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What temporal resolution is required for remote sensing of regional aerosol concentrations using the Himawari-8 geostationary satellite

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Abstract

Few studies have directly addressed the question of what temporal resolution is required for air quality studies using geostationary remote sensing data. If timescales are too large, there is a risk that events affecting air quality may be missed; and if too small, there is a possibility that large data files may be processed frequently, at significant computing cost and potentially without concomitant improvements in the monitoring of air quality. The problem is particularly significant in sparsely populated regional areas such as the Pilbara in Western Australia, where air quality issues arising from a range of events, dispersed over a vast area, increase the risk of environmental health and ecosystems impacts and where the use of conventional monitoring is impractical. This study aimed to establish an optimum temporal sampling interval for air quality studies using geostationary data and determine the impact of different timescales on ground level concentrations. The study was based on an analysis of Himawari-8 satellite data relating to a dust storm within a roll cloud which occurred near Onslow in Western Australia on 8 March 2017. Data from the Himawari-8 satellite were obtained from the Australian Bureau of Meteorology relating to the event and were used to: (1) assess the probability of a satellite overpass coinciding with the event; (2) determine scale factors of different time periods during the event; and (3) undertake an analysis of event duration using remote sensing data. The analysis identified numerous sub-phases of the dust event, each lasting between 30 and 50 minutes. Data analysis considered all thermal infrared bands and Taylor plot analysis reduced the ten wavelength bands to six independent bands. Principal component analysis of brightness temperature difference between these six bands identified the rate of aerosol compositional change and established that an optimal geostationary sampling frequency of five to ten minutes would be required to quantify these temporal changes effectively.

Keywords: temporal resolution, geostationary, particulate matter, brightness temperature difference, Himawari-8

Abbreviations

AOD	Aerosol Optical Depth
BOM	Australian Bureau of Meteorology
BT	Brightness temperature
BTD	Brightness temperature difference ($BT_{\lambda 1} - BT_{\lambda 2}$)
GEO	Geostationary earth orbiting satellites
GLCs	Ground level concentrations
LOD	Limit of detection (three times background)
LOQ	Limit of quantification (ten times background)
PCA	Principal component analysis
PM	Particulate matter (primarily PM_{10} in this study)

1. Introduction

Remote sensing is appealing as a method to estimate concentrations over a vast region due to its spatial coverage, but it has been limited in the past by the single daily snapshot from polar-orbiting satellites which can miss events and not be representative of daily average concentrations (Guo et al., 2017a). Remote sensing

satellites supply data used for air quality metrics at various spatial and temporal scales. Polar-orbiting satellites provide periodic measurements (e.g. MODIS once per day (Levy et al., 2013)) while second-generation geostationary earth orbiting (GEO) satellites such as SEVIRI (Fernandes et al., 2015), GOCI (Choi et al., 2012), Himawari-8 (Yumimoto et al., 2016) and GOES-R (Wang et al., 2014a) supply hourly and sub-hourly data. Aerosol Optical Depth (AOD) (Hsu et al., 2013; Levy et al., 2013; Levy et al., 2009; Remer et al., 2005) is one such air quality metric and is a measure of the extinction of electromagnetic radiation by dust and haze which can absorb or scatter light (ESRL, 2018). AOD is dimensionless and is related to the total amount of aerosol in the vertical column of atmosphere over a location. AOD measurements have been extrapolated to surface concentrations (Achad et al., 2013; Kumar et al., 2007; Le et al., 2014; Muhammad and Nguyen Thi, 2015; Yoon et al., 2016; You et al., 2016b; Zhang et al., 2012) and compared with daily surface measured average concentrations (You et al., 2016a). Apart from the temporal bias of comparing different timescales (seconds against hourly and daily monitoring), short-term events such as fires and inversion weather conditions may be inactive during infrequent satellite observations, or clouds may obscure the scene, leading to the event being missed (Baldassarre et al., 2015; Freeborn et al., 2014; O'Loingsigh et al., 2015; Philip et al., 2016; Zhang et al., 2011). Low-cost monitors have been used to assess the spatiotemporal variability of aerosols in cities (Gao et al., 2015; Saraswat et al., 2013). These inter-day PM_{2.5} spatiotemporal variations in concentrations have been confirmed in monitored data from 31 Chinese cities (Wang et al., 2014b) and regional hourly AOD measurements using Himawari-8 (Kikuchi et al., 2018). These rapid fluctuations in air pollution concentration levels have been ascribed to changing meteorological conditions which affect all emission sources (Li et al., 2014).

The temporal resolution of GEO satellites is a substantial improvement over polar-orbiting satellites and the hourly resolution of most dispersion models (Holmes and Morawska, 2006). The temporal resolution of GEO satellites is comparable to most real-time land-based monitoring instruments (Chow, 1998) and has improved over time, as evidenced by the progression of GEO satellites from GOCI (hourly) (Choi et al., 2012), SEVIRI (15 min) (Fernandes et al., 2015), GEOS-R (Schmit et al., 2018), and Himawari-8 (10 min) (Yumimoto et al., 2016). Himawari can supply finer resolution temporal data with 2.5-minute updates during severe weather events over a smaller targeted region (JMA, 2015), while China's Gaofen-4 satellite has a temporal resolution of one minute (CHEOS, 2018) over the entire domain.

Despite the improvement in the temporal resolution of GEO satellites, few studies have directly addressed the question of what temporal resolution is optimal for air quality studies using geostationary remote sensing data. If the time intervals are too large an event may be missed. Conversely, if they are too short, they may affect computing resources, such as larger files and CPU utilisation. Similarly, studies that only consider daytime impacts, using visible spectra (Kikuchi et al., 2018), will miss dust events that occur at night and early morning inversion conditions. Addressing the timescale requirements of remote sensing for air quality estimates of aerosol species and concentration requires an understanding of both the fundamental drivers of air quality change and an estimation of how aerosol change drives, remotely-sensed, spectral changes (Guo et al., 2017b; Luna et al., 2018).

Particulate Matter Air Quality

PM composition is dependent on the source; for example, desert dust is principally crustal but may include biological material (Goudie, 2014) while smoke from wildfires (Bell and Adams, 2008) is chiefly organic (combustion by-products) but may include inorganic compounds in the fly-ash. The composition of PM at any moment may be influenced by multiple source emissions (e.g. sea-spray, wind erosion, industry) resulting in a complex mix of compounds, and these compositional changes must therefore, be analysed separately.

In regional areas, the contribution made by sources such as fires and dust storms is uncertain. The number of sources (e.g. fires) and the scale over which emissions occur may result in substantial PM emissions which may be transported vast distances and affect air quality in areas far removed from the source (Wuebbles et al., 2007). Hourly (or sub-hourly) measurements are required to understand the transport, dispersion and resulting PM concentrations from significant short-term events where the exposure (concentration) is sporadic but severe in magnitude. For example, a dust storm usually lasts less than a day while a fire may change its path in minutes yet have a total duration of days to weeks.

The concentration differences between short and long-term timescales are primarily related to the changes in wind speed, direction, and emission strength. Decomposing the wind spectrum into frequencies determined that the primary factors driving wind change are short-term wind-gusts (lasting between one second and five minutes), the diurnal cycle (24-hours) and the passage of fronts (about four days) (Hoven, 1957). Wind gusts cause air turbulence, and this turbulence drives air quality events (Stull, 1984; Stull, 2012). In contrast, laminar

wind flow occurs at longer wind frequencies (hourly to daily) and these wind frequencies have low variability (Hoven, 1957).

The optimum monitoring interval is therefore expected to be on the cusp of the turbulent zone, i.e. five to ten minutes, for air quality events to achieve reproducible results and yet also be fast enough to detect those events. Despite this known variability of the daily diurnal cycle, the accredited PM sampling method (Chow, 1995, 1998) draws a predetermined volume of air through a filter using a size-selective inlet and captures the total mass on the filter throughout a day (i.e. a 24-hour average). In contrast, electronic monitors, such as Beta attenuation monitors, usually record hourly or sub-hourly data. Given the temporal nature of dust events, it is vital that monitoring timescales be taken into consideration when comparing monitoring results. Health-related studies suggest that the minimum requirements for monitoring atmospheric events are a spatial resolution one kilometre and a temporal resolution of an hour (Chow, 1995, 1998).

Remote sensing of PM

The limitation of a single daily snapshot from polar-orbiting satellites has been overcome by the rapid data updates from geostationary satellites (Kikuchi et al., 2018; She et al., 2018). The primary function of these geostationary satellites is to supply weather-related data, but as the weather is a strong driver of concentration (Stull, 2012), geostationary satellites may also be ideal for determining GLCs (She et al., 2018).

Remote sensing has been used to monitor GLCs using both visible wavelengths (detecting scattering) and infrared wavelengths (detecting thermal radiation) (She et al., 2018). Clouds impact the aerosol analysis (Levy et al., 2013) using reflectance methods, and the strong water-vapour absorption affects the thermal infrared portion of the electromagnetic spectrum (Schmidt et al., 2016; She et al., 2018). Methods to monitor GLCs based on visible wavelengths yield stronger responses as reflected energy is greater than thermal vibrational energy. Scattering is inversely proportional to the incident wavelength raised to a power (dependent on particle size), and there is, therefore, minimal scattering observed at thermal infrared wavelengths (Mhawish et al., 2018; Sifakis and Iossifidis, 2014). However, thermal infrared allows for continuous monitoring (i.e. 24 hours a day) while scattering by visible light requires direct light from the sun (She et al., 2018) (i.e. daytime only). In addition, using thermal infrared increases the number of potential wavelength bands from six to ten which may improve the ability to determine composition from satellite data. Thermal infrared absorption is computed as the brightness temperature (BT) by the satellite sensor (BOM, 2017; JMA, 2015).

Traditional AOD methods rely on spectral signatures to determine speciation (She et al., 2018). However, the spectral properties of stationary surface soil and aerosol from wind-blown eroded soils are similar, as they have similar mineralogy. The lower mass density of the aerosol means that lateral heat loss is not compensated for by heating from other nearby particles, and this results in slight thermal differences between aerosol particles and surface soil (Han et al., 2012; Mahowald et al., 2014; Takemura et al., 2005) which can be used to quantify aerosol plume concentrations.

Most of the BT measurements relate to land and sea surfaces, which predominate (across the study region), rather than clouds and aerosols which are of short duration and limited in spatial extent. A method is required that highlights the aerosol rather than the land/sea BT change. Brightness temperature difference (BTD) between two thermal infrared wavelengths (λ) (i.e. $BT_{\lambda1} - BT_{\lambda2}$) (She et al., 2018; Sowden et al., 2018) is a simple high-pass filtering method that enhances the differences between two similar wavelength bands while minimising commonality between two wavelengths. For a satellite with N bands, there are $N!/2!(N-2)!$ or $N(N-1)/2$ potential dual band BTD combinations. Himawari-8 has ten infrared bands, and therefore there are 45 possible BTD combinations. Temporal implications must be considered in efforts to better understand air quality events, by using a wider spectrum of wavelengths, and obtaining continual coverage - rather than a singular, daily measurement.

2. Methodology

2.1. Study design

This study set out to investigate the optimum temporal sampling interval using GEO data from Himawari-8 and surface PM concentration data from the Port Hedland region in Western Australia. A rare meteorological event of a dust storm within a roll cloud was used as a case study. The incident included an on-shore wind (diurnal event) - which brought in maritime air, and a subsequent wind reversal (diurnal event) - which generated crustal aerosols. The air mass containing crustal aerosols, blowing offshore, then collided with fresh maritime air which led to the dust storm and roll cloud (rare event) and subsequent rain storm (regular event). This storm was,

therefore, a composite event and, although rare in its severity and formation of the roll cloud, was an outcome of regular, daily, air mass movements.

The first phase of the study considered the probability of a polar-orbiting satellite overpass coinciding with dust events, i.e. how well does the instantaneous measurement reflect the daily concentration variability? The second phase investigated if monitoring for one time period can be used to predict for a different period, i.e. is it feasible to extrapolate an instantaneous measurement to a daily average? Lastly, the duration of each sub-phase of the dust storm was determined to identify the rate of compositional change using geostationary remote sensing data.

2.2. Data

Surface PM₁₀ concentration data

The effect timescales have on concentration was investigated using ten-minute surface PM₁₀ monitoring data from July 2016 to July 2017 for six sites in and near Port Hedland in the Pilbara region in the north-west of Australia. The Pilbara is a large arid regional area spanning approximately 1,600 × 400 km², known for its resource extraction (mining) and pastoral (rangeland) industries. The Pilbara was selected as a case study as the environment is dusty with comparatively low vehicle usage and is profoundly affected by local industry and experiences widespread regional fires and dust storms (DOE, 2004; Physick, 2001; Van Vreeswyk et al., 2004). In addition to the storm that occurred during the case study, Port Hedland experiences on average 54 cloudy days per annum (http://www.bom.gov.au/climate/averages/tables/cw_004032.shtml).

Data for these six surface monitoring sites were obtained from the Port Hedland Industrial Council (PHIC), and the location of these monitoring sites are depicted on the PHIC website (<http://www.phicmonitoring.com.au/>). Of the six PM₁₀ monitoring sites, Yule River (YUL) is the most remote. The airport site managed by the Bureau of Meteorology (BOM) is located some distance away from port operations while the other four sites are affected by port operations. Preference was given to analysing the monitored PM concentrations from remote sites, as previous studies have demonstrated that local sources would dominate concentrations from monitoring sites located within Port Hedland (DOE, 2004; Harper, 2015; Harper and Tuxford, 2007; Physick, 2001).

Himawari-8 data

Raw data files of all ten thermal infrared bands from the Himawari-8 satellite were obtained from the Australian Bureau of Meteorology (BOM) for the period from July 2016 to July 2017. These data files were cropped to the study domain and analysed using the climate data operators (CDO) (CDO, 2018). Table 1 lists the wavelength bounds for each band (BOM, 2017; EUMETSAT, 2011; JMA, 2015), the central wavelength for each band (from the metadata), and typical applications for each band (EUMETSAT, 2011; Miller et al., 2012; Schmit et al., 2018; She et al., 2018; Wickramasinghe et al., 2016). Specifically, the literature indicates that bands 8 (6.2 µm), 9 (6.9 µm), and 10 (7.3 µm) are characteristic of strong water vapour bands (EUMETSAT, 2011; Miller et al., 2012; Schmit et al., 2018). This water vapour may be in the form of clouds or may be an indication of the water content of an aerosol plume. Bands 13 (10.4 µm), 14 (11.2 µm), and 15 (12.4 µm) have been associated with aerosol plumes (Liu et al., 2013; She et al., 2018). The remaining bands may indicate chemical composition as band 7 (3.9 µm) has been associated with fires (potentially CO₂) (Freeborn et al., 2014; Koltunov et al., 2012), band 11 (8.6 µm) with SO₂ (Corradini et al., 2010; Taylor et al., 2015), band 12 (9.6 µm) with O₃ (Hache et al., 2014; Schmit et al., 2018) and band 16 (13.3 µm) with sea surface temperature, clouds (potentially water) (EUMETSAT, 2011; Miller et al., 2012) and CO₂ (Schmit et al., 2018).

Table 1: Himawari-8 bands and characteristic wavelengths

Band	Wavelength (µm)			Applications
	Low	High	Central	
1	0.43	0.48	0.471	vegetation, aerosol
2	0.50	0.52	0.510	vegetation, aerosol
3	0.63	0.66	0.639	low cloud, fog
4	0.85	0.87	0.857	vegetation, aerosol
5	1.60	1.62	1.610	cloud phase
6	2.25	2.27	2.257	particle size
7	3.74	3.96	3.885	low cloud, fog, forest fire
8	6.06	6.43	6.243	mid and upper-level moisture
9	6.89	7.01	6.941	mid-level moisture
10	7.26	7.43	7.347	mid and low-level moisture

11	8.44	8.76	8.593	cloud phase, SO ₂
12	9.54	9.72	9.637	ozone content
13	10.30	10.60	10.407	cloud top, “clean longwave window”
14	11.10	11.30	11.240	cloud, sea surface temperature
15	12.20	12.50	12.381	cloud, sea surface temperature, “dirty longwave window”
16	13.20	13.40	13.281	cloud top, CO ₂

2.3. Determining the probability of a satellite overpass coinciding with a dust event

The ratio of the maximum and daily ten-minute concentrations of the PHIC surface data was calculated, and the frequency distribution of the resulting ratios was determined. A concentration ratio was calculated to preserve confidentiality by depicting relative not absolute concentrations. This ratio provides a means for identifying if a dust event occurred during the day, as a dust event would have higher concentrations than background levels (i.e. scale ratio greater than one). For this study, it was assumed that a dust event day had a ratio greater than two (based on the mean of the analysis).

The cumulative frequency distribution of the ratios was calculated for the BOM and Yule River sites a) using all the data and b) by restricting the analysis to match Terra and Aqua’s (MODIS) overpass times of approximately 10:30 and 13:30 respectively. The difference between these six curves (2 sites x 3 overpasses (all, 10:30, 13:30)) indicated low or high measurements at the time of the overpass in relation to the daily average. The difference in the cumulative frequency between the three curves (per site) reflects the temporal bias of over/underdetermination and indicates the proportion of dust events detected at the fixed satellite overpass times. Ignoring issues of sensitivity, the probability of a satellite detecting an event (i.e. the probability of a satellite being overhead at the time of a dust event) is related to the number of measurements and the duration of an event.

2.4. Scale factors for different time periods

Scale factors are needed where monitoring data are reported for a period (e.g. instantaneous MODIS overpass), and an estimate is required for another period (e.g. daily). Similarly, there is a need to extrapolate hourly dispersion modelling to estimate short term (3-10 minute) odour estimates (Dourado et al., 2012; VIC EPA, 2013). Variability in emission source strength and changing meteorological dispersion parameters imply that measurements from a rapidly varying dust event monitored and recorded for ten-minute, hourly, or daily values will be different to measurements recorded as an instantaneous snapshot and these differences may not be directly related to the duration of measurements.

Scale factors for varying time periods were calculated using the formula from dispersion modelling guidelines of $C_i/C_0 = (t_0/t_i)^{0.2}$ for scaling between different time periods (where C is concentration, t is time, and the subscript 0 and i are the two time-periods of interest) (Dourado et al., 2012; VIC EPA, 2013). Centred moving averages were calculated instead of period averages, to keep the number of data points constant between the different statistics (i.e. 24 x hourly, 1 x daily or a constant 144 moving ten-minute averages irrespective of the period). To investigate if the conversion is universally applicable, exponents were calculated for time ratios to scale from ten-minute data to 20 minutes, 30 minutes, an hour, and a day.

2.5. Analysis of event duration using remote sensing data

The brightness temperature (BT) changes across the region were used to determine the duration of a dust event which impacted Onslow in Western Australia on 8 March 2017 (The West Australian, 2017). Given the sparseness and limited monitoring of the region, there are few records of such storms, and social media photographs and secondary sources such as newspapers are currently the most widely available sources of information. Brightness temperature histograms across the region were calculated using band seven (3.9 µm) of the Himawari-8 satellite for each observation period across the day of the incident and the following day (for comparison). Band seven was used as it had the greatest range (i.e. sensitivity) to BT changes across the day and region (Schmit et al., 2018). A temperature-time distribution was calculated from the histograms where the counts of temperature (y-axis) for each time interval (x-axis) was displayed as a colour coded distribution.

Intensity changes across multiple wavelength bands, rather than just a single wavelength band, were used to identify compositional changes during the event as different compounds exhibit different spectral properties. Taylor diagrams (Taylor, 2001) were used to identify where a change in one band correlated with a change in another band, i.e. indicative of the same compound (correlated) or different compounds (weaker correlation). Identifying compositional change (changing spectral responses) thereby enables event duration to be determined rather than concentration change (changing intensity).

Taylor diagrams are radial plots and depict standard deviation, correlation, and root mean square error (RMSE) on one diagram. Taylor diagrams allow easy visual comparisons from the clustering based on the commonality of standard deviation, correlation, and RMSE. Taylor diagrams were constructed relative to each of the ten infrared bands to check the existence of any clusters and to identify redundant wavelengths. The data were further analysed via high-pass filtering and PCA.

Most of the BT measurements relate to sea and land surface temperatures as they predominate across the region with clouds and aerosols being outliers in the temperature-time distribution plot calculated earlier in this section (Figure 4). High-pass filtering using brightness temperature difference (BTD) between bands 11 (8.6 μm) and 7 (3.9 μm), i.e. $\text{BTD}_{(8.6-3.9\mu\text{m})}$, was applied across the region over the two days to highlight aerosols and minimise commonality (i.e. sea and land) between the two wavelengths.

BTD wavelength combinations chosen from the Taylor analysis were analysed via PCA. The data were standardised by subtracting the mean and dividing by the standard deviation before undertaking the PCA analysis to give equal weight to the six BTD combinations. Paraview virtualisation software (Ayachit, 2015) was used to normalise the data, determine the weightings of the first principal component and visualise the results. For each satellite observation, the principal component weighting was determined.

3. Results

3.1. Probability of satellite overpass coinciding with a dust event

A histogram of the ratio of the daily maximum to the daily average was plotted for all six air monitoring locations across the year and is shown in Figure 1. The most rural location (YUL) had less of a discrepancy in PM_{10} concentrations between the maximum and average than the other five sites. The mean ratio across all six sites was 2.69.

The cumulative frequency distribution of the scale ratio (Figure 2) shows that for a sizable portion of the data (~15 %) the ratio was greater than four. Figure 2 also demonstrates that at YUL 95 % of the instantaneous concentrations at the time of the MODIS overpasses, were lower than the daily average concentrations (i.e. scale ratio of one) compared to 70 % at BOM. This can be ascribed to the influence of wind speed on the concentrations. Night-time temperature gradients were weaker than daytime temperature gradients, and as a result, higher wind speeds were more probable in the daytime, leading to more favourable dispersion conditions and lower concentrations during the day at the time of the overpasses (10:30 and 13:30).

A dust event was deemed to have occurred if concentrations exceeded twice the background (i.e. a scale ratio of 2) – a conservative assumption given the “limit of detection” as three times background. This classification ascribed the probability, expressed as a percentage, of a dust event occurring sometime during the day as 80 % (100-20 %), at the BOM site (from Figure 2). In contrast, the probability of detecting a dust event at 10:30 or 13:30 was less than four percent (100-97 %) (conservatively rounded up). Therefore, it can be concluded that MODIS (using both Terra and Aqua sensors) will detect a sporadic event such as a fire or wind-blown dust from eroded areas in less than eight percent of cases. Furthermore, an average event duration can be crudely estimated as the probability of the ten-minute data (80 %) divided by the probability of the 10:30 (or 13:30) data (4 %) (i.e. the number of “events” a day) multiplied by the monitoring period (ten minutes). Therefore, this method estimates that elevated concentrations from a dust event are recorded for about three hours (80 %/4 % x 10 minutes) at a surface monitor before the wind changes direction, or the event ends. Given this short temporal span, the probability of MODIS detecting an event is unlikely as it is estimated at only four percent per overpass.

Figure 1: Frequency distribution of the ratios of maximum (ten-minute) and daily average PM_{10} concentrations at five monitoring sites near Port Hedland.

Figure 2: Cumulative frequency of the daily PM_{10} scale ratio (ten-minute/average) and during MODIS overpass times at two sites (BOM and YUL).

3.2. Scale factors of different time periods

The natural logarithm of the average concentration ratios divided by the time ratio, was plotted against the time ratio (plotted on a log scale), and the results are displayed in Figure 3 for four time-ratios (2, 3, 6 and 24). The results show that at longer time ratios the factor is site-specific, but averages to 0.2. In contrast, there is less site-specific variability at shorter time ratios but for a much smaller exponent of about 0.05. Thus, the equation does not hold, and the results imply that instantaneous concentrations from dust events cannot be used to predict average concentrations over longer periods (and vice-versa) with a constant exponent.

Figure 3: Exponent for converting between averaging time-periods.

3.3. Analysis of event duration using remote sensing data

The temperature-time distribution of the BT measurements for band seven ($3.9 \mu m$) was calculated for the two days and is displayed in Figure 4a. For comparison, the surface monitored temperature at the BOM site is given in Figure 4b. The frequency distribution of the BT (y-axis) for each time-interval (x-axis) is presented as a colour-coded frequency (depicted as counts) for all points across the region. The graph shows that most of the observed temperatures were from the diurnally fluctuating surface temperature (mostly depicted as orange and red) and the stable sea temperature (mostly depicted as magenta), which together (i.e. greater than 560 counts) account for 83 % of the measured data. The result was as expected as the region had few clouds (as verified by MODIS cloud imagery) and isolated aerosol plumes during the two days despite the severe but localised dust event. Therefore, the background or “noise” in the temperature-time distribution graph depicts typical diurnal sea and land temperature changes (83 %) and the small variances from the background (17 %) were due to localised temperature effects such as clouds, tidal sea level changes, active fire hot spots, and aerosol plumes.

Figure 4: a) Brightness temperature (band 7) vs. time and b) surface temperature at BOM on the 8th and 9th March 2017.

These “outliers” (17%) in the BT data, therefore, reflect the radiometric signal of interest. Rapid cooling was observed during the day of the incident, starting late in the afternoon and extending over a series of five disjointed temperature changes, each lasting approximately two hours. From analysing the spectral time-series, it is postulated that these jumps reflected afternoon diurnal cooling (2-4 PM), clouds forming (4-6 PM), strong winds created from updrafts leading to the dust storm (6-8 PM), rain washout occurring (8-10 PM), and finally the dry remnants of the dust storm (10 PM-12 AM). Some of these changes are reflected in surface meteorological data and the afternoon MODIS overpass at specific sites, but the sparseness of surface monitoring precludes a definitive analysis.

Taylor plots were used to identify correlations between satellite bands as this could indicate redundant information if the bands were strongly correlated, i.e. compositional changes yielded similar spectral changes across multiple bands. Taylor plots are depicted in Figure 5(a-c) where bands 7 (3.9 μm), 11 (8.6 μm), and 12 (9.6 μm) were used as the reference. Three common clusters, or groups, were noted in each of the plots. The water vapour bands 8 (6.2 μm), 9 (6.9 μm), and 10 (7.3 μm) have less correlation to the other bands; the aerosol bands 13 (10.4 μm), 14 (11.2 μm), and 15 (12.4 μm) have high correlation and minimal variance; and the remaining “chemical” bands 7 (CO_2) (3.9 μm), 11 (SO_2) (8.6 μm), 12 (O_3) (9.6 μm), and 16 (sea surface temperature and H_2O) (13.3 μm). These clustering patterns reflect the similarities between the bands for the event studied and the grouping could be different for a different event such as a volcanic plume or fire. The selection of the three reference bands in the Taylor plots was to avoid producing ten plots depicting similar information, and three of the “chemical” bands were chosen as the reference as the “chemical” clustering had the most differences.

Figure 5: Taylor diagrams depicting variances of brightness temperatures across the study region using bands 7, 11 and 12 as reference.

The Taylor plots indicated that there was potentially redundant information in the three aerosol bands (13, 14, and 15). Furthermore, the three water vapour bands (8, 9, and 10) indicate cloud, not aerosol, movements (Schmit et al., 2018). Therefore, most of the BTD differences, which may be indicative of aerosol plumes, were expected to be contained in the bands 7, 11, 12, 16 and any one of the aerosol bands (15 was chosen). This reduced the 45 BTD combinations to 10, which was further reduced to six combinations (11-7; 12-7; 12-11; 15-12; 16-11; 16-12) based on the Taylor analysis and visually inspecting the satellite images and (1) ignoring those BTD combinations that resulted in minor changes between spectra, and (2) ensuring that the resulting images were consistent with plume behaviour (i.e. growth/dissipation of plumes) during the event.

PCA of the six BTD combinations demonstrated the changing spectral response during the event. The PCA weightings are depicted in Figure 6 for the six BTD combinations indicating how the weightings of the first principal component change over time across the day of the incident. (The first principal component accounted for approximately two-thirds of the variability in the data.) From the graph, it was apparent that dramatic shifts in the PCA weightings occurred over a period of about half an hour followed by stable periods (of about two hours). It was postulated, based on the air movement evident in the video in the supplementary material, and as highlighted in Figure 7 which depicts $\text{BTd}_{(8.6-3.9\mu\text{m})}$ at various times during the day, that the four aerosol phases represented in Figure 6 were due to sea-spray (frames 0–13), wind-blown dust (frames 18–47), initial dust storm (wind-blown aerosol colliding with incoming maritime air creating a roll cloud) (frames 52–57), rain washout (frames 64–70) and the dry residual dust storm (frame 75 onwards).

Each phase of the event was defined by the rate of change of the primary principal component and the direction of the plume movement (on/offshore). Aerosol-type for each phase was postulated based on this primary PCA rate of change and plume movement. The results show that the timing of each stage matched the description and details given in the news report. Figure 7 demonstrates the progression of the storm as the aerosol plume was forced up and over itself by the incoming maritime air which created the roll cloud. This level of temporal resolution and spatial understanding of a dust storm with an associated roll cloud is unique in the literature and only possible with the availability of GEO data such as that from Himawari-8.

Figure 6: Weight of the first principal component of six BTD combinations indicating changes to probable aerosol types. Frame 0 (UTC) represents 8 AM local time. (Legend depicts wavelength bands, not wavelengths).

368 *Figure 7: BTD (3.9–6.2 μm) depicting the development of the dust incident. 2 PM) wind reversal to off-shore; 4 PM) start of*
369 *dust storm; 6 PM) maritime air colliding with the wind blowing off-shore; 9 PM) storm dissipated.*

370

371 **4. Discussion**

372 This study has investigated the optimum temporal sampling interval for determining GLCs from rapidly changing
373 dust events in the Pilbara region of WA. The analysis of the temporal resolution of the Himawari-8 geostationary
374 earth orbiting (GEO) satellite's data has contributed to a better understanding of the formation and dissipation
375 of a rare meteorological and dust event of a dust storm being formed as part of a roll cloud. While a rare event,
376 the causes were ascribed to regular daily air mass movements. In contrast to previous studies, no assumptions
377 were made about the relevance of individual bands for determining composition. Instead, spectral differences
378 were used to infer the duration of compositional changes. Similarly, the stronger signals from scattering in the
379 visible portion of the electromagnetic spectrum were rejected in favour of the weaker thermal infrared
380 absorbance bands, because of their continual radiation in contrast to daytime only scattering of light.

381 Taylor plots identified four independent bands which were used by BTD as a high-pass filter to improve the
382 spatial resolution, and PCA identified the first principal component for each time interval. The rate of change of
383 the weight of the first principal component identified each phase of the event and allowed the aerosol type to
384 be postulated based on video inspection of the plume direction (on/offshore). The timing of each stage matched
385 the description and details given in the news report. It was not within the scope of this study to elucidate
386 composition but merely to reflect on what observation periods are required for geostationary data to monitor
387 plume movements accurately. The PCA analysis may exhibit entirely different factors for other compositions,
388 mineralogy, or smoke.

389 The inflection points in Figure 6 showed that these compositional changes occurred over three to five frames of
390 ten minutes, i.e. 30 to 50 minutes, while the dust storm (frames 52 to 57) lasted 50 minutes before the rain,
391 which lasted 60 minutes (frames 64 to 70). Monitoring methods define a limit of detection (LOD) as three times
392 the background variance and the limit of quantification (LOQ) as ten times the variance. Using these definitions
393 against the 50-minute dry dust storm phase implies that a fifteen-minute frame rate for LOD (50/3) is required,
394 compared to a 5-minute frame rate for LOQ (50/10).

395 Himawari's ten-minute data resolution was adequate to detect rapidly changing air quality events. Some benefit
396 may be achieved by halving the scan time to five minutes, but this will simultaneously double the already large
397 data files and processing time. As shown by Hoven (1957), there is no benefit in reducing the scan time even
398 further as the scan time will have to be faster than seven seconds to achieve the same variability as ten-minute

data and this is not practical. Therefore, the five to ten-minute data rate represents an ideal balance as it is on the cusp of the turbulent range, which enables the rapid detection of changes, and the spectral gap region, which yields lower variability. Hourly averaging will reduce the variability, but the reduction in variability will come at the cost of early quantification, and rapidly changing aerosol plumes may be missed.

5. Conclusions

There are three timescales relevant to air quality: (1) the instantaneous [daily] snapshot from a polar-orbiting satellite (Levy et al., 2013); (2) the minimum requirement of hourly monitoring (Chow, 1998); and (3) the five-minute turbulent drivers of atmospheric change (Hoven, 1957; Stull, 2012). This study has shown that air quality studies require a sufficiently fine temporal resolution to quantify sporadic dust events and that this high temporal resolution is lacking in data from polar-orbiting satellites (such as MODIS). It has demonstrated, based on a case study of a short set of measurements made of an opportunistic single dust storm event, that turbulent drivers of air quality are evident in geostationary data of high temporal resolution and emphasises that these drivers must be accounted for by remote sensing methods.

The analysis reiterated that MODIS is unsuitable for monitoring sporadic dust events - as less than four percent of events coincided with the satellite overpass. Using the infrared sensors on these satellites could potentially double the number of events detected - but would still miss ninety percent of short-term dust events because of the available temporal resolution. Remote sensing is therefore critically reliant on geostationary satellites such as Himawari to provide the required temporal resolution for air quality analysis using the infrared bands and not be limited by the daytime only restriction of visible wavelengths.

PCA analysis of six BTDR ratios identified each phase of the event and allowed the aerosol type to be postulated based on video inspection of the plume direction (on/offshore). Using the LOQ definition on the duration of compositional changes indicated that an optimum temporal resolution of five-minute is required. This is faster than the current ten-minute Himawari-8 data rate which may constrain the quantification of aerosol types during rapid aerosol compositional changes. However, given that these "rates of change" were calculated as the average across the domain, it is expected that the ten-minute data would be more than adequate when the location is taken into consideration.

It is vital that the frequency of severe events be better understood and that long-term data records be established to estimate health risks of sporadic air quality events on resident populations. The spatiotemporal information provided by GEO data unambiguously resolves the critical *where* and *when* for atmospheric scientists. However, the subsequent *what* (composition) and *how much* (concentration) is mostly unresolved especially in the light of historical reliance on visible spectra. Work is currently being undertaken to determine composition using thermal infrared methods.

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