

Article

Optimizing Surface Type Definitions in Radiance-to-Irradiance Conversions for Future Earth Radiation Budget Satellite Measurements

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Highlights

What are the main findings?

- Consensus clustering applied to an ensemble of K-means solutions shows that seven surface groups optimize the clustering space for both radiance- and anisotropic-factor-based analyses.
- Clustering results show that water bodies, snowy surfaces, and bright deserts form distinct surface groups, while vegetated surface classes can be consolidated.

What are the implications of the main findings?

- The derived surface groups provide a statistically based framework to support Libera ADM development and evaluation.
- Water bodies, snowy surfaces, and a bright desert surface remain as distinct surface groups. A few surface classes, such as tundra and closed shrublands, may be reclassified and grouped with other surfaces, refining the CERES–TRMM surface classification.

Abstract

Angular Distribution Models (ADMs) are essential for converting observed radiances from satellite sensors to the energy-budget-relevant quantity of irradiance. In preparation for the NASA Libera mission, this study presents a data-driven framework to identify optimal groupings of International Geosphere–Biosphere Programme (IGBP) surface types for Libera’s split-shortwave ADMs, in an effort to minimize the uncertainty associated with radiance-to-irradiance conversions while maintaining operational feasibility. Using data from the Clouds and the Earth’s Radiant Energy System (CERES) Flight Model 5 (FM-5), K-means clustering is applied within angular bins to capture viewing-geometry-dependent radiometric behavior. These angular clustering solutions are then assessed via hierarchical consensus clustering to derive consistent surface groups. The analysis suggests seven surface groups ($K = 7$) optimize the surface clustering space. The resulting classifications are broadly consistent with historical CERES–TRMM ADM surface definitions, preserving radiometrically distinct surfaces such as water bodies and snowy surfaces while highlighting opportunities to consolidate vegetative IGBP surface classes. This study provides an objective and physically grounded basis for defining Libera ADM surface groups, ensuring a robust balance between model accuracy and operational simplicity.



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1. Introduction

Earth's Radiation Budget (ERB) quantifies the difference between incoming and outgoing energy at the top of the atmosphere [1–4]. Incoming energy is almost exclusively solar [5], while outgoing energy consists of both reflected solar and emitted terrestrial radiative energy. The rate at which the Earth-atmosphere system warms or cools is directly linked to the magnitude of the imbalance between these two quantities [6–9]. The Clouds and the Earth's Radiant Energy System (CERES) [10] has provided and maintained an ERB climate data record that now spans more than 25 years, enabling detection and interpretation of long-term climate trends. Maintaining continuity of this record is critical for climate studies that rely on stable and traceable observations rather than short-term variability [11].

NASA's next-generation ERB satellite mission, Libera, which is scheduled to launch in 2027, has three overarching objectives. Two of these are particularly relevant to this study. The first is to ensure continuity of the multi-decade ERB climate data record provided by the CERES [10,11], as the existing CERES instruments are operating beyond their original design lifetimes. As the duration of operation beyond the nominal mission lifetime increases, so does the risk of an unplanned gap in the long-term ERB climate record, a record that has been continuously maintained since 2000. Ensuring continuity through a follow-on mission is therefore critical for extending this long-term record. This objective is achieved using Libera's broadband shortwave (0.2–5 μm), longwave (5–50 μm), and total (0.3–100+ μm) spectral channels. The second objective is to demonstrate new and enhanced measurement capabilities, including the addition of a new “split-shortwave” spectral channel (0.7–5 μm) [12–14]. This split-shortwave channel is intended to improve understanding of where shortwave energy deposition occurs within the Earth-atmosphere system. Each of these objectives demands different modes of operation of the Libera instruments. Libera's main operational mode, cross-track scanning mode, will primarily be used to provide continuity to the multi-decade ERB record. A secondary operating mode, Rotating Azimuth Plane Scan (RAPS) mode, will be used together with an on-board camera [15,16] to develop and evaluate new split-shortwave Angular Distribution Models (ADMs). ADMs are wavelength-, solar-viewing geometry-, and scene-dependent sets of anisotropic factors that are used for radiance-to-irradiance conversion [15,17,18]. This conversion is necessary because radiance is the direct measurement made by the current CERES and future Libera instruments, while irradiance is the ERB-relevant quantity needed for climate applications.

This study provides a statistically driven, traceable quantification of the surface type grouping that is applied when defining ADM scene types. In previous work [19], we outlined the rationale for adopting the ADM scene types defined for the CERES instrument on the Tropical Rainfall Measuring Mission (TRMM), henceforth “CERES-TRMM” [20], for the Libera mission. The CERES-TRMM ADM scene types define surface types based on the International Geosphere-Biosphere Programme (IGBP) surface classification system [21], augmented with dynamic snow and sea ice information, providing a total of 20 surface classifications. Given the limited angular sampling from CERES-TRMM, which will also be a limitation for the Libera mission [19], the IGBP surfaces for ADMs were combined into six groups that exhibited similar anisotropic behavior over a limited range of sun-satellite viewing geometries [20]. These surface groupings proved effective for CERES-TRMM and provide a logical starting point for Libera; however, their adoption has largely been

motivated by historical precedent rather than by a comprehensive statistical justification across the full range of surface types and observing geometries relevant to Libera. We extend these earlier findings by applying a more comprehensive clustering approach to CERES observations over the full range of IGBP surface types and solar-viewing geometries. In doing so, we quantitatively justify surface type groupings that minimize within-cluster variance in reflected solar radiance and empirically derived anisotropic factors. This approach seeks to balance operational feasibility with the accuracy of derived ADMs, providing a statistically grounded basis for optimizing surface groupings for Libera and future ERB missions. While the surface type groupings that emerge from our analysis are broadly consistent with those defined for CERES-TRMM, some subtle differences emerge, providing guidance for new Libera ADMs.

The paper proceeds as follows: Section 2 reviews CERES-TRMM scene definitions, IGBP surface classifications, and the theoretical basis for ADM development. Section 3 introduces the CERES RAPS mode observations used in this analysis. Section 4 outlines the methodology. Section 5 applies this framework to radiance and anisotropic factor datasets to determine the optimal number of surface groups and to evaluate similarities among IGBP surface classes. Section 6 concludes with a summary of the main findings.

2. Background

2.1. CERES-TRMM Scene Types and IGBP Surfaces

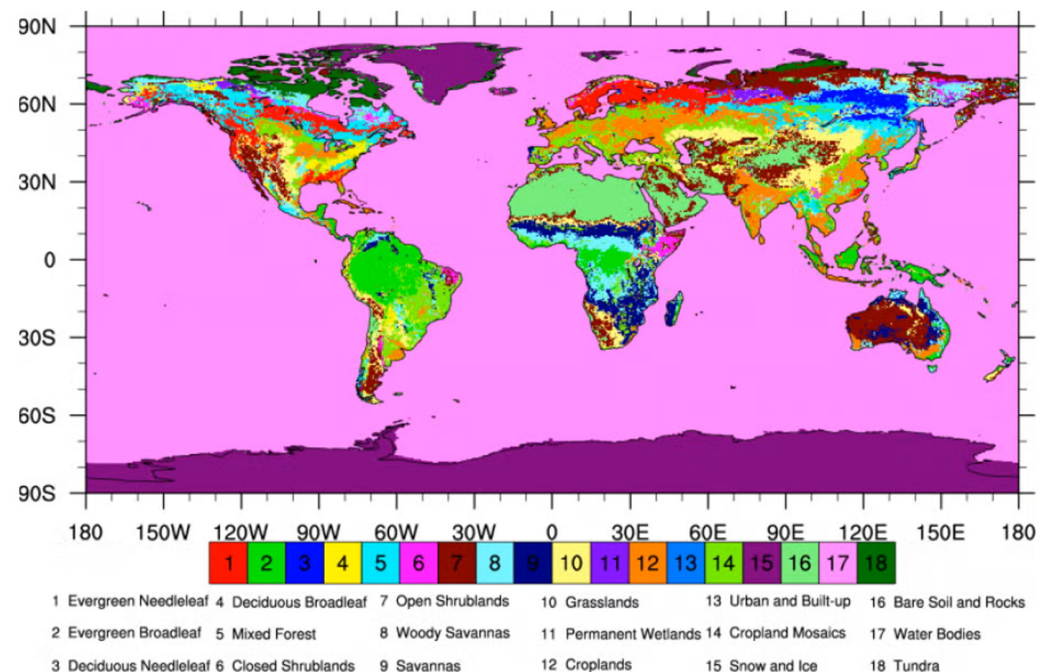
Each CERES-TRMM scene type combines a surface classification with atmospheric properties such as cloud fraction, cloud thermodynamic phase, and cloud optical depth. While detailed binning of these atmospheric properties is described in Loeb et al. (2003) [20], here we focus solely on the surface type component.

The surface type for a given observation is determined primarily from the IGBP land cover map (Figure 1), which provides a static latitude–longitude mapping of surface classifications. CERES-TRMM scene types are composed of six surface groups formed from IGBP surface classes. These groups include ocean, dark and bright deserts, low-to-moderate trees and shrubs, moderate-to-high trees and shrubs, and snowy surfaces [20]. The mapping from the 20 IGBP surface classes to the six TRMM surface groups is shown in Table 1. Focusing on the surface type alone allows us to isolate how land cover affects radiative variability and suggests ways to refine ADM development for Libera. In this study, the IGBP surface classes shown in Figure 1 form the starting point for the surface grouping analysis, providing the spatial context for evaluating similarities and differences in surface-dependent radiative behavior and for quantitatively assessing how the existing CERES-TRMM surface groups may be refined for Libera ADM development.

The IGBP land cover classification gives a global view of surface types using satellite data. It was originally created from 1 km Advanced Very High Resolution Radiometer (AVHRR) observations [21,22]. The IGBP scheme defines 18 distinct land cover categories, representing a range of forest, shrubland, grassland, cropland, urban, snow and ice, and water surfaces. Two additional surface types, fresh snow and sea ice, were introduced for use in the CERES project to better capture the dynamic and distinct radiative characteristics of snow-covered regions. Unlike the other IGBP classes, these two surfaces are updated daily using National Snow and Ice Data Center (NSIDC) data, so they capture seasonal and short-term changes in snow and sea ice [23].

Table 1. Mapping of IGBP land cover classifications to CERES-TRMM surface type categories.

IGBP Surface Type	TRMM-like Surface Definition
Evergreen Needleleaf Forest	Moderate-to-High Trees/Shrubs
Evergreen Broadleaf Forest	Moderate-to-High Trees/Shrubs
Deciduous Needleleaf Forest	Moderate-to-High Trees/Shrubs
Deciduous Broadleaf Forest	Moderate-to-High Trees/Shrubs
Mixed Forest	Moderate-to-High Trees/Shrubs
Closed Shrublands	Moderate-to-High Trees/Shrubs
Open Shrublands	Dark Desert
Woody Savannas	Moderate-to-High Trees/Shrubs
Savannas	Low-to-Moderate Trees/Shrubs
Grasslands	Low-to-Moderate Trees/Shrubs
Permanent Wetlands	Low-to-Moderate Trees/Shrubs
Croplands	Low-to-Moderate Trees/Shrubs
Urban and Built-up	Low-to-Moderate Trees/Shrubs
Cropland and Mosaics	Low-to-Moderate Trees/Shrubs
Snow and Ice (permanent)	Snow
Bare Soil and Rocks	Bright Desert
Water Bodies	Ocean
Tundra	Low-to-Moderate Trees/Shrubs
Fresh Snow	Snow
Sea Ice	Snow

**Figure 1.** Global distribution of the first 18 IGBP land cover classes used in this study. These surface classes define the input categories for the surface grouping analysis described in Sections 4 and 5. Fresh Snow and Sea Ice (the two additional IGBP classes) are updated using NSIDC datasets [24].

2.2. Fundamentals for the Development of Empirical TRMM-like ADMs

ERB broadband radiances are converted to irradiances using ADMs, which consist of sets of anisotropic factors. Thus, we will later apply clustering to anisotropic factors for different surface types to optimize the grouping of surface types for ADMs. For completeness, we include a short summary on how empirical anisotropic factors are calculated. The general relationship between radiance (L) and irradiance (F) is described in Equation (1),

$$F(\theta_s) = \int_0^{2\pi} \int_0^{\pi/2} L(\theta_s, \theta_v, \varphi) \cos(\theta_v) \sin(\theta_v) d\theta_v d\varphi, \quad (1)$$

where θ_s , θ_v , and φ are the solar zenith angle, viewing zenith angle, and relative azimuth angle, respectively.

Since we cannot acquire the instantaneous radiance, L , in all θ_v and φ directions via a single instrument, we require the utilization of empirical anisotropic factors R , which represent how the radiance at a given solar-viewing geometry deviates from an isotropic radiation case. This modified equation is shown in Equation (2).

$$F(\theta_s) = \frac{\pi L(\theta_s, \theta_v, \varphi)}{R(\theta_s, \theta_v, \varphi)}, \quad (2)$$

The construction of empirical anisotropic factors is shown in Equation (3), where $\bar{L}_j$ is the average daily mean radiance for scene j and the set of angular bins, $\theta_{s,x}$, $\theta_{v,y}$, φ_z , while F_j is the upwelling irradiance for scene j and angular bin $\theta_{s,x}$,

$$R_j(\theta_{s,x}, \theta_{v,y}, \varphi_z) = \frac{\pi \bar{L}_j(\theta_{s,x}, \theta_{v,y}, \varphi_z)}{F_j(\theta_{s,x})}. \quad (3)$$

Equation (3) requires a calculation of $\bar{L}_j(\theta_{s,x}, \theta_{v,y}, \varphi_z)$ as well as an estimation of $F_j(\theta_{s,x})$. The calculation of the average daily mean radiances for scene j are described by Equation (4), where $\bar{L}_{j,d}(\theta_{s,x}, \theta_{v,y}, \varphi_z)$ is the mean radiance in angular bins $\theta_{s,x}$, $\theta_{v,y}$, φ_z for day d and scene j .

$$\bar{L}_j(\theta_{s,x}, \theta_{v,y}, \varphi_z) = \frac{\sum_{d=1}^D \bar{L}_{j,d}(\theta_{s,x}, \theta_{v,y}, \varphi_z)}{D}. \quad (4)$$

The upwelling irradiance in Equation (3) is estimated via Gaussian Quadrature as shown in Equation (5) [20],

$$F_j(\theta_{s,x}) = \sum_{z=1}^{N_z} w_z \sum_{y=1}^{N_y} w_y \bar{L}_j(\theta_{s,x}, \theta_{v,y}, \varphi_z) \cos \theta_{v,y}, \quad (5)$$

where w_z and w_y are the Gaussian quadrature weights, and N_z and N_y are the number of Gaussian quadrature points used in the integration. For this calculation to be observationally based, the directionally dependent radiance field $\bar{L}_j(\theta_{s,x}, \theta_{v,y}, \varphi_z)$ must be populated with observations across the relevant $\theta_{v,y}$ and φ_z angles. This broad angular coverage has been effectively achieved through RAPS mode observations during the CERES mission. Angular bins that are not populated with observations must be filled in via other methods, such as with radiative transfer theory, reciprocity, or interpolation.

3. Data

This study uses Single Scanner Footprint (SSF) shortwave observations from the CERES Flight Model 5 (FM-5) sensor on board the Suomi National Polar-orbiting Partnership (Suomi-NPP) satellite. FM-5 onboard Suomi-NPP was selected because it provides extensive Rotating Azimuth Plane Scan (RAPS) observations and orbital characteristics closely aligned with those planned for the Libera mission, enabling representative sampling of surface-viewing geometry space relevant to ADM development. The Level-2 SSF data product provides top-of-atmosphere radiances, Sun–Earth–satellite viewing geometry, surface classification, and atmospheric properties for each observation. Surface type information is derived from the IGBP map, while cloud properties are retrieved from the Visible Infrared Imaging Radiometer Suite (VIIRS) aboard Suomi-NPP [25]. The analysis

spans a four-year period from 1 October 2019 to 30 September 2023. This interval begins when FM-5 entered regular RAPS mode, and FM-5 remained primarily in RAPS mode throughout this period, which allows the instrument to sample a broad range of viewing zenith and relative azimuth angles. Such angular diversity supports the development of single surface anisotropic factors and the later K-means clustering within individual angular bins of these same anisotropic factors.

Since our goal is to determine groups of IGBP surface classes with similar shortwave reflectance properties, we apply three broad data screens. (1) We limit analyses to day-side observations with solar zenith angles (θ_s) $\leq 90^\circ$. (2) To isolate the effects of the surface type on the reflected solar radiance, we exclude observations where clouds are present. This was done following the TRMM scene definition of cloud-free. Thus, we require footprints to contain less than 0.1% cloud fraction [20]. (3) We consider only footprints composed of a single IGBP class to avoid convoluting our results and analysis. The CERES datasets utilize a 10-arcminute ($1/6^\circ$) IGBP surface resolution [24], enabling each CERES footprint to be mapped to one or more of the 20 classes, depending on the location of the observation. The “Urban and Built-up” IGBP surface class is absent from the screened dataset because no footprints meet both the clear-sky and single-surface criteria. This is partially due to the “Urban and Built-up” surface being one of the smallest IGBP surface types by land area, comprising roughly 2.5% of global land area or about 0.7% of Earth’s surface area [26].

Although these data screens reduce the number of observations considered, the dataset remains highly representative of clear-sky conditions for operational ADM applications. The 0.1% cloud fraction limit is consistent with the conditions under which Libera will define clear-sky scene types, and the day-side restriction applies to both shortwave and split-shortwave ADMs. The primary factor limiting the number of considered observations is the single-surface footprint requirement, while the effective angular coverage is constrained by the fact that surfaces have not yet been aggregated into broader surface-type groups. As a result, the screened dataset provides a robust basis for identifying surface groups, even though it does not represent cloudy or mixed-surface conditions. These surface groupings will guide the selection of broader scene types, which can later be applied to heterogeneous or partially cloudy scenes in operational datasets.

In addition to the extended RAPS observations, Suomi-NPP was selected as the primary data source because its orbit closely matches that of NOAA’s future Joint Polar Satellite System-4 (JPSS-4), which will carry Libera. Both platforms operate, or plan to operate (JPSS-4), in near-polar, sun-synchronous orbits with $\sim 98.7^\circ$ inclination and similar altitudes (824 km for Suomi-NPP vs. 833 km for JPSS-4) and cross the equator at $\sim 13:30$ local time. These similarities ensure comparable surface type and solar zenith angle distributions. Although Libera’s split-shortwave channel (0.7–5 μm) differs spectrally from CERES shortwave observations, Libera initially intends to utilize the same scene type definition between the shortwave and split-shortwave channels for processing consistency. The goal of the split-shortwave channel is to provide new insights into where radiation is being absorbed in the Earth-atmosphere system, but it requires cross-analysis with the shortwave channel. Thus, the Suomi-NPP dataset remains a suitable proxy for evaluating surface-type clustering strategies relevant to Libera’s ADM development needs.

4. Methodology

4.1. Dataset Preparation

To study surface impacts on outgoing shortwave radiance, we prepared two datasets: mean radiances and anisotropic factors. Observations were restricted to clear-sky, single-surface, day-side conditions. Solar zenith, θ_s , and viewing zenith, θ_v , angles were binned with a 0.2 bin-width in cosine (θ_s or θ_v), and relative azimuth angles, ϕ , in 20° bins. To

minimize the biases in observed radiances near θ_s bin edges, each observed radiance was normalized to the center of its corresponding solar zenith angle bin using:

$$L'_j = L_j \frac{\cos \theta_{s,x}}{\cos \theta_s}, \quad (6)$$

where L_j is the radiance observation for surface j , L'_j is the normalized radiance observation, $\theta_{s,x}$ is the solar zenith angle at the mid-point of solar zenith angle bin x . The mean radiance for each IGBP surface class and angular bin is determined by averaging the normalized radiances, which are used as the inputs for the radiance-based clustering analysis. No additional statistical scaling was applied to the radiances before input to the K-means algorithm. Anisotropic factors were generated following Section 2.2 and serve as inputs for anisotropic factor-based clustering.

The final analysis includes 47 angular bins for the radiance-based clustering and 141 angular bins for the anisotropic factor-based clustering, corresponding to all angular bins that contain at least one observation from the 19 IGBP surface types considered. No minimum sample size threshold was imposed for a surface type to be considered present within a given angular bin; all bins containing at least one observation were retained. Clustering analysis is performed on both the observed mean radiance and derived anisotropic factor datasets to provide complementary perspectives on surface shortwave radiative behavior, with anisotropic-factor-based clustering serving as the primary analysis, as anisotropic factors capture the full angular dependence of surface reflectance and are directly relevant for the development of ADMs. Hereafter, “IGBP surface classes” refers to the original land-cover categories defined by the IGBP classification, “clusters” denotes the angular-bin-specific outputs of the K-means algorithm, and “surface groups” refers to the final consensus-derived groupings used for ADM scene definitions.

Radiance-based clustering is performed using the observed mean radiances within individual angular bins and then aggregated across all bins to identify surface groups that exhibit consistent similarities over a wide range of viewing geometries. Surfaces that display similar mean radiances across many angular bins are expected to have correspondingly similar anisotropic factors and comparable directional reflectance properties. Since this approach relies only on observed measurements, it avoids the need to interpolate radiances in unobserved portions of angular space. As a result, radiance-based clustering is particularly useful for surface types with limited angular sampling, for which anisotropic factors may be less robustly constrained.

4.2. K-Means Clustering

To investigate both the optimal number of surface groups and the membership of individual IGBP surface classes within those groups, we employed K-means clustering as the primary classification technique. K-means offers explicit control over the number of clusters (K) and produces non-overlapping, easily interpretable groupings [27].

The first step in the algorithm is to assign K initial centroid locations, which represent the mean position of data points within each cluster in the parameter space. Each data point is then assigned to the nearest centroid, forming K initial clusters. The centroid for each cluster is updated as the mean location of all data points within that cluster and all data points are reassigned to the closest centroid. This iterative process of centroid updating and cluster reassignment continues until the cluster memberships converge to a local minimum of the within-cluster sum of squares (WCSS). The WCSS is defined as

$$\text{WCSS} = \sum_{k=1}^K \sum_{i \in C_k} \|x_i - \mu_k\|^2, \quad (7)$$

where C_k is the set of data points in cluster k , x_i is the location of an observation, and μ_k is the location of the centroid for cluster k .

Since centroid initialization can strongly influence the final solution, we adopted the K-means++ initialization scheme [28], which selects initial centroids sequentially with probabilities proportional to their squared distance from existing centroids. This approach spreads centroids across the dataset, improving stability and reducing the risk of convergence to suboptimal configurations. To further mitigate random-seed effects, the algorithm was executed 10,000 times for each angular bin and each value of K , and the run yielding the lowest overall WCSS was retained.

4.3. Determining the Optimal Number of Clusters

A central challenge in K-means clustering is selecting an appropriate number of clusters (K). Some choices of K can lead to suboptimal outcomes: a K that is too large may overfit individual observations (IGBP surfaces in our case) and fragment clusters unnecessarily, whereas a K that is too small may force distinct surface groups together. To guide selection, we employed three complementary evaluation metrics: the silhouette coefficient [29], Calinski–Harabasz Index [30], and gap statistic [31]. Since these indices emphasize different clustering properties and no single metric is a priori preferred, we combine the results using an unweighted average.

To constrain the range of K values tested, we adopted historical precedent from CERES-TRMM. In ADM development for TRMM, CERES partitioned the Earth’s surface into six broad categories: two vegetation-dominated classes, two desert classes, one water class, and one snow class. These six surface groups served as a reference point. Using this reference, we tested K values as low as four, which corresponds to the earlier Earth Radiation Budget Experiment (ERBE) classification that used fewer, broader categories [32]; and as high as eight, avoiding extremes that would yield operationally infeasible clustering solutions [19]. The final decision on K is determined by examining the distribution of values favored by the three indices across all angular bins. If the mean-radiance-based and anisotropic-factor-based diagnostics suggest different values of K , each value is propagated independently through K-means and consensus clustering. A single clustering solution is selected only at the final interpretation stage, prioritizing anisotropic-factor-based results for ADM development, with radiance-based clustering providing supplementary context.

4.3.1. Silhouette Coefficient

The Silhouette Coefficient quantifies cluster cohesion and separation [29]. For a sample i , let $a(i)$ be the average distance to all other points in the same cluster (intra-cluster distance) and $b(i)$ the minimum average distance to points in any other cluster (nearest-cluster distance). The silhouette score is

$$s(i) = \frac{b(i) - a(i)}{\max\{a(i), b(i)\}}, \quad (8)$$

ranging from -1 to 1 . Scores near 1 indicate the point is well classified, and negative scores indicate potential misassignment. We computed the average silhouette across all samples for each candidate K , selecting the K that maximized this value. This metric is sensitive to both cluster separation and cohesion and is widely used for evaluating the quality of geometric clustering.

Once the plausible range of K values was established, we computed the silhouette coefficient to identify the most appropriate number of clusters. By applying the silhouette only within the reduced set of K values, we avoid the risk of maxima far outside the range. This way, we can use the silhouette score as a fine-tuning mechanism, rather than as a

coarse filter. This metric has been successfully implemented in Earth-science applications, including climate data mining and marine-heatwave classification [33,34].

4.3.2. Calinski-Harabasz Index

The Calinski-Harabasz Index evaluates clustering quality based on the ratio of between-cluster dispersion to within-cluster dispersion [30]. For n samples and K clusters, the index is defined as:

$$CH(K) = \frac{BCSS(K)}{WCSS(K)} \frac{(n-K)}{(K-1)}. \quad (9)$$

Here, the BCSS is the Between-Cluster Sum of Squares, and it quantifies the dispersion of cluster centroids relative to the global mean. It is calculated using Equation (10),

$$BCSS = \sum_{k=1}^K n_k \|\mu_k - \mu\|^2, \quad (10)$$

where n_k is the number of observations in cluster k , μ_k is the centroid of cluster k , and μ is the global centroid. A high value of the Calinski-Harabasz Index indicates a clustering configuration with strong separation between clusters and a high degree of internal cohesion. Using both the silhouette and Calinski-Harabasz indices provides complementary perspectives: silhouette emphasizes pairwise distances, while Calinski-Harabasz emphasizes variance. This dual approach has been applied in Earth-science clustering [35].

4.3.3. Gap Statistic

The gap statistic estimates the number of clusters by comparing the within-cluster dispersion of the data to that of a reference null distribution [31]. For each candidate K , the total within-cluster variation W_k is computed, and B reference datasets are generated. The gap statistic is

$$Gap(k) = \frac{1}{B} \sum_{b=1}^B \log(W_k^*(b)) - \log(W_k). \quad (11)$$

The optimal number of clusters is determined by the smallest K such that:

$$Gap(K) \geq Gap(K+1) - s_{K+1} \quad (12)$$

where s_{K+1} is the standard deviation of the log dispersions for the $(K+1)^{th}$ reference datasets. The gap statistic is a safeguard against overfitting, ensuring identified clusters are genuinely informative.

4.4. Co-Association Matrix and Consensus Clustering

After selecting the optimal number of clusters, we constructed a co-association matrix to quantify the consistency of surface groups across bins. By aggregating results across bins, the matrix reveals stable pairings that persist despite local angular variability. Each angular bin produces an independent clustering solution, which may vary due to angular-dependent radiative characteristics. To quantify the consistency of these solutions, we constructed a 19×19 co-association matrix C , where C_{ij} represents the fraction of bins in which IGBP surface classes i and j were assigned to the same cluster. Large values of C_{ij} indicate that two surfaces consistently appear in the same cluster across angular bins, whereas small values indicate inconsistent association. To aid in interpretation, the matrix is visualized as a heat map, highlighting which IGBP surfaces exhibit similar shortwave radiative behavior under varying viewing geometries.

To identify surface groupings that consistently appear across all angular bins, we employed a consensus clustering framework that aggregates the K-means results from each

bin into a unified classification. The co-association matrix C serves as an input. Hierarchical clustering operates on distances rather than similarities, so the co-association matrix was converted to a dissimilarity matrix D via:

$$D_{ij} = 1 - C_{ij} \quad (13)$$

Hierarchical clustering was applied to D to construct a dendrogram representing the merging of surface types as similarity thresholds are relaxed. Three common linkage criteria (single, average, and complete) were tested to evaluate the sensitivity of the results to different distance aggregation metrics. Clusters were merged iteratively based on the chosen linkage. In the dendrogram, each branch represents a surface or cluster, and the height at which branches merge corresponds to the dissimilarity between them: merges that occur near the bottom of the dendrogram indicate stronger similarity.

Figure 2 provides a schematic overview of the analysis workflow described in Section 4, summarizing the progression from SSF observations to the final consensus surface groupings. The figure is intended as a visual guide to the methodological steps outlined above.

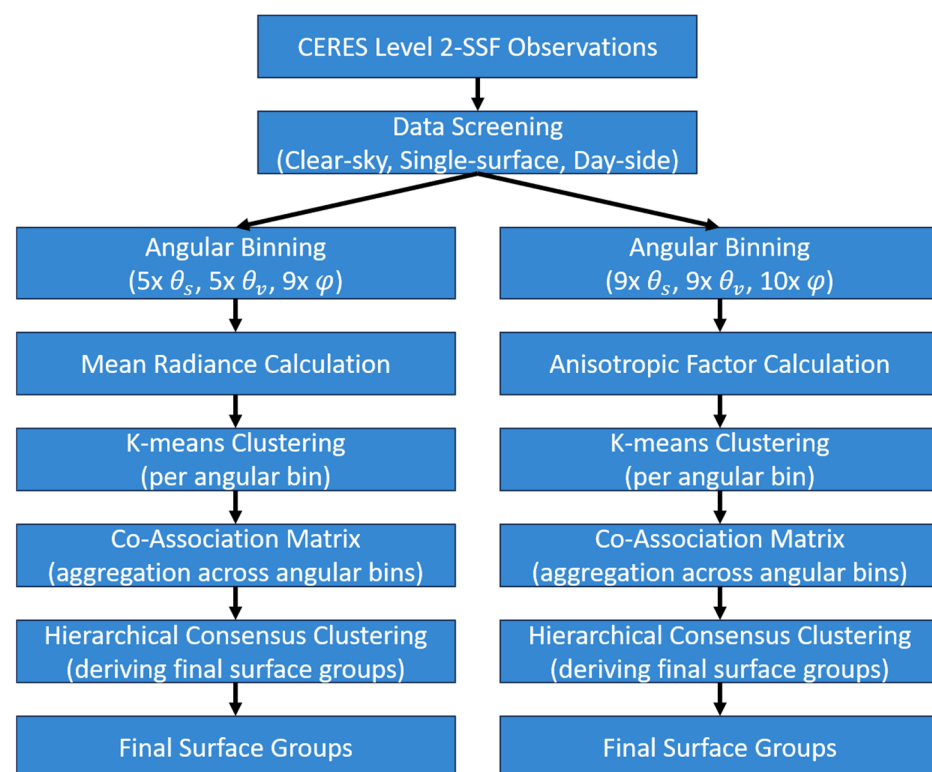


Figure 2. Schematic overview of the analysis workflow used to derive consensus surface groupings from CERES Single Scanner Footprint (SSF) observations. The diagram summarizes the major processing steps, including data screening, angular binning, mean radiance and anisotropic factor estimation, per-bin clustering, aggregation via a co-association matrix, and hierarchical consensus clustering leading to the final surface groups.

5. Results and Discussion

The number of clusters was initially constrained by historical precedent from ERBE and CERES-TRMM classifications [20,32], as well as recent analysis that investigated the amount of scene and viewing geometry space that Libera will observe during RAPS mode operations [19]. The silhouette coefficient, Calinski–Harabasz index, and gap statistic were applied to each angular bin, and their results were combined to yield a bin-by-bin measure of cluster quality, guiding the selection of a plausible number of clusters (K).

Applying this consensus-based approach across all angular bins, we found mean suggested values of $K = 7.17$ for the anisotropic factor clustering and $K = 6.64$ for the radiance clustering. Since K must be an integer, both averages indicate an optimal cluster number of $K = 7$. Figure 3 provides additional context by showing the distribution of K values favored across angular bins, with vertical lines marking the mean suggested K in each case. For the anisotropic factor analysis, although the highest single-bin occurrence within the histogram lies in the $K = 7.5$ – 8 range, substantial support is also found in the adjacent bins centered near $K \approx 7$. Taken together, the combined frequency of the 6.5 – 7 bin and 7 – 7.5 bin is comparable to that of the 7.5 – 8 bin, consistent with the mean value of $K = 7.17$. However, for a more comprehensive view of the clustering behavior and its sensitivity to the choice of K , the radiance clustering results for $K = 6$ and the anisotropic factor clustering results for $K = 8$ are provided in Appendix A.

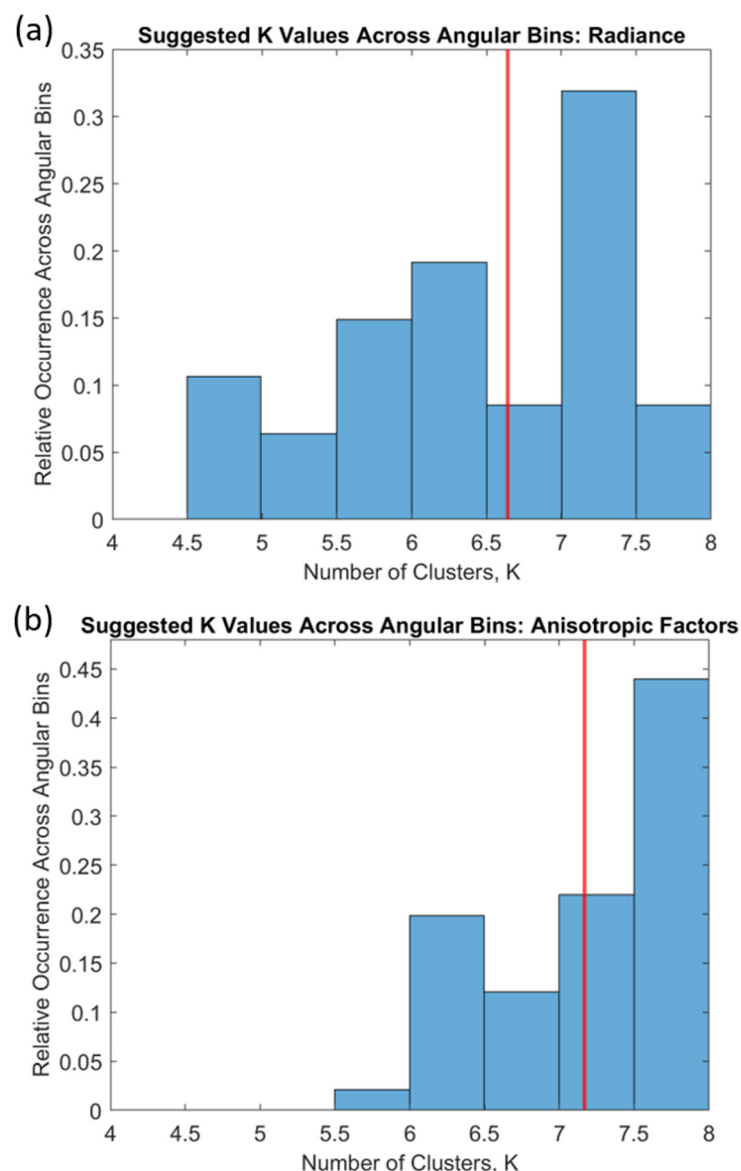


Figure 3. Histograms showing the relative frequency with which a given number of clusters (K) is suggested across angular bins by the three cluster selection criteria (gap statistic, silhouette coefficient, and Calinski–Harabasz index). Results are shown for (a) the radiance-based analysis and (b) the anisotropic factor analysis. In both panels, K values range from 4 to 8 with a bin width of 0.5. Red vertical lines indicate the mean suggested K value across angular bins. The radiance analysis exhibits a broader distribution of suggested K values, with the highest occurrence near $K \approx 7$ – 7.5 . The anisotropic

factor analysis shows stronger support for larger K , with the highest single-bin occurrence at $K \approx 7.5$ –8, but substantial support is also found in adjacent bins near $K \approx 7$, yielding a mean suggested value of $K = 7.17$ across angular bins.

Given that radiances and anisotropic factors are clustered separately for each angular bin, the consistency of clusters across angular bins must be assessed. This is achieved by aggregating the surface type clusters across angular bins to form a pairwise co-association frequency matrix (Figure 4). High values indicate surfaces that consistently cluster together across angular bins, while low values suggest weaker or bin-dependent associations.

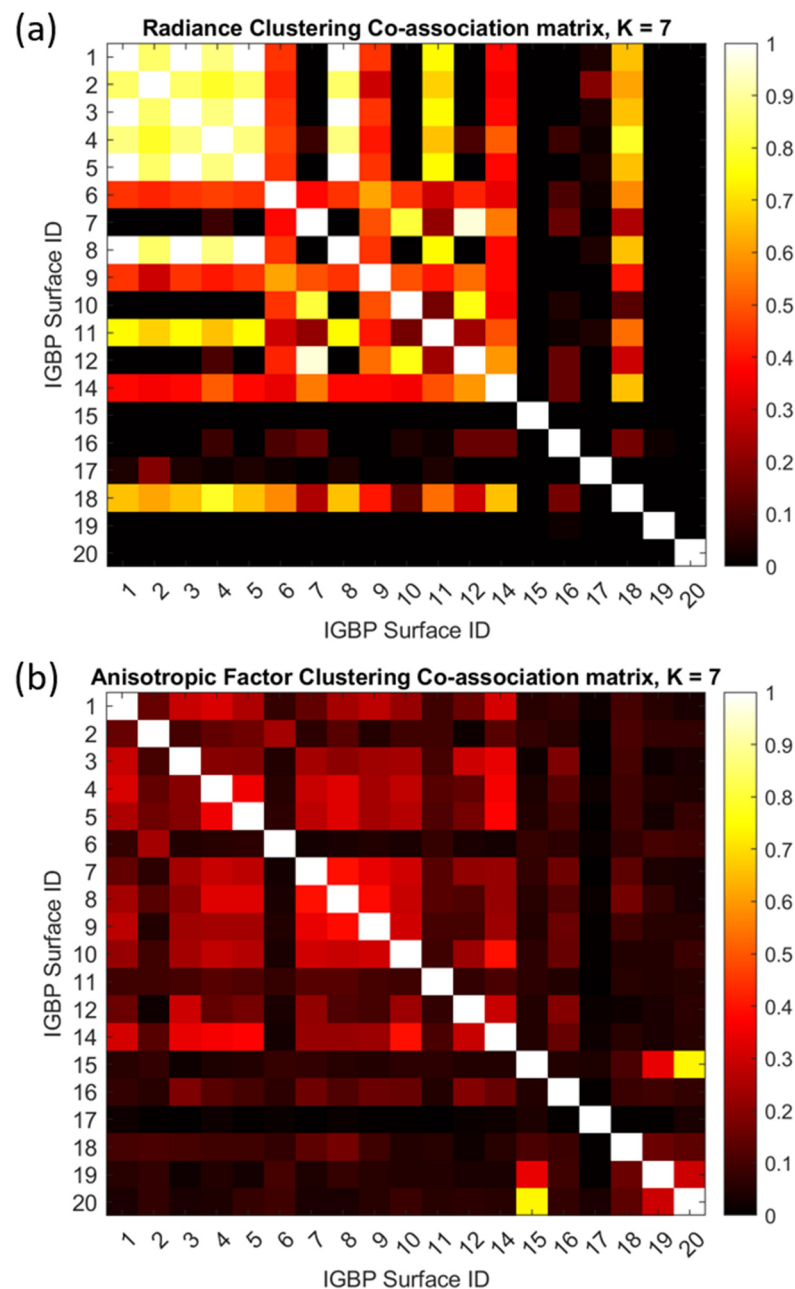


Figure 4. Pairwise co-association matrices showing the consistency of clustering across angular bins for $K = 7$: (a) radiance-based clustering and (b) anisotropic-factor-based clustering. Each matrix is symmetric about the diagonal, where element (i, j) represents the frequency with which IGBP surfaces i and j were assigned to the same cluster across all angular bins. Values closer to 1 indicate surfaces that consistently cluster together across viewing geometries, while values closer to 0 indicate weaker or angular-dependent relationships.

Figure 4a shows the radiance-based co-association matrix. Co-association matrices are symmetric about the diagonal, with yellow and white indicating high co-association values (closer to 1) and thus, strong agreement in cluster membership across angular bins. The diagonal elements all equal 1 by definition, as each surface is perfectly co-associated with itself and therefore carries no interpretive meaning. Both the upper and lower triangles are shown to fully convey the pairwise relationships among surface types and to facilitate visual analysis. Due to this symmetry, examining either a row or a column provides the complete clustering behavior for a given surface. High to moderate co-association values are observed for IGBP surfaces 1–14 and 18, indicating that these vegetated and land-dominated surfaces tend to cluster together consistently across viewing geometries. In contrast, surfaces 15 (permanent snow/ice), 16 (bare soil and rocks), 17 (water bodies), 19 (fresh snow), and 20 (sea ice) exhibit lower co-association values, showing that these surfaces are more distinct within the radiance feature space.

Figure 4b illustrates the clustering consistency among the anisotropic factor dataset. In contrast to Figure 4a, where the snowy surfaces (IGBP surfaces 15, 19, and 20) each formed their own distinct clusters due to their exceptionally high radiances, Figure 4b reveals that these surface anisotropic factors cluster together. This suggests that while absolute radiance differences previously drove the separation of the snow surfaces, the co-association patterns captured here emphasize their relative similarity in anisotropy. Additionally, water bodies (17) remain largely isolated, rarely clustering with any other surface, underscoring their distinct anisotropic characteristics.

To translate the co-association matrix into a single global clustering, we applied agglomerative hierarchical clustering using the co-association-derived distances. This method successively merges the most similar clusters, producing a dendrogram that naturally illustrates which surfaces are most consistently linked. By cutting the dendrogram at the chosen K , we obtained a stable clustering solution that reflects both angular diversity and overall consistency. As discussed in Section 4.4, we applied three separate linkage criteria to each set of analysis.

Figure 5 shows the hierarchical clustering results for the radiance dataset and $K = 7$ (indicated by the horizontal black lines on each panel) under the three linkage criteria. Across all methods, water bodies (17), bare soil and rocks (16), permanent snow/ice (15), fresh snow (19), and sea ice (20) each form their own distinct clusters, consistent with their strong radiometric and anisotropic contrasts. In both the average and complete linkage solutions, closed shrublands (6), open shrublands (7), savannas (9), grasslands (10), and croplands (12) form a bright vegetation class. Under single linkage, only closed shrublands (6) and savannas (9) pair together, while open shrublands (7), grasslands (10), and croplands (12) merge with the remaining land surface types at higher levels of the hierarchy. These results further emphasize that, although linkage choice slightly affects the grouping of vegetated surfaces, the primary clustering structure, particularly the separation of snow, bright desert, and water surfaces, remains robust across methods.

Figure 6 illustrates the hierarchical clustering of the anisotropic factor dataset under three different linkage criteria. In all dendrograms, water bodies (17) consistently separate first, highlighting that it has the most distinct anisotropic factor across all viewing geometry bins. While the detailed hierarchy varies slightly across linkage methods, cutting the dendrograms at $K = 7$ reveals largely consistent surface groups. Both single and average linkage produce identical clusters: water bodies (17), snowy surfaces (15, 19, 20), tundra (18), permanent wetlands (11), Evergreen Broadleaf Forest/Closed Shrublands (2, 6), bare soil and rocks (16), and finally, the rest of the IGBP surfaces which all consist of vegetative and land-based surfaces (1, 3–5, 7–10, 12–14). Complete linkage differs slightly by grouping Deciduous Needleleaf Forest (3) and croplands (12) with bare soil and rocks (16), but otherwise produces the same clusters. These

results demonstrate that, despite minor variations in cluster composition, the overall patterns of surface similarity and separation are again robust to the choice of linkage method.

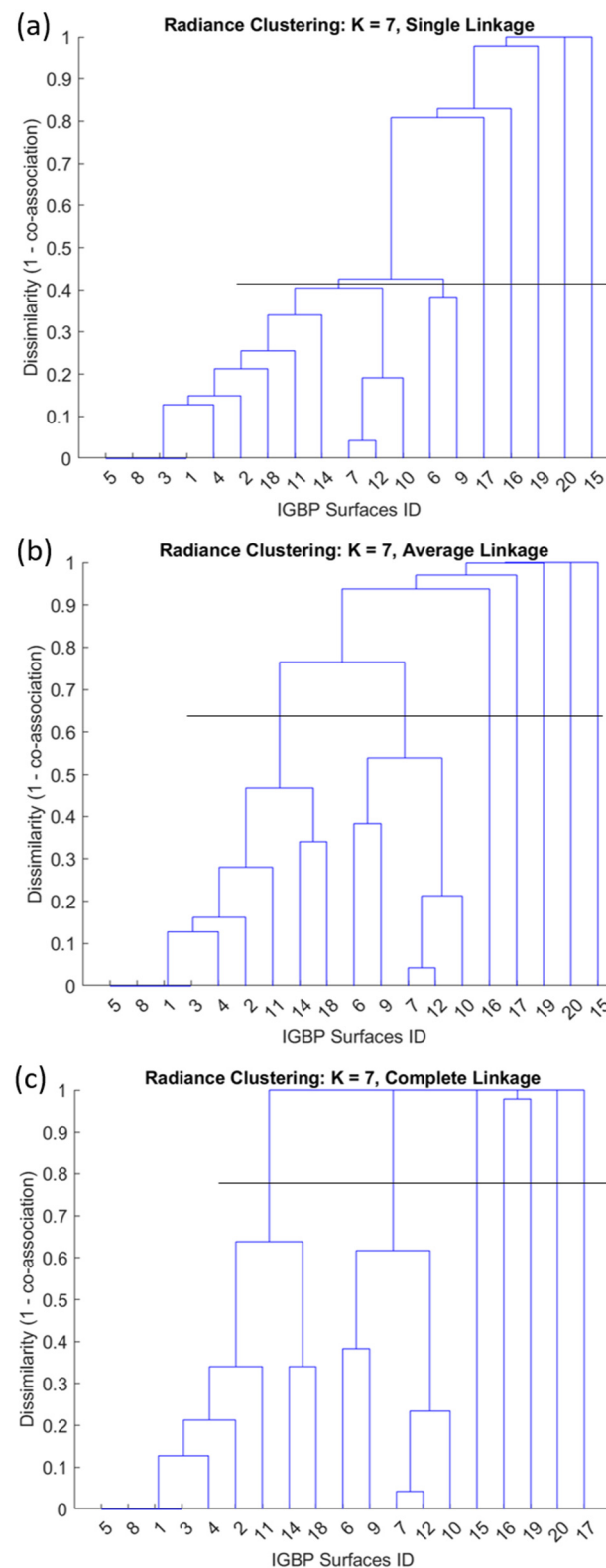


Figure 5. Dendrograms illustrating hierarchical clustering of the radiance dataset and $K = 7$, using different linkage criteria: (a) single linkage, (b) average linkage, and (c) complete linkage. Each dendrogram shows the stepwise merging of surfaces based on co-association-derived distances. The horizontal black line denotes the clustering threshold corresponding to seven groups ($K = 7$), representing the level at which clusters were defined.

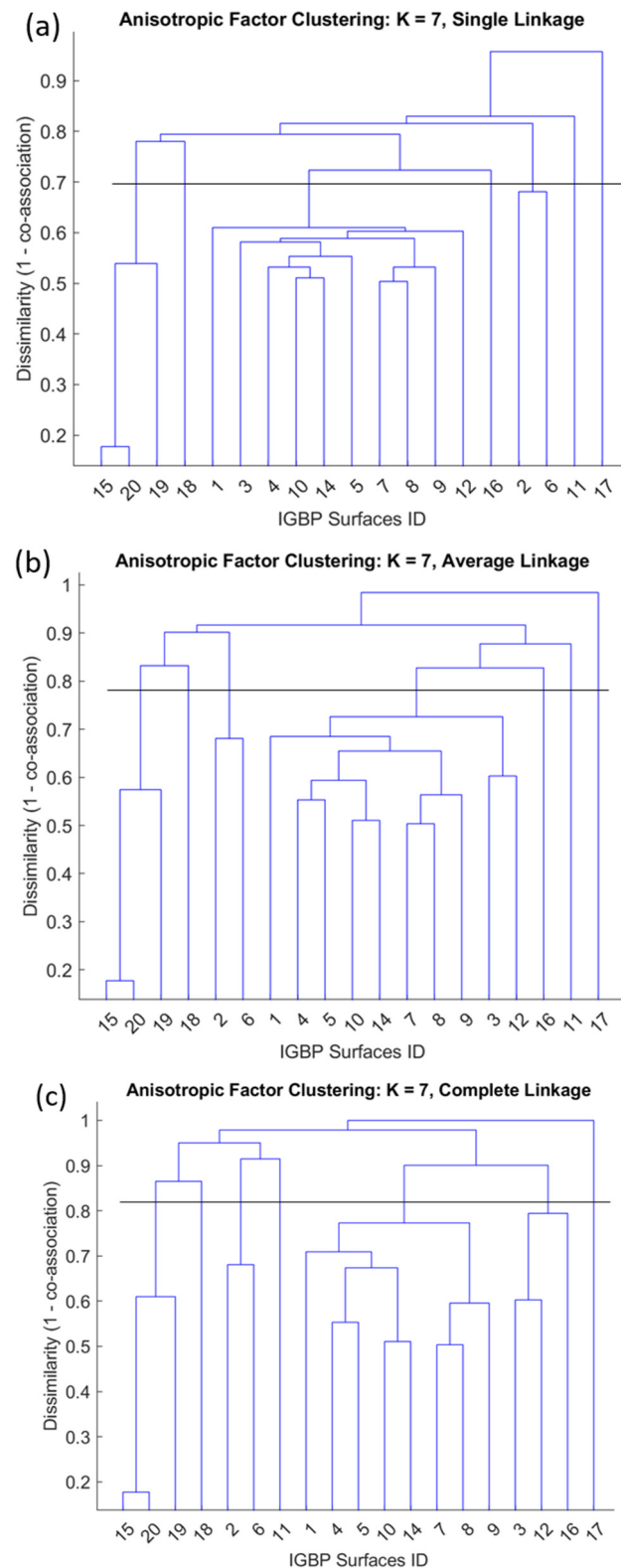


Figure 6. Dendrograms illustrating hierarchical clustering of the anisotropic factor dataset using different linkage criteria: (a) single linkage, (b) average linkage, and (c) complete linkage. Each dendrogram shows the stepwise merging of surfaces based on co-association-derived distances, highlighting how clustering patterns vary with the choice of linkage method. The horizontal black line denotes the clustering threshold corresponding to K = 7.

Table 2 compares our final surface groups derived from the consensus clustering to the original CERES-TRMM surface classifications. The comparison highlights both the

alignment and refinement of surface definitions achieved through the clustering analysis. Many of the resulting clusters correspond closely to established CERES-TRMM categories such as snow/ice, water, and bright desert. This mapping provides a useful reference for interpreting the derived surface clusters in the context of existing surface-type frameworks.

Table 2. IGBP surface types with corresponding CERES-TRMM surface groups, radiance-based cluster assignments, and anisotropic-factor-based groupings. Background colors indicate qualitative similarity between the original CERES surface groupings and the surface clusters derived in this study from radiance and anisotropic factor analyses.

	IGBP Surface Type	CERES Surface Groups	Radiance	Anisotropic Factor
1	Evergreen Needleleaf Forest	Mod/Hi Tree/Shrub	Dark Vegetation	Tree/Shrub/Grass
2	Evergreen Broadleaf Forest	Mod/Hi Tree/Shrub	Dark Vegetation	Evergreen Broadleaf Forest/Closed Shrublands
3	Deciduous Needleleaf Forest	Mod/Hi Tree/Shrub	Dark Vegetation	Tree/Shrub/Grass
4	Deciduous Broadleaf Forest	Mod/Hi Tree/Shrub	Dark Vegetation	Tree/Shrub/Grass
5	Mixed Forest	Mod/Hi Tree/Shrub	Dark Vegetation	Tree/Shrub/Grass
6	Closed Shrublands	Mod/Hi Tree/Shrub	Bright Vegetation	Evergreen Broadleaf Forest/Closed Shrublands
7	Open Shrublands	Dark Desert	Bright Vegetation	Tree/Shrub/Grass
8	Woody Savannas	Mod/Hi Tree/Shrub	Dark Vegetation	Tree/Shrub/Grass
9	Savannas	Low/Mod Tree/Shrub	Bright Vegetation	Tree/Shrub/Grass
10	Grasslands	Low/Mod Tree/Shrub	Bright Vegetation	Tree/Shrub/Grass
11	Permanent Wetlands	Low/Mod Tree/Shrub	Dark Vegetation	Permanent Wetland
12	Croplands	Low/Mod Tree/Shrub	Bright Vegetation	Tree/Shrub/Grass
13	Urban/Built-up	Low/Mod Tree/Shrub		
14	Cropland Mosaics	Low/Mod Tree/Shrub	Dark Vegetation	Tree/Shrub/Grass
15	Snow/Ice (permanent)	Snow/Ice	Snow/Ice	Snow/Ice
16	Bare Soil/Rocks	Bright Deserts	Bright Deserts	Bright Deserts
17	Water Bodies	Water	Water	Water
18	Tundra	Low/Mod Tree/Shrub	Tree/Shrub	Tundra
19	Fresh Snow	Snow/Ice	Fresh Snow	Snow/Ice
20	Sea Ice	Snow/Ice	Sea Ice	Snow/Ice

Since ADMs for the CERES and Libera ERB missions are defined in terms of anisotropic factors, it is not surprising that the anisotropic factor clustering provides the more directly relevant insight for Libera’s future ADM development. However, the radiance-based analysis also has merit by revealing the underlying radiometric similarities; moreover, it is less sensitive to sparse or uneven angular sampling. When analyzed together, the similarities and differences between the radiance and anisotropic factor clustering provide insights into why surfaces cluster together.

For the radiance-based clustering (Table 2, column 4), vegetated surfaces form a cohesive group, indicating their broadly similar radiometric characteristics. Water surfaces remain distinct, consistent with their generally low radiances except in specular directions. High reflectance surfaces, such as bare soil and rocks, permanent snow and ice, fresh snow, and sea ice, exhibit sufficiently high radiances to form individual clusters. Within the vegetated group, subtle variations in brightness drive additional differentiation between

brighter and darker vegetative surfaces, which are consistent with expectations for radiance-based classifications.

The anisotropic factor clustering (Table 2, column 5) reveals some notable differences from the results of the radiance-based clustering. Most evident is that the three snowy surfaces—permanent snow/ice (15), fresh snow (19), and sea ice (20)—form a single cluster, capturing their shared angular reflectance behaviors, in agreement with the CERES snowy surface group. This result emphasizes that similar anisotropy can result from surfaces with different reflected radiance magnitudes. A notable difference between the anisotropic factor clustering results and the CERES-TRMM surface categorizations (Table 2, column 3) is the separation of evergreen broadleaf forest (2), closed shrublands (6), and permanent wetlands (11) from the main vegetated surface groups.

The evergreen broadleaf forests (2) and closed shrublands (6) cluster separation is likely an artifact of limited angular sampling, which introduces larger uncertainties in the estimation of upwelling irradiance (Equation (5)) and consequently in the derived anisotropic factors (Equation (3)). Extremely common and well-sampled surfaces such as water bodies (17) have tens of thousands of observations per angular bin (32,946 on average), while the overall mean across all 19 surfaces is 6199. In contrast, evergreen broadleaf forests (2) have only 78 observations per bin (occurring on average over 24 days), while similar forested surfaces such as evergreen needleleaf (1) and deciduous broadleaf forests (4) have 244 (over 70 days) and 192 (over 57 days) observations per bin, respectively. The under sampling is even more pronounced for closed shrublands (6), which have only 38 observations per bin (over 16 days), compared to 6932 (546 days) for open shrublands (7). Such sampling limitations illustrate a key challenge in developing anisotropic factors for individual surface types, where the reduced number of observations amplifies sensitivity to missing or interpolated angular bins. In this case, the radiance-based clustering provides a more reliable indicator of true surface similarity: evergreen broadleaf forests most closely align with darker vegetative surfaces, while closed shrublands cluster with brighter vegetation types, particularly savannas (9).

Importantly, the increased uncertainty associated with under sampled surfaces does not imply that the inferred surface groupings themselves are unstable or overly sensitive to sampling limitations. Although anisotropic factor estimates for these surfaces are more uncertain due to incomplete angular coverage, the relationships among surface types remain consistent. Across a range of cluster numbers ($K = 6\text{--}8$), the same surfaces are observed to cluster together, with changes in K primarily leading to the subdivision or merging of closely related surface groups, rather than reassignment of fundamentally different surface types, as illustrated by the anisotropic factor dendrograms in Figure 7. This indicates that the clustering reflects a stable underlying surface similarity structure, even in the presence of uneven sampling density. In this context, $K = 7$ represents a practical operational choice rather than a uniquely determined solution, and the separation of evergreen broadleaf forests (2) and closed shrublands (6) in the anisotropic factor clustering should be interpreted as a consequence of increased uncertainty in angular integration, rather than evidence of fundamentally distinct surface behavior.

Permanent wetlands (11) form a distinct surface group, likely due to their combination of vegetation and standing water, which sets them apart from other vegetated surfaces. Examination of the dendrograms, both radiance (Figure 5) and anisotropic factors (Figure 6), shows that permanent wetlands are more closely related to vegetative surfaces than to water bodies (17). The tundra surface class (18) also forms its own surface group; however, the dendrograms indicate that it is most closely related to other snowy surface classes, highlighting a subtle difference from previous CERES classifications, where it is either included with vegetative surfaces or with dark desert surfaces [36].

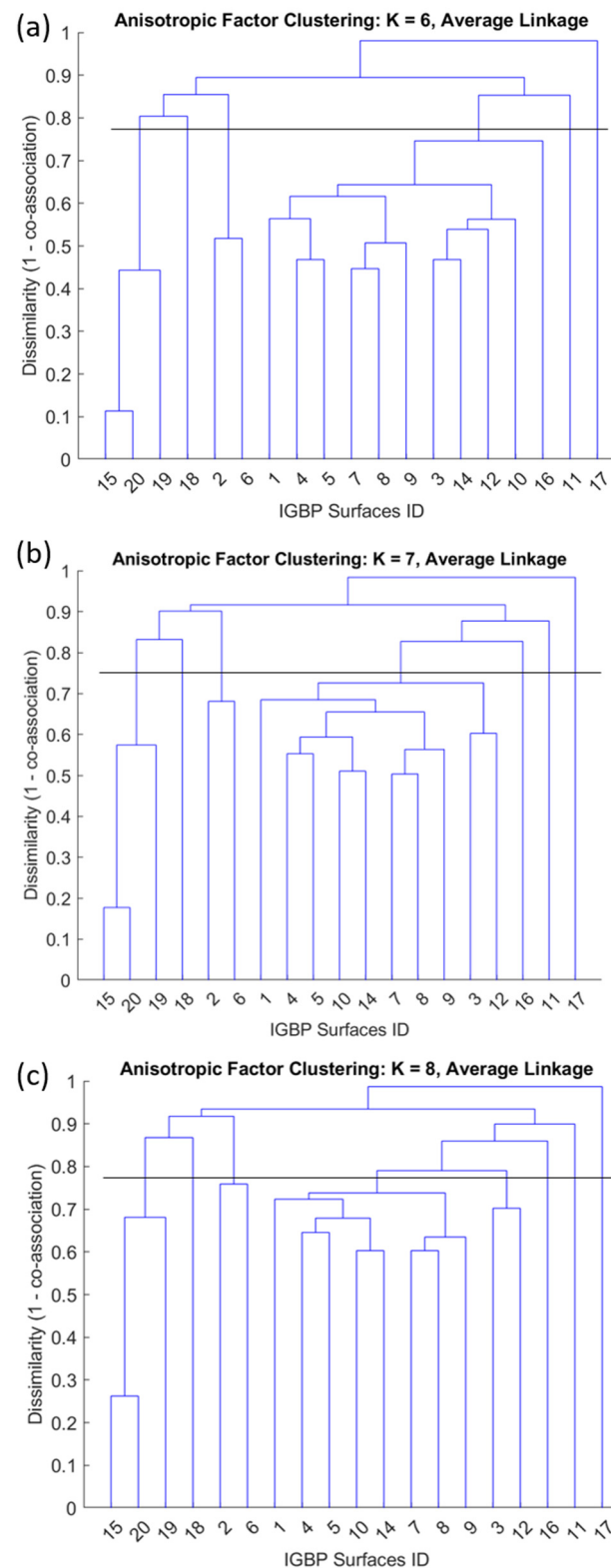


Figure 7. Dendrograms illustrating hierarchical clustering of the anisotropic factor dataset for different choices of cluster number: (a) $K = 6$, (b) $K = 7$, and (c) $K = 8$. Each dendrogram shows the stepwise merging of surfaces based on co-association-derived distances, illustrating the consistency of surface affinities across a range of K values. The horizontal black line in each panel denotes the clustering threshold corresponding to the indicated number of clusters.

Across both the anisotropic factor and radiance-based clustering approaches, dark deserts are consistently excluded from major groupings, indicating their intermediate

radiometric and anisotropic characteristics relative to bright deserts and vegetated surfaces. In the anisotropic factor clustering, open shrublands (7) are consistently grouped with woody savannas (8) across all linkage methods. These two surfaces also exhibit the second-highest similarity in anisotropic factors across the angular domain, surpassed only by the pairing of permanent snow/ice (15) and sea ice (20). The radiance-based analysis shows that open shrublands (7) have upwelling radiances most similar to croplands (12) for all three linkage methods.

6. Conclusions

This study establishes a framework for quantifying the grouping of IGBP surface classes to support the development of ADMs for the Libera mission. Using K-means clustering, co-association matrices, and hierarchical consensus clustering, we quantified radiometric and anisotropic similarities among IGBP surface types. The optimal number of clusters for both the radiance- and anisotropic-factor-based analyses was found to be seven ($K = 7$), yielding seven final surface groups. These results provide the first comprehensive assessment of surface-type consolidation strategies directly linked to ADM development for Libera's shortwave and split-shortwave channels.

When applying clustering to the reflected radiance from different surface types across solar-viewing geometries, the clustering of IGBP surface classes is primarily governed by surface brightness. Vegetated surfaces form a cohesive group, while water and bright surfaces, such as bare soil and rock, permanent snow/ice, fresh snow, and sea ice, emerge as distinct clusters. The absence of a dark desert cluster indicates that arid regions share closer radiometric affinity with sparsely vegetated surfaces than previously suggested by the CERES–TRMM classification. Within the vegetated group, subtle differences in brightness distinguish darker and brighter vegetative surfaces, providing useful information that complements the anisotropic factor clustering, especially for poorly sampled surfaces for which the clustering of anisotropic factors is less reliable.

Since Libera's ADMs are defined in terms of anisotropic factors, the anisotropic factor clustering analysis and results provide the most relevant insight for ADM development. Snowy surfaces merge into a single cluster, highlighting their shared angular reflectance behavior and aligning with the CERES–TRMM snowy-surface category. Permanent wetlands and tundra form distinct anisotropic clusters while remaining closely related to vegetated and snowy surfaces, respectively, highlighting subtle differences in these results from previous CERES–TRMM classifications. A major difference between the results of this analysis and the CERES–TRMM surface types is the omission of a dark desert surface type. Open shrublands (7), the IGBP surface most associated with dark deserts, exhibit anisotropic factors similar to other land surfaces. They are not particularly distinct; in fact, they are among the first surfaces to cluster in our consensus analysis for both anisotropic- and radiance-based clustering, suggesting that a separate classification for this surface may not be necessary.

Overall, despite the minor refinements noted above, the resulting surface partitions exhibit strong agreement with the heritage CERES–TRMM surface groups, providing reassurance in the historical classifications. The derived surface groups preserve the major CERES categories—snow/ice, water, and bright desert—while offering insight into the radiative similarities of all the vegetated surfaces and transitional regions. Their stability across viewing geometries and consistency between radiance and anisotropy domains suggest that these clusters can reliably support Libera ADM construction with the Libera camera and ADM evaluation with limited RAPS mode operations.

Operationally, the seven surface groups identified in this study are intended to inform Libera's TRMM-like scene type definitions rather than introduce new processing pathways.

As in the CERES–TRMM framework, surface groups are applied consistently across both clear-sky and cloudy scene types, with cloud properties (cloud fraction, optical depth, and phase) treated as additional scene dimensions. In this context, the present analysis primarily modifies only the surface component of the scene classification, resulting in updated scene identifiers while preserving the overall structure of the Libera processing chain.

Our approach offers a reproducible way to define ADM surface groups, supporting Libera’s goals of extending the ERB record while demonstrating new approaches for radiance-to-irradiance conversions. A caveat is that these results are based on the broadband shortwave observations of the CERES FM-5 instrument, and consistency with the split-shortwave Libera channels should be confirmed post-launch. Beyond Libera, the demonstrated framework offers a scalable approach for future missions seeking to construct ADMs from limited angular sampling, ensuring that surface-based radiative properties remain physically interpretable and consistent across successive generations of Earth radiation measurements.

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Data Availability Statement: The Level-2 Single Scanner Footprint datasets used within this study are publicly available at <https://asdc.larc.nasa.gov/data/CERES/SSF/> (accessed on 15 June 2024).

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Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

ADMs	Angular Distribution Models
AVHRR	Advanced Very High Resolution Radiometer
BCSS	Between Cluster Sum of Squares
CERES	Clouds and the Earth’s Radiant Energy System
ERB	Earth Radiation Budget
ERBE	Earth Radiation Budget Experiment
FM-5	Flight Model 5
IGBP	International Geosphere-Biosphere Programme
JPSS-4	Joint Polar Satellite System-4
NASA	National Aeronautics and Space Administration
NPP	National Polar-orbiting Partnership
RAPS	Rotating Azimuthal Plane Scan
SSF	Single Scanner Footprint
TRMM	Tropical Rainfall Measuring Mission
VIIRS	Visible Infrared Imaging Radiometer Suite
WCSS	Within Cluster Sum of Squares

Appendix A

Figure A1 presents the hierarchical clustering results for the radiance dataset and $K = 6$ under the three linkage criteria. Average and single linkage result in water bodies (17), bare soil and rocks (16), permanent snow/ice (15), sea ice (20), and fresh snow (19) forming their own distinct clusters in both the single and average linkage solutions. In contrast, the complete linkage method groups fresh snow (19) and sea ice (20) together, allowing a new cluster to form among surfaces closed shrublands (6), open shrublands (7), woody savannas (8), savannas (9), grasslands (10), and croplands (12). These correspond to the brighter vegetated surfaces. Despite these minor differences, the overall clustering structure remains consistent, again showing strong agreement between the single and average linkage criteria.

Figure A2 shows the hierarchical clustering of the anisotropic factor dataset and $K = 8$ under three different linkage criteria. In all three dendrograms, permanent wetlands (11), water bodies (17), and tundra (18) consistently separate into individual clusters, while permanent snow/ice (15), fresh snow (19), and sea ice (20) group into a single snowy cluster. Under average and single linkage criteria, bare soil and rocks (16) forms a single surface group, while complete linkage sees it joined by deciduous broadleaf forest (3) and croplands (12), and average linkage has deciduous broadleaf forest (3) and croplands (12) forming their own cluster. Under average and complete linkage criteria, evergreen broadleaf forest (2) and closed shrublands (6) cluster together, while single linkage sees these two surfaces forming individual clusters. Complete linkage has a unique cluster of open shrublands (7), woody savannas (8), and savannas (9). Each linkage criteria has a large vegetative group. For complete linkage, this is evergreen needleleaf forest (1), deciduous broadleaf forest (4), mixed forest (5), grasslands (10), and cropland mosaics (14). Average linkage sees this same group joined by open shrublands (7), woody savannas (8), and savannas (9). Finally, single linkage has the largest vegetative group, containing ten surfaces, containing the same eight as mentioned for average linkage while adding deciduous broadleaf forest (3) and croplands (12). The distinct anisotropic surface groups from $K = 7$ are preserved, those being permanent wetlands (11), bright deserts composed of bare soil and rocks (16), snowy surfaces composed of permanent snow/ice (15), fresh snow (19), and sea ice (20), water bodies (17), and tundra (18).

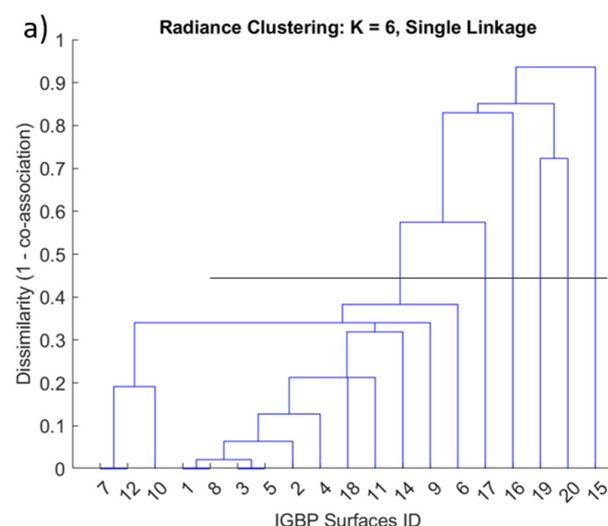


Figure A1. Cont.

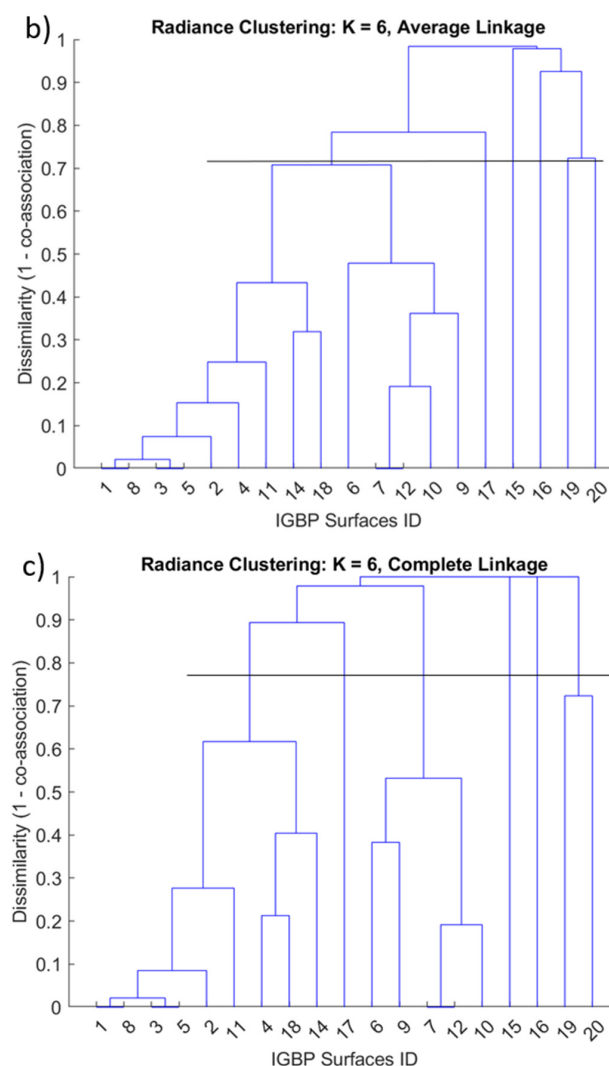


Figure A1. Dendrograms illustrating hierarchical clustering of the radiance dataset and $K = 6$, using different linkage criteria: (a) single linkage, (b) average linkage, and (c) complete linkage. Each dendrogram shows the stepwise merging of surfaces based on co-association-derived distances. The horizontal black line denotes the clustering threshold corresponding to six groups ($K = 6$), representing the level at which clusters were defined.

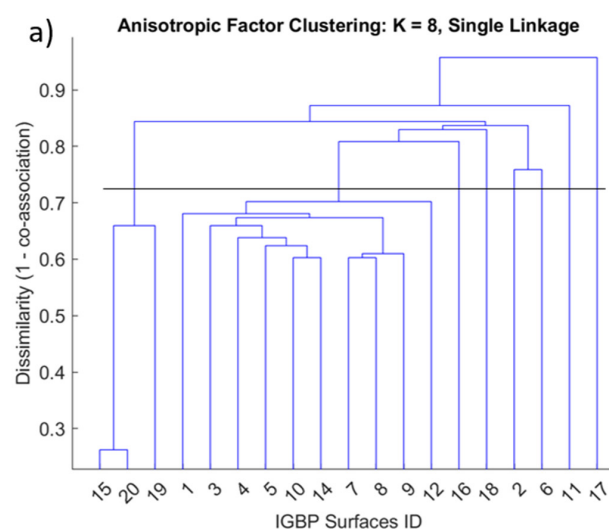


Figure A2. Cont.

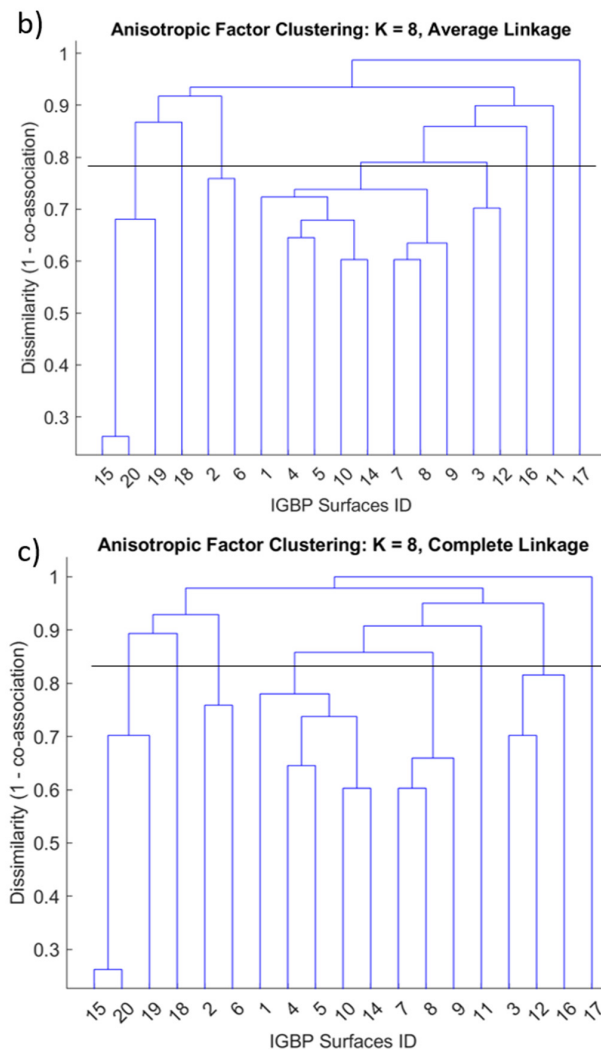


Figure A2. Dendrograms illustrating hierarchical clustering of the anisotropic factor dataset and $K = 8$, using different linkage criteria: (a) single linkage, (b) average linkage, and (c) complete linkage. Each dendrogram shows the stepwise merging of surfaces based on co-association-derived distances. The horizontal black line denotes the clustering threshold corresponding to eight groups ($K = 8$), representing the level at which clusters were defined.

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