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Observed aerosol characteristics to improve forward-modelled attenuated backscatter in urban areas

Elliott Warren\(^1\), Cristina Charlton-Perez\(^2\), Simone Kotthaus\(^1,3\), Franco Marenco\(^4\), Claire Ryder\(^5\), Ben Johnson\(^6\), David Green\(^7\), Humphrey Lean\(^8\), Sue Ballard\(^9\), Sue Grimmond\(^10\)

\(^1\) Department of Meteorology, University of Reading, UK
\(^2\) Met Office@Reading, UK
\(^3\) Institut Pierre Simon Laplace (IPSL), France
\(^4\) Met Office, Exeter, UK
\(^5\) Environmental Research Group (ERG), King’s College London, UK
\(^6\) Corresponding authors: e.l.warren@pgr.reading.ac.uk, c.s.grimmond@reading.ac.uk

Abstract
Numerical weather prediction (NWP) models often parameterise aerosol emissions to reduce computational needs, while aiming to accurately capture their impact adequately. Increasingly, aerosols are monitored in-situ directly and/or indirectly (e.g. by automatic lidars and ceilometers, ALC). ALC measure the aerosol optical characteristic of attenuated backscatter. This can also be estimated using forward models that combine forecast aerosol and relative humidity to parameterise aerosol physical and optical characteristics. The aerFO is one such forward model, designed to use Met Office NWP model output and parameterisations from the MURK visibility scheme. Given the aerFO-MURK scheme link, assessing the aerFO and its output could therefore be used to inform future developments of the MURK scheme. To identify which parameterised aerosol and optical characteristics in the scheme are the most critical in urban settings, aerFO is driven with different in-situ aerosol observations at a background site in central London. Estimated attenuated backscatter is then assessed against ALC observations. It is shown that the original MURK scheme parameterisation underestimates the variance of both dry mean volume radius and total number concentration. Representing both the accumulation and coarse mode aerosols in the aerFO reduces the median bias error of estimated attenuated backscatter by 69.1%.

1 Introduction
Forecasting aerosol characteristics accurately is important, due to their impact on radiation budgets and visibility (Roessler and Faxvog, 1981; Seinfeld and Pandis, 2016; Stull, 1988). Understanding the impact of various aerosol characteristics on radiation forecast accuracy would be beneficial for the development of efficient aerosol parameterisations while minimising additional computational resources; as some aerosol species may impact radiation differently.

Currently, it is computationally expensive to use numerical weather prediction (NWP) models with explicit representation of multiple aerosol characteristics, such as mass by species and total number concentration. NWP aims to balance computational cost and forecast accuracy by including aerosol characteristics that are the most critical for the latter. For example, the ECMWF Integrated Forecasting System (IFS) (native resolution up to ~ 9 km) contains mass mixing ratios for sea salt, desert dust, organic matter, elemental carbon and sulphate separately (Benedetti et al., 2009; ECMWF, 2018).

High-resolution Met Office (MO) NWP models, such as the MO UKV (variable resolution 1.5 km inner, 4 km outer domain) (Tang et al., 2013) only explicitly include the total dry mass of bulk aerosol to minimise computational expense (Clark et al., 2008). All other characteristics in the MO UKV, such as number concentration and mass mean radius, are parameterised from the estimated mass through the ‘MURK’ visibility scheme, which produces a visibility diagnostic from the aerosol characteristics and humidity. Estimating the multiple aerosol characteristics with greater accuracy could help improve MO operational weather forecasts for visibility, and potentially radiation, if aerosol is later coupled to the radiation scheme.

Increasingly, in-situ observations in cities include multi-site campaigns to understand spatio-temporal variations in aerosol characteristics, such as particle mass (PM, total mass of particulate matter below a given size), physical distributions and composition (Crilley et al., 2017; Hama et al., 2017a; Harrison et al., 2012; Klompmaker et al., 2015; Young et al., 2015). Extended routine aerosol monitoring provides further information about inter-annual variability with a wider range of meteorological conditions (Hofman et al., 2016; Ruths et al., 2014); relative importance of aerosol sources in cities that vary both temporally and spatially with regional background (Abdalmogith and Harrison, 2006); long-range transport (Abdalmogith and Harrison, 2005); and local sources within cities such as transport, construction and fuel burning (Liu et al., 2014; Ye et al., 2013). Interaction between these sources creates a highly diverse aerosol composition with spatial and temporal (hourly to interannual) variations (Stachlewitsch et al., 2018).

Alongside in-situ aerosol observations, automatic lidars and ceilometers (ALC; Wiegner et al., 2014) are being deployed (Flentje et al., 2010; Ilingsworth et al., 2007; Met Office, 2017; Osborne et al., 2018; Pappalardo et al., 2014). Further, ceilometers are becoming increasingly sensitive with measurements and becoming more comparable to sophisticated lidars, such as Raman (Heese et al., 2010; Madonna et al., 2014; Song et al., 2017). ALC observations have been used to derive information on aerosol and meteorological conditions, including mixed layer height (Kotthaus and Grimmond, 2018; Wagner and Schäfer, 2015) and in the absence of hydrometeors (cloud, precipitation and fog), relations between attenuated backscatter ($\beta$) and PM concentrations (Munkel et al., 2004; You et al., 2016). Calibrated and corrected ALC measurements provide the optical property $\beta$ rather than a direct measurement of physical aerosol characteristics. Thus, aerosol forward operators (FO) are required to relate aerosol physical properties to $\beta$. They allow for attenuated backscatter ($\beta_c$) to be estimated from NWP or chemistry transport model output of aerosol parameters for use in model evaluation or in data assimilation (Benedetti and Dabas, 2016; Chan et al., 2018; Charlotte-Perez et al., 2016; Geisinger et al., 2017). One such forward operator (hereafter aerFO, Warren et al., 2018), uses a bulk mass of dry aerosol ($m$) [kg kg$^{-1}$] and RH as inputs, to estimate $\beta_c$ for clear-sky conditions (i.e. without hydrometeors). aerFO, originally built for the MO MURK visibility scheme (Clark et al., 2008), shares some parameterisations with the MURK scheme to estimate aerosol optical properties but with a revised approach to estimate aerosol optical properties for multiple laser wavelengths.

One important aerosol optical property, the ratio between particle extinction and particle backscatter or lidar ratio ($S$) (Song et al., 2018), depends on the refractive index and size distribution of the aerosol particles (Müller et al., 2007). $S$ can be used to solve the lidar equation with elastic backscatter lidars, to recover the
particle extinction coefficient (Fernald, 1984; Klett, 1981), or to derive further aerosol properties including aerosol optical depth (AOD) (Seinfeld and Pandis, 2016). S has been calculated both directly from Raman lidar data (Müller et al., 2007; Papayannis et al., 2005; Wang et al., 2016) or high spectral resolution lidars (Burton et al., 2012; Hair et al., 2008; Reid et al., 2017), and indirectly from sunphotometers (Cattrall et al., 2005). However, all instruments have inherent limitations. Due to the high cost, very few Raman lidars are available and usually they are not operated continuously. Further, they only achieve complete optical overlap several hundred metres above the surface (Li et al., 2016; Wandinger and Ansmann, 2002) so near-surface aerosols are not well observed. Sunphotometers measure AOD, an integrated value for the total atmospheric column, that cannot differentiate near-surface contributions from those aloft. Hence, to derive S using a sunphotometer requires additional aerosol modelling (with inherent assumptions) without additional instrumentation (Dubovik and King, 2000). Furthermore, few instruments with the capability to derive S are being operated in urban measurement networks because of general constraints such as accessibility, communications and security (Müller et al., 2013). As the lidar ratio in cities is usually lower than for background continental aerosol types (Müller et al., 2007), applying values representative of rural settings may create uncertainty in urban studies of derived aerosol optical properties. Hence, further analysis of urban-based aerosol measurements (i.e. beyond Raman lidars or sunphotometers) could help determine lidar ratio values that are more representative of urban settings. S has been derived from aerosol observations using Monte-Carlo analysis with assumed aerosol particle size distributions and refractive indices (Barnaba et al., 2007; Dionisi et al., 2018), though without accounting for aerosol speciation. This may introduce uncertainty as aerosol species have widely varying optical properties (Warren et al., 2018). The Monte-Carlo values are broadly applicable to continental aerosol, but without the temporal variability of aerosol characteristics typical in urban environments (Hama et al., 2017b). A new approach to derive S from urban aerosol observations could improve understanding of S variability in cities.

This study is structured in two parts. First, a method is presented to estimate S at a range of common lidar wavelengths based on in-situ aerosol observations collected at an urban background site. Second, aerFO is used to assess the relative importance of different aerosol properties in the accurate estimation of forward modelled attenuated backscatter (βs). For this, parameterised aerosol characteristics are successively replaced by more realistic estimates derived from observations. Results can then inform future design of aerosol schemes in MO NWP models with respect to estimating optical properties, by suggesting which aerosol characteristics should be prioritised for inclusion or improvement in the NWP models.

2 Methods

The forward operator, aerFO (Warren et al., 2018), is used to model vertical profiles of attenuated backscatter. Improvements to the aerFO look-up-tables (LUT) (sections 3.1 and Appendix 2) are based on observations taken at North Kensington (NK) (Figure 1, section 2.1).

2.1 Observations

Measurements of attenuated backscatter (βs), aerosol properties and relative humidity (RH) are collected at an urban background site (NK) in the London Air Quality Network (LAQN) (DEFRA, 2018a).

Vertical profiles of βs are observed with a Vaisala CL31 ALC (Table 1), that is part of the London Urban Meteorological Observatory (LUMO; http://micromet.reading.ac.uk/) and has been used in pervious boundary layer studies (Kothenius et al., 2018, 2016). βs is corrected for instrument-related background and near-range artefacts (Kothenius et al., 2016). A centred moving average is applied in time and space, using 25 min windows (101 time steps) and 110 m (11 range gates), to increase the signal to noise ratio (SNR) (section 4.2 in Kothenius et al., 2016). The CL31 reaches complete overlap at 70 m (Kothenius et al., 2016). Insufficient optical overlap is corrected for internally by the sensor firmware. βs from the 2nd range gate is used in this study (20 m above ground level), which is effectively the average of the lowest 7 range gates (70 m). βs from the 1st range gate is not used given its relatively high noise (Kothenius et al., 2016).

Calibration coefficients were computed for periods using the ‘stratus cloud’ method, which has been shown to produce stable estimates (±5 % over 2015) (Hopkin et al., 2019; O’Connor et al., 2004; section 3.1 in Warren et al., 2018). Coefficients produced here are interpolated for days between status conditions with key changes in window transmission, instrument hardware and software changes accounted for. Daily calibration coefficients are applied to the smoothed profiles.

The manufacturer-specified central wavelength of the CL31 is 905 nm. The central wavelength uncertainty is ± 10 nm and full width half maxima (FWHM) is 4 nm (Kothenius et al., 2016; Wiegner and Gastelger, 2015). To incorporate this wavelength spectrum into our estimates of aerosol optical properties, we use the FWHM to define a Gaussian weighting function to calculate the dry Mie extinction efficiency (Qext,a), extinction enhancement factor (fext,a) with a dependency on RH, and the water vapour extinction coefficient (σvap,a) with a dependent on ambient water vapour mass mixing ratio (ρv) (section 2.3 gives an overview of aerFO variables).

Comparison of aerFO-derived βs, and observed βs is undertaken using seven clear-sky days when all variables (aerosol variables, backscatter and RH) are observed, ensuring a fair comparison between all the aerFO experiments.

As no RH observations are conducted at the NK site, measurements from a different central London LUMO site (KCL; 6.8 km southeast of NK, Figure 1) are used instead as input to a parameterisation of the swelling and drying of aerosol particles. To assess the representativeness of KCL RH measurements at NK, Pearson correlation between two MO UKV NWP model grid boxes containing the respective sites is calculated for hourly RH on 30 clear sky days (2014 – 2015). RH at both locations varied between 40 and 95 % and a good correlation (r = 0.99) was found (Table 1).

With measurements of the mass of ammonium sulphate and ammonium nitrate aerosol unavailable, we use the CLASSIC aerosol scheme (Bellouin et al., 2011; Martin et al., 2006) to model this with the observed mass of reactants (Table 2). This assumes the entire ammonium (NH4) reacts with sulphate (SO4) preferentially, and only the remaining NH4 reacts with Nitrate (NO3). Sea salt mass is calculated from observed Chloride (Cl) mass, assuming all Cl was in sea salt. Ammonium nitrate, ammonium sulphate and sea salt aerosol 15 min mass data are averaged to hourly resolution. To obtain hourly masses of elemental carbon (EC) and organic carbon (OC) the daily masses are linearly interpolated, given the lack of additional information. As EC contains a large fraction of black carbon (strongly absorbing particles, Briggs and Long, 2016), the density and shape factor of black carbon have been used from the literature for EC.
interpreted the optical properties of no non used to convert the diameter conversion properties (e.g. extinction coefficient) than common particle size, \(D\), based on Mie theory.

The diameter conversion equations require additional aerosol parameters that can vary slightly by species (Table 2). For instance, the dynamic shape factor \(\chi\) is used to convert \(D_a\) or \(D_p\) and the particle density \(\rho_p\) is required to convert \(D_p\) to \(D_a\). \(\chi\) describes the sphericity of a particle: \(\chi = 1\) for a perfect sphere and \(\chi > 1\) for non-spherical particles (Hinds, 1999). Often the Cunningham slip correction factor \(C_v\) is used when converting between equivalent diameters to account for the no-slip condition for small particles (Seinfeld and Pandis, 2016). However, we assume \(C_v\) can be ignored given the contribution by small particles (< ~0.07 \(\mu\)m) to the optical properties of total aerosol is negligible (section 3.2).

From the merged number distribution, three aerosol mode ranges are defined (\(D_a\): fine < 0.08 \(\mu\)m; accumulation 0.08 – 0.8 \(\mu\)m; coarse > 0.8 \(\mu\)m). These are interpreted based on the mean dV/dlogD of the dry particle number distribution (where \(V\) is the volume) between 01/01/2014 – 31/12/2015 at NK.

The SMPS and APS datasets together cover a large range of particle sizes, enabling a more representative estimate of aerosol physical and optical properties to be derived. Unfortunately, the SMPS and APS observe aerosol particle diameters in slightly different ways. The SMPS provides the mobility diameter \((D_m)\) or particle diameter relative to a perfect sphere with the same electrical mobility in a constant electrical field (DeCarlo et al., 2004). The APS provides aerodynamic diameter \((D_a)\) or diameter relative to an aerodynamic property measured (DeCarlo et al., 2004). Therefore, to merge these datasets together, both are first converted to a common particle size, i.e. the volume equivalent diameter \((D_v)\). \(D_v\) is based on particle surface area, and chosen as it is more closely related to aerosol optical properties (e.g. extinction coefficient) than \(D_m\) or \(D_a\) (Seinfeld and Pandis, 2016). The diameter conversions to \(D_v\) are done prior to computing particle optical properties based on Mie theory.

\[
\frac{D_v}{D_a} = \frac{1}{\sqrt{1 - \frac{\rho_p D_a^3}{\rho_D D_m^3}}}
\]

where \(\rho_p\) is the aerosol particle density and \(\rho_D\) is the density of the surrounding medium (e.g. air). Solving for \(D_v\), we get:

\[
D_v = D_a \left(1 - \frac{\rho_p D_a^3}{\rho_D D_m^3}\right)^{1/2}
\]

The SMPS and APS data are combined to extend the range of particle sizes defined by the SMPS, and the APS data are used to provide additional information on the larger aerosol particle range. The SMPS and APS data are combined using the dynamic shape factor \(\chi\) (DeCarlo et al., 2004) to describe the sphericity of aerosol particles. \(\chi\) is calculated as

\[
\chi = \frac{D_m}{D_v}\n
\]

with \(D_m\) and \(D_v\) in the same unit. For aerosol particles, \(\chi\) ranges from 1 (perfect spheres) to \(\chi < 1\) for non-spherical particles. The SMPS data are converted to the particle distribution using the dynamic shape factor \(\chi\), and the APS data are used to define the aerosol mass distribution. The combined dataset provides a more comprehensive understanding of the aerosol optical properties and their role in atmospheric processes.
2.2 Using observations to model the lidar ratio (S)

The extinction-to-backscatter ratio, or lidar ratio $S$, is a key component of aerFO as it links the modelled extinction to the modelled backscatter. As is common (Doherty et al., 1999; Müller et al., 2007), Warren et al. (2018) assumed a constant value ($S = 60\text{ sr}$ typical of continental aerosol) to estimate $\beta_e$ from $\sigma_a$ in aerFO. Here, a more detailed parameterisation is developed to model $S$ (e.g. for use in aerFO) using aerosol observations of particle size distribution, speciated aerosol mass and RH.

To estimate $S$ (Figure 2), the overall approach is to model the aerosol optical properties based on the aerosol physical properties, including the observed dry number distribution by aerosol species ($N_{\text{obs}}(D)$) binned by diameter (D). The extinction and backscatter properties for each aerosol species (Table 2) are modelled separately, assuming an external aerosol mixture. Hysrogscopic growth and consequential changes in the complex index of refraction of each aerosol species, from additional water, are also parameterised.

Initially, with only non-speciated observations of dry number distribution by diameter ($N_{\text{obs}}(D)$) available, $N_{\text{spec}}(D)$ is estimated by speciating $N_{\text{obs}}(D)$ using observed hourly PM$_{10}$ mass of different aerosol types ($m_{\text{aer}}$, Figure 2, part 1). $m_{\text{aer}}$ is used with observed aerosol density of each species from the literature ($\rho_{\text{aer}}$. Table 2) to create volumetric weights ($V_{\text{aerotot}}$, ratio of each species ($V_{\text{aer}}$) to total aerosol ($V_{\text{aer}}$) volume). The $V_{\text{aerotot}}$ provide a priori weights for each bin of $N_{\text{obs}}(D)$ to obtain $N_{\text{spec}}(D)$ by species:

$$N_{\text{spec}}(D) = N_{\text{obs}}(V_{\text{aerotot}})$$  \hspace{1cm} (1)

After estimating $N_{\text{spec}}(D)$ for each species, the hygroscopic effects on aerosol particles are parameterised. As RH increases, hydophilic aerosol particles swell (i.e. increase in size) and the complex index of refraction changes, reaching some state between that of a dry particle and a water droplet (Haeffelin et al., 2016). For hydrous species, the parameterised physical growth of each binned diameter follows the CLASSIC aerosol scheme (Bellouin et al., 2011) such that the swollen diameters $D_{\text{swollen}}$, and dry diameters $D_{\text{dry}}$, are calculated using ambient RH. In this study, the hygroscopic parameterisations require the observed dry SMPS particle sizes to be swollen to find $D_{\text{swollen}}$, and the observed humidified APS particle sizes to be dried to find $D_{\text{dry}}$. Once $D_{\text{dry,aer}}$ and $D_{\text{swollen,aer}}$ for the merged number distribution are calculated, the physical growth factor $g_{\text{aer}}$ is estimated (Figure 2 part 2). $g_{\text{aer}}$ is used with the size parameter $X_{\text{aer}}$ (eqn. 15.6 in Seinfeld and Pandis, 2016) for each size bin and each species, to estimate the mixed complex index of refraction between that of dry aerosol and of pure water ($\sigma_{\text{aer}}$) using the volume mixing method (Liu and Daum, 2008). Once $D_{\text{dry,aer}}$ and the mixed complex index of refraction are calculated, Mie scattering code is used with the swollen particles to calculate the optical properties: extinction and backscatter efficiencies ($Q_{\text{aer}}$, $Q_{\text{baser}}$), and extinction and backscatter cross-sections ($C_{\text{aer}}$, $C_{\text{baser}}$). The Mie scattering code used was written with the pyMiecoated module for Python 2.7 (version 0.1.1) [https://code.google.com/archive/p/pymiecoated/]. Following this, the total extinction and backscatter for each aerosol species ($\sigma_{\text{aer}}$, $\sigma_{\text{baser}}$) is calculated using $N_{\text{spec}}(D)$ with $C_{\text{aer}}$ and $C_{\text{baser}}$, respectively. The sum of $\sigma_{\text{aer}}$ and $\sigma_{\text{baser}}$ is used to compute the overall $\sigma_{\text{aer}}$ and $\beta$. Finally, $S$ is computed as the ratio of $\sigma_{\text{aer}}$ to $\beta$ (Figure 2, part 3).

As optical properties of aerosol particles are highly sensitive to particle size (Jacobson, 2005), the number and arbitrary position of diameter bins in the observed number distribution can affect the final modelled $\sigma_{\text{aer}}$, $\sigma_{\text{baser}}$, and $S$ results. To minimise the impact of number and arbitrary bin diameters sizes on optical property results, we follow Geissinger et al. (2017 section 2.2.4) in part 2 (Figure 2). This increases the total number of diameter bins by a factor of 4, by interpolating between the adjacent diameter bins. $X_{\text{aer}}$ and $n_{\text{dry,aer}}$ are calculated for each interpolated bin, and the optical properties for each original bin (D) are derived as the average of the interpolated bins for that size interval.

For some particles (both pure and mixed species aerosols), particle hygroscopic growth has been observed to exhibit hysteresis (Figure 3) with a differing shrinking and growing relation with changes in RH (Fierz-Schmidhauser et al., 2010; Tang and Munkelwitz, 1994). Thus, these particles have no simple relation between RH and their extinction coefficient. For example, many particles that are originally dry, solid and without any water condensation on them, can be defined as being below their efflorescence RH limit and on the lower branch (Figure 3, red). Particles already swollen through hygroscopic growth that are liquid solutions containing aerosol, can be defined as being above their deliquescent RH limit and on the upper branch (Figure 3, blue). When ambient conditions change so that RH is between these limits, the particles may not shrink or swell until they reach the other RH limit (Figure 3, grey). Particles originally above the deliquescent RH limit, may remain relatively large, despite a decrease in RH until the critical efflorescence limit is reached at which point the particle suddenly crystallises and loses all remaining condensed water (Tang and Munkelwitz, 1994). Conversely, dry particles below the efflorescence RH limit may stay dry and solid as ambient RH increases until reaching the deliquescent RH limit, then suddenly swell with water.

Given the importance of particle size on aerosol optical properties, the hysteresis effect was incorporated into the model to estimate $S$. The magnitude of the hysteresis effect for ambient aerosol varies (Figure 5 in Fierz-Schmidhauser et al., 2010). Therefore, we parameterise the hysteresis effect for ammonium sulphate, ammonium nitrate and sea salt separately (Figure 3). Originally dry particles (begin below efflorescence limit: Table 2) did not swell and were treated as being in a ‘dry’ crystalline state ($s_i$, $s_d$). Once RH exceeds the deliquescence limit (per aerosol type) the parameterised particles are considered to be in a ‘wet’ liquid state ($s_l$, $s_d$) and their growth follows the aerosol type swelling method (Table 2). While in the ‘wet’ state, growth of particles continues due to swelling until RH falls below the efflorescence limit. Particles then return to a ‘dry’ state and no swelling method is applied. Hysteresis is not assumed for OC as its efflorescence and deliquescence limits are unclear and the hygroscopic growth has been observed to be smooth without an apparent hysteresis (Varutbangkul et al., 2006).

---

Figure 2: Lidar ratio (S) calculation flow chart. The main inputs are diameter bins (D), number distribution by diameter ($N_{\text{obs}}(D)$), and aerosol species mass at a given size range ($m_{\text{aer}}$), e.g. PM$_{10}$ and relative humidity (RH). See section 7 for notation.
aerFO estimates the bulk aerosol physical properties of the aerosol accumulation mode, including dry mean radius (\(r_{\text{md}}\)) and total number concentration (\(N\)) using observed and empirically derived constants (Figure 4, part 1). These include the climatological mean dry mass of aerosol (\(m_0\)), climatological mean volume mean radius for the aerosol mode (\(r_0\)), climatological mean total number concentration for the aerosol mode (\(N_0\)) and a scaling factor (\(p\)). Following the MO visibility scheme (Clark et al., 2008) for the parameterisations of \(N\) and \(r_{\text{md}}\), a fixed geometric standard deviation (\(d_7\)) of 1.7 is used for the accumulation mode as calculated from observations. Properties calculated include: aerosol optical (e.g. \(Q_{\text{aer}}\)) and \(f_{\text{ext}}\); backscatter and transmission (Figure 4, part 4). aerFO can represent multiple aerosol modes (e.g. fine, accumulation and coarse) by calculating \(\sigma_{\text{ext,aer}}\) (Figure 4, parts 1 – 2) for each mode and adding them to obtain the overall \(\sigma_{\text{ext,aer}}\). The effect of water vapour absorption (\(\sigma_{\text{ext,wv}}\)) is also included in the total extinction coefficient (\(\sigma_{\text{ext,aer}}\)).

For computational efficiency, \(Q_{\text{aer,dry}}\) and \(f_{\text{ext,dry}}\) (Figure 4, part 2) are pre-calculated for aerFO. As the relative composition of aerosols may vary (e.g. by month Young et al., 2015), a monthly climatology of urban aerosol composition is derived from NK aerosol observations (Table 2, section 2.1).

1) Physical properties

\[
\begin{align*}
\sigma_{\text{ext,aer}} &= Q_{\text{ext}} \pi r_{\text{md}} \\
\beta &= \frac{\sigma_{\text{ext,aer}}}{S} \\
\end{align*}
\]
2.4 Aerosol forward operator experiments

The improvement in $\beta_0$ estimates when using observed aerosol characteristics (e.g. size, total number) is evaluated using a set of aerFO experiments (Table 4). For these we use observations (rather than NWP model forecasts) as inputs to aerFO. As observations replace parameterised variables, $\beta_0$ is changed (Figure 4, part 1). For comparison, we define a control run (ID = 0, Table 4), with physical properties $N$ and $\text{rpm}$ (Figure 4, part 1) estimated based on aerFO parameterisations, with measured $PM_{10}$ mass and RH (Table 1). In experiments 1 – 7 parameterised variables (e.g. $N$ and $\text{rpm}$) are replaced by estimates from aerosol observations (Table 4). Experiments 1 – 3 consider the accumulation mode whereas experiments 4 – 7 address multiple aerosol modes (e.g. fine, accumulation and coarse).

Parameterised $N$ is replaced by observed $N$ for the accumulation mode (ID = 1); observed $\text{rpm}$ for the accumulation mode is used (ID = 2); both observed $N$ and $\text{rpm}$ are provided (ID = 3) to eliminate the need for a mass estimate as input to aerFO. Each subsequent experiment (ID > 3) uses more observations and accounts for more aerosol modes. Using observed $N$ and $\text{rpm}$ for two (accumulation and fine) aerosol modes (ID = 4) allows assessment of the importance of the fine mode to accurately calculate the aerosol optical properties. To represent multiple modes in aerFO (Figure 4, parts 1 -3) each mode is treated separately when obtaining the extinction coefficient. Experiment 5 uses observed $N$ and $\text{rpm}$ for the fine, accumulation and coarse aerosol modes. Experiment 6 is as 5, but with hourly aerosol composition used to calculate hourly varying $Q_{\text{ext,co}}$ and $f_{\text{ext,co}}$ LUT. Experiments 0 – 6 use a mean $S$ (section 2.2), whereas 7 is as 6, but with hourly estimates of $S$.

The experiments are limited to seven clear-sky days (in 2014: 06/06; 03/07; and 2015: 07/03; 20/04; 21/04; 04/06; 02/08) by the limited simultaneous data availability of all measurements. Although the evaluation of $\beta_0$ is done at 905 nm, $\beta_0$ can be computed for other ALC wavelengths (e.g. 355, 532, 1064 nm) but is not assessed as observations at other wavelength are unavailable.

### Table 4: Experiments (ID) assumptions for number concentration (N) and optical properties as input to aerFO with which aerosol characteristics are replaced with observations measured at NK (Figure 1).

<table>
<thead>
<tr>
<th>ID</th>
<th>Aerosol variables estimated based on observations</th>
<th>Aerosol observations used</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>$m = PM_{10}$</td>
<td>Particle mass</td>
</tr>
<tr>
<td>1</td>
<td>$N$ (accumulation mode)</td>
<td>Particle number distribution (fine and coarse)</td>
</tr>
<tr>
<td>2</td>
<td>$\text{rpm}$ (accumulation mode)</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>$N$, $\text{rpm}$ (accumulation mode)</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>$N$, $\text{rpm}$ (fine and accumulation mode)</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>$N$, $\text{rpm}$ (fine, accumulation and coarse mode)</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>$N$, $\text{rpm}$ (fine, accumulation and coarse mode), $Q_{\text{ext,co}}, f_{\text{ext,co}}$</td>
<td>Particle number distribution (fine and coarse) and mass by species</td>
</tr>
<tr>
<td>7</td>
<td>$N$, $\text{rpm}$ (fine, accumulation and coarse mode), $Q_{\text{ext,co}}, f_{\text{ext,co}}, S$</td>
<td></td>
</tr>
</tbody>
</table>

### 3 Results

#### 3.1 Lidar ratio ($S$) sensitivity to aerosol type and size

Aerosol lidar observations are commonly conducted at typical Raman lidar channels (e.g. 355, 532 nm) or at the wavelengths used by ALC (e.g. 905, 1064 nm). To account for differences in lidar wavelengths, the lidar ratio $S$ is estimated from aerosol observations at NK at these four wavelengths (Figure 5). Across all wavelengths $S$ varies between ~14 – 80 sr. This wide range of $S$ and corresponding $\beta$ (not shown) are similar to those obtained using aerosol characteristics with Monte-Carlo methods (Barnaba et al., 2007; Dionisi et al., 2018). The 905 nm $S$ average of 43.1 sr is similar to that measured in urban areas by Raman lidars (Müller et al., 2007; Stachlewska et al., 2018; Wang et al., 2016), but is low compared to that derived using sunphotometer observations (Cattrall et al., 2005).

To date, there is little published research on the relation between $S$ and RH. $S$ generally has a positive linear relation to RH. This is strongest at ALC wavelengths 905 and 1064 nm (Pearson correlation of 0.83 and 0.78, respectively). The dependence of $S$ on RH (Figure 5) is linked to the relation between the aerosol size distribution and $S$, and likely to the relative position of the accumulation mode size range (Figure 6). For OC and any particles in the ‘wet’ deliquescent state (section 2.2), particles swell or shrink in response to changing RH, as water vapor condenses onto or evaporates from them. Consequently, particles move up or down the curve (Figure 3). Many particles in the particle size distribution lie within the accumulation mode, and the smaller half of the accumulation mode, are on a monotonic part of the curve, before the first inflection point (e.g. ~ 0.2 μm at 355 nm for most aerosol types). For these particles, changes in RH, and subsequent changes in particle size, lead to monotonic changes in $S$.

In the accumulation mode size range (diameter: 0.08 – 0.8 μm), the number of inflection points varies with wavelength for all aerosol species considered (Figure 6). At the longer 905 and 1064 nm wavelengths (Figure 6c, d), the first local maximum of $S$ is associated with larger particles compared to the Raman channels (Figure 6a, b) so there are fewer inflection points across the accumulation size range (Figure 6, dashed lines). At shorter wavelengths (355, 532 nm) there are more inflection points within the accumulation range causing a more variable response (greater scatter) of $S$ to changes in RH (Figure 5a, b).

Additionally, $S$ is influenced by the proportions of aerosol species at some wavelengths and humidities. At 355 (Figure 7) and 532 nm (not shown) and at low RH, $S$ increases with greater relative EC abundance as EC absorbs radiation more efficiently than other aerosol types. However, when RH increases, the relation between EC and $S$ is less clear which could be because the other hygroscopic aerosol types may be in the ‘wet’ deliquescent state, have swollen and increased their size. Consequently, the swollen hygroscopic aerosol $S$ values increase to a magnitude like or above those of dry (un-swollen) EC. Though the relation between EC and $S$ is most pronounced at shorter wavelengths, it is unclear at longer wavelengths including at low RH (905, 1064 nm; not shown). In addition to the impact of aerosol proportion on $S$, a clear impact is found for $f_{\text{ext,co}}$ at 355, 532, 905 and 1064 nm (905 nm shown in Appendix 2).

Some assumptions made in calculating $S$ may reduce $S$ by changing RH (Figure 5). Applying Mie theory based on spherical particles might limit variability in $S$ of both EC and hygroscopic particles at low RH before the hygroscopic particles become swollen (i.e. pre-spherical). Speciating N(D) evenly across all bins based on the total mass of each species available (section 2.2) likely does not portray the actual diversity in size distributions. This simplification does not allow individual species to contribute more to one specific mode; for example, sea salt could contribute more to the coarse mode.

In the parameterisation of $S$ (Figure 2) internal aerosol mixing is not considered. This would lead to a wide range of efflorescence and deliquescence RH limits for different particles and hence change the particle physical growth factor with respect to water ($g_{\text{ext}}$). Omitting internal mixing likely means hysteresis-related variability is not fully represented. In laboratory conditions Pierz-Schmidhauser et al. (2010) found a clear hysteresis effect on enhanced scattering from several pure aerosol species, but in field conditions with ambient aerosol hysteresis it was not always detected. Similarly, Smith et al. (2012) found that varying the fractions of organic material to ammonium sulphate changed the efflorescence and deliquescence RH limits of ammonium sulphate greatly, with any apparent RH limits eliminated once organic material volume fractions exceeded 0.6.

Evaluation of $\beta_0$ (section 3.2) uses several different parameterisations of $S$ (e.g. linear regression with RH) to help identify which should be the default in aerFO. Given this evaluation (not shown), as well as the remaining uncertainty and various causes for variability in estimating $S$, the mean $S$ for each wavelength is used as the default value in aerFO. The mean $S$ for 905 nm is 43.1 sr (median 44.1 sr), calculated from a sample size of 4699 hours (across 17 months in 2014 – 2015).
Figure 5: Calculated lidar ratio (\(S, \text{sr}\), Figure 2) as a function of relative humidity (RH) [%] and elemental carbon proportion of total aerosol (% colour) at four wavelengths that are typical of: Raman lidar (a) 355, (b) 532 nm; and ALC (c) 905 (Vaisala CL31) and (d) 1064 nm (Lufft CH15MK). Calculated hourly using NK (Figure 1) data for the period 01/01/2014 – 31/12/2015.

Figure 6: Lidar ratio (\(S, \text{sr}\)) of pure monodisperse aerosol species for four wavelengths (as Figure 5) using Mie scattering and assuming perfect sphericity. Accumulation diameter range (~80 – 800 nm) indicated (vertical dashed lines) (Figure 1).
Because EC and OC have a relatively high absorption of radiation compared to other ambient aerosols, their presence impacts the bulk aerosol absorption (Esteve et al., 2014). However, the imaginary component of the complex index of refraction (CIR) for these species (which governs absorption), as well as the physical growth factor of OC (g_{oc}) from the absorption of water are relatively uncertain because of the large number of chemical species present and the extent of external mixing (Esteve et al., 2014). Measurements in areas with distinct aerosol sources (e.g. South American biomass burning (Kotchenruther and Hobbs, 1998; Figure 3 in Thornhill et al., 2018), biogenic sources in North America, (Lowenthal et al., 2009; Taylor et al., 2017)) highlight the vast uncertainty in g_{oc}. Observed water soluble fractions of OC vary with location, between 20 and 65% of total OC (Du et al., 2014; Miyazaki et al., 2006; Sullivan et al., 2004; Zappoli et al., 1999) indicating the hygroscopicity of total OC. Uncertainty in g_{oc} arises at NK as the OC sources differ from previous g_{oc} studies, with urban contributions from cooking and fuel burning, and local vegetation differences. To explore the impact of CIR and g_{oc} uncertainty on S variability, five combinations of variables at 905 nm are used (Table 5). For experiment 5, an adjusted g_{oc} (growth is ~1/3 of fresh OC, model 2 in Kotchenruther and Hobbs (1998) hereafter KH98) gives the scattering enhancement factor closest to the literature.

The positive RH - S relation occurs in all experiments (not shown) with the range of S mostly unchanged. Sensitivity analyses suggest that the uncertainty of the imaginary component of CIR for OC and EC is small when estimating S at NK. Using either fresh or aged OC growth factor has a minor impact. Using KH98 adjusted g_{oc} reduced the inter-quartile range (IQR) and the mean S (30.1% not shown). Hence, constraining g_{oc} uncertainty is expected to reduce the lidar ratio uncertainty. This is in agreement with Esteve et al. (2014) who found the physical growth factor of OC to be important for the calculation of the bulk aerosol optical properties. However, their results also indicate that the uncertainty of the imaginary component of CIR should be accounted for, which is not considered critical in the current analysis.

### 3.2 Improvement to forward-modelled attenuated backscatter using observed aerosol characteristics

Multiple aerFPE experiments are conducted with different combinations of aerosol observations to identify which aerosol characteristics are most important for estimating $\beta_o$ (section 2.4). Estimates of $\beta_o$ are compared with observed $\beta_o$, and summary statistics across all the experiments are shown in Table 6. Statistics computed include the Spearman rank correlation ($R_s$) and Pearson correlation ($R_p$) between $\beta_o$ and $\beta_o$, as well as a normalised standard deviation (nSD = $SD/\beta_o$). $\beta_o$ is most relevant for the near surface (height level of in-situ aerosol measurements), whereas $\beta_o$ was taken at 20 m above ground level (section 2.1).

In the control experiment (ID = 0), $PM_{10}$ is in the aerosol mass $m$, used to parameterise $N$ and $r_{scat}$. Modelled and observed attenuated backscatter are highly correlated with both $R_s$ and $R_p$ (0.78 and 0.74, respectively) and statistically significant (>99.9%). However, $\beta_o$ is generally underestimated with a median bias error (medBE) of ~1.1 ×10^{-6} sr. nSD is low (0.37, i.e. small modelled standard deviation) as the monotonic function of $m$ ($PM_{10}$ Figure 8) does not account for the large variance observed.

In experiment 1 (ID = 1) observed aerosol number concentration of the accumulation mode replaces the parameterised $N$, bringing a slight reduction in error. The parameterised aerosol number concentration has slightly underestimated $N$ when $m > 20 \mu g \cdot kg^{-1}$ compared to a locally weighted scatter smoothing function (Cleveland, 1979) through $N$ observations (Figure 8a, black (parameterisation) and red (LOWESS) lines). Providing more variable and realistic values of $N$ enhances the modelled variability and increases nSD to 0.68.

For experiment 2, observed dry mean volume radius replaces the parameterised $r_{scat}$ causing poorer (cf. ID = 1) correlation coefficients $R_s$ and $R_p$. Experiment 2 has the lowest nSD (0.32) of all the experiments despite introduced observed variability in $r_{scat}$ (Figure 8b). These results suggest the variance of $\beta$ is controlled more...
by the variation in aerosol number concentrations in the accumulation mode than by variation of \( r_{\text{aq}} \) at NK. Hence, a more realistic estimate of \( N \) is more beneficial to accurately reproducing \( \beta_a \) by adjusting \( r_{\text{aq}} \). Overall, underestimation of \( \beta_a \) is greater for experiment 2 (cf. ID = 1). This is likely explained by underestimation of \( N \) by aerFO for \( N > \sim 20 \, \mu g \, kg^{-1} \) (Figure 8a).

Experiment 3, with both observed \( N \) and \( r_{\text{aq}} \) for the accumulation mode used, still has a negative medBE (\( \sim -1.1 \times 10^{-6} \) sr). This suggests other characteristics are important to accurately obtain \( \beta_a \).

In experiment 4, the \( N \) and \( r_{\text{aq}} \) observations used are for both fine and accumulation modes. This addition of fine aerosol mode information has little impact on the results as \( R_e, R_s, \beta_a, \text{medBE} \) and nSD only differ slightly (cf. ID = 3). This is explained by the impact of aerosol size and surface area on extinction. Given \( r_{\text{aq}} \propto Q_{\text{ext,dry}} \propto \sigma_{\text{aq}} \), and the average \( r_{\text{aq}} \) of the accumulation mode (0.142 \( \mu m \)) distinctly exceeds that of the fine mode (0.029 \( \mu m \)) by definition, the extinction coefficient \( (\sigma_{\text{aq}}) \) of the fine mode is \( \sim 100 \) times smaller than that of the accumulation mode at a wavelength of 905 nm. Although more small particles are present, and both \( N \) and \( f_{\text{med}}(r_{\text{aq}}) \) are greater for the fine mode, the effect of number concentration does not outweigh the size and surface area effects. Hence, we conclude that representing the fine mode and \( r_{\text{aq}} \) is not critical to accurately estimating \( \beta_a \) at the 905 nm wavelength.

For experiment 5, when \( N \) and \( r_{\text{aq}} \) observations for three aerosol modes (fine, accumulation and coarse) are used, \( \beta_a \) is overestimated (medBE - \( 3.6 \times 10^{-7} \) sr). This demonstrates the strong impact of coarse mode particles (\( D_p > 0.8 \mu m \)) on the bulk optical properties. The underestimation in experiments 0 - 4 is likely caused by the lack of coarse mode aerosol information (cf. medBE - \( 1.1 \times 10^{-6} \) sr (ID = 3, 4)). This is likely to be more important at \( \sim 900 \) nm than \( 300 - 500 \) nm.

A strong horizontal advection event likely affects this positive bias. On 04/06/2015 a change in wind direction (not shown) is associated with advection of (NH\(_4\))\(_2\)SO\(_4\) and NH\(_4\)NO\(_3\), leading to a 3 – 4-fold increase in NH\(_4\) of mass and a 2 – 3 increase in NO\(_x\) and SO\(_x\). This impacts the five hours after the air mass change with a larger nSD (2.1). The assumption, all available NH\(_4\) combining with SO\(_x\) and NO\(_x\) when estimating \( S \) (section 2.1), might not hold during this period causing the relative amount of (NH\(_4\))\(_2\)SO\(_4\) and NH\(_4\)NO\(_3\) to be overestimated. The associated increase of \( f_{\text{med}} \) would explain some of the overestimation of \( \beta_a \). Removing the affected period (5 hours) reduces the nSD to 1.56. The medBE also improves from \( 3.6 \times 10^{-7} \) to \( 2.8 \times 10^{-6} \) sr.

Experiment 6 uses hourly estimates of \( Q_{\text{ext,dry}} \) and \( f_{\text{med}} \) to replace the monthly LUT. The medBE, nSD and correlation statistics are similar to experiment 5. As additional relative mass of different aerosol species information does not improve \( \beta_a \), the default monthly LUT of \( Q_{\text{ext,dry}} \) and \( f_{\text{med}} \) appear adequate. However, other uncertainties within aerFO may limit its ability to improve \( \beta_a \). For instance, assuming particles are perfectly spherical when using Mie theory will introduce errors. As particles likely interact and aggregate, their interaction with water and light is altered. Hence, not considering internal mixing in aerFO or its LUT, is another source of uncertainty. Measurement inconsistencies arise in \( \beta_a \) from imperfect overlap correction and calibration. Height differences between the near-surface in-situ aerosol observations and ceilometer \( \beta_a \) also cause uncertainties.

Finally, experiment 7 uses hourly \( S \) estimates (section 3.1) to ID=6. The error is greater than experiments 5 and 6 with a larger standard deviation and interquartile range in \( \beta_a - \beta_e \). Correlations between model results and observations (\( R_e \) and \( R_s \)) are the lowest across all experiments. The large differences between \( \beta_a \) and \( \beta_e \) is reflected in a high nSD (3.5) but excluding the five hours (see experiment 5 discussion) reduces nSD to 1.83. The reduced overall performance of experiment 7 suggests the method to compute \( S \) (section 3.1) is unable to provide hourly variability. Specifically, uncertainties in estimating \( S \) (section 3.1) are likely varying with aerosol as particles interact and age, including through hysteresis, relative aerosol speciation across the size distribution, as well as OC and EC characteristics. Hence, the method is currently limited to providing only the overall behaviour of the lidar ratio.

### Table 6: aerFO model estimates for experiments (ID) with different aerosol observations (Table 4), observed attenuated backscatter and \( \beta_a - \beta_e \) evaluation statistics. Metrics: standard deviation (SD), interquartile range (IQR), normalised standard deviation (nSD = SD/(\( \beta_a \))/ SD(\( \beta_e \))), Spearman rank (\( R_s \)) and Pearson (\( R_e \)) correlation coefficient between \( \beta_a \) and \( \beta_e \). All correlation coefficients are statistically significant (> 99.9%). Equal sample size of 106 hours from the seven days for all experiments.

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Figure 8: Hourly observations for two years (2014 – 2015) at NK (Figure 1) of \( \text{PM}_{10} \) concentrations and aerosol characteristics for the accumulation diameter range (80 – 800 nm): a) total particle number concentration \( (N) \) and b) dry volume mean radius \( (r_{\text{med}}) \) with a locally weighted scatterplot smoothing function (LOWESS, red). The aerFO parameterisations (black) are a function of aerosol mass \( (m) \) derived from \( \text{PM}_{10} \) concentration.

4 Conclusions

The Warren et al. (2018) aerosol forward operator (aerFO) is used to quantify the relative importance of accurately describing different aerosol characteristics.
when estimating attenuated backscatter ($\beta_a$) at an urban background site. Observations are used to calculate aerosol variables by aeroF in increasing detail, including total aerosol mass, number concentration and mean volume radius for fine, accumulation and coarse modes. Results inform the development of the Met Office MURK visibility scheme for application in urban settings, as the aeroF links the output of this scheme to observed aerosol characteristics.

aeroF is used to assess the relative importance of various aerosol characteristics when modelling aerosol optical properties at an urban background site in London, UK. It is concluded that:

- Monotonic parameterisations within aeroF for total particle number concentration and dry volume mean radius from aerosol mass alone lead to an understimation of the variance of attenuated backscatter by about 2/3.
- A more realistic representation of total particle number concentration is the most critical factor for estimating accurate attenuated backscatter and should be considered a priority in future developments of Met Office NWP aerosol schemes for estimating aerosol optical properties.
- Using more realistic values of dry volume mean radius has little effect.
- Improving the representation of aerosol physical characteristics in the accumulation and coarse mode will likely lead to better model performance:
  - Providing a more realistic estimate of the total particle number concentration for the accumulation mode (diameter: 0.08 – 0.8 µm) based on observations improves the modelled variability.
  - More realistic coarse mode (diameter: > 0.8 µm) aerosol information leads to a clear increase in $\beta_a$ bringing the model results closer to the observations and reducing the mean bias error by 69.1 %. Hence, this aspect bears potential for the improvement of the Met Office MURK aerosol scheme.
- aeroF needs to represent the coarse mode in addition to the accumulation mode to better estimate the magnitude of $\beta_a$.
- At a wavelength of 905 nm the extinction coefficient of the fine mode aerosol (diameter: < 0.08 µm) is ~100 times smaller than that of the accumulation mode, so that more realistic fine mode information has no clear benefit.
- Constraining aerosol species relative mass has little impact on modelled results, however, this may be attributed to a limitation of the aeroF which does not account for internal mixing but rather used some simplifications with respect to aerosol hygroscopic and optical properties.

A new method to estimate the lidar ratio ($S$) from observations is developed that uses relative humidity and in-situ aerosol observations. This extends the possibility to calculate the lidar ratio without the need for the rare measurements from Raman lidars or sunphotometers. $S$ can be used to derive further aerosol optical properties (e.g. effective radius, extinction coefficient). The ratio can be parametrized before use in forward models, to minimize computational expense. For the London background site, modelled $S$ varies with wavelength between 14 – 80 sr across four common lidar wavelengths (355, 532, 905 and 1064 nm), values consistent with the literature. A strong dependence of the lidar ratio on relative humidity is found which varies between common lidar wavelengths; a relation not found in the wider literature. The relation found is due to another relation between lidar wavelength and aerosol size.

Adequately representing elemental carbon (EC) is important when estimating $S$ at shorter wavelengths (355 and 532 nm) and low relative humidity, given its characteristically high absorption of radiation. The effect of hygroscopic aerosol swelling likely explains why EC is less important at longer wavelengths and at higher relative humidity. Remaining uncertainties when estimating $S$ are associated with the assumption of particle sphericity for use with Mie theory, the speciation of the number distribution, and not including the effect of internal aerosol mixing which would lead to errors in the hygroscopic growth of particles, and by hysteresis effects. These uncertainties could not be constrained in the current study due to a lack of appropriate observations. As here only the near surface variability of $S$ is estimated from aerosol and relative humidity variations, future work should investigate how the input variables vary with height and if near surface $S$ estimates could be applied to full vertical profiles of $\beta_a$.

The current study uses a range of very detailed aerosol observations. However, data availability of number concentrations is slightly limited for relatively large particles (here > 0.6 µm). While small particles are a critical research topic given their impact on health, the fundamental impact of larger particles on bulk optical characteristics of aerosols warrant additional, increased and simultaneous monitoring of number concentrations in both the accumulation and the coarse mode. Furthermore, to estimate optical properties at more and diverse locations, more observation of speciated aerosol mass alongside number size distributions are needed.

5 Acknowledgements

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6 References


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7 Notation and abbreviations

aerFO Aerodynamic forward operator
ALC Automatic lidars and ceilometers
AOD Aerosol optical depth
APS Aerodynamic particle sizer
C Cunningham slip correction factor
Cα Aerosol species’ particle extinction cross section
Cα,λ,α,τ Aerosol species’ particle backscatter cross section
CH Chilbolton
CIR Complex index of refraction
CPC Condensation particle counter
D Particle diameter
Dα Aerosol species dry particle diameter
Dα,e Aerosol species aerodynamic equivalent diameter
Dα,m Particle mobility equivalent diameter
Dv Particle volume equivalent diameter
Dα,r Aerosol species particle diameter at ambient RH
DMPs Differential mobility particle sizer
del. Deliquescence relative humidity limit
EC Elemental carbon
ECMWF European Centre for Medium-Range Weather Forecasts
ERG King’s College London Environmental Research Group
eff Efflorescence relative humidity limit
εε Extinction enhancement factor
FO Forward operator
IFS Integrated Forecasting System
IQR Inter-quartile range
εε,α Aerosol species’ particle physical growth factor with respect to water
εcoc Organic carbon physical growth factor with respect to water
JULES Joint UK Land Environment Simulator
LAQN London Air Quality Network
LUT Look up table
LUMO London Urban Meteorological Observatory
m Aerosol mass mixing ratio
m0,α ‘Standard’ mass mixing ratio
m0,α,MEUK MURK aerosol mass mixing ratio
m0,α Aerosol species mass
medBE Median biased error
MO Met Office
N Total particle number concentration for aerosol mode
N0 ‘Standard’ or climatological mean, total particle number concentration for aerosol mode
Nα Aerosol species’ dry number distribution
Nα,NS Non-specified number distribution
Nα Total number of particles across all size bins
NK North Kensington
NPL National Physics Laboratory
nSD Normalised standard deviation
NWP Numerical weather prediction
n Number of particles in bin
nα Aerosol species refractive index
nα,refr Aerosol species mixed partial refractive index with water
OC Organic carbon
PM10 Total mass of particles with diameter less than 10 μm
Qα,ext Aerosol species particle extinction efficiency
Qα,ext,dry Dry particle extinction efficiency
R Spearman correlation coefficient
Appendix 1. Estimation of geometric mean radius from volume mean radius by aerosol mode

The geometric mean radius \( r_g \) is calculated using linear regression and the dry mean volume radius \( r_v \) as \( r_g \) is not estimated by the aerFO (Figures A1.1 – A1.3). The dry geometric number mean radius \( r_g \) is calculated as (Hinds, 1999):

\[
r_g = \left( \Pi D_i^n \right)^{1/N_{tot}}
\]

where \( D_i \) is the mid-point particle size in bin \( i \), \( n \) is the number of particles in bin \( i \) and \( N_{tot} \) the total number of particles across all bins. Calculations are done for dry particles.

The dry mean volume radius \( r_v \) is:

\[
r_v = \frac{\Sigma (dn_i/dlogD_i \cdot dlogD_i \cdot D_i^3)}{\Sigma (dn_i/dlogD_i \cdot dlogD_i \cdot D_i^2)}
\]

Figure A1.1: Observed dry geometric number mean radius \( r_g \) with observed dry mean volume radius \( r_v \) for the accumulation mode (radius: 0.04 – 0.4 μm) at North Kensington (NK) 01/01/2014 – 12/31/2015, from combined TSI SMPS and APS data. APS data are ‘dried’ based on physical growth factors calculated from observed RH at KCL (section 2.1, Figure 1). Linear regression (line), Pearson correlation \( (R_P) = 0.65 \) and statistically significant > 99 %. 
Figure A1.2: As Figure A1.1 but for fine mode (radii: < 0.04 μm). Pearson correlation (R_P) = 0.83 and statistically significant > 99%.

Figure A1.3: As Fig A1.1 but for the coarse mode (radii: > 0.4 μm). Linear regression (line), Pearson correlation (R_P) = 0.57 and statistically significant > 99%.

Appendix 2. Extinction enhancement factor (f_{ext,\text{rh}})

Because bulk aerosol optical properties vary strongly based on the hygroscopic properties, and the relative proportion of different aerosol species present (Warren et al., 2018), it is useful to understand how the common urban aerosol species contribute to extinction enhancement factor f_{ext,\text{rh}} calculations.

Daily mean f_{ext,\text{rh}} are estimated from hourly observed aerosol species for three UK sites: North Kensington (urban, NK), Chilbolton (rural, Ch) and Harwell (rural, Ha), for a fixed r_{md} = 0.11 μm and a RH range of 0 – 100 %. f_{ext,\text{rh}} is appreciably lower when the relative volumes of EC are greater (Figure A2.1). Across all sites the mean relative volume of EC is 7.25 %. The lower f_{ext,\text{rh}} values (Fig. A2.1 red, EC relative volume 9 – 100 %) reflect the hygrophobic nature of EC which has a constant f_{ext,\text{rh}} of 1.0. Hence, aerosol mixtures with greater volumes of EC have a lower combined f_{ext,\text{rh}}.

The reduction in f_{ext,\text{rh}} is greatest at higher RH (Figure A2.1). As RH increases, f_{ext,\text{rh}} increases exponentially for hygroscopic aerosols, but as f_{ext,\text{rh}} for EC remains constant the exponential increase in f_{ext,\text{rh}} of the total aerosol is limited. The variability in f_{ext,\text{rh}} increases with RH associated with the increased variability in f_{ext,\text{rh}} between different aerosol species at higher RH values (Warren et al., 2018). Greater relative volumes of sea salt lead to higher daily estimates of f_{ext,\text{rh}} (not shown) due its highly hygrophilic nature. Greater relative volumes of OC are related to lower f_{ext,\text{rh}} values (not shown). Though OC is not strongly hygrophobic, the relatively high-volume fractions (average 41.7 %) makes it proportionally important when computing the optical properties of the combined aerosol.

In section 3.1, the impact of hysteresis is discussed as it relates to calculation of S. The hysteresis effect is not accounted for in the f_{ext,\text{rh}} parameterisation as SOCRATES (which is used) does not include this effect. We recognize that hysteresis should be considered in future computation of LUTs of f_{ext,\text{rh}} to provide more realistic extinction enhancement.
Figure A2.1: Modelled daily extinction enhancement factors ($f_{ext,rh}$) stratified by relative humidity (RH) [%] and relative volume of elemental carbon [%] using observed daily mean relative volumes of each aerosol species as input. Median, IQR, 5th and 95th percentile whiskers, and outliers (crosses) shown with sample size. Estimates calculated for 0 – 100 % RH for a radius of 0.11 μm using data from three sites: North Kensington (n=1378), Chilbolton (n=192) and Harwell (n=1071). Note log scale on y-axis.