Simulation of the optical properties of plate aggregates for application to the remote sensing of cirrus clouds

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In regions of deep tropical convection, ice particles often undergo aggregation and form complex chains. To investigate the effect of the representation of aggregates on electromagnetic scattering calculations, we developed an algorithm to efficiently specify the geometries of aggregates and to compute some of their geometric parameters, such as the projected area. Based on in situ observations, ice aggregates are defined as clusters of hexagonal plates with a chainlike overall shape, which may have smooth or roughened surfaces. An aggregate representation is developed with 10 ensemble members, each consisting of between 4–12 hexagonal plates. The scattering properties of an individual aggregate ice particle are computed using either the discrete dipole approximation or an improved geometric optics method, depending upon the size parameters. Subsequently, the aggregate properties are averaged over all geometries. The scattering properties of the aggregate representation closely agree with those computed from 1000 different aggregate geometries. As a result, the aggregate representation provides an accurate and computationally efficient way to represent all aggregates occurring within ice clouds. Furthermore, the aggregate representation can be used to study the influence of these complex ice particles on the satellite-based remote sensing of ice clouds. The computed cloud reflectances for aggregates are different from those associated with randomly oriented individual hexagonal plates. When aggregates are neglected, simulated cloud reflectances are generally lower at visible and shortwave-infrared wavelengths, resulting in smaller effective particle sizes but larger optical thicknesses. © 2011 Optical Society of America

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1. Introduction

In recent years, significant research has been performed to improve the representation of the bulk-scattering and absorption properties of ice clouds within the atmosphere. Ice cloud bulk-scattering models have been developed by Baum et al. [1,2] for remote sensing applications from visible (VIS) through infrared (IR) wavelengths, and the ice clouds were assumed to be composed of ice crystals with a set of idealized particle habits, i.e., solid bullet rosettes, solid and hollow columns, droxtals, aggregates of solid columns, and hexagonal plates. The release of new microphysical ice cloud data from in situ measurements [3,4] suggests that the representation of complex particles needs modification, such as in the bullet rosette and aggregate models. The conventional solid bullet rosettes have been modified to have a hollow structure at the end of the columnar part of each bullet branch [5]. In addition to homogeneous ice particles, ice crystals with hexagonal habits were observed to contain internal air bubbles with spherical or spheroidal geometries [6].
Furthermore, due to collisions with water droplets or other ice cloud particles during the formation process, nonspherical ice crystals in ice cloud models are regarded as more realistic when their surfaces are not assumed to be perfectly smooth. The scattering of radiation by nonspherical ice crystals with rough surfaces has been discussed by Macke et al. [7], Yang and Liou [8], Shcherbakov et al. [9], and Yang et al. [10,11].

The representation of aggregated ice particles in cloud studies is an area needing further refinement and clarification. Aggregates are frequently found in regions of deep tropical convection [12–23] and are responsible for the generation and growth of precipitation particles that may coexist with supercooled water droplets at temperatures warmer than −30 °C [12]. Ice particles grown in supersaturated air fall through the atmosphere at various speeds. Although the exact mechanism for aggregate formation is not well understood [17], ice particles can form aggregates from collisions resulting from the relative motion and aerodynamic interactions or in the presence of a strong electric field. Aggregation is significantly influenced by the presence of strong electric fields that tend to exist in clouds with strong updrafts [24]. It has also been suggested that ice particles within tropical convective clouds are more likely to form aggregates in the presence of an electric field [13,17,25].

The coalescence rate is related to the habits of the individual ice particles and the ambient cloud temperature. Extensive laboratory studies (e.g., Hobbs et al. [26]) have demonstrated that hexagonal ice crystals that form at relatively warm temperatures (between −10 °C and −15 °C) may increase the aggregation rate. Furthermore, individual ice aggregates have often been found to be chains of plate-shaped crystals [13,27].

Current ice cloud bulk-scattering and absorption models used in the operational Moderate Resolution Imaging Spectroradiometer (MODIS) cloud property retrievals involve a percentage of roughened aggregates with large maximum dimensions [1,2]. A specific aggregate geometry defined by Yang and Liou [8], includes eight hexagonal columns. The aggregate dimension can be scaled when each hexagonal column is enlarged or reduced while the aspect ratio is kept invariant. The ice aggregate model was modified into a chainlike aggregate by Baran and Labonnote [28] and used for remote sensing applications based on Polarization and Directionality of Earth’s Reflectances data. The original model was transformed into the chainlike aggregates by stretching and rotating two of the original hexagonal columns to make the aggregate particle less dense (i.e., decreasing the volume-to-area ratio) and, therefore, to better fit the in situ observations.

Evans et al. [20] generated three types of aggregates consisting of 6–40 randomly oriented hexagonal columns and plates. Each aggregate monomer had a predetermined aspect ratio and particle size, and a larger particle was constructed by interlocking the fixed monomers. The discrete dipole approximation (DDA) method [29–32] was used to compute the scattering properties of the aggregates for application to the simulation of the radiances measured by the Compact Scanning Submillimeter Imaging Radiometer and the Cloud Radar System on NASA’s ER-2 aircraft. The aggregate ice particles were represented in the DDA code with each dipole size set to be the thickness of a hexagonal plate monomer. Um and McFarquhar [22] defined geometries of aggregates using ice particles formed from seven hexagonal plates, and the scattering properties of the aggregates were computed by the geometric ray-tracing technique [7,21,22,23,34].

In this study, we define a new set of aggregate ice particles made from plates and investigate the scattering properties from VIS to IR wavelengths. A computationally efficient method is presented in Section 2 to generate numerical aggregate geometries that are similar to those obtained from in situ measurements. In Section 3, we develop an aggregate representation from an ensemble of aggregate geometries and compute the resulting scattering properties. Section 4 is a discussion of the capability of the aggregate representation to represent general aggregates within ice clouds. The influence of the aggregate particles on the remote sensing of ice cloud microphysical and optical properties is discussed in Section 5, and conclusions are provided in Section 6.

2. Numerical Models for the Aggregation of Hexagonal Ice Crystals

The geometries of aggregate ice particles are available from in situ data collected during field campaigns [12–18,20]. Based on observations and on the formation processes, aggregates most likely contain hexagonal monomers. Furthermore, the aggregates tend to contain significantly more hexagonal plates than columns, indicating the cloud temperatures corresponding to the formation of the ice particles. The hexagonal ice monomers vary in the aspect ratio, and they can be attached together in planar and in more complex three-dimensional forms. Thus, one specific aggregate geometry will be insufficient to realistically represent natural aggregates. However, as demonstrated by Stith et al. [13], aggregates of plates often exhibit chain-style shapes instead of more compact shapes.

In the present study, the geometries of aggregates are defined by attaching hexagonal plates together in a chain-style structure. The monomer plates are in random orientations in the aggregates. The aspect ratios of the hexagonal plates, representing the relationship between the width and length of the particle, follow the in situ measurements reported by Pruppacher and Klett [35]. For a hexagonal plate larger than 5 μm, the aspect ratio is determined by the relationship [35]:

$$L = 2.4883a^{0.474},$$  (1)
where \( a \) and \( L \) represent the semiwidth and length of the ice crystal, respectively. The units of \( a \) and \( L \) are micrometers. Because aggregates consist of plates with similar sizes, \( a \) in Eq. (1) is given by

\[
a = 20 + 20\xi_1, \tag{2}
\]

\[
a = 40 + 40\xi_2, \tag{3}
\]

for generating relatively small and large aggregates, where \( \xi_1 \) and \( \xi_2 \) are independent random numbers distributed uniformly in \([0, 1]\).

Following Yang and Liou [8], we define aggregate ice crystals in a three-dimensional Cartesian coordinate system, \( \text{oxyz} \), where the geometric coordinate of each hexagonal plate can be determined by the width, length, particle-center coordinates, and the Euler angles on the basis of a \( z^-y^-z^+ \) convention. Figure 1(a) shows an example of a hexagonal particle that is specified in the \( \text{oxyz} \) coordinate system (the laboratory system) and in \( o_px'py'z'_p \) (the particle system). The transfer from the particle \( (o_px'py'z'_p) \) to the laboratory system \( (\text{oxyz}) \) through an intermediate coordinate system \( (o'_x'y'_z'_p) \) is given by

\[
\begin{bmatrix}
x'_p \\
y'_p \\
z'_p
\end{bmatrix}
= \begin{bmatrix}
x_p \\
y_p \\
z_p
\end{bmatrix}
+ \begin{bmatrix}
x'_0 \\
y'_0 \\
z'_0
\end{bmatrix}, \tag{4}
\]

\[
\begin{bmatrix}
x \\
y \\
z
\end{bmatrix}
= R
\begin{bmatrix}
x'_p \\
y'_p \\
z'_p
\end{bmatrix}, \tag{5}
\]

where \( (x'_0, y'_0, z'_0) \) are the coordinates of the origin of the \( o_px'py'z'_p \) system in the \( o'_x'y'_z'_p \) coordinate system and \( R \) is a rotational transformation matrix given by

\[
R = \begin{bmatrix}
\cos \gamma & -\sin \gamma & 0 \\
\sin \gamma & \cos \gamma & 0 \\
0 & 0 & 1
\end{bmatrix}
\begin{bmatrix}
\cos \beta & 0 & -\sin \beta \\
0 & 1 & 0 \\
-\sin \beta & 0 & \cos \beta
\end{bmatrix}
\begin{bmatrix}
\cos \alpha & \sin \alpha & 0 \\
-\sin \alpha & \cos \alpha & 0 \\
0 & 0 & 1
\end{bmatrix},
\]

where \( \alpha, \beta, \) and \( \gamma \) respectively, are the Euler angles that represent three consecutive rotations around the \( z, y, \) and \( z \) axes. The positive values of the Euler angles indicate clockwise rotations in their rotating planes. To represent aggregates having random orientations, the Euler angles of the coordinate rotations are given by

\[
\begin{align*}
\alpha &= \pi(2\xi_3 - 1), \tag{7} \\
\beta &= \cos^{-1}(2\xi_4 - 1), \tag{8} \\
\gamma &= \pi(2\xi_5 - 1), \tag{9}
\end{align*}
\]

where \( \xi_3, \xi_4, \) and \( \xi_5 \) are independent random numbers uniformly distributed in \([0, 1]\). As shown in Fig. 1(a), the valid range of \( \alpha, \beta, \) and \( \gamma \) is \((-\pi, \pi]\).

The particle centers of the hexagonal ice particles are determined in the \( \text{oxyz} \) coordinate system by

\[
\begin{align*}
x_0 &= d\xi_6 \sin \theta \cos \varphi, \tag{10} \\
y_0 &= d\xi_6 \sin \theta \sin \varphi, \tag{11} \\
z_0 &= d\xi_6 \cos \theta, \tag{12} \\
\theta &= \cos^{-1}(2\xi_7 - 1), \tag{13} \\
\varphi &= 2\pi\xi_8. \tag{14}
\end{align*}
\]

where \( d \) is initially set as a large value, e.g., 1000 \( \mu \)m; \( \xi_6, \xi_7, \) and \( \xi_8 \) are independent random numbers distributed uniformly in \([0, 1]\); and \( \theta \) and \( \varphi \) are the polar and azimuthal angles in the \( \text{oxyz} \) coordinate system [see Fig. 1(b)].

With the representations of an ice particle in the \( \text{oxyz} \) coordinate system, the distance between multiple ice particles can be computed numerically by considering the shortest distances among all the vertices and boundaries of the ice particles. The distance may be reduced with adjustments to the particle-center coordinates of an ice particle [specifically adjusting \( d \) in Eqs. (10)-(12)] while retaining all the other elements. Two ice particles can join if they do not overlap and the distance between them is negligible. Appendix A provides a detailed procedure for estimating the relative position between two hexagonal particles, computing their distance, and identifying whether or not they are overlapped.
the preceding process attaches more hexagonal plates to the particle. Because of the geometry of the particles, a new particle with determined \( a, L, \alpha, \beta, \) and \( \gamma \) may not necessarily touch some existing aggregate elements. Therefore, the aggregation process begins again by testing the possibility that the aggregate elements can be attached to the new particle. To define chain-style aggregates, the test is performed with the newly attached aggregate elements while the parameters in Eqs. (7)–(9) are revised. For example, let

\[
\beta_N = \begin{cases} 
\cos^{-1}(2z_N - 1) & \text{for } N = 1 \\
\beta_{N-1} + \cos^{-1}[2.0 \times (0.9^{0.5} - 0.5)] & \text{for } N > 1
\end{cases}
\]

where \( N \) indicates the \( N \)th hexagonal plate in the aggregation process.

Using the aforementioned procedure, we defined the numerous aggregates shown in Figs. 2 and 3. Figure 2 shows samples of “small” aggregates (hereafter referred to as aggregates 1–5) consisting of four or five hexagonal plates. The dimensions of the aggregates in Fig. 2 can be scaled to fit the size parameters involved in the single-scattering computations. However, as suggested by recent in situ measurements [3,4,20], aggregates with extremely large particle sizes are achieved by increasing the monomer numbers instead of only scaling the sizes of each monomer. As shown in Fig. 3, “large” aggregates are represented by five models (hereafter referred to as aggregates 6–10), each consisting of 8–12 hexagonal plates. In general, the ice cloud effective particle size for a given particle size distribution
is defined by the maximum dimensions $D_m$, projected areas $A_i$, and volumes $V_i$ of the individual particles. Counting the largest distance between all the aggregate vertices determines the maximum dimensions of the aggregates shown in Figs. 2 and 3. An algorithm based on the Monte Carlo method computes the projected areas of the aggregates, and the details are provided in Appendix B.

Figures 4(a) and 4(b) illustrate the ice crystal projected area and volume, respectively, for aggregates 1–5 as functions of the particle maximum dimension. Among the five habits used to represent small aggregates, aggregate 2 has a significantly larger projected area than the other habit realizations. Aggregate 5 has the smallest and largest values of projected area and volume, respectively, which indicates a much more compact aggregate. Aggregate 4 exhibits a less compact particle compared to aggregates 1, 3, and 5 and has a smaller volume and a larger projected area than the other habits. Figures 4(c) and 4(d) show the particle projected area and volume for aggregates 6–10. For aggregates having the same particle sizes, aggregates 7 and 9 have very similar volumes, whereas their projected areas are much smaller than those of the other habits. However, the volume of aggregate 10 is not distinct from aggregates 7 and 9. The parameters associated with the aggregates in Figs. 2 and 3 can be found in Tables 1 and 2.

### Table 1. Parameters Associated with the Five Aggregates with Small Particle Sizes

<table>
<thead>
<tr>
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<th>$L$</th>
<th>$a(^\circ)$</th>
<th>$\beta(^\circ)$</th>
<th>$\gamma(^\circ)$</th>
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<th>$y_0$</th>
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</table>

**Aggregate 2:** $D_m = 149.21 \mu m, A = 9.71955E + 03 \mu m^2, V = 1.48618E + 05 \mu m^3$

<table>
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<th>$a(^\circ)$</th>
<th>$\beta(^\circ)$</th>
<th>$\gamma(^\circ)$</th>
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<td>70.653</td>
<td>26.702</td>
<td>-12.658</td>
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**Aggregate 3:** $D_m = 162.32 \mu m, A = 7.26631E + 03 \mu m^2, V = 1.77345E + 05 \mu m^3$

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<th>$a(^\circ)$</th>
<th>$\beta(^\circ)$</th>
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<td>7.916</td>
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**Aggregate 4:** $D_m = 174.08 \mu m, A = 8.72443E + 03 \mu m^2, V = 1.66768E + 05 \mu m^3$

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**Aggregate 5:** $D_m = 101.73 \mu m, A = 2.15088E + 03 \mu m^2, V = 6.82456E + 04 \mu m^3$

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<th>$\beta(^\circ)$</th>
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*The units of $a$, $L$, and $(x_0, y_0, z_0)$ are micrometers.*
The root mean square (rms) relative errors from the ADDA are quite small for cases when \( m_r < 1.4 \), where \( m_r \) is the real part of the refractive index. However, the ADDA requires sufficient electric dipoles in the computational domain to resolve detailed geometric features of the scattering particle.
and to achieve numerical accuracy. As a result, chained-particle aggregates tend to consume a substantial amount of computing time because of the multiple electric dipoles in a relatively large computational domain. In our study, ADDA v 0.79 [36] is used to compute the scattering properties of aggregates. The size of the electric dipoles in the ADDA is given as follows:

\[
\begin{align*}
\frac{D_s}{20} \text{ for } & X \leq 1 \\
\frac{\lambda}{20|m|} \text{ for } & 1 < X \leq 5 \\
\frac{\lambda}{10|m|} \text{ for } & 5 < X \leq 15 \\
\frac{\lambda}{5|m|} \text{ for } & X > 15
\end{align*}
\]

(16)

where \(d\) is the interdipole distance, \(m\) is the refractive index of the aggregates, \(\lambda\) is the wavelength, and \(\langle\rangle\) indicates the minimum value of the variables. The size parameter, \(X\), of an aggregate is defined by

\[
X = \frac{\pi D_s}{\lambda},
\]

(17)

where \(D_s\) is the diameter of a volume-equivalent sphere. Based on Yurkin and Hoekstra [37], the accuracy of the results decreases with the increase of \(d\) and is reported as several percent when \(d = \frac{\lambda}{10|m|}\).

The conventional IGOM has been extensively employed in the light scattering and radiative transfer processes for satellite-based remote sensing of ice clouds [1,2,47–50]. For computations involving large size parameters, the IGOM is an efficient method for computing the scattering properties of aggregates, and our version has been updated in numerous ways over the past few years. Compared to the computations reported by Yang and Liou [8], the current IGOM has improved the treatment of the edge effect [51–53] and enhanced the treatment of forward scattering [42] to more accurately account for the divergence of scattered energy in the forward peak. The result of the new treatment of forward scattering is that a delta-transmission term is no longer required, even for extremely large particles. As a result of the scattering model improvements, the extinction efficiency of an ice particle exhibits a smooth transition from small to large particles whose scattering properties are computed from the ADDA and IGOM, respectively. The IGOM code used in Yang and Liou [8] has been revised to adapt to various sets of parameters associated with aggregates.

Figure 5 shows the extinction efficiency, absorption efficiency, single-scattering albedo, and asymmetry factor as functions of the size parameter for the randomly oriented aggregate 1 at \(\lambda = 2.13\mu m\). The random orientations of the particles are achieved in the ADDA by using the built-in orientation averaging algorithm. A detailed discussion of the averaging process can be found in the literature [36]. The extinction and absorption efficiencies calculated with

Fig. 4. (a), (b) Variation of ice crystal projected area and volume versus maximum dimension for aggregates 1–5. (c), (d) Variation of ice crystal projected area and volume versus maximum dimension for aggregates 6–10.
the ADDA were originally derived by dividing the corresponding extinction and absorption cross sections of the scattered particle over the cross section of a volume-equivalent sphere. To be more consistent with the IGOM, we replace the cross section of the volume-equivalent sphere by a projected area computed by the process described in Appendix B. In the IGOM computations, the above-edge effect contribution to the extinction and absorption efficiencies can be approximated following Bi et al. [42]:

\[
Q_{e,edge} (\lambda) = 2c_1 \left( \frac{\lambda}{\pi D_m} \right)^{2/3},
\]

\[
Q_{a,edge} (\lambda) = 2c_2 \left( \frac{\lambda}{\pi D_m} \right)^{2/3}.
\]

The two constants, \(c_1\) and \(c_2\), are determined by the wavelength (\(\lambda_t\)) where the ADDA model switches to the IGOM:

\[
c_1 = 0.5 \left[ Q_{e,ADDA} (\lambda_t) - Q_{e,IGOM} (\lambda_t) \right] \left( \frac{\pi D_m}{\lambda_t} \right)^{2/3},
\]

\[
c_2 = 0.5 \left[ Q_{a,ADDA} (\lambda_t) - Q_{a,IGOM} (\lambda_t) \right] \left( \frac{\pi D_m}{\lambda_t} \right)^{2/3}.
\]

where \(Q_{e,ADDA} (\lambda_t)\) and \(Q_{a,ADDA} (\lambda_t)\) are the extinction and absorption efficiencies computed by the ADDA, and \(Q_{e,IGOM} (\lambda_t)\) and \(Q_{a,IGOM} (\lambda_t)\) are the efficiencies computed from the IGOM without accounting for the above-edge effect. The results in Fig. 5 indicate that the extinction efficiency for the aggregate initially rises rapidly with particle size, and it subsequently approaches a constant value of 2 with a decaying oscillation. As the size parameter increases from 40 to 1000, the absorption efficiency increases dramatically due to the increase of the ray path length within the particle, and the single-scattering albedo decreases from 1. The asymmetry factor in Fig. 5 generally increases with particle size when diffraction becomes significant compared to the scattering of light by the particle. For wavelengths with strong absorption within the particle, the scattering properties increase with particle size, as shown in Fig. 6. The results in Figs. 5 and 6 reflect smooth transitions of the scattering properties from small to large particles, although a small difference in the asymmetry factors is apparent when \(\lambda = 2.13 \mu m\). Because of improvements in the IGOM, the computations by the ADDA and IGOM are very consistent in the region where the size parameter is approximately 25. The scattering properties of the aggregates in our study are computed by the ADDA when the size parameter is smaller than 25, and they
are computed by the IGOM for aggregates with larger size parameters.

Figure 7 shows the scattering phase matrices for aggregate 1 with a maximum dimension of 100 μm. In the manner of Yang and Liou [8], the surface roughness of the aggregates is specified by many small tilted facets on the particle surface. The slopes of the roughened facets are randomly sampled assuming a Gaussian distribution [54]. The rms tilt σ can be used as the parameter to specify the degree of surface roughness. As σ increases from 0 to 1, the surface roughness varies from smooth to deeply roughened. As shown in Fig. 7, aggregates are seen to be associated with strong forward scattering at VIS wavelengths due to diffraction. In addition, the phase function for a smooth aggregate reveals halo peaks at approximately 22° and 46°. However, the maxima of the halos decrease as σ increases because of spreading of the rays associated with the minimum deviation of refraction. Figure 8 shows the independent nonzero elements of the scattering phase matrix for aggregate 10 with a maximum dimension of 1000 μm. The scattering phase function (P_{11}) for aggregate 10 has lower values at some side scattering angles compared to aggregate 1 for smooth particles, but these differences decrease as σ increases. It is interesting to note that an increasing σ tends to increase the side scattering over that of smooth particles. Additionally, the other independent nonzero elements of the phase matrices in Figs. 7 and 8 are sensitive to ice particle habit, size, and surface roughness, which indicate the potential of using polarization measurements to determine ice cloud microphysical properties. Figure 9 compares the scattering phase matrices for aggregates 1 and 10 at λ = 12.0 μm, and it can be seen that the various elements of the phase matrix tend to be nearly featureless (i.e., no halos) because of strong absorption.

4. Sensitivity of the Aggregate Ensemble Representation

Various aggregate models consisting of either one or a small number of predetermined geometric particles have been used in previous studies [8, 20, 22, 28]. Our

![Fig. 7. Scattering phase matrices for aggregate 1 at λ = 0.65 μm. The refractive index of ice at λ = 0.65 μm is 1.3080 + i1.43 × 10^{-8}.](image)

![Fig. 8. Scattering phase matrices for aggregate 10 at λ = 0.65 μm. The refractive index of ice at λ = 0.65 μm is 1.3080 + i1.43 × 10^{-8}.](image)

![Fig. 9. Scattering phase matrices for aggregates 1 and 10 at λ = 12.0 μm. The refractive index of ice at λ = 12.0 μm is 1.2799 + i4.13 × 10^{-1}.](image)
aggregate representation uses 10 aggregate geometries with various particle sizes to represent the aggregates found in ice clouds. The averaged scattering properties of the ice cloud aggregates can be used to investigate the ability of our aggregate model to represent an ensemble of particles.

Figure 10 shows the comparison of the scattering phase functions for the "aggregates" contained in ice clouds with the approximations using our aggregate representations shown in Figs. 2 and 3. To represent the variety of aggregates in ice clouds, the "aggregates" are an average of 1000 computer-generated aggregates composed of four or five hexagonal plates having aspect ratios as described by Eq. (1). Similar to the aggregate representation involving aggregates 6–10, large aggregates in the "aggregates" consist of 8 to 12 plates, except that 1000 geometries are considered. The equivalent phase functions in Fig. 10 are given by

\[
P_{11}(\Theta, D_m, \lambda) = \frac{\sum_{n=1}^{M} P_{11}(\Theta, D_m, \lambda, n) C_s(D_m, \lambda, n)}{\sum_{n=1}^{M} C_s(D_m, \lambda, n)},
\]

\[(22)\]
where $P_{11}(\Theta, D_m; \lambda, n)$ is the phase function for each aggregate geometry, $\Theta$ is the scattering angle, $C_s(D_m, \lambda, n)$ is the scattering cross section, and $M$ is 5 and 1000 for our aggregate representation and the “aggregates,” respectively. Figure 10(a) illustrates the comparison of the scattering phase functions for large aggregates at $\lambda = 0.65 \mu m$. The results indicate that the phase function of a large aggregate shows a slight sensitivity to particle geometry. Generally, for large particles, both aggregate 9 and the “aggregates” are consistent in their representation of scattering properties. However, tiny oscillations are noticeable in the phase function of a single aggregate, especially at small scattering angles. In the “aggregates” and our aggregate representation, these oscillations are averaged to be physically more meaningful. Figure 10(b) compares the phase functions of our aggregate representation for various surface roughness conditions. The phase function oscillation is reduced greatly when surface roughness is incorporated. The aggregates being considered in Fig. 10(c) are represented by aggregate 5, aggregates 1–5, and the “aggregates.” The scattering phase functions are computed by the ADDA because the size parameter is small. In the comparison between the phase functions of the “aggregates” and aggregate 5, slight differences are shown in the forward scattering region. At side and back scattering angles, the phase function of aggregate 5 is substantially different from those of the other two aggregate representations. The Student’s $t$-test [55] is used to investigate the difference between the phase functions from the two aggregate representations. The $t$-test is used because the goal is to compare the phase functions averaged over both 10 and 1000 aggregate geometries and subsequently determine if 10 aggregates can be used to represent the 1000 aggregates. The use of fewer aggregate representations greatly decreases the amount of computer time necessary to calculate the scattering properties. The samples of the Student’s $t$-test are the averaged phase functions as functions of the scattering angle. Therefore, the Student’s $t$-test can provide an estimate of the overall agreement of the phase functions from the 1000 aggregates and the approximation using 10 aggregates.

$|t| = 0.1405 < t_{0.05} = 1.96, \quad (23)$

$|t| = 0.5096 < t_{0.05} = 1.96, \quad (24)$

for the phase functions at the scattering angles of $0^\circ$–$180^\circ$ and $60^\circ$–$180^\circ$, respectively. The null hypothesis is rejected in favor of the alternative hypothesis. Therefore, the aggregate representation in this study can be used to represent the “aggregates” in the simulation of their scattering properties.

5. Aggregation Effect in the Retrieval of Ice Cloud Properties

To simulate the scattering properties of ice clouds containing individual hexagonal particles and their aggregates, we first assume the geometries shown in Figs. 2 and 3. The particle sizes of the aggregates are based on a particle size distribution, which, for ice clouds, is generally parameterized by the gamma distribution [56–58] given by

$$n(D_m) = N_0 D_m^{\alpha \beta + 0.67} e^{-\frac{b + \mu}{D_m \text{median}}},$$

(25)

where $D_m$ is the dimension of the aggregate, $N_0$ is the concentration intercept parameter, and $D_m \text{median}$ is the median of the distribution of $D_m$. The parameters, $\mu$ and $b$, are assumed to be 2.0 and 2.2, respectively [2]. Clouds containing a mixture of ice habits can be generated by the decomposition of a number of aggregates into hexagonal fractions. The geometries of the fractions are dependent on the aggregate dimensions and can be derived based on the information provided in Tables 1 and 2. The effective diameter of the ice clouds are derived as follows:

$$D_e = \frac{1}{2} \left[ (1-f) \sum_{i=1}^{24} \int_{D_{\min}}^{D_1} V_{pi} n(D_m) dD_m + \sum_{j=1}^{50} \int_{D_1}^{D_{\max}} V_{pj} n(D_m) dD_m \right] + N_0 \int_{D_{\min}}^{D_{\max}} V_a n(D_m) dD_m,$$

(26)

Aggregate 5 can be used to represent the “aggregates” when the null hypothesis is rejected. For scattering angles of $60^\circ$–$180^\circ$, the $t$-statistic, $|t| = 5.1862$, has exceeded the 95% confidence level ($t_{0.05} = 1.96$), which suggests that the differences in phase functions are significant between aggregate 5 and the “aggregates” containing 1000 geometries. The Student’s $t$-test can be carried out on the phase functions of the “aggregates” and our aggregate representation. To assess the significance of our aggregate representation, the t-statistics are computed as follows:

$$|t| = 0.1405 < t_{0.05} = 1.96, \quad (23)$$

$$|t| = 0.5096 < t_{0.05} = 1.96, \quad (24)$$

for the phase functions at the scattering angles of $0^\circ$–$180^\circ$ and $60^\circ$–$180^\circ$, respectively. The null hypothesis is rejected in favor of the alternative hypothesis. Therefore, the aggregate representation in this study can be used to represent the “aggregates” in the simulation of their scattering properties.
geometries; and $D_1$ is the threshold value of the aggregate dimensions to determine small and large aggregates. In this study, $N_a$ is 5 and $D_1$ is assumed to be 550 $\mu$m. Note that the particle size distributions of plates are different than that of the aggregates. However, the size distributions of the plates are not derived because they are not used in the computation of the effective particle sizes and scattering properties in our cloud model.

can both affect the retrieval of cloud optical thickness. A reduction in the particle number concentration caused by the aggregation process tends to decrease the ice cloud optical thickness. This feature becomes more pronounced when 90% of the plates form aggregates, as shown in Fig. 11(b). It is also clear from Fig. 11 that the retrieved ice cloud effective particle sizes generally decrease when the aggregation effect is ignored in the retrieval process.

The phase functions of ice clouds are given by

$$P_{11} = \frac{(1-f) \left[ \sum_{i=1}^{24} \int_{D_{\text{min}}}^{D_1} P_{11,pi} C_{s,pi} n(D_m) dD_m + \sum_{i=25}^{74} \int_{D_{\text{min}}}^{D_{\text{max}}} P_{11,pi} C_{s,pi} n(D_m) dD_m \right] + N_{af} \int_{D_{\text{min}}}^{D_{\text{max}}} P_{11,a} C_{s,a} n(D_m) dD_m}{(1-f) \left[ \sum_{i=1}^{24} \int_{D_{\text{min}}}^{D_1} C_{s,pi} n(D_m) dD_m + \sum_{i=25}^{74} \int_{D_{\text{min}}}^{D_{\text{max}}} C_{s,pi} n(D_m) dD_m \right] + N_{af} \int_{D_{\text{min}}}^{D_{\text{max}}} C_{s,a} n(D_m) dD_m},$$

where $P_{11,pi}$ and $C_{s,pi}$ are the phase function and scattering cross section for the plates and $P_{11,a}$ and $C_{s,a}$ are the phase function and scattering cross section for the aggregates.

To investigate the influence of ice particle aggregation on the inference of ice cloud microphysical and optical properties, reflectances are simulated by the discrete ordinates radiative transfer model [59] for two channels centered at wavelengths of 0.65 and 2.13 $\mu$m. A dark (nonreflective) surface condition is assumed to eliminate the influence of surface bidirectional reflectance features. Figure 11 compares the calculated lookup tables. The dashed curves in Fig. 11(a) denote hexagonal plates, while the solid curves are used to indicate an ice cloud model that contains the same habits with the exception that 30% of the plates form aggregates. From Fig. 11(a), it can be found that the optical thicknesses of the ice clouds are reduced when aggregates are included. Based on the scattering properties of the aggregates, the optical thickness is determined by

$$\tau = (1-f) \Delta z \left[ \sum_{i=1}^{24} \int_{D_{\text{min}}}^{D_1} C_{e,pi} n(D_m) dD_m + \int_{D_{\text{min}}}^{D_{\text{max}}} C_{e,pi} n(D_m) dD_m \right] + N_{af} \int_{D_{\text{min}}}^{D_{\text{max}}} C_{e,a} n(D_m) dD_m,$$

where $\Delta z$ is the physical thickness of the cloud and $C_{e,pi}$ and $C_{e,a}$ are the extinction cross sections for the plates and aggregates. When $f$ is 0, the optical thickness is increased to that of 100% plates. From Eq. (28), it is known that the scattering properties and particle number concentration of ice crystals can both affect the retrieval of cloud optical thickness. A reduction in the particle number concentration caused by the aggregation process tends to decrease the ice cloud optical thickness. This feature becomes more pronounced when 90% of the plates form aggregates, as shown in Fig. 11(b). It is also clear from Fig. 11 that the retrieved ice cloud effective particle sizes generally decrease when the aggregation effect is ignored in the retrieval process.

6. Summary

With a set of in situ measurements of aggregates as guidance, an algorithm is developed to efficiently define the geometries of aggregates and compute their projected areas. Aggregates result from attaching ice particle hexagonal plates together in a chainlike manner. We investigate the scattering properties of randomly oriented aggregates of plates using the ADDA and IGOM for particles whose size parameters are smaller and larger than 25, respectively. The results indicate that the scattering properties are consistent in the region where the size parameter is approximately 25. At VIS wavelengths, the scattering phase functions of the aggregates show the same typical halo peaks at scattering angles of 22° and 46° as do hexagonal ice particles. The maxima of the halos are greatly reduced when the ice crystal surface roughness is taken into account.

Using the algorithm to create geometries of aggregates and their scattering properties, an investigation was performed to explore the possibility of representing all aggregates based on the scattering properties of a more limited number of aggregate representations. To represent small aggregates, we generated five aggregate geometries, with each particle consisting of four or five hexagonal plates. Aggregates with large particles were built by increasing the monomer numbers instead of merely scaling the sizes of each monomer, and five models consisting of 8–12 plates were considered. The scattering properties of a representative aggregate were derived by averaging values over the individual aggregate geometries. To determine the ability of our aggregate representation to represent a larger number of aggregate shapes, "aggregates" were simulated from 1000 different plate aggregates, with properties compared to the use of 10 different plate
aggregates. The comparison of the scattering properties suggested that the variance of the phase function for an ensemble of 10 aggregate particles was small, indicating that this number of particles is sufficient to represent a larger set of particles.

Furthermore, the influence of the aggregate of plates was investigated for the satellite-based remote sensing of ice clouds. As cloud reflectances can be used to infer ice cloud microphysical and optical properties, we compared the lookup tables of cloud reflectances for ice cloud models involving hexagonal plates and their aggregates. The neglect of aggregates in the retrieval process leads to an overestimate of optical thickness but an underestimate of effective particle size. This result is partly due to the lower projected areas of the ice crystals during the aggregation process. More detailed investigations of the plate aggregates need to be performed in conjunction with other ice habits.

Appendix A: Estimating the Relative Position of Hexagonal Particles

Figure 12 shows the geometries of hexagonal particles used in our study. In particle A, the faces, edges, and vertices of the particle are indicated by \( F_{iA}(iA = 1, 2, ..., 18) \), \( L_{jA}(jA = 1, 2, ..., 12) \), and \( P_{kA}(kA = 1, 2, ..., 12) \), respectively. \( \vec{c}_{iA}(iA = 1, 2, ..., 8) \) are the position vectors of the centers of the particle faces, \( \vec{t}_{iA}(iA = 1, 2, ..., 8) \) indicate the normal directions of the particle faces, and \( \vec{p}_{kA}(kA = 1, 2, ..., 12) \) and \( \vec{l}_{jA}(jA = 1, 2, ..., 18) \) are the vectors of the vertices and edges, respectively.

The distance between two hexagonal particles that are not overlapped in the \( oxyz \) coordinate can be written by

\[
D = \left\{ \frac{D(P_{kA}, F_{iB}, kA = 1, 2, ..., 12, iB = 1, 2, ..., 8)}{D(P_{kB}, F_{iA}, kB = 1, 2, ..., 12, iA = 1, 2, ..., 8)}, \frac{D(L_{jA}, L_{jB}, iA = 1, 2, ..., 18, jB = 1, 2, ..., 18)}{\langle D(P_{kA}, L_{iBm}, iA = 1, 2, ..., 8(\text{or 6})), (kA = 1, 2, ..., 12, iB = 1, 2, ..., 8) \rangle} \right\}
\]

where \( \langle \rangle \) indicates the minimum value of the variables.

\( D(P_{kA}, F_{iB}, kA = 1, 2, ..., 12, iB = 1, 2, ..., 8) \) are the distances between a vertex \( (P_{kA}, kA = 1, 2, ..., 12) \) of particle A and a face \( (F_{iB}, iB = 1, 2, ..., 8) \) of particle B, and they can be determined by

\[
D(P_{kA}, F_{iB}, kA = 1, 2, ..., 12, iB = 1, 2, ..., 8) = \left\{ \begin{array}{ll}
|\vec{p}_{kA} - \vec{p}_{iB}|(kA = 1, 2, ..., 12, iB = 1, 2, ..., 8) & \text{for } P_{kA} \in F_{iB} \\
\langle D(P_{kA}, L_{iBm}, iA = 1, 2, ..., 8(\text{or 6})), (kA = 1, 2, ..., 12, iB = 1, 2, ..., 8) \rangle & \text{for } P_{kA} \not\in F_{iB}
\end{array} \right.
\]
where \( L_{iBm1} \) represents the edges on face \( F_{iB} \) and \( \vec{p}_u \) is the position vector of \( P_u \) and can be given by

\[
\vec{p}_u = \vec{p}_{kA} + \vec{f}_{iB} \left( \frac{\vec{f}_{iB} \cdot (\vec{c}_{iB} - \vec{p}_{kA})}{|\vec{f}_{iB}|^2} \right). 
\]

(A3)

The distance between \( P_{kA} \) and \( L_{iBm1} \) can be derived as follows:

\[
D(P_{kA}, L_{iBm1}, m1 = 1, 2, \ldots, 4\text{ (or 6)}) = \left\{ \begin{array}{ll}
|\vec{p}_{kA} - \vec{p}_v| & \text{for } P_v \in L_{iBm1} \\
\langle \vec{p}_{kA} - \vec{p}_{iBm12} \rangle (m2 = 1 \text{ and 2}) & \text{for } P_v \notin L_{iBm1},
\end{array} \right.
\]

(A4)

where \( P_{iBm12} \) represents the vertices on \( L_{iBm1} \) and \( \vec{p}_v \) is the position vector of \( P_v \) and can be given by

\[
\vec{p}_v = \left( \frac{\vec{p}_{kA} - \vec{p}_{iBm12}}{|\vec{p}_{iBm12}|^2} \right) \frac{\vec{p}_{iBm12} \cdot \vec{p}_{iBm11}}{|\vec{p}_{iBm12} \cdot \vec{p}_{iBm11}|^2} \vec{p}_{iBm11} \\
- \vec{p}_{iBm12} + \vec{p}_{iBm11} (m1 = 1, 2, \ldots, 4\text{ (or 6)}). 
\]

(A5)

\[
D(L_{ja}, L_{jb}, jA = 1, 2, \ldots, 18, jB = 1, 2, \ldots, 18) \text{ in Eq. (A1) is the distance between } L_{ja}(jA = 1, 2, \ldots, 18) \text{ and } L_{jb}(jB = 1, 2, \ldots, 18) \text{ from particles A and B, respectively, and can be given as follows:}
\]

\[
D(L_{ja}, L_{jb}, jA = 1, 2, \ldots, 18, jB = 1, 2, \ldots, 18) \\
= \langle D(P_{ja3}, L_{jb}, m3 = 1 \text{ and 2}) \rangle, \\
D(P_w, L_{ja}) \text{ for } P_w \in L_{jb}
\]

where \( D(P_{ja3}, L_{jb}, m3 = 1 \text{ and 2}) \) and \( D(P_{ja4}, L_{ja}, m4 = 1 \text{ and 2}) \) can be derived from Eq. (A4). The position vector of the \( P_w \) in Eq. (A6) is given by

\[
\vec{p}_{ja1} = \vec{p}_{ja} + (\vec{l}_{ja} \times \vec{l}_{jb}) \left( \frac{(\vec{l}_{ja} \times \vec{l}_{jb}) \cdot (\vec{p}_{ja} - \vec{p}_{ja1})}{|\vec{l}_{ja} \times \vec{l}_{jb}|^2} \right), 
\]

(A8)

\[
\vec{p}_{ja} = \vec{p}_{ja} + (\vec{l}_{ja} \times \vec{l}_{jb}) \left( \frac{(\vec{l}_{ja} \times \vec{l}_{jb}) \cdot (\vec{p}_{ja2} - \vec{p}_{ja})}{|\vec{l}_{ja} \times \vec{l}_{jb}|^2} \right), 
\]

(A9)

Fig. 13. Two types of faces for a hexagonal ice crystal.

Fig. 14. Schematic illustrating the computation of the projected area of an aggregate ice crystal.
The derivation of $D(P_{iA}, P_{iB}, kA = 1, 2, ..., 12, iB = 1, 2, ..., 8)$ and $D(P_{iA}, P_{iB}, kB = 1, 2, ..., 12, iA = 1, 2, ..., 8)$ can be found in Eqs. (A1) and (A2). Figure 13 shows two types $F_{iB}$. If $F_{iB}$ has a rectangular shape, the relationship between $L_{jA}$ and $F_{iB}$ in Eq. (A10) can be derived as follows:

\[
\begin{align*}
L_{jA} \cap F_{iB} & \neq \emptyset \quad \text{for} \quad \sum_{m=5}^{4} D(L_{jA}, L_{iBM5}) \neq a_B + L_B \\
L_{jA} \cap F_{iB} & = \emptyset \quad \text{for} \quad \sum_{m=5}^{4} D(L_{jA}, L_{iBM5}) = a_B + L_B,
\end{align*}
\]

(A11)

where $D(L_{jA}, L_{iBM5}, m5 = 1, 2, ..., 4)$ is the distance between $L_{jA}$ and the boundaries of $F_{iB}$. The derivation of $D(L_{jA}, L_{iBM5}, m5 = 1, 2, ..., 4)$ can be found in Eq. (A6). If $F_{iB}$ has the hexagonal structure shown in Fig. 13, $L_{jA} \cap F_{iB}$ can be given by

\[
\begin{align*}
L_{jA} \cap F_{iB} & \neq \emptyset \quad \text{for} \quad \sum_{m=6}^{6} D(L_{jA}, L_{iBM6}) \neq 3\sqrt{3}a_B \\
L_{jA} \cap F_{iB} & = \emptyset \quad \text{for} \quad \sum_{m=6}^{6} D(L_{jA}, L_{iBM6}) = 3\sqrt{3}a_B,
\end{align*}
\]

(A12)

Appendix B: Compute Projected Area of an Aggregate

Figure 14 shows aggregate $A$ in the oxyz coordinate system. The projected area of an aggregate can be computed by an algorithm based on the Monte Carlo method. Consider a random disk $D_i$ that is perpendicular to its center position vector $\vec{p}_i$. The radius of $D_i$ is equal to the maximum dimension of the aggregate $D_m$, and a random point $P_i$ on the disk can be derived from

\[
\begin{align*}
|\vec{p}_i - \vec{p}_0| &= D_m \sqrt{\xi_A}, \\
\vec{p}_i \cdot \vec{p}_0 &= |\vec{p}_0|^2, \\
(\vec{p}_i - \vec{p}_0) \cdot (\vec{p}_B - \vec{p}_0) &= D_m \sqrt{\xi_B} |\vec{p}_B - \vec{p}_0| \cos(2\pi \xi_B),
\end{align*}
\]

where $\xi_A$ and $\xi_B$ are independent random numbers that are uniformly distributed on $[0, 1]$ and $\vec{p}_B$ is the position vector of a fixed point on the face containing $D_i$ and can be given by

\[
\vec{p}_B = \left(0, 0, \frac{|\vec{p}_0|^2}{|\vec{p}_0|^2}\right).
\]

For a line $L_i$ that satisfies

\[
\begin{align*}
P_i \in L_i \\
L_i = \vec{p}_i
\end{align*}
\]

we consider a $M_i$ given by

\[
M_i = \begin{cases} 
1 & \text{for } L_i \cap \sum_{i=1}^{N} F_j = \emptyset \\
0 & \text{for } L_i \cap \sum_{i=1}^{N} F_j = \emptyset,
\end{cases}
\]

where $F_j$ indicates a face of aggregate $A$ in Fig. 14 and $N$ is the number of the hexagonal particles in $A$. The relationship between $L_i$ and $F_j$ can be derived using Eqs. (A11) and (A12).

The projected area of aggregate $A$ can be derived by

\[
S = \pi D_m^2 \sum_{i=1}^{N} \frac{M_i}{N_L},
\]

(B7)

where $N_L$ is the number of $D_i$ in the computation. The algorithm to compute the projected area can be verified by replacing aggregate $A$ with a hexagonal column whose projected area can be simply determined by

\[
S = \frac{3}{4} a (\sqrt{3}a + 2L),
\]

(B8)

where $a$ and $L$ represent the semiwidth and length of the hexagonal column, respectively. This result is obtained by using the fact that the projected area of a convex body at random orientation is simply one-fourth of its surface area. Our results indicate that the projected area of an aggregate can be accurately computed for the case $N_L > 100,000$.

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