



HAL
open science

Statistical uncertainty of top of atmosphere cloud-free shortwave Aerosol Radiative Effect

T. A. Jones, S. A. Christopher

► **To cite this version:**

T. A. Jones, S. A. Christopher. Statistical uncertainty of top of atmosphere cloud-free shortwave Aerosol Radiative Effect. *Atmospheric Chemistry and Physics Discussions*, 2007, 7 (2), pp.3557-3588. hal-00302647

HAL Id: hal-00302647

<https://hal.science/hal-00302647>

Submitted on 18 Jun 2008

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

**Aerosol Radiative
Effect**

T. A. Jones and
S. A. Christopher

Statistical uncertainty of top of atmosphere cloud-free shortwave Aerosol Radiative Effect

T. A. Jones and S. A. Christopher

Department of Atmospheric Sciences, The University of Alabama in Huntsville, Huntsville, AL,
USA

Received: 11 December 2006 – Accepted: 28 February 2007 – Published: 8 March 2007

Correspondence to: S. Christopher (sundar@nsstc.uah.edu)

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures

⏪

⏩

◀

▶

Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion

Abstract

The statistical uncertainty of globally averaged MODIS aerosol optical thickness at $0.55\ \mu\text{m}$ (AOT) and top of atmosphere CERES cloud-free shortwave radiative effect (SWRE) is presented. All analysis is presented at the CERES footprint level which we call “raw data”. Statistical uncertainty may result from the raw data not being normally distributed. Both the AOT and SWRE data derived from clear-sky CERES-SSF products show significant deviations from a normal distribution as evidenced by high skewness values. The spatial and temporal distribution of the data is also not uniform, with a greater concentration of data being in aerosol heavy regions. As a result, globally averaged AOT and SWRE are overestimated when derived from raw data. Raw data are gridded into 2×2 degree grid-cells (called “gridded” data) to reduce the effect of spatial non-uniformity. However, the underlying non-normal distribution remains and manifests itself by increasing the uncertainty of grid-cell values. Globally averaged AOT and SWRE derived from a gridded dataset are substantially lower than those derived from raw data alone. The range of globally averaged AOT and SWRE values suggests that up to a 50% statistical uncertainty exists, much of which is directly tied to how the data are manipulated prior to averaging. This uncertainty increases when analyzing aerosol components (e.g. anthropogenic) since component AOT (and SWRE) may not exist at all locations where AOT is present. As a result, regions where a particular component AOT does not exist must either not be included in the global average or have data within these regions set to null values. However, each method produces significantly different results. The results of this work indicate that placing raw observations on to a uniform grid is a necessary step before calculating global statistics. However, this by no means eliminates statistical uncertainty, while adding its own set of assumptions. When reporting any globally averaged statistic, it is important to report corresponding distribution and coverage information, in the form of skewness values, probability density functions, and spatial distribution plots, to help quantify its usefulness and robustness.

Aerosol Radiative Effect

T. A. Jones and
S. A. Christopher

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures

◀

▶

◀

▶

Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion

1 Introduction

The difference between top of atmosphere (TOA) clear and aerosol skies in the short-wave ($<4\ \mu\text{m}$) portion of the electromagnetic spectrum for all aerosols is called the shortwave aerosol radiative effect (SWRE). Previous studies have used various methods to determine the global, ocean-only, TOA SWRE (see Anderson et al., 2005 and Yu et al., 2006 for reviews). These studies report a globally averaged SWRE between -4.6 and $-5.4\ \text{Wm}^{-2}$. The negative value indicates that over global oceans the aerosols are more reflective than the background in contrast to the greenhouse gas forcing values that are positive. The uncertainties associated with this number include instrument calibration, quality of angular models for converting shortwave (SW) radiance into flux, the effect of cloud contamination, assumptions in aerosol and surface properties (Zhang and Reid, 2006), and the assumptions made during the calculation of a clear-sky, aerosol free SW flux background, have been well documented (Zhang et al., 2005a). These uncertainties can account for a variation in SWRE of approximately 30% in some instances (Anderson et al., 2005; Zhang et al., 2005a).

However, one source of uncertainty has received much less attention, namely the implicit assumptions made when reporting a globally averaged statistic. Both TOA SW flux and aerosol optical thickness (AOT) vary substantially over the large spatial and temporal domains used by these studies. An “average” value is only representative if the source data has a normal (or Gaussian) distribution (Wilks 2006). In this paper we will show that SWRE is not normally distributed, and will note the importance of evaluating additional statistical measures in describing a global data set.

Additional statistical uncertainties originate from the manner in which the data are manipulated prior to reporting the global average. Satellite derived datasets such as that used by Christopher and Zhang (2004) do not have a uniform spatial distribution due to satellite orbit and sensor observing characteristics. They used CERES pixel level data that has a nominal spatial resolution of 20 km at nadir that also contains the MODIS AOT convolved within the CERES pixel. We call the pixel level CERES informa-

Aerosol Radiative Effect

T. A. Jones and
S. A. Christopher

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures

◀

▶

◀

▶

Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion

tion as “raw data”. To overcome non-uniform spatial distribution, raw data are gridded (generally to a 2×2 latitude-longitude grids) that we call “gridded data”. The term “raw data” refers to AOT and SWRE values derived from individual CERES-resolution pixels. While gridding ensures a uniform distribution (assuming some data exist for all grid-cells), each grid-cell within the gridded data set has a different statistical meaning. Since the raw data are not uniformly distributed, each grid-cell contains differing numbers of raw pixels. Over a global domain, the number of pixels used in each grid cell can vary from a single pixel to over a thousand. The effect of outliers present within sparse data regions will be magnified, increasing the uncertainty of the SWRE reported in these regions.

Another common statistic used to describe global radiative effect is the “*aerosol radiative efficiency* (E_{τ})”. E_{τ} is defined simply as the SWRE divided by AOT. This value can either be calculated on a pixel-by-pixel (or grid-cell) basis or simply calculated using one global mean SWRE and AOT value. Since this statistic is calculated by dividing a very small number (AOT) into a number two orders of magnitude greater (SWRE), E_{τ} is very sensitive to small variations in AOT. For example, Christopher and Zhang (2002) reported an average maritime AOT of 0.04 with a corresponding SWRE of -0.9 Wm^{-2} , resulting in an efficiency of $-22 \text{ Wm}^{-2} \tau^{-1}$. Other works such as (Kaufman et al., 2005a) note a maritime AOT of 0.06, which if used to calculate E_{τ} would result in a value of $-15 \text{ Wm}^{-2} \tau^{-1}$. Thus, even a small error in AOT can have a large impact on reported E_{τ} . E_{τ} can also be defined as the linear regression coefficient between SWRE and AOT (Christopher and Jones, 2007). This value is much more resilient to changes in AOT average and provides a method to determine the uncertainty of this statistic.

A further complication arises when analyzing SWRE as a function of aerosol type. Using the technique developed by Kaufman et al. (2005a), total aerosol optical thickness can be separated into maritime, dust, and anthropogenic components. However, mathematical limitations in this algorithm result in cases where one or two aerosol types may not exist. This is a perfectly reasonable result as some areas are dominated

Aerosol Radiative EffectT. A. Jones and
S. A. Christopher

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures

◀

▶

◀

▶

Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion

**Aerosol Radiative
Effect**T. A. Jones and
S. A. Christopher

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures

◀

▶

◀

▶

Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion

by certain aerosol types (e.g. dust in the eastern Atlantic). The complication arises when computing global averages of component AOT and SWRE and determining regions where a particular aerosol component exists. Two possibilities are explored. First, pixels where component AOT does not exist will be ignored and global averages computed. Another method used by Christopher et al. (2006), set anthropogenic AOT and SWRE equal to zero where anthropogenic aerosols are not present, though it was not explicitly stated. The implications of this assumption will be explored in Sect. 3 and 4.

Various averaging techniques, which are described in Sect. 3, will be compared to document the uncertainty in SWRE as a function of method used. It will be shown that the statistical uncertainties can meet or even exceed those present in the actual data. Advantages and disadvantages of each technique will be analyzed to determine which best represents global SWRE. All SWRE values reported throughout this work will be instantaneous. No diurnal or sample bias adjustments (Sample bias exists when using coarse spatial resolution data sets when compared to higher resolution MODIS data) will be applied (Zhang et al., 2005b). This is done to maintain focus on the statistical properties of the dataset without introducing the additional uncertainties associated with the various adjustment techniques.

2 Data

2.1 Terra CERES SSF data

We utilize 12 months of the CERES Single Satellite Footprint (SSF) FM1, Edition 2B data from the Terra polar orbiting satellite (December 2000–November 2001) over the global oceans between $\pm 60^\circ$ latitude. The CERES SSF product contains the point spread function weighted MODIS (Collection 4) aerosol and cloud properties for each CERES footprint. The CERES SSF reports measured TOA radiances, which are inverted to fluxes using angular dependence models (ADM's). We use the Terra ADM's

Aerosol Radiative Effect

T. A. Jones and
S. A. Christopher

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures

◀

▶

◀

▶

Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion

derived by Zhang et al. (2005b), which are a function of AOT, surface wind speed and fine mode fraction. Use of ERBE or TRMM ADM's in place of Terra ADMs can affect global instantaneous SWRE by $\pm 1 \text{ Wm}^{-2}$, although regional differences could be much larger (Zhang et al., 2005a).

The SWRE is calculated by subtracting CERES SW flux where aerosols are present from clear-sky flux. Clear-sky is defined as cloud and aerosol-free regions are areas where the percentage of a CERES pixel covered by clouds and the separately measured MODIS cloud fraction are both $\leq 1\%$ (for viewing and zenith solar angles less than 60°). Clear sky flux values are calculated on a CERES pixel-by-pixel basis by assuming that a linear relationship exists between AOT and TOA flux for $\tau_{0.55} < 0.2$ for 6° solar zenith angle bins and by subtracting the AOT*slope values from the CERES fluxes (Zhang et al., 2005a).

2.2 Dust, Maritime, and Anthropogenic AOT Components

To determine the maritime, dust, and anthropogenic components of the total TOA SWRE, the CERES footprint AOT ($\tau_{0.55}$) is separated into three components including maritime sea spray (τ_{ma}), atmospheric dust (τ_{du}), and anthropogenic aerosols (τ_{an}) (Eq. 1) based on Kaufman et al. (2005a).

$$\tau_{0.55} = \tau_{ma} + \tau_{an} + \tau_{du} \quad (1)$$

The maritime contribution can be estimated using surface wind speed (W) derived from the European Centre for Medium-Range Weather Forecasts (ECMWF) that is reported within the CERES SSF product. (Eq. 2).

$$\tau_{ma} = 0.007W(\text{ms}^{-1}) + 0.02 \quad (2)$$

The MODIS total fine mode fraction (f), can be separated into the same three components where f_{ma} , f_{du} , and f_{an} correspond to the fine mode fraction of maritime, dust, anthropogenic aerosols respectively (Eq. 3).

$$f = [f_{ma}\tau_{ma} + f_{du}\tau_{du} + f_{an}\tau_{an}] / \tau_{0.55} \quad (3)$$

Aerosol Radiative Effect

T. A. Jones and
S. A. Christopher

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures

◀

▶

◀

▶

Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion

Dust AOT can then be derived by combining Eqs. (1–3) and solving for τ_{du} (Eq. 4) using the assumption that f is bounded by: ($f_{ma} \leq f \leq f_{an}$). Anthropogenic AOT are calculated by subtracting τ_{du} and τ_{ma} from $\tau_{0.55}$, which is consistent with Christopher et al. (2006).

$$\tau_{du} = [\tau_{0.55}(f_{an} - f) - \tau_{ma}(f_{an} - f_{ma})] / (f_{an} - f_{du}) \quad (4)$$

5 To calculate τ_{du} , values for f_{ma} , f_{du} , and f_{an} are required. Kaufman et al. (2005) estimated these values for the tropical southern Atlantic (0–30° S) and reported an error 10–15% in the retrieved dust AOT (Eq. 5).

$$f_{ma} = 0.3 \pm 0.1, f_{du} = 0.5 \pm 0.05, f_{an} = 0.9 \pm 0.05 \quad (5)$$

SWRE is then scaled by the ratio of component AOT to total AOT to determine the
10 SWRE for each aerosol component (Christopher and Jones, 2007).

3 Averaging Methods

3.1 Simple average

The first averaging method to be analyzed is the sample mean, which is also the simplest and most readily used statistic to describe large datasets (Wilks 2006). The mean, or average, is defined as simply the sum of the sample data values (x_i) divided
15 by the total sample size (n) (Eq. 6). The resulting average is generally thought of as a central value, which best describes a total dataset. Information about the variability of the data around the mean value can be determined by calculating its standard deviation (Eq. 7). Often, error bars are defined as ranging one or two standard deviations
20 from the sample mean.

$$\bar{x} = \frac{1}{n} \sum_{i=1}^n x_i \quad (6)$$

$$s = \sqrt{\frac{1}{n-1} \sum_{i=1}^n (x_i - \bar{x})^2} \quad (7)$$

Unfortunately, the mean statistic is only adequate when the source data is normally distributed, which is rather uncommon for atmospheric datasets (Wilks 2006). The skewness statistic can be used to determine the degree to which a dataset does not conform to a normal distribution (Eq. 8).

$$\gamma = \frac{\frac{1}{n-1} \sum_{i=1}^n (x_i - \bar{x})^3}{s^3} \quad (8)$$

A positive value of the skewness statistic indicates that the data is biased towards low values with fewer larger values, which manifest themselves on the right-hand side of a probability density function. Conversely, negative values of skewness indicate the presence of many large value data points, with fewer small values. Skewness values larger than ± 2 * Standard error of skewness (SEK) indicate that a particular data distribution cannot be considered normal, that also indicates that basic mean and standard deviation statistics may not be reliable. The standard error of skewness can be estimated by Eq. (9).

$$SEK = \sqrt{\frac{6}{n}} \quad (9)$$

The CERES-SSF AOT and SWRE datasets used here are also not homogeneously distributed over space and time that can potentially bias the results toward a space and time where observed data may be more common. None of these statistics take into account the natural spatial and temporal variability present in a global dataset.

The radiative efficiency (E_τ) will also be calculated from the raw data set. The SWRE/AOT and linear regression methods for calculating E_τ will be compared. One

Aerosol Radiative Effect

T. A. Jones and
S. A. Christopher

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures

◀

▶

◀

▶

Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion

advantage of this statistic is that the SWRE-AOT relationship should remain fairly insensitive to the temporal and spatial variations within the data. An aerosol pixel of a particular type with a certain reported AOT should have the same effect on SW flux no matter when or where the aerosols are located, assuming a uniform background such as the ocean.

3.2 Random sampling

To determine the resiliency to outliers of the simple average technique, a subset of pixels is randomly sampled and statistics from that random sample computed. For this analysis, each random sample consists of 5% of the total number of raw pixels. Mean AOT and SWRE are computed from each random sample. This process is repeated 500 times to determine the stability of the overall average. Smaller variations would indicate that the overall data is resilient to outliers, which would appear in some, but not all the random samples. The resulting statistics could then be used to define a “sampling uncertainty”, one of many uncertainties actually present. However, even if this sample uncertainty proves low, it may not adequately describe the data due to the distribution issues discussed above. Also, the random samples used here will still have the same spatial and temporal variations present in the complete dataset.

3.3 Gridded data

To overcome the problem of spatial inhomogeneities, raw data pixels binned into a uniform grid of 2×2 degree latitude-longitude cells. Each grid-cell value represents the simple average of all raw pixels location within that particular cell. The standard deviation, skewness, and number of raw pixels within each grid-cell are also recorded. There are several advantages to gridding. The biggest advantage is that it forces a spatially homogeneous dataset from data that was previously non-uniformly distributed. Given this quality, additional parameters, such as the areal coverage of a certain aerosol type can be calculated. Global AOT and SWRE statistics are recomputed from the gridded

Aerosol Radiative Effect

T. A. Jones and
S. A. Christopher

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures

◀

▶

◀

▶

Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion

data set are compared with those computed from the raw data set.

However, gridding data is not a cure-all to the distribution issues present in the raw data. Recall that each grid-cell is calculated as the mean of all pixels that fall within its boundaries. However, the number of raw pixels that may lie within a particular grid-cell may vary substantially, from only a few to over 1000. In sparse data regions, grid-cell values are defined by only a few pixels. As a result, outliers in these regions can significantly affect the grid cell value, causing it to now be a grid-cell outlier. Since the gridded data sample size is much smaller than the raw sample size, the effect of this outlier will be magnified in the globally averaged statistics. Another problem occurs when 1000 or more data points may be available for a particular grid cell. Here, a few outliers are not the problem, but the distribution of the data within that grid-cell is important. Like the raw data, the data used in a particular grid cell may not be normally distributed. Recall that a grid-cell value is the simple mean of all raw data within its boundaries, and that a mean statistic is only robust when the data is normally distributed. If a normal distribution does not exist, then the resulting grid cell values will be biased one way or the other. This bias will in turn influence any statistics derived from a gridded dataset.

3.4 Random gridding

As with the raw data, the gridded data are tested using a random sample analysis to determine its stability and resilience to outliers. Grid cell values are computed by randomly selecting three raw data pixels within a 2×2 degree bin and taking the average. (Larger random samples were not used since they would have required the removal of a significant number of grid-cells from this analysis). This is repeated for each grid cell in the global field and global statistics computed. The entire process is repeated 100 times to determine the sample uncertainty of the gridded data values. It must be noted that since the raw data is not uniformly distributed, some grid cells will be more “random” than others. The three random pixels used for each grid cell mean always originate from the original number of pixels present within that grid cell, whether it is 10

Aerosol Radiative Effect

T. A. Jones and
S. A. Christopher

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures

◀

▶

◀

▶

Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion

or 1000. Thus, grid cells that encompass a larger number of raw data points will have a larger variation in values owing to a greater number of random combinations of points possible within these grid cells. As a result, only a subset of grid-cell values will vary significantly with each random perturbation. Still, this analysis will show if the variations in those grid-cells represent a significant effect to the overall gridded statistics.

3.5 What if anthropogenic AOT do not exist?

An additional complication arises when components of AOT SWRE are analyzed. Since, some components (e.g. dust or anthropogenic) may not exist for all pixels and grid-cells, each component sample size will differ. One solution, used by Christopher et al. (2006) for anthropogenic aerosols, is to set component AOT and SWRE equal to zero when that component was not present, but a total radiative effect value does exist.

However, this method presents several problems. The first is that the assumption of AOT and radiative effect equal to zero where the Kaufman et al. (2005) technique (Eq. 4) fails may lead to an under-estimation of component values. For example, if anthropogenic aerosols only exist for 70% of data where any aerosol type exist, then the remaining 30% in the anthropogenic average will be comprised of zeros (or null data), substantially lowering the average. The argument can be made that if an aerosol component does not exist, then its values should be set to zero. However, the matter really depends on what one is trying to show. For example, if one is only interested in analyzing dust SWRE independently of other aerosols, it makes sense to only analyze data where dust aerosols are actually present (e.g. Christopher and Jones, 2007). Conversely, if one is trying to determine the relative importance of maritime, dust, and anthropogenic aerosols to SW radiative effect, then the creation of homogenous component datasets using the method described above becomes necessary.

The other significant problem introduced by setting component values equal to zero occurs when these data are gridded. Null data can contribute a large proportion of data to some grid-cells, increasing its influence and further removing the data from a normal distribution. This is especially true in sparse data regions where only a few

Aerosol Radiative Effect

T. A. Jones and
S. A. Christopher

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures

◀

▶

◀

▶

Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion

data points feed into grid-cell values. When including null component data, AOT and SWRE values for these grid cells will be decreased substantially compared to pixels with a larger concentration of data that included all AOT components. The net result is that average component values derived from gridded data will be significantly lower than their non-gridded counterparts. This underestimation of component SWRE may bias a researcher's conclusions as to the importance of a particular AOT component. The effect of the null data assumption of component AOT and radiative effect statistics will be explored for both raw and gridded datasets.

4 Results

4.1 Simple average

Using non-gridded data, the globally averaged MODIS AOT in the CERES-SSF and instantaneous SWRE are 0.17 and -8.4 Wm^{-2} respectively (Table 1). The large spatial and temporal variations within these data lead to large sample standard deviations of 0.10 and 7.6, exceeding all known uncertainties present within the data. The skewness statistics for AOT and SWRE indicate that the data are not normally distributed, with values greatly exceeding $2 \times \text{SEK}$ (0.01) (Table 1). The mean values for both AOT and SWRE are displaced from the peak of the PDF functions in Fig. 1, also indicative of a non-normal distribution. The AOT data are biased towards smaller values, resulting in something approximating a Gamma distribution (Fig. 1a). The SWRE is biased in the opposite direction with a greater probability of pixels values occurring where the radiative effect is weak (e.g. near zero) (Fig. 1b). Interestingly, SWRE has a somewhat smaller skewness factor (in an absolute sense) than does AOT (Table 1). As a result, the global AOT and instantaneous SWRE values reported from the raw data averages are substantially larger than those (6.4, 7.6 Wm^{-2}) reported by previous studies (e.g. Christopher and Zhang 2002, Loeb and Manalo-Smith 2005). Note that the diurnal adjustment has been removed from the Loeb and Manalo-Smith (2005) value for com-

Aerosol Radiative Effect

T. A. Jones and
S. A. Christopher

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures

◀

▶

◀

▶

Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion

parison to the instantaneous values use here. The values associated with the peaks in the AOT and SWRE PDF functions are approximately 0.10 and 5.0 Wm^{-2} respectively.

The primary reason of the overestimation of AOT and SWRE by the simple average is due to the spatial distribution of the data. Figure 2 shows gridded ($2 \times 2^\circ$) instantaneous SWRE for the entire globe. It is evident from this figure that high values of are concentrated in a few geographic regions, most notably west of Africa between $10\text{--}20^\circ \text{ N}$, the East Coast of China, and the Bay of Bengal. These regions are also associated with the greatest variation in SWRE, which is evident in Fig. 3, which shows the standard deviation of SWRE within each grid-cell. Note that the regions of highest variability correspond with the regions of greatest SWRE. Grid-cells within these regions also contain the greatest number of raw pixels (Fig. 4). At first glance, it appears odd that valid data should be concentrated where only high aerosol concentrations exist. However, this is a result of the use of only cloud-free data in this analysis. Figure 5 shows globally averaged MODIS cloud fraction for all (clear and cloudy) data. Note that the regions associated with high SWRE also happen to have low mean cloud fraction. As a result, data within these regions is more likely to pass the cloud-free threshold and included in the SWRE analysis. Since a greater number of pixels are available in high AOT and SWRE regions, globally averaged AOT and SWRE are overestimated using this averaging technique.

A comparison of average AOT and SWRE, calculated from 500 random simulations, shows that the overall statistic is not sensitive to outliers. The variation in AOT is only 0.17 ± 0.0005 and is normally distributed (Fig. 6a). Similarly, the variation in SWRE is also very small, ± 0.04 (Fig. 6b). Since, these variations are well within 1% of the mean value, the sample data can be declared robust against outliers. Even though the sample average is stable, each random sample has the same distribution and non-uniformity issues present in the total dataset. Thus, these values remain an overestimate of global AOT and SWRE.

Using the standard definition of E_τ ($\text{SWRE} \div \text{AOT}$), the instantaneous global E_τ is $-49.4 \text{ Wm}^{-2} \tau^{-1}$, much lower than previous observations of near $-70 \text{ Wm}^{-2} \tau^{-1}$ (Yu

Aerosol Radiative EffectT. A. Jones and
S. A. Christopher

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures

◀

▶

◀

▶

Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion

Aerosol Radiative EffectT. A. Jones and
S. A. Christopher

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures

◀

▶

◀

▶

Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion

et al. 2004; Zhang et al. 2005a). The primary reason for the underestimation of E_{τ} is due to the high global AOT averaged reported above (Table 1). The regression based method produces a substantially different value, $-67.4 \text{ Wm}^{-2}\tau^{-1}$, in close agreement with the $-70 \text{ Wm}^{-2}\tau^{-1}$ value reported by Christopher and Zhang (2002) and the $72 \text{ Wm}^{-2}\tau^{-1}$ value by Yu et al. (2004) (with diurnal adjustment removed). The AOT-SWRE relationship, shown in Fig. 7, is approximately linear with a linear correlation coefficient of -0.89 . This indicates the model coefficient, which can also be interpreted as E_{τ} , is a robust statistic and not very susceptible to outliers.

4.2 Gridded data

Upon gridding the raw data, sample size falls from nearly eight million data points to approximately 7000 grid-cells (Table 1). The number of raw pixels contained within each grid cell ranges from 1 to 4013. The highest concentration of raw pixels occurs in aerosol-heavy regions, where the mean MODIS cloud fraction is generally lower (Figs. 4, 5). As a result, these regions are more likely to contain the cloud-free data required for calculation of SWRE. The grid-cell containing the most pixels (4013) is centered at 19° N and 69° E within the Arabian Sea. The SWRE for this grid-cell is $-12.2 \pm 5.7 \text{ Wm}^{-2}$, but with a skewness statistic of only -0.2 . For this grid-cell in particular, the raw pixels are approximately normally distributed indicating that the grid-cell average is representative in this case (Fig. 8a). Future works may be able to utilize regions where AOT and SWRE are normally distributed to compare results of differing research techniques, since the statistical uncertainty is reduced compared to the global data set. However, there are many grid-cells that do not contain a normal distribution of data such as the grid-cell center and 19° N, 19° W, and are generally biased in a manner similar to the global data set (Fig. 8b). The SWRE distribution in this grid-cell is likely a reflection of different aerosol regimes present over this region, which can change from dust to anthropogenic depending on time of year (e.g. Ramana and Ramanathan 2006).

No matter what the underlying cause, the gridded data set also suffers from a lack of

a normal distribution. The globally averaged gridded statistics make this point evident. Gridded average AOT and SWRE are substantially lower than their non-gridded counterparts ($0.12, -5.7 \text{ Wm}^{-2}$) (Table 1). However, the skewness statistic for both gridded AOT and SWRE are higher, indicating that the gridded average is less representative than before.

The globally averaged gridded AOT and SWRE are substantially lower than their non-gridded counterparts since gridding removes the bias towards data in high aerosol concentration regions. Thus, the gridded data set has a fewer number of high AOT pixels incorporated into the average. The more uniform spatial distribution creates a globally averaged instantaneous SWRE that is somewhat lower than the previously reported values of -6.4 and -7.6 Wm^{-2} (Zhang et al. 2005b; Loeb Manalo-Smith 2005); however, the lack of a normal distribution leaves a large uncertainty as to the true globally averaged values.

As with the raw data, the gridded data was randomly sampled to determine its resiliency to outliers. The technique differs from that used for the raw data in that grid-cell values calculated by randomly sampling three raw data pixels included within that cell. This process was repeated 100 times over the entire global domain to determine the variability of AOT and SWRE as a function of grid-cell uncertainty. The results indicate that the gridded data set, like the raw data set before, is very resilient to outliers. AOT and SWRE also vary less 1% from their gridded mean values (Fig. 9). Note that varying grid-cell sizes from 1 to 4 degrees did not make a substantial difference in the results shown.

Calculation of E_{τ} using the gridded data set produces some interesting results. The traditional definition results in an E_{τ} value of $-49.1 \text{ Wm}^{-2}\tau^{-1}$, with the regression method producing the same value. Both these values match the non-gridded, traditional E_{τ} , but not the one calculated by regressing from the raw data. Still, it is the latter that best agrees with previous research. The additional step of gridding results in an underestimation of SWRE for some grid-cells, which leads to an artificial change in the AOT-SWRE relationship. This relationship should be resilient to non-normal and

Aerosol Radiative EffectT. A. Jones and
S. A. Christopher

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures

◀

▶

◀

▶

Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion

non-uniformly distributed data. Since no evidence to the contrary could be found, the E_{τ} calculated from the raw data regression is likely the best estimator of this statistic.

4.3 Anthropogenic Aerosols

The methods described by Christopher and Jones (2007) and Sect. 2 were used to derive anthropogenic AOT and SWRE over a global domain for both gridded and non-gridded data (Table 2). As with total aerosol AOT and SWRE, anthropogenic AOT and SWRE also lack a normal distribution with anthropogenic AOT probability maximized at very low values (Fig. 10). Non-gridded average anthropogenic AOT and instantaneous SWRE are quite high (0.09, -5.5 Wm^{-2}) compared to previously reported values of 0.033 and -2.8 Wm^{-2} (these values have been converted to instantaneous) by both Kaufman et al. (2005b) and Christopher et al. (2006). The high values reported here are the result of two factors. First, as with total AOT, more anthropogenic aerosol data points exist in regions of heavy aerosol concentrations due to the greater probability of cloud-free observations being present (Figs. 4, 5). The second is that the averages presented above do not take into account regions where no anthropogenic aerosols exist. Christopher et al. (2006) set anthropogenic AOT and SWRE in these regions equal to 0 prior to computing their global averages. Applying this assumption to the non-gridded data results in globally averaged values of 0.08 and -4.3 Wm^{-2} (Table 2).

Statistics for gridded anthropogenic AOT and SWRE are also reported (Table 2). Two sets of gridded data were generated, one including only data where a particular aerosol type exists and the other incorporating the null assumption for data points where anthropogenic aerosols did not exist. As with the non-gridded data, the use of this assumption reduces globally averaged AOT and SWRE, to 0.045 and -2.5 Wm^{-2} when including null data in the gridding process (Table 2). These values are much closer to those reported by Kaufman et al. (2005b) and Christopher et al. (2006).

Additional uncertainty in anthropogenic AOT and SWRE results from the method used to separate the anthropogenic component. Recall that anthropogenic AOT was defined as the residual of total AOT, dust, and maritime components. Thus, any AOT

Aerosol Radiative Effect

T. A. Jones and
S. A. Christopher

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures

◀

▶

◀

▶

Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion

remaining after dust and maritime components have been calculated is assigned as anthropogenic. This assumption represents an artificial increase in the importance of anthropogenic aerosols relative to the other components Kaufman et al. (2005b) do solve Eqs. (1–5) for anthropogenic AOT instead of dust AOT. However, the resulting anthropogenic equation is not 100% mathematically consistent with the dust equation (Eq. 4). As a result, dust AOT would need to be calculated using the residual method, artificially increasing its importance. The only solution to this would be to develop mathematically consistent equations for the calculation of dust and anthropogenic AOT, which is left for future research.

5 Conclusions

The question remains as to what is the actual TOA instantaneous shortwave radiative effect from aerosols over a global domain. This work has shown that significantly different values can be returned depending on the technique used to analyze the data. No one method for calculating globally averaged AOT and SWRE generates values without substantial statistical uncertainty. The “raw data” average suffers from a non-uniform spatial distribution, weighted towards regions with high aerosol concentrations. As a result, statistics derived from these data overestimate global AOT and SWRE, despite the probability distribution favoring lower values of both. The gridded data is close to spatially uniform (over ocean regions), and the resulting average does not show the high bias produced by the non-gridded data. However, the distribution of raw data within each grid-cell leads to significant uncertainty as to some grid-cell values. Grid-cells with non-uniform distributions are generally biased toward low AOT and SWRE values, with the resulting grid-cell average likely being an underestimate of the actual value. Thus, we are left with a range of values for global AOT and SWRE ($0.12 < \text{AOT} < 0.17$; $-5.7 < \text{SWRE} < -8.4 \text{ Wm}^{-2}$), with true values likely lying somewhere in between, which represents an uncertainty of nearly 50%. Due to the much greater probability of aerosol data existing in aerosol-heavy regions, the actual value for AOT and SWRE lies

Aerosol Radiative Effect

T. A. Jones and
S. A. Christopher

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures

◀

▶

◀

▶

Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion

closer to the gridded value than the non-gridded value. Just how close remains uncertain, but the gridded dataset produces more realistic results. Fortunately, the random sample analysis for both gridded and non-gridded datasets showed that globally averaged values are not susceptible to outliers present in the data.

5 Attempting to determine maritime, dust, and, anthropogenic component statistics is even more difficult depending on the treatment of regions where one or more aerosol types do not exist. Including regions of null-data in the computation of a globally averaged mean reduces anthropogenic AOT and SWRE. The magnitude of this decrease is also uncertain as it relies on the method used to separate AOT components (see
10 Sect. 4c). When reporting globally averaged component values, it is vital to state whether or not null data are being included and show distribution of component data. Otherwise, it is impossible to determine the significance of any reported globally averaged AOT or SWRE statistics.

The primary conclusion of this work is that a globally average AOT or SWRE value
15 is not meaningful unless additional statistics are supplied. It is important to know the underlying distribution of the sample data as well as its spatial and temporal variability. When dealing with observational datasets such as the one used here, data are not likely to be present on a uniform spatial or temporal domain. Eliminating this issue requires that the raw data be placed onto a uniform as described in Sect. 3c. The
20 resulting globally averaged AOT and SWRE are much closer to previously reported values, but significant statistical uncertainties remain. No single averaging technique or statistics provides an adequate description of global AOT and SWRE.

Only a combination of statistical and distribution information can provide an estimate
25 as to the magnitude and uncertainty of globally averaged values. In addition to globally averaged values, future works should also report data distribution statistics, such as skewness and probability density functions. When non-normal distributions are encountered, its needs to be reported what effect the actual distribution will have on a globally averaged value. Also important to note are all forms of data manipulation, such as gridding, diurnal/sample bias adjustments performed on the data. Manipulat-

Aerosol Radiative Effect

T. A. Jones and
S. A. Christopher

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures

⏪

⏩

◀

▶

Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion

ing data in various ways often improves its statistical quality, but can also change its underlying meaning. Without this rigorous documentation, results from various works, even when done over the same spatial and temporal domain may not be comparable.

Acknowledgements. This research was supported by NASA's Radiation Sciences, Interdisciplinary Sciences, EOS and ACPMAP programs. The CERES data was obtained from the NASA Langlely Research Center Atmospheric Sciences Data Center, the MODIS data were obtained through the Goddard Space Flight Center Data Center.

References

- Anderson, T. L., Bellouin, N., Charlson, R. J., et al.: An "A-Train" Strategy for Quantifying Direct Climate Forcing by Anthropogenic Aerosols, *Bull. Amer. Meteor. Soc.*, 1795–1809, 2005.
- Bellouin, N., Boucher, O., Haywood, J., and Reddy, M. S.: Global estimate of aerosol direct radiative forcing from satellite measurements, *Nature*, 438, 1138–1141, doi:10.1038/nature04348, 2005.
- Christopher, S. A. and Zhang, J.: Shortwave aerosol radiative forcing from MODIS and CERES observations over the oceans. *Geophys. Res. Lett.*, 29, 1859, doi:10.1029/2002GL014803, 2002.
- Christopher, S. A., Kaufman, Y. J., Remer, L. A., and Zhang, J.: Satellite-based assessment of top of atmosphere anthropogenic radiative forcing over cloud-free oceans, *Geophys. Res. Lett.*, 33, L15816, doi:10.1029/2005GL025535, 2006.
- Christopher, S. A. and Jones, T. : Satellite-based assessment of cloud-free net radiative effect of dust aerosols over the Atlantic Ocean, *Geophys. Res. Lett.*, 34, L02810, doi:10.1029/2006GL027783, 2007.
- Fan, S., Ginoux, P., Kaufman, Y. J., Koren, I., Remer, L. A., and Tanre, D.: Dust transport and deposition observed from the Terra-Moderate Resolution Imaging Spectroradiometer (MODIS) spacecraft over the Atlantic Ocean, *J. Geophys. Res.*, 110, D10S12, doi:10.1029/2003JD004436, 2005a.
- Kaufman, Y. J., Boucher, O., Tanre, D., Chin, M., Remer, L. A., and Takemura, T.: Aerosol anthropogenic component estimated from satellite data, *Geophys. Res. Lett.*, 32, L17804, doi:10.1029/2005GL023125, 2005b.

Aerosol Radiative Effect

T. A. Jones and
S. A. Christopher

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures

◀

▶

◀

▶

Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion

- Li, F., Ramanathan, V., and Vogelmann, A. A.: Saharan Dust Radiative Forcing Measured from Space, *J. Clim.*, 17, 2558–2571, 2004.
- Loeb, N. G. and Manalo-Smith, N.: Top-of-atmosphere direct radiative effect of aerosols over global oceans from merged CERES and MODIS observations, *J. Climate*, 18, 3506–3526, 2005.
- Ramana, M. V. and Ramanathan, V.: Abrupt transition from natural to anthropogenic aerosol radiative forcing: Observations at the ABC-Maldives Climate Observatory, *J. Geophys. Res.*, 111, D20207, doi:10.1029/2006JD007063, 2006.
- Wilks, D. S.: *Statistical Methods in the Atmospheric Sciences*, Academic Press, 627 pp, 2006.
- Yu, H., Dickinson, R. E., Chin, M., Kaufman, Y. J., Zhou, M., Zhou, L., Tian, Y. Dubovik, O., and Holben, B. N.: The direct radiative effect of aerosols as determined from a combination of MODIS and GOCART simulations, *J. Geophys. Res.*, 109, D03206, doi:10.1029/2003JD003914, 2004.
- Yu, H., Kaufman, Y. J., Chin, M., et al.: A review of measurement-based assessment of aerosol direct radiative effect and forcing, *Atmos. Chem. Phys.* 6, 613–666, 2006.
- Zhang J., Christopher, S. A., Remer, L. A., and Kaufman, Y. J.: Shortwave aerosol radiative forcing over cloud-free oceans from Terra: 2, 2005a: Seasonal and global distributions, *J. Geophys. Res.*, 110, D10S24, doi:10.1029/2004JD005009, 2005.
- Zhang J., Christopher, S. A., Remer, L. A., and Kaufman, Y. J.: Shortwave aerosol radiative forcing over cloud-free oceans from Terra: 1, 2005b: Angular models for aerosols, *J. Geophys. Res.*, 110, D10S23, doi:10.1029/2004JD005008, 2005.
- Zhang, J. and Reid, J. S.: MODIS aerosol product analysis for data assimilation: Assessment of over-ocean level 2 aerosol optical thickness retrievals, *J. Geophys. Res.*, 111, D22207, doi:10.1029/2005JD006898, 2006.

Aerosol Radiative EffectT. A. Jones and
S. A. Christopher

[Title Page](#)[Abstract](#)[Introduction](#)[Conclusions](#)[References](#)[Tables](#)[Figures](#)[◀](#)[▶](#)[◀](#)[▶](#)[Back](#)[Close](#)[Full Screen / Esc](#)[Printer-friendly Version](#)[Interactive Discussion](#)

**Aerosol Radiative
Effect**T. A. Jones and
S. A. Christopher[Title Page](#)[Abstract](#)[Introduction](#)[Conclusions](#)[References](#)[Tables](#)[Figures](#)[I◀](#)[▶I](#)[◀](#)[▶](#)[Back](#)[Close](#)[Full Screen / Esc](#)[Printer-friendly Version](#)[Interactive Discussion](#)**Table 1.** Gridded and non-gridded global AOT and SWRE statistics.

No-Grid	N	Mean	Stddev	Skewness
AOT	772232	0.17	0.1	1.9
SWRE	772232	−8.4	7.6	−1.5
Grid				
AOT	6929	0.12	0.061	2.4
SWRE	6929	−5.7	3.9	−1.8

**Aerosol Radiative
Effect**T. A. Jones and
S. A. Christopher

Table 2. Non-gridded and gridded, globally averaged anthropogenic AOT and SWRE for datasets that include and do not include null data where anthropogenic AOT do not exist.

	AOT	SWRE
N	548790	548790
Non-null	0.09	−5.5
Null	0.08	−4.3
N	6011	6011
Grid	0.06	−3.4
Null-Grid	0.05	−2.5

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures

I◀

▶I

◀

▶

Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion

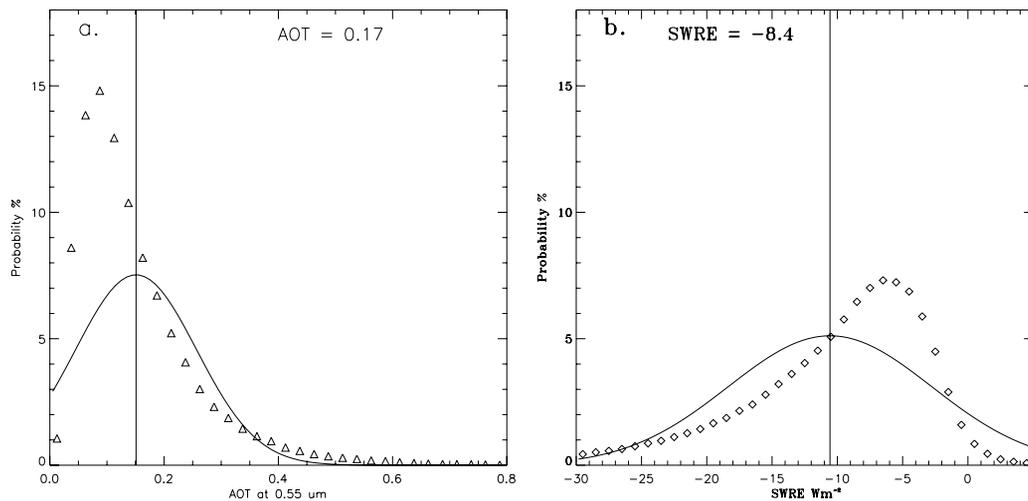
Aerosol Radiative
EffectT. A. Jones and
S. A. Christopher

Fig. 1. Probability density functions of non-gridded, global AOT **(a)** and SWRE **(b)** with idealized Gaussian (normal) distributions overlotted.

[Title Page](#)[Abstract](#)[Introduction](#)[Conclusions](#)[References](#)[Tables](#)[Figures](#)[◀](#)[▶](#)[◀](#)[▶](#)[Back](#)[Close](#)[Full Screen / Esc](#)[Printer-friendly Version](#)[Interactive Discussion](#)

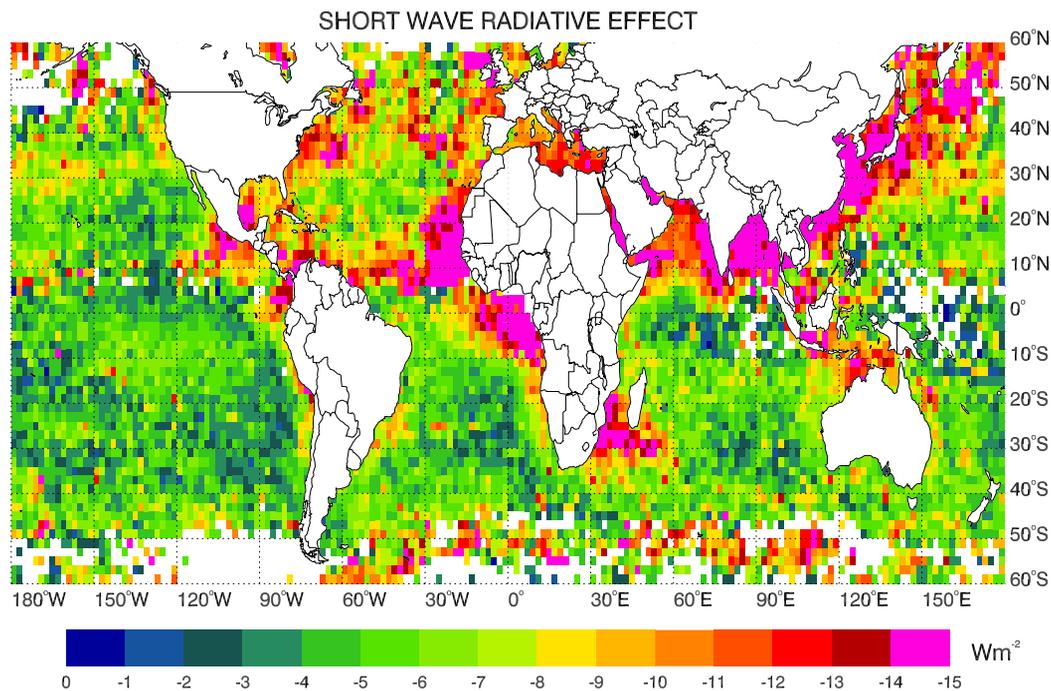
Aerosol Radiative EffectT. A. Jones and
S. A. Christopher

Fig. 2. Global SWRE gridded into 2×2 degree grid-cells.

[Title Page](#)[Abstract](#)[Introduction](#)[Conclusions](#)[References](#)[Tables](#)[Figures](#)[◀](#)[▶](#)[◀](#)[▶](#)[Back](#)[Close](#)[Full Screen / Esc](#)[Printer-friendly Version](#)[Interactive Discussion](#)

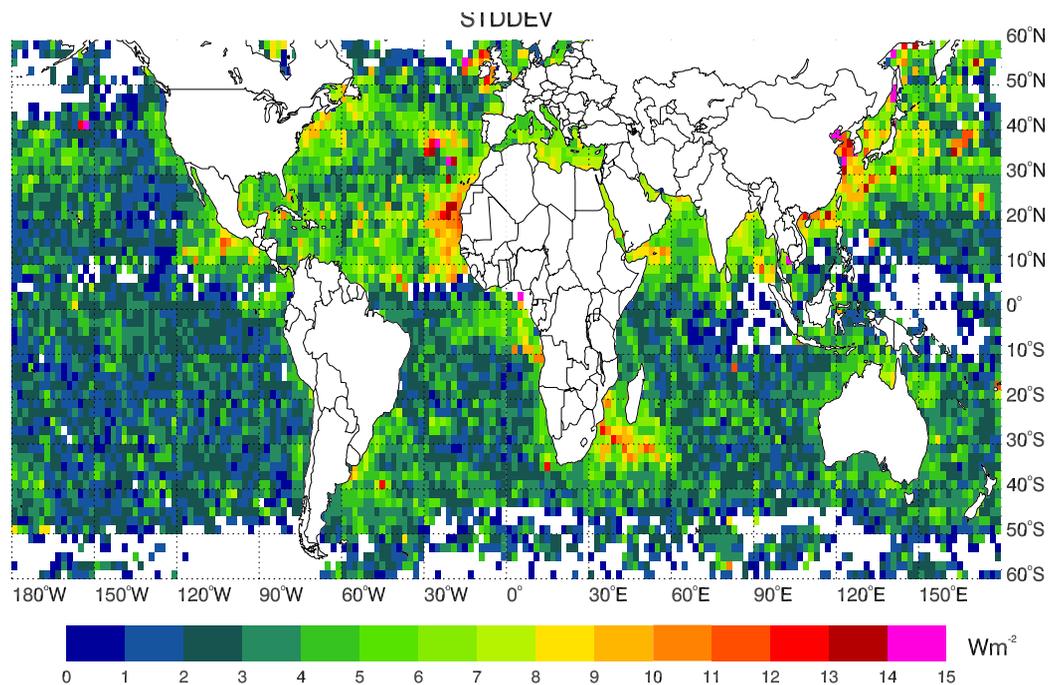
**Aerosol Radiative
Effect**T. A. Jones and
S. A. Christopher

Fig. 3. Standard deviation of SWRE within each 2×2 degree grid-cell.

[Title Page](#)[Abstract](#)[Introduction](#)[Conclusions](#)[References](#)[Tables](#)[Figures](#)[◀](#)[▶](#)[◀](#)[▶](#)[Back](#)[Close](#)[Full Screen / Esc](#)[Printer-friendly Version](#)[Interactive Discussion](#)

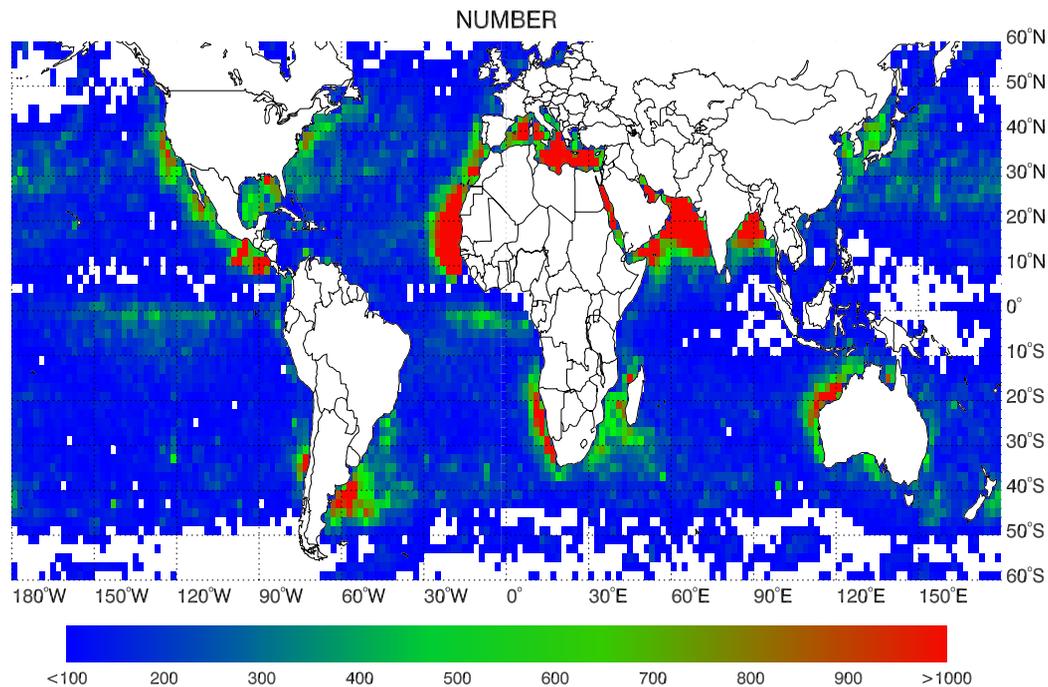
**Aerosol Radiative
Effect**T. A. Jones and
S. A. Christopher

Fig. 4. Number of raw pixels present within each grid-cell.

[Title Page](#)[Abstract](#)[Introduction](#)[Conclusions](#)[References](#)[Tables](#)[Figures](#)[◀](#)[▶](#)[◀](#)[▶](#)[Back](#)[Close](#)[Full Screen / Esc](#)[Printer-friendly Version](#)[Interactive Discussion](#)

**Aerosol Radiative
Effect**T. A. Jones and
S. A. Christopher

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures

◀

▶

◀

▶

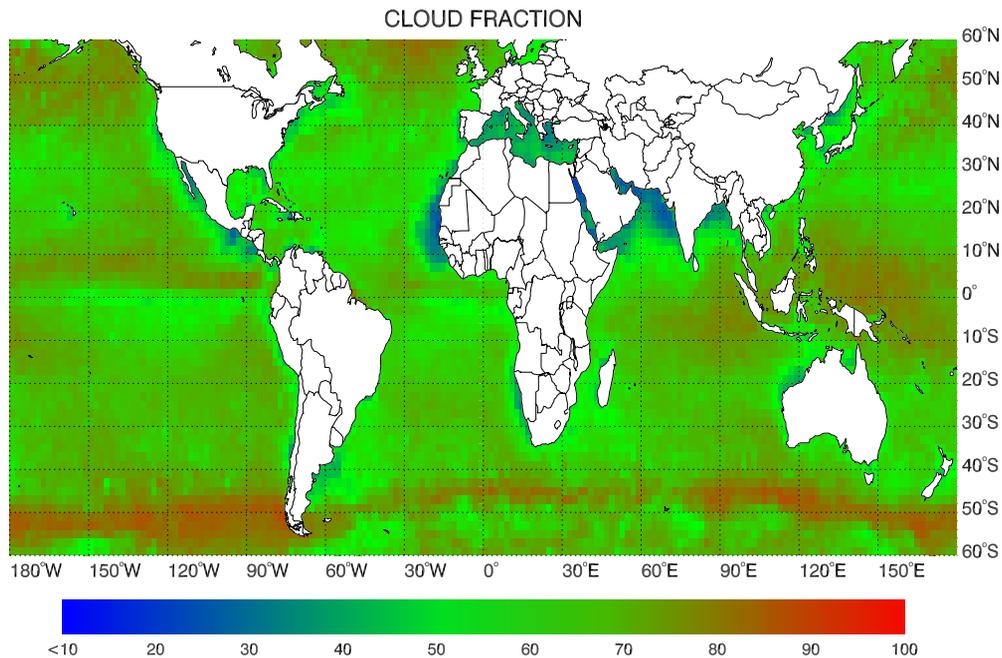
Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion

**Fig. 5.** Global MODIS cloud fraction for each grid-cell.

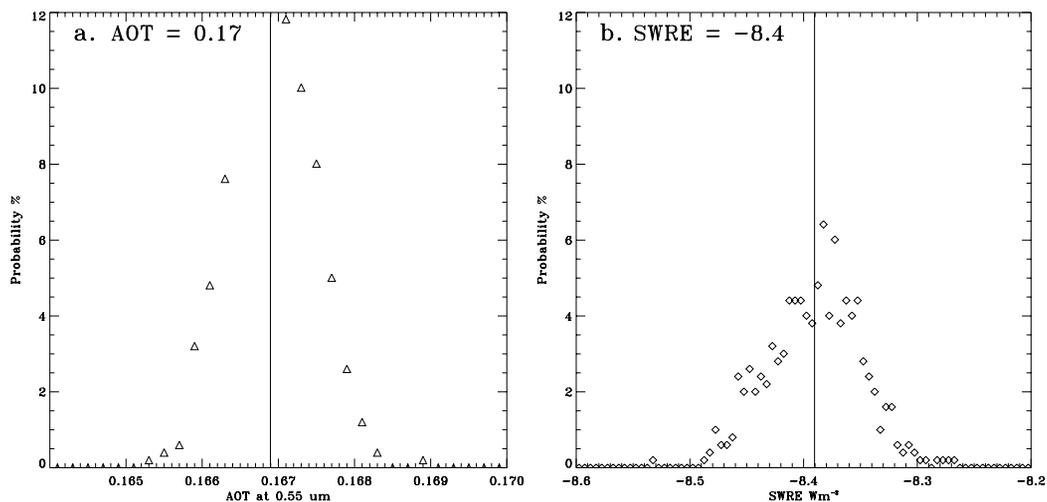
Aerosol Radiative
EffectT. A. Jones and
S. A. Christopher

Fig. 6. Probability density functions of mean AOT **(a)** and SWRE **(b)** derived by randomly sampling 5% of the total number of pixels and computing the average, and repeating the process 500 times.

[Title Page](#)[Abstract](#)[Introduction](#)[Conclusions](#)[References](#)[Tables](#)[Figures](#)[◀](#)[▶](#)[◀](#)[▶](#)[Back](#)[Close](#)[Full Screen / Esc](#)[Printer-friendly Version](#)[Interactive Discussion](#)

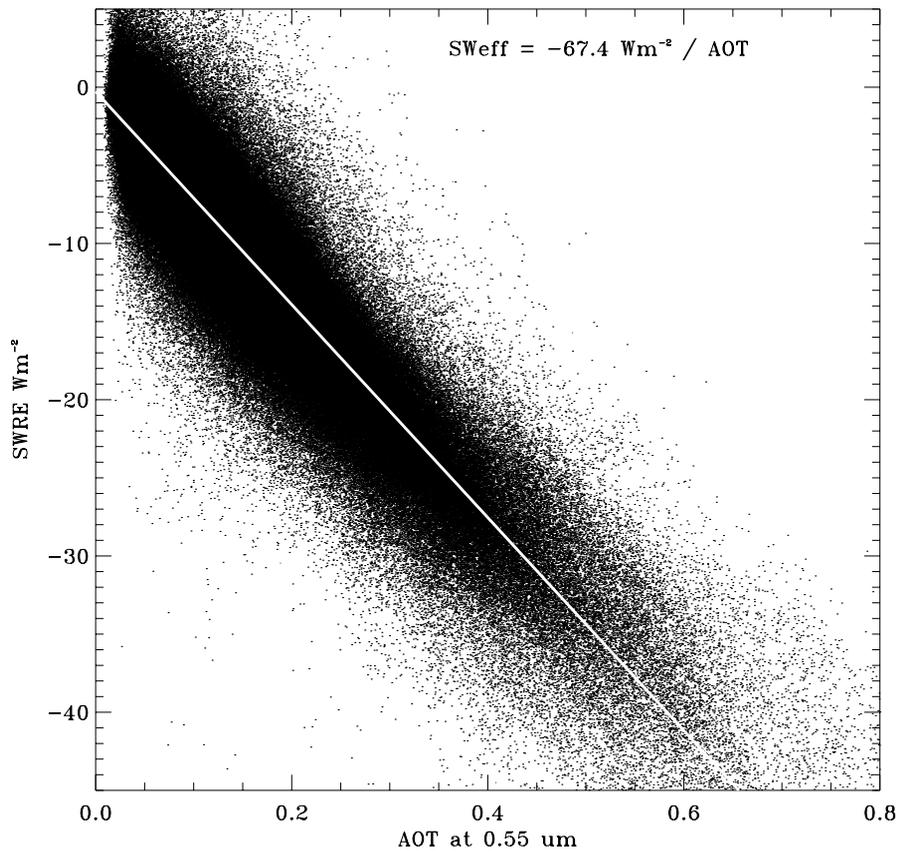


Fig. 7. Scatterplot of AOT vs. SWRE with linear regression line overplotted.

Aerosol Radiative Effect

T. A. Jones and
S. A. Christopher

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures

◀

▶

◀

▶

Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion

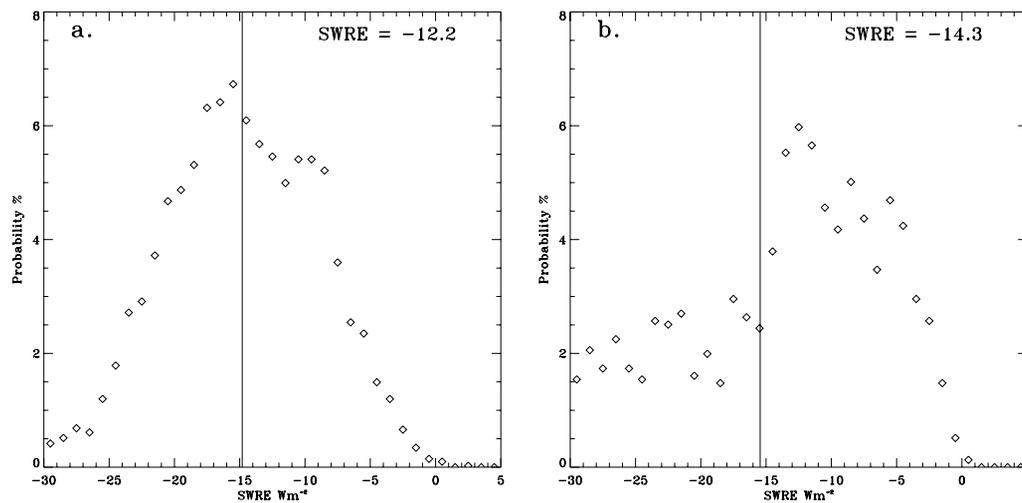
Aerosol Radiative
EffectT. A. Jones and
S. A. Christopher

Fig. 8. Probability density function of raw data points present in selected grid-cells at 19° N, 69° E (a), and 19° N, 19° W (b).

[Title Page](#)[Abstract](#)[Introduction](#)[Conclusions](#)[References](#)[Tables](#)[Figures](#)[◀](#)[▶](#)[◀](#)[▶](#)[Back](#)[Close](#)[Full Screen / Esc](#)[Printer-friendly Version](#)[Interactive Discussion](#)

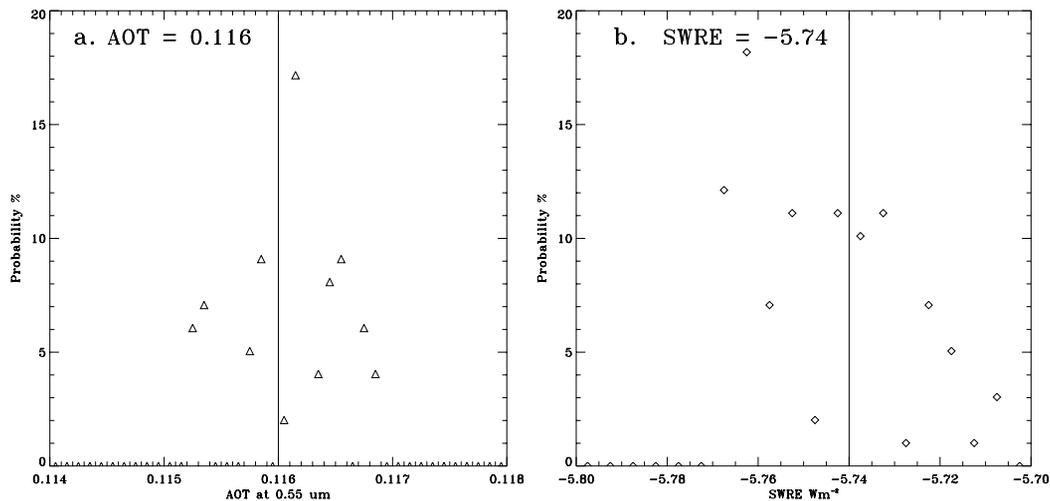
Aerosol Radiative
EffectT. A. Jones and
S. A. Christopher

Fig. 9. Probability density function of randomly sampled gridded AOT **(a)** and SWRE **(b)** data.

[Title Page](#)[Abstract](#)[Introduction](#)[Conclusions](#)[References](#)[Tables](#)[Figures](#)[◀](#)[▶](#)[◀](#)[▶](#)[Back](#)[Close](#)[Full Screen / Esc](#)[Printer-friendly Version](#)[Interactive Discussion](#)

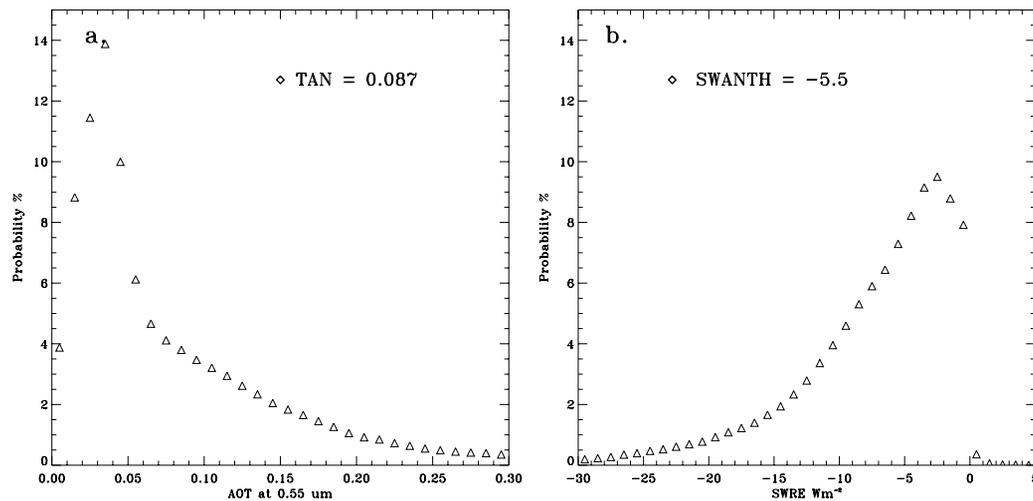
Aerosol Radiative
EffectT. A. Jones and
S. A. Christopher

Fig. 10. Dust and anthropogenic component AOT **(a)** and SWRE **(b)** probability density functions. (Maritime AOT and SWRE not shown).

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures

◀

▶

◀

▶

Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion