Why Is Satellite Observed Aerosol’s Indirect Effect So Variable?

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Abstract

Although evidence has shown that enhanced aerosol concentration reduces cloud drop size and increases cloud albedo, this phenomenon is not always observed by satellite. Satellite derived correlation between cloud drop size and aerosol concentration can be either negative, insignificant or even positive, depending on the location of the clouds. In this study, we propose an analytical model describing the coupled effects of aerosol concentration and cloud depth on cloud drop size and explain one major cause of the puzzling correlation. Marine stratocumulus observed over northeastern Pacific during summer is analyzed to support the proposed explanation. The result also reassures the aerosol indirect radiative effect being still at work even for the regions where it appears no negative correlation between aerosol concentration and cloud drop size observed by satellite.
1. Introduction

An enhanced aerosol concentration may increase the number of cloud drops by providing more cloud condensation nuclei (CCN), which in turn results in a higher cloud albedo. This process is often referred to as the aerosol indirect effect (AIE). Many in situ and remote sensing observations support this hypothesis [Han et al., 1994; Durkee et al., 2000; Pawlowska and Brenguier, 2000; Ramanathan et al., 2001; Twohy et al. 2001; Liu et al. 2003; VanReken et al., 2003]. However, satellite observed relations between aerosol concentration and cloud drop size are not always in agreement with the AIE. Based on global analysis of cloud effective radius ($r_e$) and aerosol number concentration ($N_a$) derived from satellite data, Sekiguchi et al. [2003] found that the correlation between the two variables can be either negative, or positive, or none, depending on the location of the clouds. They discovered that negative $r_e - N_a$ correlations can only be identified along coastal regions where abundant continental aerosols inflow from land, whereas Feingold et al. [2001] found that the response of $r_e$ to aerosol loading is the greatest in the region where aerosol optical depth ($\tau_a$) is the smallest. It was also reported that the discrepancy among satellite observed AIE might result from the use of different cloud retrieval methods or different types of satellite data [Rosenfeld and Feingold, 2003]. For example, over ocean the Advanced Very High Resolution Radiometer measured AIE [Nakajima et al. 2001] is as twice as that measured by the Polarization and Directionality of the Earth Reflectances [Bréon et al., 2002].

Why is the satellite observed AIE so variable? Is it due to the differences in the aerosol’s properties themselves, or other cloud dynamical variables, such as the cloud geometric depth ($H$) as suggested by Brenguier et al. [2003]? In this paper, we introduce
a concept of “coherent pattern problem”, then use the coherent pattern between \( \tau_a \) and \( H \) in the northeastern Pacific as an example to answer the above questions.

2. The Coherent Pattern Problem and Analytic Model

AIE usually refers to the impact of aerosol loading on Earth albedo through the change of cloud microphysics. Here, we refer the process of aerosol’s impact on cloud microphysics as AIE-C. As hypothesized in AIE-C, \( r_e \) can be modified by aerosol concentration. Since \( r_e \) also increases as cloud develops, using satellite observable \( \tau_a \) as a proxy of aerosol concentration, the variation of \( r_e \) with respect to \( \tau_a \) may be expressed by

\[
\frac{d r_e}{d \tau_a} = \left( \frac{\partial r_e}{\partial \tau_a} \right)_H + \left( \frac{\partial r_e}{\partial H} \right)_{r_e} \frac{d H}{d \tau_a}.
\]

The left hand side on (1) describes the overall change of \( r_e \) with \( \tau_a \), which is apparent AIE-C often observed by satellite. Because AIE-C is a measure of the \( r_e \) change due to aerosol loading, it should not be measured by \( dr_e/d\tau_a \), but by \( (\partial r_e/\partial \tau_a)_H \). Therefore, the second term on right hand side of (1) denotes the difference between the satellite observed and real AIE-C. Assuming that \( H \) and \( \tau_a \) are not randomly distributed in space, rather, follow certain patterns that are not orthogonal, so that \( dH/d\tau_a \neq 0 \). It should be emphasized that the variations of \( H \) might not be caused directly by the variations of \( \tau_a \), or vice versa. They may just happen to be coherently distributed in space, due to other physical processes such as those related to boundary layer depth and prevailing wind. (1)
indicates that even though the relation among \( r_e, \tau_a \) and \( H \) is known, AIE-C measured by satellite is still variable depending on the spatial distributions of \( H \) and \( \tau_a \).

Since \( r_e \) increases as \( H \) increases, \( (\partial r_e / \partial H)_{\tau_a} \) is positive. From (1), we may conclude that: if \( dH/d\tau_a < 0 \), \( dr_e/d\tau_a \) becomes more negative than \( (\partial r_e / \partial \tau_a)_H \). Hence the apparent AIE-C observed by satellite is intensified. Likewise, if \( dH/d\tau_a > 0 \), \( dr_e/d\tau_a \) becomes less negative than \( (\partial r_e / \partial \tau_a)_H \), or even positive. A weak or even opposite AIE-C may be induced from satellite data under this kind of spatial distributions. In this study, we call this spatial distribution impact on the observed \( r_e - \tau_a \) relation the “coherent pattern problem”.

Next, we derive an analytical model of the function of \( r_e(H, \tau_a) \) for marine stratocumulus. For an adiabatic cloud, \( r_e \) may be related to cloud drop number concentration \( (N_c) \) and \( H \) by \( r_e \propto N_c^{-1/3} H^{1/3} \) [Brenguier et al., 2003]. Although it cannot be simply parameterized, the effect of non-adiabatic processes such as entrainment-mixing on \( r_e \) seems to be small based on in situ measurements [Brenguier et al., 2003]. Therefore, we assume that \( r_e-H \) relation in stratocumulus only shows a small departure from the adiabatic model, while preserving a similar functional relationship. Based on previous studies [e.g., Nakajima et al., 2001], let us approximate \( N_c \) by a power function of \( \tau_a \). We may then write

\[
r_e = \sigma \tau_a^{-\alpha} H^{\beta},
\]

where \( \sigma \) is a coefficient, and the exponents \( \alpha \) and \( \beta \) reflect the importance of aerosol and cloud depth in determining the cloud drop size, respectively. It should be mentioned that
for clouds with $r_e > \sim 14$ µm precipitation may start to alter the above relation. Therefore, in our data analysis we will apply a threshold to filter out potential drizzle pixels.

3. Data Analysis and Results

We use stratocumulus observed over the northeastern Pacific during summer (June, July and August) 2000 as an example to explain the coherent pattern problem, and further to determine AIE-C. Cloud effective radius, cloud optical depth and drizzle index are derived from combined visible, near-infrared and microwave data of the Tropical Rainfall Measuring Mission (TRMM) satellite [Shao and Liu, 2004]. To ensure that measurements are from warm, non-precipitating stratocumulus, we use the following criteria to select our dataset: 1) infrared cloud top temperature between 280 and 288 K, 2) drizzle index less than 1.0, i.e., no drizzle occurring in the clouds, and 3) the product of the variances of $r_e$ and cloud optical depth within a TRMM Microwave Imager’s 37 GHz field of view (~12 km) less than 8.0 µm$^2$ (a threshold used to filter out non-uniform convective clouds). Six-hourly NCEP/NCAR reanalysis surface data are utilized to obtain air temperature and relative humidity near surface. Using the air temperature and relative humidity, we evaluate the temperature at the lifting condensation level (LCL) by assuming air mass ascent from near surface following a dry adiabatic lapse rate. The temperature difference between LCL and cloud top (determined by infrared satellite data) is then used to calculate cloud depth by assuming an in-cloud lapse rate of 7.5 K km$^{-1}$. Data of $\tau_a$ are from the Moderate Resolution Imaging Spectroradiometer (MODIS) atmospheric aerosol product archived by NASA [Kaufman and Tanré, 1998].

The three-monthly geometric mean distributions of $\tau_a$, $H$ and $r_e$ are shown in Figure 1. One feature is that the gradient of both $\tau_a$ and $H$ is almost perpendicular to the
California coastline. The gradient of $\tau_a$ and $H$ has the opposite sign near coastal region (i.e., $H$ increases while $\tau_a$ decreases away from the coast), but the same sign far off the coast. Consulting (1), this coherent pattern should cause a strong negative $r_e - \tau_a$ correlation near the coast, and a weak negative or even positive correlation to the west of region.

Using the above three-monthly geometric mean $1^\circ \times 1^\circ$ data of $r_e$, $\tau_a$ and $H$, the multivariate linear regression of $\ln r_e$ on $\ln \tau_a$ and $\ln H$ based on the logarithm form of (2) and single linear regression of $\ln r_e$ on $\ln \tau_a$ are performed to obtain $\partial \ln r_e / \partial \ln \tau_a$ and $\partial \ln r_e / \partial \ln \tau_a$, respectively. Table 1 summarizes the coefficients and $R^2$ values of these regressions together with the width of 95% confidence interval for each coefficient (shown in the parentheses). Regression coefficients and their 95% confidence intervals indicate that the correlations between $r_e$ and $\tau_a$ (negative) and between $r_e$ and $H$ (positive) are statistically significant. The $R^2$ value shows the multivariate regression explains 73.4% of the total variance in the observed $r_e$, indicating that the relationship described by (2) is statistically robust for our dataset. It is interesting to see that our result of $-\partial \ln r_e / \partial \ln \tau_a = 0.070$ is consistent with the value of 0.085 obtained by Bréon et al. [2002], while our result of $-\partial \ln r_e / \partial \ln \tau_a = 0.297$ is comparable to the value of $\sim 0.17$ obtained by Nakajima et al. [2001]. Bréon et al. calculated AIE-C using a back-trajectory technique, which may have avoided the coherent pattern problem. Meanwhile, Nakajima et al.’s analysis was based on a Eulerian method, which may have suffered from the coherent pattern problem.

To illustrate the coherent pattern problem in the satellite dataset, we analyze the data by binning them along the $H$ gradient (NE-SW) direction. Although $H$ and $\tau_a$ are
multidimensional variables in general, in this particular case, we simplify them to one-dimensional variables because they mainly vary in NE-SW direction. We divide data into 12 bins according to their distance \( s \) to California coast (distance to the red line shown in Figure 1a). All variables are then averaged within each bin. Figure 2 shows \( H \) and \( \tau_a \) as a function of \( s \); circles and triangles are the so averaged \( H \) and \( \tau_a \), respectively, where the curves are their fittings, i.e., \( H(s) \) and \( \tau_a(s) \).

In Figure 3, the large dots show the \( r_e - \tau_a \) relation for observed data averaged in the 12 bins. Small dots show the \( r_e - \tau_a \) relation calculated using (2) with \( H(s) \) and \( \tau_a(s) \) in Figure 2 and the regressed \( \sigma, \alpha \) and \( \beta \) in Table 1. The curves show the \( r_e - \tau_a \) relation at constant values of \( H \) calculated with (2) and the regressed \( \sigma, \alpha \) and \( \beta \) in Table 1. The small dots captures the general trends of the large dots, suggesting that the coherent pattern between \( H \) and \( \tau_a \) is the major factor responsible for the varying correlation between satellite observed \( r_e \) and \( \tau_a \). For a given point A, the slope of AB represents the apparent AIE-C, \( \frac{dr_e}{d\tau_a} \), while the slope of AC represents the real AIE-C, \( \frac{\partial r_e}{\partial \tau_a} \). The distance BC is proportional to the difference between the apparent and the real AIE-C. It is seen that in the region where \( H(s) \) gradient has the opposite sign to \( \tau_a(s) \) gradient (i.e., \( s < \sim 1800 \) km or \( H < \sim 0.7 \) km), \( \frac{dr_e}{d\tau_a} > -\frac{\partial r_e}{\partial \tau_a} \), while the opposite is true for the regions where the gradients of \( H(s) \) and \( \tau_a(s) \) have the same sign. The correlation between observed \( r_e \) and \( \tau_a \) changes sign at the same location (\( H \sim 0.7 \) km) as \( dH/d\tau_a \) does, while \( r_e \) and \( \tau_a \) are always negatively correlated at a constant \( H \) as indicated by curves. It is also noted from Figure 3 that for \( H > 0.7 \) km, \( \frac{\partial r_e}{\partial \tau_a} \) is still negative although satellite data derived \( r_e \) and \( \tau_a \) are positively correlated. In other words, for those regions where
increasing $\tau_a$ appears to increase $r_e$, AIE-C still works if we exclude the artifact caused by
the coherent pattern problem.

4. Conclusions

Using an analytical model, we explained how the coherent nature between $H$ and $\tau_a$ misidentify AIE, if the $H$ gradient is not orthogonal to $\tau_a$ gradient. In the northeastern Pacific during summer, the gradients of both variables are almost normal to the California coastline with opposite signs near the coast and the same sign far off the coast. As a result, the apparent AIE observed by satellite is enhanced near the coast while it is reduced far off the coast. This may partially explain the findings of Sekiguchi et al. [2003] that negative correlation between $N_a$ and $r_e$ is the most evident near coastal regions, while the correlation becomes less significant or even turns to positive far off shore. Our study also manifests that in the regions where increasing $\tau_a$ appears to increase $r_e$, the real AIE still works in the direction of reducing cloud drop size with the increase of aerosol loading. Since AIE is such a complex process that involves a series of interactions among aerosol, cloud, dynamics and thermodynamics, there should be other possible causes responsible for varying $r_e - \tau_a$ correlation, for example, different cloud type, dynamics, or influence by turbulence [e.g., Novakov et al., 1994; Leaitch et al., 1996; Reid et al. 1999]. In addition, the values of $\alpha$ and $\beta$ may vary depending on regions and seasons. However, because our analytical model explains the observed data well, the coupled effects of aerosol concentration and cloud depth on cloud drop size due to their coherent pattern should be a major cause for the variable values of satellite derived AIE.
Analyzing field experiment data, Brenguier et al. [2003] pointed out that whether cloud optical depth is positively or negatively correlated to $r_e$ depends on the relation between $N_c$ and $H$. Our finding corroborates their results. However, there are noticeable differences between the two. While their relation among $r_e$, $H$ and $N_c$ is derived from 8 cloud cases, our study covers an area of thousands of kilometers and over a period of 3 months. Therefore, our results rather reflect a climatological mean for the study region and season than AIE for individual clouds. Another unexpected result revealed in this study is that $\tau_a$ in the western portion of the study area increases away from the coast, the cause of which is an interesting topic to study in the future.

Due to the persistence of clouds in the study region, satellite aerosol data are not available on a daily basis. Therefore, three-monthly mean data are used to represent the mean states of both cloud and aerosol. The assumption is that the aerosol properties between clear and cloudy days are similar. Since the overall distributions of $r_e$, $\tau_a$ and $H$ over northeastern Pacific during summer are very steady, it is plausible that analysis using the time-averaged data preserves the mean characteristics of AIE although aerosol impact on individual clouds has a much shorter timescale. Further studies based on shorter timescale are needed in the future to assess its impact on the estimated AIE.

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References


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Table 1. Summary of Regressions (Sample number = 403)

<table>
<thead>
<tr>
<th></th>
<th>R²</th>
<th>Variables</th>
<th>Coefficients</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Multivariate</strong></td>
<td>0.734</td>
<td>$\ln r_d$</td>
<td>$-\alpha$: -0.070 (± 0.031)</td>
</tr>
<tr>
<td>Regression</td>
<td></td>
<td>$\ln H$</td>
<td>$\beta$: 0.241 (± 0.023)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Constant</td>
<td>$\ln \sigma$: 2.477</td>
</tr>
<tr>
<td><strong>Single Regression</strong></td>
<td>0.443</td>
<td>$\ln r_d$</td>
<td>$-0.297$ (± 0.033)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Constant</td>
<td>1.698</td>
</tr>
</tbody>
</table>
Figure 1. Three-monthly (June to August, 2000) $1^\circ \times 1^\circ$ geometric mean distributions of (a) aerosol optical depth $\tau_a$, (b) cloud depth $H$, and (c) cloud effective radius $r_e$. 
Figure 2. Cloud depth $H$ and aerosol optical depth $\tau_a$ as a function of $s$. Circles and triangles are $H$ and $\tau_a$ averaged in the 12 $s$-bins, respectively. The curves, $H(s)$ and $\tau_a(s)$, are their best fits. Indicated by dashed line is the distance where the gradient of $\tau_a$ changes sign.
Figure 3. Relation between $r_e$ and $\tau_a$ for observed and calculated data. The large dots show the $r_e - \tau_a$ relation for observed data averaged in the 12 s-bins with darkness indicating cloud heights. Small dots show the $r_e - \tau_a$ relation calculated using (2) with $H$ and $\tau_a$ in Figure 2 and $\sigma$, $\alpha$, and $\beta$ values in Table 1. The curves show the $r_e - \tau_a$ relation at constant values of $H$. 