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Extending and Merging the Purple Crow Lidar Temperature Rayleigh and Vibrational Raman Climatologies

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Graduate Program in Physics

A thesis submitted in partial fulfillment of the requirements for the degree in Master of Science

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EXTENDING AND MERGING THE PURPLE CROW LIDAR TEMPERATURE RAYLEIGH AND VIBRATIONAL RAMAN CLIMATOLOGIES

(Thesis format: Monograph)

by

Ali Jalali

Graduate Program in Physics

A thesis submitted in partial fulfillment of the requirements for the degree of Masters of Science

The School of Graduate and Postdoctoral Studies
The University of Western Ontario
London, Ontario, Canada

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Abstract

Rayleigh and Raman scatter measurements from The University of Western Ontario Purple Crow Lidar (PCL) have been used to develop temperature climatologies for the stratosphere, mesosphere, and thermosphere using data from 1994 to 2013 (Rayleigh system) and from 1999 to 2013 (vibrational Raman system). Temperature retrievals from Rayleigh-scattering lidar measurements have been performed using the methods by Hauchecorne and Chanin (1980; henceforth HC) and Khanna et al. (2012). Argall and Sica (2007) used the HC method to compute a climatology of the PCL measurements from 1994 to 2004 for 35 to 110 km, while Iserhienrhien et al. (2013) applied the same technique from 1999 to 2007 for 10 to 35 km. Khanna et al. (2012) used the inversion technique to retrieve atmospheric temperature profiles and found that it had advantages over the HC method. This thesis presents an extension of the PCL climatologies created by Argall and Sica (2007) and Iserhienrhien et al. (2013). Both the inversion and HC methods were used to form the Rayleigh climatology, while only the latter was adopted for the Raman climatology. Then, two different approaches were used to merge the climatologies from 10 to 110 km. In the first approach, the climatologies were calculated from the nightly temperature profiles and then merged. In the second approach, a climatology was calculated after merging the nightly PCL temperature profiles. The results show that the temperature climatologies produced by the HC method when using a seed pressure are comparable to the climatologies produced by the inversion method. It is not close to the inversion method when using a seed temperature. The Rayleigh extended climatology is slightly warmer below 80 km and slightly colder above 80 km. There are no significant differences in temperature between the extended and the previous Raman channel climatologies. Among four different functional identities, a trigonometric hyperbolic relation results in the best choice for merging temperature profiles, with an estimated uncertainty of ±0.9 K.

Keywords: Lidar, atmosphere temperature, Rayleigh, Raman, climatology, merging, uncertainties
Acknowledgements

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Chapter 1

Introduction

Most studies on the atmosphere focus on the lowest layer of the atmosphere, called the troposphere, as the troposphere has direct impact on our life by influencing weather systems. The upper atmosphere is also important in the Earth’s life cycle due to effects such as greenhouse effect which have been one of the main concerns in the last few decades. Many observational and theoretical studies indicate that there is a coupling between the different layer of the atmosphere including the lower and upper parts, and it is shown that understanding of the lower atmosphere and the global circulation of the atmosphere requires understanding of the upper atmosphere. As an example, gravity waves produced in the lower atmosphere and then propagate toward the upper atmosphere where they start dissipating and breaking down. Another example of coupling between different layers can be seen in the study of ”global change” in which the increase of temperature in the lower atmosphere results in a strong decrease of temperature in the middle and upper atmosphere regions, and the wave-driven general circulation in the middle atmosphere affects climate in the troposphere. Thus the middle atmosphere plays an important role in understanding of the atmosphere as a whole too [Houghton, 1986], and a careful study of this region beside the upper atmosphere seems essential in the analyses of the lower atmosphere. Driven by this motive, we study the temperature structure of the middle and upper atmosphere regions with the goal of providing a better understanding for these regions.
Through this study, we discuss the data collected by a lidar instrument for a long term (1994–2013) up to 120 km. A lidar provides a high vertical resolution and accuracy which makes it a suitable candidate in the study of such high altitudes.

1.1 The Structure of the Atmosphere

The atmosphere has been divided into four regions based on its structure, temperature, thermodynamics and dynamics. A typical temperature profile in the atmosphere is shown in Figure 1.1. From the ground up, the layers are troposphere, stratosphere, mesosphere and thermosphere. These layers are separated by isothermal regions. Each region of the Earth’s atmosphere is characterized by its temperature and pressure variables with height and the basis for distinguishing between layers is the variation of the temperature profile with altitude. In troposphere which goes up to altitudes of 8 to 16 km (depending on latitude and season), temperature decreases strongly. This region contains about 85% of mass of the atmosphere (Marshall and Plumb, 2007b). The stratosphere is characterized by an increase in temperature with altitude, which is due to ozone heating and absorption of solar UV by ozone. The temperature in this region reaches a maximum near 50 km. On the other side, though the mesopause at about 80 to 90 km altitude, temperature decreases moving up to a minimum at about 90 km in the summer and about 105 km in the winter. The air in the mesosphere is less dense and the atmospheric pressure is very low, averaging around 1 hPa, and only 0.1% of the total mass of the atmosphere is above this level, with the other 99.9% contained below it. Above the mesopause is the thermosphere in which the temperature is very high and variable. In this region, covering from about 80 km to 400 km, there is a warm layer due to $N_2$ and $O_2$ short wavelength UV absorption. In this warm layer, the molecular diffusion is the primary mixing mechanism. Another way to label the regions in atmosphere is by defining of lower, middle, and upper atmosphere. The lower atmosphere refers to the troposphere where most of the data by different instruments are collected from, such as radiosonde. The middle atmosphere includes the stratosphere and
1.1. The Structure of the Atmosphere

mesosphere extending from 10 km to about 85 km. Above the middle atmosphere, the thermosphere layer extends from about 100 km and is known as the upper atmosphere. Conducting measurements of the middle atmosphere is difficult as it is beyond the range of aircrafts and balloons. One of the instruments that can be used to do measurements on the middle atmosphere is lidar. Rayleigh-scatter lidar systems are designed to detect Rayleigh backscattered rays from molecules in the atmosphere, and these systems provide a high temporal and vertical resolutions making them suitable candidates to study the dynamics of the middle atmosphere, gravity waves, planetary waves, climatology and other aspects of the atmosphere.

Figure 1.1: The structure of the atmosphere and the mean temperature profile versus altitude (the U.S. Standard Atmosphere) (Marshall and Plumb, 2007a).
1.2 The Composition of the Earth’s Atmosphere

The Earth’s atmosphere is mainly composed of N₂ (78%), O₂ (21%), CO₂, H₂O, CO, SO₂, etc (a complete description of the composition of the atmosphere can be found in Table 1.1 (Pidwirny, 2008)). Different chemical elements existing in the atmosphere show different spectral properties as it can be seen in the study of scattered light passing through different regions. Depending on the size and composition of a region of the atmosphere energy is absorbed in different wavelengths with different intensity.

<table>
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<tr>
<th>Gas Name</th>
<th>Chemical Formula</th>
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<tr>
<td>Nitrogen</td>
<td>N₂</td>
<td>78.08</td>
</tr>
<tr>
<td>Oxygen</td>
<td>O₂</td>
<td>20.95</td>
</tr>
<tr>
<td>Water</td>
<td>H₂O</td>
<td>0 to 4</td>
</tr>
<tr>
<td>Argon</td>
<td>Ar</td>
<td>0.93</td>
</tr>
<tr>
<td>Carbon Dioxide</td>
<td>CO₂</td>
<td>0.0360</td>
</tr>
<tr>
<td>Neon</td>
<td>Ne</td>
<td>0.0018</td>
</tr>
<tr>
<td>Helium</td>
<td>He</td>
<td>0.0005</td>
</tr>
<tr>
<td>Methane</td>
<td>CH₄</td>
<td>0.00017</td>
</tr>
<tr>
<td>Hydrogen</td>
<td>H₂</td>
<td>24 m</td>
</tr>
<tr>
<td>Ozone</td>
<td>O₃</td>
<td>0.000004</td>
</tr>
</tbody>
</table>

Table 1.1: The composition of the atmosphere.

1.3 Scattering and Absorption Processes in the Atmosphere

In general, there are three major types of scattering processes in the atmosphere involving of atoms, molecules and aerosols. These processes are called Mie, Rayleigh, and Raman scattering. The scattered light through these processes can be either coherent or incoherent.
1.3.1 Elastic Backscattering

The wavelength of backscattered photons in an elastic scattering process is equal to that of incident photons. This wavelength is determined based on the size of molecules and aerosols. Mie scattering occurs if the radius of the particle is much larger than the wavelength of incident photons or the size atom is comparable to the wavelengths. Usually, in the atmosphere, Mie scattering is associated with aerosols whose radii are large. Rayleigh scattering happens when the size of a particle is much smaller than the interacting photon’s wavelength. In the formulation of Rayleigh scattering, it is assumed that the scattering particles are spherical, and their radii are less than 0.2 times the wavelength of the incident radiation. Most of the scattering processes in the atmosphere are elastic processes and the energy and wavelength of the scattered photon from an atmospheric particle is typically equal to that of the incident photon. In fact, in an elastic scattering process when a photon interacts with a particle’s electron, it excites the electron from its initial energy level to an unstable level. The electron in the unstable level decays quickly to its initial energy level emitting a photon with the same wavelength as that of the initial incident photon.

The Rayleigh lidar photon-count profile is usually written (Kovalev and Eichinger, 2004) as

$$\quad N(z) = \frac{\beta n(z)\sigma}{z^2} + B(z) \quad (1.1)$$

With $N(z)$ being the number of counts at an altitude $z$, $B(z)$ being the background counts, $\beta$ standing for the product of a number of system and atmospheric parameters, $n(z)$ standing for the total atmospheric number density at altitude $z$, and $\sigma$ presenting the Rayleigh backscatter cross-section for air which is a function of $\lambda$, wavelength of the scattered light. This formula is derived by assuming that the atmosphere is well mixed and it behaves like an ideal gas system in a hydrostatic equilibrium. Also, the presence of aerosols is neglected to allow only Rayleigh scattering process in the considered volume. $N_2$ and $O_2$ are well mixed gases, chemically inert and their volume mixing ratios are uniform throughout the middle atmosphere. Therefore,
middle atmosphere can be considered a well mixed gas, allowing one to use the above formula in the analyses of the lidar data from this region. When a laser beam with a wavelength $\lambda$ is sent through this region, the particles in the air back-scatter the radiation with a cross-section proportional to $\lambda^{-4}$ up to altitudes of about 100 km. This implies that if one shortens the wavelength of the laser, the Rayleigh lidar photon-count will increase significantly.

1.3.2 Inelastic Backscattering

The second type of the scattering processes is called Raman scattering. Raman scattering is an inelastic scattering phenomena in which a ray of light scatters off a molecule at different wavelengths than the incident ray. In the Raman scattering the incident photon interacts with the electron of the molecule exciting it to an upper stable energy state. The excited electron eventually decays to a lower energy level emitting a photon with a wavelength proportional to $\Delta E / h$ where $\Delta E$ is the energy difference between the excited and final states of the electron and $h$ is the Plank constant. The magnitude of $\Delta E$ varies several orders depending on the type of the interacting energy states. An electron in a molecule has three types of energy states known as electronic, vibrational and rotational states. The electronic energy states are related to the orbital energy of the electrons, the vibrational energy states correspond to vibrations of the nuclei, and the rotational energy states are associated with rotations of the nuclei around its center of mass (Bransden et al., 2000). A transition from one electronic state to another electronic state involves an energy of the order of several eV, whereas a vibrational transition between vibrational energy states results in energies of the order of 0.1 eV. The rotational transitions connecting rotational energy levels are comparatively weaker with energies on the order of 0.001 eV. The change of vibrational or rotational or vibrational-rotational energy states of an electron in inelastic Raman scattering results in a scattered photon with a longer wavelength (Stokes Raman scattering) or a shorter wavelength (anti-Stokes Raman scattering) than that of
the incident photon. In Stokes Raman scattering with

\[ \nu_{out} = \nu_{in} - |\Delta \nu| = \frac{\Delta E}{h}, \]  

(1.2)

the frequency of the scattered light, \( \nu_{out} \), compared to the frequency of incident light, \( \nu_{in} \), is shifted by \( |\Delta \nu| \). In the anti-Stokes scattering, the frequency of the scattered photon is increased by \( |\Delta \nu| \) as

\[ \nu_{out} = \nu_{in} + |\Delta \nu| = \frac{\Delta E}{h}. \]  

(1.3)

In this condition, the electron looses energy to the incident photon by decaying to an energy level lower than its initial energy state.

The shift of frequency (or wavelength) of the incident photon makes it easier to detect a Raman scattering phenomena compared to a Rayleigh scattering one, although the intensity of Raman-scattered beam is much smaller than the intensity of a Rayleigh scattered beam. Knowing the Raman shifts frequency of N\(_2\) and H\(_2\)O molecules in atmosphere can be used to analyze the Raman data from those regions. The Raman lidar can be used to measure atmospheric temperature profiles knowing that the population of energy levels of molecules is given by the Boltzmann’s distribution law, and the intensity distribution within the Raman bands contains information on the temperature in the scattering volume (Weitkamp, 2005). The Purple Crow Lidar (PCL) employs both Raman and Rayleigh scattering techniques to acquire data, and it transmits a laser beam at 532 nm to study the atmosphere in different regions. The Raman lidar is mainly used to collect data from the surface to the altitude of about 35 km, and Rayleigh is used to explore altitudes between 30 to 110 km.

1.3.3 Overview

Variations of the thermal and dynamical structure of the atmosphere layers cause different scattering processes in the different layers of atmosphere. The Purple Crow Lidar (PCL) consists of three channels: Raman, Low Level Rayleigh and High Level Rayleigh channels.
These channels overlap each other in some regions. Atmospheric lidars measure the backscattered photon counts which is proportional to the density in the atmosphere. Different techniques have been suggested to retrieve the temperature from lidar measurements. The first objective of this research is evaluation and comparison of these techniques. In order to investigate these techniques, performing temperature climatologies using each method were chosen. The calculated climatologies using different methods were compared to each other to evaluate each method. Temperature profiles for each lidar’s channels including Raman, Low Level Rayleigh (LLR) and High Level Rayleigh (HLR) are presented in Figure 1.2. Each profile has an overlap area with other profiles. In overlapped regions, the temperature must be identical but there are differences between them. In order to have a single temperature profile for the atmosphere from lidar channels measurement, it is necessary to merge the profiles with each other. In this research temperatures were used to merge the profiles. Figure 1.3 shows the sample merging temperature profile between the PCL temperature profiles. Another way for this is merging the photon count profiles that will explain in section (5.1), though this is not the purpose of this research. Different functions can be used to merge the temperature profiles, where the second objective is finding best function with least uncertainty.

Figure 1.2: PCL temperature profile for three channels for a sample night, (Blue: High Level Rayleigh channel, green: Low Level Rayleigh channel, red: Raman channel)
1.3. Scattering and Absorption Processes in the Atmosphere

Figure 1.3: Merging the temperature profiles for a sample night (Green: Low Level Rayleigh temperature profile, blue: Raman temperature profile, black: merged temperature profile between them)
Chapter 2

Purple Crow Lidar

2.1 Lidar System

In this chapter, we briefly discuss the general structure of a lidar system specifically the Purple Crow Lidar used in this project. A lidar system is a remote sensing system which uses a laser as a source of energy. The short laser pulses which are well collimated offer a better spatial resolution for a lidar system compared to other atmospheric sensors such as radar or sodar. A lidar is generally made of three main sections, a transmitter, a receiver and a detector system. The transmitter has a laser which sends monochromatic, intense beam at one or more wavelengths into the atmosphere. In the atmosphere, molecules and particles backscatter and absorb the laser beam. The receiver, consisting of a telescope, collects the backscattered signal and focuses it on the photodetector. In the photodetector, the amount of backscattered light is measured by transforming it to an electrical signal. In general, there are two types of systems for detecting the backscattered signal. One system uses an analog mode by transforming the amount of backscattered light to a current. Another system employs a digital mode and uses a photon counting system which is based on photon counting mode. The analog mode uses high-speed digitization of the signal from the photodetector. The signal decreases with height squared and signal to noise ratio decreases; therefore, using the analog system maximizes the
the near-field spatial resolution while minimizing the far-field spatial resolution. In contrast, the photon counting mode is required for long-range sounding which returning photons are recorded over long periods of time in comparison to the analog mode (Kovalev and Eichinger, 2004). Photon counting is an effective technique used to detect very low-level light. The methods of processing the output signal of a photomultiplier tube can be broadly divided into analog and digital modes. The photon counting method can detect each pulse and the number of counted pulses equals the signal. This photon counting mode uses a pulse height discriminator that separates the signal pulses from the noise pulses, enabling high-precision measurement with a higher signal-to-noise ratio compared to the analog mode and making photon counting exceptionally effective in detecting low-level light. Computer/recording system for data acquisition contains a digitizer for converting analog to digital signal and records it as a function of distance from the lidar, power supply and cooling system for the laser are the essential parts.

### 2.2 PCL

The Purple Crow Lidar (PCL) was first located at Delaware observatory (42.52 N, 81.23W, 225 m) from 1992 to 2010. In 2010, the PCL was moved to the Environmental Science Western Field Station (43.07 N, 81.33W, 275 m) and since 2012, it is again operational. The PCL comprises of three channels: Raman channel with 532 nm beam to measure the temperature of the upper troposphere and lower stratosphere, digital Rayleigh channel and analog Rayleigh channel to measure temperature in the upper mesosphere and lower thermosphere. A Neodymium: Yttrium-Aluminium-Garent (Nd:YAG) solid state laser is used to produce 532 nm beam for Rayleigh and Raman lidars. At Delaware, the intensity of these pulses was 600 mJ at repetition rate of 20 Hz. After relocating, PCL was upgraded with a more powerful laser, counting electronics, new photomultiplier tubes and physical infrastructure. The new laser has a repetition rate of 30 Hz with 1000 mJ energy per pulse at 532 nm wavelength. First the Nd:YAG laser output passes through collimation lenses and a pre-amplifier, then entering an oscillator with a
10 ns pulse of coherent 1064 nm light. The laser beam wavelength still is at 1064 nm, and we need to convert it to 532 nm. In order to make this change, the laser beam is sent into a doubler which is a crystal of potassium titanyl phosphate (KTiOPO4) or KTP. This crystal is typically used in Nd:YAG at a temperature around 313 K to convert 1064 nm beam into 532 nm. This is the general design used in PCL. The new PCL is improved in some aspects that can be seen in the following table 2.1. This table compares the features of the old and new PCL. All data used in this project are collected by the described PCL from 1994 to 2013.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Delaware observatory</th>
<th>EchoBase observatory</th>
</tr>
</thead>
<tbody>
<tr>
<td>Years of operation</td>
<td>1992-2010</td>
<td>2012-present</td>
</tr>
<tr>
<td>Wavelength</td>
<td>532 nm</td>
<td>532 nm</td>
</tr>
<tr>
<td>Energy</td>
<td>600 mJ/pulse</td>
<td>1000 mJ/pulse</td>
</tr>
<tr>
<td>Repetition Rate</td>
<td>20 Hz</td>
<td>30 Hz</td>
</tr>
<tr>
<td>Laser Average Power</td>
<td>12 W</td>
<td>30 W</td>
</tr>
<tr>
<td>Pulse Length</td>
<td>7 ns</td>
<td>8 ns</td>
</tr>
<tr>
<td>Beam Diameter</td>
<td>27 mm</td>
<td>11 mm</td>
</tr>
<tr>
<td>Beam Divergence</td>
<td>0.2 mrad</td>
<td>0.5 mrad</td>
</tr>
<tr>
<td>Rayleigh Scattering</td>
<td>24 m</td>
<td>7.5 m</td>
</tr>
<tr>
<td>Raman</td>
<td>250 m</td>
<td>24 m</td>
</tr>
<tr>
<td>Water vapour</td>
<td>250 m</td>
<td>24 m</td>
</tr>
</tbody>
</table>

Table 2.1: PCL properties (Wing, 2012)

The new PCL laser requires a significant amount of power approximately (9600 W) in which the electrical energy is converted to light with an efficiency of less than 3% (Wing, 2012). The large amount of heat produced in this process dissipates in 200m underground loops of a cooling system consist of cooling fans. The maximum efficiency of the laser system is at temperatures between 291 to 298 K. Therefore, the laser temperature and the temperature of the room that laser is in use should be within the mentioned range.

### 2.2.1 The Receiver and Detector System

The PCL has taken advantage of a liquid Hg mirror (telescope) instead of glass telescope. The diameter of this telescope is 2.65 m and its focal length is about 5.17 m. This mirror is a rotating dish of liquid mercury of volume 8 L. The signal acquisition unit consists of two sub
units: the lidar signal detectors (photomultiplier tube or PMT) and the detection electronics. A Photomultiplier tubes are typically used in the photon counting mode as a detector in the lidar systems. The detector system consists of photomultiplier tubes along with a multichannel scalar counter which records the number of counts collected at different altitudes. Signal processing methods of photomultipliers tube can be separated into analog and digital modes. The analog photomultiplier current and signal photon counting is combined in one acquisition system. The Licel transient recorder is a data acquisition system that designed for all remote sensing applications where fast and accurate detection of photomultiplier or other electrical signals is required at high repetition rates. Its recorder is consist of different units: a fast transient digitizer with on-board signal averaging, a discriminator for single photon detection and a multichannel scalar combined with preamplifier for both analog and photon counting systems. However the signal part in the high frequency domain is amplified and a fast discriminator detects single photon events above the selected threshold voltage.

Currently, PCL has two PMTs for Rayleigh channel. The new one, labeled as Rayleigh Licel, and old Rayleigh channel labeled as Rayleigh Hamamatsu. The old Rayleigh channel was used for calibration and alignment while testing the linearity of the new Licel system. The analog detection mode is operated to detect intense lidar signals coming from relatively short distances. A transient recorder operating in the analog detection mode is based on an analog-to-digital converter (ADC), which samples and digitizes the lidar signals. The photon counting detection mode is operated under single electron conditions, which usually is used to detect very low intensity lidar signals coming from relatively large distances. When a single photon strikes the photocathode of a photomultiplier tube, photoelectrons are emitted. These photoelectrons are multiplied $10^6$ to $10^7$ times by the cascade process of secondary emission through the dynodes, finally reaching the anode. Single photons are integrated to produce proportional voltage pulses, which are passed by a discriminator to a pulse counter. The schematic of a photomultiplier tube is shown in Figure 2.1.

If we look at the output signal of a photomultiplier tube with an oscilloscope, output pulses
like those shown in 2.2. The incident light intensity and the bandwidth of the output processing circuit are two factors to determine the mode of PMT (Donovan et al., 1993). At high level light, the output pulse intervals are narrow and they overlap each other, producing an analog waveform look like Figures 2.2(a, b). In contrast, in low-level light, the ratio of the AC component in the signal increases and the output signal will be discrete pulses 2.2(c).

If these discrete pulses discriminate, the number of the signal pulses can be counted in a digital mode, the number of counted pulses equals the signal. This method is known as photon counting. The schematic of a photon counting system is demonstrated in Figure 2.3 pulse height discriminator separates the signal pulses from the noise pulses which sends out a
uniform pulse to the counter whenever the input voltage reaches to the discriminator threshold. This system causes high precision measurement even in detecting low-level light.

*Figure 2.3: Schematic of a photon counting system (Donovan et al., 1993)*

Using PMTs has some restrictions in the region where signal levels are low and the responses of the PMT and the pulse discrimination/counting system are linear, since, signal to noise ratio (SNR) approaches 1. In this low-light-level regime, using PMTs for photon counting and obtaining SNR is better than the other detection systems. In the photon counting systems, the incident light intensity is proportional to the output count rate. At low count rates there is a one-output pulse, corresponding to a photon incident and the relation between light intensity and output count rate is linear. But in the at higher count rates, the system can not discriminate and count the pulses with respect to the true count rate which will cause nonlinearity the observed count rate. Depending on the pulse height in the discriminator and the proximity of pulses the overlapping of pulses (pulse pileup) can occur. If two pulses or more have overlap with each other while they are above threshold level, they might count as a one pulse causing a pulse loss \(^2\text{4}(A)\). In other hand, if two pulses or more have overlap with each other and they are below the threshold level, it is possible for them to sum together, causing the height pulse to reach the discriminator level, counting as a one pulse \(^2\text{4}(B)\). In our lidar (PCL), we encounter wide a range of signal levels from very weak from lower thermosphere to very strong from
upper troposphere. The pile up effect causes a loss of a few kilometres from the bottom of each channel.

Figure 2.4: Pulse pile up effect: A) losing pulse; B) gaining pulse

(Donovan et al., 1993)

2.3 Lidar Equation

In the previous sections, the scattering process in the atmosphere and general structure of lidar were described. In this section, we talk about lidar equation which is a mathematical relation between the number of backscattered photons detected by lidar and the measurable quantities such as altitudes, etc. The lidar equation is derived based on three assumptions which are the following:

1) It is assumed that there is only single scattering events from each photon.
2) The laser pulse length is shorter than the recording time in an altitude bin.
3) The density of the atoms or molecules that backscatter the radiation beam in the altitude interval $\Delta z$ is constant.
Based on these assumptions, the lidar equation takes the following form (Measures, 1984):

\[
N(z) = \xi_{\text{sys}} \cdot \tau_{\text{emitted}}(z, \lambda) \tau_{\text{return}}(z, \lambda) \cdot O(z) \frac{P_{\text{laser}}}{h_{\text{laser}} \lambda_{\text{laser}}} \cdot \sigma n(z) \cdot A \frac{1}{4\pi z^2} \cdot \Delta t \cdot \Delta z + B
\] (2.1)

with \( N \) being the number of returned photons which are detected by lidar, \( z \) being the altitude above the detector, \( \xi_{\text{sys}} \) indicating the system specific receiver efficiency, \( \tau_{\text{emitted}}(z, \lambda) \) showing the transmittance of the photons through the atmosphere, \( \tau_{\text{return}}(z, \lambda) \) standing for the return transmittance of the photons through the atmosphere, \( O(z) \) being the overlap function of the receiver field of view, \( \frac{P_{\text{laser}}}{h_{\text{laser}} \lambda_{\text{laser}}} \) representing the laser power, \( \sigma \) indicating the scattering cross section of the target, \( n(z) \) standing for the number density of scatterers in the atmosphere, \( A/(4\pi z^2) \) presenting the effective area of the primary telescope, \( \Delta t \) and \( \Delta z \) being respectively the temporal integration for data collection and the spatial range over which photons in a bin are integrated and finally \( B \) indicating the background counts. The above equation is the general form of the lidar equation used for all scattering types. It can be shown that depending on the type of the scattering event considered, this equation can take a simpler form. For instance, in a Rayleigh scattering event, the transmittance can be assumed to be a constant while for a Raman scattering event the transmittance differs by the wavelength of the backscattered photon and it is required to consider aerosol cross section. The background noise and dark counts can be found by taking the average of the measured counts between 120 and 147 km and subtracting it from the data (Sica et al., 1995). After subtracting the noise, if we consider all atmospheric parameters in the lidar equation to be constant, the lidar equation reduces to

\[
n(z) = C(N(z) - B(z))(z - z_0)^2
\] (2.2)

where \( C \) is a constant standing for a combination of all the constants occurring in the simplified lidar equation and \( B(z) \) is the background count due to different radiation sources other than the lidar laser.
2.4 Photon Count Profiles

In this section, the procedures that have been implemented on raw photon counts are discussed including the pre-processing steps and corrections that are applied to the raw lidar signals before using them.

2.4.1 Dead Time Correction

The first correction applied to the lidar photon counting measurements is called dead time correction. The detector for the lidar requires a certain amount of time to record and process a single photon counting event. If a second photon arrives during that interval of time the detector will not record it. This waiting time for a detector to discriminate and process two separate events is referred to as ”dead time”. Dead time may be due to counting electronics or limitations of the processing parts of the detector. The arrival times of photons are random, therefore there are always some photons that arrive within the dead time and are not counted. This oftenly happens at high-count rates and the resulting photon count signal becomes weaker than its true pulse. In order to account for those photons, a dead time correction is required. In the data analyses of atmosphere profiles, this correction is more important in the lower altitudes where the rate of photon counting events is high compared to the higher altitudes.

There are two methods to determine the true number of events and as a result a counting system are generally classified as paralyzable and nonparalyzable [Donovan et al., 1993]. In a paralyzable system, any event within the dead time is not recorded but the dead period is extended after a lost event. In this system, the sampling time is longer than \( \tau \) and the true count rates obey Poisson statistics. One can write the following relation:

\[
N = S \exp(-S \tau) \quad (2.3)
\]

between the mean observed count-rate \( N \) and the mean true count-rate \( S \) in a paralyzable system [Donovan et al., 1993]. In the above relation, \( \exp(-S \tau) \) is the Poisson probability
function indicating that no counting events occurs within the dead time. In a non-paralyzable
detector system, any counting event which occurs during the interval $\tau$ following the detection
is not recorded and does not effect the duration of the dead time too. The statistical equation
used in a non-paralyzable detector system to relate the mean observed and the mean true is:

$$N = \frac{S}{1 + S\tau}$$

In both systems, the given relations between the observed and true quantities are valid for the
low-count rates but fail when the term $S\tau$ becomes larger than one. In the PCL, all the three
channels of Raman, Low Level Rayleigh, and High Level Rayleigh are digital. At the bottom
of the Rayleigh channels the count-rate is very high and saturation occurs, while at the top of
the channels the count rate decreases. The saturation prevents accurate measurements at the
bottom, and a filter can be used in front of the Rayleigh PMT to extend the range of photon
counting to moderate this condition. The Low Level Rayleigh channel was used to record
data from 25 to 50 km to increase the accuracy of the measured Rayleigh temperatures at the
lower altitudes while the High Level Rayleigh channel was operated to record data from 35 to
110 km.

2.4.2 Nonlinearity Correction

The signal recorded from the stratosphere backscatter is weaker than the true signal because
of the photomultiplier paralyzation and pulse pile-up effects. The nonlinear correction should
be applied to the raw-count profiles due to photomultiplier tube nonlinearity at high count rates
(in the stratosphere) because of variation in photomultiplier gain with time. For finding the
correction, light-emitting diode (LED) have been used as a source of light similar in intensity
to the sky returns signal. Rayleigh scatter measurement using neutral density filter have also
been used, but the results are consistent [Sica et al., 1995]. For finding the correction curve,
each of the sets of data is initially averaged for several hours each nights and then background is
removed from each profile. However, the background is quite small. Then the count rate using
the neutral density filter is scaled to the level of the unfiltered count rates. By dividing the
unfiltered data by the filtered data at 30 km, the multiplication factor is determined and the 5th
order polynomial is fitted to the scaled filtered counts. The critical signal for PCL is 2.6 MHz,
which the correction becomes significant above this count rate (Sica et al., 1995). Using this
value (2.6 MHz), we could find the critical height for each night where is the altitude that below
it the correction is large. Figure 2.5 shows schematic of this point when the measurements
begin to deviate from the dotted line that indicates the linear relation between output and input.
The error bars in the curve are ±1σ standard deviation of the variation of the 12 calibration
runs used to determine the correction.

![Figure 2.5: Non-Linear correction curve for Rayleigh channel of PCL. Raw signal is on the
x-axis while the corrected signal is on the y-axis (Sica et al., 1995).](image)

Formula 2.5 has been applied to convert the lidar properties to the photon count signal.

\[
N(Hz) = \frac{c}{2 \times \text{laser(rate)} \times dt \times dz}
\]
2.5. Photon Count Uncertainty

In this formula \( dt \) is bin width which PCL based on the time to convert it to altitude. For Delaware observatory: \( dt \) is 1 min, laser rate is 20Hz, \( dz \) is 24m. For EchoBase observatory: \( dt \) is 1 min, laser rate is 30 Hz, \( dz \) is 7.5 m. It is necessary to mention that, because in this thesis co-add time and co-add height are used for retrieving temperature from lidar photon count, \( dt \) in this formula is time of operation for each night and \( dz \) is 1008 m. Then based on critical signal (2.6 MHz), the corrected photon count is found, using formula \( \text{CriticalN} = 2.6 \times 10^6 / N(\text{Hz}) \) and then from that, the corrected height is found corresponding the critical photon count. This critical height, which is special for each individual night, represents the altitude that below which, the photomultiplier has saturated and the photon count is nonlinear and above which the non-linear correction is applied to photon count profile.

2.5 Photon Count Uncertainty

Lidar measurements such as other empirical results include two types of uncertainty which are known as systematic uncertainties and random uncertainties. The systematic uncertainties are originated from different assumptions in defining parameters or derivation of formulas such as assumption about accuracy of gravity with altitude, using hydrostatic equilibrium, or assuming that the atmosphere behaves like an ideal gas. The uncertainties such as signal offset remaining after subtracting background component of the lidar measurements or imprecise selection of the particulate backscatter-to-extinction ratio are also categorized as systematic uncertainties [Kovalev and Eichinger 2004]. The random uncertainties are statistical uncertainties related to photon counting process and they can be characterized by Poisson distribution. In this project, we are only focused on systematic uncertainties due to the photon count profiles and merging them, the statistical uncertainties in the process of retrieving temperature from lidar measurements, and in merging profiles from different channels.

In a photon count profile, the two main uncertainties are: nonlinear count correction uncertainty and statistical uncertainty related to the photon counting process. The non-linear cor-
rection is large at the bottom of each channel’s profile where the counts rate are high. Figure 2.6 shows the raw-count profile from PCL in the Low Level Rayleigh channel. The region this profile describes is about 25 km to the top, and it can be seen that in higher altitudes the signal to noise ratio is smaller. This is because the backscattered signal with density, exponentially decreases with height while the background signal remains constant in each scan, therefore causing the signal-to-noise ratio to decrease dramatically at the top. Averaging the pulses or co-adding them is often used to increase the good range of the system in which the signal-to-noise ratio is large. The averaged (or co-adding) profiles have larger signal-to-noise ratio over wider range. The co-adding can be done in the time or the bins. The averaging method also has this deficiency causing it to decrease the resolution while increasing the signal-to-noise ratio (Kovalev and Eichinger 2004).

The Figure 2.7 shows the co-added corrected photon count for Low Level Raleigh channel in the range of 25 km to 28 Km where the non liner correction is maximum.

![Sample co-raw PCL photon count profile for LLR channel.](image)

In contrast to random uncertainties, the statistical uncertainties are minimum in the mentioned range (25-28 km). Therefore, in lidar measurements which are based on photon counting, the statistical uncertainty is governed by Poisson distribution, and the standard deviation
of number of counts is given by

\[ \sigma = \frac{\sqrt{N}}{N} = \frac{1}{\sqrt{N}} \]  

(2.6)

which is the standard deviation of a random process. The above formula indicates that when the number of counting \( N \) is higher, the statistical uncertainty becomes smaller. This can be easily seen in the uncertainty measurements of each profile where the statistical uncertainty is large at the top of the profile where the number of counts is small, while the uncertainty is small at the bottom where \( N \) is large. The Figure 2.8 illustrates the temperature profiles from different PCL channels with their statistical uncertainties. For each profile the highest statistical uncertainty exist at the top.

2.6 Database and Data Selection

The database for the temperature measurements includes three channels; High Level and Low Level Rayleigh channels in which the measurements are conducted since 1994 to the present, and Raman channel with data collected from 1999 to the present except for a few periods that the instrument was down. The lidar system operates during the night when the background light is minimum. The start and stop times are set manually for the operating
system each night. The average operating time is around 5.5 hours per night. There are several procedures that need to be carried out before collecting data by PCL. One of these procedures which is the last step of the preparation of the PCL is the centering of the laser beam on the mirror and aligning the beam angel to get the maximum signal. The oscilloscope program is used to maximize the signal by adjusting the laser beam. It might be required that the laser be shut down while the data is collected, which could happen for any reason such as strong environmental light affecting the precision of the signal, however more likely is because of clouds. During these occasions, the PCL continues recording the signal, but this part of the data are not useful and must be eliminated. Therefore, the first step in the analyses of the raw data is to mark down good and bad lidar photon counts for each profile. Currently, we use a software package written by the lidar group called Picon to process the PCL raw data (Doucet 2009). Picon has a graphical tool that contains a set of standard plots for each night. These plots can be used to examine visually the raw-count scans with the standard profiles (Figure 2.9). As the density decreases exponentially with altitude ($\rho = \rho_0 e^{-(Z/H)}$), the photon counts change with altitude should be logarithmic. Before the temperatures can be used for climatology, it is necessary to separate the good data from the bad one. In Picon, this is done

Figure 2.8: Sample PCL temperature profiles from all channels, Blue: High Level Rayleigh channel, Green: Low Level Rayleigh channel, Red: Raman channel.
using the standard density profile shape in the atmosphere, signal strength and background, and consequently each raw-photon count profile is marked as a 'good scan' or 'bad scan'.

![Figure 2.9: Marking good and bad minute PCL photon count profiles using Picon software.](image)

**2.7 Digital Filter**

After processing the raw photon counts profiles and data selection, the temperature profiles can be retrieved from the lidar measurements. The temperature retrieval procedure is explained in details in the next chapter. In the climatology procedure, a digital filter called 3’s and 5’s filter is used for smoothing the individual temperature profiles \[\text{[Argall and Sica, 2007]}\]. In the lidar data analyses, various types of digital filters are used among which are 3’s and 5’s filters. A simple approach to smoothing data is taking the average of data points. In this case, if a set of noisy raw data is shown by \([y_1, y_2, ..., y_N]\) and \((y_k)_s\) is an array of smoothed data, then \((y_k)_s\) which indicates the average of an odd number of consecutive \(2n + 1(n = 1, 2, 3, \ldots)\) points of the raw data is given by:

\[
(y_k)_s = \frac{\sum_{i=n}^{i=n} y_{k+i}}{(2n + 1)}. \tag{2.7}
\]

The odd number \(2n+1\) is generally used to define the filter width. A better approach to smoothing data is the least squares in which a polynomial is fitted to a small number of consecutive...
data points, and then the central point of the fitted polynomial curve is set as the new smoothed data point. Savitzky and Golay showed that a set of weighting coefficients known as convolution can be used to perform the smoothing operation \cite{Savitzky:1964}. Applying these weighting coefficients is equivalent to fitting data to a polynomial equation. In the data analysis of PCL, we used seven data points for the temperature filtering purpose. The convolution coefficients of this seven-point filter are \( y_n = \frac{1}{15} [12 3 3 3 2 1] \). These coefficients in the case of using only a three-point filter modify to \( y_n = \frac{1}{3} [1 1 1] \) and for a five-point filter, they become \( y_n = \frac{1}{5} [1 1 1 1 1] \). Smoothing by using only 3-point results in a poor filtration with sharp points in some parts of the plot, whereas using 5s improves the filtration slightly. Using both 3s and 5s has a better smoothing results that even the sharpening areas too \cite{Bandoro:2012}. This low-pass digital filter removes high frequencies from the signal.
Chapter 3

Temperature retrieval methods

In Chapter 2 we discussed the basics of lidar beside the pre-processing procedure and corrections made on the raw-count profiles. In this chapter, we review the algorithms for retrieving temperature from measurements corrected photon-count profiles. There are two methods for retrieving temperature from lidar measurements, these methods are called the conventional method and the inversion method. Each approach has its own deficiencies and benefits.

3.1 Conventional Method

When the pressure gradient of an air parcel in the atmosphere is in balance with its gravitational force, the atmosphere is in the hydrostatic equilibrium, and it is dynamically and thermally stable. The hydrostatic equilibrium equation can be expressed as

\[
\frac{dp}{dz} = -\rho(z)g(z)
\]

(3.1)

where \(P\) is the atmospheric pressure, \(\rho\) is the density and \(g\) is the gravitational acceleration of the earth at an altitude \(z\). We can also assume that the atmosphere behaves like an ideal gas.
system and write the ideal gas law as:

\[ P(z) = \frac{R \rho(z) T(z)}{M} \quad (3.2) \]

with \( R \) being the ideal gas constant, \( T(z) \) being the temperature at an altitude \( z \), and \( M \) standing for the mean molecular mass of air which is usually considered as a constant within the range of 30 to 100 km. Using the hydrostatic equilibrium, the ideal gas law and the reduced lidar equation \[2.2\] we can find a relation between observed lidar output and the temperature at each altitude in the lidar range. This method was first proposed by Hauchecorne and Chanin (henceforth, the HC method) in 1980, and is also known as the conventional method. Using equations \[3.1\] and \[3.2\] one can derive the equation

\[ \frac{dp}{p} = \frac{M g(z)}{R T(z)} dz \quad (3.3) \]

using the ideal gas law and the hydrostatic equilibrium equation, this equation can be integrated from \( z - \frac{\Delta z}{2} \) to \( z + \frac{\Delta z}{2} \) for a layer with thickness \( \Delta z \) as following

\[ \log\left(\frac{P(z_i + \frac{\Delta z}{2})}{P(z_i - \frac{\Delta z}{2})}\right) = - \int_{z_i - \frac{\Delta z}{2}}^{z_i + \frac{\Delta z}{2}} \frac{M g(z)}{R T(z)} dz. \quad (3.4) \]

The resulting relation is a function of temperature. Hauchecorne and Chanin followed the same procedure and derived the above equation. Then they assumed that the temperature is constant in each layer with thickness \( \Delta z \) and simplified the above relation to express the temperature as

\[ T(z_i) = \frac{M g(z_i) \Delta z}{R \log\left(\frac{P(z_i - \frac{\Delta z}{2})}{P(z_i + \frac{\Delta z}{2})}\right)}. \quad (3.5) \]
One can also use the hydrostatic equilibrium equation to express the pressure for each layer upon downward integration as

\[ P(z_i + \frac{\Delta z}{2}) = P(z_n + \frac{\Delta z}{2}) + \sum_{j=i+1}^{n} \rho(z_j)g(z_j)\Delta z, \quad (3.6) \]

and

\[ P(z_i - \frac{\Delta z}{2}) = P(z_i + \frac{\Delta z}{2}) + \rho(z_j)g(z_j)\Delta z \quad (3.7) \]

where the term \( P(z_n + \frac{\Delta z}{2}) \) is the pressure at the \( n^{th} \) layer. In these equations, the atmospheric density profile \( \rho(z_j) \) can be obtained from lidar measurements using the lidar equation discussed in Chapter 2.

In order to integrate the pressure relation from the top to bottom, it is necessary to know the value of the seed pressure at the top. Because the temperature and density measurements in the thermosphere have large fluctuations, the initial guess of the pressure at the top has a large uncertainty, and this uncertainty will be carried through the computation process of retrieved temperatures in lower altitudes. The seed pressure is usually obtained from other atmospheric models such as CIRA model and is used in the computation of temperature in this method. In Figure 3.1, the pressure integration in the conventional method for retrieving the temperature is illustrated by starting the integration from the highest altitude downward using the hydrostatic equilibrium principle. The procedure is started by using initial value for the seed pressure at the top and, as mentioned before, this initial value can lead to large uncertainties in the temperature profile of the lower layers. The starting point at the top for Rayleigh channel for the PCL is set between 100 to 110 km, and the corresponding pressure is obtained from the CIRA model. Because of the uncertainty in the value of seed pressure, the uncertainty of retrieved temperatures is large for the first 15 km below the highest altitude. This value drops rapidly at altitudes 20 km from the top (Chanin and Hauchecorne, 1984). Therefore, it is common to remove the first 10 to 15 km from the temperature profiles in order to achieve more accurate results. However, we lose valuable information on the top layers, and this is
Figure 3.1: The conventional method of downward integration of pressure from the highest altitude for temperature retrieval (Bandoro, 2012).

the a disadvantage of this method. The main disadvantage of this technique is the assumption about seed value at highest layer. If we want to extend our results to include an extra 10 km on the top, we need to use another lidar whose power-aperture is increased by a factor of four and this is not an economical solution (Khanna et al., 2012). Another drawback of the conventional method is the assumption of constant temperature in the atmospheric layers. This assumption results in regions with sharp temperature gradients near temperature inversion regions such as the stratopause and the mesopause (layers in which the temperature trend switches from a positive slope to a negative one and vice-versa). The algorithm described in this section can also be initiated by choosing a "seed temperature" instead of a "seed pressure" at the top of the atmosphere (Gardner et al., 1989). Considering hydrostatic equilibrium in a region between a lower level specified by \((z_i, T_i, P_i)\) and the top observational level specified by \((z_0, T_0, P_0)\), one can write

\[
\int_{P_i}^{P_0} dp = -\int_{z_i}^{z_0} \rho(z) g(z) dz. \tag{3.8}
\]
3.1. Conventional Method

From the ideal gas law, we can also write

\[ P_i = \rho_i R T_i / M \]  \hspace{1cm} (3.9)

\[ P_0 = \rho_0 R T_0 / M \]  \hspace{1cm} (3.10)

with \( T_0 \) being the seed temperature at the top of the observational range. By substituting the results from the ideal gas law into Eq. 3.8, one can derive the following relation for the temperature

\[ T_i = T_0 \frac{\rho_0}{\rho_i} + \frac{M}{R} \int_{z_i}^{z_0} \frac{\rho(z) g(z)}{\rho(z_i)} \frac{\rho(z_i)}{R \rho_i} \frac{d\rho}{g(z)} \]  \hspace{1cm} (3.11)

which is in terms of \( T_0 \).\(^1\) This equation can be also rewritten in terms of the seed pressure as

\[ T_i = P_0 \frac{M}{R \rho_i} + \frac{M}{R} \int_{z_i}^{z_0} \frac{\rho(z) g(z)}{\rho(z_i)} \frac{d\rho}{g(z)} \]  \hspace{1cm} (3.12)

In both equations 3.11 and 3.12 the second term on the right hand side is independent of the seed value of either temperature or pressure, and it is the first term in which the uncertainty of the seed value can result in possible errors in the calculations. Seed values consist of true value plus some uncertainty.

\[ P_0 = P_{true} + \Delta P, \]  \hspace{1cm} (3.13)

\[ T_0 = T_{true} + \Delta T \]  \hspace{1cm} (3.14)

The uncertainty in the temperature measurements can be determined using:

\[ \Delta T = \frac{M \Delta P}{R \rho_i}, \]  \hspace{1cm} (3.15)

\(^1\)It is also necessary to point out that in the above equations the value of \( T_0 \) and \( \rho_0 \) are obtained from other atmospheric models but the \( \rho_i \) is acquired from the lidar constant which is found by normalizing to a model.
in which a direct relation between the pressure uncertainty and the temperature uncertainty can be seen. The Eq. 3.15 also indicates an inverse proportionality between the density and uncertainty as the density ($\rho$) decreases the $\Delta T$ increases. For this reason, in the conventional method, the results for the top 10-15km are disregarded as the density is smaller in those altitudes and consequently $\Delta T$ is significant. In this way, we lose important information about the upper atmosphere. One solution for this deficiency of the conventional method, is to integrate the pressure profile upward instead of downward. In the upward integration method, the seed pressure and temperature, which are defined at the bottom (30–35km), can be measured accurately using a variety of methods. Therefore, using this method will decreases the uncertainties. In [Khanna et al. (2012)], the upward integration was used to retrieve the temperature profiles, but it was shown that these profiles quickly start diverging at altitudes of about 50km. The reason for this malfunction can be seen in the hydrostatic equilibrium equation 

\begin{equation}
(P(z_i) = P_0 - \sum_{j=1}^{i} \rho(z_j)g(z_j)\Delta z)
\end{equation}

in which using the pressure at the bottom ($P_0$) leads to negative values for the pressure and divergent in the profiles. In [Khanna et al. (2012)], another solution called the Grid search method was proposed for the mentioned problem in the conventional method and comprehensive details on this method was reported in [Khanna (2011)]. In the following section, we briefly discuss the inversion method.

### 3.2 Inversion Method

In this section the summary of Grid search or inversion method is presented based on the work [Khanna et al. (2012)]. In the inversion or global optimization method, a parameter that is not directly measured can be calculated from an existing relationship between directly observed data and the parameter which is sought. This relationship can be shown by the forward model of the system:

\begin{equation}
F(m) = d
\end{equation}
where \( \mathbf{d}_{N \times 1} \) and \( \mathbf{m}_{N \times 1} \) respectively indicate the vector of observed data and the vector of the unknown parameter. The matrix \( \mathbf{F} \) represents the forward model. The inversion method is an optimization scheme that uses an iterative approach to estimate the true value of parameters by starting from an initial guessed value of the parameter vector \( \mathbf{m} \) in equation (3.16) and proceeding by updating the parameters with their improved values step by step until it reaches the best estimate for \( \mathbf{d} \). In this iterative approach, the difference between the estimated and true value of \( \mathbf{m} \) is minimized by reducing the difference between the estimated and observed value of \( \mathbf{d} \) to the smallest possible value (Khanna et al., 2012). The minimization is applied with a weighted least-squares function (or cost function \( \chi^2 \)) which can be expresses in an expanded form as:

\[
\chi^2(x) = \frac{1}{N} \sum_{j=1}^{N} \frac{(x_j - \bar{x}_j)^2}{\sigma_j^2}
\]

with \( N \) presenting the size of the variable vector \( x \), \( x_j \) indicating an element of the data vector, \( \bar{x}_j \) standing for the expected value of that variable and \( \sigma_j^2 \) being variance of the data of the \( j^{th} \) variable. The model is initialized with a temperature profile whose parameters are varied until the difference between the model and measurements reaches a minimum. The minimization procedure is terminated when the change in \( \chi^2 \) for each parameter per minimization step is less than or equal to 0.1%. Lidar temperature retrieval uses a relationship for the forward model between observed data of backscattered counts and the temperature. Starting from equation (3.3) and integrating the pressure from the lower to higher altitudes, one can obtain the equations:

\[
\int_{P(z_0)}^{P(z_i)} \frac{dp}{p} = -\frac{M}{R} \int_{z_0}^{z_i} \frac{g(z)}{T(z)} dz, \tag{3.18}
\]

\[
P(z_i) = p(z_0) \exp\left(-\frac{M}{R} \int_{z}^{z_i} \frac{g(z)}{T(z)} dz\right) \tag{3.19}
\]

Substituting for \( P(z) \) from the ideal gas law equation (3.2) then leads to the following relation

\[
\frac{R}{M} p(z_i) T(z_i) = p(z_0) \exp\left(-\frac{M}{R} \int_{z}^{z_i} \frac{g(z)}{T(z)} dz\right). \tag{3.20}
\]
One can also use the lidar equation (2.2) to substitute $\rho(z_i)$ with the lidar backscattered counts as $N(z_i)$ which will be used for the forward model:

$$N(z_i) = \frac{P_0 M}{CR_i^2 T(z_i)} \exp\left(-\frac{M}{R} \int_{z}^{z_i} \frac{g(z)}{T(z)} \, dz\right)$$  

(3.21)

Contrary to the conventional method, $P_0$ is the pressure at the bottom and the integration is upward. Determining $P_0$ at the bottom, where reliable data exist improves the accuracy of the results for temperature profiles in this method. Furthermore, the inversion method does not use the assumption of isothermal layers, unlike the conventional method.

Since the Grid Search method does not provide statistical model or model parameter uncertainties, the uncertainties of its results can be estimated using Monte Carlo techniques, whereas in the conventional method the uncertainties are calculated analytically. In the Monte Carlo analysis of the results, a statistical error analysis has been performed for the final temperature converged upon the inversion method. An error analysis of the final counts profiles produced using the inversion method was done by a Monte Carlo method with 150 iterations. For each iteration, noise was added by taking the average number of Gaussian distributed generated noisy profiles. The final error in the temperature profiles was taken to be the standard deviation of all the temperature profiles. More details of this error analysis can be found in the (Bandoro, 2012).
Chapter 4

Temperature climatology

4.1 Introduction

This chapter summarizes the procedures used to generate the temperature climatology, details of which we presented in the previous chapters. The temperature climatologies for PCL channels: Rayleigh channel (Low Level Rayleigh and High Level Rayleigh) and Raman channel corresponding to the different explained methods in last chapter, are presented.

4.2 Generating the Climatology

The following procedure is based on the processes presented in Argall and Sica (2007). They determined the PCL temperature climatology from 1994 to 2004 using the HC method. Nightly averaged temperature profiles were used to perform the temperature climatology in this study. First, the quality of the nightly averaged measurements was determined by marking each one-minute scan profile of measurements as good or bad by the Picon software as explained in Chapter 2. Next, trend of averaged nightly temperature profiles was considered for eliminating the wrong profiles. Then, we just consider the averaged temperature profiles with minimum signal-to-noise ratio 2 at minimum altitude specified for temperature integration initialization, 95 km. This was done by an automated cut off and setting in the Picon software. The following
procedure is used to determine the average temperature profile for individual nights (Argall and Sica, 2007).

1. Individual photon count profiles are corrected for detector system non-linearity.

2. Each profile is co-added for an entire night and the co-added altitude has a resolution of 1008 m.

3. The background counts are found by taking the average of the measured counts between 120 to 176 km and subtracting it from the signal profile (Argall and Sica, 2007).

4. Profiles are corrected for range and ozone absorption correction based on the method of Sica et al. (2001).

5. The photon count profiles are scaled to match the density profile of the CIRA-86 model in the altitude range 45 to 60 km.

6. The calculated temperature profiles are smoothed with a 7 point, a 3’s and 5’s point filter.

It is necessary to mention here that there is a difference between the filtering of temperature retrieval for the conventional method and the grid search optimization method. In the conventional method, the counts are passed through the point filter and the counts profile result is smoothed and consequently temperature profiles are smoothed. However, the inversion method uses a different approach to retrieve the temperature. It uses a guessed initial temperature profile to minimize the cost function which is proportional to the difference between the observation counts and guessed counts (model counts). If we apply the filter to observation counts, it does not smooth the model counts, therefore, the filter is applied to the retrieved temperature profile directly in the grid search method.

Temperature profiles calculated according these steps were used the CIRA pressure to initiate the pressure integration in the conventional method. Therefore, the top 10 km of each temperature profile was eliminated in order to reach the accurate temperature at top in. However, this step is not necessary for the inversion method because of the reasons mentioned in
previous chapter. In order to make a composite year from all lidar temperature profiles, follow-
ing steps are performed. As an example, the corresponding Figures to each step for High Level Rayleigh channel are shown according to each step in the following of this section. Only those nightly averaged profiles extending to altitudes of at least 85 km, after removing the top 10 km, were used to form a temperature composite year (Figure 4.1). As well as if the statistical standard deviation due to photon counting correspond to temperature be greater than 6 K at the greatest altitudes, the top altitudes were removed to satisfy this condition Figure 4.2. The difference between part a and b in Figure 4.2 shows the effect of the seeding pressure in temperature profiles and why the top 10 km has to be removed. Each temperature and standard deviation profile is then interpolated to a standard altitude level, between 35 to 110 km with an interval of 1 km. As there existed more than one measurement for an individual date of the year on nights where multiple temperature measurements exists, they were averaged together to determine the temperature for that composite day. A 33-day triangular filter is applied to the result shown in Figure 4.3 and finally, linear interpolation was used to fill the gaps where no measurements existed (Figure 4.4). Linear interpolation is also used to fill the gaps for temperature standard deviation calculations. The final result after the entire procedure is shown in Figure 4.6

(a) Before removing top 10 km
(b) After removing top 10 km

Figure 4.1: Composite year without any filtering for an HLR channel climatology.
Chapter 4. Temperature climatology

Figure 4.2: Standard deviation of composite year for an HLR channel climatology.

Figure 4.3: Composite year using 3’s 5’s filter for an HLR channel climatology.
4.2. Generating the Climatology

Figure 4.4: Interpolated composite year for an HLR channel climatology.

(a) Before removing top 10 km  
(b) After removing top 10 km

Figure 4.5: Interpolated standard deviation (statistical noise).
4.3 Climatology Results

In this section the climatology results for each channel according to the different conditions are presented. Pressure seeding and temperature seeding were used to initiate the integration conventional method (HC), where the seeding values were calculated using the CIRA model. The grid search optimization method (inversion) was only used for the High Level Rayleigh channel, as reaching higher altitude was important for this channel. Beside climatologies from PCL, temperature climatology was calculated using the CIRA data. In summary, temperature climatologies were performed with the HC method with both seeding values as well as the inversion method for HLR channel, and only the HC method was used for the Low Level Rayleigh and Raman channels. The results for each method, according to seeding value, are presented in this next section and they are compared together as well as temperature climatology from CIRA model.
4.3. Climatology Results

4.3.1 High Level Rayleigh Channel

Rayleigh channel measurements obtained from 1994 to 2013 have been used to calculate a temperature climatology between 35 to 110 km. However, the PCL was out of commission for several years due to upgrading and moving locations, specially in; 2001, 2004, 2010 and 2011. This channel is called High Level Rayleigh (HLR) because it’s range for measuring the density releases up to the lower thermosphere. The details of number of nights are brought in Table 4.1 and its distribution histogram is in Figure 4.7. In total, 585 nights were used which the number of nights in the summer is more than the winter, because PCL operates only on clear nights.

<table>
<thead>
<tr>
<th>Month</th>
<th>Number of profiles</th>
</tr>
</thead>
<tbody>
<tr>
<td>January</td>
<td>9</td>
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<tr>
<td>February</td>
<td>17</td>
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<td>March</td>
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<tr>
<td>May</td>
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<td>June</td>
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<tr>
<td>July</td>
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<tr>
<td>August</td>
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<td>September</td>
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<tr>
<td>October</td>
<td>42</td>
</tr>
<tr>
<td>November</td>
<td>29</td>
</tr>
<tr>
<td>December</td>
<td>17</td>
</tr>
<tr>
<td>Total</td>
<td>582</td>
</tr>
</tbody>
</table>

Table 4.1: Number of profiles used to calculate the PCL HLR temperature climatology

4.3.2 Conventional Method Results

Figure 4.8 shows the HC method climatology with the seeding pressure (left) and temperature (right) taken from the CIRA model before cutting off the top 10 km from the top of each profile. It is clear that, above 85 km there are differences between them. Figure 4.8 (left) presents warmer temperature above 85 km and even the pattern of temperature in comparison with Figure 4.8 (right) is different. Figure 4.8 and temperature standard deviation (Figure 4.9) show why top 10 km remove to reach accurate data, because the standard deviation is high.
Figure 4.7: Histogram distribution of number of nights for HLR.

Figure 4.8: Temperature climatology for HLR channel calculated with HC method before cut off 10 km.
4.3. Climatology Results

After removing 10 km from top of each profile for each night and creating the climatology, the results in Figure 4.10 which is focused on 75 km to the top because below it the differences are negligible. Figure 4.11 (a) is difference before removing 10 km and Figure 4.11 (b) is after that. The huge difference after removing is disappeared and results are close together.

Figure 4.9: Temperature Standard deviation for HLR channel for HC method above 70 km.

Figure 4.10: Temperature climatology for the HLR channel using the HC method after a removing of 10 km.
4.3.3 **Inversion Method Results**

The standard deviation of temperatures calculated with the inversion method (Figure 4.13) in comparison to those calculated the HC method (Figure 4.9) is smaller in the top layers. The differences between the inversion and the HC method before eliminating the top 10 km is about 30 degrees (Figure 4.14). But after removing the mentioned altitudes this amount decreases significantly (Figure 4.15).

Figure 4.12: Temperature climatology for the HLR channel with inversion method.
4.3. Climatology Results

Figure 4.13: Standard deviation of temperature in the HLR channel by the inversion method.

Figure 4.14: Temperature difference between the inversion and HC method (before removing 10 km) calculated from the HLR channel.
4.3.4 CIRA Model Results

The CIRA model is an atmospheric model that gives us monthly mean temperature, for all latitudes up to 120 km. The CIRA data was taken from 1963-1973 and derived from the National Meteorological Center (NMC, Washington, D.C.), the National Center for Atmospheric Research (NCAR, Boulder, Colorado), Ocean Station Vessels (OSV), the British Meteorological Office (Bracknell, England), and the National Climatic Center (Asheville, N). The data have been interpolated from station network level to regular global grid levels. CIRA used global climatological data sets in tabular form, generated at the Atmospheric Physics Department, and Clarendon Laboratory in Oxford, England in 1985 up to 80 km. Using the mentioned data and MSIS-86 temperature at 85 km, linear interpolation was used to find data between 80 to 85 km (Chandra et al., 1990). Temperature climatology has been calculated (Figure 4.16) using the CIRA data and then temperature differences between the CIRA climatology with the HC and inversion climatologies are calculated. The common point in temperature differences between the CIRA model and the retrieved techniques (Figures 4.17 and 4.18) are that above 90 km the CIRA model is too warm in comparison with measurements and between 75 to 90 km it is cold.
4.3. Climatology Results

Figure 4.16: Temperature climatology for CIRA model.

Figure 4.17: Temperature difference between CIRA model and HC method for HLR channel.

Varying Seed Pressure Value

In order to evaluate our methods, another test is done; calculating the effect of a wrong choice of seed pressure. In order to evaluate of this error, first the effect of it on individual
profile should be assessed. Figures 4.19 and 4.20 (taken from Khanna et al., 2012) show the effect of varying seeding values on individual profiles calculated by the HC and inversion technique respectively. The HC method profiles diverge towards the top of the profile due to the variation in the top seed pressure. The 10% error in the estimate of the top seed pressure, is caused by a difference of almost 25 K at the top and it is not until below 75 km that the uncertainty due to the guess is negligible and the profiles converge. However, the maximum difference for inversion method is about 5 to 6 K due to the choice of seed pressure. Due to computational issues with the inversion technique, just +10% value of seed pressure was perturbed to perform the climatology. The results of using wrong seeding values is shown in Figures 4.21 and 4.22. The corresponding temperature difference are shown in Figures 4.23 and 4.24 consequently. A 10% error in the estimate of the top seed pressure results in almost a 20 to 30 K difference at the top. That difference is why it is necessary to remove the top 10 to 15 km of a nightly temperature profile, so that the uncertainty due to the seed pressure is
4.3. Climatology Results

within the statistical uncertainty for temperatures. However, the sensitivity of the temperature climatology created with the HC method to wrong temperature seeding is less than the pressure climatology, but in some parts there are more than a 30 K difference which spread to even 85 km. On the other hand, the inversion method differences in almost all parts are about 6 K; however, in a very small region this error reaches to 20 K. This is the merit of this method, which is due to the minimization of the cost function regardless of the seeding value.

![Retrieved temperatures using the HC method at 5 values of seed pressure on September 1st, 2005](Khanna et al., 2012).

Figure 4.19: Retrieved temperatures using the HC method at 5 values of seed pressure on September 1st, 2005 (Khanna et al. 2012).

It is necessary here to note that the daily variability of temperatures in the lower thermosphere which is place HC method uses as seeding value is greater than in the middle to upper stratosphere where the inversion method seeds. Therefore, the probability of choosing incorrect seed pressure for the HC method is higher than that of the inversion method. Figure 4.25 shows the day-to-day variability of density in the atmosphere for the months of January and July. In both months the variability of density and therefore temperature is greater in higher
altitudes than in the lower altitudes. Thus, one should consider that when comparing the result of changing 10% seed pressure for both methods, the HC method result is underestimated and the inversion result is overestimated.

4.3.5 Comparison with Previous Rayleigh Channel Climatology

Argall and Sica (2007) calculated the PCL temperature climatology using data over an 11-year period (1994 to 2004) with the HC method. The result is presented in Figure 4.26. In total, they used 453 profiles to form the climatology (Argall and Sica, 2007). In the first step, the climatology is calculated using the same days as Argall and Sica (2007) to validate the developed code to calculate climatology. The total number of profiles was used for this purpose was 442. The difference between these two numbers is because there was no exact list of profile dates for the previous climatology. The result is presented in Figure 4.27. The result
4.3. Climatology Results

Figure 4.21: Temperature climatology using the HC method with 10% perturbed seeding values.

shows there are no differences between the previous climatology and the reformed climatology except at some points, which is due to the difference in the number of profiles that were used. The extended climatologies are compared with Argall and Sica (2007) climatology to see how the temperature has changed. The results for the HC method using seed pressure (Figure 4.28 left) and the inversion method (Figure 4.28 right) show that the extended climatologies are slightly warmer below 80 km and colder above 80 km in both methods, which means that the temperature has increased between the altitudes of 35 to 80 km and has decreased above 80 km. The result for the HC method using seed temperature is presented in Figure 4.29. While the HC method with pressure seeding and the inversion method are in agreement with each other, the HC method with temperature seeding shows an increase in temperature above 80 km, except for September. However, all three methods have the same result below 80 km.
Figure 4.22: Temperature climatology using the inversion method with 10% perturbed seeding pressure.

Figure 4.23: Temperature difference using HC method between 10% perturbed and non-perturbed seed value.
4.3. Climatology Results

Figure 4.24: Inversion method temperature difference between a 10% perturbed and non-perturbed seed value.

Figure 4.25: Mean variability of density in the atmosphere at 45 N deg latitude for the months of January and July (Adapted from Cole et al., 1985).
Figure 4.26: The temperature climatology by (Argall and Sica, 2007) using measurements from 1994 to 2004 (Argall and Sica, 2007).

Figure 4.27: The Rayleigh channel temperature difference between previous and re-formed previous temperature climatology.
4.3. Climatology Results

(a) HC method using pressure seeding

Figure 4.28: Rayleigh channel temperature differences between the previous and extended temperature climatology.

(b) Inversion method

Figure 4.29: Rayleigh channel temperature difference between the previous and extended temperature climatology using the HC method with temperature seeding.
4.3.6 Low Level Rayleigh channel

Another Rayleigh channel was used (Low Level Rayleigh channel, henceforth LLR) to perform temperature climatology from 1999 to 2013 between the heights of 25 to 60 km. Only the conventional method was used for this channel, because reaching higher altitudes is not a priority for this channel. Because the density at lower altitudes is higher and more accurate in the upper levels. The top 10 km from each profile and because seeding pressure and temperature are more precise, accurate result should be achieved between 25 to 50 km. In total, 357 nights were used from this channel. The details of the nights and their distribution are in Table 4.2 and Figure 4.30. The same procedure as the High Level Rayleigh channel is used for this channel.

<table>
<thead>
<tr>
<th>Month</th>
<th>Number of profiles</th>
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<td>September</td>
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</tr>
<tr>
<td>October</td>
<td>19</td>
</tr>
<tr>
<td>November</td>
<td>16</td>
</tr>
<tr>
<td>December</td>
<td>8</td>
</tr>
<tr>
<td>Total</td>
<td>357</td>
</tr>
</tbody>
</table>

Table 4.2: Number of profiles used to form the PCL Rayleigh (LLR) temperature climatology.

The temperature climatology for the LLR channel between 25 to 50 km is presented in Figure 4.31. The bottom part of Figure 4.31 is reds indicates the saturation of the PMT for those altitudes. Therefore, those altitudes should be eliminated from result which is shown in Figure 4.32. The temperature standard deviation (Figure 4.33) is less than the High Level Rayleigh channel’s. The other important point is the difference between using a seed pressure and temperature. The difference between temperate climatologies with different seeding parameters is
4.3. Climatology Results

Figure 4.30: Histogram distribution of number of nights for LLR channel.

negligible. Figure 4.34 shows that this difference for the most part is less than 0.2 K and close to zero.

Figure 4.31: LLR channel temperature climatology between 25 to 50 km.
Figure 4.32: LLR channel temperature climatology between 28 to 50 km.

Figure 4.33: LLR channel temperature Standard deviation.
4.3. Climatology Results

Figure 4.34: LLR channel temperature difference between seeding pressure and seeding temperature.

4.3.7 Raman Channel

Raman channel measurements between 1999 to 2013 were also used produce a temperature climatology. The Raman channel records data from 10 to 45 km, and the top 10 km was removed in order to provides precise data. Similar to the Low Level Rayleigh channel, only the conventional method was used to retrieve the temperature. For Raman temperature climatology, 317 nights were used. Table 4.3 and Figure 4.35 contain their details.

The white/zero-data region in Figure 4.36 is due to the small number of profiles. The temperature climatology calculated from the PCL Raman channel is given in Figure 4.36. The temperature standard deviation (Figure 4.37) is grown about from 30 km to higher altitude and therefore, the difference between the LLR channel seeding temperature and the HC method temperature seeding is negligible (Figure 4.38).
Table 4.3: Number of profiles used to form the PCL Raman temperature climatology

<table>
<thead>
<tr>
<th>Month</th>
<th>Number of profiles</th>
</tr>
</thead>
<tbody>
<tr>
<td>January</td>
<td>5</td>
</tr>
<tr>
<td>February</td>
<td>5</td>
</tr>
<tr>
<td>March</td>
<td>6</td>
</tr>
<tr>
<td>April</td>
<td>8</td>
</tr>
<tr>
<td>May</td>
<td>44</td>
</tr>
<tr>
<td>June</td>
<td>52</td>
</tr>
<tr>
<td>July</td>
<td>90</td>
</tr>
<tr>
<td>August</td>
<td>53</td>
</tr>
<tr>
<td>September</td>
<td>15</td>
</tr>
<tr>
<td>October</td>
<td>15</td>
</tr>
<tr>
<td>November</td>
<td>17</td>
</tr>
<tr>
<td>December</td>
<td>7</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>317</strong></td>
</tr>
</tbody>
</table>

Figure 4.36: Raman channel temperature climatology between 10 to 35 km.
4.3. Climatology Results

Figure 4.35: Histogram distribution of number of nights for Raman channel.

Figure 4.37: Raman channel temperature Standard deviation.
Figure 4.38: Raman channel temperature difference between seeding pressure and seeding temperature.

4.3.8 Comparison with Previous Raman Channel Climatology

Iserhienrhi (2013) has calculated the temperature climatology for the Raman PCL channel using measurements from 1999 to 2007 (Figure 4.39). The temperature differences between previous climatology with recalculated climatology (Figure 4.40) by my developed code shows good agreement between them and there is almost no difference between them. However there are small differences caused by using a different number of profiles to form the climatology. In general, the temperature differences between the previous and extended climatology (Figure 4.41) shows almost no change in temperature over time. However, the temperature slightly increases in April and December and decrease in June.
4.3. Climatology Results

Figure 4.39: Previous temperature climatology using measurements from 1999 to 2007 (Taken from [Iserhienhien et al., 2013]).

Figure 4.40: Raman channel temperature differences between the old and recalculated climatology.
4.4 Summary

In this chapter, temperature climatologies were generated corresponding to the HC method using seed pressure and seed temperature, as well as the inversion method. In this study, the Argall and Sica (2007) methodology was followed to form the temperature climatologies. The temperature climatology was calculated for PCL channels separately for the Raman, Low Level Rayleigh and High Level Rayleigh channels. First, the sensitivity of the HC method was tested by changing seed values and the results were compared with the inversion method. Next, the CIRA climatology was performed and its results were compared with the retrieved temperature techniques. Also, the climatologies were formed using 10% perturbed initial guesses to evaluate the sensitivity of each technique to accuracy of seed values. After that, extended climatologies compared to the previous climatology formed by Argall and Sica (2007). In the next step, the temperature climatologies for the LLR and Raman channels measurements were calculated. Finally, the Raman climatology was compared with the climatology calculated by Iserhienrhien et al. (2013). The discussion of these results will be presenting in Chapter 7. In next chapter, the methods and functions for merging these three climatologies will be considered.
Chapter 5

Merging methods

5.1 Introduction

In order to extend the range of lidar measurements, two lidar detection systems have been used: analog and photon counting (PC) system. These systems overlap each other in altitude. Then the two ranges are combined to have an individual profile for the entire atmosphere up to 110 km and are known as "merged" profile. Although both recorded data can be analyzed separately, their combination obtained through gluing gives the advantage of the high linearity of the analog for high light-level signals (especially in the low range) and the high sensitivity of the PC mode for low light-level signals (in the high range). There are two methods to merge the measurements from one channel to another. One method is to merge the photon counts signal density or analog signals and then retrieve the temperature from that glued density profile. The other way is to merge retrieved temperature profiles from photon count signals and analog signals directly. Each method has its merits and limitations. As density varies exponentially with height in the atmosphere, the variation in the photon count profile is much more than the temperature (which is more linear), therefore, the first method is much more sensitive to change the merged area and altitude and the difference between measurements is greater. This makes it harder to glue. Another cons for photon count merging is due to conversion of analog signal
to photon count signal. The analog channel signal unit is mV while using an equation to convert it to photon count. This processes insert uncertainty to data and propagate entire profile. Temperature climatologies for each lidar’s channels including Raman, Low Level Rayleigh (LLR) and High Level Rayleigh (HLR) have been presented in previous chapter. Each profile has an overlap area with other profiles. In order to find one temperature profile for entire in range atmosphere, different weighting functions must be used in merged temperature profiles. In this work, four functions were investigated for temperature merging: sine/cosine, simple linear, error function (erf), and hyperbolic functions. The merging results with details for each function are presented in this chapter. It is necessary to mention that there is no systematic study of merging exists that compare the results. Papers have only mentioned that the temperature profiles for different channels were merged together without an explanation of the method used.

5.2 Determining the Merging Region

Several factors were considered in order to find the best merging altitudes, which these factors evaluate lidar temperatures from different aspects. These factors include: photon counts, temperature variance, and temperature differences between different channels.

5.2.1 Photon counts

Pressure decreases exponentially with altitude. Using the Ideal Gas Law and hydrostatic equilibrium, we can find the relation between pressure and height that is known as the Barometric relation (equation\ref{eq:5.1}). In equation\ref{eq:5.1}, \(P\) is pressure at different altitudes, \(P_0\) is pressure at surface, \(z\) the height from surface and \(H\) is scale height. The scale height is a distance over which pressure or density decreases by a factor of e. At 80 km altitude the atmospheric pressure is down to 0.01 hPa, meaning that 99.99\% of the atmosphere is below that altitude. For a mean atmospheric temperature \(T = 250\) K, the scale height is \(H = 7.4\) km. Similarly, we could find
the vertical dependence of the air density. For every $H$, which is known as scale height, rise in altitude, the pressure and density of air drop by a factor $e$ (equation 5.2). Equation 5.3 shows the scale height equation, which is defined as the height where the density in the atmosphere drops by a factor of $e$. In this equation $h$ is Boltzmann’s constant. Below 100 km, the scale height is constant and we can plot temperature variation with either height or the logarithm of pressure. Above 100 km altitude, instead of pressure, height is used because the pressure and corresponding density is very small above 100 km and also scale height increases as the temperature increases. Thus, the relation between the logarithm of lidar photon counts with altitude should be linear. Therefore, the part of the profile which is acceptable is the part where the logarithm of photon counts with height is linear. Lidar measurements are calculated from backscattered intensity, which is proportional to density and temperature profiles are calculated from lidar measurements. The aerosols in lower stratosphere and troposphere scatter the incident laser light beside the molecular scatter signal. In addition, because of pile up effect and aerosols backscattered temperature cannot be determined in the altitude lower than 10 km.

\[ P = P_0 \exp\left(-\frac{Z}{H}\right), \]  
\[ n = n_0 \exp\left(-\frac{Z}{H^*}\right), \]  
\[ H^*(z) = \left(\frac{1}{H(z)} + \frac{1}{T} \frac{dT}{dz}\right)^{-1}, \]  
\[ H(z) = \frac{kT}{mg(z)}. \]  

Figures 5.1, 5.2 and 5.3 show the photon count profiles for Raman, Low Level Rayleigh and High Level Rayleigh channel respectively.
Chapter 5. Merging methods

Figure 5.1: Sample Raman channel photon counts profile.

Figure 5.2: Sample Low Level Rayleigh channel photon counts profile.

Figure 5.3: Sample High Level Rayleigh channel photon counts profile.
5.2. Determining the Merging Region

Instead of considering individual photon counts over each minute, co-added photon counts over each hour can be used for removing noise from profile. The Figures 5.4, 5.5 and 5.6 such as above are plotted to get better view of the signal noise.

![Figure 5.4: Sample Raman channel co-added photon counts profile](image)

![Figure 5.5: Sample Low Level Rayleigh channel co-added photon counts profile](image)
5.2.2 Temperature Standard Deviation

The temperature standard deviation profiles are another parameter that must be considered for finding merging area. In each channel the top of the profile has more statistical uncertainty and it decreases as it goes down, which is obvious from Figure 5.7. Figure 5.8 shows the standard deviation of an entire year for the Raman and LLR channel. For the Raman channel the standard deviation increases dramatically above 35 km and is reasonable between 30 to 35 km; however, the standard deviation for the LLR channel below 45 km is reasonable.
5.2. Determining the Merging Region

Figure 5.7: Sample Raman temperature standard deviation profile with vertical resolution of 1008 m and co-added time for entire night.

Figure 5.8: Temperature standard deviation.

(a) Raman channel

(b) LLR channel
5.2.3 Temperature Difference between Channels

The auxiliary factor that could be considered for finding the best area for merging is the temperature difference between different channels in a common area. Each channel has between 10 to 15 km overlap with other channels in common measurements. In the best scenario, the profiles from different channels would be identical, but in reality it is observed that there are differences between them. In Figure 5.9 the difference between the Raman and the LLR increase dramatically somewhere below 29 km. This is because at the bottom of channels count rate is very high and saturation occurs. The saturation prevents accurate measurements at the bottom of LLR channel, therefore the temperature differences between the Raman and LLR channel are high below 29 km. Thus, below this altitude is not a good region for merging.

![Figure 5.9: Temperature difference.](image)

5.2.4 Result for Merging

After considering all the mentioned parameters, the best regions for merging are chosen between channels. Table 5.1 represents the effective range of each channel, as well as their merging regions. The best merging area between the Raman and LLR channels is 30 to 35 km and 35 to 40 km for LLR and HLR channel.
5.3 Merging Functions

Retrieved temperatures for each channel have more statistical accuracy at the bottom rather than the top of each profile. As a result, some regions for each channel are more reliable in a common area. Therefore, instead of using simple averages between temperatures, several functions were chosen to merge the temperature profiles between different channels. These functions are: sine/cosine functions, simple linear functions, error functions, and hyperbolic functions. In this section the results for mentioned functions based on the Table 5.1 have been plotted. Consequently, the different temperatures between merged profiles and each channel is presented. Two factors should be considered when evaluating the merging functions. First, how each function could effect on merged results, and second, how much is each one sensitive to extending the merging region. For these, the results are shown in following Figures and also as a numeric result. For each function, according to limitation of channel, the channels were extended between 500 m to 1 km extra to test the sensitivity of each function when extending merging area.

### 5.3.1 Weighted Average for Nonuniform Uncertainties

The most probable estimate of the mean of a random set of observations is the average of the observations, based on the assumption that distribution of the measurements is according to a Gaussian distribution (Bevington and Robinson, 2003). In some circumstances, measurements have been obtained with better or worse precision because each lidar channel measurement in a

<table>
<thead>
<tr>
<th>Bottom altitude</th>
<th>Top altitude</th>
<th>Merging altitudes (km)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Raman</td>
<td>10</td>
<td>35</td>
</tr>
<tr>
<td>LLR</td>
<td>28</td>
<td>50</td>
</tr>
<tr>
<td>HLR</td>
<td>35</td>
<td>110</td>
</tr>
</tbody>
</table>

Table 5.1: Merging height result
common area has a different precision. In this case, the data points are expressed by assuming
the same distribution with the same mean but with different standard deviations. Therefore the
weighted average of the measurements is the most probable value, and is defined as:

\[
\mu = \frac{\sum \left( \frac{x_i}{\sigma_i} \right)}{\sum \left( \frac{1}{\sigma_i} \right)}, \tag{5.4}
\]

and the uncertainty of the mean is expressed by:

\[
\sigma^2_\mu = \frac{1}{\sum \left( \frac{1}{\sigma_i} \right)}. \tag{5.5}
\]

The weighted average for the Raman and LLR channel between 30 to 35 km as well as LLR and
HLR channel between 35 to 40 km were calculated. The weighted average result was chosen as
a reference for evaluating merging functions. The related errors for the PCL are combination
of statistical errors due to the photon counting and systematic errors due to applied corrections.
Although, the applied corrections in merging area are fairly small. That is the reason the
weighted average function was chosen as a reference for evaluation of the merging functions.

### 5.3.2 Sine and Cosine function

We can use equation [5.6] as a weighting function by converting each height point in the
merging area to an angle.

\[
\sin^2(\theta) + \cos^2(\theta) = 1. \tag{5.6}
\]

The angle in each altitude is found by:

\[
\theta = 90 - (\text{altitude} - \text{start(altitude)}) \left[ 90 / \left( \frac{\text{stop(altitude)} - \text{start(altitude)}}{\text{bin}} \right) \right]. \tag{5.7}
\]

The bin is the height resolution (here 1km), "start(altitude)” and "stop(altitude)” are the begin-
ing and ending height for merging. This relation converts each data point to an angle which
was used in the weighting function.

\[
\begin{align*}
\text{Temperature}(\text{merge}) &= \sin^2(\theta) \times \text{Raman}(\text{temperature}) + \cos^2(\theta) \times \text{LLR}(\text{temperature}), \\
\text{Temperature}(\text{merge}) &= \sin^2(\theta) \times \text{LLR}(\text{temperature}) + \cos^2(\theta) \times \text{HLR}(\text{temperature}).
\end{align*}
\]

As an example, the calculation of angles for the Raman and LLR are presented in Table 5.2. As presented in Figure 5.10, the sine/cosine function is not a symmetric weighting function it gives more weight to one function rather than the other, which the more weight is given to the channel with less uncertainty at each altitude. For example, at 35 km all weight is given to the LLR and it is allocated to the Raman in 30 km.

<table>
<thead>
<tr>
<th>altitude(km)</th>
<th>(\theta)</th>
<th>(\sin^2(\theta))</th>
<th>(\cos^2(\theta))</th>
</tr>
</thead>
<tbody>
<tr>
<td>35</td>
<td>0</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>34</td>
<td>12.90</td>
<td>0.049</td>
<td>0.95</td>
</tr>
<tr>
<td>33</td>
<td>25.75</td>
<td>0.188</td>
<td>0.81</td>
</tr>
<tr>
<td>32</td>
<td>38.60</td>
<td>0.38</td>
<td>0.61</td>
</tr>
<tr>
<td>31</td>
<td>51.36</td>
<td>0.61</td>
<td>0.38</td>
</tr>
<tr>
<td>30</td>
<td>64.30</td>
<td>0.81</td>
<td>0.188</td>
</tr>
<tr>
<td>29</td>
<td>77.15</td>
<td>0.95</td>
<td>0.049</td>
</tr>
<tr>
<td>28</td>
<td>90</td>
<td>1</td>
<td>0</td>
</tr>
</tbody>
</table>

Table 5.2: Angels used for merging Raman and LLR profiles.

The merging result using equation 5.8 between the Raman and Low Level Rayleigh channel is plotted in Figure 5.11. Corresponding Figure for merging the Low Level Rayleigh and High Level Rayleigh channel is presented in Figure 5.13. The Raman-LLR result (Figure 5.12) shows that the temperature difference between weighted averaged profiles with Raman-LLR merged profiles is about 2K warmer. In some points it reaches to 4K, but with extending the merging area this maximum decreases to 3K. The merged LLR-HLR (Figure 5.14) is an average 1K colder and the maximum difference is about 4K.
Chapter 5. Merging methods

Figure 5.10: Sine and cosine as a weighting function

Figure 5.11: Merging temperature climatology, using sine/cosine function for merging the Raman and LLR channels.

(a) Merged region: 30 to 35 km

(b) extended view
5.3. Merging Functions

Figure 5.12: Temperature differences between weighted averaged profiles with the Raman-LLR merged profiles using the sine/cosine function.

Figure 5.13: The temperature climatology using sine/cosine function produced by merging the LLR and HLR channels.
Figure 5.14: Temperature differences between weighted averaged profiles with LLR-HLR merged profiles, using the sine/cosine function.
5.3.3 Linear function

We could consider line $y_1 = x$ and $y_2 = 1 - x$, with domain [0 1] as another weighting function, Figure (5.15). According to the mentioned lines, temperature in each height is found by

$$
Temperature(merge) = y_2 \times \text{Raman(temperature)} + y_1 \times \text{LLR(temperature)},
$$

$$
Temperature(merge) = y_2 \times \text{LLR(temperature)} + y_1 \times \text{HLR(temperature)}.
$$

Figure 5.15 shows the shape of linear weighting function for merging the temperatures between different channels using equation 5.9. The corresponding results are presented in Figures 5.16 and 5.18.
Figure 5.16: Merged temperature climatology using the linear function for merging the Raman and LLR channels.

Figure 5.17 shows that the temperature difference between weighted average profiles and Raman-LLR merged profiles is about 3K warmer. In some points it reaches to 5K, but with extending the merging area the result doesn’t change. The merged LLR-HLR (Figure 5.19) is an average 1K colder and the maximum difference is about 4K.

Figure 5.17: Temperature difference between weighted averaged profiles with Raman-LLR merged profiles using the linear function.
5.3. **Merging Functions**

Figure 5.18: Temperature climatology using the linear function for merging LLR and HLR channels.

(a) Merged region: 35 to 40 km

(b) Extended view

Figure 5.19: Temperature difference between weighted averaged profiles with LLR-HLR merged profiles using the linear function.

(a) Merged region: 35 to 40 km

(b) Merged region: 35 to 41 km
5.3.4 The Error and Complementary Error Functions

An error function was chosen as another function for merging. The error function is obtained by integrating the normalized Gaussian distribution.

\[ \text{erf}(x) = \frac{2}{\sqrt{\pi}} \int_0^x e^{-t^2} \, dt, \quad 0 \leq t \leq x, \quad (5.10) \]

where the coefficient in front of the integral normalizes to 1 when \( x \) equals infinity. The error function is defined for all values of \( x \) and is considered an odd function in \( x \). The complementary error function is defined as:

\[ \text{erfc}(x) = 1 - \text{erf}(x), \]
\[ \text{erf}(x) = \frac{2}{\sqrt{\pi}} \int_0^x e^{-t^2} \, dt, \quad x \leq t \leq \infty \quad (5.11) \]

As shown below, the superposition of the error function and the complementary error function, when the argument is greater than zero, produces a constant value of unity. Because the erf

![Figure 5.20: Erf and erfc function.](image-url)
function converges very fast to 1, for our purpose just the values between zero and 1 were considered for a merging function. As an example, the result for Raman and LLR are shown in Table 5.3.

<table>
<thead>
<tr>
<th>altitude(km)</th>
<th>i</th>
<th>x = i/10</th>
<th>erf(x)</th>
<th>erfc(x)</th>
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</thead>
<tbody>
<tr>
<td>35</td>
<td>8</td>
<td>0.8</td>
<td>0.7421</td>
<td>0.2579</td>
</tr>
<tr>
<td>34</td>
<td>7</td>
<td>0.7</td>
<td>0.6778</td>
<td>0.3222</td>
</tr>
<tr>
<td>33</td>
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<td>0.6</td>
<td>0.6039</td>
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</tr>
<tr>
<td>32</td>
<td>5</td>
<td>0.5</td>
<td>0.5205</td>
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</tr>
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<td>4</td>
<td>0.4</td>
<td>0.4284</td>
<td>0.5716</td>
</tr>
<tr>
<td>30</td>
<td>3</td>
<td>0.3</td>
<td>0.3286</td>
<td>0.6714</td>
</tr>
<tr>
<td>29</td>
<td>2</td>
<td>0.2</td>
<td>0.2227</td>
<td>0.7773</td>
</tr>
<tr>
<td>28</td>
<td>1</td>
<td>0.1</td>
<td>0.1125</td>
<td>0.8875</td>
</tr>
</tbody>
</table>

Table 5.3: Results from using the ref function to merge the Raman and LLR profiles.

\[
\text{Temperature(merge)} = \text{erf}(x) \times \text{Raman(temperature)} + \text{erfc}(x) \times \text{LLR(temperature)}
\]

\[
\text{Temperature(merge)} = \text{erf}(x) \times \text{LLR(temperature)} + \text{erfc}(x) \times \text{HLR(temperature)}.
\]  

(5.12)

The merging result using equation 5.12 between the Raman and Low Level Rayleigh channel is plotted in Figure 5.21. Corresponding Figure for merging the Low Level Rayleigh and High Level Rayleigh channel is presented in Figure 5.23. The temperature difference between the weighted average and Raman-LLR merged profiles (5.22) is about 2K with maximum difference about 4K, while extending the merging area causes to decreases this maximum to about 3K. On the other hand, the average difference for LLR-HLR merged results (Figure 5.24) is about 1K colder with the maximum difference being about 3K.
Figure 5.21: Merging temperature climatology using the erf function for merging the Raman and LLR channels.

Figure 5.22: Temperature difference between weighted average profiles and Raman-LLR merged profiles using the erf function.
5.3. Merging Functions

Figure 5.23: Temperature climatology using the erf function for merging the LLR and HLR channels.

(a) Merged region: 35 to 40 km
(b) Extended view

Figure 5.24: Temperature difference between weighted average profiles and LLR-HLR merged profiles using the erf function.

(a) Merged region: 35 to 40 km
(b) Merged region: 35 to 41 km

5.3.5 Hyperbolic function

Hyperbolic functions are defined in terms of the exponential function. Error functions and hyperbolic functions are similar, but using hyperbolic functions has merit in that it is easier to calculate. Similar to the well-known identity, \( \cos^2(x) + \sin^2(x) = 1 \), for trigonometric functions,
hyperbolic functions also have an identity relation (equation 5.13). This relation can be divided by \( \cosh^2(x) \), and the other identity relation will be equation 5.14 which is shown in Figure 5.25. Figure 5.25(a) illustrates that these hyperbolic functions rapidly converge to 1. Table 5.4 shows the response of \( \tanh^2(x) \) and \( \sech^2(x) \) to different input values. According to the Figure 5.25, the range between 0 and 2 for \( x \) is the best range to use the hyperbolic function as a weighting function. The shape must be symmetric and a reasonable weight for each function.

\[
\cosh^2(x) - \sinh^2(x) = 1. \tag{5.13}
\]

\[
\tanh^2(x) + \sech^2(x) = 1. \tag{5.14}
\]

Figure 5.25: Superposition of hyperbolic functions.

The relations in 5.15 are used to merge the temperatures from different channels, using the hyperbolic function identity, where \( \theta \) has been measured in the range of [0 2]. For converting
5.3. **Merging Functions**

<table>
<thead>
<tr>
<th>$x$</th>
<th>$\tanh^2(x)$</th>
<th>$\text{sech}^2(x)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.1</td>
<td>0.009</td>
<td>0.99</td>
</tr>
<tr>
<td>0.2</td>
<td>0.04</td>
<td>0.96</td>
</tr>
<tr>
<td>0.3</td>
<td>0.08</td>
<td>0.91</td>
</tr>
<tr>
<td>0.4</td>
<td>0.14</td>
<td>0.85</td>
</tr>
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<td>0.5</td>
<td>0.21</td>
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<tr>
<td>0.6</td>
<td>0.28</td>
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</tr>
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<td>0.7</td>
<td>0.36</td>
<td>0.63</td>
</tr>
<tr>
<td>0.8</td>
<td>0.44</td>
<td>0.55</td>
</tr>
<tr>
<td>0.9</td>
<td>0.51</td>
<td>0.48</td>
</tr>
<tr>
<td>1</td>
<td>0.58</td>
<td>0.42</td>
</tr>
<tr>
<td>2</td>
<td>0.92</td>
<td>0.07</td>
</tr>
<tr>
<td>3</td>
<td>0.99</td>
<td>0.009</td>
</tr>
<tr>
<td>4</td>
<td>0.99</td>
<td>0.001</td>
</tr>
<tr>
<td>5</td>
<td>0.99</td>
<td>$10^{-4}$</td>
</tr>
<tr>
<td>6</td>
<td>1</td>
<td>$10^{-5}$</td>
</tr>
<tr>
<td>7</td>
<td>1</td>
<td>$10^{-6}$</td>
</tr>
</tbody>
</table>

Table 5.4: Output of $\tanh^2(x)$ and $\text{sech}^2(x)$ for different input values.

Each altitude to this range, relation (5.16) was used, where $i$ is the counter for merging altitude.

\[
\text{Temperature(merge)} = \text{sech}^2(\theta) \times \text{Raman}(T) + \tanh^2(\theta) \times \text{LLR}(T)
\]

\[
\text{Temperature(merge)} = \text{sech}^2(\theta) \times \text{LLR}(T) + \tanh^2(\theta) \times \text{HLR}(T),
\]

(5.15)

\[
\theta = i \times \frac{2}{\text{stop(altitude)} - \text{start(altitude)}}.
\]

(5.16)

The merging results are presented in Figures 5.26 and 5.28 for merging the Low Level Rayleigh channel with Raman and High Level Rayleigh channel respectively. The Raman-LLR result (Figure 5.27) illustrates that the temperature difference between weighted average profiles and Raman-LLR merged profiles is about 1.5K warmer, and in some points it reaches to 3K. Extending the merged area doesn’t show any difference. The result for merged LLR-HLR (Figure 5.29) is an average 1K colder and the maximum difference is about 4K.
Figure 5.26: Merging temperature climatology using the hyperbolic function for merging the Raman and LLR channels.

(a) Merged region: 30 to 35 km
(b) extended view

Figure 5.27: Temperature difference between weighted average profiles and Raman-LLR merged profiles using the hyperbolic function.

(a) Merged region: 30 to 35 km
(b) Merged region: 29.5 to 35 km
5.3. **Merging Functions**

(a) Merged region: 35 to 40 km

(b) Extended view

**Figure 5.28**: Temperature climatology using the hyperbolic function for merging the LLR and HLR channels.

(a) Merged region: 35 to 40 km

(b) Merged region: 35 to 41 km

**Figure 5.29**: Temperature difference between weighted average profiles and the LLR-HLR merged profiles, using the hyperbolic function.
5.3.6 Merging Results

The Figures, the differences between weighted average temperatures and merged parts are considered as matrices, where these matrices represent the average uncertainty for each function for an entire year. In order to evaluate each function, the standard deviation of these matrices were calculated (Table 5.5). The same procedure is followed to find the results for extending the merged region (Table 5.6). The results show that the hyperbolic function is the best function for merging the Raman and LLR channel with uncertainty of 0.9 K, which has a smaller standard deviation even after increasing the merged area. The simple linear function is a better function for the LLR and HLR with an uncertainty 1 K. All functions show an increased standard deviation for the extended area. Finally, the climatology for the entire lidar range (Figure 5.30) for three temperature climatology channels is plotted using the chosen functions as merging function between the Raman and LLR channel and as well as the LLR and HLR channels.

<table>
<thead>
<tr>
<th>Difference</th>
<th>Merged region</th>
<th>sine/cosine</th>
<th>Linear</th>
<th>erf</th>
<th>Hyperbolic</th>
</tr>
</thead>
<tbody>
<tr>
<td>WA-(Raman-LLR)</td>
<td>30 - 35 km</td>
<td>1.4</td>
<td>1.9</td>
<td>1.5</td>
<td>0.9</td>
</tr>
<tr>
<td>WA-(LLR-HLR)</td>
<td>35 - 40 km</td>
<td>2.1</td>
<td>1.0</td>
<td>1.2</td>
<td>1.9</td>
</tr>
</tbody>
</table>

Table 5.5: Standard deviation of matrices show the difference between weighted average temperature and the merged parts, in the range 30 to 35 km for the Raman and LLR channels and 35 to 40 km for the LLR and HLR channels

<table>
<thead>
<tr>
<th>Difference</th>
<th>Merged region</th>
<th>sine/cosine</th>
<th>Linear</th>
<th>erf</th>
<th>Hyperbolic</th>
</tr>
</thead>
<tbody>
<tr>
<td>WA-(Raman-LLR)</td>
<td>29 - 35 km</td>
<td>1.1</td>
<td>2</td>
<td>1.25</td>
<td>0.9</td>
</tr>
<tr>
<td>WA-(LLR-HLR)</td>
<td>35 - 41 km</td>
<td>2.2</td>
<td>1.3</td>
<td>1.5</td>
<td>2.1</td>
</tr>
</tbody>
</table>

Table 5.6: Standard deviation of matrices show the differences between weighted average temperature and the merged parts, in the range 29 to 35 km for the Raman and LLR channels and 35 to 41 km for the LLR and HLR channels
5.3.7 Comparison PCL Climatology with Other Climatologies

The temperature climatology of the structure of the middle atmosphere has been studied since 1950s. Some previous works are: (Clancy and Rusch, 1989), (Hauchecorne et al., 1991), (Leblanc et al., 1998), (She et al., 2000) and (Randel et al., 2004). The climatology presented by (Leblanc et al., 1998) includes the following lidars’ measurements: Observatories de Haute Provence (OHP) at 44.0 N, Centre d’Essais des Landes (CEL) at 44.0 N, Colorado State University (CSU) sodium lidar (40.6 N), the two Rayleigh lidars of the NASA-Jet Propulsion Laboratory, located at Table Mountain, California (TMF, 34.4 N) and at Mauna Loa, Hawaii (MLO, 19.5 N). This study (Leblanc et al., 1998) is chosen to compare PCL climatology with it. The PCL climatology obtained using the Rayleigh and Raman channels overlaps OHP and CEL climatology as well as the CSU. Figure 5.31 presents the results of Leblanc’s climatology. In Figure 5.31(a,b,d) for OHP, CEL and TMF the summer stratopause has a temperature
maximum of 272 K in May-June and a minimum of 255 K for winter in early November at altitude of 47 km. The PCL climatology (Figure 5.30) shows the temperature maximum of 269 K in late May at 47 km for stratopause at summer, which is 1 K cooler and 1 km lower than previous PCL climatology and winter stratopause the minimum temperature for PCL is 253 K at 50 km in late November, which is 3 km higher than determined by Leblanc et al. (1998). Therefore, the PCL temperature climatology in comparison with OHP and CEL is 3 K cooler at same altitude for summer stratopause and 2 K cooler at 3 km higher for winter stratopause. The coldest temperature is summer mesopause, which for the CSU climatology the extremely cold temperatures are less than 180 K at 85 km (Figure 5.31c). However, for the PCL the minimum temperature is 172 K at 84 km in late May and early Jun, which these measures for previous PCL climatology were 165 K at 87 km. Which means, the minimum is 7 K warmer and 3 km higher than previous climatology. The minimum for the CSU winter mesopause is 195 K located at 103 km and for the PCL is 194 K at 94 km.

Figure 5.31: Temperature climatologies obtained from lidar measurements at (a) OHP (44.0N, 6.0E), (b) CEL (44.0N, 1.0W), (c) CSU (40.5N, 105.1W), (d) TMF (34.4N, 117.7W), and (e) MLO (19.5N, 155.6W), taken from Leblanc et al. (1998).
5.4 Summary

In order to extend the range of lidar measurements, four functions were used to merge temperature climatologies calculated from different channels measurements. These functions are: sine/cosine functions, simple linear functions, error functions, and hyperbolic functions. The first step was finding the best merging region between the PCL channels. For this purpose several parameters considered to find the merging area: photon count linearity, temperature standard deviation and temperature differences between channels was used as an auxiliary factor. After finding the merging altitudes, merging functions were evaluated to determine the best function. A weighted average function was chosen as a reference for evaluation of the merging functions. The merged temperature climatology was calculated using the weighted average function as a merging function between the Raman and LLR channels as well as the LLR and HLR channels. Then, the temperature differences between weighted average climatology and the calculated climatology using each merging function were plotted. Finally, the standard deviation of each Figure was calculated in order to find the uncertainty for each merging function. In the next stage, temperature climatologies were merged into a single climatology and this climatology was compared to the Leblanc et al. (1998) climatology. The results of these discussion will be presented in Chapter 7.
Chapter 6

Merged Climatology

6.1 Introduction

Temperature climatologies for each channel were formed in Chapter 4, then the results were merged together (Chapter 5). Another way to create the climatology is to merge individual night profiles over common nights between channels and then calculate the climatology. In this technique, the calculated temperature for each day has a different weight because the number of nights of data per channel were different due to different periods of operation.

6.2 Nightly Merging

The first step is performing individual merge between PCL channels is finding the common dates between Raman, LLR and HLR channel validated for the Delaware data. This choice is because the nonlinearity correction function has not yet been calculated for EchoBase measurements. The number of common nights between channels is contained in Table 6.1 and their distribution is presented in histogram 6.1.
6.2. Nightly Merging

<table>
<thead>
<tr>
<th>Month</th>
<th>Number of profiles</th>
</tr>
</thead>
<tbody>
<tr>
<td>January</td>
<td>8</td>
</tr>
<tr>
<td>February</td>
<td>5</td>
</tr>
<tr>
<td>March</td>
<td>11</td>
</tr>
<tr>
<td>April</td>
<td>7</td>
</tr>
<tr>
<td>May</td>
<td>41</td>
</tr>
<tr>
<td>June</td>
<td>43</td>
</tr>
<tr>
<td>July</td>
<td>84</td>
</tr>
<tr>
<td>August</td>
<td>47</td>
</tr>
<tr>
<td>September</td>
<td>13</td>
</tr>
<tr>
<td>October</td>
<td>13</td>
</tr>
<tr>
<td>November</td>
<td>16</td>
</tr>
<tr>
<td>December</td>
<td>9</td>
</tr>
<tr>
<td>Total</td>
<td>297</td>
</tr>
</tbody>
</table>

Table 6.1: Number of common dates between the PCL’s channels.

Figure 6.1: Histogram distribution of the number of nights of common dates between the PCL’s channels.
6.3 Methodology for Nightly Merging

In the PCL system, the backscattered light from an altitude of 120 km should be detected by the photomultipliers after a few tens of nanoseconds. This high dynamic range is a challenge in the detection of lidar signal. As already mentioned, the photon counting (PC) method is used to detect low level light intensities, but it tends to have a nonlinear signal response at higher light intensities. An analog system is used for high light intensities and a combination of two techniques aids in increasing the linear dynamic range. An explanation of these corrections is given in Chapter 2. The nonlinearity correction is greater in regions with high count rates, where is lower altitudes close to merging region while, the statistical errors are lowest for HLR channel at same location. As mentioned in Chapter 2, the critical signal for the PCL is 2.6 MHz, and the correction becomes significant above this count rate. The percentage of the nonlinearity correction is calculated for each night between 40 to 50 km, and the most of the nights have less than a 2% correction. Based on the critical signal, the critical height is defined for each night such that the correction below that altitude increases significantly. The time series of critical heights from all nights are plotted in Figures 6.2 and 6.3 for the LLR and HLR channels, respectively. For the LLR channel, the critical heights are up to about 28 km and the HLR channels are up to 42 km. Unlike the last chapter where the merged area was constant, another method is used to merge the nightly profile. In this method, first, critical height is calculated for each night, and then the merged area is defined as the critical height plus 5 km, if this summation were less than 50 km for merging HLR-LLR. In the case that the result of critical height + 5 km is larger than 50 km for the HLR-LLR merging, the merged area is set between 45 to 50 km. The LLR-Raman merged area is chosen between 30 to 35 km. After merging, the profile extends from 10 to 100 km and includes: Raman for lower part, merged temperature between the Raman and LLR, the LLR and the HLR for merged region, and the HLR using inversion method for upper atmosphere. After finding merged profiles, the same methodology as the last chapter is followed to produce the temperature climatologies of the PCL lidar measurements.
6.3. **Methodology for Nightly Merging**

Figure 6.2: Time series critical height for LLR channel

Figure 6.3: Time series critical height for HLR channel
6.4 Merged Temperature Sensitivity to Seed Values

The retrieved temperature from different channels should be identical in a merged area. But, it has been observed that the results vary according to different seed values, which are considered in rest of this section. Different seed values are tested in order to inspect this matter for the Raman and LLR channels. Three possibilities exist for seeding the Raman and LLR channels: pressure seeding, (CIRA model) temperature seeding and PCL’s HLR channel temperature seeding. The HLR channel range is between 35 to 110 km, therefore, it can be used for initiating the downward integration for the Raman channel (45 km) and LLR channel (60 km), however the inversion method is used in all case for HLR channel. The results are shown that in case of using seeding pressure for Raman and LLR channels, the temperature profiles are not identical in the merging region. However, when the HLR temperature seed value is used, the differences between the channels’ temperatures vanish and the differences are minimum (Figures 6.4 and 6.5). To allow better understanding of this issue, Table 6.2 illustrates a number of profiles in various conditions using different seed values. In this table, Good means there is an overlap and at least one intersection between the Raman and LLR as well as the LLR and HLR channels, Good (Raman-LLR) and Good (LLR-HLR) mean there is an overlap between showed channels and Bad means there is no intersection between channels. The differences between the number of Goods and Bads for various seed values are huge. Also it necessary to mention here that the total number of nights in Table 6.2 is different than Chapter 5, which is because only common nights between PCL’s channels are considered here but in Chapter 5 all available measurements for each channel were considered. The HLR temperatures are used as seed value for retrieving the Raman and LLR channels nightly temperature profiles in this chapter.
6.4. Merged Temperature Sensitivity to Seed Values

(a) Using seed pressure to retrieve temperature profiles
(b) Using seed HLR temperature to retrieve profiles for LLR and Raman channels

Figure 6.4: Temperature overlap between PCL channels in merging area for 19991209 (Blue: HLR, Green: LLR, Red: Raman).

(a) Using seed pressure to retrieve temperature profiles
(b) Using seed HLR temperature to retrieve profiles for LLR and Raman channels

Figure 6.5: Temperature overlap between PCL channels in merging area for 19990926 (Blue: HLR, Green: LLR, Red: Raman).
### 6.5 Merging Functions Climatology Results

The same 4 functions as Chapter 5 were used for weighting: sine/cosine, simple linear, error function and hyperbolic functions were considered for nightly temperature merging. Retrieved temperature profiles for the PCL’s channels were merged first, and then the [Argall and Sica (2007)](#) methodology was followed to perform climatologies. Next, a temperature climatology is performed using a weighted average function (Figure 6.6), and this climatology is considered as a reference for evaluating each function. Temperature climatology differences between the weighted average result and each function was calculated and finally, the standard deviation of each difference matrix (each figure) was determined as the uncertainty for each function. The calculated temperature climatologies using each merging function as well as their differences with weight average climatology are presented in Figures (6.7), (6.8), (6.9) and (6.10). The white color in the figures shows the missing data. Only common dates were used, and the Raman channel did not have enough measurements for the February. Therefore, from February the data from other channels were not considered as well. An analysis of Figures (6.7), (6.8), (6.9) and (6.10), shows that the linear and ref functions show larger differences in thicker layers. However, the sine/cosine and hyperbolic functions provide better results with less uncertainty. Table 6.3 confirms these results and shows that the hyperbolic functions have the best result between these functions with ±0.9 K uncertainty. However, it is necessary to consider at this point that, this uncertainty is for all month including the months with a smaller number of profiles and higher uncertainty. Considering the months with a high number of measurements causes a decrease in the uncertainty.

<table>
<thead>
<tr>
<th>Seed value</th>
<th>Good</th>
<th>Good (Raman-LLR)</th>
<th>Good (LLR-HLR)</th>
<th>Bad</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pressure seeding</td>
<td>49</td>
<td>101</td>
<td>35</td>
<td>112</td>
<td>297</td>
</tr>
<tr>
<td>Temperature seeding</td>
<td>135</td>
<td>31</td>
<td>95</td>
<td>31</td>
<td>297</td>
</tr>
</tbody>
</table>

Table 6.2: Conditions of overlapped profiles in merging region, showing each situation with number of profiles.
6.5. Merging Functions Climatology Results

Figure 6.6: Temperature climatology using weighted average as merging function

(a) Temperature climatology using Sine/Cos function

(b) Temperature difference between the weighted average and the sine/cosine function climatology

Figure 6.7: Sine/Cosine function result
Chapter 6. Merged Climatology

(a) Temperature climatology using linear function

(b) Temperature difference between the weighted average and the linear function climatologies

Figure 6.8: Linear function result

(a) Temperature climatology using erf function

(b) Temperature difference between the weighted average and erf function climatologies

Figure 6.9: Erf function result

<table>
<thead>
<tr>
<th>Merging function</th>
<th>Sine/Cos</th>
<th>Linear</th>
<th>erf</th>
<th>hyperbolic</th>
</tr>
</thead>
<tbody>
<tr>
<td>STD (K)</td>
<td>1.3</td>
<td>2.2</td>
<td>1.8</td>
<td>0.9</td>
</tr>
</tbody>
</table>

Table 6.3: Standard deviation of differences between the weighted average climatology and climatologies using merging functions
6.6 Summary

In this chapter another method was tested to evaluate the merging functions. This method was based on merging individual profiles first and then forming the climatology. First, the common dates between the PCL channels were found. In this method the merging altitudes varied and depended on critical height. Next, the Raman and LLR profiles were retrieved using the HLR temperature as a seed value. Then, the same methodology as Argall and Sica (2007) was followed to calculate climatologies using each merging function. As in Chapter 5, the same four functions were tested as merging functions and the weighted average function was considered as a reference. Then, the temperature differences between the weighted average climatology and the climatology calculated using each merging function were plotted. Finally, the standard deviation of each figure was calculated in order to find the uncertainty of each merging function. The results of this chapter will be discussed in Chapter 7.
Chapter 7

Conclusions and Future Work

Khanna et al. (2012) used a new approach for retrieving the atmospheric temperature from lidar measurements as an alternative to the conventional method of HC. Khanna’s method showed a significant improvement in the integration of temperature profiles using the lidar equation when compared to the conventional technique. In this study, temperature climatologies were calculated for all available PCL Rayleigh measurements in order to investigate and evaluate the new method. Given the same uncertainty level, the inversion method had the advantage of gaining approximately an extra 10 km in retrieved temperatures. The disadvantages of the new method are that it uses very time consuming computations and is sensitive to co-add time and co-add height. It was also found that during calculation of temperature profiles, in some cases the computation stopped because of singularity in calculations when the co-add time and height were changing.

The temperature differences for the HC method, using seed pressure and seed temperature for the HLR channel (Figure 4.11), shows the huge difference between various seed values before removing a 10 km, as expected. However, after removing the difference decreased. The same plots for the inversion method result (Figures 4.14 and 4.15) show that the HC method, using seed pressure is more consistent with the inversion method. The HC method using seed temperature results in colder temperatures than the inversion method. The differences between
the CIRA model and the retrieved techniques (Figures 4.17 and 4.18) were shown that: above 90 km the CIRA model is too warm in comparison with measurements and between 75 to 90 km it is cold. These results illustrate that the inversion approach using the seed pressure from the CIRA model and the HC method is closer to the actual temperature than using the temperature from the CIRA model. Also, the CIRA model is more consistent with the HC method when using seed temperature. Further tests on seed values showed that the HC method is more sensitive to varying seed value when initiating downward integration to retrieve temperature. Figures 4.23 and 4.24 are the corresponding temperature difference results of using seeding values offset by 10 percent. The temperatures related to top seed pressure are changed by 20 to 30 K at the top, and after removing top 10 km, these differences are reasonable. The variation of pressure for the inversion seed value in the middle atmosphere is less than its conventional counterpart in the upper atmosphere. As a result, the inversion method is less sensitive to the initial guess. These results are in agreement with Khanna et al. (2012). A comparison with the previous Rayleigh channel climatology (Figures 4.28 and 4.29) revealed that climatologies corresponding to the HC method using seed pressure (Figure 4.28 left) and the inversion method (Figure 4.28 right) are slightly warmer (about 1 K) below 80 km and colder above 80 km in both methods. But, the HC method using seed temperature climatology (Figure 4.29) shows an increase in temperature above 80 km, except for September. Also, comparisons between the extended climatology and the previous Raman channel climatology (Figure 4.41) showed that there was almost no change in temperature over time, except a slight increase in April and December and a couple of degrees decrease for June.

The PCL is capable of measuring temperature from altitudes from 10 to 110 km, using three channel measurements. These three channels overlap with one another, and once merged, produce a single profile. In this work, sine/cosine, linear, error function, and hyperbolic functions were examined for use as merging functions, using two different methods. In the first method, in order to extend the range of lidar measurements, calculated temperature climatologies from different channels were merged together. First, merging altitudes were found by considering...
several factors including photon count linearity, temperature standard deviation and temperature differences between different channels. The best altitude range between the Raman and LLR channels was 30 to 35 km and between the LLR and HLR was 35 to 40 km. Then a weighted average function was chosen as a reference to evaluate the merging functions. Two different approaches were resorted to merge the climatologies for 10 to 110 km. Firstly, the climatologies were formed and then merged together. Secondly, a climatology was calculated by merging the nightly PCL temperature profiles. In the first approach, the results (Table 5.5 and 5.6) revealed that the hyperbolic function had the best result for merging Raman and LLR channels, with an uncertainty of ±0.9 K. Also, the linear function yields a better result for merging temperatures between LLR and HLR channels, with a ±1 K uncertainty. Using the hyperbolic and linear functions as merging functions, temperature climatologies were merged into a single climatology (Figure 5.30). Then, the calculated climatology was compared to the Leblanc et al. (1998) climatology. Also, Argall and Sica (2007) were compared to the previous climatology with the Leblanc et al. (1998) climatology. A comparison between the extended PCL climatology with the Leblanc et al. (1998) climatology showed that the PCL temperature maximum for summer stratopause was 1 K cooler and 1 km lower than the previous PCL climatology, while the PCL temperature climatology in comparison with the Leblanc et al. (1998) is 3 K cooler at a common altitude of 47 km. In addition, the PCL temperature minimum in the summer mesopause is 7 K warmer and 3 km higher than the previous climatology. However, in comparison with Leblanc et al. (1998) result, it is 1 K cooler and 9 km lower. The second approach involved merging the nightly temperature profiles together first and then creating the temperature climatology. Unlike the first method, the merging altitudes were variable and it changed night by night based on calculated critical height. Instead of using seed pressure or temperature from the CIRA model for retrieving the temperature from the Raman and LLR channels measurements, a temperature from the HLR channel was used as an initial guess. This causes profiles from different channels to be more similar and reliable results were obtained. The same procedure as the first approach was followed to evaluate each merging function, that
is the temperature differences between the weighted average climatology and the calculated climatology using each merging functions were calculated, and the standard deviation of each figure was calculated in order to find the uncertainty for each merging function. The second method result (Table 6.3) confirmed the first method result that the hyperbolic function demonstrated a better result, with the same uncertainty of ±0.9 K. Some other tests and future work can be done to improve this research.

1. The LLR temperature climatology was calculated in this project. In order to get more accurate results for the HLR channel climatology, the seed value for the inversion method can be obtained from the LLR channel temperature. Then, the other calculated climatologies can be compared with this climatology.

2. The temperate climatology was performed for the Raman channel as well. There was a gap during February in the Raman climatology due to the small number of profiles. This gap in the Raman climatology can be filled by interpolation to create a complete temperature climatology or by obtaining more measurements.

3. Only the HC method was used to calculate the temperature climatologies for the Raman and LLR channels. The inversion technique can be used to form climatologies for these channels, as well as the HC method using the HLR temperature as the seed value.
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