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Working with the enemy? Social work education and men who use intimate partner violence

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Review of Surface Particulate Monitoring of Dust Events Using Geostationary Satellite Remote Sensing

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Abstract

The accurate measurements of natural and anthropogenic aerosol particulate matter (PM) is important in managing both environmental and health risks; however, limited monitoring in regional areas hinders accurate quantification. This article provides an overview of the ability of recently launched geostationary earth orbit (GEO) satellites, such as GOES-R (North America) and HIMAWARI (Asia and Oceania), to provide near real-time ground-level PM concentrations (GLCs). The review examines the literature relating to the spatial and temporal resolution required by air quality studies, the removal of cloud and surface effects, the aerosol inversion problem, and the computation of ground-level concentrations rather than columnar aerosol optical depth (AOD).

Determining surface PM concentrations using remote sensing is complicated by differentiating intrinsic aerosol properties (size, shape, composition, and quantity) from extrinsic signal intensities, particularly as the number of unknown intrinsic parameters exceeds the number of known extrinsic measurements. The review confirms that development of GEO satellite products has led to improvements in the use of coupled products such as GEOS-CHEM, aerosol types have consolidated on model species rather than prior descriptive classifications, and forward radiative transfer models have led to a better understanding of predictive spectra interdependencies across different aerosol types, despite fewer wavelength bands. However, it is apparent that the aerosol inversion problem remains challenging because there are limited wavelength bands for characterising localised mineralogy.

The review finds that the frequency of GEO satellite data exceeds the temporal resolution required for air quality studies, but the spatial resolution is too coarse for localised air quality studies. Continual monitoring necessitates using the less sensitive thermal infra-red bands, which also reduce surface absorption effects. However, given the challenges of the aerosol inversion problem and difficulties in converting columnar AOD to surface concentrations, the review identifies coupled GEO-neural networks as potentially the most viable option for improving quantification.

Keywords: Geostationary Earth Orbiting satellites; Aerosol Optical Depth; Particulate Matter; Thermal infra-red; spatiotemporal resolution.

Abbreviations:

Note in the interests of brevity, and apart from MODIS, this list of abbreviations specifically excludes the full dispersion model and satellite names for which the commonly used abbreviation has been used.

AOD: Aerosol Optical Depth

BT: Brightness temperature

BTR: Brightness temperature reduction, i.e. $BT_1 - BT_2$ where the suffix could be time or wavelength

IDDI: Infrared Differential Dust Index, BTR but restricted to time-based differences

GEO: geostationary earth orbit satellites

GLCs: ground level concentrations

LEO: low earth orbit satellites

MODIS: MODerate-resolution Imaging Spectro-radiometer instrument

NIR: Near infra-red portion of the electromagnetic spectrum

PM: particulate matter

TIR: Thermal infra-red portion of the electromagnetic spectrum

UV: Ultra-violet portion of the electromagnetic spectrum

Vis: Visible portion of the electromagnetic spectrum

Highlights:

• Excellent temporal resolution (10 minutes) but coarse spatial resolution (2 km);

• Continuous infrared instead of visible bands are required;

• Challenging aerosol inversion compounded by fewer and less sensitive infrared bands;

• Vertical profile required for extrapolating AOD to ground-level concentration;

• Uncertainty analysis of speciated ground-level concentration needs to be improved;

1. Introduction

Elevated concentrations of airborne particulate matter (PM) are a cause of global concern given the associated environmental (Leibensperger et al., 2012) and human health risks to both cardiovascular and respiratory systems (Li et al., 2016c; Weng et al., 2014). High concentrations can cause haze (or smog) to form, which may affect visibility, and soiling via deposition of fine material can lead to amenity degradation (Brunner et al., 2016; Lin and Li, 2016). Airborne PM concentrations are dependent on the magnitude of source emission rates (Ge et al., 2016; Streets et al., 2013) whilst the type of emission affects the spatial concentration distribution as a large area source typically results in lower concentrations (mass/volume) but may impact a wider region (i.e. larger initial volume) that would be the case if it were a coherent plume from a point source. Similarly, sources such as industrial stacks or hot gas from fires can inject material at a high elevation but with minimal initial horizontal variance, and the plume may then be dispersed over large distances before being diluted (Li et al., 2015; Ma and Yu, 2015; Wainwright et al., 2012). During the plume dispersion, the compounds in the air may undergo chemical (Athanasopoulou et al., 2016; Philip et al., 2016) (such as photochemical reactions) and physical (such as deposition) transformations which alter the amount and composition carried in the plume (Aquila et al., 2012; Ridley et al., 2012; Solomos et al., 2015; Tu et al., 2015).

Unlike industrial emissions from point sources, which are highly regulated and monitored with in-line stack analysers and/or fence-line monitoring, diffuse PM area sources present unique challenges in that fugitive emissions and events are usually unquantified. A large fire may be monitored due to its potential danger and damage to life and property, but the secondary effects of smoke from fires are seldom documented regarding magnitude, frequency, and spatial extent. Similarly, significant fugitive emissions of PM arise from the movement of people (Kishcha et al., 2014), biomass burning (Chan and Chan, 2017; D'Andrea et al., 2016; Li et al., 2016a), wind erosion (Basha et al., 2015; El-Askary et al., 2015; Wong et al., 2015), and volcanic events (Ge et al., 2016; Ortore et al., 2014). Whilst modern technology and regulations can force reductions of industrial emissions, fugitive emissions are difficult to monitor and manage. As such, fugitive emissions require indirect mitigation strategies to reduce impacts such as the use of controlled burning to reduce fuel loads (Lasslop and Kloster, 2015) and creating windbreaks to reduce wind speed dependent dust erosion (Tao, 2014).

Elevated concentrations coupled with the difficulty in managing these emissions have led to a need to understand the impacts and consequences of these emissions. PM health studies (Weber et al., 2016; Weng et al., 2014) predominantly characterised health impacts in terms of particle size (Brindley and Ignatov, 2006; Colarco et al., 2014; D'Andrea et al., 2016; Zhao et al., 2015), but more recent studies document the role of PM composition on health impacts (Philip et al., 2014; Trivitayanurak et al., 2012). Contemporary research is unanimous that these health effects are critically dependent on both particle size and composition (Čupr et al., 2013; Li et al., 2016c; Poschl, 2005). It is therefore imperative not only to determine total PM concentration or apportion to size fractions (i.e. PM_{10} and $PM_{2.5}$), but to quantify and fully classify the source by particle size, composition and/or source type (i.e. biomass burning, wind erosion, sea -salt, volcanic, urban etc.) (Philip et al., 2014) so that the full impact of elevated concentrations can be determined.

These impacts need to be quantified using monitoring, modelling and/or estimation techniques (Wong et al., 2015; You et al., 2016a). Dedicated surface-based monitors are preferred for their accuracy and temporal resolution (Holben et al., 1998), but cost and infrastructure requirements limit the number and distribution of surface monitors. It is impractical and costly to continually monitor for all pollutants across large regions at the fine monitoring scale needed by air quality studies. Most monitoring is performed in populated urban areas as this maximises cover per capita and urban areas have the necessary infrastructure to support the monitoring. However, fugitive dust sources such as wildfires and dust storms regularly occur in regional areas as these areas have the necessary biomass or bare exposed soil to support emissions from large area sources and these sources, therefore, have the potential to influence air quality on local regional populations and impact regional air quality.

Quantification at a local level will minimise confounding chemical and physical plume dispersion effects in determining source emissions which make it difficult to quantify emissions further downwind from the sources. These dispersion effects arise from changes in wind direction and wind speed along the plume's path, which result in the monitored concentration depending on plume age and path. Regional scale quantification considers the cumulative frequency and spatial extent of long-range transported events, particularly where this impacts populated urban areas (Lin et al., 2015), and global scale quantification determines the impact an event has on background concentration levels.

Where monitors are not available, mathematical tools such as dispersion modelling (Li et al., 2016b; Lin and Li, 2016; Philip et al., 2016; Yasunari et al., 2016), neural networks (Taylor et al., 2016; Wong et al., 2015; Xiao et al., 2015) and statistical procedures such as source apportionment (Belis et al., 2013) methods can model impacts. However, these calculation methods have higher uncertainties than direct monitoring due to approximations and input assumptions inherent to the chosen model (Solomos et al., 2015). Increasingly, remote sensing has been used as a surrogate method to determine aerosol concentrations (Li et al., 2015; van Donkelaar et al., 2015; Wu et al., 2016; You et al., 2016a). The advantages of remote sensing are that it can monitor a wide area simultaneously, does not require an emissions inventory (Athanasopoulou et al., 2015), and does not need a dense monitoring network to determine concentrations. Indeed, in many areas of the world, including regional Australia, remote sensing offers the only potential alternative to understanding and estimating the surface concentration of $PM_{2.5}$ and PM_{10} where direct monitoring is not available (Li et al., 2016b; Lin et al., 2015; Tsay et al., 2016). Where direct monitoring or emission inventories are available, remote sensing using the latest geostationary satellites can augment these data, improving the temporal resolution to ten minutes, and emission factors can be constrained based on aerosol optical density (Stafoggia et al., 2017). This was demonstrated in an Italian study which used 686 surface PM_{10} monitors to refine the spatial concentration estimates (Stafoggia et al., 2017).

Launching and placing heavy equipment in space is both difficult and costly. As a result, polar orbiting, low earth orbit (LEO) satellites were initially favoured for remote sensing (Chance et al., 2013; Ruddick et al., 2014; Vanhellemont et al., 2014). The MODerate-resolution Imaging Spectro-radiometer (MODIS) instrument is an example of a LEO satellite that has supplied daily data for two decades, utilising extensively peer-reviewed algorithms (Levy et al., 2013). Older LEO satellites (Carn et al., 2016) are now being decommissioned, whilst "second generation" new satellites at higher geostationary earth orbits (GEO) are being deployed in greater numbers. A list of currently orbiting GEO satellites is provided in Table 1. GEO satellites rotate at the speed of the earth and thereby generate a continuous view of one hemisphere of the earth (Carrer et al., 2014; Naeger and Christopher, 2014; Romano et al., 2013), in contrast to LEO satellites which return overhead once per orbit cycle. Because these GEO satellites stay over a fixed point and the temporal resolution is dependent on sensor technology rather than orbit periodicity this results in continuous data acquisition rates for all locations. However, the enhanced temporal resolution comes at the cost of reduced spatial resolution, because of the higher orbit. Furthermore, the curvature of the earth restricts useful retrievals to a 120-degree arc, making GEO data unsuitable for polar and other high latitude studies. GEO satellites such as Himawari-8 (Asia and Oceania) (Sekiyama et al., 2016; Wickramasinghe et al., 2016; Yumimoto et al., 2016) and GOES-R (North America) (Greenwald et al., 2016), typify the sub-hourly data with half the spatial resolution of MODIS.

Table 1: Current Earth Observational GEO satellites (excluding military, communications, and GPS satellites). Source: Union of Concerned Scientists Satellite Database https://www.ucsusa.org/nuclear-weapons/space-weapons/satellite-database

Name of Satellite, Alternate Names	Longitude (degrees)	Launched (year)
GOCI/COMS-1 (Communication, Ocean, and Meteorological Satellite; Cheollian)	128	2010
Electro-L1 (GOMS 2 [Geostationary Operational Meteorological Satellite 2]	76	2011
Electro-L2	77.8	2015
Fengyun 2D (FY-2D)	86.51	2006
Fengyun 2E (FY-2E)	123.59	2008
Fengyun 2F (FY-2F)	105	2012
Fengyun 2G (FY 2G)	0	2014
Gaofen 4	105.5	2015
GOES 13 (Geostationary Operational Environmental Satellite, GOES-N)	-75	2006
GOES 14 (Geostationary Operational Environmental Satellite, GOES-O)	-104.41	2009
GOES 15 (Geostationary Operational Environmental Satellite, GOES-P)	-135	2010
GOES 16 (Geostationary Operational Environmental Satellite GOES-R)	-75	2016
Himawari 8	140	2014
Himawari 9	140	2016
INSAT 3A (Indian National Satellite)	93.53	2003
INSAT 3D (Indian National Satellite)	82	2013
INSAT 3DR (Indian National Satellite)	74	2016
Kalpana-1 (Metsat-1)	74.07	2002
SEVIRI/Meteosat 10 (MSGalaxy-3,MSG 3)	0	2012
SEVIRI/Meteosat 11 (MSG 4)	0	2015
SEVIRI/Meteosat 8 (MSGalaxy-1, MSG-1)	41.5	2002
SEVIRI/Meteosat 9 (MSGalaxy-2, MSG 2)	-0.02	2005
MTSAT-2 (Multi-Functional Transport Satellite)	145.06	2006

Numerous research articles and reviews of aerosol remote sensing have considered history, platforms, orbits, the theory of scattering (Rayleigh and Mia) and adsorption (infra-red) in detail (Hoff and Christopher, 2009; Reid et al., 2013; Streets et al., 2013). Considerable success of a qualitative nature (depicting the plume spatially and temporally) has been achieved to verify emissions inventory changes (Yang et al., 2015), study large-scale long-range transport events (LRT) (Athanasopoulou et al., 2016; El-Askary et al., 2015) and short-term exceptional events (i.e. fires and volcanoes) (Guehenneux et al., 2015; Wickramasinghe et al., 2016). Whilst fires are significant for the frequency of events, volcanoes are significant in terms of the size of emissions. Fire agencies routinely use fire detection methods to estimate resultant emissions (Freeborn et al., 2014) and track the movement of fire and smoke using remote sensing data (Wickramasinghe et al., 2016). Similarly, recent volcanic eruptions have resulted in a refinement of plume detection methodology and improved understanding of the vertical plume structure. Passive scattering, with the Multi-angle Imaging Spectro-radiometer (MISR) (El-Askary et al., 2015; Liu et al., 2011), and active laser back-scattering using the Cloud-Aerosol Lidar and Infrared Pathfinder Satellite Observations (CALIPSO) (Lee et al.,

2016) instruments have been used to determine the vertical profile. AERONET and other ground-based sun photometers have provided method validation over large regions (Tegen et al., 2013; van Donkelaar et al., 2013). Aerosol Optical Depth (AOD) measurements have been integrated with Chemical Transport Models (CTM) (Li et al., 2016b; Lin and Li, 2016; Philip et al., 2016), Bayesian analysis (Karlsson et al., 2015; Weber et al., 2016) or neural networks (Lary et al., 2016) to improve the identification of background events and assist quantification.

Whilst remote sensing of particulate matter is a suitable tool for qualitative analysis (spatial and temporal) to identify dust events, there are significant problems that limit quantification (Hoff and Christopher, 2009; Reid et al., 2013; Streets et al., 2013). These limitations arise from poor temporal resolution, inadequate background AOD determination, circular assumptions in the aerosol inversion model and vertical parameterisations of the dust plume. Of these limitations, the circular assumptions of the aerosol model are the most significant. The aerosol inversion problems are a consequence of deriving solutions with more unknown intrinsic aerosol properties (size, shape, composition, refractive index) from known extrinsic scattering and absorption properties (Mei et al., 2014; Ruddick et al., 2014; Xiao et al., 2014). The inversion retrieval is constrained to aerosol types included in the lookup table and the accuracy of the retrieval is dependent on the degree of independence in the spectral patterns (signatures), per aerosol type, which is further complicated by poorer spectral resolution on GEO satellites.

This literature review was undertaken to examine the limitations in remote sensing of ground-level particulate matter concentrations and the quantification challenges. The review sought to determine which of the methodology changes maximise the benefits from the enhanced temporal resolution of the GEO data. A "Web of Science" search for all review articles containing the topics aerosol and remote sensing shows that the number of review articles peaked in 2012/3 but that there has been a steady growth in the number of citations, indicative of a potentially greater acceptance of remote sensing.

The literature that was reviewed focussed on the derivation of surface concentrations of particulate matter using GEO data rather than the more commonly reported, aerosol optical depth remote sensing product, as it is the surface concentrations that directly affect health, not the total column parameter. The review has considered the large-scale movement of aerosols from fugitive dust sources (such as fires, dust storms, and volcanoes) rather than localised industrial sources which typically affect one or two neighbouring pixels. Fugitive sources are generated over large areas and are widely dispersed but less represented in sparse surface-based monitoring. The review has identified changes that occurred since Street's 2013 review (i.e. from 2014), during which both Himawari (July 2015) and GOES-R (Dec 2016) satellites were launched, in order to narrow down and identify progress and/or current trends in the methodology. The review ignores case-studies that simply use existing AOD product data without contributing additional information to the resolution of quantification challenges, nor does it replicate extensive historical theoretical frameworks which are discussed in other recent reviews (Hoff and Christopher, 2009; Reid et al., 2013; Streets et al., 2013).

2. Challenges and Emerging Solutions

2.1. Spatial and Temporal Resolution

One of the biggest criticisms of polar-orbiting satellites (such as MODIS), from an air quality perspective, is that they supply a single instantaneous measurement and not a period average (Levy et al., 2013). Although numerous researchers have compared AOD to daily average concentrations (You et al., 2016a), AOD reflects a short-term, temporal monitoring, gathered once a day, for the few seconds that the satellite was flying overhead. Apart from the temporal bias of comparing dissimilar timescales (seconds against hourly and daily monitoring), short-term events such as fires may be inactive during the satellite overpass, or clouds may obscure the scene, leading to the event being missed during the satellite overpass (Baldassarre et al., 2015; Freeborn et al., 2014; O'Loingsigh et al., 2015; Philip et al., 2016; Zhang et al., 2011).

Whilst health and regulatory considerations include daily and annually averaged concentrations of particulate matter (Brauer et al., 2012), hourly (or sub-hourly) measurements are required to understand the transport and concentration of particulate matter from short-term significant events such as fires and dust storms. It has been shown experimentally (Hoven, 1957), and proven theoretically (Stull, 2012), that turbulence drives air dispersion. Turbulence, therefore, determines the spatial and temporal scales required for monitoring and the spatial resolution and timing of samples should be dependent on average wind speeds to ensure that the plume movement between pixels can be detected in the monitored period. This supports the findings of health-related studies which suggest that a spatial resolution of about one kilometre and a temporal resolution of an hour are the minimum requirements for monitoring atmospheric events (Chow, 1995, 1998). Second generation GEO satellites such as SEVIRI (15 min, 3 km) (Fernandes et al., 2015), GOCI (hourly, 500 m (NIR)) (Choi et al., 2012), Himawari-8 (10 min, 2 km) (Yumimoto et al., 2016) and GOES-R (15 min, 2 km) (Wang et al., 2014) meet the hourly and sub-hourly requirements overcoming the previous temporal resolution restriction of LEO satellites albeit with a reduction in spatial resolution.

Most case studies using GEO data take advantage of the enhanced temporal resolution which implies a higher probability of cloud-free measurements and fewer missed events. These studies do not utilise the motion of the aerosols but simply subtract a static background (Fukuda et al., 2013). Aerosols, carried by turbulent air, implies motion as gravity will cause deposition of particulate matter under calm conditions (Al-Dousari et al., 2013; Mackie et al., 2008). Therefore, motion detection methods including frame differences and tracking moving objects can be used to improve aerosol movement detection and quantification (Tewkesbury et al., 2015), and this has been demonstrated by some neural network solutions (Lary et al., 2016; Wong et al., 2015). Similarly, consistency tests can identify clouds and aerosols using the spatial differences in the homogeneity (i.e. standard deviation) across neighbouring pixels as clouds are patchier than an aerosol plume (Chang and Christopher, 2016). In the Infrared Differential Dust Index (IDDI) method the minimum reflectance over the chosen time period is subtracted from the current reflectance and so highlights areas of change (movement) (Xiao et al., 2015). As most pixels do not change between frames there is a significant reduction in the number of background pixels which are masked out if they have not changed between frames. The IDDI methodology has been used for time periods of three days (Di et al., 2016), unspecified “days” (Hu et al., 2008), fortnights (Xiao et al., 2015) and months (Mishra et al., 2014); however, there is no agreement on the choice of the correct timespan for the differentiation.

Whilst GEO satellites improve the temporal resolution, this is at a marginal cost to spatial resolution as evidenced by the latest GEO satellites such as Himawari-8 (10 min, 2 km) (Yumimoto et al., 2016) and GOES-R (15 min, 2 km) (Wang et al., 2014). To address what spatial resolution is required for GEO data the question is rephrased to consider how far a low wind speed would move an individual “puff” within a plume to be discernible either along the plume boundary (i.e. edge detection) or to a pixel with a different concentration within the plume (i.e. dispersion). For both cases, it is assumed that the concentration remains above detectable limits. A low wind speed of 1 m/s would disperse a plume/puff 600 m over ten minutes and this is, therefore, the minimum spatial resolution required to detect a plume at this wind-speed. This is three times the spatial resolution of Himawari’s infra-red spectral bands and double that of the visible and near infra-red bands. In an attempt to improve the spatial resolution of GEO data various mathematical treatments have been used. The greater spatial resolution of LEO (MODIS) satellites was used to refine GEO data in multi-satellite studies by determining a daily sub-grid calibration from the MODIS data and applying the sub-grid scale factors to the GEO data (Naeger et al., 2016; Vanhellemont et al., 2014). This is not ideal as it assumes that the spatial calibration is not temporally dependent, which is not the case where an aerosol plume moves across an area. Other studies have demonstrated the ability to enhance the spatial scale of the infra-red channels by scaling the data using higher resolved visible and near infra-red (NIR) data during daylight hours (Wickramasinghe et al., 2016; Wooster et al., 2015). This can yield satisfactory results during daylight hours where there is a strong correlation between the higher resolved visible or near infra-red data and the infra-red data. This is similar to a method of detecting fire locations at sub-pixel resolution by applying a deconvolution filter that is reliant on the wavelength dependent decrease in fire radiance power across neighbouring pixels (Wooster et al., 2015).

Whilst there is potential to improve the spatial resolution using correlated channels of higher resolution, they cannot improve the spatial resolution during the night or across uncorrelated channels. Spatial averaging techniques such as Kriging may be able to double the perceived spatial resolution but do not yield further spatial improvements (Firas and Fawzi, 2013) as they cannot improve the detection of a plume which is unresolved in the original data.

Therefore, these studies show that the temporal resolution of GEO data is a substantial improvement over polar-orbiting satellites and is better than the hourly resolution from most dispersion models and is comparable to the temporal resolution of most on-line analytical instruments (Chow, 1998). Unfortunately, this is at a marginal cost in spatial resolution which is adequate for global and regional studies but too coarse for local studies. The ideal spatial resolution for local studies requires an order of magnitude improvement to be comparable to the resolution of dispersion model studies (Solomos et al., 2015). In contrast to the Meteosat, Himawari and GOES series of satellites, China's Gaofen-4 satellite claims an order of magnitude improvement in spatial (50m VIS and 400m IR) and temporal resolution (1 minute) (CHEOS, 2018). The spatial and temporal resolution required for air quality studies is a fundamental aspect of remote sensing that has not received sufficient attention in the literature.

2.2. Background (i.e. zero) AOD

Determining Aerosol Optical Depth (AOD) from scattered reflectance and absorption temperatures uses Beer's law to integrate the extinction coefficients across the vertical column (Hoff and Christopher, 2009). The determination of the integral from the surface to the top of the plume requires the surface extinction coefficients (i.e. background AOD) to be known or determined. Determining background AOD from scattering of electromagnetic energy in the visible part of the spectrum is complicated by reflective backgrounds such as roofs, bright reflective mineral sands in deserts and even the presence or absence of vegetation cover. Different algorithms are used to account for these reflective backgrounds. They depend on the nature of the surface background such as dark target (DT) algorithm (Tanré et al., 1997) over the ocean, dark target (DT) algorithm over vegetation and deep blue (DB) algorithm (Hsu et al., 2013) over bright land surfaces such as deserts (Levy et al., 2013). In addition to MODIS, there are multiple sensors and satellites, each with slight differences in how AOD is calculated (Mhawish et al., 2018). The retrieval of aerosol properties from these systems is impacted by cloud, surface, and molecular effects. These impacts must be accounted for before the aerosol properties can be determined.

To account for the variances in reflective backgrounds across an area, the surface reflectance has traditionally been averaged spatially when determining background AOD, for example, the MODIS algorithms average across 10x10 km^2 (at nadir) (collection 5) or 3x3 km^2 (at nadir) (collection 6) (Levy et al., 2013). However, both these spatial resolutions are inadequate for monitoring air quality events which require approximately a 0.6x0.6 km^2 resolution, based on the time for a 1 m/s wind speed event to cross a pixel. The spatial resolution of the MODIS AOD product has been improved using the MAIAC algorithm which uses temporal changes to improve the spatial resolution (Lyapustin and Wang, 2007) and the SARA algorithm which uses the resolution of the raw reflectances (500 m) and data from the AERONET surface based AOD monitoring to refine the spatial resolution.

In addition to difficulties in determining background AOD from the surface variability, clouds may obscure the surface reflectance. This severely constrains the usefulness of AOD scattering methods to determine aerosol movement on a global basis - especially in cloudy, tropical regions - as it leads to masked (i.e. unmeasurable) pixels where significant clouds are present or the surface is not sufficiently homogeneous (Tsay et al., 2016). The high temporal volume of GEO data can reduce cloud masking by using the temporal minimum reflectance across longer time frames with the IDDI method. IDDI only requires a single cloud free period (per pixel) during the longer timeframe and does not average across pixels, thus preserving the full pixel resolution with fewer masked events (Kim et al., 2015; Xu et al., 2013). An implicit assumption in the IDDI approach is that the period compared should have minimal surface reflectance changes (i.e. exclude seasonal effects) and it is thus suited for comparison across days rather than weeks or months.

The radiation energy received by a satellite sensor is inversely related to the wavelength and therefore scattering in the visible spectrum is more sensitive to changes in particle composition and size than absorption at thermal infrared wavelengths (Bond and Bergstrom, 2006; Guehenneux et al., 2015). Similarly, scattering effects from different surface backgrounds are more problematic than absorption in determining background AOD. Despite these problems, using the enhanced sensitivity of scattered reflectance is preferred to absorption when determining AOD. However, with the rapid temporal updates, there is a requirement to use wavelengths that are continually available (such as infra-red absorption) and not restricted to daylight hours. Therefore, GEO methods may need to use a combination of daytime scattering and infra-red absorption at night to maximise both signal strength and data availability. The NASA/NOAA products favour scattering using visible wavelengths to derive AOD estimates as used by MODIS (Hsu et al., 2013; Levy et al., 2013; Tanré et al., 1997), newer sensors such as VIIRS (Jackson et al., 2013), GOES-R GEO satellites (Matter, 2010) and future missions using TEMPO (Zoogman et al., 2017). In contrast the EUMETSAT methods (BOM, 2012; Naeger and Christopher, 2014; Wooster et al., 2015; Xiao et al., 2015) used by Meteosat and Himawari use thermal infrared bands to identify aerosol plumes and a lookup table to convert AOD to plume mass and average particle size (Wen and Rose, 1994).

The high temporal volume of data from GEO satellites allows a cloud-free background to be determined which enables the determination of AOD from remote sensing data. The relative signal intensities at different wavelengths allow the aerosol type to be determined.

2.3. Aerosol Model Inversion Problem

The main limitation of using current AOD calculations to determine surface particulate matter concentrations is not the lack of temporal resolution, which is overcome using GEO data, nor the determination of background AOD but the choice of the aerosol model (Carrer et al., 2014). Atmospheric concentrations and the spatial distribution of particulate matter depend on the emission of new particles, the dispersion, chemical transformation, and physical removal of those particles (Streets et al., 2013). Knowing the intrinsic properties of aerosols (size, shape, composition, and refractive indices) allows determination of the extrinsic spectral properties (radiance and brightness temperature) with a radiative transfer model (Bond and Bergstrom, 2006; Hess et al., 1998). The cumulative effect of the substrate (e.g. soil type, vegetation type, barren rock, urban), moisture (e.g. sea, snow, ice, cloud, liquid, vapour) gaseous and particulate matter determine the total spectral property which can be calculated at each wavelength (Christopher, 2014; Huang et al., 2011).

Whilst the theoretical framework for calculating extrinsic optical properties from intrinsic source specific properties is well understood, it is not always possible to calculate the reverse (Bioucas-Dias et al., 2012). Remote sensing methods use inversion techniques to solve the inverse of the radiative transfer equations in determining aerosol optical depth, particle composition, size, and number. These inversion equations cannot be solved explicitly as there are more unknown intrinsic aerosol properties than known extrinsic measurable parameters. This is worsened by GEO satellites with limited spectral resolution (for instance MODIS has 36 spectral bands compared to the Spinning Enhanced Visible and Infrared Imager (SEVIRI) with 12 bands) (Naeger and Christopher, 2014; Wooster et al., 2015). An aerosol model assumes a fixed set of intrinsic aerosol properties (size, composition, humidity) and extrinsic radiances/absorption are calculated for each wavelength band. These extrinsic and intrinsic properties are used to populate a lookup table of aerosol properties (Huneeus et al., 2011; Sessions et al., 2015). The most probable aerosol type, AOD and particle size (intrinsic) are determined using the best match spectral approximations (extrinsic) from the lookup table and particle number (or concentration) is calculated based on signal intensity (Safarpour et al., 2014). However, the inversion method introduces circular assumptions as the accuracy of the solution is dependent on correctly including localised aerosol types and particle sizes (Mann et al., 2014) in global datasets.

The most significant recent contribution to knowledge in the field has been refinements to the aerosol model's lookup tables in preparation for the launch of new GEO satellites by pseudo-AOD datasets generation (Brunner et al., 2016). Radiative transfer (RT) model outputs were compared as part of the Modern Era Retrospective-analysis for Research and Applications Aerosol Reanalysis (MERRAero) which compared 16 RT models (Ma and Yu, 2015) against each other. Results suggest that assimilation of AOD data tends to improve the $PM_{2.5}$ temporal variability (i.e. temporal correlation) but cannot correct systematic errors in surface concentrations (i.e. spatial correlation or over/under predicting). The authors note that systemic errors were due to inadequate aerosol optical properties, missing species, and/or deficiencies in aerosol vertical structure (Buchard et al., 2016). Closure studies compared four aerosol models (NASA Global Modeling Initiative, GEOS-Chem v9, baseline GEOS-Chem with radiative transfer calculations (GC-RT), and the Optical Properties of Aerosol and Clouds (OPAC) package (Hess et al., 1998) with data gathered during the 2008 Arctic Research of the Composition of the Troposphere from Aircraft and Satellites (ARCTAS) campaign. These studies found significant differences (10-23%) between the four models which were attributed to assumptions concerning fixed size distributions, external mixture assumptions and refractive indices used in the models (Alvarado et al., 2016).

Improvements to the RT models have encouraged aerosol classification changes from the vague "strongly absorbing" (Levy et al., 2013) and "non-spherical" (Di et al., 2016) to more meaningful GEOS-CHEM species of dust, namely black carbon, other carbon, sea salt, sulphate and urban (Athanasopoulou et al., 2015; Naeger et al., 2016). These classification changes considered the natural abundance of particulate species (Brindley et al., 2015). Whilst the GEOS-CHEM (and similar) model species do not by themselves result in detailed chemical compound classifications, the refined species definition is a better source classification scheme (Curci et al., 2015) and by including local speciation effects (different mineral compositions for instance) (Colarco et al., 2014) could allow the generation of more regionally specific, compound and size, lookup tables.

Comparative radiative transfer studies have highlighted that it is important to understand and optimise the inversion process and in this regard, a Jacobian error matrix approach (i.e. optimising a matrix of first order derivatives instead of signal intensity against explicit aerosol parameters) that supplies a measure of uncertainty and quantification of the inversion process has been proposed (Wang et al., 2014). The authors suggest that their study "should be viewed as the starting point for the development of a framework for objective assessment of aerosol information content for any real or synthetic measurements and that further development of particle scattering codes for non-spherical particles is essential, especially for large particles that are difficult to handle with current implementations of [radiative transfer] theory."

In tandem with, or possibly as a result of the errors in the uncertainty model approach, research has focussed on a dust index approach (Wen and Rose, 1994) using generic aerosol model lookup tables. This has used single spectra (0.550 µm or 11 µm) (Kim et al., 2016), double band brightness temperature reduction (BTR) (3.7 µm -11µm) (Di et al., 2016; Guehenneux et al., 2015), triple band BTR (12 µm -11 µm, 4 µm -11 µm or 9 µm -11 µm) (Lee et al., 2014; Wong et al., 2015), four BTR bands (10.3 µm –11.3 µm, 11.5 µm –12.5 µm, 6.5 µm –7.0 µm, 3.5 µm –4.0 µm) (Kim et al., 2016), ratio of NIR/Red (Wickramasinghe et al., 2016) and IDDI methodologies (Di et al., 2016) using simple cloud masking ratios. These dust index methodologies could be described as a rudimentary supervised classification scheme, based on expert knowledge of predominant spectral characteristics (Lee and Lee, 2015).

However, these dust index products are dependent on the intensity of an event, so the identification of a minor dust storm which relies on the temperature differences between the land surface and the cooler aerosols may be missed (i.e. BTR < detection threshold) (Basha et al., 2015; O'Loingsigh et al., 2015). Dust storms can influence ambient surface temperatures by shielding the sun's energy from reaching the surface, thereby influencing the AOD/BTR relationship (Colarco et al., 2014), and moisture effects need to be properly accounted for in the lookup table (Guehenneux et al., 2015) to correct the non-linearity in the AOT/BTR relationship for cooler BTR thresholds.

Given the uncertainty of the inverse aerosol model retrievals and influences of external parameters such as humidity, temperature, topography, cloud cover, cloud optical depth, local mineralogy and size parameters on the AOD/GLCs relationship, several studies have suggested using neural networks (Athanasopoulou et al., 2016; Lary et al., 2016; Wong et al., 2015) or Bayesian studies (Weber et al., 2016) to improve the inverse aerosol retrievals. These multivariate, non-linear, and non-parametric approaches have been used in data assimilation of incompatible timescales (daily and hourly) or different satellite products of varying spatial resolution. However, whilst these methods can identify hidden nodes or relationships in the data, they are computationally expensive for large, near-real-time rapidly updating datasets unless the classification steps are predetermined during the initial training phase for the region (Puttaswamy et al., 2014).

Quantifying AOD and determining aerosol type remains an ongoing challenge in determining GLCs. However, despite the ongoing uncertainties related to quantifying AOD, the spatiotemporal qualitative aspects are one of the successes of remote sensing. Relative increases and/or decreases in AOD indicate sources and sinks of particulate matter (Roberts et al., 2015; Sessions et al., 2015), verify emission rate changes (Huang et al., 2014), justify control strategies (Zhang et al., 2014) and help understand the diurnal and annual transportation of aerosols both from local sources and long-range transport (Hu et al., 2015; Naeger et al., 2016). Whilst knowing the columnar AOD is important, ground level pollution is the important parameter from a human health and management perspective.

2.4. Vertical Profiles

Surface visibility has been used as a proxy for GLCs of particulate matter (Brunner et al., 2016; Di et al., 2016), but where neither visibility nor concentration is measured, there is a need to extrapolate AOD to GLCs using mathematical methods. The methods may include simple linear approximation or multiple regression taking into consideration secondary effects such as hygroscopic and meteorological parameters (Bukowiecki et al., 2016; Sotoudeheian and Arhami, 2014). However, these approaches assume a well-mixed, steady-state plume which results in a predictable smooth Gaussian-plume vertical relationship where the concentration at different altitudes is correlated to ground level PM concentration (Sotoudeheian and Arhami, 2014). Dispersion modelling studies show that a well-mixed neutral state (i.e. plume buoyance determined by adiabatic lapse rate) occurs half of the time where there is a moderate to high amount of cloud cover and wind speeds greater than 3 m/s at night or 5 m/s during the day) (Hagemann et al., 2014). If the plume is rising rapidly (e.g. near source, or from fires or volcanoes), or if temperature inversion conditions are present, then the assumption of well-mixed neutral plumes is invalid. Temperature inversions and increased wind speeds, leading to heightened dust-lift-off, are an indication of non-neutral weather conditions that commonly occur during dust storms (Basha et al., 2015). Where plume stratification occurs from high wind-speeds trapping the plume in layers, or inversion conditions trap a plume below the mixing layer, or if the plume rises rapidly, the vertical distribution of the plume may be significantly non-Gaussian and AOD may be uncorrelated to GLCs as detailed in some LRT dust studies (Athanasopoulou et al., 2016).

Various methods exist for determining the vertical profile of the plume. Dispersion modelling can produce satisfactory results, but the accuracy of the vertical concentration profile depends on determining the correct meteorological profile for the model, which may lead to high uncertainties. Several studies have considered using Lidar backscattering from the CALIPSO satellite or forward multi-angular remote sensing methods such as from the MISR satellite (Basha et al., 2015; Solomos et al., 2015; You et al., 2016b). However, both CALIPSO and MISR have reduced temporal and spatial resolution and a hybrid approach is therefore common, where the dispersion model's vertical profile is constrained using limited satellite-derived approximations.

Hybrid methodologies have been noted as an emerging technology in the recent literature. Initially, a dispersion model such as CMAQ (Roberts et al., 2015) or CAMx (Baldassarre et al., 2015) was coupled to an independent meteorological model such as WRF (Greenwald et al., 2016) and AOD input data was used to constrain the dispersion model. However, with the advent of the GEOS-CHEM and HYSPLIT (Naeger et al., 2016) models, meteorological fields are now obtained and processed directly from NCAR reanalysis files by the dispersion model, eliminating the separate pre-processing step (Lin et al., 2014; Xu et al., 2015). In a typical coupled modelling scenario, an emissions inventory is estimated and constrained by AOD data, in order to generate surface consistent concentrations taking into consideration the modelled mixing height and concentration at multiple internal heights. This is done by using the magnitude and spatial distribution of the AOD as initial emission input to a dispersion model and then rescaling the emissions to ensure a best match of the predicted AOD from the coupled model against the satellite-derived AOD data (Stafoggia et al., 2017). Studies have demonstrated that best results are obtained by matching the model's grid resolution and internal time-steps to the underlying AOD spatiotemporal resolution and the need to understand the overall accuracy of the coupled methods (Philip et al., 2016).

2.5. Validation/Accuracy

It is vital that improvements to the methodology are developed to enhance accuracy. The current accuracy of the regression method (AOD to GLCs) is estimated to be twenty percent and the uncertainty of the aerosol model (wavelength signal intensity to AOD) is estimated to be thirty percent (Basha et al., 2015; Tu et al., 2015). However, researchers caution that the regression coefficients are not transferable to other regions and the true uncertainty could be an order of magnitude higher if assumptions in the aerosol model are not taken into consideration (Basha et al., 2015; Tu et al., 2015). This has been clearly demonstrated in validation studies that have compared multiple satellite products across an area and significant disagreements between them were ascribed to uncertainties in the aerosol retrieval properties of mass, size, and composition (Reid et al., 2013).

The Jacobian error matrix approach discussed earlier allows the uncertainty of the aerosol's model output to be directly quantified, which can aid in optimizing the matrix solution by testing alternative aerosol types and/or wavelengths. The uncertainty associated with converting aerosol radiation to ground level concentrations is reduced by the matrix optimised solution which requires using a chemical transport model (CTM), driven by assimilated meteorology and verified against observations to simulate radiative impacts and surface concentrations. It is critical for an accurate evaluation of aerosol concentrations and impacts that the matching of observations and simulations accounts for the timeframe differences between instantaneous satellite measurements and hourly dispersion predictions or daily measured concentrations in the comparisons between measured and predicted concentrations (Heald et al., 2014).

Most validation studies have used descriptive statistics to compare AOD-derived GLCs to ground-based measurements. Common statistical tools used to assess the accuracy of the method include Pearson's correlation coefficient (R) and the Root Mean Squared Error (RMSE) (Wu et al., 2016; Xu et al., 2014). However, this approach neglects the statistical assessment of spatial (between pixels) and temporal (within time) accuracy (Wang et al., 2014), i.e., it does not clarify whether the variability in space and time is included in the descriptive statistics for each field or parameter being compared. This issue is evident in a recent study which compared surface $PM_{2.5}$ and PM_{10} concentrations and particle size ratios from four different countries (Israel, Italy, France, and the United States (California and NE-USA)), against collocated sun-photometer AERONET measurements and AOD products derived from MODIS Dark Target Collection 06 algorithm and the MultiAngle Implementation of Atmospheric Correction (MAIAC) algorithm (Sorek-Hamer et al., 2016). Sorek-Hamer et al. (2016) concluded that there was a very poor correlation between predicted and measured concentrations and apart from a slight seasonal bias were unable to account for the poor correlation. Despite having data from many sites, they restricted their spatial analysis to amalgamating across the five regions. Taylor diagrams have compared measured concentrations (or AOD) with monitored data and correlations across multiple sites have been evaluated to determine if algorithm improvements have led to improved correlations (Kim et al., 2016) in describing temporal variability at monitoring sites. Similarly, Maximum Covariance Analysis has been used to compare monthly spatial variances between different satellite products and ground-based measurements and these variances were depicted graphically (Li et al., 2015). What is lacking are statistical tools that combine the spatial, temporal, and field (or parameter) variability in one diagram.

Whilst AERONET sites are well distributed about the globe, there remain many locations without monitored data where it is impossible to determine if the aerosol retrieval has made reasonable choices, either for pixel selection, cloud screening, aerosol model type or surface reflectance assumptions (Wind et al., 2016). If the spatiotemporal variability at monitoring sites is poorly defined this is amplified when aerosol model uncertainty must be included in the assessment of the overall accuracy of the predicted GLCs.

2.6. Emerging solutions

One of the perceived problems with working with remote sensing is the difficulty of finding suitable products, downloading large files, and converting those files into meaningful data in a suitable format (Duncan et al., 2014). Web-based graphical interface tools (such as those presented in Table 1 of Mhawish et al.) are gaining popularity as a means of rapidly screening and acquiring data (Mhawish et al., 2018).

Whilst these tools are excellent for routine screening, more intensive investigations may require the use of raw data files. Increasing standardisation on the netCDF (ver. 4) standard has seen the proliferation of simple command line tools such as the University of California's netCDF Operators (NCO) and the Max-Planck's Climate Data Operators (CDO) (CDO, 2018). Both tools allow easy data manipulation. A secondary benefit of the standardisation is the development of improved visualisation software, such as Paraview (Ayachit, 2015), which use the netCDF data standard and are preconfigured to take advantage of supercomputers.

However, the biggest change, in computing AOD, has come about with the development of the Meteosat/SEVIRI AOD algorithms. The Meteosat series of satellites has led the development of GEO satellites methodologies as reflected in Table 1 and Table 2. Table 2 describes recent literature which specifically considered the derivation of AOD and GLCs, rather than simple lookup of products. These studies show that the NASA/NOAA products predominantly determine AOD using scattering of visible wavelengths as demonstrated across a range of current and future satellite platforms including MODIS (Hsu et al., 2013; Levy et al., 2013; Tanré et al., 1997), VIIRS (Jackson et al., 2013), GOES-R (Matter, 2010) and future planned satellites such at TEMPO (Zoogman et al., 2017). In contrast to NASA, EUMETSAT methods favour using thermal infrared bands to identify and quantify aerosol plumes using thermal infra-red to determine a dust index (BOM, 2012; Naeger and Christopher, 2014; Wooster et al., 2015; Xiao et al., 2015).

Table 2: Recent literature describing GEO aerosol algorithms

Satellite/Sensor (Reference, Year)	Title	Source types	Algorithm/comments
GOES-R (Wang et al., 2014)	A numerical testbed for remote sensing of aerosols, and its demonstration for evaluating retrieval synergy from a geostationary satellite constellation of GEO-CAPE and GOES-R	Unspecified lookup table	Scattering
SEVIRI (Zawadzka and Markowicz, 2014)	Retrieval of Aerosol Optical Depth from Optimal Interpolation Approach Applied to SEVIRI Data	Mineral dust, sea salt, particulate sulphates (SO_4) and smoke	AOD from 0.6 µm & 1.6 µm. Uses scattering Describes algorithms Compare to AERONET
SEVIRI (Naeger and Christopher, 2014)	The identification and tracking of volcanic ash using the Meteosat Second Generation (MSG) Spinning Enhanced Visible and Infrared Imager (SEVIRI)	Volcanic ash	RGB dust index using Red (12-10.8 µm), Green (10.8-8.7 µm), and Blue (10.8 µm)
SEVIRI (Fernandes et al., 2015)	Comparisons of aerosol optical depth provided by SEVIRI satellite observations and CAMx air quality modelling	CAMx aerosol model species	AOD (0.6 µm) Top of Atmosphere reflectance, corrections. Compare to AERONET
SEVIRI (Roberts et al., 2015)	LSA SAF Meteosat FRP products - Part 2: Evaluation and demonstration for use in the Copernicus Atmosphere Monitoring Service (CAMS)	Wildfires	Heat of combustion proportional to amount being burnt not vegetation type. Uses MIR, NIR, burnt areas
SEVIRI (Guehenneux et al., 2015)	Improved space borne detection of volcanic ash for real-time monitoring using 3-Band method	Volcanic ash	RGB dust index Displays thermal BTR spectra for common aerosols Compare to Mie theory
Himawari-8 (Wickramasinghe et al., 2016)	Development of a Multi-Spatial Resolution Approach to the Surveillance of Active Fire Lines Using Himawari-8	Wildfires	Multispectral, Red, MIR & TIR
Himawari-8 (Sekiyama et al., 2016)	Data Assimilation of Himawari-8 Aerosol Observations: Asian Dust Forecast in June 2015	Asian Dust	AOD from 470, 510 and 640 µm
Himawari-8 (Yumimoto et al., 2016)	Aerosol data assimilation using data from Himawari-8, a next-generation geostationary meteorological satellite	Not stated, total AOD	Used AOD from visible (0.47, 0.51, and 0.64 nm) and near-infrared (0.86 nm)
INSAT (Di et al., 2016)	Dust Aerosol Optical Depth Retrieval and Dust Storm Detection for Xinjiang Region Using Indian National Satellite Observations	Dust storm	Suggests not spectral but dust index (BTD & IDDI) to identify aerosol Included spectral graphs BTD detects event (by threshold exceedance) but not related to intensity. Compared to AERONET AOD from 1.6 µm
Himawari-8 (Wang et al., 2017)	Deriving Hourly PM2.5 Concentrations from Himawari-8 AODs over Beijing-Tianjin-Hebei in China	Urban regions	AOD (500 nm) & AE from Himawari-8 compared to AERONET sites. Use statistical model with inputs of relative humidity, boundary height, NDVI (surface categories) and topography (DEM)
SEVIRI (Gonzalez and Briottet, 2017)	North Africa and Saudi Arabia Day/Night Sandstorm Survey (NASCube)	Sandstorms	NASCube compared to DB + AERONET pseudo-true colour day and night 10-day minimum Wide spectral range 0.6, 0.8, 1.6, 3.9, 8.7, 9.7, 10.8, and 12.0 µm RGB (12-10.8. 10.8-8.7, 10.8) AOD (12-10.8)
TEMPO (Zoogman et al., 2017)	Tropospheric emissions: Monitoring of pollution (TEMPO)	Wide range of pollutants	Vis & UV wavelengths

3. Conclusions

This review has highlighted the challenges faced with determining GLCs from remote sensing data. Because of these challenges, atmospheric scientists have in the past not fully utilised remote sensing to routinely determine GLCs (Duncan et al., 2014). GEO is a significant step forward in supplying highly resolved data that satisfy the temporal requirements for sub-hourly data. It goes beyond the hourly resolution of most dispersion models supplying sub-hourly data that allow aerosol and cloud dynamics to be investigated with almost near-real-time capabilities for the first time. Spatially the infra-red resolution is slightly coarse (Himawari 2 km) for localised studies, but adequate for regional and global studies. Kriging algorithms could potentially refine the continuous representation of the discrete observations in the spatial scale to be similar to local dispersion model studies, but this only produces a smoothed estimate and does not improve the underlying spatial resolution.

Currently, AOD methods utilise the enhanced temporal resolution of GEO data to obtain a cloud-free measurement and increase the analysis frequency. Methods that use the additional information supplied by the rate of change are notably absent and should be developed. The aerosol model supplies the concentration vector; the rate of change of this vector presumably determines the rate at which material is added, removed, or chemically transformed in the plume, and the second derivative determines if the plume is in an equilibrium state (i.e. stable constant emission) or an active source/sink. Analysis of these rate of change variables should allow for a better understanding of emissions and resulting chemical and physical transformations even if the underlying aerosol inversion model contains assumptions. However, the extent to which particle emission changes are reflected in satellite data is severely constrained by the resolution of the data (Mhawish et al., 2018). The spatial resolution determines if the plume is discernible against background concentrations and if the plume spans multiple pixels or is fully contained within one pixel. The temporal resolution determines if the underlying chemical and physical changes can be discernible with the data frequency, for example, rapid photochemical reactions may be faster than the rate of data updates. The data resolution (or sensitivity) determines the concentration changes that are detectable; for instance, Himawari-8 has a brightness temperature resolution of 1/16 Kelvin or 1/1024 of scaled radiance (based on personal inspection of the data). The spectral sensitivity is impacted by the width and number of bands: this determines what species can be identified. For instance, a hyperspectral instrument can determine targeted organic compounds while the broad bands of GEO satellites are limited to compound classes such as black carbon (Adão et al., 2017).

Understanding the error matrix of aerosol models is vital and this should become routine instead of the lookup table of current methods. At a minimum, this will encourage the use of more than simple two or three band methodologies in the development of dust indices and instead utilise all wavelength bands measured by the satellite to better determine the aerosol type. Given the rapid near real-time availability of the data, processing should at most take half the data rate, allowing the balance of time for slower data transfers. This implies that processing of all data products has at most five minutes to complete and this may involve approximations rather than exact solutions.

It is unlikely that GEO aerosol remote sensing will provide a complete standalone solution and in this, we agree with Hoff and Christopher: so long as the number of intrinsic properties to solve is greater than the number of reactive wavelengths, the circular assumptions of an aerosol model imply that quantification remains an approximation. It is highly probable that hybrid methods of neural networks, Bayesian probabilities and coupled CTM models such as GEOS-CHEM will continue to be developed and improved. However, the time constraints of near real-time modelling make a fully coupled CTM unlikely and favour the pre-processing of existing data from statistical neural network models into enhanced dust index products that take into consideration local mineralogy and particle size distributions, resolve the vertical profile and account for moisture and other external effects.

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