The Retrieval of Profiles of Particulate Extinction from Cloud-Aerosol Lidar Infrared Pathfinder Satellite Observations (CALIPSO) Data: Algorithm Description

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ABSTRACT

This work describes the algorithms used for the fully automated retrieval of profiles of particulate extinction coefficients from the attenuated backscatter data acquired by the lidar on board the Cloud-Aerosol Lidar Infrared Pathfinder Satellite Observations (CALIPSO) spacecraft. The close interaction of the Hybrid Extinction Retrieval Algorithms (HERA) with the preceding processes that detect and classify atmospheric features (i.e., cloud and aerosol layers) is described within the context of the analysis of measurements from scenes of varying complexity. Two main components compose HERA: a top-level algorithm that selects the analysis pathway, the order of processing, and the analysis parameters, depending on the nature and spatial extent of the atmospheric features to be processed; and a profile solver or “extinction engine,” whose task it is to retrieve profiles of particulate extinction and backscatter coefficients from specified sections of an atmospheric scene defined by the top-level algorithm. The operation of these components is described using synthetic data derived from Lidar In Space Technology Experiment (LITE) measurements. The performance of the algorithms is illustrated using CALIPSO measurements acquired during the mission on 1 January 2007.

1. Introduction

The Cloud-Aerosol Lidar Infrared Pathfinder Satellite Observations (CALIPSO) mission (Winker et al. 2003) joined the A-Train (Stephens et al. 2002) constellation of satellites in late April 2006 and began acquiring scientific data in mid-June of that year. CALIPSO carries three, co-aligned, nadir-viewing instruments: a dual-wavelength, dual-polarization lidar (Winker et al. 2007), an imaging infrared radiometer (Chomette et al. 2003) and a wide-field camera (Pitts et al. 2007). The main aims of the CALIPSO mission are to acquire global profile data on the distribution and properties of clouds and aerosols, to ultimately, improve the performance of weather and climate models. The achievement of these goals is aided by flying in formation with the other satellites, thereby allowing the analysis of clouds and aerosols to be enhanced by the synergistic combination of data from other instruments viewing the same atmospheric targets almost simultaneously.

CALIPSO’s lidar (the Cloud-Aerosol Lidar with Orthogonal Polarization, CALIOP) is a dual-wavelength, dual-polarization, elastic backscatter lidar that transmits linearly polarized pulses of laser light at wavelengths of 1064 and 532 nm. Energy backscattered from the atmosphere is received in a 1-m-diameter telescope and separated into one channel where the 1064-nm signal is detected using an avalanche photodiode, and one channel for each of the orthogonal polarizations at 532 nm where photomultipliers are used. (Hunt et al. 2009) CALIPSO data products are available in various “levels” that, according to National Aeronautics and Space Administration (NASA) Earth Observing System (EOS) standards, reflect the degree of processing involved (King...
et al. 2004). Level 1 data products include the calibrated, attenuated backscatter profiles at the two wavelengths along with various ancillary atmospheric and navigational data. These level 1 data are used to create the higher-level data products. Primary level 2 data products from the lidar are the locations of atmospheric regions containing particulate matter (clouds and aerosols), the identification of these particles according to type, and profiles and layer integrals of particulate backscatter and extinction in these regions. This paper focuses on the fully automated retrieval of profiles of particulate backscatter and extinction. Note that the level 2 algorithms covered here are applied to measurements made by a single instrument (CALIOP). Multisensor algorithms [e.g., CALIOP plus *Aqua*'s Moderate Resolution Imaging Spectroradiometer (MODIS)] are not presently being utilized in the production of the CALIOP level 2 lidar data products and, hence, are not presented in this work.

The analysis of space-based lidar data must contend with numerous complexities not typically encountered in ground-based measurements. Many atmospheric features (clouds and aerosol layers) are tenuous, and the large distance of the satellite from these features combined with the limits placed on the energy of the laser transmitter by the satellite power budget and eye-safety requirements can lead to low signal-to-noise ratios (SNRs) in the recorded data. This problem is exacerbated during daylight operations, when the weakly backscattering features are viewed against brightly illuminated backgrounds like dense water clouds or snow-covered or sandy surfaces. The usual method of increasing the SNR is to average many profiles. However, along-track inhomogeneities in the atmospheric features, combined with the high speed (typically 7.5 km s$^{-1}$) of the satellite across these features and the relatively low firing rate of the laser ($\sim 20$ s$^{-1}$), lead to situations where it is simply not possible to acquire a sufficient number of profiles before the subsatellite atmosphere changes significantly.

An added complication, not limited to the analysis of space lidar data, is the presence of both strongly scattering and weakly scattering features in the same atmospheric region. As the lidar equation is nonlinear, any attempt to retrieve profiles of particulate extinction from the averages of profiles containing features of grossly different intrinsic or extrinsic optical properties (and hence, ratios of the particulate volume extinction and backscatter coefficients) could produce results that would be unrepresentative of the real atmosphere.

A unique feature of the CALIPSO lidar analysis is that it attempts to average signals in atmospheric regions where the optical properties are uniform and the signal strengths are comparable (Vaughan et al. 2009). The way in which the CALIPSO analysis can identify and process regions of different horizontal and vertical extents in the same atmospheric region is outlined in section 2 below. The CALIPSO lidar analysis is a multistage process that includes the correction of signals for instrumental effects; the detection, boundary location, and classification of atmospheric features; and, finally, the retrieval of the backscatter and extinction of these features. In section 2 we explain the analysis architecture and how, in order to improve SNRs, the analysis is performed simultaneously at multiple horizontal resolutions using processes that work either on individual profiles or on whole "scenes" and the information on the features contained therein. The extinction retrieval process is intimately linked to the preceding stages of feature detection, boundary location, and feature classification. Because a clear understanding of this interaction is required before the extinction retrieval is discussed, a brief summary of the preceding processes and the information provided to the extinction algorithm is also presented.

In section 3 the rationale for the selection of the algorithm used in the CALIPSO analysis for the retrieval of profiles of particulate backscatter and extinction is outlined, along with details of its implementation, including the use of constrained and unconstrained solutions and retrieval stability issues. The methods by which the CALIPSO extinction profile algorithm are used to retrieve the extinction in a scene containing features of differing horizontal and vertical extents and features of different types that are vertically adjacent or are embedded in other, larger features are described in section 4 with the aid of a representative complex atmospheric scene simulated using measurements acquired by LITE (Winker et al. 1996). The performance of the CALIPSO Hybrid Extinction Retrieval Algorithm (HERA) is discussed in section 5 and an example of the analysis of an actual scene measured by CALIPSO is presented.

For reasons of available space, an analysis of the sensitivity of the extinction algorithm to errors and uncertainties in the input data and their propagation as the solution proceeds down through the atmosphere will be published separately. Similarly, a detailed description of the treatment of multiple scattering in the CALIPSO extinction retrieval algorithm, which takes account of the different features types and their locations in an atmospheric scene, will be presented in a future publication.

2. CALIPSO lidar analysis architecture

a. Definition of scene and profile processes in the CALIPSO lidar analysis

In our description of the CALIPSO lidar analysis, we refer frequently to features and scenes. We define a
CALIPSO scene as a consecutive set of profiles of attenuated backscatter, extending 80 km along the CALIPSO track and to an altitude of 30 km, and containing a number of atmospheric features. Scenes are sections of what are commonly referred to as CALIPSO curtain files, which are two-dimensional, height versus along-track distance, sections through the atmosphere (e.g., see Fig. 3). For the purposes of our detection scheme, we define a feature as any extended and contiguous region of enhanced backscatter signal that rises significantly above the expected “clear air” value. The CALIPSO extinction analysis uses horizontal resolutions of 5, 20, and 80 km, which correspond, respectively, to averages of 15, 60, and 240 consecutive, single-shot profiles, and are the same spatial scales at which the feature finder detects features. The CALIPSO lidar analysis proceeds one 80-km scene at a time.

In the CALIPSO extinction analysis, features are analyzed or “solved” (their particulate backscatter and extinction profiles retrieved) using lidar ratios appropriate to the type of cloud or aerosol layer of which they are composed. As a scene, or any profile for that matter, can contain features of different types, different lidar ratios are used in different regions of the scene or profile. First, however, features need to be located and classified.

Although it is recognized that the lidar ratio may vary continuously as a function of range within a layer (e.g., Pappalardo et al. 2004), the approximation used here is the standard method used in the analyses of data from elastic backscatter lidars (e.g., Campbell et al. 2003; Comstock and Sassen 2001; Fernald 1984; Hlavka et al. 2005; Mitrescu et al. 2005; Platt 1979; Stephens et al. 2001; Welton et al. 2000). Within HERA, the lidar ratio is considered to be constant over certain intervals within each backscatter profile, as determined by the layer detection and scene classification algorithms. Unlike more sophisticated instruments, such as high spectral resolution lidar (HSRL) and Raman lidar, the measurements made by elastic backscatter lidars like CALIOP simply do not contain the additional information required for deriving estimates of range-resolved lidar ratios. Furthermore, it must also be recognized that while Raman and HSRL can derive extinction and backscatter directly, and thus derive range-varying lidar ratios, accurate retrieval of these data requires profile SNRs much higher than are readily available in the current generation of operational space-based lidars. Given the very high speed at which the CALIPSO satellite traverses its ground track, the extensive spatial averaging that would be required to generate SNR levels for Raman–HSRL retrievals (especially during daylight operations) would likely require averaging over dissimilar layer types, thus rendering the lidar ratio retrievals highly suspect at best. Thus, while CALIPSO cannot produce fine-resolution profiles of the lidar ratio, the analysis scheme employed by HERA improves on standard elastic backscatter lidar analyses by constraining the extinction retrievals with measurements of layer transmittance wherever possible, or by employing different lidar ratios in different regions of a scene according to the classification of the detected features. These lidar ratios have been derived from an extensive analysis of Aerosol Robotic Network (AERONET) sun-photometer data (Omar et al. 2009, hereafter OJTECH).

b. Analysis module dependencies

The CALIOP automated analysis consists of three primary modules: a feature-finding routine that detects layer boundaries, a suite of scene classification algorithms (SCAs) that differentiates between the various types of clouds and aerosols, and HERA, which is responsible for retrieving the optical properties of all layers detected. The operation of all three components relies on a nested, multitgrid averaging scheme initially incorporated into the feature-finder module. As the SNRs of all but the strongest features are usually too low to permit their detection in single profiles, varying numbers of consecutive profiles are averaged in order to improve the SNR. Note that we average first and then analyze the averaged profile rather than the converse. The non-Gaussian nature of the noise in the CALIPSO profiles of weak features and the nonlinear nature of the lidar retrieval can lead to biases if single profiles are analyzed first and their retrieved extinction profiles averaged afterward. The process of averaging profiles and locating features is quite complex, and is fully covered in VJTECH; so, only sufficient detail to permit the understanding of the extinction algorithm will be provided here.

Prior to the execution of HERA, a selective, iterated boundary location (SIBYL) algorithm generates a map of all features detected within each 80-km scene. The spatial resolutions of these features vary according to the amount of horizontal averaging required to provide reliable differentiation of clouds and/or aerosol layers from the weaker molecular background signal. More tenuous layers require more averaging; robust features, on the other hand, require little or no averaging. The features in regions of heterogeneous backscatter intensity—for example, fair weather cumulus embedded in boundary layer aerosols, or the fall streaks in cirrus clouds—are frequently detected not at one single resolution, but instead at several different averaging resolutions, according to the magnitude of the localized signal strength. Conceptually, the result of this sort of analysis resembles a coarse contour plot of backscatter
intensity within each 80-km scene. As a consequence of this behavior, features found at different spatial resolutions may lie vertically adjacent to one another, and features found at high spatial resolution may be wholly embedded within some other feature detected at a coarser spatial resolution.

After locating the layers within a scene, the CALIPSO feature finder identifies those elevated layers for which a reliable estimate of the 532-nm-layer two-way transmittance can be computed from the clear-air regions immediately above and below the feature. Using these estimates, together with the measured integrated attenuated backscatters of the elevated layers, SIBYL derives an initial estimate of the 532-nm lidar ratio (Young 1995). Where transmittance measurements are not possible, or are of low quality, the initial lidar ratios are assigned according to feature type. For clouds, the lidar ratios at both 532 and 1064 nm are assigned according to ice-water phase (Hu et al. 2009, manuscript submitted to J. Atmos. Oceanic Technol., hereafter HJTECH). For aerosols, an aerosol subtyping algorithm selects lidar ratios at 532 and 1064 nm for each feature in the scene by using the scattering characteristics provided by SIBYL for each layer, along with the ancillary surface type from the International Geosphere-Biosphere Programme (IGBP) and the National Snow and Ice Data Center (NSIDC) (OJTECH).

Approximations used in the correction of the retrieved extinction profiles for the effects of multiple scattering are also selected at this time. These functions depend on the nature of the particles in the feature and on the proximity of the feature to any overlying features. Although the algorithm has been written to accommodate a range-dependent multiple-scattering function, for the current (version 2.01) data release a constant value of unity is used in all situations with the exception of cirrus layers, where a constant value of 0.6 is used.

Once all the features in a scene have been located and classified, the relevant information on the vertical locations, horizontal extents, and optical properties of the features is passed to HERA along with the 16 profiles of attenuated backscatter that have each been averaged to a horizontal resolution of 5 km. The task of HERA is to retrieve particulate extinction coefficients from the various regions of the CALIPSO scene, which can be considered as an array 16 columns wide, 1 for each of the 5-km resolution profiles, by 550 rows deep, each row corresponding to a range step or altitude. HERA combines an algorithm that selects which regions of the scene to process, and in which order, with an algorithm that retrieves profiles of particulate extinction from profiles of attenuated backscatter (the profile solver). These profiles of attenuated backscatter are created for each feature by averaging those sections of all the 5-km resolution profiles that lie within the boundaries of the features detected by the feature boundary locater (SIBYL).

The extinction retrieval process works from the top of the atmosphere downward to the surface, correcting the signals from lower regions for the attenuation caused by higher features as this is retrieved. However, in complex scenes, where dissimilar features can be vertically adjacent to, or embedded in, larger features, the solution pathway needs significant modification. The process by which regions of a complex scene are selected and analyzed is described in section 4.

Signals from features detected lower in the atmosphere suffer wavelength-dependent attenuation by higher regions. As this attenuation is unknown until the extinction profiles for the upper regions have been retrieved, the initial classification of the lower features, based on attenuated data, may be in error. Use of incorrect lidar ratios based on these incorrect classifications would result in incorrect retrievals of the attenuation of these lower features and subsequent propagation of these errors to still lower features in the scene. Therefore, once the attenuation of a region of the atmosphere above a feature to be solved has been retrieved, the SCA is invoked to use the just-retrieved overlying attenuation to provide an updated classification of the feature and its associated lidar ratios. The way in which the various analysis modules interact is depicted in Fig. 1.

3. Retrieval of profiles of particulate backscatter and extinction

a. The elastic backscatter lidar equation

The signal detected by an elastic-backscatter lidar, like that used in CALIPSO, is described by the following two-component lidar equation:

\[
P(r) = \frac{1}{\pi^2} E_0 \xi [\beta_M(r) + \beta_P(r)] T_M^2(0, r) T_O^2(0, r) T_P^2(0, r) + P_o,
\]

where

- \( P(r) \) is the backscattered signal power detected from range \( r \) from the lidar;
- \( \xi \) is the lidar system parameter such that \( \xi = G_A C \)
  where \( G_A \) is the amplifier gain and \( C \) is the lidar calibration coefficient;
- \( E_0 \) is the (average) laser energy for a single or averaged profile; and
- \( \beta_M(r) \) is the molecular volume backscatter coefficient, which is proportional to the molecular number density profile;
is the molecular two-way transmittance between the lidar and range \( r \), in which

\[
T_M^2(0, r) = \exp\left[-2 \int_0^r \sigma_M(r') dr' \right]
\]

(2)

is the particulate optical depth summed over the various layers of the atmosphere between the lidar and range \( r \), and

\[
\sigma_P(r) = S_P \beta_P(r)
\]

(5)

is the particulate volume extinction coefficient, where

\( S_P \) is the particulate extinction-to-backscatter (lidar) ratio, which is assumed to be constant within identified layers (features).

The term \( P_0 \) here represents the combined effects of signals from background illumination and from electrical or digital offsets applied during the electronic amplification or digitization of the detected signals. For CALIPSO, the background signal is determined from a measurement in the near field over the altitude range from 112 to 97 km where the molecular backscatter signal is effectively zero. The amplifier and digitizer zero offsets are measured and removed from the signal on board the satellite. At 532 nm, the lidar calibration coefficient is determined by comparing the measured signal, averaged over 55-km along-track distances and between altitudes of 30 and 34.2 km, with the modeled molecular signal in the same region (Powell et al. 2009).
In the analysis of CALIPSO data, the profiles of the molecular number density and the ozone absorption coefficient are obtained from the NASA Global Modeling and Assimilation Office (GMAO) (Bloom et al. 2005). The initial estimate of the particulate lidar ratio, \( S_p \), and the multiple-scattering factor profile, \( \eta(r) \), are provided by the SCA (HJTECH; OJTECH).

Once the background and offset have been removed from the lidar signal, Eq. (1) can be rearranged to provide the attenuated backscatter, a quantity that is dependent only on atmospheric quantities and range:

\[
\beta'(0, r) = [\beta_M(r) + \beta_p(r)] T_M^2(0, r) T_p^2(0, r) = \frac{[P(r) - P_o]^2}{E_0 G_A C T_O^2(0, r)}. \tag{6}
\]

b. Choice of the CALIPSO extinction retrieval algorithm

Various algorithms are available for retrieving profiles of particulate backscatter and extinction from signals measured using elastic backscatter lidars like that used by CALIPSO. The algorithms fall broadly into two classes. Closed-form analytical solutions, based on the solution to the Bernoulli equation and developed for the analysis of rainfall radar measurements (e.g., HITSCHFELD and BORDAN 1954), were adapted for the analysis of lidar data by early lidar researchers (e.g., BARRETT and BEN DOV 1967; VIEZEE et al. 1969; DAVIS 1969). These solutions considered only one atmospheric scattering component and are not applicable to conditions where molecular and particulate scattering may be comparable in magnitude, as is the case in CALIPSO lidar signals. Two-component analytical solutions were developed by FERNALD et al. (1972), FERNALD (1984), and KLETT (1985), among others, for the analysis of data recorded under these conditions. Iterative, numerical solutions (e.g., GAMBLING et al. 1971; GAMBLING and BARTUSEK 1972 a,b; PLATT 1973) were also developed following those used by ELTERMAN (1966) for the analysis of searchlight studies of aerosols.

The solutions described so far, with the exception of those of DAVIS (1969) and PLATT (1973), assume that the signals detected by the lidar result from single interactions of the transmitted photons with the atmosphere. Under many conditions, determined by the lidar geometry and the nature of the scattering medium, this single-scattering approximation is not valid. Solutions using PLATT’s (1973, 1979) parameterization of multiple scattering, in which the particulate extinction is modified by an efficiency factor, \( \eta(r) \), have been developed (e.g., SASSEN and CHO 1992) for use under these conditions. For analysis of CALIPSO signals, however, \( \eta(r) \) modifies the optical depth as in Eq. (3). Also, unlike the common practice of replacing \( \eta(r) \) with a constant value, range-dependent functions are under development to describe the multiple scattering for each of the cloud and aerosol classes considered by CALIPSO (WINKER 2003).

For this implementation of the multiple-scattering function, the above algorithms are not suitable, so the CALIPSO analysis uses an iterative algorithm as described below. As the iteration usually converges in two to three steps, the increased processing time is not a significant concern.

c. Constrained and unconstrained retrievals and stability considerations

Solutions to the lidar equation essentially involve the calculation of the two-way particulate transmittance losses in Eq. (6) in order to solve for the particulate extinction or backscatter profile. The transmittance corrections are calculated using the retrieved backscatter and extinction from the preceding steps and, consequently, are sensitive to the boundary conditions set at the first point, and to the assumed values of the lidar ratio and the multiple-scattering function. For solutions that are initialized in the near field (forward solutions), the two-way transmittance decreases as the solution proceeds away from the near point. As both analytical and iterative algorithms working in the forward direction involve the correction of the attenuated backscatter profile by this decreasing transmittance, which appears in the denominator in both analytical and iterative expressions, solutions can diverge rapidly from the correct values, particularly in situations of moderate to high optical depth.

KLETT (1981) explained the instability of the forward analytical solutions and showed that stable solutions could be ensured by initializing in the far field, beyond the feature being analyzed, and then working backward toward the lidar (backward solutions). Backward iterative solutions are also stable because the transmittance correction factor approaches unity as the solution approaches the near point, and it appears in the numerator. However, it is important to realize that stability does not imply accuracy. Some early researchers used backward-iterative solutions, primarily because far-point boundary values of backscatter could be assumed to be close to molecular values above 30 km for their aerosol studies in the stratosphere (ELTERMAN 1966) or near the tropopause for their tropospheric (GAMBLING and BARTUSEK 1972a) aerosol studies, thereby ensuring that their retrievals were both stable and accurate. For lidar systems operating from space, however, backward solutions are often problematical because it is usually difficult to determine accurate, far-field boundary conditions with any confidence, especially under the conditions of
d. The HERA profile solver

To permit the tuning of various analysis parameters based on the experience gained from processing actual atmospheric data, and to permit the adjustment of these parameters in order to compensate for the expected reduction in performance (basically in SNR) over time or for significant changes in the atmosphere that would occur following the injection into the stratosphere of material from a major volcanic eruption, many parameters used to control the behavior of the software modules that create the CALIOP data products are read from a configuration file. These parameters include various thresholds and convergence tolerances, limiting values of retrieved optical depth or backscatter, and various default values of the lidar ratio. The parameters are kept constant during any data release version or some model value. At the next step of the iteration, the particulate backscatter at range \( r \) can then be calculated as

\[
\beta_N'(r) = \beta'(0,r)/C_N(r_N). \tag{8}
\]

Strictly speaking, \( \beta_N'(r) \) represents a family of curves, \( \beta_N(r_N, r) \), as its magnitude depends on the renormalization range \( r_N \). However, to simplify notation, we indicate renormalized attenuated backscatter with the subscript \( N \).

For forward retrievals, \( r_N < r \), so the transmittance factorizes as

\[
T^2(0, r) = T^2(0, r_N)T^2(r_N, r), \tag{9}
\]

and we can write the renormalized attenuated backscatter as

\[
\beta_N'(r) = [\beta_M(r) + \beta_P(r)]T^2_M(r_N, r)T^2_P(r_N, r). \tag{10}
\]

Solving for the particulate backscatter at range \( r \), we have

\[
\beta_P(r) = \beta_N'(r)/[T^2_M(r_N, r)T^2_P(r_N, r)] - \beta_M(r). \tag{11}
\]

We note, however, that \( \beta_P(r) \) appears in the particulate transmittance factor:

\[
T^2_P(r_N, r) = \exp\left[-2\eta(r)S_P\int_{r_N}^r \beta_P(z)dz\right] = \exp\left[-2\eta(r)\tau_P(r_N, r)\right]. \tag{12}
\]

We are, therefore, seeking a solution to an equation of the form \( x = F(x) \). Equations of this form are commonly solved using fixed-point iteration algorithms (e.g., Fröberg 1966, section 2.5). Simple, iterative methods have been employed (e.g., Elterman 1966; Gambling and Bartusek 1972) where, at each range increment in the retrieval, the particulate backscatter in the transmittance factor [Eqs. (11) and (12)] is initially set to zero, or the value from the previous range increment, or some model value. At the next step of the iteration, the particulate backscatter calculated using Eq. (11) is substituted into Eq. (12), and iteration is performed using Eqs. (11) and (12) until successive calculations of \( \beta_P(r) \) differ by less than some threshold. The particulate extinction at that range can then be calculated using Eq. (5) and the process repeated at subsequent range steps.

Tests using simulated data have shown that, in conditions of moderate to high particulate extinction, the convergence is much more rapid if, instead of the simple linear iteration described above, a Newtonian (Newton–Raphson) method (e.g., Fröberg 1966, section 2.2) iteration is used. In this method, successive estimates, \( k \), of the particulate backscatter at any range, \( r \), from the lidar are obtained from the following familiar formula:

\[
C_N(r_N) = T^2_M(0, r_N)T^2_P(0, r_N). \tag{7}
\]

where \( r_N \) is the renormalization range.

The first action of the profile solver is to calculate the “renormalized” attenuated backscatter:
\[
\beta_{p,k+1}(r) = \beta_{p,k}(r) - \frac{f[\beta_{p,k}(r)]}{f'[\beta_{p,k}(r)]}.
\]  

(13)

In the implementation of the method in the HERA profile solver,

\[
f[\beta_{p,k}(r)] = \frac{\beta_N'(r)}{T_S^2(0,r)} \exp [2\eta(r)\tau_P(r_N,r)]
- \beta_M(r) - \beta_{p,k}(r).
\]

(14)

Here,

\[
f'[\beta_{p,k}(r)] = \frac{\eta(r)S_P\delta r \beta_N'(r)}{T_S^2(0,r)} \exp [2\eta(r)\tau_P(r_N,r)] - 1.0,
\]

(15)

is the derivative of \(f[\beta_P(r)]\) with respect to \(\beta_P(r)\) at \(\beta_{p,k}(r)\) and \(\delta r\) is the range increment at range \(r\). The initial value of \(\beta_{p,k}(r)\) at each range step [i.e., \(\beta_{p,\text{initial}}(r)\)] is obtained from Eq. (11). Once convergence of \(\beta_P(r)\) is attained, the particulate transmittance is calculated using Eq. (12) and the analysis proceeds to the next range step.

As explained earlier, the retrieved profile of \(\beta_P(r)\) may diverge from the correct values if incorrect estimates of the lidar ratio, multiple scattering function, or correction for the attenuation of overlying features are used. Although any of these quantities could be adjusted to prevent divergence, as the uncertainties in the lidar ratio usually tend to be the largest, and the retrieval usually most sensitive to adjustments in this parameter, we choose to adjust the lidar ratio to prevent divergence in features. The profile solver detects if the retrieval is diverging in the positive direction (growing too large) by testing if successive estimates of \(\beta_{p,k}(r)\) in Eq. (13) are not converging and by testing the values of \(f[\beta_{p,k}(r)]\) at inflection points in its derivative, if any exist. Divergence in the negative direction is indicated by the existence of a specified number of negative values in the profile of \(\beta_P(r)\), where the corresponding attenuated backscatter \(\beta_N(r)\) is positive. Upon detecting divergence, the profile solver algorithm is terminated, and then started anew using a modified value of the lidar ratio. For solutions diverging in the positive direction, the lidar ratio is reduced, and for solutions diverging in the negative direction, the lidar ratio is increased. As an adjustment of the lidar ratio in one direction may subsequently cause divergence in the opposite direction, the adjustments are linked. If fewer than five previous adjustments have been made in either direction, then the lidar ratio is adjusted by 1% in the required direction. Further reductions are by 5%, while further increases are determined by the average of the two previous values that were respectively too small and too large.

Whenever possible, extinction solutions are constrained by a determination of the two-way transmittance provided by SIBYL. This is done by adjusting the particulate lidar ratio iteratively using a variable secant algorithm (e.g., Fröberg 1966, section 2.2) until the retrieved particulate two-way transmittance differs from the supplied constraint by less than some predefined tolerance parameter. We choose to solve for \(S_P\) iteratively rather than using an analytical equation as in Young (1995) because we use a range-dependent multiple-scattering function, which we may implement as an inline calculation in the future.

For the analysis of aerosol layers in contact with the surface, no such constraint is available from the lidar measurements alone. In these situations, the retrieval of the correct extinction profile obviously depends on the correct identification of features and the selection of lidar ratios by the SCA.

e. Rescaling below solved regions of a CALIPSO scene

After the retrieval of the extinction profile through a feature, the attenuated backscatter profiles in all underlying regions are rescaled by dividing the attenuated backscatter data by the retrieved two-way transmittance ascribed to the feature. As features may not occupy all 16 of the 5-km columns, only the attenuated backscatter signals in those columns directly below the feature just analyzed are rescaled. This is identical to renormalizing the attenuated backscatter profile in each column to the molecular backscatter signal expected at an altitude just below the base of the feature just analyzed. However, the method we use is preferable to renormalization because the SNR in clear regions is often poor, especially below attenuating features in the 5-km resolution profiles, and renormalization in clear regions is not an option for the 1064-nm analysis, as there is little molecular signal at that wavelength. The first step in the analysis of those features detected below the features just analyzed is to create an average profile of attenuated backscatter from those columns and rows occupied by the feature as specified by SIBYL. The process just described ensures that attenuated backscatter profiles in the different columns contributing to the average will be correctly rescaled for the attenuation caused by overlying features before they are combined in the average profile. For features occupying several columns, this attenuation correction may be different in each column. This novel procedure used in the CALIPSO analysis ensures that we can now average “like with like” and
thereby avoid nonlinear effects in the processing of the underlying features. (By “nonlinear,” we mean that the feature transmittance in the averaged profile would not be linearly related to the integrated attenuated backscatter in the averaged profile except for very low values of particulate backscatter and optical depth.) By correcting for the varying attenuation of overlying features before creating the averaged attenuated backscatter profile of the lower feature, we hope to retrieve physically meaningful data on the optical and radiative properties of the lower features.

4. The extinction retrieval process in a representative CALIPSO scene

Features to be analyzed by HERA are detected by SIBYL at horizontal resolutions of 5, 20, or 80 km; that is, they are only detectable after averaging over these horizontal resolutions. Therefore, as there is no information on how the material in a feature is distributed horizontally within the limits specified by SIBYL, the CALIPSO analysis algorithms assume that the material is distributed evenly across these horizontal dimensions, that is, that they occupy 1, 4, or 16 columns of the analysis arrays describing a CALIPSO scene.

Features in a scene can be either simple or complex. Simple features are vertically and horizontally contiguous at some horizontal resolution, are assumed to contain one type (or mixture) of particulates, and, consequently, are described by one set of optical parameters \([S_p, \eta(r)]\). Simple features are not vertically adjacent to other features; that is, the tops and bases of simple features are bounded everywhere above and below by clear air and, thus, do not touch any part of any other feature. Complex features contain a number of otherwise simple features that share an upper or lower boundary with (i.e., are vertically adjacent to) another feature, or are wholly embedded in other features. We define embedded features as those that are totally enclosed within the boundaries of another feature of coarser horizontal resolution and do not share a common top or base (although embedded features may share a common side boundary with the enclosing feature). The main task of HERA is to recognize the different situations and to use the appropriate analysis pathways.

a. A representative complex scene

Figure 2 is a simplified representation of a scene containing both simple and complex features. For clarity, the number of rows (altitudes) in the array has been reduced from 550 to 36, and the vertical resolution set to 0.5 km for all altitude bins. All features are numbered, and any one feature may span several rows and/or several columns. Features F2–F7 and F11 are simple features, where there is only one unknown lidar ratio for each feature. These can all be solved with one call to the profile solver, and constrained retrievals are possible if a measurement of two-way transmittance can be determined from the reduction of the clear-air signal below each feature. In complex features there are more unknowns (lidar ratios) than possible measurements (two-way transmittances), so a unique, constrained solution does not exist. Here, we seek a solution (essentially a set of lidar ratios) that gives a retrieved optical depth, averaged across the whole complex feature, that is consistent (within a specified tolerance) with the value, measured over the same columns, of the reduction in the signal from the clear air below the complex feature. Provided that the optical thicknesses and their uncertainties are satisfactory, the consistency is achieved by adjusting the lidar ratios, which are initially set to model values, one at a time within acceptable limits, starting with the feature with the strongest integrated attenuated backscatter. (Note that the lower SNRs and the consequent, higher uncertainties usually preclude the use of this routine with daytime measurements.) For features in contact with the surface, like the complex surface layer shown here, a forward, unconstrained solution is used. In Fig. 2 there are three complex features. The first contains F1 and F8–F10, the second F12–F20, and the third F21–F38. Note that F11 is not considered to be part of the second complex feature because it is not vertically adjacent to any other feature and it can be solved simply in the same manner as F2–F7. Embedded features (like F20) pose an extra degree of difficulty, because the solution of F16 cannot be achieved without knowing the attenuation of its lower regions by F20, and the embedded feature (F20) cannot be solved until the attenuation caused by the top part of F16 is known.

It can be seen that the backscatter from clear-air regions is used in the calculation of the layer transmittances required for constrained and consistent solutions. Although SIBYL has detected no features in these regions, there may be features present that escape detection because of low SNR or low backscatter contrast against the molecular signal. Weakly backscattering features may still have appreciable particulate optical depth if their lidar ratios are high and if they are distributed diffusely over a wide height range. However, for the reasons just given, the particulate backscatter from the regions will be low, so any errors in measured layer transmittances resulting from the presence of aerosols in the clear regions are expected to be small.
b. Retrieval pathways

While the general philosophy of HERA is to solve the regions of a scene from the top of the atmosphere down to the surface, working across all horizontal resolutions and progressively rescaling profiles in underlying regions for the retrieved attenuation, the retrieval pathways for simple, complex, and embedded features are of increasing complexity. Note that “clear” regions can be solved in a similar manner to that for simple features, but this capability is only available at 532 nm, as there is generally insufficient signal at 1064 nm. If performed, retrievals of extinction profiles in these regions use default lidar ratios for the free troposphere or stratosphere as listed in the data product metadata.

The analysis procedures used to create the version 2.01 data products were similar for both 532 and 1064 nm. In the analysis, it was assumed that clear regions were completely clear of particles and thus, by definition, the particulate transmittance in these regions was unity. Therefore, only regions identified as containing features were processed. Also, the adjustment of lidar ratios in complex features in order to achieve “consistent” solutions as described in the previous section was not implemented in the analysis software in time for the version 2.01 data release. All features were processed using the lidar ratios provided by the SCA and only adjusted to prevent divergence.

We now describe the retrieval pathway for the 532-nm data with reference to Fig. 2. Note that, although in the current CALIPSO data release, the analysis routines are configured not to solve in clear regions, the description that follows is of the complete algorithm in which the whole scene is solved. Here, we assume that the clear regions are also to be solved. The first step is to create an average profile for clear-air region 1 from the 16 attenuated backscatter profiles. The number of columns contributing to the average will vary from 16 in rows 1 to 3 down to 3 in rows 5 and 6. The average profile is then solved and the attenuated backscatter...
profiles in all columns rescaled by the retrieved attenuation of that part of the clear region that overlies them. (Remember that we are assuming that the material in the features and clear regions is distributed evenly across their horizontal extents.) The attenuation correction will be greatest in columns F–H, where the clear region is deepest, and smallest in columns N–P, where it is shallowest. Because the highest unsolved feature is a member of a complex feature, the average optical depth of the complex feature to which it belongs is determined by measuring the reduction in the clear-air signal in rows 7–21 of columns M–P. An average attenuated backscatter profile is created for F1 from columns M–P and the resulting profile is solved initially using lidar backscatter profile is created for F1 from columns M–P. An average attenuated profile for F8 is then rescaled, temporarily, by the attenuation caused by F1 in row 4, column N, and its extinction profile retrieved, again using values of $S_\rho$ from the SCA. The attenuated backscatter profile for F8 is then rescaled, temporarily, by the attenuation caused by F1 in row 4, column N, and its extinction profile retrieved, again using values of $S_\rho$ from the SCA. F9 and F10 are solved similarly. The total optical depth in each column of the complex feature is then calculated from the retrieved extinction profiles, and the average is compared with the previously “measured” value. If the values differ by more than some threshold value, the lidar ratio of the strongest of the four features is adjusted and the complex feature solved again in an attempt to achieve agreement. If adjustments within acceptable limits do not produce agreement, the lidar ratio of the next strongest feature is adjusted, and so on, until agreement is achieved or the maximum number of iterations is reached and the retrieval quality flag set to indicate this. After the complex feature is solved, the profiles underlying each of the constituent features are rescaled by the corresponding attenuations.

Next, each of the simple features F2–F7 is solved, using a transmittance constraint if one is available, and the underlying regions rescaled. The second clear-air region is analyzed next, using an average of the rescaled profiles in columns A–P. F11, a simple feature, is solved in the same manner as F2–F7. The second complex feature is solved in a similar manner to the first, with the exception of the embedded features F17, F18, and F20. The solution of the combination of F16 and F20 is performed in three steps. In the first step, the creation of the average profile constituting F16 initially assumes the attenuation caused by F20 is zero, and the extinction profile of F16 is then retrieved. Then, F20 can be rescaled correctly for the attenuation caused by that part of F16 that overlies it and is solved. The lower regions of F16 are rescaled for the attenuation caused by F20 and solved correctly. Once a satisfactory solution has been achieved for the second complex feature and the underlying regions rescaled, the third clear region is solved followed by the complex surface layer.

5. The algorithm in action

The correct performance of the extinction retrieval algorithm has been verified using a wide variety of simulated data (Powell 2005). Some tests have been of HERA operating in isolation with “perfect” feature boundaries and optical parameters supplied by SIBYL and the SCA, while others have been of all the algorithms operating together with “realistic” inputs supplied to HERA. The sensitivity of HERA to errors in the input parameters will be reported upon in another publication. Simulations using “noise free” data provide a very stringent test of the accuracy of the algorithm, as the effects of some of the weaker features in a complex scene like that discussed above can be subtle and hidden in any noise. In several tests, noise-free attenuated backscatter profiles were simulated based on variations of the arrangement of the features in Fig. 2. The results of the analysis with HERA showed that, when supplied with the correct input parameters, the retrieved extinction in all cells of the arrays differed from the input, modeled values by values that were comparable with the numerical precision of the computer.

Now we examine in Fig. 3 the performance of the algorithms using actual CALIPSO data recorded along the west coast of southern Africa on 1 January 2007. Variables are plotted as height versus latitude and longitude using color scales, as indicated at the base of each panel. In Fig. 3a, we present the 532-nm attenuated backscatter. The main features are a strong aerosol layer, elevated in places, extending from the left of the figure to 8.5°S. Between about 2° and 6°S this layer is obscured by a cloud layer that attenuates the signal completely. In the middle latitudes a strong signal from a cirriform cloud near 14 km can be seen, with a higher, more tenuous cloud farther to the south. A low, dense water cloud that, in places, attenuates the signal completely can be seen in the southern half of Fig. 3a. Figure 3b shows the horizontal distance over which profiles had to be averaged in order to detect the features shown. The strong water cloud was detected at single-profile resolution, while the very tenuous cloud in the upper right of Fig. 3b required averaging over 80 km and even then some sections of the cloud were below the detection threshold. In Fig. 3c, we plot the cloud–aerosol discrimination feature mask in which orange indicates aerosol and midblue cloud. It can be seen that some sections of the aerosol layer on the left (especially between the approximate latitudes −1.0° to −1.5°) have been misclassified as a result of the SNR or other characteristics of the signals (Liu et al. 2009). This can have significant consequences for the extinction products.
FIG. 3. The creation of input data for the extinction retrieval algorithm (a) 532-nm attenuated backscatter (km sr)$^{-1}$, (b) horizontal averaging required for the detection of the cloud and aerosol features, (c) cloud-aerosol discrimination, (d) aerosol subtyping algorithm, and (e) ice–water cloud classification.
FIG. 4. Outputs from HERA (km\(^{-1}\)): (a) 532-nm particulate backscatter [(km sr\(^{-1}\)]), (b) 532-nm particulate extinction at native resolution, (c) 532-nm cloud extinction product, (d) 532-nm 40-km aerosol extinction product, and (e) 1064-nm 40-km aerosol extinction product.
In Figs. 3d and 3e, respectively, we show the classification subtypes of the aerosol and cloud features. These subtypes determine the initial lidar ratios supplied to HERA. The aerosol subtyping algorithm has shown the aerosol layer to be predominantly polluted dust overlying dust, with some embedded smoke. As expected, the high clouds are identified as being predominantly ice and the low clouds water, although there are occasional apparent anomalies.

Finally, in Fig. 4, we present the outputs of the extinction retrieval process. Figures 4a and 4b, respectively, show the 532-nm particulate backscatter and extinction. These are the primary retrieval outputs and show the backscatter and extinction of all particulates (cloud and aerosol) at the native 5-, 20-, and 80-km resolutions of HERA. (Note that HERA does not distinguish clouds from aerosols but simply produces a total particulate backscatter.) The remaining panels in Fig. 4 show the results of the postextinction processing (the boxes on the right in Fig. 1): panels c and d, respectively, show the 532-nm cloud and aerosol and extinction, and panel e presents the 1064-nm aerosol extinction retrievals after they have been reduced to the horizontal resolutions of 5 km (clouds) and 40 km (aerosols) and vertical resolutions of 60 m (clouds) and 120 m (aerosols) used in the CALIPSO level 2 extinction data products available from the Langley Atmospheric Sciences Data Center. While the effects of the occasional misclassification of aerosols as water clouds in the layer on the left can be seen in Fig. 4b and 4c, the overall performance of the chain of algorithms is very good.

6. Conclusions

A Hybrid Extinction Retrieval Algorithm (HERA) has been developed that successfully retrieves particulate backscatter and extinction profiles from attenuated backscatter profiles measured by the CALIPSO lidar in atmospheric scenes of varying complexity, where features (cloud or aerosol layers) of differing horizontal scales may be vertically adjacent or embedded in larger features. The accuracy of these retrievals depends to a large degree on the accuracy of the calibration of the data and of the lidar ratios supplied to HERA by the preceding algorithms in the processing chain. The sensitivity of the analysis to errors in these inputs will be treated in detail in a later publication. HERA is composed of two main elements: a top-level algorithm that selects the analysis pathway, order of processing, and analysis parameters that depend on the nature and spatial extent of the atmospheric features to be processed; and a profile solver or “extinction engine” that retrieves profiles of particulate extinction and backscatter coefficients from specified sections of an atmospheric scene defined by the top-level algorithm.

Where possible, retrievals of extinction profiles from simple, vertically isolated features are constrained by measurements of two-way transmittance determined by the reduction in the clear-air backscatter through the feature. For complex features, where there are more unknown lidar ratios than possible transmittance measurements, the algorithm attempts to find a solution in which the retrieved optical depth, averaged across the horizontal extent of the feature, is consistent with the average value determined from the clear-air signal reduction across the complex feature. (As noted above, however, this capability has not been implemented in the version 2.01 data release. Also, because of the virtual lack of 1064-nm backscatter from “clear” regions, enabling this capability at that wavelength is contraindicated.)

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