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7 **Dust source identification using MODIS: a comparison of techniques**
8 **applied to the Lake Eyre Basin, Australia**

9
10 ^aMatthew C. Baddock, ^{a*}Joanna E. Bullard, and ^bRobert G. Bryant.

11 ^aDepartment of Geography, Loughborough University, Loughborough,
12 Leicestershire, LE11 3TU UK.

13 ^bDepartment of Geography, The University of Sheffield, Western Bank,
14 Sheffield, S10 2TN UK

15 * Corresponding author

16
17 **Abstract**

18 The impact of mineral aerosol (dust) in the Earth's system depends on particle
19 characteristics which are initially determined by the terrestrial sources from
20 which the sediments are entrained. Remote sensing is an established
21 method for the detection and mapping of dust events, and has recently been
22 used to identify dust source locations with varying degrees of success. This
23 paper compares and evaluates five principal methods, using MODIS Level 1B
24 and MODIS Level 2 aerosol data, to: (a) differentiate dust (mineral aerosol)
25 from non-dust, and (2) determine the extent to which they enable the source
26 of the dust to be discerned. The five MODIS L1B methods used here are: (1)
27 un-processed false colour composite (FCC), (2) brightness temperature
28 difference, (3) Ackerman's (1997: J.Geophys. Res., 102, 17069-17080)
29 procedure, (4) Miller's (2003:Geophys. Res. Lett. 30, 20, art.no.2071) dust
30 enhancement algorithm and (5) Roskovensky and Liou's (2005: Geophys.
31 Res. Lett. 32, L12809) dust differentiation algorithm; the aerosol product is
32 MODIS Deep Blue (Hsu et al., 2004: IEEE Trans. Geosci. Rem. Sensing, 42,
33 557-569), which is optimised for use over bright surfaces (i.e. deserts). These

34 are applied to four significant dust events from the Lake Eyre Basin, Australia.
35 OMI AI was also examined for each event to provide an independent
36 assessment of dust presence and plume location. All of the techniques were
37 successful in detecting dust when compared to FCCs, but the most effective
38 technique for source determination varied from event to event depending on
39 factors such as cloud cover, dust plume mineralogy and surface reflectance.
40 Significantly, to optimise dust detection using the MODIS L1B approaches,
41 the recommended dust/non-dust thresholds had to be considerably adjusted
42 on an event by event basis. MODIS L2 aerosol data retrievals were also found
43 to vary in quality significantly between events; being affected in particular by
44 cloud masking difficulties. In general, we find that OMI AI and MODIS AQUA
45 L1B and L2 data are complementary; the former are ideal for initial dust
46 detection, the latter can be used to both identify plumes and sources at high
47 spatial resolution. Overall, approaches using brightness temperature
48 difference (BT10-11) are the most consistently reliable technique for dust
49 source identification in the Lake Eyre Basin. One reason for this is that this
50 enclosed basin contains multiple dust sources with contrasting geochemical
51 signatures. In this instance, BTD data are not affected significantly by
52 perturbations in dust mineralogy. However, the other algorithms tested
53 (including MODIS Deep Blue) were all influenced by ground surface
54 reflectance or dust mineralogy; making it impossible to use one single MODIS
55 L1B or L2 data type for all events (or even for a single multiple-plume event).
56 There is, however, considerable potential to exploit this anomaly, and to use
57 dust detection algorithms to obtain information about dust mineralogy.

58
59

59 **Dust source identification using MODIS: a comparison of techniques**
60 **applied to the Lake Eyre Basin, Australia**

61

62 **1. Introduction**

63

64 Atmospheric mineral aerosols (termed here dust) play an important role
65 in the land-atmosphere-ocean system (Ridgwell, 2002; Jickells et al., 2005;
66 Waeles et al., 2007). For example, they affect soil nutrients at source and
67 sink (McTainsh & Strong, 2007; Muhs et al., 2007; Li et al., 2007; Reynolds et
68 al., 2006; Soderberg & Compton, 2007; Swap et al., 1992; Wang et al., 2006),
69 the radiative forcing of the atmosphere (Haywood & Boucher, 2000; Hsu et
70 al., 2000; Satheesh & Moorthy, 2005; Yoshioka et al., 2007) and may regulate
71 phytoplankton activity of oceans (de Baar et al., 2005; Erickson et al., 2003;
72 Mackie et al., 2008; Piketh et al., 2000; Wolff et al., 2006). The impact of dust
73 in the Earth's system depends on characteristics such as particle size, shape
74 and mineralogy (in particular iron content: Jickells et al., 2005; Mahowald et
75 al., 2005). Whilst these characteristics can change during dust transport
76 (Desboeufs, 2005; Mackie et al., 2005) they are initially determined by the
77 terrestrial sources from which the particles are entrained.

78

79 The detection and mapping of dust events and dust transport pathways
80 has benefited greatly from the use of remote sensing, and at the global scale
81 major dust source regions have been identified using satellite data, such as
82 from the Total Ozone Mapping Spectrometer (TOMS; Prospero et al., 2002;
83 Washington et al., 2003). The passage of dust along specific regional
84 transport pathways over land and ocean and the behavior of individual dust
85 events have also been tracked using TOMS and OMI (Ozone Monitoring
86 Instrument; e.g. Alpert et al. 2004) and at higher temporal and spatial
87 resolutions using data from, amongst others, AVHRR (Advanced Very High
88 Resolution Radiometer; e.g., Evan et al., 2006; Zhu et al., 2007), GOES-
89 VISSR (Geostationary Operational Environmental Satellite, Visible Infra-Red
90 Spin-Scan Radiometer, e.g., MacKinnon et al., 1996), METEOSAT (e.g.,
91 Moorthy et al., 2007), MODIS (Moderate Resolution Imaging
92 Spectroradiometer, e.g., Badarinath et al., 2007; Gassó & Stein, 2007;

93 Kaskaoutis et al. 2008; McGowan & Clark, 2008; Zha & Li, 2007), MSG-
94 SEVIRI (Meteosat Second Generation-Spinning Enhanced Visible and
95 InfraRed Imager; e.g., Schepanski et al., 2007) and SeaWiFS (Sea-viewing
96 Wide Field-of-View Sensor; e.g., Eckardt & Kuring, 2005). Sensor-retrieved
97 parameters (such as MODIS aerosol size parameters; Dubovik et al., 2008;
98 Jones & Christopher, 2007; Kaufman et al. 2005) or complex statistical
99 analyses (such as Principal Component Analysis; e.g. Argarwal et al. 2007;
100 Jones & Christopher, 2008; Zubko et al. 2007) have also been used to
101 differentiate dust and non-dust with some success.

102

103 Systematic determination of both the geomorphological and
104 geochemical variability of dust sources, and hence the variability of the
105 sediments which are entrained and transported, requires as accurate and
106 precise an identification of the upwind (source) end of the dust plume as
107 possible. Researchers have recently started to use remote sensing data to
108 achieve this (e.g., Bullard et al., 2008; Lee et al., 2008; Zhang et al., 2008),
109 but with varying levels of success. The ability to use remotely-sensed data
110 both to detect a dust plume and identify the location from which it has
111 originated is affected by several factors including the radiative transfer
112 properties of the material emitted, the radiative properties of the ground/ocean
113 surface over which the plume is transported, the size and density of the dust
114 plume, the time of satellite overpass relative to dust emission, the presence or
115 absence of cloud, the horizontal and vertical plume trajectory, and the sensor
116 characteristics and radiative transfer model used to detect dust. In many
117 respects, the relative impacts of these factors on dust source determination
118 are hard to determine without close reference to surface meteorological data
119 (e.g. wind speed and visibility records) and ground-based aerosol
120 determination records (e.g. AERONET – Aerosol Robotic Network) which can
121 allow comparative characterisation of individual dust events (e.g. Bullard et
122 al., 2008; Mahowald et al., 2007). Even where these records exist, the direct
123 comparison of ground and remote sensing data retrievals to determine dust
124 sources can be problematic, with some remote sensing data products being
125 unable consistently to detect dust events due to the factors listed above;
126 particularly the presence of cloud, and the existence of low contrast between

127 dust plume and ground/ocean surface (e.g. Gassó & Stein, 2007; Bullard et
128 al., 2008). The principal aim of this paper is to evaluate in detail the use of
129 MODIS data, one of the most widely and successfully-used sensors, for
130 improved identification of dust source locations. This paper varies in emphasis
131 from many previous studies because the focus is on the *precision* with which
132 the upwind (source) location of the plume can be discerned, rather than on
133 the simple determination of plume location, density and trajectory.
134 Specifically, we compare five methods of using MODIS Level 1 band data and
135 one MODIS Level 2 aerosol product and evaluate them in terms of: (a) how
136 well they enable the differentiation of dust and non-dust (cloud, smoke,
137 volcanic aerosols) and, (b) the extent to which it is possible to discern the
138 location of the dust source (i.e. the upwind part of the dust plume - or 'dust
139 head') and how much this varies from method to method. The influence of
140 environmental factors such as plume density and mineralogy on source
141 detection by MODIS will also be evaluated.

142

143 **2. Data and Methods**

144

145 *2.1 Data*

146

147 Mineral aerosol (dust) can be detected and mapped through remote
148 sensing via inversion of radiative transfer models which operate in the
149 following wavelengths: (a) ultraviolet (UV 0.315-0.4 μm) via absorption (e.g.
150 TOMS AI; Torres *et al.*, 1998), (b) visible (VIS 0.38-79 μm) via scattering (e.g.
151 Tanré and Legrand, 1991), and (c) thermal infrared (TIR 8-15 μm) via
152 contrasting land/aerosol emissivity and/or temperature (e.g. Ackerman, 1997).
153 Due to constraints of sensor design, observations by remote sensing systems
154 operating in VIS wavelengths can be determined at higher resolution (pixel
155 size = x) than those made in the TIR (pixel size = $x*2-4$) and UV (pixel size =
156 $x*100-200$), and this has implications for both plume and source detection
157 using these approaches. Radiative transfer model inversion of aerosol
158 observations made within (or via combinations of) each of the three
159 wavelength ranges often provides either a relative indication of aerosol
160 concentration (e.g. via TOMS AI), or a calibrated (e.g. through comparison

161 with AERONET observations) measure of wavelength-dependent total aerosol
162 optical thickness/depth (AOT/D). The success of the radiative transfer model
163 inversion in each case is often complicated by factors such as the non-
164 spherical nature of the mineral aerosol, changes in the chemical/physical
165 nature of the material, and location within the atmosphere during transport. In
166 addition, over very bright surfaces (e.g. desert regions and urban areas), in
167 the presence of cloud, and at night, mineral aerosol detection using
168 UV/VIS/TIR wavelengths can become increasingly uncertain (e.g. Kaufman et
169 al., 2000). The short-term nature of some mineral aerosol events (often <1
170 day) also means that an understanding of any bias associated with mineral
171 aerosol detection at the time of satellite over-passes and temporal sampling
172 (i.e. either am or pm data collection time) is needed in order to characterize
173 fully the emission and transport process. In order to evaluate, compare and
174 contrast mineral aerosol detection approaches, a range of remote sensing
175 data are used here (see Table 1).

176

177 <Insert Table 1>

178

179 *2.1.1 MODIS Data*

180 Data from the Moderate Resolution Imaging Spectroradiometer
181 (MODIS) were used to make comparisons of retrievals using VIS and TIR
182 (often combined) approaches. MODIS makes observations using 36 spectral
183 bands with wavelengths from 0.41 to 14.4 μm and nadir spatial resolutions of
184 0.25 km, 0.5 km, and 1 km. It is currently operating onboard the NASA Earth
185 Observing System (EOS) Terra and Aqua satellites, launched in December
186 1999 and May 2002, respectively. Daily MODIS Level 1B (L1B) 1 km data
187 (MOD021KM = Terra, and MYD021KM = Aqua) used in this work have been
188 processed to convert the sensor's on-orbit responses in digital numbers to
189 radiometrically calibrated and geo-located data products (v5.06 processing for
190 Terra and v5.07 for Aqua). Data were obtained from the Level 1 and
191 Atmosphere Archive and Distribution System (LAADS;
192 <http://ladsweb.nascom.nasa.gov/>). Details of images dates and subsequent
193 processing of MODIS L1B data are outlined below.

194

195 Daily MODIS Level 2 Aerosol data are produced at the spatial
196 resolution of a 10 x 10 km (at nadir) pixel array. There are two MODIS Aerosol
197 data product file types: MOD04_L2, containing data collected from the Terra
198 platform and MYD04_L2, containing data collected from the Aqua platform.
199 Here we only use the MYD04 Aqua product because to date Deep Blue (see
200 below) retrievals are not yet available for MOD04 Terra data. Aerosol
201 properties within MYD04_L2 are derived by the inversion of MODIS observed
202 reflectances at 500 m resolution using pre-computed radiative transfer look-up
203 tables based on dynamical aerosol models (Kaufman et al., 1997; Remer et
204 al., 2005). Derivation of aerosol from these data is far from straightforward
205 and, in initial versions of the MODIS aerosol product, the ability to retrieve
206 aerosol optical thickness (AOT) and single scattering albedo over bright-
207 reflecting surfaces has been problematic because the algorithm relies in part
208 on the initial detection of dark surfaces or targets (Kaufman et al., 2000). In
209 addition, the cloud screening has been shown to have problems where mis-
210 identification of some dust plumes as cloud has led to artifacts in the final data
211 (e.g. as noted by Brindley and Ignatov, 2006). These products have been
212 under continued and careful evaluation and development, and product
213 MYD04 (see [http://modis-](http://modis-atmos.gsfc.nasa.gov/C005_Changes/C005_Aerosol_5.2.pdf)
214 [atmos.gsfc.nasa.gov/C005_Changes/C005_Aerosol_5.2.pdf](http://modis-atmos.gsfc.nasa.gov/C005_Changes/C005_Aerosol_5.2.pdf)) has recently
215 received an improved aerosol determination (via reprocessing to collection
216 5.1/2; Levy et al., 2006, 2007; Remer et al., 2006) over bright surfaces
217 through the integration of a revised determination of AOT over land (Levy et
218 al., 2007), and inclusion of the Deep Blue algorithm (Hsu et al., 2004; Hsu et
219 al., 2006). Here we evaluate the Deep Blue algorithm, which relies on the blue
220 wavelengths and libraries of surface reflectance to make retrievals over bright
221 surfaces (Hsu et al., 2004).

222

223 The Deep Blue processing approach involves the following processing
224 elements: (1) Rayleigh Correction for Terrain Elevation in the following
225 MODIS channels: R8 (0.405-0.42 μm), R3 (0.459-0.479 μm) and R1 (0.62-
226 0.67 μm); (2) Cloud Screening using: R8 (3 x 3 pixel spatial variance) and
227 R3/R8 AI; (3) the surface reflectance for a given pixel is determined from a
228 clear-scene database based upon its geo-location; (4) R8, R3 and R1

229 reflectances are then compared to radiances contained in a lookup table with
230 dimensions consisting of solar zenith, satellite zenith, and relative azimuth
231 angles, surface reflectance, AOT, and single scattering albedo; (5) a
232 maximum likelihood method is used to compute a mixing ratio between dust
233 and smoke models until the calculated spectral reflectances make the best
234 match with those that are measured; and (6) for mixed aerosol conditions,
235 once the aerosol models and the mixing ratio that produce the best match are
236 determined, the values of AOT and Ångström exponent are reported. For
237 dust-dominant cases, the values of single scattering albedo are retrieved in
238 addition to these parameters. MODIS Deep Blue data within MYD04_L2
239 includes AOT (τ) determination at 0.412, 0.47, 0.55 and 0.66 μm , although
240 only the 0.412 μm data are used here. MYD04_L2 data were obtained from
241 the Level 1 and Atmosphere Archive and Distribution System (LAADS;
242 <http://ladsweb.nascom.nasa.gov/>). The typical aerosol optical thickness for
243 visible light in clear air is 0.1, very hazy skies have AOTs of ≥ 0.3 . During initial
244 processing, typical scale (0.001) and offset (0) values were applied to
245 MYD04_L2 AOT data prior to display and subsequent data processing.

246

247 2.1.2 AURA OMI

248 This paper focuses on an evaluation of MODIS data but for each case
249 study, in addition to MODIS L1B and L2 aerosol data, co-incident data from
250 an independent sensor, the Ozone Monitoring Instrument (OMI) were also
251 acquired. OMI is on the Aura satellite (launch date: July 2004) which flies as
252 part of the NASA A-Train constellation (http://aqua.nasa.gov/doc/pubs/A-Train_Fact_sheet.pdf) a few minutes behind the Aqua satellite. OMI is
253 designed to continue the Total Ozone Mapping Spectrometer (TOMS) record
254 for total ozone and other atmospheric parameters related to ozone chemistry
255 and climate. OMI measurements are sensitive to aerosol absorption in UV
256 wavelengths, thus providing an independent source of information relating to
257 mineral aerosol detection in the scene under observation. In addition, and
258 unlike MODIS, OMI AI (Absorbing Aerosol Index: e.g. Torres et al., 2007) is
259 sensitive to aerosol absorption even when the particles are above cloud and
260 AAI is therefore derived successfully in both cloudless and cloudy conditions
261 (although see Ahn et al., 2008). OMI has a ground resolution of 13 x 24 km

263 (nadir) and uses a retrieval algorithm similar to the one used by TOMS
264 (Torres *et al.*, 1998). The OMI AI is defined as follows:

265

$$266 \quad \text{OMI AI} = 100 \log_{10} (I_{360}^{\text{Meas}} / I_{360}^{\text{Calc}})$$

267 (Eq.1)

268

269 where I_{360}^{Meas} is the measured 360 nm OMI radiance and I_{360}^{Calc} is the
270 calculated 360 nm OMI radiance for a Rayleigh atmosphere. Under most
271 conditions, the AI (Eq.1) is positive for absorbing aerosols and negative for
272 non-absorbing aerosols (pure scattering). An AI >1 is typical of absorbing
273 aerosols such as smoke or dust (Gassó & Stein, 2007; Kubilay *et al.*, 2005;
274 Washington *et al.*, 2003). In this instance, we have chosen to use the OMI-
275 Aura_OMTO3E data, which is a daily Level 3 global gridded product which is
276 generated by binning the original pixels from the Level 2 data products (15
277 orbits per day; 13 x 24 km spatial resolution at nadir) into a 0.25 x 0.25 degree
278 global grid.

279

280 **2.2 Methods**

281

282 *2.2.1 Study region and event selection*

283 The performance of different MODIS dust detection methods in
284 identifying source locations involved the analysis of four dust events which all
285 originate in the same drainage basin. The Lake Eyre Basin (LEB), Australia
286 was chosen for several reasons. First, it has been identified as a persistent
287 and significant southern hemisphere dust source on the basis of surface
288 observations (Middleton, 1986) and using TOMS AI (Washington *et al.*, 2003).
289 Second, it is the only inland basin dust source region in Australia, a
290 geographically-isolated continent distant from other dust sources.
291 Consequently, within the LEB there is less potential for interaction with other
292 major dust sources than would be the case, for example, in the Sahara
293 (Prospero *et al.* 2002) or China (Shao & Wang, 2003). Third, the basin is large
294 enough to give rise to several major dust events each year, but not such an
295 intense dust source as to make it difficult to discern individual plumes.

296

297 The LEB covers 1.14 million km², with mean annual rainfall of less than
298 125 mm and annual potential evaporation in excess of 2500 mm. There are
299 several different sedimentary environments in the LEB, all of which emit dust.
300 The most significant of these are: (1) aeolian deposits covering 33% of the
301 basin area and accounting for 37% of the dust plumes, (2) alluvial deposits
302 and floodplains (11.55% area, 30% dust plumes), and (3) ephemeral lakes
303 and playas which cover only 2.26% of the basin area but from which originate
304 29% of the dust plumes making these the most intense dust sources (figures
305 averaged over 2003-6: Bullard et al., 2008). Inter- and intra-annual variability
306 of dust storm frequency in the LEB is high, responding to changes in synoptic
307 pressure distributions across the continent (Ekstrom et al., 2004). The Sprigg
308 Model, which characterizes dust transporting wind systems in Australia
309 (Sprigg, 1982), suggests that as frontal systems pass over the LEB, pre-
310 frontal northerly and post-frontal southerly winds can entrain dusts which
311 travel southeast or northwest respectively. It is important to note, however,
312 that the estimated total annual number of dust events in the LEB varies not
313 only in response to climate but also as a result of differences in how events
314 are defined. In a previous study (Bullard et al., 2008), we examined MODIS
315 imagery for all days (between July 2003 and June 2006) where at least one
316 meteorological station in the LEB (or within 250 km of the catchment
317 boundary) recorded a dust-induced reduction in visibility to ≤ 1 km (which
318 corresponds to the WMO definition of a dust storm). Whilst there are some
319 inconsistencies in the relationship between visibility records from
320 meteorological stations and other indicators of dust emissions, (including
321 AERONET, TOMS AI and TOMS AOD: Mahowald et al., 2007) and the spatial
322 distribution of meteorological stations across the arid LEB is sparse which
323 means a number of events will be missed, visibility remains a useful criteria
324 for identifying days on which significant dust events have occurred. From the
325 43 days on which dust events were identified four case studies were chosen
326 to illustrate key types of event that occur in the LEB, and also to include
327 factors which can significantly affect dust plume and source identification (i.e.
328 single /multiple dust plumes and varying amounts of cloud; see Figure 1;
329 Table 2). Although there are versions of some dust detection algorithms
330 designed to work at night (e.g. Wald et al., 1998), we focus on daytime events

331 here so that the influence of surface reflectance on dust source identification
332 can be explored.

333

334 <Insert Figure 1> -

335 <Insert Table 2>

336

337 *2.2.2 MODIS Level 1B Processing Algorithms*

338 As outlined earlier, mineral aerosol is sometimes detectable on un-
339 adjusted VIS satellite images (particularly over the ocean), but because
340 mineral aerosol can have similar reflectivity to the desert surfaces from which
341 it is entrained it can be difficult to detect over land. In addition, mineral aerosol
342 is often hard to differentiate from cloud, sea salt and anthropogenic pollution.
343 As a result of this, and also due to problems with the performance of MODIS
344 L2 aerosol products (section 2.1.1), a number of studies have used changes
345 in brightness temperature (TIR) to detect mineral aerosol over land surfaces.
346 Initial attempts using single TIR channel data, such as that by Shenk & Curran
347 (1974) using Nimbus-THIR (Temperature Humidity Infrared Radiometer) 11
348 μm data, had limited success because changes in surface emissivity at this
349 wavelength can be misinterpreted as dust (Roskovensky & Liou, 2003; 2005).
350 As a result of observed variability in the emissive and transmissive nature of
351 mineral aerosols within multiple TIR wavelength ranges, other researchers
352 have used methods based on brightness temperature difference (BTD) in
353 either two or three wavelength ranges, typically 11-12 μm bands (bi-spectral
354 split window technique) or near 8, 11 and 12 μm bands (tri-spectral) (e.g.
355 Ackerman, 1997). BTD values from this method reveal temperature
356 differences that exist between the ground surface and cooler mineral aerosol
357 while at the same time are largely unaffected by absorption from other
358 atmospheric gases (Darmenov & Sokolik, 2005). In addition to detecting dust
359 over land, these approaches may also allow discrimination between cloud and
360 dust when both exist in the vicinity of each other.

361

362 Here we initially apply the simple BTD approach detailed by Ackerman
363 (1997) to MODIS L1B data (Table 3). Using this methodology it has been
364 inferred that (BTD; 11.03-12.02 μm or MODIS $\text{BT}_{31}-\text{BT}_{32}$) values <0 K signify

365 the presence of mineral aerosol (dimensionless) and BT_D values ≥ 0 K
366 indicate no mineral aerosol. While developing the MODIS cloud mask,
367 Ackerman et al. (2002) have also placed the mineral aerosol detection
368 threshold at < -1 K. Although Ackerman's (1997) analysis implied that the 0 K
369 threshold could be widely used over a range of land surfaces, it is likely that
370 this will vary slightly according to variability in the emissive/transmissive
371 nature of the mineral aerosol. This in turn is determined by factors such as
372 mineralogy as well as processes acting upon the aerosol as it is transported in
373 the atmosphere. Mineralogical composition is an important control on the TIR
374 radiative properties of mineral aerosol and can vary significantly from region
375 to region (e.g. Claquin et al., 1999; Caquineau et al., 2002; Satheesh &
376 Moorthy, 2005). Darmenov and Sokolik (2005) investigated the TIR radiative
377 signature of dust transported over oceans from 7 different regions and located
378 the BT_D (11.03 -12.02 μm) aerosol detection threshold at 0.5, -0.2, -1.0 and -
379 0.4 K for the Nubian, Thar, Gobi/Taklimakan and Australian deserts
380 respectively; but could not locate a clear threshold to distinguish mineral
381 aerosol from cloud for dust over oceans sourced from NW Africa, Libya or the
382 Iranian desert. It may also be the case that the threshold varies for a single
383 geographical region, the precise value being dependent on factors such as
384 the density of the dust plume (Darmenov and Sokolik, 2005) or local variation
385 in dust source mineralogy (e.g. iron-rich sources versus illite-rich sources).
386 This simple bi-spectral split window approach will be applied here to identify
387 appropriate aerosol detection thresholds over land for the Lake Eyre Basin.

388

389 Using BT_D as a basis, a range of more complex algorithms has been
390 developed that combine BT_D and VIS wavelengths to detect mineral aerosol
391 over land and remove the effects of dense cloud cover, which can obscure
392 dust, and cirrus clouds which have similar reflectance and BT_D properties to
393 fine dust particles. In this paper we evaluate two of these cloud-removal
394 approaches applying them to MODIS L1B data for the LEB. The first is the
395 multispectral dust enhancement algorithm of Miller (2003) which exploits the
396 fact that dust particles can have contrasting VIS reflective properties when
397 compared to cloud (Table 3). In this model, an inverse brightness
398 temperature difference is used (BT_D; 12.02-11.03 μm or MODIS BT₃₂ – BT₃₁)

399 which is rescaled/normalized to lie within the -2 to $+2$ K range. Based on
400 Miller's (2003) algorithm the mineral aerosol output (D) has values
401 constrained between 1.3 and 2.7 (dimensionless). In addition this approach,
402 through manipulation of the red (R), green (G) and blue (B) display, enables
403 mineral aerosol to be visually differentiated from cloud using colour (D is
404 loaded on the red color gun). The second approach is that of Roskovensky
405 and Liou (2005) and Hansell et al., (2007) which focuses on the differentiation
406 of mineral aerosol from cirrus clouds by combining BTD (11.03 - 12.02 μm) and
407 VIS wavelengths (reflectance ratio of 0.54 $\mu\text{m}/0.86$ μm). In the final output
408 image, values of $D > 1$ (dimensionless) indicate mineral aerosol is present and
409 values ≤ 1 indicate cirrus cloud or non-mineral aerosol in the scene (Table 3).
410 Inclusion of the reflectance ratio in this case reduces the amount of false
411 detection of dust over land observed by Ackerman et al. (2002).

412

413 Although the majority of studies cited above have used data from
414 MODIS it is worth noting that similar approaches have been explored using
415 data from other sensors such as AVHRR, HIRS/2, GOES-8 and MSG-SEVIRI
416 with varying degrees of success (e.g. Legrand et al. 1989, Sokolik, 2002,
417 Schepanski et al., 2007).

418

419 <Insert Table 3>

420

421 Table 3 includes a summary of the default threshold values used to
422 differentiate dust from non-dust in each of the original algorithms used here.
423 The threshold values used in these algorithms are sensitive to varying
424 atmospheric conditions, surface reflectance, dust density and dust
425 mineralogy, but are formulated in a manner such that they allow a certain
426 degree of tuning to adjust for specific conditions such as regional variability
427 (Darmonov & Sokolik, 2005), or for dust blowing over land or ocean
428 (Roskovensky & Liou (2005). In this study, we verified the published models
429 by using the authors' original data and study-events both to check the set up
430 of the algorithms and to ensure we could reproduce the initial values of
431 dust/non-dust threshold and coefficients used. For the four case studies
432 presented here, we therefore established event-specific thresholds using the

433 approach suggested by each author (Table 4). The definition of thresholds
434 therefore involved the interrogation of pixel histograms for each scene-
435 algorithm combination (see below). In each case, peaks were found to be
436 attributable to specific scene components (e.g. densities and types of cloud
437 and aerosol), and thresholds were chosen to represent the value which was
438 best able to identify dust in the scene, as judged by the user (Figure 2a). In
439 each case, peaks representing dust were relatively easy to identify and
440 disinter from other scene components, and the effects of the choice of dust
441 threshold in each case is outlined below. Given the rather inflexible nature of
442 this approach, data from other study regions, where atmospheric conditions
443 and water vapor concentrations vary more significantly, may pose a challenge
444 to the straightforward identification and threshold determination for dust peaks
445 outlined here.

446 Figure 2 shows the histograms used to derive BTD thresholds and
447 Miller's D for each event. For the Roskovensky and Liou (2005) output the
448 dust/non-dust threshold remained at 1, but the D-parameter scaling factor 'a'
449 and BTD offset 'b' were adjusted for each event by using the midpoints
450 between the clear sky and dust histograms of the reflectance ratio and BTD
451 respectively (Figure 3).

452

453 <Insert Figure 2>

454 <Insert Figure 3>

455 <Insert Table 4>

456

457 2.2.3 Evaluation of output images

458 To evaluate the different MODIS dust detection algorithms it is
459 necessary to have a common reference against which to compare the output
460 data. For each of the four dust events examined, an eight panel figure was
461 produced. In each case, panel (a) represents the MODIS VIS image (where
462 red = band 1, green = band 4, blue = band 3). Panel (b) represents the bi-
463 spectral brightness temperature difference ($BTD = BT_{31} - BT_{32}$) with no dust
464 threshold applied. This is the principal image against which the outputs from
465 the different algorithms outlined in panels (c) Ackerman (1997), (d)
466 Roskovensky & Liou (2005) and (e) Miller (2003) were compared, because a

467 bi-spectral BTM is a common component of each of these Level 1B MODIS
468 algorithms. What is evaluated therefore is the extent to which the additional
469 components of the algorithms actually led to improved dust source detection.
470 In addition, a simple objective comparison of the outputs from each of the
471 Ackerman (1997), Roskovensky & Liou (2005) and Miller (2003) algorithms is
472 shown in panel (f). To produce this, boolean outputs from panels (c), (d) and
473 (e), where pixels were categorized as dust (=1) or non-dust (=0) were colored
474 red, green and blue respectively and combined to create a color composite
475 output image. For example, if a pixel was categorized as dust following
476 Ackerman's (1997) procedure it will appear red; if categorized as dust by both
477 Ackerman (1997) and Miller (2003) it will appear pink; if all three algorithms
478 categorize it as dust it will appear white; if all three categorize it as non-dust it
479 will appear black (Figure 4).

480

481 <Insert Figure 4>

482

483 Panels (g) and (h) represent the two dust products, MODIS L2 aerosol
484 (MYD04) Deep Blue AOT and OMI AI respectively. Although the spatial
485 resolution of the data is lower than the MODIS, OMI AI provides an
486 independent check on the spatial extent and intensity of aerosol retrieval for
487 all panels because it is not derived from MODIS.

488

489 Whilst a comparison of the different approaches to dust detection will
490 help to understand how MODIS can best be used to identify the presence or
491 absence of dust, the main aim of this paper is to evaluate the use of MODIS
492 for identifying dust sources. This means that the way in which the upwind
493 edge of the dust plume is depicted is of most interest. In these comparison
494 figures, the areas highlighting the active sources for each event (denoted by
495 coloured squares; e.g. figure 5), which were used to compare the outcome of
496 the techniques, were determined by an informed approach. Since the BTM
497 principle is a component of all of the evaluated algorithms (panels c-e),
498 sources were determined from a combination of the scene BTM plus other
499 readily available information, including the use of wind direction data to
500 ascertain the upwind side of plumes. From the companion dust source

501 inventory work of Bullard et al. (2008), certain sources in the LEB region could
502 be identified as relatively recurrent points of emission; locations which had a
503 record of acting as source areas for several different dust events across the
504 three year study period. The case study events here were therefore chosen to
505 ensure that several of the plume origins used for comparison were from
506 'proven' dust sources. Consequently, it is worth noting that the persistence of
507 certain key sources allowed their identification with a further confidence when
508 flagged as active in each BTM scene. One such example is the point-source
509 located at the south east margin of Lake Callabonna, South Australia (centred
510 on 140°15'0E, 30°S.). This well-studied source location was seen to be active
511 in both the third and fourth case studies, where BTM data are able accurately
512 to indicate it as an area where a plume has originated (Figures 7 and 8). The
513 relative performance of the dust enhancement models was evaluated on this
514 basis. It is worth noting that extensive background knowledge of dust events
515 in the LEB was used to help verify source locations determined from BTM
516 data and this may not be possible in areas where comparable auxiliary data
517 are unavailable. Nevertheless, in this study, we were able to carefully and
518 thoroughly assess model performance for detection of dust emanating from
519 known source locations.

520

521 As noted earlier, there are some additional caveats to the use of
522 remote sensing to determine (or infer) dust source locations; these include the
523 relative timings of the satellite overpass and the onset of dust emissions
524 (which might affect not only the location of the plume head, but also the
525 density of the dust), and the fact that only the upwind dust source can be
526 located with any additional contributing sources lying under the dust plume
527 possibly going undetected. To test the likely impact of some of these issues,
528 HYSPLIT (<http://www.arl.noaa.gov/ready>) was used to calculate possible
529 trajectories and plume concentrations for each event. These data are not
530 presented here but confirm that the dust emitted during the events was close
531 to, or at, source at the time of data capture and rarely reached an altitude of
532 more than 500 m. This suggests that overpass timings for remote sensing
533 data capture were likely to have provided data suitable for source
534 identification.

535

536 **3. Results**

537

538 **3.1 Event 1: 7th October 2005**

539

540 For this event, raised dust is quite difficult to observe in the visible
541 scene (Figure 5a) and sources are not at all apparent regardless of the level
542 of contrast enhancement applied. However, BTM analysis (Figure 5b) reveals
543 the presence of dust plumes, which appear as dark streaks at the centre of
544 the image. Much of the cloud in the lower left of Figure 5b also appears dark,
545 indicating some overlap in the thermal signature of cloud and dust in this
546 scene. This is further highlighted in Figure 5c where a dust/non-dust threshold
547 of 0 (dust <0, cloud > 0) has been applied. Here, not only are parts of the dust
548 plumes categorized as dust, but so too are some of the patches of cloud.
549 Although this simple threshold effectively separates cirrus cloud (white/light
550 grey in Figure 5b) from the dust plumes, the thicker areas of cloud (which
551 have similar BTM values to the dust) are mis-identified. Adjustment of the
552 dust/non-dust threshold for this scene highlighted that there was no single
553 BTM value that could differentiate these two components. In terms of
554 identification of the sources of dust in this scene, there was an observed
555 offset between the upwind dust heads shown in Figure 5c and the dust
556 sources identified using Figure 5b. This is most likely to be because the dust
557 at source is still close to the ground surface and therefore has a less
558 pronounced thermal contrast with the ground surface than airborne dust
559 further downwind of the source which will have risen to a higher atmospheric
560 level. Given the dust/non-dust threshold applied to the scene is 0, this also
561 indicates that some of the dust from this location can have a BTM value of >0
562 (Figure 5b).

563

564 <Figure 5>

565

566 Application of the Roskovensky and Liou (2005) algorithm (Figure 5d)
567 effectively removes the cirrus cloud from the scene, and only a small area of
568 the remaining cloud is included when a dust threshold (using event-specific 'a'

569 and 'b' coefficients; Table 4) is applied. The upwind ends of the main dust
570 plumes map on to the same source locations inferred from BTM (Figure 5b),
571 with the exception of the most northwestern plume which is not detected.
572 Miller's (2003) algorithm clearly differentiates the cloud from the main dust
573 plume (Figure 5e) which is picked out in red. With the exception of the
574 northernmost plume, source detection is comparable to those in Figure 5b.
575 However, there are some parts of this scene where dust is likely to have been
576 mis-identified. These areas (marked 'FS' in Figure 5e) are patches on the
577 ground surface where fires have changed the ground surface reflectance
578 characteristics significantly (Jacobberger-Jellison, 1994), and suggest that the
579 Miller algorithm is sensitive to ground reflectance variability. Given that the fire
580 scar is clearly discernible in the visible image (Figure 5a), but not when the
581 other techniques (which rely more heavily on BTM to detect dust) are used,
582 this implies that the component within the Miller (2003) algorithm that uses
583 VNIR wavelengths is slightly over weighted in this application. Figure 5f
584 shows the extent to which the three MODIS L1B algorithms agree and
585 highlight co-incident pixels containing dust. Whilst all three pick out the main
586 central plumes of dust, there are considerable differences elsewhere in the
587 scene. In particular, the Miller (2003) algorithm suggests a much more
588 extensive plume of dust than the other two approaches, especially in the
589 northeast. All of the techniques misidentify some of the most dense cloud as
590 dust, with Ackerman (1997) and Miller (2003) performing particularly poorly.

591

592 The MODIS Deep Blue AOT image (Figure 5g) shows that the cloud
593 mask applied in this instance is effective in separating the clear or dusty sky
594 from the clouds, and some dust is detected (AOT values close to 0). The dust
595 plumes in the far right of the scene that are highlighted in previous panels
596 (Figure 5 b, c, and d) are clearly defined, but the main central plume is less
597 obvious. In comparison, despite the relatively coarse resolution, the OMI AI
598 image (Figure 5h) depicts clearly the central and far right plumes, and with
599 similar AI values. This suggests that the inability of Deep Blue to detect both
600 of these plumes is not likely to be due to vastly different aerosol densities in
601 each plume. Instead, one possibility (explored further in section 4.6) is that
602 MODIS Deep Blue data are actually more sensitive to variations in dust colour

603 (mineralogy) than OMI. There is also an area in Figure 5g that is excluded by
604 the Deep Blue cloud mask (marked 'FP' in Figure 5g) where cloud is not
605 apparent. On the ground, this is a floodplain and the high surface reflectance
606 characteristics also cause confusion for the cloud mask when applied to event
607 3 (Figure 7g). Overall, the location of the dust plumes outlined by OMI AI data
608 correspond very closely to the position of the plumes in the MODIS 1B
609 algorithm outputs. In addition, the gridded AI data capture the extent and
610 variation of aerosol density apparent in the other panels. Although plume
611 identification is acceptable, the coarse resolution of the aggregated OMI AI
612 data ($0.25^\circ \times 0.25^\circ$) mean these data are less able to define the dust source
613 location or the nature of the surface sedimentary environments with the same
614 precision as can be achieved using the combination of outputs from the
615 MODIS L1B algorithms (e.g., Bullard et al., 2008; Lee et al., 2008).

616

617 3.2 Event 2: 24th September 2006

618

619 In the second event, the downwind (northerly) limit of the advancing
620 dust is very distinct in the MODIS VIS (Figure 6a). The upwind edges of the
621 plume are, however, not distinct and are in places difficult to differentiate from
622 the underlying bright desert surface. For Event 1, the dust/non-dust
623 thresholds or coefficients chosen are the same as those recommended in the
624 published techniques. However, if these values are applied to Event 2 some
625 problems become evident. Figure 6 shows the visible MODIS (panel a) and
626 BTD values (panel b) for Event 2 and the results of applying the Event 1
627 thresholds (Table 4; Figure 6 panels c-f). There is no possibility of identifying
628 dust sources using the Roskovensky and Liou (2005) or Miller (2003)
629 algorithms with these thresholds. The Roskovensky and Liou (2005) output
630 suggests that the dust plume fills most of the panel, whilst no dust is
631 highlighted using the Miller (2003) approach. This is emphasized in Figure 6f
632 which shows there are no areas of the image that all the different approaches
633 identify as containing dust.

634

635 <Figure 6>

636

637 For this reason, thresholds and parameters appropriate to this event
638 were determined using the histogram approach (see Table 4 for values). The
639 results of applying these event-specific thresholds are shown in Figure 7. The
640 dust source areas for this event and extent of the plume are reasonably well
641 discerned using BTD (Figure 7b), which also reveals several other minor
642 plumes that are not evident in the VIS. When an event-specific threshold is
643 applied to the BTD (Figure 7c) most of the plume is highlighted but some of
644 the thin, discrete plumes are not identified as dust or are foreshortened. This
645 again suggests the use of the dust/non-dust threshold can affect the accurate
646 identification of dust sources. The main plume is successfully identified using
647 Roskovensky and Liou's (2005) algorithm (Figure 7d) but the source areas
648 are poorly represented. Despite extensive experimentation with the 'a' and 'b'
649 coefficients to improve dust detection, it was not possible to pick out the
650 westernmost dust plumes without introducing a significant component of the
651 ground surface reflectivity to the dust determination.

652

653 <Figure 7>

654

655 Using Miller's (2003) algorithm (Figure 7e), the maximum D value for
656 this event falls below the published dust >1.3 threshold (see Table 3)
657 necessitating an adjustment of this threshold such that dust >-0.55 . Although
658 this adjustment enhances the dust visualization significantly, it does not do so
659 without introducing further artifacts. First, some areas of the plume evident in
660 Figure 7b were not highlighted, for example the thin streaks to the left of the
661 main plume that were also not identified using the default Ackerman (1997) or
662 Roskovensky and Liou (2005) thresholds (Figures 7c and d). Second, whilst
663 detection of airborne dust is improved, some areas of the ground surface are
664 also mis-identified as dust. Some of these are the same areas (marked FS in
665 Figure 7e) that caused difficulties in event 1 due to changes in surface
666 reflectivity caused by fire scars, and can clearly be seen in other panels
667 (Figure 7 a-d).

668

669 Figure 7f shows that the agreement between the MODIS L1B
670 enhancement methods for dust (white) is restricted to the most dense part of

671 the plume. Ackerman (1997) performs best at highlighting the more subtle
672 (perhaps less dense) dust plumes in the west of the scene. The Roskovensky
673 and Liou (2005) threshold mis-identifies dust not only to the west but also to
674 the south and so under-represents its spatial extent; with obvious implications
675 for upwind source detection.

676

677 The central dust plume is shown clearly in the MODIS Deep Blue
678 aerosol product for this event (Figure 7g). Not only is the sharp advancing
679 dust front apparent, but these data also indicate higher dust concentrations in
680 the southerly, upwind source area of the plume. At best, however, these data
681 are only able to provide a broad regional indication of the plume's source
682 because the thin, discrete plumes in the west are not detected. The MODIS
683 Deep Blue product also suggests that the highest AOT values in the scene
684 are associated with the plume at the extreme eastern edge of the scene
685 (marked 'X'). This contrasts with the MODIS BTD analyses where dust
686 appears to have a higher concentration at the furthest downwind edge of the
687 plume (marked 'Y'). Similarly, OMI AI data clearly outline the main plume, and
688 also suggest higher aerosol density in the east (Figure 7h). Comparison of the
689 Deep Blue and OMI data highlight the performance of the cloud masks used
690 in these products. The Deep Blue cloud mask only removes the cloud in the
691 top left of the scene, which is clearly present in MODIS VIS, whilst the OMI
692 cloud-mask obscures as much as 15% of the scene.

693

694 3.3 *Event 3: 2nd February 2005*

695

696 Event 3 was an extensive dust event during which 35 meteorological
697 stations recorded a reduction in visibility to ≤ 1 km. Here we concentrate on
698 two areas in the central LEB: the first is where two parallel dust plumes can
699 clearly be seen blowing northwards out of Lake Eyre North and the second is
700 in the lower right corner of the image and is difficult to see in the VIS (Figure
701 8a), but is clearly shown on the BTD (Figure 8b). The previous two events
702 used a BTD threshold of < 0 with varying success. For this event (Figure 8c), a
703 significantly lower threshold for dust detection (dust < -1.2) was required to
704 identify dust plumes (Table 4). Using this value, most of the pixels highlighted

705 contain dust although the area marked 'GS' on Figure 8c is not dust, but is the
706 ground surface. Crucially, the <-1.2 threshold in this instance does allow the
707 observed dust plumes to be traced all the way back to the source areas.

708

709 <Figure 8>

710

711 The Roskovensky and Liou (2005) algorithm (Figure 8d) is effective at
712 picking out the two main dust areas, but the origin of the twin plumes is
713 situated north of the known dust source (the bed of Lake Eyre North). The
714 parallel plumes are also visible when Miller's (2003) algorithm (Figure 8e) is
715 applied with an adjusted dust threshold, but this dense dust is only enhanced
716 by the model (coloured red) at the downwind end of the plume, and not in the
717 source locations. Furthermore, in comparison to BTD (Figure 8b), the origin of
718 the dust in Figure 8e (in white) would be placed approximately 70km north of
719 the actual lake bed source. The 'best' dust threshold that could be determined
720 for the Miller (2003) algorithm in this instance also seems to divorce the
721 apparent upwind boundary of the plume from the source area marked 'X'
722 in the right of the image (Figure 8e). However, the entire aerosol outbreak to the
723 lower right is highlighted in red using this approach, and the plume clearly
724 extends back to the assumed source. This demonstrates that there can be
725 significant variability in the performance of this enhancement approach within
726 a single scene. The composite image (Figure 8f) for the MODIS L1B
727 enhancement techniques highlights the problem of surface reflectance evident
728 when applying the Miller algorithm, as to the northwest of the twin plumes the
729 fire scar (FS) is clearly shown in blue.

730

731 In Figure 8g, the distinctive parallel dust plumes are mainly excluded
732 by the Deep Blue cloud mask, and only the downwind end of the plume is
733 detected. Other parts of the image, where no cloud is present (cf. Figure 8a),
734 are also excluded by the cloud mask. For example, the dry bed of Lake Eyre
735 and small patches across the whole area of the scene are flagged as no-data.
736 In Figure 8h, the OMI AI data show dust over the majority of the scene,
737 suggesting a widespread dust haze. The AI maximum of 5.4 is very high for
738 Australia but, whilst all the main areas of dust are identified in a manner

739 broadly consistent with the MODIS L1B algorithms, the spatial resolution is
740 insufficient to illustrate the detail of the parallel plumes or the specific source
741 locations. Indeed, although these data clearly have limited utility for
742 determining the specific point-sources in this scene, the OMI data do suggest
743 the presence of diffuse raised dust across the scene which would be expected
744 given the number of meteorological stations recording the event.

745

746 3.4 *Event 4: 30th August 2005*

747

748 The weather systems that promote LEB dust storms (thunderstorms,
749 pre- and post-frontal winds; Sprigg, 1982) mean that dust events are often
750 associated with cloud cover. Event 4 was selected to explore further the
751 extent to which dust and cloud can be distinguished. Dust is visible in the
752 centre of the VIS scene between the bands of cloud (Figure 9a) and can also
753 be identified using BTM (Figure 9b); although large areas of thicker cloud can
754 be seen which exhibit a similar BTM as the dust, making initial interpretation of
755 this scene using BTM alone problematic. A dust threshold of <-0.35 was
756 applied to BTM in this instance (Figure 9c), and was effective in isolating the
757 major dust plumes that exist between the clouds, but at the expense of the
758 thinner plumes which are removed when this particular threshold is applied.

759

760 <Figure 9>

761

762 Most of the cloud is removed from the image by application of
763 Roskovensky and Liou's (2005) algorithm (Figure 9d) and the inferred sources
764 for the two main dust plumes clearly map on to those identified from BTM
765 (Figure 9b). For this event, the Miller (2003) algorithm (Figure 9e) was scaled
766 using $\text{dust} > 0.45$, and can be seen to be very effective as the principal dust
767 plumes are easily discernable and source determination is possible. The
768 enhancements discussed here are unable to ameliorate the blanketing effect
769 of thick cloud when it obscures active dust sources or plumes; they can only
770 enhance the dust that can be 'seen' between the cloud banks. Interestingly,
771 none of the BTM-based methods pick up the thin plume which is best seen on
772 the MODIS visible panel (marked 'X', Figure 9a). The most notable feature,

773 other than the general agreement of spatial extent and source location for the
774 two plumes shown in Figure 9h, is the appearance of the blue areas where
775 the Miller (2003) output has confused the thickest cloud with dust.

776

777 The cloud masking of the Deep Blue (Figure 9g) scene seems to work
778 well for much of the cloud coverage in the image, but does also remove much
779 of the northernmost dust evident in the other panels (Figures 9b-f). The shape
780 and downwind extent of the central plume is indicated by raised AOT values,
781 but the MODIS Deep Blue data also suggest an origin for the dust that is
782 some distance removed downwind from the source when compared with the
783 BTD-based approaches. The OMI data (Figure 9h) again show more of the
784 dust plume than the MODIS Deep Blue product, and less of the image is
785 affected by cloud masking.

786

787 **4. Discussion**

788

789 The main aim of this paper is to evaluate the use of MODIS for
790 detecting dust sources. In some instances dust plumes may be discernible on
791 the MODIS VIS (e.g. Figure 6); but this certainly is not always the case (e.g.
792 Figure 4). From the results presented above, we can confirm that all the dust
793 enhancement techniques used here make it easier to detect dust. However,
794 with respect to source determination, the results suggest that, of the MODIS
795 L1 processing techniques, the 'best' approach varies from event to event. For
796 events 1 and 2 arguably the best source detection came from the simple
797 brightness temperature difference calculation (BTD), often with no dust
798 threshold applied. Of the more complex processing techniques, that of
799 Roskovensky & Liou (2005) works well for event 1 (Figure 5) as it is very
800 effective at removing cloud cover, whereas the Ackerman (1997) is better for
801 events 2 and 3, where cloud cover is less of an issue. The cloud cover in
802 event 4 (Figure 8) makes it much harder to determine sources from the BTD
803 alone, but both Roskovensky & Liou (2005) and Ackerman (1997) work well.
804 For these four events, the Miller (2003) algorithm is extremely useful for
805 visualizing dust, but there are significant problems with precise source
806 identification and determination of dust plume extent in all cases except event

807 4. For the majority of events and algorithms the published, or indicative,
808 thresholds under-perform and the values vary from event to event. This
809 makes it difficult to suggest appropriate regional scale thresholds. Whilst
810 some of this variation is due to factors specific to the algorithms or individual
811 events, other causes such as diurnal and seasonal variations in surface
812 temperature/dust contrast (which affect BTD) will affect all the methods. The
813 advantages and disadvantages of each of the approaches from an operational
814 perspective are discussed in detail below.

815

816 4.1 *Brightness Temperature Difference (bispectral split window)*

817

818 Calculating BTD is straightforward, and keeping the full range of values
819 (rather than applying a dust threshold) is often preferable for both dust plume
820 and source detection. The procedure does not appear to be very sensitive to
821 observed mineralogical variability either within or between plumes, and so all
822 dust, regardless of source, is enhanced provided it can be differentiated
823 thermally from the ground surface. The main disadvantages are that because
824 no definition of dust/non-dust is applied the interpretation of the BTD data
825 becomes subjective and data retrieval can suffer through lack of cloud cover
826 elimination. With the exception of event 4, this is not a major problem in the
827 case studies presented here, but it is likely to be important for anyone
828 interpreting the data, to have a good understanding of how and why ground
829 surface characteristics may vary.

830

831 4.2 *Ackerman (1997)*

832

833 Although Ackerman (1997) did not explicitly present a dust/non-dust
834 threshold of zero, he observed negative differences in $BT_{11}-BT_{12}$ for dust
835 storms and a universal threshold of $dust < 0$ could be implied. Darmenov &
836 Sokolik (2005) demonstrated that this dust threshold was in fact variable when
837 applied to dust over oceans and suggested that dust sourced from the Lake
838 Eyre Basin and travelling southeast over the Tasman Sea had a value of $< -$
839 0.4 K. All the dust plumes examined here are over land, and whilst the
840 threshold of zero worked effectively for events 1 and 2, adjustments had to be

841 made for events 3 and 4. For event 3, in order to eliminate interference from
842 the ground surface, the threshold had to be lowered to <-1.2 K; for event 4 the
843 threshold was <-0.35 to eliminate cloud. Interestingly, whilst it was possible to
844 find a dust/non-dust threshold for event 4 where all cloud could be removed
845 this was not possible for event 1. Here (Figure 5c), a dust threshold lower
846 than zero removed more dust in the scene so the threshold was left at 0.
847 Another factor affecting the BTD threshold is likely to be the thickness of the
848 dust plume. Where there is low AOT (as confirmed by comparison with
849 MODIS Deep Blue) we have determined BTD differences of >0 for pixels
850 populated by dust. One possibility is that where the dust plume
851 thickness/density is low, BTD becomes increasingly affected by the ground
852 surface temperature signal. Using this approach, therefore, may involve a
853 compromise between dust detection and the elimination of cloud. If both dust
854 and cloud are dense/opaque then it is straightforward to identify and
855 implement a dust threshold. If the dust is thin and cloud cover is dense (as in
856 event 1), then it can be hard to identify an appropriate dust/non-dust
857 threshold. Where the cloud cover is sparse and the dust plume is
858 dense/opaque (as in event 4) then their differentiation through threshold
859 adjustment is straightforward. From this study it is also apparent that the
860 thickness/density of the dust plume also affects the degree to which the dust-
861 head can be pinpointed, and an inappropriate threshold value may
862 foreshorten plumes.

863

864 4.3 *Roskovensky & Liou (2005)*

865

866 This approach was designed explicitly as a simple method for the
867 differentiation of dust from cirrus cloud, and is very effective at doing so in
868 both of the cloudy scenes examined here (events 1 and 4). For all events it
869 was necessary to adjust the scaling factor 'a' and BTD offset value 'b'.
870 Roskovensky and Liou (2005) calculated these to be 1.1 and 0 over ocean
871 (around the Korean peninsula) and 3 and 0 over land (the Gobi desert). All of
872 the events examined here occurred over land and the coefficients determined
873 were variable (values of 'a' ranged from 0.25 to 1.2 and values of 'b' ranged
874 from -0.5 to $+1$) and made a significant difference to both the number of

875 pixels classified as dust and the inferred location of the dust sources.
876 Although the algorithm is slightly more computationally complex to calculate
877 than simple BTD, it is easy to tune it for specific events, and certainly worth
878 the extra effort. Overall this model worked best on dense dust; there was little
879 observed confusion with ground surface reflectance, and the inferred upwind
880 plume source locations compared well with those suggested by BTD alone.

881

882 4.4 *Miller (2003)*

883

884 The Miller (2003) algorithm is designed to provide improved
885 differentiation of dust from water/ice clouds over bright desert surfaces and
886 was found to be visually very effective for all events observed in this study. In
887 particular, there is generally a clear distinction between dust and cloud. In a
888 similar manner to optimizing the Ackerman (1997) data, the Miller (2003) dust
889 threshold also had to be tuned for each event to be effective (Table 4) and in
890 most cases it was necessary to decrease the lower threshold value to well
891 below Miller's suggested +1.3 (as low as -0.55 in one instance). Unfortunately
892 tuning this algorithm was not straightforward, and although it worked very well
893 for some events, this was not always the case.

894

895 4.5 *The Aerosol Products (Deep Blue and OMI)*

896

897 The main utility of the aerosol products is in the detection of dust
898 because for dust source identification the coarse spatial resolution of the
899 products is a limitation. Average AI values over a long time series have been
900 used to detect persistent, regional scale dust sources (e.g. Washington et al.,
901 2003) but accurate and event-specific source identification requires the clear
902 delineation of the upwind margin of the plumes. We have presented values of
903 Deep Blue AOT and OMI AI which, whilst not comparable in terms of absolute
904 values can be compared relatively. There are occasions where OMI agrees
905 well with the much higher resolution MODIS, but often the upwind margin of a
906 dust plume is difficult to detect using AI.

907

908 In some cases, it was difficult to determine not only the upwind dust
909 sources but also the extent of the dust plumes because the in-built cloud
910 masks of the products eliminated them. For example, in Figure 8g, the origin
911 of the parallel twin plumes was not discernible because MYD04 returned no
912 data from the bright dry lake surface, which was classified as cloud. This is a
913 recognised limitation and is probably due to the colour and density of the dust
914 or reflectance of the surface. The twin parallel plumes comprise white
915 coloured dense dust sourced from Lake Eyre and are sufficiently bright to
916 saturate the pixels causing misidentification as cloud (a known problem with
917 Level 2 aerosol product [http://modis-](http://modis-atmos.gsfc.nasa.gov/MOD04_L2/ga.htm)
918 [atmos.gsfc.nasa.gov/MOD04_L2/ga.htm](http://modis-atmos.gsfc.nasa.gov/MOD04_L2/ga.htm)). There are obvious implications for
919 dust source identification – ephemeral lakes are often very bright surfaces
920 and have been seen in this study to be routinely masked out as cloud even in
921 cloud-free and dust-free scenes, yet are common dust sources not only in the
922 LEB (Bullard et al. 2008), but also in the USA (e.g. Reynolds et al. 2007),
923 southern Africa (Mahowald et al. 2003) and other dryland regions. The
924 authors are also evaluating the Aura-OMI Aerosol Data Product; OMAERUV
925 (V003) which provides aerosol extinction and optical depth via swath data
926 (rather than global gridded) at the native 13 x 24 km pixel (see:
927 <http://daac.gsfc.nasa.gov/Aura/OMI/omaeruv.shtml>). This may offer further
928 potential for dust source identification, but requires further validation.

929

930 *4.6 Impacts of Dust Mineralogy and Surface Reflectance on Data Retrieval*

931

932 One issue that can be explored briefly here, and will be developed
933 further as a future project, is the impact of dust mineralogy on both the Miller
934 (2003) dust thresholds and MODIS Deep Blue retrievals. A range of different
935 sedimentary environments emit dust within the Lake Eyre Basin (Bullard et al.,
936 2008) and these have different mineralogical compositions which in turn
937 control the infrared radiative properties of the dust (Claquin et al., 1999;
938 Sokolik, 2002). An example can be seen in event 3 (Figure 8) where a dust
939 plume was observed originating from the bed of Lake Eyre (which is illite-rich),
940 in the west of the scene and a dust plume originating from dune sands with
941 iron-rich coatings in the southeast of the scene. Using threshold values

942 where $0.6 < \text{dust} < 1.98$ it was possible to pick out the dust sourced from the
943 dunes in red, but not the near-source dust from the lake (although part of the
944 distal end of the plume is highlighted). When a threshold was selected to
945 highlight both plumes large areas of ground surface were also included.

946

947 The effect of dust mineralogy on detection is also apparent in the
948 MYD04 Deep Blue data presented here. In the Deep Blue algorithm, surface
949 reflectivity over desert regions is assumed to be low in blue wavelengths and,
950 dust aerosol slightly more reflective (Hsu et al., 2004). However, dust
951 reflectivity is variable depending on its chemistry and can decrease
952 significantly with increased iron concentration (Dubovic et al., 2002; Arimoto
953 et al., 2002). Consequently red, or iron-rich, dust will have relatively low blue
954 reflectivity and therefore potentially lower contrast relative to background
955 reflectance, whereas white dust (composed of carbonates, bleached quartz or
956 evaporite minerals) will have higher reflectance in the VIS and significantly
957 higher contrast with respect to underlying soils and vegetation. This is
958 illustrated in Figures 7g and 8g where the white, dry lake bed sources of dust
959 are more distinct than the iron-oxide rich dust from dune sources (noting
960 however that the OMI product suggests these red plumes are also less dense
961 than the white dust plumes which will affect AOT).

962

963 For the Lake Eyre Basin events there are some problems with the
964 differentiation of dust from the underlying desert surface. Specifically, large
965 areas of the LEB dunefields comprise red brown to orange, highly reflective
966 sands with a partial vegetation cover; although sand color is variable
967 especially between the redder Simpson dunefield and the less red Strzelecki
968 dunefield (Pell et al., 2000; Bullard and White, 2002). Where the vegetation
969 cover has not been disturbed by fire, the Miller (2003) algorithm works well.
970 However, where vegetation has been removed by fire and large areas of
971 bright sand are exposed the algorithm cannot distinguish dust from the
972 surface. Fire changes both surface reflectance characteristics, through the
973 removal of absorbing vegetation, and sediment reflectance characteristics,
974 through fire-induced reddening or changes in mineralogy (Jacobberger-
975 Jellison, 1994). The way in which the performance of the Miller (2003)

976 algorithm is affected by these changes has important implications for dust
977 provenance because areas which have been de-vegetated through fire may
978 be mis-identified as a dust source. A complicating issue is that fire scars can
979 act as sources of dust under certain conditions (Bullard et al. 2008; McGowan
980 & Clark, 2008). This highlights two issues. First, it is important to deploy
981 event-specific dust/non-dust thresholds to limit the influence of surface
982 reflectance as far as possible. Second, familiarity with the underlying surface
983 characteristics is essential, and examination of more than one scene,
984 including known dust-free images is desirable. The latter means that
985 permanent or semi-permanent ground characteristics can be discerned. For
986 example, the firescars in the LEB have distinctive shapes that can be
987 identified on most of the VIS images taken post-2001 when widespread
988 burning occurred. Cross-referencing with other MODIS-derived output can
989 also be useful. For example, in event 1 the fire scar is only clearly discernible
990 on the VIS and Miller (2003) panels which suggests that it was not a dust
991 source. In contrast, in event 2 the fire scars are discernable in all panels
992 (Figure 7 a-e) which may suggest that they acted as dust sources at this time.

993

994 4.7. *Tools for dust source detection*

995

996 Figure 10 presents a summary of the how the different data sources
997 and analyses used here complement one another. At the global-regional
998 scale, dust events can be detected using visibility criteria, as in this paper, or
999 OMI AI. An alternative that we have not discussed in detail here is the
1000 MOD/MYD08 Global Gridded Atmospheric Product (1 x 1 deg) which could
1001 also be used (Bryant et al., 2007), although it has some limitations over bright
1002 desert surfaces (Chu et al., 2002). If none of these three indicates dust it does
1003 not necessarily mean that dust is not present as the relative timing of satellite
1004 overpass or visibility observation may result in no dust being recorded (see
1005 quality control indicators), but the events missed are likely to be minor. If any
1006 one of these indicates the presence of dust then there is the potential for
1007 determining dust sources at higher resolution. The choice of higher resolution
1008 technique depends on the precise research question to be answered. The
1009 MOD/MYD04 aerosol products give data processed to a common standard

1010 that enables comparison from one region to another. The versatile
1011 MOD/MYD02 data can be processed simply using brightness temperature
1012 difference to enhance the dust signal. Where cloud is present, or if it is
1013 necessary to highlight the dust plume then one of the methods for employing
1014 a dust/non-dust threshold can be used, but it is recommended that event-
1015 specific thresholds are calculated where possible (as opposed to using global
1016 or regional thresholds).

1017

1018

1019 **5. Conclusions**

1020 This paper set out to evaluate the use of MODIS data for identifying dust
1021 sources. Through objective and subjective comparison of several different
1022 approaches to dust detection several conclusions can be drawn. Whilst these
1023 conclusions have implications for regional and global scale studies of dust,
1024 the clear outcomes are that even within a single drainage basin, dust events
1025 should be examined on an event by event basis, and that the 'best' algorithm
1026 for identifying dust sources varies considerably.

1027 (1) For the region examined here (the Lake Eyre Basin), no single MODIS
1028 technique was found to be ideal for source determination.

1029 (2) MODIS VIS full colour composite data can be useful but are often
1030 insufficient to discern dust plumes over reflective desert surfaces. In
1031 particular, for event detection MODIS VIS (particularly via quicklooks)
1032 should be used with caution, or in combination with other data sources,
1033 because not all dust plumes will be visible over the bright surfaces. An
1034 ideal combination for rapid detection of dust activity is OMI AI (or
1035 equivalents) and MODIS but the former can not be used to derive
1036 source location due to its low spatial resolution.

1037 (3) BTM data are simple to calculate and very effective at highlighting dust
1038 that is not seen in VIS data. If the user is familiar with the underlying
1039 ground surface characteristics and has the VIS image available to
1040 discern cloud cover, this can be the most simple and possibly most
1041 accurate method of source determination. From the four example
1042 events presented here, BTM is the approach that is least sensitive to
1043 dust mineralogy.

- 1044 (4) For scenes where cloud is present, there is potential for confusion
1045 between cloud and dust using just BTM and the algorithms designed to
1046 differentiate these have been demonstrated as effective for screening
1047 out cirrus cloud (for which they were designed) although thick cloud
1048 can remain.
- 1049 (5) Whilst there are published dust/non-dust thresholds for each method
1050 compared here, for each method thresholds may need adjusting on a
1051 regional and/or event scale. Although there are clear guidelines for
1052 positioning thresholds, a considerably amount of informed (but
1053 subjective) judgement can be required. It is important therefore for
1054 users of these techniques to consider the effects of not adjusting
1055 thresholds for each event. This paper suggests that for an event-
1056 based study it is essential to derive event-specific thresholds. However
1057 it seems likely that for global or longer-term studies of this nature to be
1058 effective, it may be pragmatic to use regional thresholds.
- 1059 (6) In the Lake Eyre Basin, it is not possible to use a single dust/non-dust
1060 threshold for all events for any of the algorithms tested here. One
1061 possible reason is that it is a basin with multiple potential dust sources
1062 with different mineralogies; where different sources (e.g. iron-rich
1063 dunes, illite-rich lake beds) can emit dust simultaneously it is necessary
1064 to use event-specific, or even plume-specific thresholds. In regions
1065 with a single definable source (for example a large playa such as the
1066 Magkadigadki, Botswana) it may be possible to discern a single
1067 dust/non-dust threshold, however any use of a regional (or global)
1068 threshold is likely to result in errors or inconsistencies.
- 1069 (7) Some sedimentary environments are more intense dust sources than
1070 others. In particular, previous studies have noted ephemeral lakes and
1071 areas devegetated by fire as prominent dust sources. Significantly,
1072 these are two of the ground surface types that have proved most
1073 problematic for establishing dust/non-dust thresholds due to confusion
1074 caused by their bright surfaces which cause false positive dust signals
1075 or may be falsely identified as cloud.
- 1076 (8) Whilst the findings of this research may be challenging in some
1077 respects, what is clear is that there is considerable potential for using

1078 MODIS data to obtain information about dust mineralogy by interpreting
1079 the shifts to the thresholds (or coefficients) that need to be made.
1080 Possible mineral aerosol information that could be gained can not only
1081 assist in identifying the dust source, but also its radiative properties.

1082

1083 Using data from sensors such as MODIS will inevitably mean that some
1084 dust activity is missed due to the relative timing of overpass and dust
1085 emissions or cloud cover. Other sources of data such as MSG can minimize
1086 the problem of overpass timings but cloud cover is still a problem and
1087 coverage is not yet global. This paper has focused on daytime dust
1088 emissions only, but analysis of night time dust emissions and source
1089 identification are the subject of future research. It is worth noting that the
1090 products and data used here are subject to continual development and
1091 improvement and consequently some of the issues raised here may be
1092 resolved or change.

1093

1094

1095

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1101 **References**

1102

1103 Ackerman, S.A. (1997). Remote sensing aerosols using satellite infrared
1104 observations, *Journal of Geophysical Research*, 102, 17069–17080

1105 Ackerman, S.A., Strabala, K.I., Menzel, W.P., Frey, R., Moeller, C., Gumley, L.,
1106 Baum, B.A., Seeman, S.W., & Zhang, H. (2002). Discriminating clear-
1107 sky from cloud with MODIS algorithm theoretical basis document
1108 (MOD35). In ATBD Ref.ATBD-MOD-06, version 4.0, 115 pp. Greenbelt,
1109 Maryland: NASA Goddard Space Flight Center

1110 Ahn, C., Torres, O., & Bhartia, P.K. (2008). Comparison of ozone monitoring
1111 instrument UV aerosol products with Aqua/Moderate Resolution Imaging
1112 Spectroradiometer and Multiangle Imaging Spectroradiometer
1113 observations in 2006. *Journal of Geophysical Research*, 113, D16S27

1114 Agarwal, A., El-Askary, J.M., El-Ghazawi, T., Kafatos, M. and Le-Moigne, J.
1115 (2007). Hierarchical PCA techniques for fusing spatial and spectral
1116 observations with application to MISR and monitoring dust storms.
1117 *IEEE Geoscience and Remote Sensing Letters*, 4, 4, 678-682.

1118 Alpert, P., Kishcha, P., Shtivelman, A., Krichak, S.O. & Joseph, J.H. (2004).
1119 Vertical distribution of Saharan dust based on 2.5-year model
1120 predictions. *Atmospheric Research*, 70, 109-130.

1121 Arimoto, R., Balsam, W., Schloesslin, C. 2002. Visible spectroscopy of
1122 aerosol particles collected on filters: iron-oxide minerals. *Atmospheric
1123 Environment*, 36, 89-96.

1124 Badarinath, K.V.S., Kumar Kharol, S., Kaskaoutis, D.G. & Kambezidis, H.D.
1125 (2007). Dust storm over Indian region and its impact on the ground
1126 reaching solar radiation – a case study using multi-satellite data and
1127 ground measurements. *Science of the Total Environment*, 384, 316-
1128 332.

1129 Brindley, H. E., & Ignatov, A. (2006). Retrieval of mineral aerosol optical depth
1130 and size information from Meteosat Second Generation SEVIRI solar
1131 reflectance bands. *Remote Sensing of Environment*, 102, 344-363,
1132 doi:10.1016/j.rse.2006.02.024

1133 Bryant, R. G., Bigg, G. R., Mahowald, N. M., Eckardt, F. D., & Ross, S. G.,
1134 (2007). Dust emission response to climate in southern Africa. *Journal of*

- 1135 *Geophysical Research*, 112, D09207, doi:10.1029/2005JD007025.
- 1136 Bullard, J. E., Baddock, M. C., McTainsh, G. H., & Leys, J. F., (2008). Sub-
1137 basin scale dust source geomorphology detected using MODIS.
1138 *Geophysical Research Letters* 35, 1, art.no.L15404,
1139 doi:2008GL033928.
- 1140 Bullard, J. E., & White, K. H., (2002). Quantifying iron oxide coatings on dune
1141 sands using spectrometric measurements: an example from the
1142 Simpson-Strzelecki Desert, Australia. *Journal of Geophysical*
1143 *Research*, 107, doi:10.1029/2001JB000454.
- 1144 Caquineau, S., Gaudichet, A., Gomes, L., & Legrand, M. (2002). Mineralogy
1145 of Saharan dust transported over northwestern tropical Atlantic Ocean
1146 in relation to source regions. *Journal of Geophysical Research*,
1147 107(D15), 4251, doi:10.1029/2000JD000247
- 1148 Chu, D.A., Kaufman, Y.J., Ichoku, C., Remer, L.A., Tanré, D. & Holben, B.N.
1149 (2002). Validation of MODIS aerosol optical depth retrieval over land.
1150 *Geophysical Research Letters*, 29, 12, 8007,
1151 doi:10.1029/2001GL013205.
- 1152 Claquin, T., Schulz, M., & Balkanski, Y.J. (1999). Modeling the mineralogy of
1153 atmospheric dust sources. *Journal of Geophysical Research*, 104,
1154 22243-22256
- 1155 Darmenov, A. & I.N. Sokolik (2005). Identifying the regional thermal-IR
1156 radiative signature of mineral dust with MODIS. *Geophysical Research*
1157 *Letters*, 32, L16803, doi:10.1029/2005GL023092
- 1158 de Baar, H.J.W. and 33 others (2005). Synthesis of iron fertilization
1159 experiments: from the iron age in the age of enlightenment. *Journal of*
1160 *Geophysical Research-Oceans*, 110, C9, C09S16.
- 1161 Desboeufs, K.V., Sofikitis, A., Losno, R., Colin, J.L., & Ausset, P. (2005).
1162 Dissolution and solubility of trace metals from natural and
1163 anthropogenic particulate matter. *Chemosphere*, 58, 2, 195-203.
- 1164 Dubovik, O., Holben, B., Eck, T.F., Snirnov, A., Kaufman, Y.J., King, M.D.,
1165 Tanré, D. & Slutsker, I. 2002. Variability of absorption and optical
1166 properties of key aerosol types observed in worldwide locations.
1167 *Journal of the Atmospheric Sciences*, 59, 590-608.
- 1168 Dubovik, O., Lapyonok, T., Kaufman, Y.J., Chin, M., Ginoux, P., Kahn, R.A. &

- 1169 Sinyuk, A. (2008). Retrieving global aerosol sources from satellites
1170 using inverse modeling. *Atmospheric Chemistry and Physics*, 8, 2,
1171 209-250.
- 1172 Eckardt, F.D., & Kuring, N. (2005). SeaWIFS identified dust sources in the
1173 Namib Desert. *International Journal of Remote Sensing*, 26, 19, 4159-
1174 4167
- 1175 Ekstrom, M., McTainsh, G.H., & Chappell, A. (2004). Australian dust storms:
1176 temporal trends and relationships with synoptic pressure distributions
1177 (1960-1999). *International Journal of Climatology*, 24, 12, 1581-1599.
- 1178 Erickson, D.J., Hernandez, J.L., Ginoux, P., Gregg, W.W., McClain, C., &
1179 Christian, J. (2003). Atmospheric iron delivery and surface ocean
1180 biological activity in the Southern Ocean and Patagonian region.
1181 *Geophysical Research Letters*, 30, 12, doi:10.1029/2003GL017241
- 1182 Evan, A. T., A. K. Heidinger, and M. J. Pavolonis (2006) Development of a
1183 new over water Advanced Very High Resolution Radiometer dust
1184 detection algorithm. *International Journal of Remote Sensing*, 27(18),
1185 pp. 3903-3924. doi: 10.1080/01431160600646359
- 1186 Gassó, S. & A.F. Stein (2007). Does dust from Patagonia reach the sub-
1187 Antarctic Atlantic Ocean. *Geophysical Research Letters*, 34, L01801,
1188 doi:10.1029/2006GL027693
- 1189 Hansell, R.S., Ou, S.C., Liou, K.N., Roskovensky, J.K., Tsay, S.C., Hsu, C., &
1190 Ji, Q. (2007). Simultaneous detection/separation of mineral dust and
1191 cirrus clouds using MODIS thermal infrared window data. *Geophysical*
1192 *Research Letters*, 34, L11808, doi:10.1029/2007GL029388
- 1193 Haywood, J., & Boucher, O. (2000). Estimates of the direct and indirect
1194 radiative forcing due to tropospheric aerosols: a review. *Reviews of*
1195 *Geophysics*, 38, 4, 513-543.
- 1196 Hsu, N.C., Herman, J. R. & Weaver, C. (2000). Determination of radiative
1197 forcing of Saharan dust using combined TOMS and ERBE data.
1198 *Journal of Geophysical Research*, 105, 20649–20661
- 1199 Hsu, N. C., Tsay, S. C. King, M. D. & Herman J. R. (2004). Aerosol properties
1200 over bright-reflecting source regions, *IEEE Transactions on Geoscience*
1201 *and Remote Sensing*, 42, 557-569
- 1202 Hsu, N.C., Tsay, S-C, King, M.D., & Herman, J.R. (2006). Deep Blue retrievals

1203 of Asian aerosol properties during ACE-Asia. *IEEE Transactions on*
1204 *Geoscience and Remote Sensing*, 44, 11, 3180-3195.
1205 doi:10.1109/TGRS.2006.879540

1206 Jacobberger-Jellison, P.A. (1994). Fire-induced reddening of dune sands.
1207 *Journal of Arid Environments*, 26, 305-313.

1208 Jickells, T.D. and 18 others, (2005). Global iron connections between desert
1209 dust, ocean biogeochemistry and climate. *Science*, 308, 67-71

1210 Jones, T.A. & Christopher, S.A. (2007). MODIS-derived fine mode fraction
1211 characteristics of marine dust and anthropogenic aerosols over the
1212 ocean constrained by GOCART, MOPITT and TOMS. *Journal of*
1213 *Geophysical Research – Atmospheres*, 112, D22, D22204.

1214 Jones, T.A. & Christopher, S.A. (2008). Multispectral analysis of aerosols over
1215 oceans using principal components. *IEEE Transactions on*
1216 *Geoscience and Remote Sensing*, 46, 9, 2659-2665.

1217 Kaskaoutis, D.G., Kambezidis, H.D., Nastos, P.T. & Kosmopoulos, P.G.
1218 (2008). Study on an intense dust storm over Greece. *Atmospheric*
1219 *Environment*, 42, 9, 6884-6896.

1220 Kaufman, Y.J., Tanré, D., Remer, L., Vermote, E.F., Chu, A., & Holben, B.N.
1221 (1997). Operational remote sensing of tropospheric aerosol over the
1222 land from EOS-MODIS. *Journal of Geophysical Research*, 102, 17051-
1223 17068

1224 Kaufman, Y.J., Karnieli, A., & Tanré, D. (2000). Detection of dust over deserts
1225 using satellite data in the solar wavelengths. *IEEE Transactions on*
1226 *Geoscience and Remote Sensing*, 38, 1, 525-531

1227 Kaufman, Y.J., Boucher, O., Tanré, D., Chin, M., Remer, L.A. & Takemura, T.
1228 (2005). Aerosol anthropogenic component estimated from satellite
1229 data. *Geophysical Research Letters*, 32, 17, L17804.

1230 Kubilay, N, Oguz, T., Kocak, M., & Torres, O. (2005). Ground-based
1231 assessment of Total Ozone Mapping Spectrometer (TOMS) data for
1232 dust transport over the northeastern Mediterranean. *Global*
1233 *Biogeochemical Cycles*, 19, GB1022.1

1234 Lee, J.A., Gill, T.E., Mulligan, K.R., Acosta, M.D., & Perez, A.E. (2008). Land
1235 use/land cover and point sources of the 15 December 2003 dust storm

1236 in southwestern North America. *Geomorphology*, 105, 1-2. 18-27,
1237 doi:10.1016/j.geomorph.2007.12.016.

1238 Legrand, M., Nertrand, J.J., Desbois, M., Menenger, L., & Fouquart, Y. (1989).
1239 The potential of infrared satellite data for the retrieval of Saharan dust
1240 optical depth over Africa. *Journal of Climatology and Applied*
1241 *Meteorology*, 28, 309-318.

1242 Levy, R.C., Remer, L.A., Kaufman, Y.J., Tanré, D., Mattoo, S., Vermote, E. &
1243 O. Dubovik, (2006). Revised Algorithm Theoretical Basis Document:
1244 MODIS Aerosol Products MOD/MYD04. Available at [http://modis-](http://modis-atmos.gsfc.nasa.gov/reference_atbd.html)
1245 [atmos.gsfc.nasa.gov/reference_atbd.html](http://modis-atmos.gsfc.nasa.gov/reference_atbd.html)

1246 Levy, R.C., L.A. Remer, S. Mattoo, E.F. Vermote, & Y.J. Kaufman (2007).
1247 Second-generation operational algorithm: Retrieval of aerosol
1248 properties over land from inversion of Moderate Resolution Imaging
1249 Spectroradiometer spectral reflectance, *Journal of Geophysical*
1250 *Research*, 112, D13211, doi:10.1029/2006JD007811

1251 Li, J., Okin, G.S., Alvarez, L., & Epstein, H. (2007). Quantitative effects of
1252 vegetation cover on wind erosion and soil nutrient loss in a desert
1253 grassland of southern New Mexico, USA. *Biogeochemistry*, 85, 3, 317-
1254 332

1255 Mackie, D.S., Boyd, P.W., Hunter, K.A., & McTainsh, G.H. (2005). Simulating
1256 the cloud processing of iron in Australian dust: pH and dust
1257 concentration. *Geophysical Research Letters*, 32, 6, L06809

1258 Mackie, D.S., Boyd, P.W., McTainsh, G.H., Tindale, N.W., Westberry, T.K., &
1259 Hunter, K.A. (2008). Biogeochemistry of iron in Australian dust: from
1260 eolian uplift to marine uptake. *Geochemistry, Geophysics,*
1261 *Geosystems*. 9, doi:10.1029/2007GC001813

1262 MacKinnon, D. J., Chavez, P. S., Jr., Fraser, R. S., Niemeyer, T. C., and
1263 Gillette, D. A., (1996), Calibration of GOES-VISSR, visible-band
1264 satellite data and its application to the analysis of a dust storm at
1265 Owens Lake, California, *Geomorphology* 17, pp. 229 - 250

1266 McGowan, H.A., & Clark, A. (2008). A vertical profile of PM10 dust
1267 concentrations measured during a regional dust event identified by
1268 MODIS Terra, western Queensland, Australia. *Journal of Geophysical*
1269 *Research*, 113, F02S03, doi:10.1029/2007JF000765.

- 1270 McTainsh, G. H. & Strong, C.S. (2007). The role of aeolian dust in
1271 ecosystems. *Geomorphology*, 89, 1-2, 39-54
- 1272 Mahowald, N.; Baker, A.; Bergametti, G.; Brooks, N.; Duce, R.; Jickells, T.;
1273 Kubilay, N.; Prospero, J.; Tegen, I.(2005) Atmospheric global dust
1274 cycle and iron inputs to the ocean *Global Biogeochemical Cycles*, Vol.
1275 19, No. 4, GB4025,doi: 10.1029/2004GB002402, 2005
- 1276 Mahowald, N., Ballentine, J.A., Feddema J., & Ramankutty N. (2007). Global
1277 trends in visibility: implications for dust sources, *Atmospheric Chemistry
1278 and Physics*, 7, 3309-3339.
- 1279 Mahowald, N.M., Bryant, R.G., del Corral, J. & Steinberger, L. (2003).
1280 Ephemeral lakes and dust sources. *Geophysical Research Letters*, 30,
1281 2, art.no.1074.
- 1282 Middleton, N.J., Goudie, A.S. & Wells, G.L. (1986). The frequency and source
1283 areas of dust storms. In Nickling, W.G. (ed) *Aeolian Geomorphology*.
1284 Allen & Unwin, Boston, 237-259.
- 1285 Miller, S.D. (2003). A consolidated technique for enhancing desert dust
1286 storms with MODIS. *Geophysical Research Letters*, 30, 20,
1287 art.no.2071.
- 1288 Moorthy, K.K., Babu, S.S., Satheesh, S.K., Srinivasan, J., & Dutt, C.B.S.
1289 (2007). Dust absorption over the "Great Indian Desert" inferred using
1290 ground-based and satellite remote sensing. *Journal of Geophysical
1291 Research – Atmospheres*, 112, D9, D09206.
- 1292 Muhs, D.R., Budahn, J.R., Prospero, J.M., & Carey, S.N. (2007).
1293 Geochemical evidence for African dust inputs to soils of western
1294 Atlantic islands: Barbados, the Bahamas and Florida. *Journal of
1295 Geophysical Research – Earth Surface*. 112,
1296 doi:10.1029/2005JF000445.
- 1297 Pell, S.D., Chivas, A.R., & Williams, I.S. (2000). The Simpson, Strzelecki and
1298 Tirari Deserts: development and sand provenance. *Sedimentary
1299 Geology*, 130, 1-2, 107-130.
- 1300 Piketh, S.J., Tyson, P.D., & Steffen, W. (2000). Aeolian transport from
1301 southern Africa and iron fertilization of marine biota in the South India
1302 Ocean. *South African Journal of Science*, 96, 244-246.

1303 Prospero, J.M., Ginoux, P., Torres, O., Nicholson, S.E. & Gill, T.E. (2002).
1304 Environmental characterization of global sources of atmospheric soil
1305 dust identified with the Nimbus 7 Total Ozone Mapping Spectrometer
1306 (TOMS) absorbing aerosol product. *Reviews of Geophysics*, 40, 1,
1307 art.no.1002.

1308 Remer, L.A., Tanré, D., Kaufman, Y.J., Levy, R. & Mattoo, S. (2006).
1309 Algorithm for Remote Sensing of Tropospheric Aerosol from MODIS for
1310 Collection 005 Products: 04_L2, 08_D3, 08_E3, 08_M3. Available from:
1311 [http://modis-](http://modis-atmos.gsfc.nasa.gov/_docs/MOD04:MYD04_ATBD_C005_rev1.pdf)
1312 [atmos.gsfc.nasa.gov/_docs/MOD04:MYD04_ATBD_C005_rev1.pdf](http://modis-atmos.gsfc.nasa.gov/_docs/MOD04:MYD04_ATBD_C005_rev1.pdf)

1313 Remer, L.A., Kaufman, Y.J., Tanré, D., Mattoo, S., Chu, D. A., Martins, J. V.,
1314 Li, R.-R., Ichoku,, Levy, R. C., Kleidman, R. G., Eck, T. F., Vermote, E.,
1315 & Holben, B. N. (2005). The MODIS aerosol algorithm, products and
1316 validation, *Journal of Atmospheric Sciences*, 62, 4, 947–973.Reynolds,
1317 R., Neff, J., Reheis, M., & Lamothe, P. (2006). Atmospheric dust in
1318 modern soil on Aeolian sandstone, Colorado Plateau (USA): variation
1319 with landscape position and contribution to potential plant nutrients.
1320 *Geoderma*, 130, 1-2, 108-123.

- 1321 Reynolds, R., Neff, J., Reheis, M. & Lamothe, P. (2006). Atmospheric dust in
1322 modern soil on aeolian sandstone, Colodaro Plateau (USA): variation
1323 with landscape position and contribution to potential plant nutrients.
1324 *Geoderma*, 130, 1-2, 108-123.
- 1325 Reynolds, R., Yount, J.C., Reheis, M., Goldstein, H., Chavez, P., Fulton, R.,
1326 Whitney, J., Fuller, C. & Forester, R.M. 2007. Dust emission from wet
1327 and dry playas in the Mojave desert, USA. *Earth Surface Processes
1328 and Landforms*, 32, 12, 1811-1827.
- 1329 Ridgwell, A.J. (2002). Dust in the Earth system: the biogeochemical linking of
1330 land, air and sea. *Philosophical Transactions of the Royal Society of
1331 London*, A. 360, 1801, 2905-2924.
- 1332 Roskovensky, J.K. & K.N. Liou (2003). Detection of thin cirrus from 1.38
1333 mm/0.65 mm reflectance ratio combined with 8.6– 11 mm brightness
1334 temperature difference. *Geophysical Research Letters*, 30, 19,
1335 doi:10.1029/2003GL018135
- 1336 Roskovensky, J.K. & K.N. Liou (2005). Differentiating airborne dust from cirrus
1337 clouds using MODIS data. *Geophysical Research Letters*, 32, L12809,
1338 doi:10.1029/2005GL022798.
- 1339 Satheesh, S.K. & Moorthy, K.K. (2005). Radiative effects of natural aerosols,
1340 *Atmospheric Environment*, 39, 2089-2110.
- 1341 Shao, Y.P., & Wang, J.J. (2003). A climatology of northeast Asian dust events.
1342 *Meteorologische Zeitschrift*, 12, 4, 187-196.
- 1343 Shenk, W.E. & Curran, R.J. (1974). The detection of dust storms over land
1344 and water with satellite visible and infrared measurements, *Monthly
1345 Weather Review*, 102, 830-837.
- 1346 Schepanski, K., Tegen, I., Laurent, B., Heinold, B. & Macke, A. (2007). A new
1347 Saharan dust source activation frequency map derived from MSG-
1348 SEVIRI IR-channels. *Geophysical Research Letters*, 34, L18803,
1349 doi:10.1029/2007GL030168.
- 1350 Soderberg, K. & Compton, J.S. (2007). Dust as a nutrient source for fynbos
1351 ecosystems, South Africa. *Ecosystems*, 10, 550-561.
- 1352 Sokolik, I. (2002). The spectral radiative signature of wind-blown mineral dust:
1353 implications for remote sensing in the thermal IR region. *Geophysical
1354 Research Letters*, 29, 2154, doi:10.1029/2002GL015910.

- 1355 Sprigg, R.C. (1982). Alternating wind cycles of the Quaternary era, and their
1356 influence on Aeolian sedimentation in and around the dune deserts of
1357 southeastern Australia. In Wasson, R.J. (ed). *Quaternary Dust Mantles*
1358 *of China, New Zealand and Australia*. Proceedings International Union
1359 for Quaternary Research (INQUA) Loess Commission Workshop,
1360 Canberra, 211-240.
- 1361 Swap, R., Garstang, M., Greco, S., Talbot, R. & Kallberg, P. (1992). Saharan
1362 dust in the Amazon Basin. *Tellus Series B- Chemical and Physical*
1363 *Meteorology*, 44, 2, 133-149.
- 1364 Tanré, D. & Legrand, M., (1991). On the satellite retrieval of Saharan dust
1365 optical thickness over land: Two different approaches, *Journal of*
1366 *Geophysical Research*, 96, 5221–5227.
- 1367 Torres, O., Bhartia, P.K., Herman, J. R., Ahmad, Z. & Gleason J. (1998).
1368 Derivation of aerosol properties from a satellite measurement of
1369 backscattered ultraviolet radiation: theoretical basis, *Journal of*
1370 *Geophysical Research*, 103, 17,099-17,110.
- 1371 Torres, O., Tanskanen, A., Veihelmann, B., Ahn, C., Braak, R., Bhartia, P. K.,
1372 Veefkind, P. & Levelt P. (2007). Aerosols and surface UV products
1373 from Ozone Monitoring Instrument observations: an overview, *Journal*
1374 *of Geophysical Research*, 112, D24S47, doi:10.1029/2007JD008809.
- 1375 Waeles, M., Baker, A.R., Jickells, T., & Hoogewerff, J. (2007). Global dust
1376 teleconnections: aerosol iron solubility and stable isotope composition.
1377 *Environmental Chemistry*, 4, 4, 233-237 doi:10.1071/EN07013.
- 1378 Wald, A.E., Kaufman, Y.J., Tanré, D., Gao, B.C. (1998). Daytime and
1379 nighttime detection of mineral dust over desert using infrared spectral
1380 contrast. *Journal of Geophysical Research-Atmospheres*, 103, D24,
1381 32307-32313.
- 1382 Wang, X.B., Enema, O., Hoogmed, W.B., Perdok, U.D., & Cai, D.X. (2006).
1383 Dust storm erosion and its impact on soil carbon and nitrogen losses in
1384 northern China. *Catena*, 66, 3, 221-227.
- 1385 Washington, R., Todd, M., Middleton, N.J., & Goudie, A.S. (2003). Dust-storm
1386 source areas determined by the Total Ozone Monitoring Spectrometer
1387 and surface observations. *Annals of the Association of American*
1388 *Geographers*, 93, 2, 297-313.

1389 Wolff, E.W. and 28 others. (2006). Southern Ocean sea-ice extent,
1390 productivity and iron flux over the past eight glacial cycles. *Nature*, 440,
1391 7083, 491-496.

1392 Yoshioka, M., Mahowald, N.M., Conley, A.J., Collins, W.D., Fillmore, D.W.,
1393 Zender, C.S., & Coleman, D.B. (2007). Impact of desert dust radiative
1394 forcing on Sahel precipitation: relative importance of dust compared to
1395 sea surface temperature variations, vegetation changes and
1396 greenhouse gas warming. *Journal of Climate*, 20, 8, 1445-1467,
1397 doi:10.1175/JCL14056.

1398 Zha, Y., & Li, L. (2007). Influence of the 17 April 2006 dust storm on Moderate
1399 Resolution Imaging Spectroradiometer data for land cover
1400 identification. *Journal of Geophysical Research*, 112, D14205,
1401 doi:10.1029/2006JD007869.

1402 Zhang, B., Tsunekawa, A. & Tsubo, M. (2008). Contributions of sandy lands
1403 and stony deserts to long-distance dust emission in China and
1404 Mongolia during 2000-2006. *Global and Planetary Change*, 60, 3-4,
1405 487-504.

1406 Zhu, A., Ramanathan, V., Li, F. & Kim, D. (2007). Dust plumes over the Pacific,
1407 Indian and Atlantic oceans: climatology and radiative impact. *Journal of*
1408 *Geophysical Research – Atmospheres*, 112, D16, D16208.

1409 Zubko, V., Kaufman, Y.J., Burg, R.I. & Martins, J.V. (2007). Principal
1410 components analysis of remote sensing of aerosols over oceans. *IEEE*
1411 *Transactions on Geoscience and Remote Sensing*, 45, 3, 730-745.
1412

1412 **Figure Captions**

1413

1414 Figure 1. The Lake Eyre Basin of Australia, and the coverage extents of
1415 the four dust event case studies by event number.

1416

1417 Figure 2. Histograms illustrating (a) the basic method for determining
1418 dust/non-dust threshold; (b) dust/non-dust thresholds derived for BTD
1419 (Ackerman, 1997) (dust < threshold; and (c) dust/non-dust threshold derived
1420 for Miller (2003) algorithm outputs (dust > threshold) for events 1-4.

1421

1422 Figure 3. Histograms showing the derivation of scaling factor 'a', based on
1423 reflectance ratio, for events 1-4 (graphs a-d), and BTD offset 'b' for events 1-4
1424 (graphs e-h) necessary for applying Roskovensky & Liou's (2005) algorithm.
1425 For event 4 the scaling factor = 0.25 (not shown). Note: vertical axes vary.

1426

1427 Figure 4. Key to interpreting the colour composite combining dust/non-
1428 dust detection using Ackerman (1997), Miller (2003) and Roskovensky & Liou
1429 (2005) and shown in Figures 5-8, panel (f).

1430

1431 Figure 5. Event 1: 7th October 2005. Across all panels, squares highlight
1432 the prominent active dust source areas, as identified from the BTD split
1433 window product. The dust/non-dust thresholds used are detailed in Table 4.
1434 Panels (a) to (e) are derived from MODIS (Aqua) data. (a) MODIS visible
1435 (wind direction marked with arrow); (b) BTD ($BT_{11}-BT_{12}$); (c) threshold applied
1436 to BTD (after Ackerman, 1997); (d) Roskovensky & Liou (2005) dust
1437 enhancement algorithm; (e) Miller's (2003) dust enhancement algorithm (dust
1438 is red); (f) Composite image of Ackerman, Miller and Roskovensky and Liou
1439 output for key see Fig.4. Panels (g) and (h) are aerosol products for the same
1440 event where (g) MYD04 Deep Blue AOT $0.1^\circ \times 0.1^\circ$ spatial resolution; (h) OMI
1441 AAI $0.25^\circ \times 0.25^\circ$ spatial resolution.

1442

1443 Figure 6. Event 2: 24th September 2006. Dust/non-dust thresholds used
1444 are those recommended in the published literature and the same as those
1445 used for Event 1.

1446

1447 Figure 7. Event 2: 24th September 2006. Dust/non-dust thresholds used
1448 are specific to Event 2 and adjusted using the histogram approach (Figure 3).

1449

1450 Figure 8. Event 3: 2nd February 2005. For panel explanations see Figure
1451 5. Dust/non-dust thresholds used are specific to Event 3 and adjusted using
1452 the histogram approach (Figure 3)

1453

1454 Figure 9. Event 4: 30th August 2005. For panel explanations see Figure 5.
1455 Dust/non-dust thresholds used are specific to Event 4 and adjusted using the
1456 histogram approach (Figure 3)

1457

1458 Figure 10. Summary of the relationships between the methods and
1459 approaches discussed in this paper.

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1461

1461 Table 1. Spatial and temporal characteristics of remote sensing data used in
 1462 this study.
 1463

Data Type	Spatial Resolution at Nadir (km)	Scenes used per day	Archive Length	Typical Overpass: (am/pm)
MOD02 [Terra]	0.25 x 0.25 (VIS ¹) 0.5 x 0.5 (VIS + NIR ²) 1 x 1 (TIR ³ + all bands)	1	1999 - date	am (10:30) ect [†]
MYD02 [Aqua]	0.25 x 0.25 (VIS) 0.5 x 0.5 (VIS + NIR) 1 x 1 (TIR + all bands)	1	2002 - date	pm (13:30) ect
MYD04 [Deep Blue]	10 x 10	1	2002 - date	pm (13:30) ect
OMI	13 x 24	1	2004 - date	pm (13:38) ect

1464 ¹Visible; ²Near-infrared; ³Thermal-infrared; [†]Equatorial crossing time
 1465
 1466
 1467

1467 Table 2. Summary of dust event case studies used in this study to evaluate
 1468 MODIS dust detection algorithms
 1469

Event	Date DD/MM/YY (Julian)	Satellite overpass time (UTC)	BoM [†] stations recording visibility ≤1km	Selection Criteria	Synoptic Conditions
1	07/10/05 (2005:280)	AQUA (01:35) AURA (01:46)	1	Dust and 30% cloud cover	Pre-frontal northerly
2	24/09/06 (2006:267)	AQUA (04:20) AURA (04:31)	2	Dust - Single frontal plume	Post-frontal southerly
3	02/02/05 (2005:033)	AQUA (04:10) AURA (04:21)	35	Dust - Multiple plumes and source types	Post-frontal southerly
4	30/08/05 (2005:242)	AQUA (04:50) AURA (05:01)	1	Dust and 50% cloud cover	Pre-frontal northerly

1470 [†]Bureau of Meteorology

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 1473

1473 Table 3. Summary of dust detection algorithms applied to MODIS L1B
 1474 data in this study
 1475

Algorithm	Display parameters	Source
$D = (BT_{31} - BT_{32})$ <p>where: $BT_{31} = BT_{10.780-11.280} \mu m$ $BT_{32} = BT_{11.770-12.27} \mu m$</p>	Dust < 0.0	Ackerman (1997) Sokolik (2002)
$D = \exp \left\{ - \left[\frac{R_4}{R_{16}} * a + ((BT_{31} - BT_{32}) - b) \right] \right\}$ <p>where: a=Scaling Factor (0.8) $R_{16} = R_{0.862-0.877} \mu m$ b=btid offset (2.0) $BT_{31} = BT_{10.780-11.280} \mu m$ $R_4 = R_{0.545-0.565} \mu m$ $BT_{32} = BT_{11.770-12.27} \mu m$</p>	Dust > 1.0	Roskovensky & Liou (2003) Roskovensky & Liou (2005) Hansell et al., (2007)
$D = \left[(BT_{32} - BT_{31})^a + (2R_1 - R_3 - R_4 - BT_{31})^b - (R_{26})^c + (1 - BT_{31})^d \right]$ <p>where: $R_1 = R_{0.620-0.670} \mu m$ $R_3 = R_{0.459-0.479} \mu m$ $R_4 = R_{0.545-0.565} \mu m$ $R_{26} = R_{1.360 - 1.390} \mu m$ $BT_{31} = BT_{10.780-11.280} \mu m$ $BT_{32} = BT_{11.770-12.27} \mu m$</p> <p>Normalization: a =(-2 to +2) b=(-5 to +0.25) c= (if $M_{26} > 0.05$, c=0, otherwise c=1) d= occurrences of M_{31} are normalized in this equation as $(M_{31max} - 21K$ if $M_{31max} < 301K$) or $((M_{31max}-273)/4 + 273)$ otherwise.</p>	1.3 < Dust < 2.7	Miller (2003)

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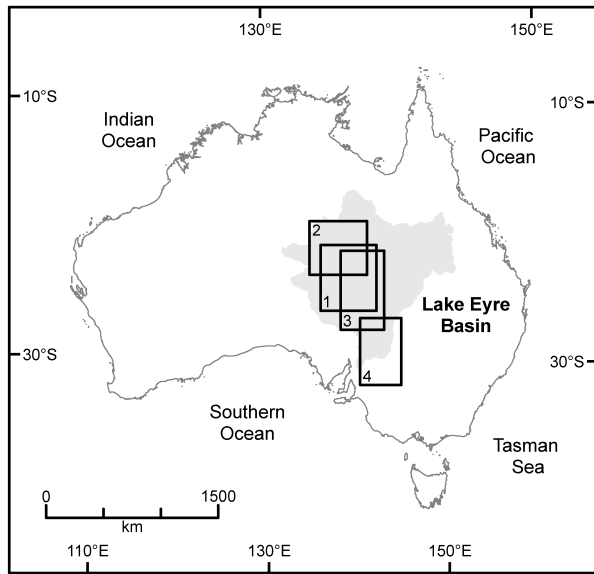
1478 Table 4. Comparison of recommended dust/non dust thresholds and
 1479 thresholds identified for events
 1480 described in this study.

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 1482

Technique	Suggested threshold values	Dust/non-dust thresholds			
		Event 1 7 Oct 2005	Event 2 24 Sept 2006	Event 3 2 Feb 2005	Event 4 30 Aug 2005
Ackerman (1997)	Dust < 0.0	Dust < 0.0	Dust < 0.0	Dust < -1.2	Dust < -0.35
Miller (2003)	1.3 < Dust < 2.7	1.3 < Dust < 2.27*	-0.55 < Dust < 1.11*	0.3 < Dust < 2.05*	0.45 < Dust < 1.08*
Roskovensky & Liou (2005)	Dust > 1.0 a = 0.8, b = 2	Dust > 1.0 a = 0.8, b = 1	Dust > 1.0 a = 0.9, b = -0.5	Dust > 1.0 a=1.2, b=-0.5	Dust > 1.0 a=0.25, b=0.5

1483 *upper value is scene maximum
 1484
 1485

1485 Figure 1



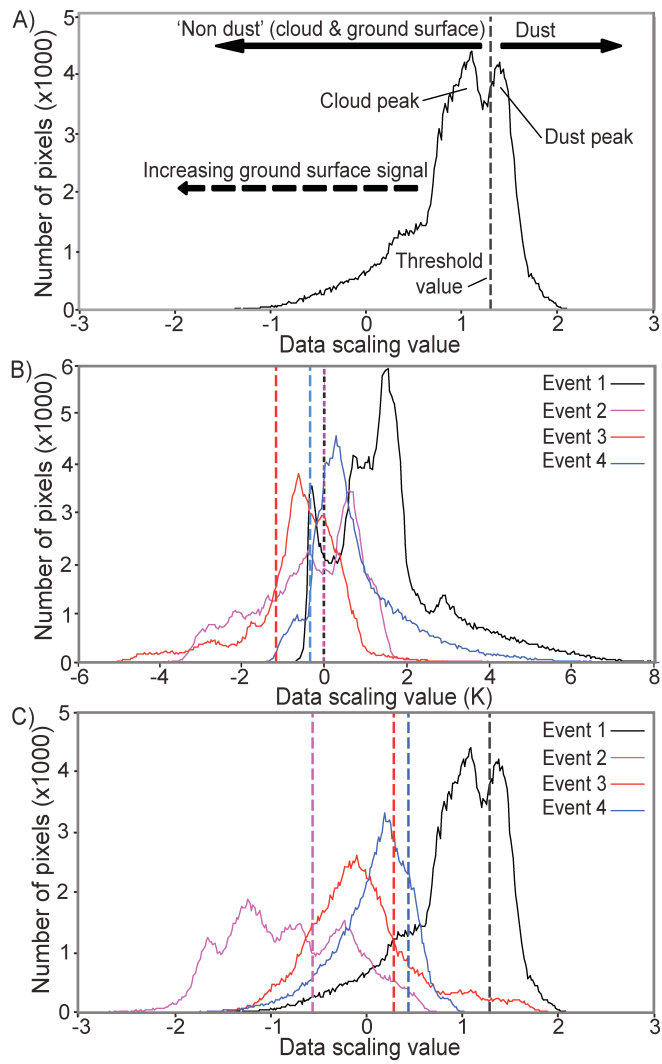
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1488 Figure 2

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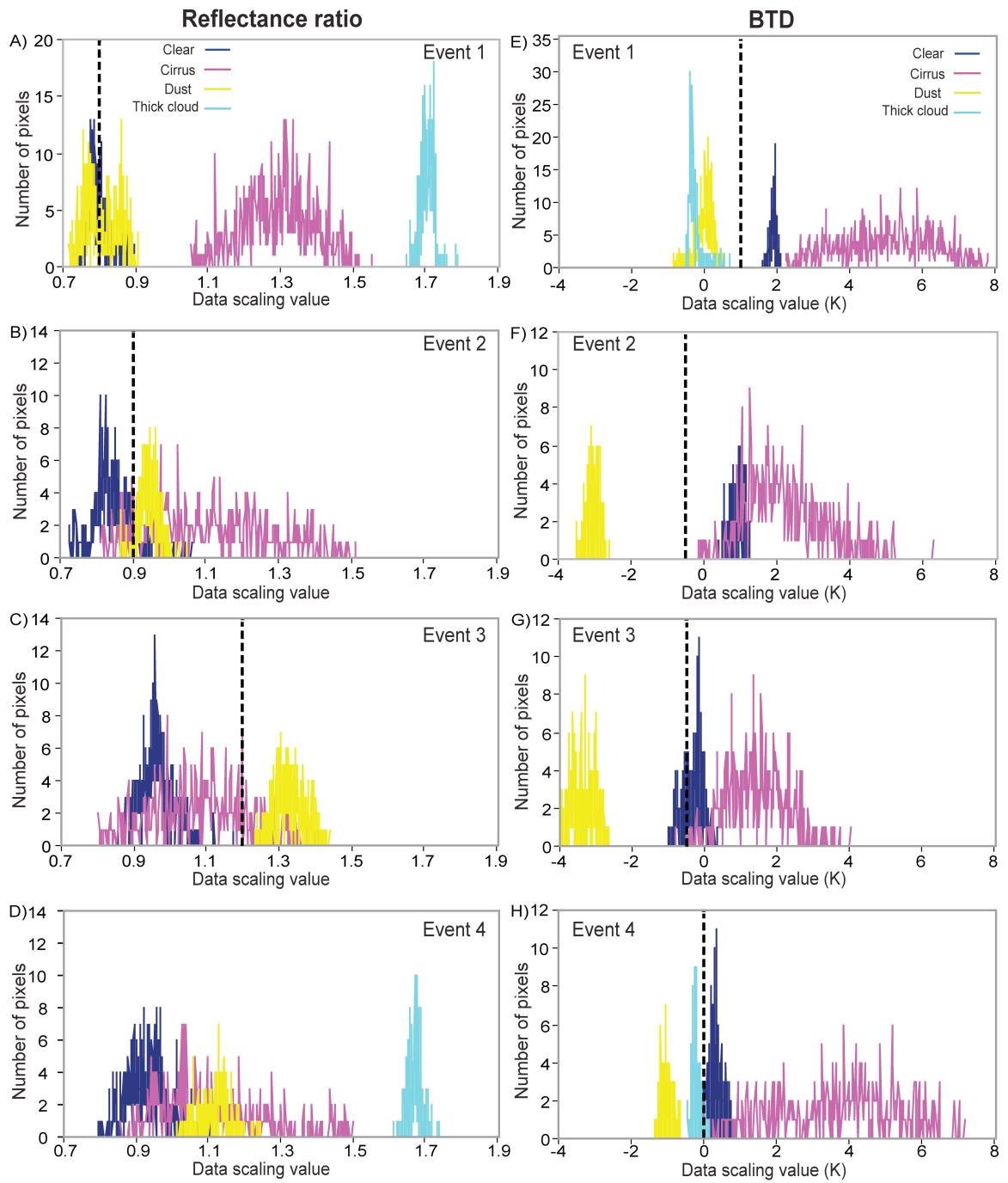
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1492 Figure 3

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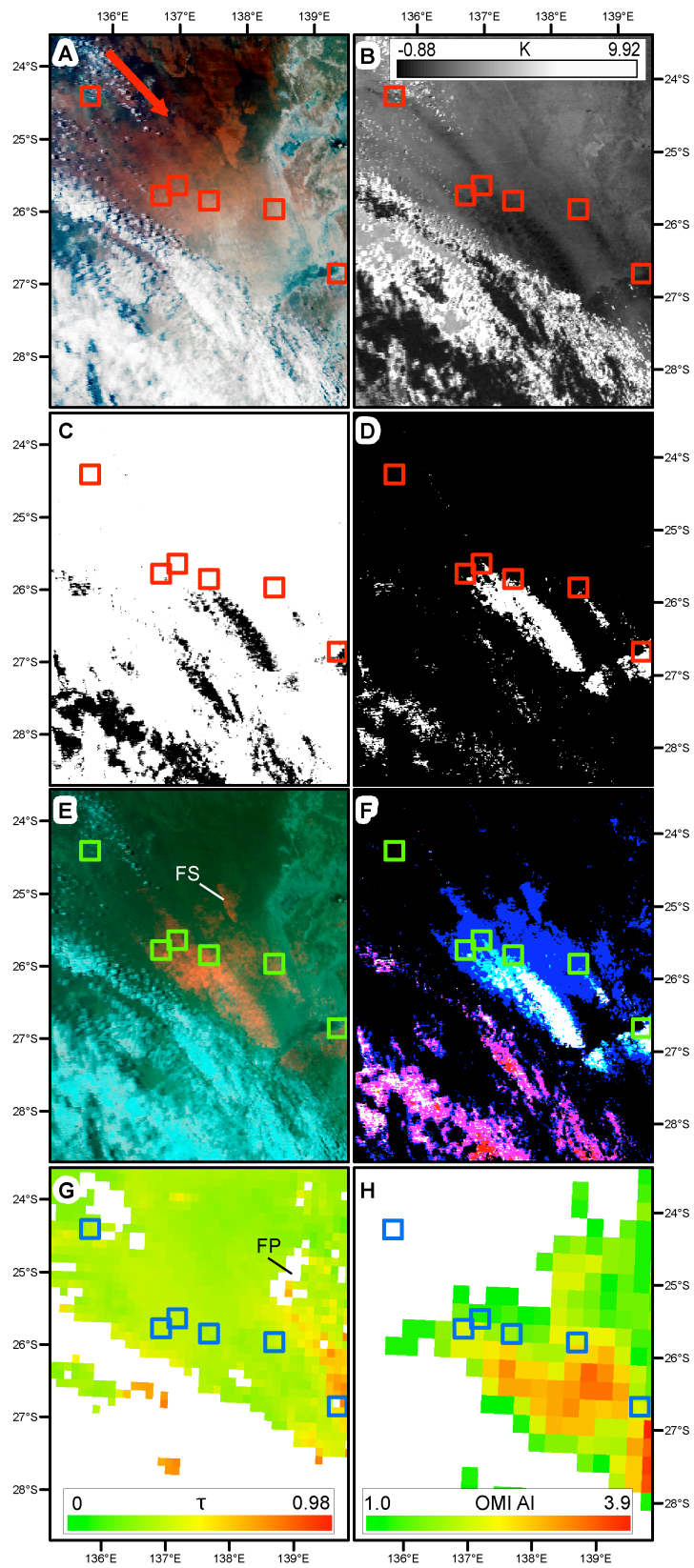
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Figure 4

		Dust pixels		
		A	M	R & L
Dust pixels	A			
	M			
	R & L			
ALL indicate dust pixels				
ALL indicate non-dust pixels				

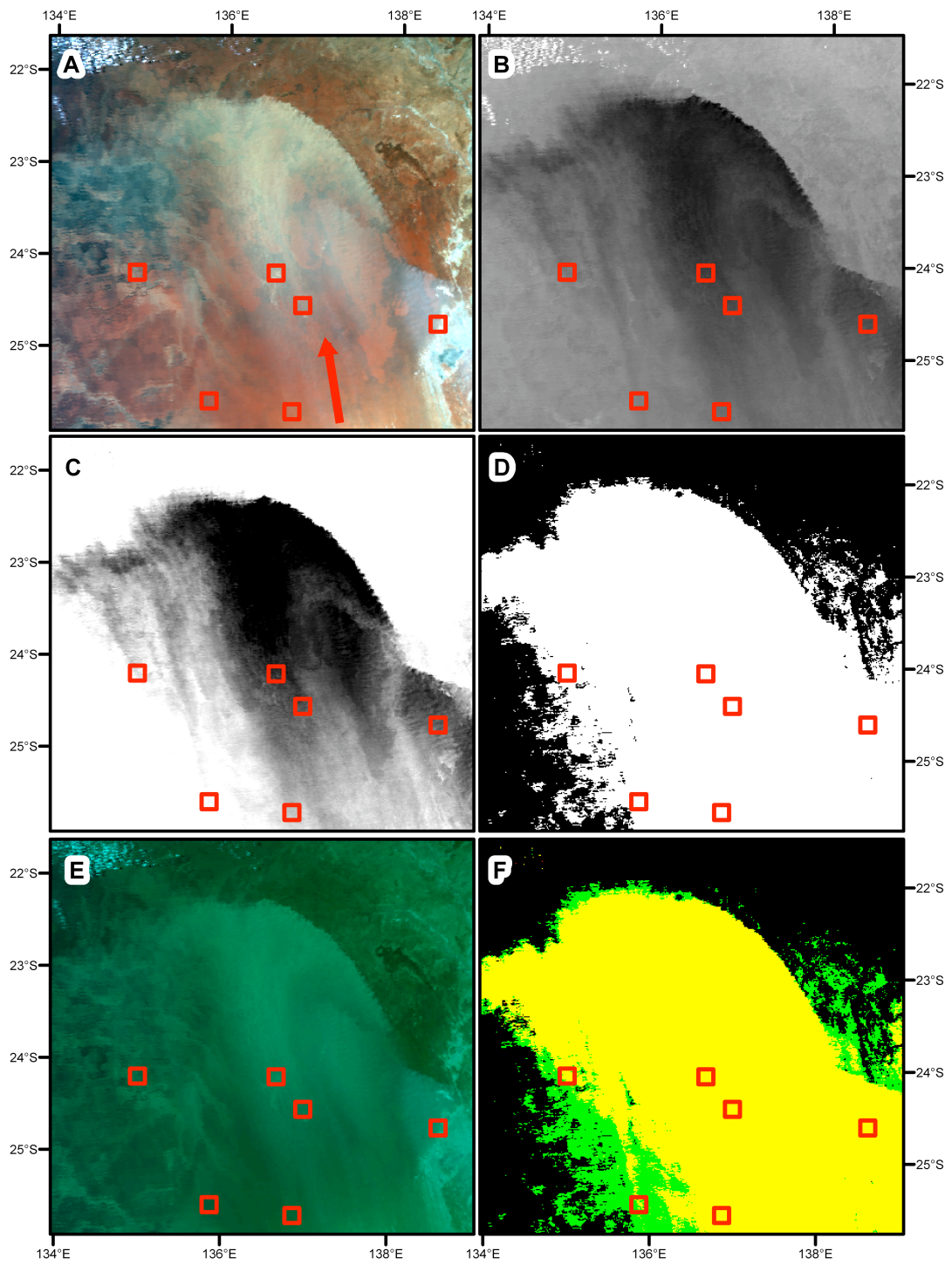
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Figure 5



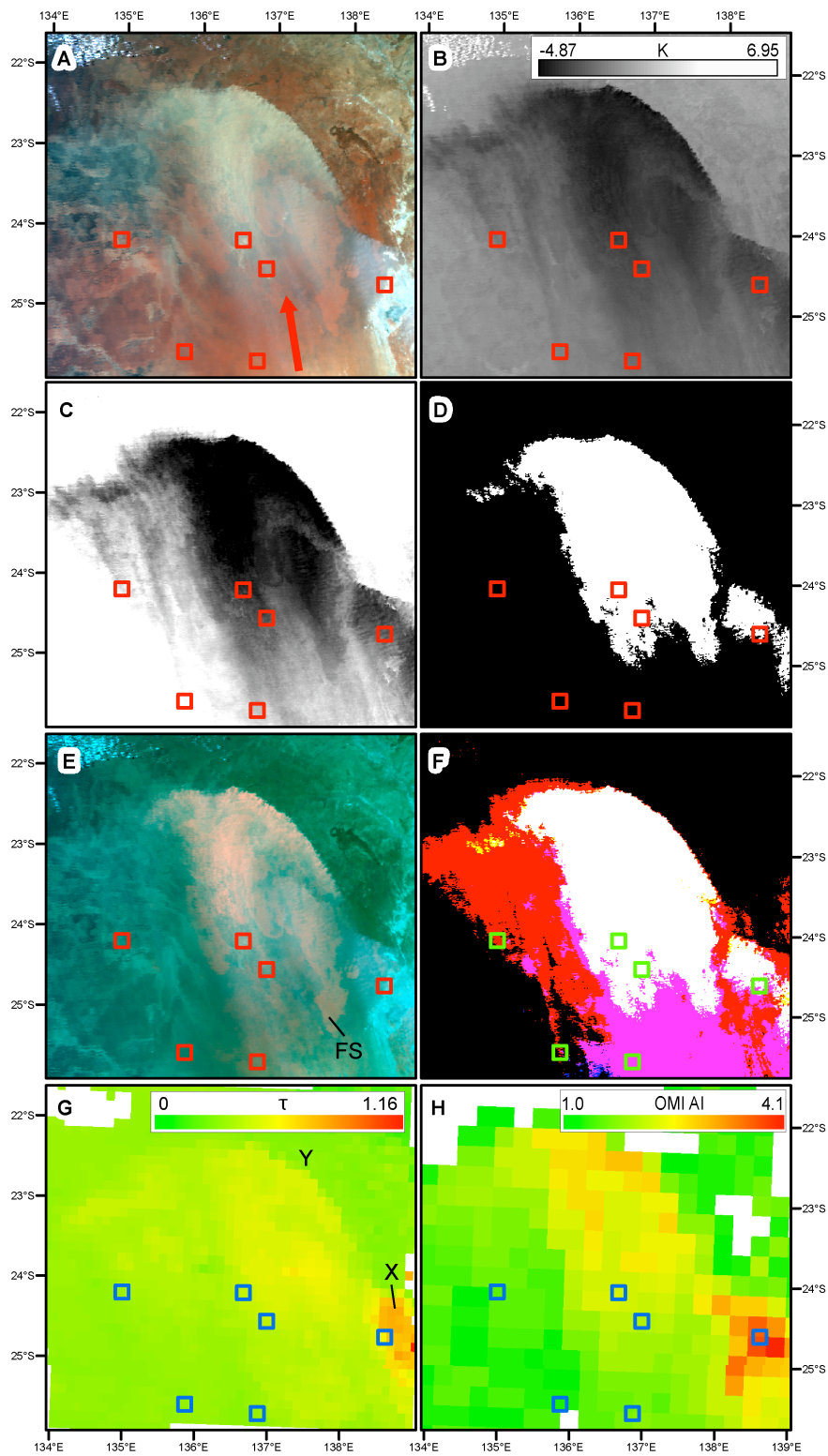
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1498 Figure 6



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1500 Figure 7



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Figure 8

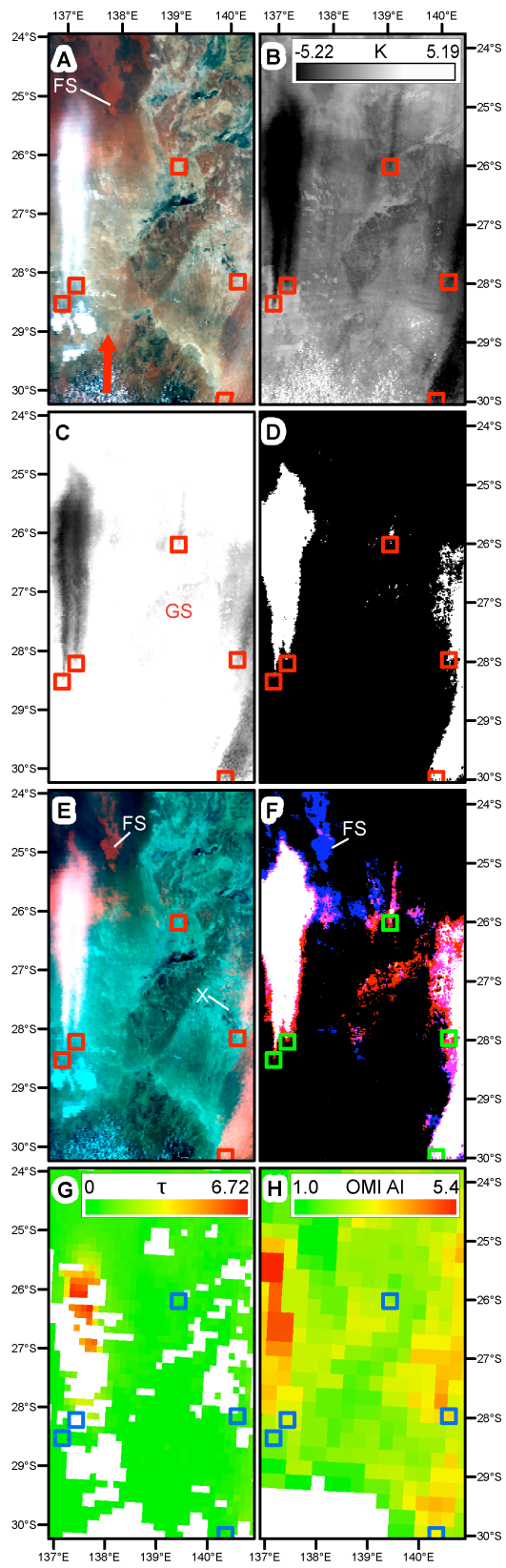
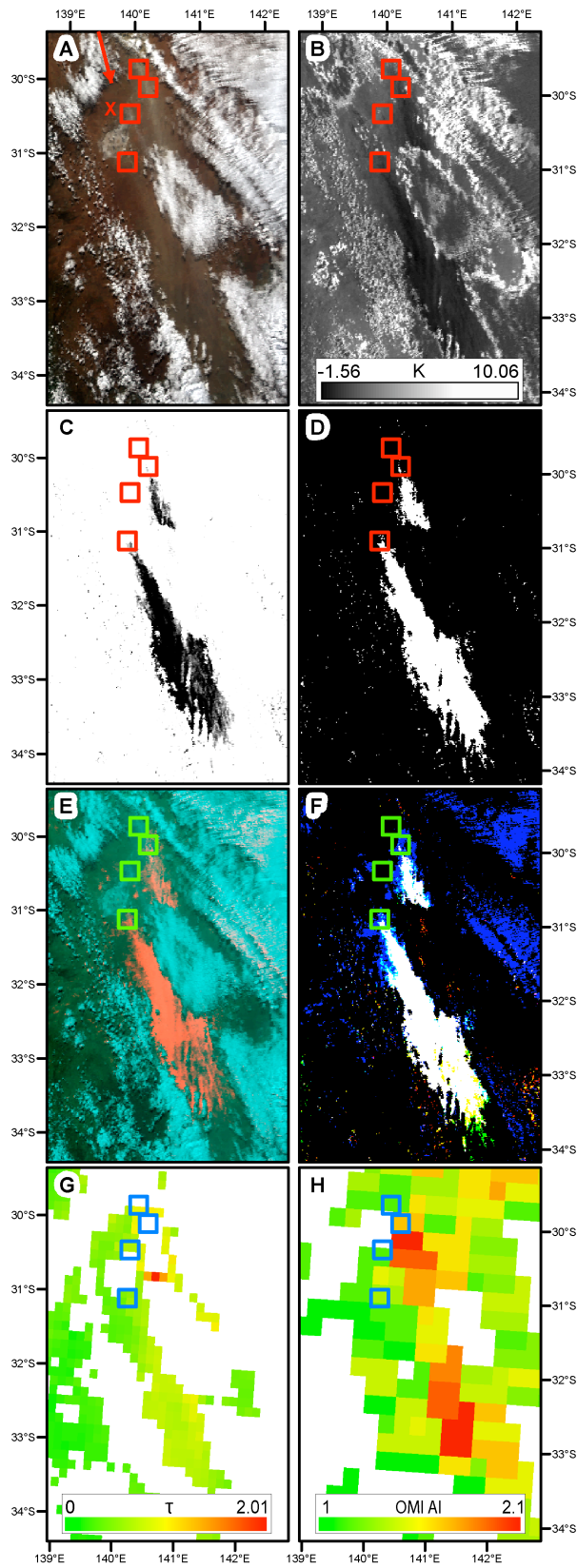
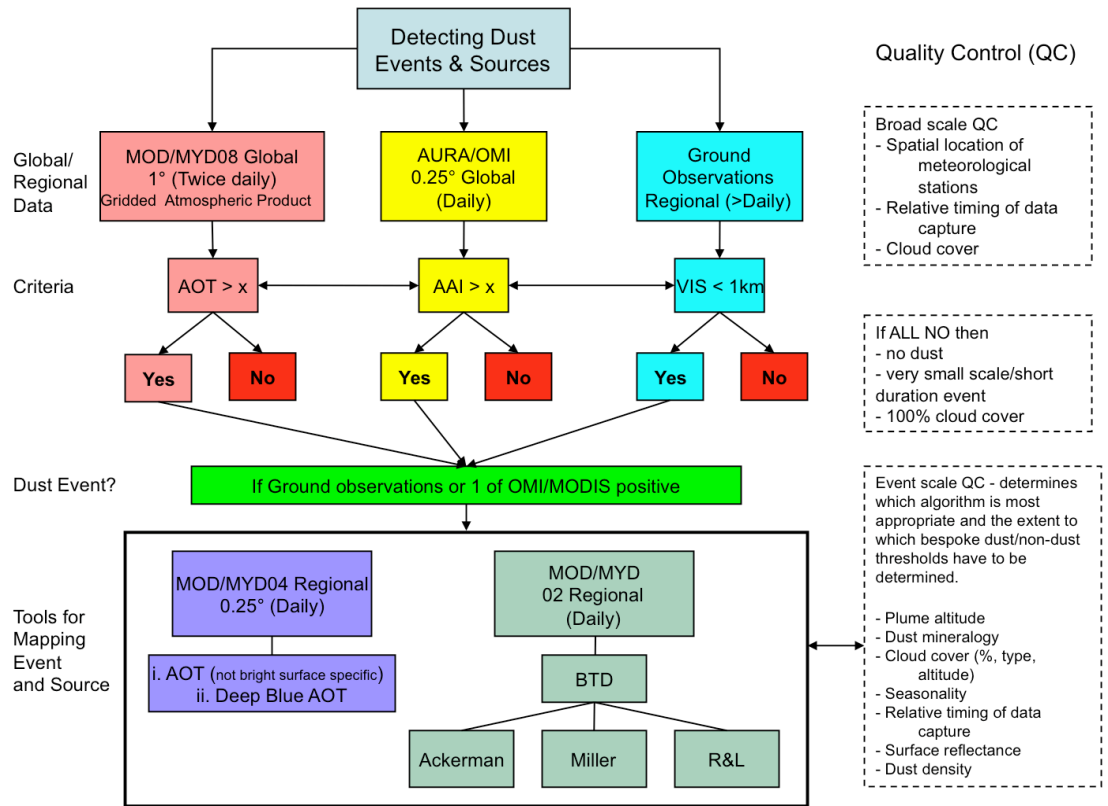


Figure 9



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1503 Figure 10
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