} \quad (10)$$

where Δn denotes the bias on parameter n , and the subscripts s and ns denote that the parameters were inferred from simulation results accounting for or neglecting saturation effects, respectively. Thus, a negative bias implies an underestimate of the respective parameter.

We performed the above simulation for a range of laser pulse energies up to 100 mJ, otherwise using the lidar system parameters from Table 2, with the increased beam divergence of 270 μrad . The results are shown in Figure 6, for a potassium temperature of 150 K (left column) and of 200 K (right column). The “equal relative uncertainties” scan strategy (dashed curves) results in general in smaller biases than the “equal absolute uncertainties” approach (solid curves), and the assumption of a Lorentzian beam profile (orange curves) results in smaller biases in general than the assumption of a Gaussian profile (blue curves). In all cases, the biases on

line-of-sight wind start to become significant for pulse energies around ~ 10 mJ and can exceed 10 m/s; depending on scan strategy and beam profile, the temperature biases can also be significant. It is important to note that these claims are particular to a potassium resonance lidar with the given system parameters. Saturation effects for sodium, iron, and helium resonance lidars are discussed in Geach and Kaifler (2026).

These biases arise primarily due to the asymmetry of the spectrum of saturation, which in turn arises due to the differential strength of the individual hyperfine transitions, as detailed in Section 2. The wind and temperature biases that would be expected based on the effective rather than the intrinsic relative line strengths are shown in Figure S2 of Supporting Information S1 and have in general significantly lower magnitudes than the biases shown here, particularly in the case of winds. The predicted temperature biases in Figure 6 are consistent with the results of Höffner and Fricke-Begemann (2005), who compared temperature measurements made simultaneously by co-located potassium and iron lidar systems and found agreement within the measurement uncertainties. Given that their scan strategy approximated the “equal relative uncertainties” approach, the resulting temperature bias is expected to be small.

5. Discussion

The saturation model presented in Geach and Kaifler (2026) is capable of reproducing the degree of saturation observed by Lautenbach et al. (2017). Furthermore, it predicts that attempts to fit measured spectra of the scattering cross-section while neglecting saturation effects will be imperfect; model predictions of the resulting residuals agree well with observations in both the spectral pattern of the residuals and the approximate magnitude, in particular under the assumption of a Lorentzian laser profile.

As seen in Figure 6, a robust prediction of the saturation model is the presence of negative saturation-induced biases in the line-of-sight wind. A straightforward test of this prediction would be to make measurements with a system such as the one described in Lautenbach et al. (2017) with an absolute wavelength reference, so that line-of-sight winds could be retrieved. According to the model, a persistent negative line-of-sight wind would be observed, regardless of laser line shape or scan strategy. Unfortunately, for the measurements by Lautenbach et al. (2017), no such absolute wavelength reference was used, so this clear-cut test was not possible. Instead, we examined the relative changes in line-of-sight wind as a function either of altitude or of lidar signal (as determined by the strength of the Rayleigh returns from an altitude of 40–50 km). Since the laser energy concentration at the potassium layer decreases with increasing altitude or decreasing laser power, one would expect a positive correlation between retrieved wind speed and altitude and a negative correlation between wind speed and Rayleigh signal. Though these tests showed weak evidence of the expected trend, the noise in the measurement rendered the tests inconclusive.

A further prediction of the model is that the magnitude of the residuals discussed in the previous section would depend on the strength of the laser beam reaching the potassium layer (although this test is not unique to the saturation model applied here—any plausible description of saturation would produce the same prediction). We attempted to test this by comparing the measurements shown in Figure 5 (for which the lidar signal was relatively good) with measurements for which the lidar signal was $\sim 60\%$ of the maximum signal. If the reduction in Rayleigh signal was due to increased atmospheric absorption or reduced laser power, then the observed degree of saturation (and the magnitude of the observed residuals) would be expected to be smaller. However, this attempt was unsuccessful, as any change in the magnitude of the observed residuals is obscured by an increase in measurement noise, as shown in Figure 7 for two such nights with weaker Rayleigh signal. Though the average observed residuals are still roughly consistent with the model residuals, they are also consistent with zero; thus, any attempt to quantify the amplitude of the resulting “W” pattern will have prohibitively high uncertainty for the purposes of correlating the degree of saturation to the strength of the Rayleigh signal.

Furthermore, the above tests are complicated by uncertainty as to the causes of the reduction in signal and their respective effects on saturation: saturation would scale roughly linearly with fluctuations in laser power and as the square root of fluctuations in atmospheric transmission (since the observed signal is proportional to the two-way transmission of the atmosphere, but saturation depends only on the one-way transmission) but would depend only weakly on fluctuations in signal due to beam/field-of-view mismatch and not at all on fluctuations in signal due to variable receiver efficiency (e.g., due to cleaning or fogging over of the primary telescope mirror).

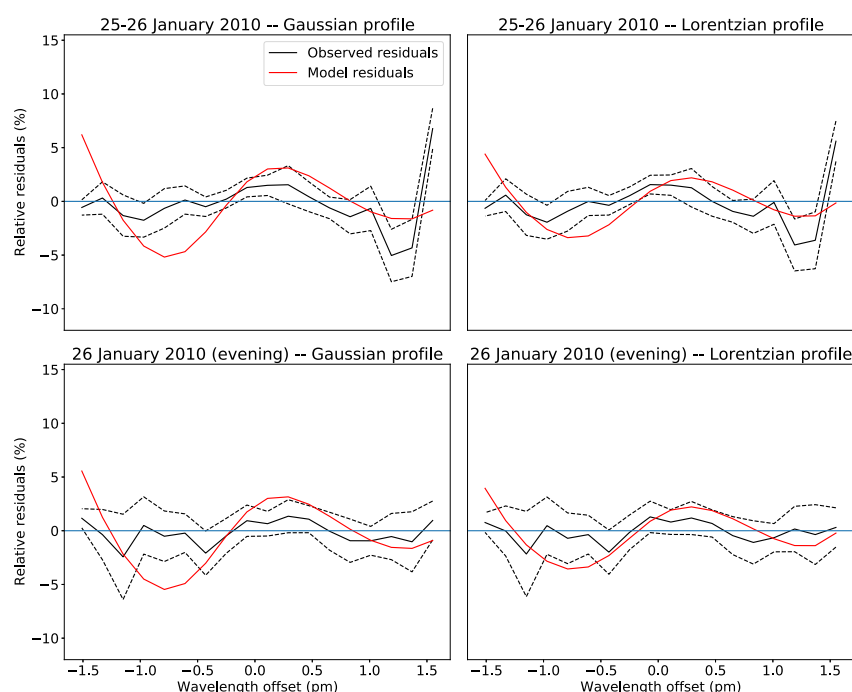


Figure 7. Same as Figure 5, but for two dates with weaker Rayleigh signal: 25–26 January 2010 (top row, 9.5 hr of data) and the evening of 26 January 2010 (bottom row, 5.9 hr of data). As before, a laser with a FWHM linewidth of 20 MHz was assumed, either with a Gaussian profile (left column) or a Lorentzian profile (right column).

The above discussion highlights an important point for estimating saturation. The degree of saturation depends on a large set of parameters, many of which are in general only poorly known. An accurate estimate of saturation requires knowledge of the pulse-to-pulse energy, linewidth, and line shape of the laser, the transmission of the atmosphere, and the divergence of the laser beam (including increases to the divergence due to atmospheric seeing), to highlight a few. Although it is in principle possible to calculate and correct for the effects of saturation, uncertainties in the above parameters would lead in turn to uncertainties in retrieved temperatures and winds; the only reliable way of avoiding saturation-induced biases is an instrumental design that avoids saturation.

6. Summary and Conclusion

Since it was first identified as a potential issue by Megie et al. (1978), saturation has taken on increasing importance, due to the trend toward higher laser energy concentrations (through increases in laser power and decreases in laser linewidth and beam divergence) in modern resonance lidar systems. However, models of saturation have not kept pace with instrumental development; the instrument described in Lautenbach et al. (2017) suffered from significant saturation that remained so far unexplained. Here, we demonstrate that the observed degree of saturation, approximately 70%, is consistent with the model of saturation presented in Geach and Kaifler (2026).

The model predicts further that an idealized lidar system, with system parameters based on the instrument described in Lautenbach et al. (2017), would suffer from a significant saturation-induced bias, leading to an underestimate of inferred temperatures potentially approaching 20 K, though the magnitude of the bias depends on the precise form of the laser line shape and on the scan strategy employed. A bias on line-of-sight wind speed would also arise, potentially exceeding 10 m/s for all laser line shapes and scan strategies. In principle, a scan strategy could be employed that minimizes the saturation-induced biases in the wind and temperature measurements, but such an optimization would rely on perfect knowledge of parameters (such as atmospheric transmission, atmospheric seeing, pulse-to-pulse laser line shape and pulse energy, etc.) that are only imperfectly knowable. Thus, these results highlight the importance of an instrument design that minimizes saturation effects, which is only possible when saturation effects can be reliably estimated. To that end, the code for the saturation calculator discussed here is available at Geach (2026) and may be freely used or adapted.

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Availability Statement

The potassium lidar data and code for the saturation calculator used here have been made publicly available (Geach, 2026).

Acknowledgments

The authors thank Michael Gerding for retrieving the measurement data from the archive and Frank Heymann for his suggestions of improvements to this manuscript. Open Access funding enabled and organized by Projekt DEAL.

References

- Bowman, M. R., Gibson, A. J., & Sandford, M. C. W. (1969). Atmospheric sodium measured by a tuned laser radar. *Nature*, 221(5179), 456–457. <https://doi.org/10.1038/221456a0>
- Chu, X., & Papen, G. (2005). Resonance fluorescence lidar for measurements of the middle and upper atmosphere. In T. Fujii & T. Fukuchi (Eds.), *Laser remote sensing* (pp. 179–432). Taylor and Francis Group.
- Felix, F., Keenliside, W., Kent, G., & Sandford, M. (1973). Laser radar observations of atmospheric potassium. *Nature*, 246(5432), 345–346. <https://doi.org/10.1038/246345a0>
- Geach, C. (2026). Saturation calculators. <https://doi.org/10.5281/zenodo.20286875>
- Geach, C., & Kaifler, B. (2026). Saturation effects in narrowband resonance lidar measurements, Part 1: Theoretical consideration of sodium, iron, and helium lidar systems. *Journal of Geophysical Research: Space Physics*, <https://doi.org/10.1029/2026JA035269>. (Unpublished manuscript).
- Höffner, J., & Fricke-Begemann, C. (2005). Accurate lidar temperatures with narrowband filters. *Optics Letters*, 30(8), 890–892. <https://doi.org/10.1364/OL.30.000890>
- Kramida, A., Ralchenko, Y., & Reader, J., & NIST ASD Team. (2024). *NIST Atomic Spectra Database (ver. 5.12)*, [Online]. National Institute of Standards and Technology. Retrieved from <https://physics.nist.gov/asd>
- Lautenbach, J., Höffner, J., Lübken, F.-J., Kopp, M., & Gerding, M. (2017). Ten-year climatology of potassium number density at 54°N, 12°E. *Journal of Atmospheric and Solar-Terrestrial Physics*, 162, 172–177. <https://doi.org/10.1016/j.jastp.2017.06.010>
- Megie, G., Bos, F., Blamont, J., & Chanin, M. (1978). Simultaneous nighttime lidar measurements of atmospheric sodium and potassium. *Planetary and Space Science*, 26(1), 28–35. [https://doi.org/10.1016/0032-0633\(78\)90034-X](https://doi.org/10.1016/0032-0633(78)90034-X)
- Papen, G. C., Gardner, C. S., & Pfenninger, W. M. (1995). Analysis of a potassium lidar system for upper-atmospheric wind-temperature measurements. *Applied Optics*, 34(30), 6950–6958. <https://doi.org/10.1364/AO.34.006950>
- Papen, G. C., Pfenninger, W. M., & Simonich, D. M. (1995). Sensitivity analysis of NA narrowband wind-temperature lidar systems. *Applied Optics*, 34(3), 480–498. <https://doi.org/10.1364/AO.34.000480>
- Tiecke, T. G. (2019). Properties of potassium. Retrieved from <https://www.tobiastiecke.nl/archive/PotassiumProperties.pdf>
- von der Gathen, P. (1991). Saturation effects in Na lidar temperature measurements. *Journal of Geophysical Research*, 96(A3), 3679–3690. <https://doi.org/10.1029/90JA02420>
- von Zahn, U., & Höffner, J. (1996). Mesopause temperature profiling by potassium lidar. *Geophysical Research Letters*, 23(2), 141–144. <https://doi.org/10.1029/95GL03688>