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

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HIGHLIGHTS

- Forward operator and ceilometer evaluation highlights key aerosol characteristics.
- Coarse and accumulation aerosol mode vital for estimating bulk optical properties.
- Accurate number concentration is more critical than dry mean size in urban areas.
- Urban lidar ratio modelled using observed aerosol characteristics (14–80 sr).
- Strong relation between relative humidity and modelled lidar ratio.

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ABSTRACT

Numerical weather prediction (NWP) models often parameterise aerosols 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 output could help inform future MURK scheme developments. To identify which parameterised physical and optical aerosol 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 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%. Providing more realistic temporal (monthly to hourly) variability of relative mass for different species leads to little improvement, compared to using monthly climatological means. Numerical experiments show that having more realistic estimates of number concentration is more important than providing more accurate values of the dry mean volume radius for the accumulation mode. Hence, improving the parameterisations for number concentration should be a main focus for further development of the MURK scheme. To estimate aerosol attenuated backscatter, the aerFO requires an extinction to backscatter ratio (i.e. the *lidar ratio*). In addition to forward modelling, the lidar ratio can also be used with ALC attenuated backscatter to calculate aerosol properties estimated in aerosol forecasts. Here, a model is developed that estimates the ratio using *in-situ* observations of the number size distribution and speciated aerosol masses. The values of lidar ratio derived at the London background site (14–80 sr across selected common lidar wavelengths) compare well to the literature. However, the modelled lidar ratio is unexpectedly correlated to

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relative humidity. Further, a stronger dependence exists at shorter wavelengths (355 and 532 nm) compared to longer wavelengths (905 and 1064 nm), and is due to the critical relation of lidar wavelength to aerosol size.

1. Introduction

Forecasting aerosol characteristics accurately is important, given 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 an explicit representation of multiple aerosols 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 aerosol 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), size 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 temporarily 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 (Stachlewska et al., 2018).

Alongside *in-situ* aerosol observations, automatic lidars and ceilometers (ALC; Wiegner et al., 2014) are being deployed (Flentje et al., 2010; Illingworth et al., 2007; Met Office, 2017; Osborne et al., 2018; Pappalardo et al., 2014). Ceilometers are becoming increasingly sensitive and comparable to more sophisticated systems, such as Raman lidars (Heese et al., 2010; Madonna et al., 2018, 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 (β) and *PM* concentrations (Münkel et al., 2004; You et al., 2016). Calibrated and corrected ALC measurements provide the optical property β, rather than a direct measurement of physical aerosol characteristics. Thus, aerosol forward operators (FO) are required to relate aerosol physical properties to β. They allow for attenuated backscatter (β_m) 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; Charlton--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 β_m 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 physical 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 lidars (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. Furthermore, 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 does not 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 (Muller 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 (β_m). 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) (section 3.1 and Appendix 2) are based on observations taken at North Kensington (NK) (Fig. 1, section 2.1).

2.1. Observations

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

Vertical profiles of β_o 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 (Kotthaus et al., 2018, 2016). β_o is corrected for instrument-related background and near-range artefacts (Kotthaus 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 Kotthaus et al., 2016). The CL31 reaches complete overlap at 70 m (Kotthaus et al., 2016). Insufficient optical overlap is corrected internally by the sensor firmware. β_o 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). β_o from the 1st range gate is not used given its relatively high noise (Kotthaus et al., 2016).

Calibration coefficients are computed using the 'stratus cloud' method, as it produces stable estimates (±5% over 2015) (Hopkin et al., 2019; O'Connor et al., 2004, section 3.1 in Warren et al., 2018). Daily coefficients produced are interpolated between stratus conditions, with key changes in window transmission, instrument hardware and software changes accounted for. 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 (Kotthaus et al., 2016; Wiegner and Gasteiger, 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 ($Q_{ext,dry}$), extinction enhancement factor ($f_{ext,rh}$) with a dependency on *RH*, and the water vapour extinction coefficient ($\sigma_{ext,wv}$) with a dependent on ambient water vapour mass mixing ratio (r_v) (section 2.3 gives an overview of aerFO variables).

Comparison of aerFO-derived β_m and observed β_o 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 taken at the NK site, measurements from a different central London LUMO site (KCL; 6.8 km southeast of NK, Fig. 1) are used instead as input to the parameterisation of the swelling and drying of aerosol particles. To assess the representativeness of KCL *RH* measurements at NK, the 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 (>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 (NH_4) reacts with sulphate (SO_4) preferentially, and only the remaining NH_4 reacts with nitrate (NO_3). 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.

Two aerosol particle diameter size ranges are measured at NK (Table 1):

(i) *Smaller sizes* (0.016–0.6 μm): Scanning Mobility Particle Sizer 3081 (SMPS; TSI, 2009) with a Condensation Particle Counter 3775 (CPC; TSI, 2007) operated by King's College London Environmental Research Group (ERG) and National Physics Laboratory (NPL) measures dried particle diameters.

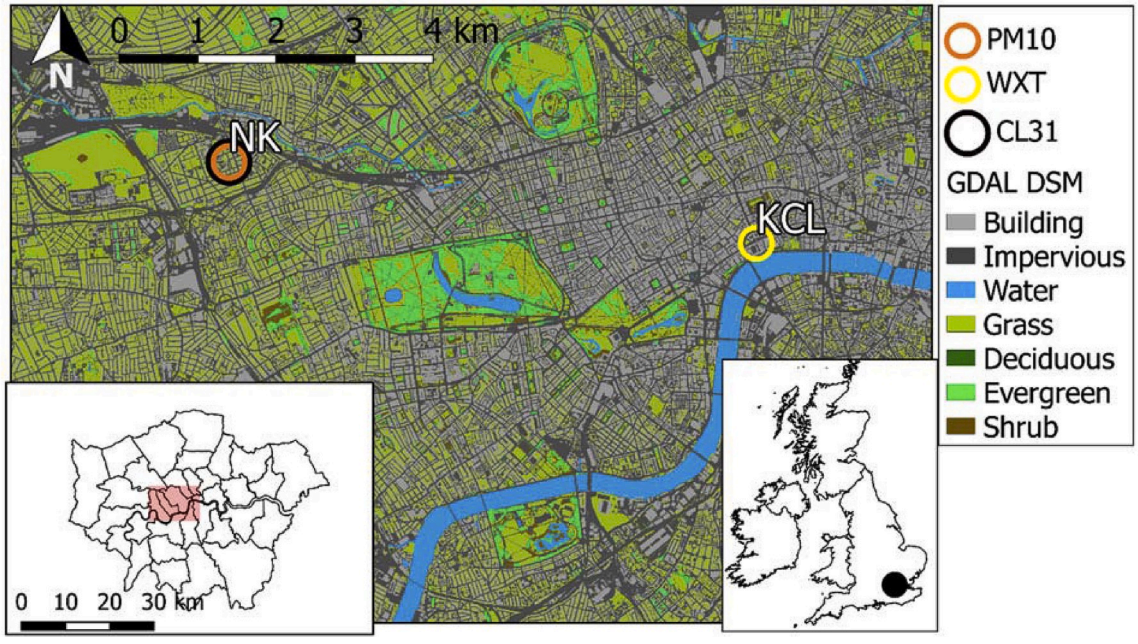

Fig. 1. LUMO (CL31, WXT) and LAQN measurement sites in central London and surface cover type (data source described in Grimmond and Lindberg, 2011); within Greater London and the British Isles (insets).

Table 1
Observations from North Kensington (NK) (Fig. 1) operated by LUMO (Kotthaus and Grimmond, 2018, 2014) and Environmental Research Group (ERG) LAQN (Mittal et al., 2016). † Particle number distribution data from two instruments (by diameter size) are combined to extend the range of particle sizes used to estimate aerosol optical properties (section 2.3). * *RH* from Strand campus King;'s College London (KSSW) is used.

Variables		Instrument	Sampling	Period	Source
Attenuated backscatter β_o		Vaisala CL31	15 s, 10 m	01/01/2014–31/12/2015	LUMO NK
PM_{10} by species	Ammonium sulphate [$(NH_4)_2SO_4$]	URG-9000B AIM	15 min	02/02/2011–07/02/2018	ERG/NPL NK
	Ammonium nitrate [NH_4NO_3]		15 min		
	Sea salt [NaCl]		15 min		
	Elemental carbon (EC)	Partisol 2025/Sunset	Daily		
	Organic carbon (OC)		Daily		
Particle number distribution †		SMPS 3081 (with CPC 3775)	~0.016–0.6 μm, 51 size bins (small)	01/01/2014 - 31/12/2015	ERG/NPL NK
		APS	~0.5–20.0 μm, 52 size bins (large)	01/01/2014–31/12/2015	ERG UK
RH *		Vaisala WXT520	5 s	01/01/2014–31/12/2015	LUMO KSSW

Table 2
Aerosol species modelled: ammonium sulphate, ammonium nitrate and sea salt. Mass calculated from respective reactants observed. † Elemental carbon assumed to be completely hygrophobic. * Efflorescence and deliquescence limits taken from swelling method source. Varutbangkul et al. (2006) found no efflorescence or deliquescence limits for organic carbon. ^ Shape factor (χ) used if particles are on the 'dry' branch of the hysteresis curve (Fig. 3). See Table 1 for aerosols species. Sources: Fi75 Fitzgerald (1975) Sc07 Schkolnik et al. (2007), SP16 Seinfeld and Pandis (2016), Va06 Varutbangkul et al. (2006), Ze06 Zelenyuk et al. (2006), Zh16 Zhang et al. (2016).

Aerosol species	Estimated from observed reactants	Swelling method applied	Efflorescence* relative humidity [%]	Deliquescence * relative humidity [%]	Dynamic shape factor		Density	
					χ ^	Source	ρ_p [kg m^{-3}]	Source
$(NH_4)_2SO_4$	NH_4, SO_4	Fi75	30	81	1.0	SP16	1770	n/a
NH_4NO_3	NH_4, NO_3	Fi75	30	61	1.0	n/a	1720	n/a
OC	n/a	Va06	n/a	n/a	1.0	Ze06	1100	Sc07
EC	n/a	n/a †	n/a	n/a	1.2	Zh16	1200	Zh16
NaCl	Cl	Fi75	42	75	1.08	SP16	2160	n/a

(ii) *Larger sizes* (0.5–20 μm): Aerodynamic Particle Sizer 3321 (APS; TSI, 2004) operated by DEFRA. Measurements of ionic components of PM_{10} by an URG-9000B Ambient Ion Monitor (DEFRA, 2018b; URG, 2011) are used to determine ammonium nitrate, ammonium sulphate and sea salt aerosol proportions. PM_{10} is sampled onto filters (Tissuquartz™ 2500 QAT-UP) with a Partisol 2025 sequential air sampler (DEFRA, 2018b; Thermo Fisher Scientific, 2015) and analysed for EC and OC using a Sunset Laboratory thermal–optical analyser according to the QUARTZ protocol (with very similar results to EUSAAR 2: Cavalli et al., 2010) (Beccaceci et al., 2013). Particles measured at ambient *RH*.

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). Whereas, the APS provides aerodynamic diameter (D_a) or diameter relative to an aerodynamic property measured (DeCarlo et al., 2004). Therefore, to merge these datasets, both are first converted to the volume equivalent diameter (D_v). D_v is based on particle surface area. This is chosen as the common particle size, 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.

The diameter conversion equations require additional aerosol parameters that can vary slightly by species (Table 2). For instance, the dynamic shape factor (χ) is used to convert D_m or D_a and the particle density (ρ_p) is required to convert D_a to D_v. χ 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_c) 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_c can be ignored given the contribution by small particles (<~0.07 μm) to the optical properties of total aerosol is negligible (section 3.2).

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

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 ($S = 60$ sr^{-1} typical of continental aerosol) to estimate β_m from σ_{ext} 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* (Fig. 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 ($N_{aer}(D)$) binned by diameter (D). The extinction and backscatter properties for each aerosol species (Table 2) are modelled separately, assuming an external aerosol mixture. Hygroscopic 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 ($N_{obs}(D)$) available, $N_{aer}(D)$ are estimated by speciating $N_{obs}(D)$ using observed hourly PM_{10} mass of different aerosol types (m_{aer}, Fig. 2, part 1). m_{aer} is used with observed aerosol density of

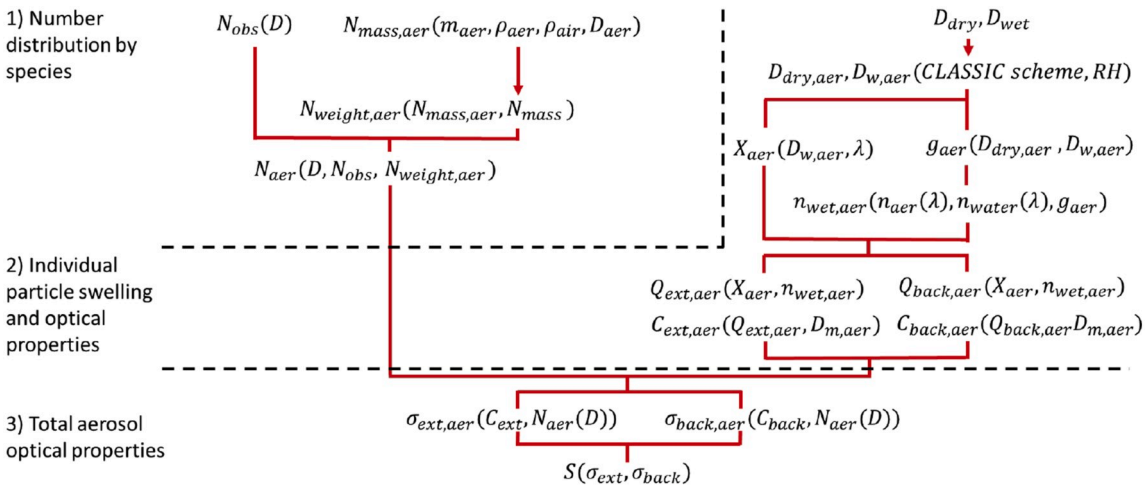

Fig. 2. Lidar ratio (S) calculation flow chart. The main inputs are diameter bins (D), number distribution by diameter ($N_{obs}(D)$), and aerosol species mass at a given size range (m_{aer}), e.g. PM_{10}, and relative humidity (RH). See section 7 for notation.

each species from the literature (ρ_{aer}, Table 2) to create volumetric weights ($V_{weight,aer}$; ratio of each species (V_{aer}) to total aerosol (V_{tot}) volume). The $V_{weight,aer}$ provide *a priori* weights for each bin of $N_{obs}(D)$ to obtain $N_{aer}(D)$ *by* species:

$$N_{aer} = N_{obs}(V_{aer} / V_{tot}) \quad (1)$$

After estimating $N_{aer}(D)$ for each species, the hygroscopic effects on aerosol particles are parameterised. As RH increases, hydrophilic aerosol particles swell (i.e. increase in size) with water, and their complex index of refraction changes, reaching some state between that of a dry particle and a water droplet (Haeffelin et al., 2016). For hydrophilic species, the parameterised physical growth of each binned diameter follows the CLASSIC aerosol scheme (Bellouin et al., 2011) such that the swollen diameters $D_{wet,aer}$ and dry diameters $D_{dry,aer}$ are calculated using ambient RH. In this study, the hygroscopic parameterisations require the observed dry SMPS particle sizes to be swollen to find $D_{wet,aer}$, and the observed humidified APS particle sizes to be dried to find $D_{dry,aer}$. Once $D_{dry,aer}$ and $D_{wet,aer}$ for the merged number distribution are calculated, the physical growth factor g_{aer} is estimated (Fig. 2 part 2). g_{aer} is used with the size parameter X_{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 ($n_{wet,aer}$) using the volume mixing method (Liu and Daum, 2008). Once $D_{wet,aer}$ 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 ($Q_{ext,aer}$, $Q_{back,aer}$), and extinction and backscatter cross-sections ($C_{ext,aer}$, $C_{back,aer}$). 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 ($\sigma_{ext,aer}$, $\sigma_{back,aer}$) is calculated using $N_{aer}(D)$ with $C_{ext,aer}$ and $C_{back,aer}$, respectively. The sum of $\sigma_{ext,aer}$, and $\sigma_{back,aer}$ is used to compute the overall σ_{ext} and β. Finally, S is computed as the ratio of σ_{ext} to β (Fig. 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 $\sigma_{ext,aer}$, $\sigma_{back,aer}$ and S results. To minimise the impact of number and arbitrary bin diameter sizes on optical property results, we follow Geisinger et al. (2017, their section 2.2.4) in part 2 (Fig. 2). This increases the total number of diameter bins by a factor of 4, by interpolating between the adjacent diameter bins. X_{aer} and $n_{wet,aer}$ are calculated for each interpolated bin, and the optical properties for each original bin (D_i) are derived as the average of the interpolated bins for that size interval.

For some particles (both pure and mixed species aerosol), particle hygroscopic growth has been observed to exhibit hysteresis (Fig. 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 (Fig. 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 (Fig. 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 (Fig. 3, grey). Particles originally above the deliquescence 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

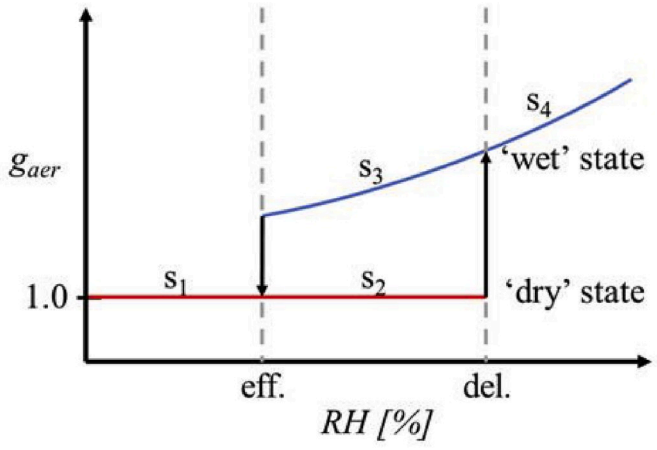

Fig. 3. Schematic of the particle physical growth factor (g_{aer}) hysteresis with RH. A particle is assumed to be in either a dry (s_2) or wet (s_3) state when between the efflorescence (eff) and deliquescence (del) RH limits. 'Dry' particles at s_1 move to s_2. Once the ambient RH reaches the deliquescence RH limit particles move from s_2 to the s_4 branch. 'Wet' particles at s_4 move to s_3, once the ambient RH reaches the efflorescence RH limit the particles have a dry branch response (s_1). This is based on observations presented in Table 2.

magnitude of the hysteresis effect for ambient aerosol varies (Fig. 5 in Fierz-Schmidhauser et al., 2010). Therefore, we parameterise the hysteresis effect for ammonium sulphate, ammonium nitrate and sea salt separately (Fig. 3). Originally dry particles (begin below efflorescence limit: Table 2) did not swell and are treated as being in a 'dry' crystalline state (s_1, s_2). Once *RH* exceeds the deliquescence limit (per aerosol type) the parameterised particles are considered to be in a 'wet' liquid state (s_3, s_4) 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).

2.3. Overview of aerFO

For a complete description of aerFO see Section 2 of Warren et al. (2018). aerFO is designed to estimate clear-sky β_m, using bulk mass of dry aerosol (m) [kg kg^{-1}] and *RH* from NWP as inputs. However, observations can also be used. Clear-sky conditions are defined as sub-saturated conditions based on the input *RH*, where no hydrometeors, such as cloud, fog or rain impact β_m, and where β_m is dominated by aerosol backscatter.

Initially, aerFO estimates the bulk aerosol physical properties of the aerosol accumulation mode, including dry mean radius (r_{md}) and total number concentration (N) using observed and empirically derived constants (Fig. 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_{md}, a fixed geometric standard deviation (d_g) of 1.7 is used for the accumulation mode as calculated from observations. Properties calculated include: aerosol optical (e.g. $Q_{ext,dry}$ and σ_{ext}; Fig. 4, parts 2–3), backscatter and transmission (Fig. 4, part 4). aerFO can represent multiple aerosol modes (e.g. fine, accumulation and coarse) by calculating $\sigma_{ext,aer}$ (Fig. 4, parts 1–2) for each mode and adding them to obtain the overall $\sigma_{ext,aer}$. The effect of water vapour absorption ($\sigma_{ext,wv}$) is also included in the total extinction coefficient (σ_{ext}).

For computational efficiency, $Q_{ext,dry}$ and $f_{ext,rh}$ (Fig. 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).

Look up tables (LUT) are derived for $f_{ext,rh}$ based on the geometric mean radius (r_g), using SOCRATES (Manners et al., 2015) Mie scattering code within the radiation suite. r_g is estimated from r_{md} using linear regression based on observations for the aerosol accumulation mode. Relations between r_{md} and r_g are derived for each aerosol mode separately (e.g. fine, accumulation and coarse mode in experiment 5; section 3.2).

N_0 is highly sensitive to the defined size range of the accumulation mode (Warren et al., 2018). Therefore, the default aerFO N_0, and the mean dry volume radius (r_0), are re-calculated for NK from the mean observed particle number distribution for the accumulation mode (Table 3) from the SMPS and APS measurements (Table 1).

2.4. Aerosol forward operator experiments

The improvement in β_m estimates when using observed aerosol characteristics (e.g. size, total number) is evaluated using a set of aerFO experiments (given a unique ID, Table 4). For these we use observations (rather than NWP model forecasts) as inputs to aerFO. As observations replace parameterised variables, β_m is changed (Fig. 4, part 1). For comparison, we define a control run (ID 0, Table 4), with physical properties N and r_{md} (Fig. 4, part 1) estimated based on aerFO parameterisations, with measured PM_{10} mass and *RH* (Table 1). In ID 1–7 parameterised variables (e.g. N and r_{md}) are replaced by estimates from aerosol observations (Table 4). ID 1–3 consider the accumulation mode whereas ID 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 r_{md} for the accumulation mode is used (ID 2); both observed N and r_{md} 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 r_{md} 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 (Fig. 4, parts 1–3) each mode is treated separately when obtaining the extinction coefficient. Experiment 5 uses observed N and r_{md} for the fine, accumulation and coarse aerosol modes. ID 6 is as 5, but with hourly aerosol composition used to calculate hourly varying $Q_{ext,dry}$ and $f_{ext,rh}$

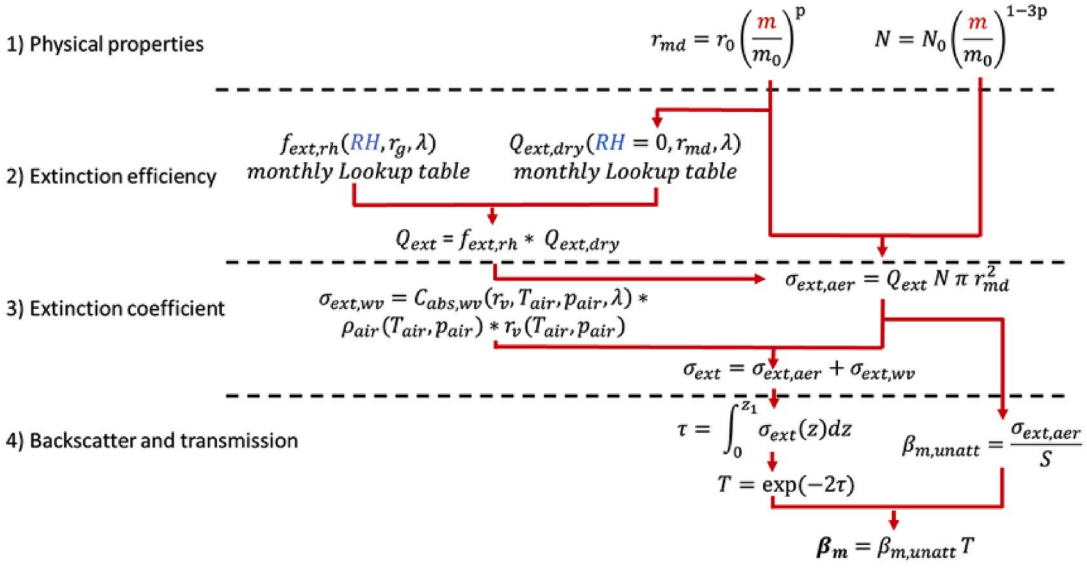

Fig. 4. The aerosol forward operator (aerFO) to estimate attenuated backscatter from the NWP inputs of aerosol mass mixing ratio (m) and relative humidity (*RH*). See section 7 for notation. Modified from: Warren et al. (2018).

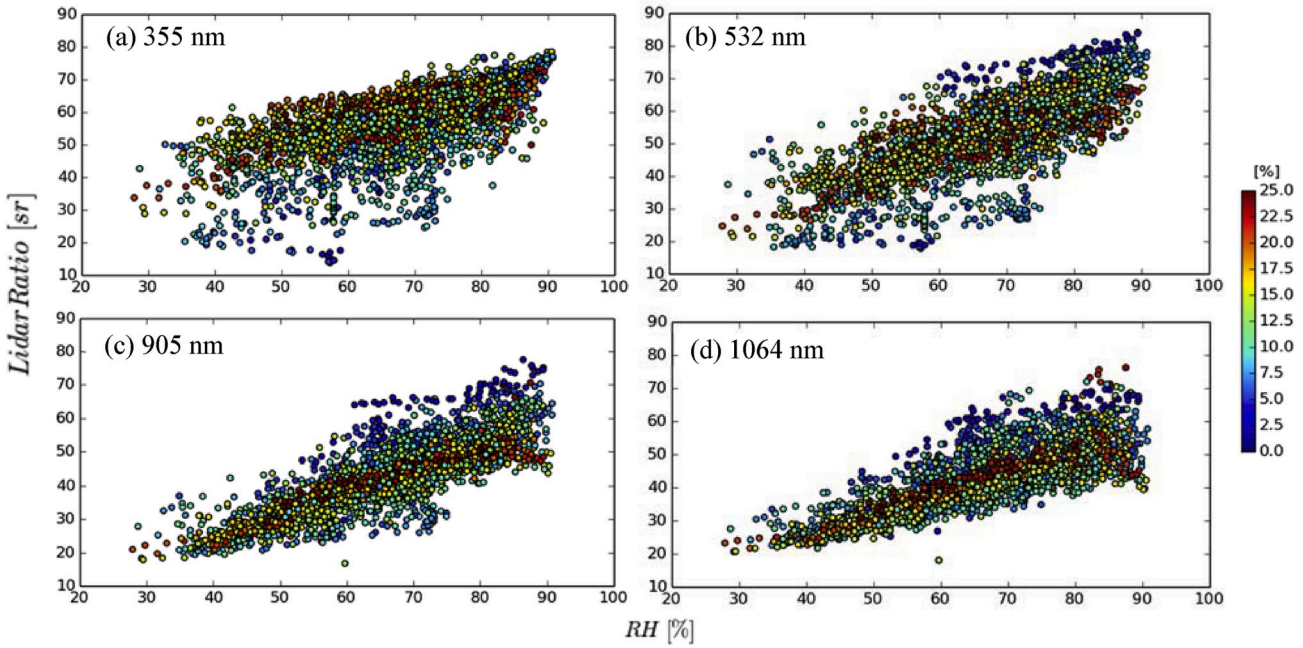

Fig. 5. Calculated lidar ratio (*S*, sr, Fig. 2) as a function of relative humidity (*RH*) [%] and elemental carbon proportion of total aerosol (%, colour) at four wavelengths that are typical of: Raman lidar (a) 355, (b) 532 nm; and ALC (c) 905 (Vaisala CL31) and (d) 1064 nm (Lufft CH15MK). Calculated hourly using NK (Fig. 1) data for the period 01/01/2014–31/12/2015. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

LUT. ID 0–6 use a mean *S* (section 2.2), whereas 7 is as 6, but with hourly estimates of *S*.

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

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 (Fig. 5). Across all wavelengths *S* varies between ~14 and 80 sr. This wide range of *S* and corresponding β (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* (Fig. 5) is linked to the relation between the aerosol size distribution and *S*, and likely caused by the relative position of the accumulation mode size range (Fig. 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 vapour condenses onto or evaporates from them. Consequently, particles move up or down the curve (Fig. 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 (Fig. 6). At the longer 905 and 1064 nm wavelengths (Fig. 6c and d), the first local maximum of *S* is associated with larger particles compared to the Raman channels (Fig. 6a and b) so there are fewer inflection points across the accumulation size range (Fig. 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* (Fig. 5a and b).

Table 3
Default input parameters for aerFO at NK (Fig. 1) using all available data.

Site (type)	Accumulation radius size range [μm]	N_0 [cm^{-3}]	r_0 [μm]
NK (urban background)	0.04–0.4	1311	0.159

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 (Fig. 1). All aerFO experiments use observed *RH* from KCL. Mode diameter ranges: < 0.08 μm (fine), 0.08–0.8 μm (accumulation) and >0.8 μm (coarse). * control run. See section 7 for notation.

ID	Aerosol variables estimated based on observations	Aerosol observations used
0*	m = PM_{10}	Particle mass
1	*N* (accumulation mode)	Particle number distribution (fine and coarse)
2	r_{md} (accumulation mode)	
3	*N*, r_{md} (accumulation mode)	
4	*N*, r_{md} (fine and accumulation mode)	
5	*N*, r_{md} (fine, accumulation and coarse mode)	
6	*N*, r_{md} (fine, accumulation and coarse mode), $Q_{ext,dry}$, $f_{ext,RH}$	Particle number distribution (fine and coarse) and mass by species
7	*N*, r_{md} (fine, accumulation and coarse mode), $Q_{ext,dry}$, $f_{ext,RH}$, *S*	

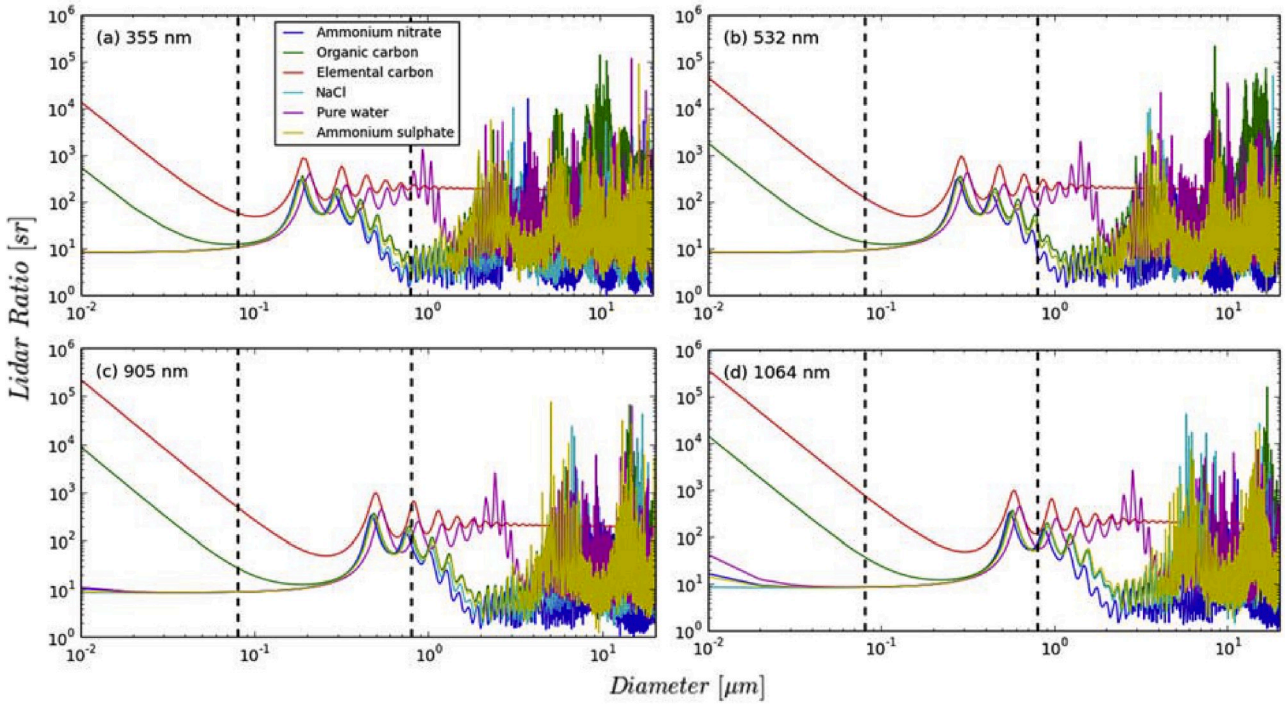

Fig. 6. Lidar ratio (*S*, sr) of pure monodisperse aerosol species for four wavelengths (as Fig. 5) using Mie scattering and assuming perfect sphericity. Accumulation diameter range (~80–800 nm) indicated (vertical dashed lines) (Fig. 1).

Additionally, *S* is influenced by the proportions of aerosol species at some wavelengths and humidities. At 355 (Fig. 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 $f_{ext,rh}$ at 355, 532, 905 and 1064 nm (905 nm shown in Appendix 2).

Some assumptions made in calculating *S* may reduce *S* variability with changing *RH* (Fig. 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* (Fig. 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_{aer}). Omitting internal mixing likely means hysteresis-related variability is not fully represented. In laboratory conditions Fierz-Schmidhauser et al. (2010) found

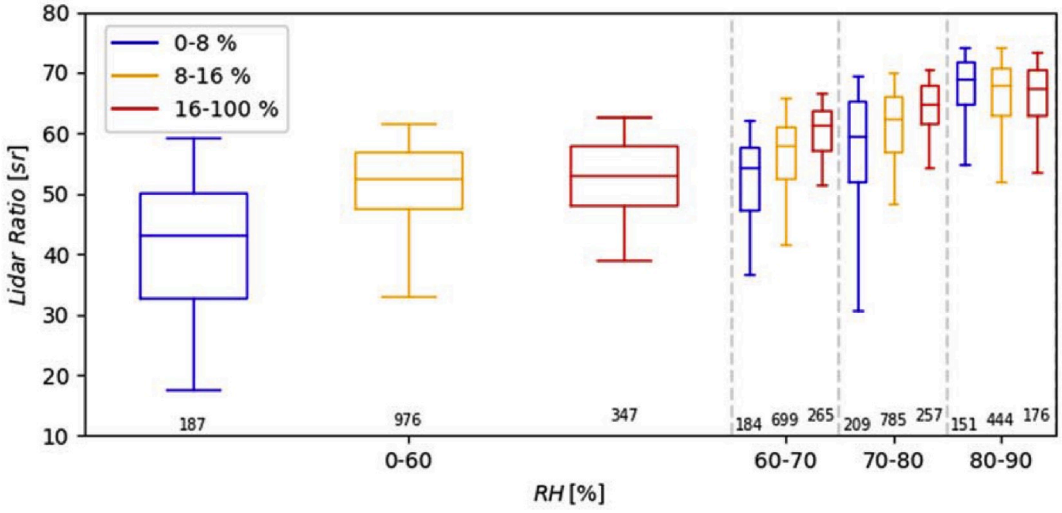

Fig. 7. Calculated lidar ratio (*S*, sr) as Fig. 5, with relative humidity (%, x-axis) stratified by relative volume of elemental carbon to total aerosol (colour), for 355 nm. Median (box centre line), inter-quartile range (box edges), 5th and 95th percentiles (whiskers). Sample size below each box plot. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

Table 5
Experiment (ID) settings for calculation of lidar ratio S: physical growth factor (g_{OC}) and imaginary component of the complex index of refraction (CIR) for organic carbon (OC) and elemental carbon (EC). Settings modified from default (shaded). Aged and fresh OC growth factors as per Met Office CLASSIC aerosol scheme (Bellouin et al., 2011). KH98 (Kotchenruther and Hobbs, 1998) adjusted growth factor best reproduced the scattering enhancement observed. All values applicable for 905 nm. ID = 0 is control (section 3.2).

ID	Physical growth factor (g_{OC})	CIR imaginary component	
Species	*OC*	*OC*	*EC*
0	Aged	0.006	0.700
1	Aged	0.006	0.440
2	Aged	0.010	0.700
3	Aged	0.000	0.700
4	Fresh	0.000	0.700
5	KH98 adjusted	0.006	0.700

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 β_m (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 with a sample size of 4699 h (across 17 months in 2014–2015).

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) of 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, Fig. 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 ID 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 interquartile range (IQR) and the mean *S* (30.1 sr, 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 aerFO experiments are conducted with different combinations of aerosol observations to identify which aerosol characteristics are most important for estimating β_m (section 2.4). Estimates of β_m are compared with observed β_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 β_m and β_o, as well as a normalised standard deviation ($nSD = SD(\beta_m)/SD(\beta_o)$). β_m is most relevant for the near surface (height level of *in-situ* aerosol measurements), whereas β_o was taken at 20 m above ground level (section 2.1).

In the control experiment (ID 0), PM_{10} is the aerosol mass *m*, used to parameterise *N* and r_{md}. 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, β_m is generally underestimated with a median bias error (medBE) of $\sim -1.1 \times 10^{-6}$ sr. *nSD* is low (0.37, i.e. small modelled standard deviation) as the monotonic function of *m* (PM_{10}, Fig. 8) does not account for the large variance observed.

In 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 $m > \sim 20$ μg kg^{-1} compared to a locally weighted

Table 6
aerFO model estimates for experiments (ID) with different aerosol observations (Table 4), observed attenuated backscatter and $\beta_m - \beta_o$ evaluation statistics. Metrics: standard deviation (*SD*), interquartile range (IQR), normalised standard deviation ($nSD = SD(\beta_m)/SD(\beta_o)$), Spearman rank ($R_S$) and Pearson ($R_P$) correlation between β_m and β_o. All correlation coefficients are statistically significant (>99.9%). Equal sample size of 106 h from the seven days for all experiments. Same β_o used for all experiments.

ID		0	1	2	3	4	5	6	7
β_m	Mean	5.6×10^{-7}	7.8×10^{-7}	4.6×10^{-7}	6.2×10^{-7}	6.3×10^{-7}	2.4×10^{-6}	2.4×10^{-6}	3.0×10^{-6}
	Median	5.3×10^{-7}	7.0×10^{-7}	4.6×10^{-7}	5.4×10^{-7}	5.4×10^{-7}	2.1×10^{-6}	2.1×10^{-6}	2.6×10^{-6}
β_o	Mean	1.8×10^{-6}							
	Median	1.6×10^{-6}							
$\beta_m - \beta_o$	Mean	-1.3×10^{-6}	-1.1×10^{-6}	-1.4×10^{-6}	-1.2×10^{-6}	-1.2×10^{-6}	5.3×10^{-6}	5.3×10^{-6}	1.1×10^{-6}
	Median	-1.1×10^{-6}	-1.1×10^{-6}	-1.2×10^{-6}	-1.1×10^{-6}	-1.1×10^{-6}	3.6×10^{-7}	4.0×10^{-7}	8.2×10^{-7}
	SD	4.7×10^{-7}	4.1×10^{-7}	5.2×10^{-7}	4.3×10^{-7}	4.3×10^{-7}	9.6×10^{-7}	9.3×10^{-7}	1.9×10^{-6}
	IQR	5.9×10^{-7}	5.1×10^{-7}	6.5×10^{-7}	6.6×10^{-7}	6.5×10^{-7}	1.1×10^{-6}	9.7×10^{-7}	9.7×10^{-7}
nSD		0.37	0.68	0.32	0.50	0.51	2.14	2.14	3.48
R_S		0.78	0.68	0.66	0.70	0.70	0.72	0.72	0.47
R_P		0.78	0.74	0.62	0.75	0.75	0.74	0.76	0.50

scatter smoothing function (Cleveland, 1979) through N observations (Fig. 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 ID 2, observed dry mean volume radius replaces the parameterised r_{md} causing poorer (cf. ID = 1) correlation coefficients R_S and R_P. ID 2 has the lowest nSD (0.32) of all the experiments despite introduced observed variability in r_{md} (Fig. 8b). These results suggest the variance of β is controlled more by the variation in aerosol number concentrations in the accumulation mode than by variation of r_{md} at NK. Hence, a more realistic estimate of N is more beneficial to accurately reproducing β_m than adjusting r_{md}. Overall, underestimation of β_m is greater for ID 2 (cf. ID 1). This is likely explained by underestimation of N by aerFO for $m > \sim 20$ μg kg^{-1} (Fig. 8a).

ID 3, with both observed N and r_{md} for the accumulation mode used, still has a negative medBE (~- 1.1 × 10^{-6} sr). This suggests other characteristics are important to accurately obtain β_m.

In ID 4, the N and r_{md} observations used are for both fine and accumulation modes. This addition of fine aerosol mode information has little impact on the results as R_S, R_P, medBE and nSD only differ slightly (cf. ID 3). This is explained by the impact of aerosol size and surface area on extinction. Given $r_{md} \propto Q_{ext,dry} \propto \sigma_{ext}$, and the average r_{md} of the accumulation mode (0.142 μm) distinctly exceeds that of the fine mode (0.029 μm) by definition, the extinction coefficient (σ_{ext}) of the fine mode is ~100 times smaller than that of the accumulation mode at a wavelength of 905 nm. Although more smaller particles are present, and both N and $f_{ext,rh}(r_{md})$ 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 N and r_{md} is not critical to accurately estimating β_m at the 905 nm wavelength.

For ID 5, when N and r_{md} observations for three aerosol modes (fine, accumulation and coarse) are used, and β_m is now overestimated (medBE ~3.6 × 10^{-7} sr). This demonstrates the strong impact of coarse mode particles (D_v: > 0.8 μm) on the bulk optical properties. The underestimation in IDs 0–4 is likely caused by the lack of coarse mode aerosol information (cf. medBE ~ -1.1 X10^{-6} sr (ID 3, 4)). This is likely to be more important at ~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 $(NH_4)_2SO_4$ and NH_4NO_3, leading to a 3 – 4-fold increase in NH_4 of mass and a 2–3 increase in NO_3 and SO_4. This impacts the 5 h after the air mass change with a larger nSD (2.1). The assumption, all available NH_4 combining with SO_4 and NO_3 when estimating S (section 2.1), might not hold during this period causing the relative amount of $(NH_4)_2SO_4$ and NH_4NO_3 to be overestimated. The associated increase of $f_{ext,rh}$ would explain some of the overestimation of β_m. Removing the affected period (5 h) reduces the nSD to 1.56. The medBE also improves from 3.6 × 10^{-7} to 2.8 × 10^{-7} sr.

ID 6 uses hourly estimates of $Q_{ext,dry}$ and $f_{ext,rh}$ to replace the monthly LUT. The medBE, nSD and correlation statistics are similar to ID 5. As additional relative mass of different aerosol species information does not improve β_m, the default monthly LUT of $Q_{ext,dry}$ and $f_{ext,rh}$ appear adequate. However, other uncertainties within aerFO may limit its ability to improve β_m. 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 uncertainties arise in β_o from imperfect overlap correction and calibration. Height differences between the near-surface *in-situ* aerosol observations and ceilometer β_o also cause uncertainties.

Finally, ID 7 uses hourly S estimates (section 3.1) to ID 6. The error is greater than IDs 5 and 6 with a larger standard deviation and interquartile range in $\beta_m - \beta_o$. Correlations between model results and observations (R_S and R_P) are the lowest across all experiments. The large differences between β_m and β_o is reflected in a high nSD (3.5) but excluding the 5 h (see ID 5 discussion) reduces nSD to 1.83. The reduced overall performance of ID 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.

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 (β_m), at an urban background site. Observations are used to calculate aerosol variables by aerFO in increasing detail, including total aerosol mass, number concentration and mean volume radius for fine, accumulation and coarse modes. Results can inform the development of the Met Office MURK visibility scheme for application in urban settings, as the aerFO links the output of this scheme to observed aerosol characteristics.

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

- Monotonic parameterisations within aerFO for total particle number concentration and dry volume mean radius from aerosol mass alone

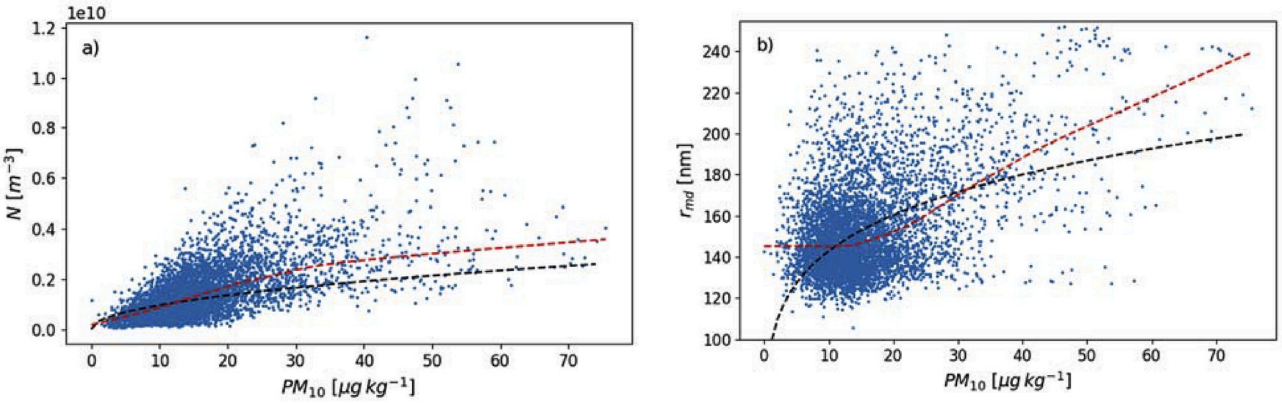

Fig. 8. Hourly observations for two years (2014–2015) at NK (Fig. 1) of PM_{10} concentrations and aerosol characteristics for the accumulation diameter range (80–800 nm): a) total particle number concentration (N) and b) dry volume mean radius (r_{md}) with a locally weighted scatterplot smoothing function (LOWESS, red). The aerFO parameterisations (black) are a function of aerosol mass (m) derived from PM_{10} concentration. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

lead to an underestimation of the variance of attenuated backscatter by about 2/3.

- A more realistic representation of total particle number concentration is a 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 β_m 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.
  - aerFO needs to represent the coarse mode in addition to the accumulation mode to better estimate the magnitude of β_m.
- 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 aerFO 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. optical depth, extinction) from elastic-backscatter lidars (e.g. ceilometers), and the ratio can be parameterised before use in forward models, to minimise computational expense. For the London background site, modelled S varies with wavelength between 14 and 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, including 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 β_m.

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.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.atmosenv.2019.117177.

Appendix 1. Estimation of geometric mean radius from volume mean radius by aerosol mode

In the aerFO, the geometric number mean radius (r_g) is estimated from the dry mean volume radius (r_v). The equations in the aerFO are parameterised, based on a linear fit between r_v and r_g calculated from observed number distribution data between 01/01/2014 and 12/31/2015, and are done seperately for the different aerosol modes. r_g in the two year period is calculated as (Hinds, 1999):

$$r_g = \frac{\left(\Pi\, D_i^n\right)^{1/N_{tot}}}{2} \tag{2}$$

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:

$$r_v = \frac{\Sigma\left(dn_i / dlogD_i * dlogD_i * D_i^4\right)}{\Sigma\left(dn_i / dlogD_i * dlogD_i * D_i^3\right)} \quad (3)$$

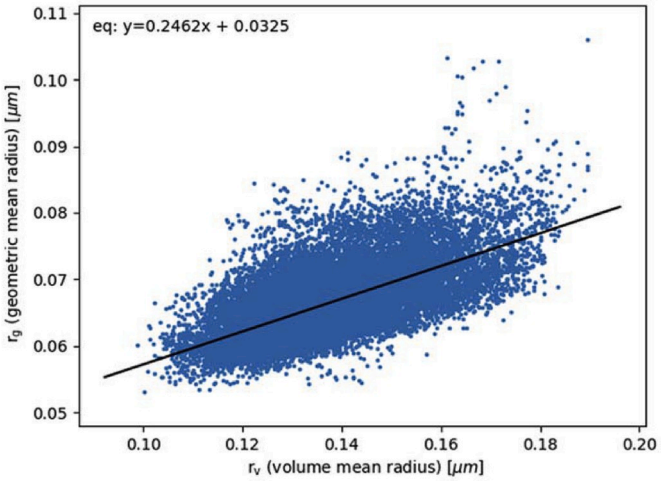

Fig. A1.1. Observed dry geometric number mean radius (r_g) with observed dry mean volume radius (r_v) for the accumulation mode (radius: 0.04–0.4 μm) at North Kensington (NK) 01/01/2014–12/31/2015, from combined TSI SMPS and APS data. APS data are 'dried' based on physical growth factors calculated from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

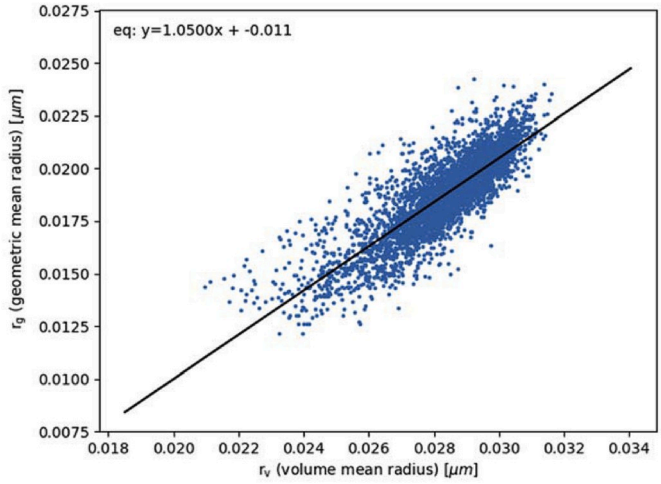

Fig. A1.2. As Figure A1.1, but for fine mode (radii: < 0.04 μm). Pearson correlation (R_P) = 0.83 and statistically significant > 99%.

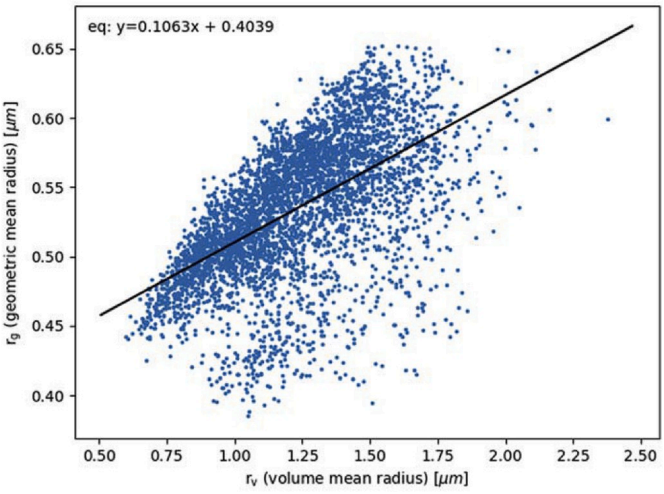

Fig. A1.3. As Fig A1.1 but for the coarse mode (radii:> 0.4 μm). Linear regression (line), Pearson correlation (R_P) = 0.57 and statistically significant > 99%.

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

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 $f_{ext,rh}$ calculations.

Daily mean $f_{ext,rh}$ 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%. $f_{ext,rh}$ is appreciably lower when the relative volumes of EC are greater (Fig. A2.1). Across all sites the mean relative volume of EC is 7.25%. The lower $f_{ext,rh}$ values (Fig. A2.1 red, EC relative volume 9–100%) reflect the hygrophobic nature of EC which has a constant $f_{ext,rh}$ of 1.0. Hence, aerosol mixtures with greater volumes of EC have a lower combined $f_{ext,rh}$.

The reduction in $f_{ext,rh}$ is greatest at higher *RH* (Fig. A2.1). As *RH* increases, $f_{ext,rh}$ increases exponentially for hygroscopic aerosols, but as $f_{ext,rh}$ for EC remains constant the exponential increase in $f_{ext,rh}$ of the total aerosol is limited. The variability in $f_{ext,rh}$ increases with *RH* associated with the increased variability in $f_{ext,rh}$ between different aerosol species at higher *RH* values (Warren et al., 2018). Greater relative volumes of sea salt lead to higher daily estimates of $f_{ext,rh}$ (not shown) due its highly hygrophilic nature. Greater relative volumes of OC are related to lower $f_{ext,rh}$ 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 $f_{ext,rh}$ parameterisation as SOCRATES (which is used) does not include this effect. We recognize that hysteresis should be considered in future computation of LUTs of $f_{ext,rh}$, to provide more realistic extinction enhancement.

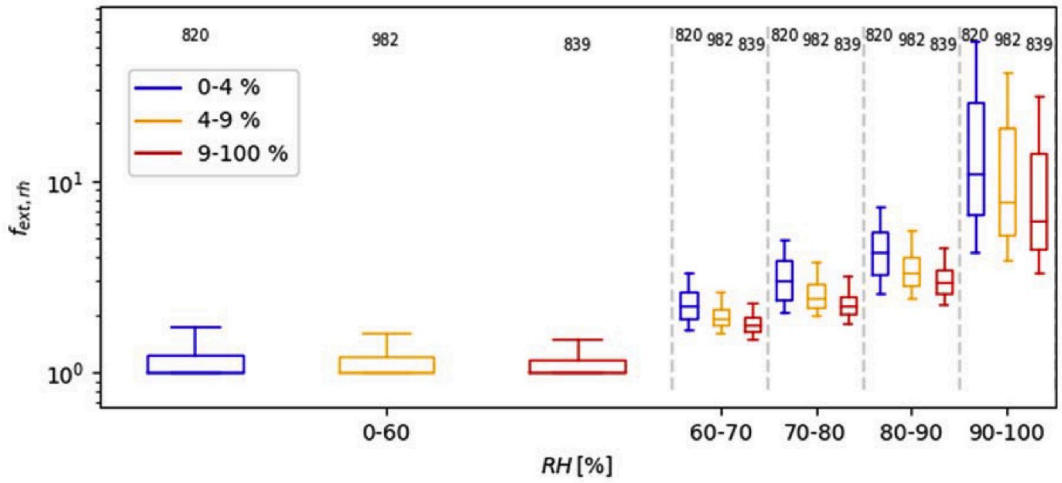

Fig. A2.1. Modelled daily extinction enhancement factors ($f_{ext,rh}$) stratified by relative humidity (*RH*) [%] and relative volume of elemental carbon [%] using observed daily mean relative volumes of each aerosol species as input. Median, IQR, 5th and 95th percentile whiskers, and outliers (crosses) 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.

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Glossary

aerFO: Aerosol forward operator
ALC: Automatic lidars and ceilometers
AOD: Aerosol optical depth
APS: Aerodynamic particle sizer
C_c: Cunningham slip correction factor
$C_{ext,aer}$: Aerosol species' particle extinction cross section
$C_{back,aer}$: Aerosol species' particle backscatter cross section
CH: Chilbolton
CIR: Complex index of refraction
CPC: Condensation particle counter
D: Particle diameter
$D_{dry,aer}$: Aerosol species dry particle diameter
D_a: Particle aerodynamic equivalent diameter
D_m: Particle mobility equivalent diameter
D_v: Particle volume equivalent diameter
$D_{wet,aer}$: 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
$f_{ext,rh}$: Extinction enhancement factor
FO: Forward operator
IFS: Integrated Forecasting System
IQR: Inter-quartile range
g_{aer}: Aerosol species' particle physical growth factor with respect to water
g_{OC}: 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
m_0: 'Standard' mass mixing ratio
m_{MURK}: MURK aerosol mass mixing ratio
m_{aer}: Aerosol species mass
medBE: Median biased error
MO: Met Office
N: Total particle number concentration for aerosol mode
N_0: 'Standard' or climatological mean, total particle number concentration for aerosol mode
N_{aer}: Aerosol species' dry number distribution
N_{obs}: Non-speciated number distribution
N_{tot}: 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
n_{aer}: Aerosol species refractive index
n_{water}: Refractive index of water
$n_{wet,aer}$: Aerosol species mixed partial refractive index with water
OC: Organic carbon
PM_{10}: Total mass of particles with diameter less than 10 μm
$Q_{ext,aer}$: Aerosol species particle extinction efficiency
$Q_{ext,dry}$: Dry particle extinction efficiency
R_s: Spearman correlation coefficient
R_P: Pearson correlation coefficient
RH: Relative humidity
r_0: 'Standard' or climatological mean, dry mean volume particle radius for aerosol mode
r_g: Dry number geometric mean radius for aerosol mode
r_{md}: Dry mean volume particle radius for aerosol mode
r_v: Water vapour mass mixing ratio
S: Lidar ratio
SNR: Signal-to-noise ratio
s: Parameterised wet/dry hygroscopic growth state
UKV: UK Variable Resolution model
V: Volume
V_{aer}: Aerosol species volume
V_{tot}: Total aerosol volume
$V_{weight,aer}$: Aerosol species volume weighting
X_{aer}: Aerosol species' size parameter
z: Height
β: Backscatter
β_m: Forward modelled attenuated backscatter
β_o: Observed attenuated backscatter
ρ_{air}: Air density
ρ_{aer}: Aerosol species density
λ: Wavelength
$\sigma_{ext,aer}$: Aerosol species' particle extinction coefficient
$\sigma_{back,aer}$: Aerosol species' particle backscatter coefficient
χ: Dynamic shape factor