

Article

UAV Hyperspectral Characterization of Spatial Color Heterogeneity in Alpine Karst Lakes

Minyuan Zhang ^{1,2}, Xiaorong Huang ^{1,2,*} , Fuquan Pu ³, Chen Ji ^{1,2}, Siyang Feng ^{1,2} and Pengnan Luo ^{1,2}

¹ State Key Laboratory of Hydraulics and Mountain River Engineering, Sichuan University, Chengdu 610065, China; 2024223065089@stu.scu.edu.cn (M.Z.)

² College of Water Resource & Hydropower, Sichuan University, Chengdu 610065, China

³ Aba Hydrological and Water Resources Survey Center, Wenchuan 623000, China

* Correspondence: hxiaorong@scu.edu.cn

Highlights

What are the main findings?

- UAV hyperspectral imagery captured fine-scale spatial variations in optical characteristics across three cascaded alpine karst lakes.
- CIE $L^*a^*b^*$ color metrics and ΔE quantified differences in lake color patterns and spatial optical heterogeneity.
- A tiered K-means clustering framework revealed optical patterns among lakes and within individual lakes while reducing inter-lake masking effects.
- Optical proxies revealed distinct spectral patterns associated with variations in bottom influence and water-column contributions.

What are the implications of the main findings?

- The proposed framework allows non-invasive assessment of optical heterogeneity in protected alpine lake systems where field measurements are limited.
- UAV hyperspectral mapping can provide a high-resolution spatial baseline for future investigations of lake optical changes.
- The framework may be applicable to other shallow-water systems with strong spatial variations in optical conditions.

Abstract

Alpine karst lakes in Jiuzhaigou exhibit spatial variations in optical properties associated with differences in water depth, underwater substrates, and travertine distribution. Conventional satellite observations may not provide sufficient spatial resolution to resolve the small-scale optical variations present in these shallow and heterogeneous lakes. In this study, UAV-based hyperspectral imagery was used to quantify spatial optical variations among three representative cascade lakes located in the “Y-shaped” valley network of Jiuzhaigou, China. Hyperspectral reflectance data were transformed into the CIE $L^*a^*b^*$ color space to quantify perceptual color variability, while the Euclidean color difference metric (ΔE) was used to assess relative spatial heterogeneity. In addition, seven empirical optical proxies were developed to describe spatial variations in apparent optical properties without attempting absolute retrieval of water constituents. A tiered unsupervised K-means clustering approach was applied to resolve optical heterogeneity across multiple spatial scales. Global-scale clustering separated the major optical differences among lakes, whereas lake-specific clustering revealed distinct intra-lake optical zones, including areas with stronger benthic influence, transitional optical conditions, and zones dominated by



Academic Editor: Teodosio Lacava

Received: 3 June 2026

Revised: 8 July 2026

Accepted: 15 July 2026

Published: 5 August 2026

Copyright: © 2026 by the authors.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and

conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

water-column signals. Non-parametric Kruskal–Wallis H tests showed significant differences among optical zones, indicating that the selected proxies can distinguish spatial optical variability. The results show that UAV hyperspectral observations combined with color metrics and empirical optical proxies can effectively describe fine-scale spatial optical variations in alpine karst lakes. Rather than retrieving absolute biogeochemical or bathymetric parameters, this approach provides a reference description of relative optical variability that may assist future repeated observations and spatial monitoring of protected aquatic ecosystems.

Keywords: alpine karst lakes; UAV hyperspectral; spatial optical heterogeneity; CIE $L^*a^*b^*$ color space; empirical proxies; tiered clustering

1. Introduction

Alpine karst lake systems, such as the cascaded network in Jiuzhaigou National Nature Reserve, China, are highly sensitive hydrological environments characterized by ultra-transparent waters and structurally complex subaqueous travertine (CaCO_3) geomorphology [1,2]. Traditionally, “lake color” in such systems has been investigated either as an aesthetic feature or as a proxy for water-quality constituents [3] (e.g., phytoplankton, suspended sediments, and CDOM) derived from apparent optical properties (AOPs) [4–8]. However, surface water color is intrinsically transient and highly susceptible to short-term biogeochemical fluctuations [9,10]. Therefore, establishing spatial baselines of optical variability provides an important foundation for future ecosystem assessment and long-term monitoring of these sensitive systems. Specifically, the spatial distribution of shallow travertine shoals versus deep-water basins fundamentally regulates hydrodynamic connectivity, longitudinal material transport, and benthic habitat integrity within these cascaded networks [11,12]. Detecting temporal deviations from these spatial optical patterns, particularly following extreme events such as the 2017 Jiuzhaigou earthquake or ongoing hydrological changes, remains a methodological challenge [13–15]. Furthermore, conventional optical remote sensing approaches heavily rely on empirical or semi-analytical bio-optical models that require synchronized in situ bathymetric or biogeochemical data for absolute physical inversion and calibration [16]. In the absence of such ground-truth data, traditional concentration-retrieval models are rendered largely inapplicable, necessitating a paradigm shift toward non-invasive methodologies [17,18].

Unmanned aerial vehicle (UAV)-based hyperspectral remote sensing, with centimeter-level spatial resolution and continuous spectral coverage, offers a powerful, non-invasive tool to capture fine-scale optical heterogeneity [19–23]. Compared with satellite imagery, UAV surveys can resolve subtle spatial gradients associated with benthic substrates, water depth, and localized optical conditions [24]. Nevertheless, UAV-based approaches are constrained by limited spatial coverage, sensitivity to illumination and weather conditions, and substantial preprocessing requirements for hyperspectral calibration and orthomosaic generation. In addition, many existing remote sensing frameworks are generally developed using global classification or clustering strategies applied across entire aquatic systems. In heterogeneous systems, large inter-lake optical baseline differences—such as the contrast between groundwater-fed, hyper-reflective shallow pools and deep, attenuation-dominated basins—may obscure localized intra-lake features, reducing the effectiveness of global-only analyses [10,25,26].

To overcome these methodological bottlenecks, this study proposes a novel, non-invasive analytical framework that shifts from absolute constituent inversion to relative,

multi-scale spatial heterogeneity characterization [3,27]. Using UAV-based hyperspectral imagery from a representative cascaded lake system in Jiuzhaigou, we developed a tiered (global and lake-specific) unsupervised spatial clustering framework. Crucially, this framework couples the quantitative perceptual CIE $L^*a^*b^*$ color space with customized, empirical optical proxies designed for multi-scale characterization of optical variability [28–30]. The specific objectives of this study are as follows:

- (1) Formulate non-invasive hyperspectral proxies and integrate them with CIELAB colorimetric parameters to characterize relative spatial optical heterogeneity associated with benthic substrates and water-column properties without requiring synchronous in situ calibration for absolute constituent retrieval [31–33];
- (2) Implement a tiered K-Means clustering strategy to mitigate the macro-scale masking effect and optical water types (OWTs) defined within the clustering framework [34];
- (3) Statistically evaluate the robustness and scale-dependent applicability of the proposed proxies for characterizing spatial optical heterogeneity in alpine karst cascade lakes [35].

2. Study Area Overview and Data Sources

2.1. Overview of Representative Lakes in Jiuzhaigou

To investigate spatial variability in lake color and optical heterogeneity, three representative lakes—Five Colored Pool, Five Flower Lake, and the Shuzheng Lakes—were selected from more than 100 lakes within the Jiuzhaigou basin. These lakes were chosen because they represent distinct hydrological, geomorphological, and optical conditions within the alpine karst lake network. Specifically, Five Colored Pool is a small groundwater-fed lake characterized by exceptionally high-water clarity and extensive shallow travertine exposure; Five Flower Lake represents a transitional lake with diverse benthic substrates and pronounced color variability; and the Shuzheng Lakes comprise the largest downstream lake group, characterized by greater water depth and more complex optical conditions. Together, these lakes capture a broad range of water clarity, benthic substrate composition, lake morphology, and hydrological connectivity observed across the Jiuzhaigou cascade system. Figure 1 illustrates the locations of the study lakes within the Jiuzhaigou alpine karst basin, the Y-shaped valley network connecting the lakes, and the elevation gradient across the basin. Therefore, the selected lakes provide a representative natural gradient for evaluating both inter-lake and intra-lake optical variability.

Five Colored Pool, located in the Zechawa Valley at an elevation of 3010 m, is a small but highly dynamic oligotrophic lake, approximately 100 m in length, 60 m in width, and 6.6 m in maximum depth, with a storage volume of about 40,000 m³. Its water is primarily supplied by inflows from Long Lake and exhibits pronounced seasonal variability driven by precipitation. Lake color variability in Five Colored Pool is mainly controlled by water depth, lakebed geomorphology, and interactions among solar radiation, travertine deposits, and benthic biological components.

Five Flower Lake, situated in the Rize Valley at an elevation of 2472 m, measures approximately 450 m in length and 227–313 m in width, with water depths ranging from 3.8 to 12 m (average depth 6 m) and a storage volume of about 600,000 m³. The lake experiences moderate water-level fluctuations and displays pronounced spatial heterogeneity in optical properties, primarily driven by calcium carbonate deposition, benthic algal distribution, and submerged vegetation patterns.

The Shuzheng Lakes, located in the Shuzheng Valley at elevations between 2187 and 2280 m, consist of 19 interconnected lakes with surface areas ranging from 24 × 10 m² to 210 × 40 m² and water depths of 1.5–16.2 m. The total lake area is approximately 50,000 m². These lakes represent downstream environments where hydrodynamic mixing and sed-

iment accumulation lead to relatively homogeneous blue–green optical characteristics (content sourced from “Research Report on Determining the Sedimentary Environment and Water Cycle System Patterns, Establishing Monitoring Systems, and Applying Landscape Conservation Technologies in the Core Scenic Areas of Jiuzhai-Huanglong”).

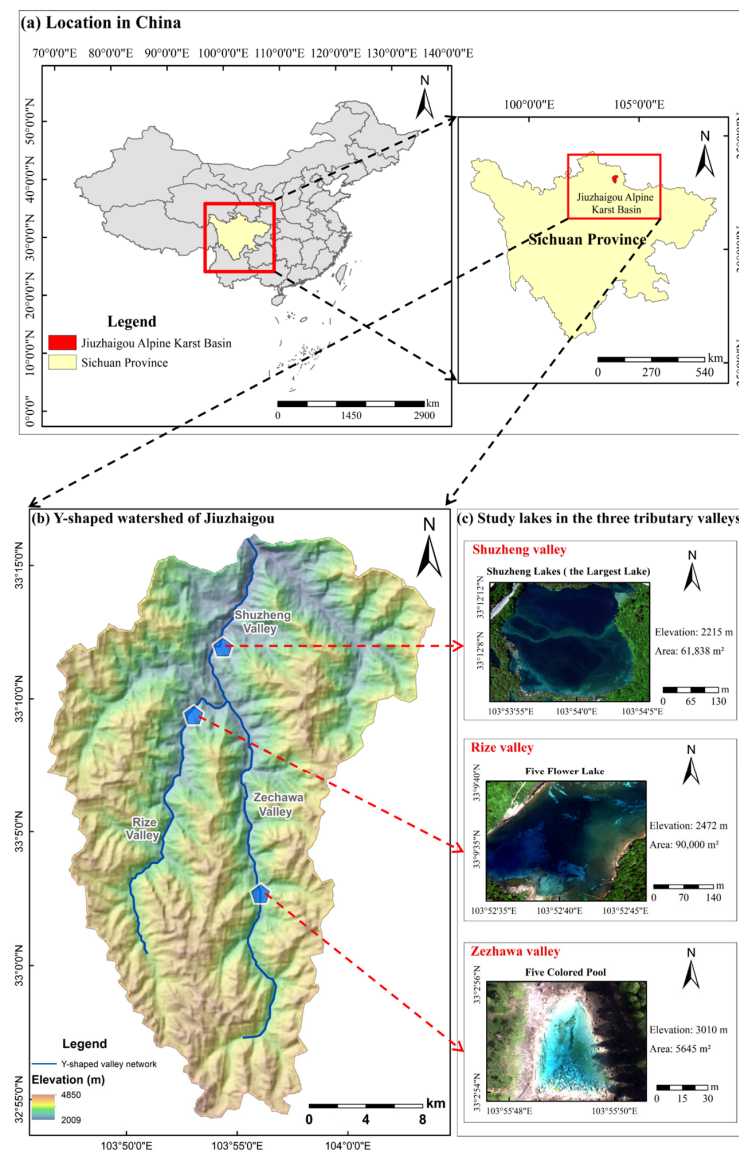


Figure 1. Location, topographic context, and spatial configuration of the study area in Jiuzhaigou National Park, southwestern China. (a) Geographic location of Jiuzhaigou National Park within China and regional context. (b) Basin-scale topographic and hydrological structure of the three cascade lake valleys (Zechawa Valley, Rize Valley, and Shuzheng Valley), showing elevation gradients and valley connectivity. (c) Detailed spatial distribution of the investigated lake systems, including Five Colored Pool, Five Flower Lake, and the Shuzheng Lakes cluster, showing relative elevation differences and lake-scale spatial characteristics.

2.2. Data Acquisition and Preprocessing

To characterize the multi-scale optical heterogeneity of cascaded alpine karst lakes without disturbing the strictly protected environment, non-invasive UAV hyperspectral surveys were conducted on 28 May 2025 under clear-sky and low-wind conditions to minimize atmospheric and illumination variability.

Data acquisition was performed using a DJI Matrice 350 RTK platform equipped with a GaiaSky-mini3-VN hyperspectral imaging system. The sensor records continuous spectral

information across the 400–1000 nm visible-to-near-infrared range with 224 spectral bands and an average spectral resolution of approximately 5 nm. UAV flights were conducted at a constant altitude of 100 m above ground level with 60% forward and side overlap to ensure sufficient spatial redundancy for subsequent orthomosaic reconstruction and geometric stability.

UAV hyperspectral data were preprocessed using standard radiometric and geometric correction workflows commonly applied in hyperspectral remote sensing. The processing chain included conversion of raw digital numbers (DN) to at-sensor radiance, radiometric calibration, and orthorectification based on onboard GNSS/IMU positioning and flight geometry information.

Atmospheric correction was performed using the empirical line method (ELM) with representative surface reflectance reference targets deployed within the study area during the UAV campaign. This procedure establishes a site-specific linear relationship between at-sensor radiance and known reference reflectance values, enabling conversion to remote sensing reflectance (R_{rs}) under the assumption of spatially uniform atmospheric conditions during the acquisition period. These reference targets were used solely for radiometric normalization and atmospheric correction purposes and were not involved in biogeochemical calibration, bathymetric validation, or the establishment of empirical inversion models.

The resulting reflectance products were mosaicked and geometrically harmonized to ensure spatial consistency across flight strips prior to analysis. Given the complex topographic and atmospheric conditions in alpine karst environments and the absence of synchronized atmospheric profile measurements, physically based radiative transfer modeling was not applied. Potential residual uncertainties related to bidirectional reflectance effects over heterogeneous travertine substrates were considered inherent limitations of UAV observations in mountainous environments, but are expected to have limited influence on relative spatial comparisons within the same acquisition period. Therefore, the derived reflectance products are interpreted as relative surface reflectance, suitable for comparative analysis of spatial optical heterogeneity rather than absolute biogeochemical inversion.

Water-body extraction was performed using the Normalized Difference Water Index (NDWI) in QGIS, followed by manual refinement in ENVI 5.6 to remove non-water features such as vegetation, exposed carbonate substrates, and shadowed areas. This combined automated–manual procedure ensures consistent delineation of water pixels across all lakes. The resulting water masks were applied to isolate valid water pixels for subsequent analysis.

Finally, spectral bands affected by noise at the extreme edges of the sensor range were removed prior to analysis, and the cleaned dataset was transformed into CIELAB space for subsequent statistical analysis and derivation of optical proxies.

3. Research Methods

To investigate the high-resolution spatial heterogeneity of lake color, this methodological framework bridges remote sensing reflectance (R_{rs}) with the CIE $L^*a^*b^*$ color space [34,35] to objectively parameterize human-perceived optical variations (Figure 2). Furthermore, a set of empirical hyperspectral indices, supported by sensitivity analysis, was designed to capture the distinct optical signatures of shallow karst waters. By integrating these perceptual metrics and spectral indices with K-Means clustering, this study mapped the spatial patterns, gradients, and localized anomalies of optical proxies across the three representative lakes. The workflow illustrated in Figure 2 summarizes the entire process, including UAV data acquisition, reflectance preprocessing (radiometric calibration, atmospheric correction, orthomosaic generation, and water-body extraction), CIE $L^*a^*b^*$ transformation, index calculation, and cluster-based spatial analysis. Ultimately, this ap-

proach avoids absolute quantitative retrievals of water constituents without in situ data, focusing instead on a robust spatial characterization that reflects the influence of distinct valley environments and hydrological connectivity on lake optical properties.

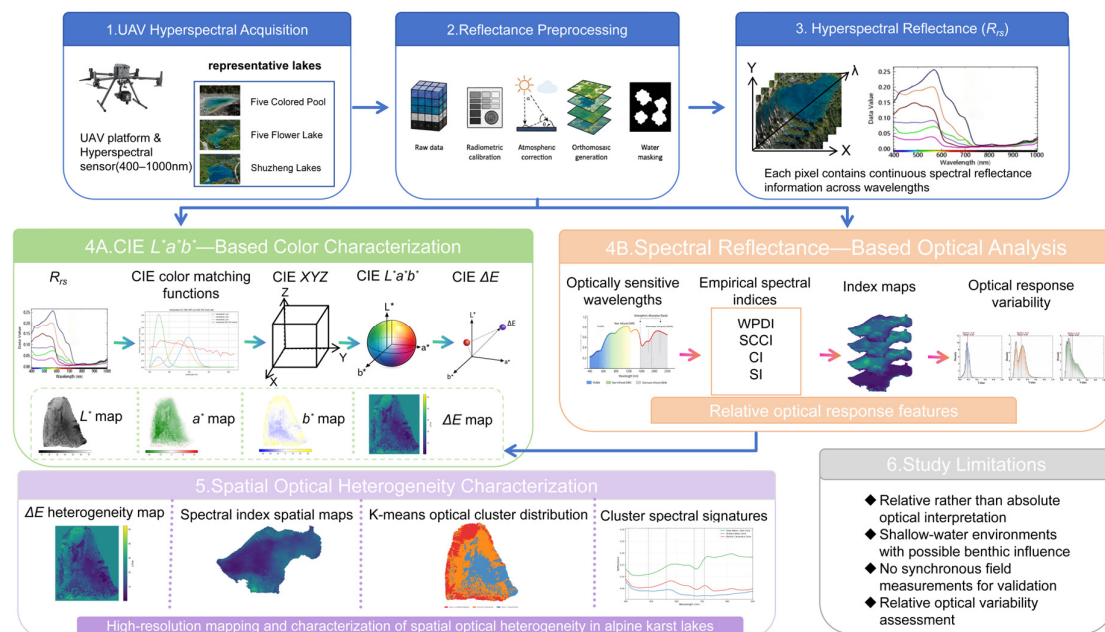


Figure 2. Workflow of the study illustrating high-resolution UAV hyperspectral data processing and spatial optical heterogeneity characterization in alpine karst lakes, including perceptual (CIELAB) and spectral analyses, optical clustering, and limitations.

3.1. Mathematical Derivation and Spatial Characterization Using CIE $L^*a^*b^*$ Color Space

To spatially characterize the optical properties of Jiuzhaigou lakes without relying on strict empirical retrievals of water quality parameters, this study employed the CIE $L^*a^*b^*$ (CIELAB) uniform color space [32,36–38]. Although originally derived to represent human visual perception, in aquatic remote sensing, CIELAB metrics can be strictly derived from Apparent Optical Properties (AOPs), specifically the remote sensing reflectance (R_{rs}) [39]. The quantitative dimensions, ranges, and specific hydrological significances of these derived colorimetric indices are systematically summarized in Table 1. This mathematical linkage ensures that the derived color parameters objectively represent the integrated spectral response of the aquatic system in the visible domain [40].

Table 1. Quantitative meaning of $L^*a^*b^*$ and ΔE indices.

Index	Dimension	Range	Hydrological/Water-Optical Significance
L^*	Lightness	0 (pure black) to 100 (ideal white)	Reflects water transparency and illumination intensity. Higher L^* values typically indicate clear water with high transparency or strong surface reflectance.
a^*	Red–Green Axis	Negative (green) to positive (red)	Indicates the presence of algae or aquatic vegetation (negative) or reddish suspended particles (positive). In pristine lakes, a^* tends to be near zero or slightly negative.
b^*	Yellow–Blue Axis	Negative (blue) to positive (yellow)	Represents blue-light scattering (negative) or the concentration of yellow substances such as DOM or suspended sediments. In Jiuzhaigou’s clear lakes, b^* values are typically negative (deep blue).
ΔE	Total Color Difference	≥ 0	Measures spatial heterogeneity in lake color. Larger ΔE values indicate greater color deviation from the mean, reflecting stronger spatial variability.

(1) Calculation of CIE XYZ Tristimulus Values from Hyperspectral Data [41,42]

The conversion of hyperspectral remote sensing reflectance, $R_{rs}(\lambda)$, into CIE XYZ tristimulus values is a fundamental integration process in colorimetry. In practical computational implementations, given the discrete nature of hyperspectral sampling, the integrations are approximated using Riemann sums with a wavelength interval $\Delta\lambda$, which corresponds to the spectral sampling interval of the hyperspectral sensor:

$$X \approx k \sum_{\lambda} R(\lambda) S(\lambda) \bar{x}(\lambda) \Delta\lambda$$

$$Y \approx k \sum_{\lambda} R(\lambda) S(\lambda) \bar{y}(\lambda) \Delta\lambda$$

$$Z \approx k \sum_{\lambda} R(\lambda) S(\lambda) \bar{z}(\lambda) \Delta\lambda$$

where

$R(\lambda)$ represents the spectral reflectance of the sample at wavelength λ .

$S(\lambda)$ denotes the relative spectral power distribution (SPD) of the standard illuminant. We selected the CIE standard illuminant D65 to match the wide-field observation conditions of natural water bodies.

$\bar{x}(\lambda), \bar{y}(\lambda), \bar{z}(\lambda)$ are the CIE Standard Observer color matching functions (CMFs).

k is a normalization constant, ensuring that $Y = 100$ for a perfectly reflecting diffuser (PRD):

$$k = \frac{100}{\int_{\lambda} S(\lambda) \bar{y}(\lambda) d(\lambda)}$$

(2) Conversion from CIE XYZ to CIELAB Color Space [41,43]

The CIELAB color space provides a perceptually uniform representation of color. The conversion from tristimulus values (X, Y, Z) to CIELAB coordinates (L^*, a^*, b^*) is dependent on the reference white point (X_n, Y_n, Z_n). In this study, the CIE 1964 10° Standard Observer white point for D65 was utilized: ($X_n = 94.811, Y_n = 100.000, Z_n = 107.304$) [44].

The conversion formulas are as follows:

$$L^* = 116 \cdot f\left(\frac{Y}{Y_n}\right) - 16$$

$$a^* = 500 \left(f\left(\frac{X}{X_n}\right) - f\left(\frac{Y}{Y_n}\right) \right)$$

$$b^* = 200 \left(f\left(\frac{Y}{Y_n}\right) - f\left(\frac{Z}{Z_n}\right) \right)$$

where

L^* : Lightness, ranging from 0 (black) to 100 (diffuse white).

a^* : Green–red axis (negative values indicate green; positive values indicate red).

b^* : Blue–yellow axis (negative values indicate blue; positive values indicate yellow).

(X, Y, Z): Sample tristimulus values.

(X_n, Y_n, Z_n): Tristimulus values of the reference white point.

Rather than directly retrieving specific constituent concentrations, these chromatic coordinates serve as robust optical proxies for the relative distribution of optically active constituents (OACs). Given the highly transparent and shallow nature of the studied karst lakes, it is important to note that these parameters represent an integrated apparent optical response combining both water column scattering/absorption and benthic reflectance.

The non-linear transformation function $f(t)$ is intended to account for the human visual system's response to different luminance levels:

$$f(t) = \begin{cases} \sqrt[3]{t}, & t > \delta^3 \\ \frac{1}{3}\delta^{-2}t + \frac{4}{29}, & t \leq \delta^3 \end{cases}$$

where the constant $\delta = \frac{6}{29} \approx 0.206897$. Consequently, the threshold $\delta^3 \approx 0.008856$ and the linear slope $\frac{1}{3}\delta^{-2} \approx 7.787$.

(3) Reference Color Selection and Spatial Color Difference [41,45]

To evaluate the spatial color consistency of the hyperspectral imagery, the spatial average color of the target area was defined as the reference color.

The reference coordinates $(\bar{L}^*, \bar{a}^*, \bar{b}^*)$ were derived from the mean reflectance spectrum $\bar{R}(\lambda)$ across all N pixels:

$$\bar{R}(\lambda) = \frac{1}{N} \sum_{i=1}^N R_i(\lambda)$$

Finally, the color difference (ΔE_{ab}^*) for each pixel j was calculated using the CIE 1976 formula relative to this spatial average reference:

$$\Delta E_{ab,j}^* = \sqrt{(L_j^* - \bar{L}^*)^2 + (a_j^* - \bar{a}^*)^2 + (b_j^* - \bar{b}^*)^2}$$

This metric quantifies the optical deviation of each pixel from the representative color of the scene. A lower ΔE indicates higher spatial color homogeneity, while higher values reflect increased spatial color variability and localized anomalies [32,46]. To ensure the robustness of this calculation and mitigate interference from specular reflection, regions exhibiting neutral chromaticity (where color saturation approaches zero) were strictly masked out prior to evaluation. Because hyperspectral imagery contains a massive number of pixels, analyzing the entire population can lead to severe spatial autocorrelation and redundant computations. Therefore, a spatially stratified random sampling approach was applied. To ensure statistical rigor, preliminary sample size sensitivity tests were conducted in two sequential phases (see Supplementary Section S1). First, an optimization phase evaluated varying sample sizes, determining that extracting 10,000 valid pixels optimally balances computational efficiency with the preservation of intrinsic spatial variance. Second, a stability phase involved repeated random sampling of the 10,000-pixel subset, which confirmed the statistical consistency and robustness of the extracted color distribution features. Consequently, 10,000 valid pixels were selected from the CIELAB raster for each lake. These representative samples were subsequently utilized for K-Means clustering and statistical comparisons using the Kruskal–Wallis test.

3.2. Customized Spectral Indices and Sensitivity Analysis

(1) Physical Justification and Index Formulation

In highly transparent alpine karst lakes, standard aquatic remote sensing indices (e.g., traditional NDWI) often underperform because the optical signal is heavily dominated by benthic (bottom) reflectance and unique mineral–algal interactions [5,47–49]. To accurately capture the localized spatial optical heterogeneity within these specific environments, a set of customized hyperspectral indices was empirically developed (Table 2).

Rather than aiming for absolute quantitative retrievals of water constituents—which requires synchronous in situ sampling—these indices were designed as optical proxies. They were formulated based on the distinct spectral absorption troughs and reflectance peaks observed in the UAV hyperspectral data cubes. The band selection principles (Table 3) align with established aquatic optics literature [50], capitalizing on the high spectral resolution to isolate specific apparent optical property (AOP) variations.

Table 2. Spectral indices.

Category	Index	Formula	Optical Proxy Target & Hydrological Significance
Macroscopic Water-Optical Indicators	Water Penetration Depth Proxy Index (WPDI)	$WPDI = \frac{R_{rs}(\lambda_{Green1})}{R_{rs}(\lambda_{Red3})}$	Optical proxy reflecting light attenuation patterns, capturing combined effects of water constituents and depth on perceived light penetration; serves as a spatial indicator of water transparency.
Scattering (Reflective) Sources	Suspended Calcium Carbonate Index (SCCI)	$SCCI = \frac{R_{rs}(\lambda_{Blue4})}{R_{rs}(\lambda_{Green2}) + R_{rs}(\lambda_{Red1})}$	Optical proxy sensitive to scattering by suspended carbonate particles; highlights spatial variability associated with particle backscattering in shallow lakes.
	Travertine (Calcium Carbonate Precipitation) Index (CI)	$CI = \frac{R_{rs}(\lambda_{Blue3})}{R_{rs}(\lambda_{Red2})}$	Optical proxy reflecting shallow benthic travertine distribution; indicates zones with high bottom reflectance due to carbonate-rich substrates.
	Sediment Deposition Index (SI)	$SI = \frac{R_{rs}(\lambda_{Red2})}{R_{rs}(\lambda_{Green1})}$	Optical proxy sensitive to substrate types and deposition patterns; highlights areas with particle accumulation affecting optical response.
Absorptive Sources	Phytoplankton-related Optical Proxy Index (PPI)	$PPI = \frac{R_{rs}(\lambda_{Red6})}{R_{rs}(\lambda_{Red3})}$	Optical proxy capturing spatial variability of algal pigments; maps relative optical response without implying absolute biomass or trophic state.
	Benthic Algae Spatial Index (BAI)	$BAI = \frac{R_{rs}(\lambda_{Red5}) - R_{rs}(\lambda_{Red3})}{R_{rs}(\lambda_{Blue5})}$	Optical proxy sensitive to benthic algal cover; reflects localized variations in bottom color tones due to submerged vegetation.
	CDOM Absorption Proxy Index (CDOMI)	$CDOMI = \frac{R_{rs}(\lambda_{Green1})}{R_{rs}(\lambda_{Blue1}) + R_{rs}(\lambda_{Blue2})}$	Optical proxy sensitive to colored dissolved organic matter; highlights spatial variability in optical absorption related to DOM, without implying water quality or absolute concentration.

Table 3. Spectral indices band selection.

Band Identifier	Sensor Band	Wavelength (nm)	Spectral Region	Spectral Feature Highlight (Empirical Tuning Basis)
λ_{Blue1}	Band 6	410.76	Violet/Short-blue	Targets the exponential absorption tail of Colored Dissolved Organic Matter (CDOM), serving as a sensitive baseline for separating organic absorption from scattering signals.
λ_{Blue2}	Band 17	439.63	Deep blue	Captures the blue absorption feature of chlorophyll-a and other photosynthetic pigments; also represents a region of high water penetration depth in ultra-clear karst waters.
λ_{Blue3}	Band 21	450.16	Deep blue	
λ_{Blue4}	Band 32	479.18	Blue-green	Serves as a transitional hinge zone. Exhibits balanced water penetration and is highly sensitive to shifts in benthic color tones and early signs of suspended particle scattering.
λ_{Blue5}	Band 36	489.77	Blue-green	
λ_{Green1}	Band 59	550.91	Green	Aligns with the minimum absorption of algal pigments and the primary reflectance peak caused by the strong backscattering of suspended calcium carbonate (travertine) particles and inorganic sediments.
λ_{Green2}	Band 62	558.92	Green	
λ_{Red1}	Band 89	631.39	Red	Targets the secondary absorption maximum of chlorophyll-a (near 670 nm). Due to the rapid increase in pure water absorption in this region, these bands are crucial for isolating shallow benthic signals and surface suspended matter from deeper water interference.
λ_{Red2}	Band 101	663.82	Red	
λ_{Red3}	Band 103	669.23	Red	
λ_{Red4}	Band 107	680.08	Red	
λ_{Red5}	Band 114	699.09	Red-edge	Captures the characteristic reflectance peak (red-edge) induced by algal cell structures. Extremely high pure water attenuation in this region ensures the signal purely reflects near-surface optical anomalies or emergent aquatic vegetation.
λ_{Red6}	Band 118	709.97	Red-edge/NIR	

Specifically, based on the unique spectral absorption troughs and reflectance peaks of the alpine karst waters, seven customized hyperspectral indices were constructed using band difference, ratio, and normalized difference formulations [51,52]. The specific definitions, mathematical formulas, wavelength selections, and the corresponding physical justifications (optical proxy targets) for all seven customized indices are systematically summarized in Table 2. The specific wavelengths utilized in the aforementioned empirical indices were carefully extracted from the UAV hyperspectral data cubes based on their dis-

tinctive optical scattering and absorption behaviors in karst aquatic environments [53]. The detailed physical justifications for selecting these specific spectral bands are summarized in Table 3.

(2) Statistical Validation and Sensitivity Analysis

To quantitatively validate the spatial sensitivity and reliability of the formulated empirical indices across varying optical regimes, a rigorous statistical framework was implemented. Given the highly non-normal distributions (e.g., extreme skewness and bimodality) and inherent heteroscedasticity characteristic of the complex karst optical environments, traditional parametric tests (e.g., one-way ANOVA) were statistically invalid for this dataset.

To characterize the distributional characteristics of optical variables, skewness analysis was performed using two complementary approaches [54]. For CIELAB-derived variables (L^* , a^* , b^* , and ΔE), conventional moment-based skewness was calculated to describe the overall asymmetry of pixel distributions [55]. For the customized spectral indices, both conventional skewness and Bowley skewness were evaluated because these empirical optical proxies exhibited stronger non-normality and localized extreme values caused by heterogeneous optical conditions.

Conventional skewness was calculated based on the third standardized moment:

$$S = \frac{1}{n} \sum_{i=1}^n \left(\frac{(x_i - \bar{x})}{\sigma} \right)^3$$

where S represents the skewness coefficient, n is the number of observations (pixels), x_i denotes the value of the i -th pixel, $\bar{x}$ represents the sample mean, and σ is the standard deviation of the distribution. Positive and negative values indicate right- and left-skewed distributions, respectively.

To reduce the influence of extreme values, Bowley skewness was additionally calculated based on quartile statistics:

$$B_S = \frac{Q_3 + Q_1 - 2Q_2}{Q_3 - Q_1}$$

where B_S is the Bowley skewness coefficient, and Q_1 , Q_2 and Q_3 represent the first quartile, median, and third quartile, respectively.

Positive and negative values indicate right- and left-skewed distributions, respectively. The use of Bowley skewness provides a robust assessment of distribution asymmetry for optical indices with strong outlier effect [54,55].

Consequently, the non-parametric Kruskal–Wallis H test was employed as the core sensitivity analysis method [56,57]. This rank-based test is highly robust to extreme outliers and unequal variances, making it optimal for evaluating the massive pixel-level hyperspectral datasets. By applying this test, the statistical significance (p -value) and the magnitude of variance (H-statistic) of the customized indices across the identified Optical Water Types (Zones A, B, and C) were rigorously assessed [34], thereby confirming their efficacy as independent optical proxies without relying on absolute biogeochemical calibration.

3.3. Unsupervised Spatial Clustering Analysis

To objectively characterize multidimensional optical heterogeneity in alpine karst lakes while minimizing subjective interpretation bias, an unsupervised machine learning framework was employed [34]. Compared with supervised classification approaches, which require spatially continuous and temporally synchronized in situ reference data, unsupervised methods are more suitable for optically complex and data-scarce environments where ground truth observations are limited.

In this study, the K-means clustering algorithm was adopted to partition hyperspectral pixel populations based on intrinsic feature similarity [58–60]. The input feature space

consisted of seven normalized spatial optical proxies (Section 3.2), which jointly describe variations in water color, suspended matter, and benthic influence. Euclidean distance was used as the similarity metric, and iterative optimization was performed to minimize within-cluster variance [61,62].

To ensure robustness in clustering configuration, multiple internal validation metrics, including the silhouette coefficient, Calinski–Harabasz index, and within-cluster sum of squares (WCSS), were evaluated across a range of k values ($k = 2–10$) [63,64]. These metrics were jointly evaluated to assess clustering stability and determine appropriate cluster configurations across different spatial scales. Based on this multi-metric evaluation and scale-dependent clustering behavior (Supplementary Section S2), Based on the multi-metric evaluation framework and the requirement for cross-lake comparability, an intermediate clustering configuration was adopted for subsequent comparative analysis.

To ensure statistical robustness and computational consistency, a fixed sample size of $N = 10,000$ pixels per lake was used for all analyses. This uniform sampling strategy was adopted to maintain methodological comparability across lakes with differing spatial extents, rather than to reflect proportional areal representation. A sensitivity analysis using multiple sample sizes (5000–50,000 pixels) and 100 repeated random samplings was conducted to evaluate potential sampling-induced variability (Supplementary Section S1).

A two-tier clustering framework was designed to capture scale-dependent optical heterogeneity. The first tier performs global clustering using pooled data from all lakes to characterize system-level variability. The second tier performs lake-specific clustering to resolve intra-lake heterogeneity [8].

It should be noted that the clustering framework is designed as an unsupervised, data-driven representation of optical heterogeneity and is independent of ecological or biological classification schemes. The resulting clusters are therefore interpreted as optically distinct zones rather than ecological units.

For subsequent interpretation, clustering outputs were labeled as three optical zones according to their relative spectral characteristics: Zone A (high-reflectance shallow or benthic-influenced areas), Zone B (transitional zones), and Zone C (low-reflectance deep or attenuation-dominated waters). These labels represent optical gradients rather than ecological classifications. These zonal representations serve as consistent analytical units for subsequent spatial heterogeneity analysis and cross-lake comparison within the cascade lake system.

3.4. Generative Artificial Intelligence Disclosure

During the preparation of this manuscript, the authors used ChatGPT (OpenAI) solely for language editing, grammatical correction, and improvement of manuscript readability. The tool was not used for data generation, data processing, methodological design, statistical analysis, interpretation of results, or formulation of scientific conclusions. All AI-assisted text was carefully reviewed and revised by the authors, who take full responsibility for the accuracy and integrity of the published content.

4. Results and Analysis

4.1. Spatial Variability of CIELAB Metric

Based on quantitative characterization of lake water color using the CIELAB color space, spatial distributions of the L^* , a^* , b^* channels were derived for Five Colored Pool, Five Flower Lake, and the largest lake within the Shuzheng Lakes (Figure 3). These maps revealed clear differences in lightness and chromaticity patterns. In aquatic optics, these colorimetric dimensions abstract distinct radiative transfer processes: the L^* channel captures variations in water clarity and bottom albedo, whereas the a^* and b^* axes trace the

competitive balance between absorptive constituents (e.g., pigments and organic matter) and scattering sources. Five Colored Pool showed relatively uniform spatial patterns with limited variation, consistent with its relatively consistent shallow depth and widespread benthic travertine coverage. In contrast, Five Flower Lake exhibited more complex spatial structures, with noticeable variations across the lake surface, reflecting its intricate underwater geomorphology, including deep subaqueous basins and submerged tree trunks. The Shuzheng Lakes displayed intermediate characteristics, with relatively stable central regions but increased variability toward the lake margins.

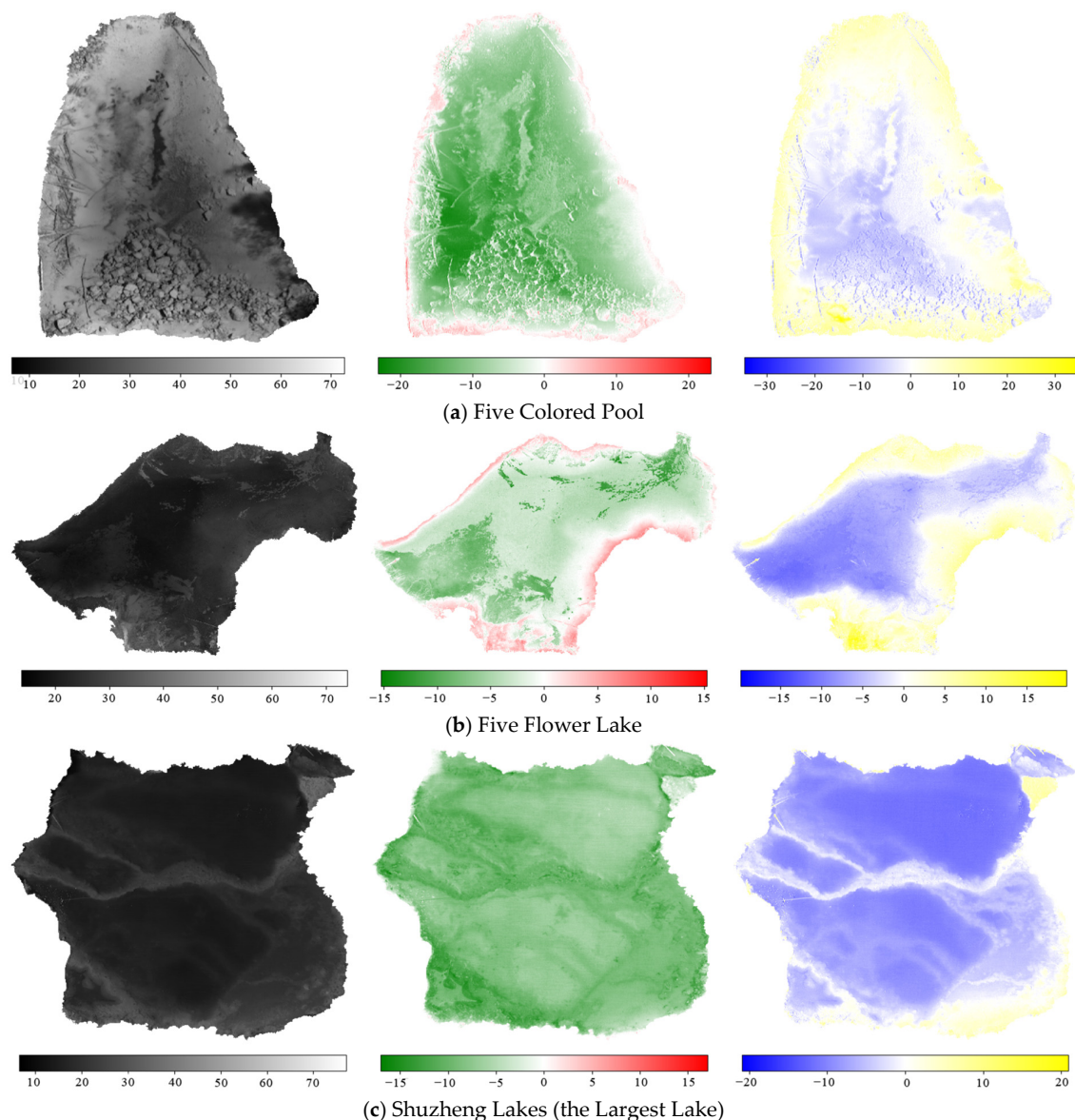


Figure 3. Spatial distribution of CIELAB color components (L^* , a^* , b^*) in the three UAV-surveyed alpine karst lakes, illustrating relative variations in perceptual color across different lake zones.

The probability density distributions of the L^* , a^* , and b^* channels (Figure 4) reveal spatial variability in lake color. Five Colored Pool showed narrow, highly leptokurtic distributions, indicating concentrated pixel values and low spatial heterogeneity. Five Flower Lake exhibited a right-skewed L^* distribution (Conventional skewness = 1.11), with a primary peak at lower lightness and a long tail toward higher values. This asymmetry corresponds to variations between deeper pelagic zones and shallower regions with stronger benthic reflectance (classified as Zone A). For the Shuzheng Lakes, the L^* distribution

was broader and more strongly right-skewed (Conventional skewness = 1.33), while the a^* and b^* channels displayed notable asymmetry (Conventional skewness = -0.49 and 0.55 , respectively). The left-skewed tail in a^* may reflect localized greening from benthic algae, and the right-shifted b^* suggests variation in yellow–blue chromaticity, potentially associated with organic matter or fine sediments. Overall, the distributions indicate an increase in spatial optical heterogeneity from upstream to downstream.

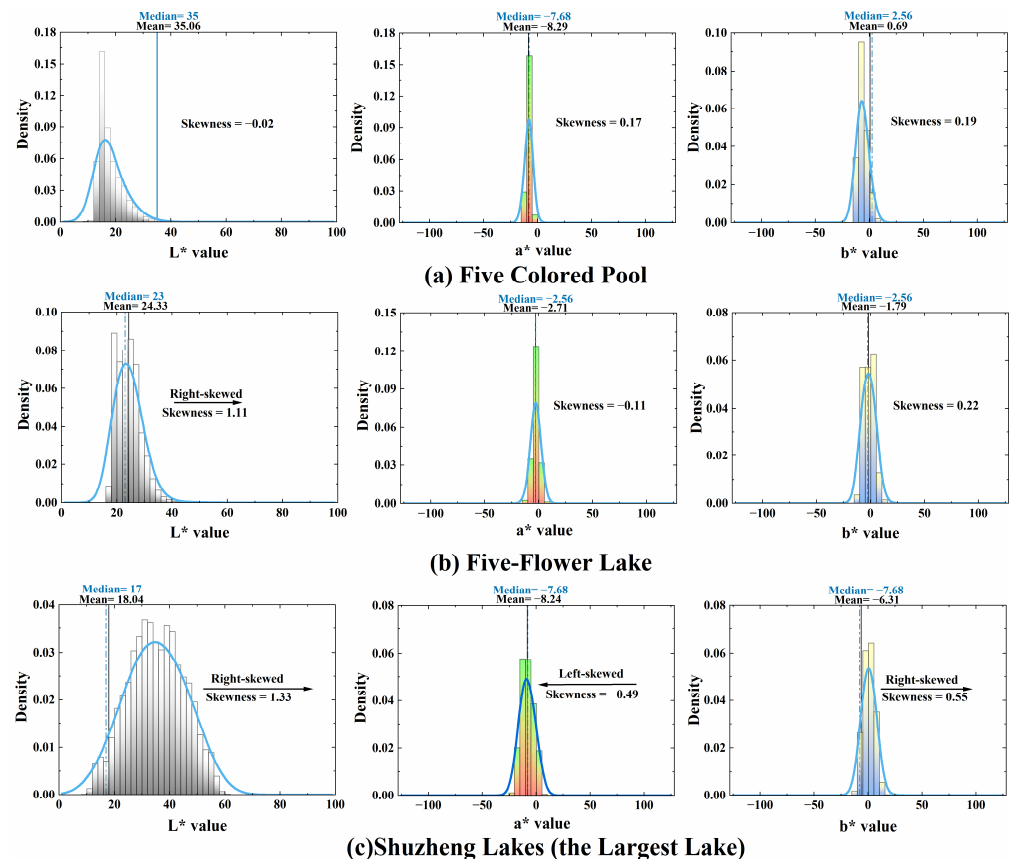


Figure 4. Histograms of the CIELAB color channels (L^* , a^* , b^*) for the three UAV-surveyed alpine karst lakes, showing the frequency distribution of perceptual color values within each lake.

Spatial variations in lake color were further quantified using color difference (ΔE) probability density distributions (Figure 5). According to commonly adopted perceptual thresholds, ΔE values greater than 3 represent clearly distinguishable color differences. Notably, nearly the entire valid surface area of all three lakes (98.93%, 99.99%, and 99.81%, respectively) exceeded this threshold, providing robust quantitative evidence of visually apparent spatial heterogeneity relative to their respective mean background colors.

The statistical distributions revealed distinct spatial patterns among the lakes. Five Colored Pool exhibited a slightly left-skewed distribution (Conventional skewness = -0.28) with a broad range of lower ΔE values and a pronounced secondary peak around $\Delta E = 25$, resulting in an overall mean of 12.94. In contrast, Five Flower Lake showed the highest overall color variation (Mean = 18.09, Median = 19.5) and a strongly right-skewed distribution (Conventional skewness = 1.96). Its density curve was dominated by a sharp primary peak with an extended tail toward higher ΔE values, quantitatively confirming extreme spatial heterogeneity.

The Shuzheng Lakes displayed the lowest central tendencies for color difference (Mean = 9.74, Median = 7.52) but presented a clearly bimodal distribution with moderate right-skewness (Conventional skewness = 0.52), concentrating into two distinct peaks at low and moderate ΔE ranges. Overall, the ΔE statistics indicated that the midstream Five

Flower Lake exhibited the most extreme color divergence, while the downstream Shuzheng Lakes had the lowest average color deviation yet maintain complex spatial structures, highlighting non-linear longitudinal patterns of optical variability across the lake cascade.

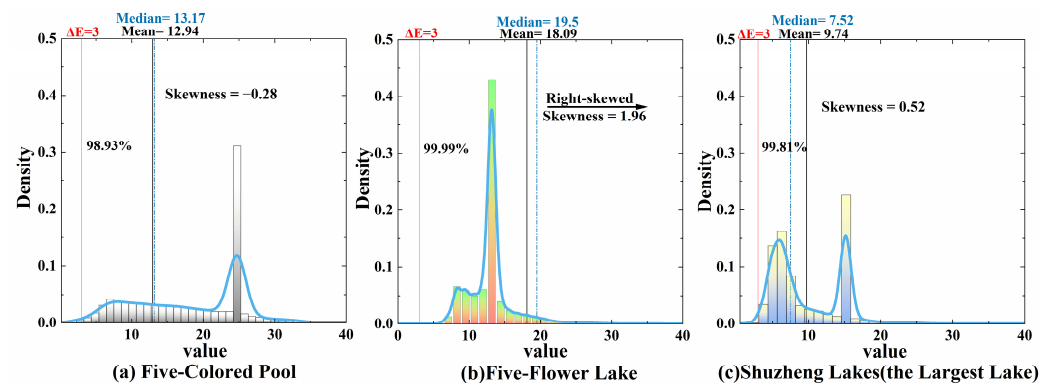


Figure 5. Probability density distributions of color differences (ΔE) for the three study lakes: (a) Five Colored Pool, (b) Five Flower Lake, and (c) Shuzheng Lakes (the Largest Lake). ΔE represents pixel-wise color variation relative to the lake mean color. The vertical red line indicates the perceptual threshold ($\Delta E = 3$), with percentages showing the proportion of pixels exceeding this threshold. Blue dashed and solid black lines denote the median and mean values, respectively. Multi-modal peaks and skewness indicate localized features with pronounced color variability.

To further quantify pixel-level chromaticity, hexagonal density plots were generated in the a^*-b^* color space using randomly sampled pixels from each lake (Figure 6). Pixels from Five Colored Pool formed a highly compact cluster with minimal dispersion, indicative of a stable and uniform chromatic baseline. In contrast, Five Flower Lake exhibited a broader dispersion across the color space, reflecting pronounced optical heterogeneity. The Shuzheng Lakes displayed an intermediate pattern, with a moderately concentrated cluster.

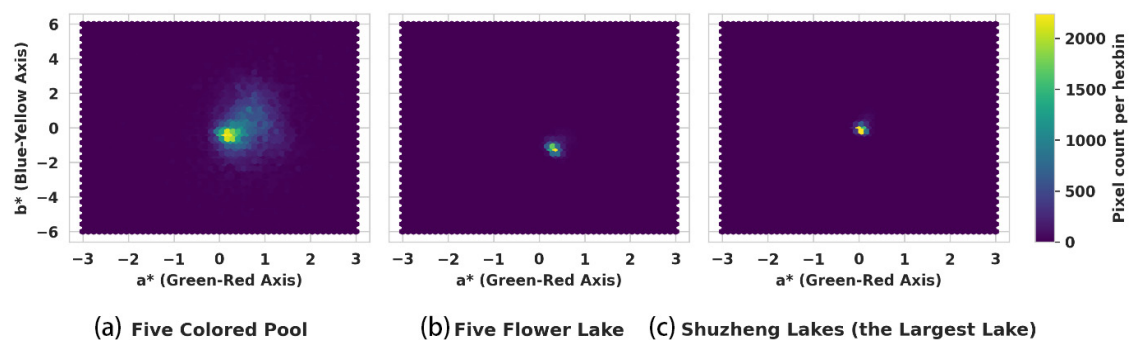


Figure 6. Hexagonal binning plots showing the distribution of randomly sampled lake pixels in the CIELAB a^*-b^* feature space for (a) Five Colored Pool, (b) Five Flower Lake, and (c) Shuzheng Lakes (the largest lake). For each lake, 10,000 valid water pixels were randomly selected from UAV hyperspectral imagery. Each hexagonal bin represents the number of pixels distributed within the corresponding a^*-b^* feature interval. The color bar indicates pixel counts per hexbin, with warmer colors representing higher pixel concentrations. These distributions characterize the intrinsic color-space structure and optical variability of each lake.

To statistically validate these spatial variances, a Kruskal–Wallis H test was applied to the sampled CIELAB components. The results revealed highly significant differences among the three lakes for all parameters (L^* , a^* , and b^* ; $p < 0.001$), confirming the distinct spatial color gradients and structural complexity observed in the density plots.

4.2. Spatial Distribution and Statistical Variance of Customized Optical Proxies

To further characterize the spatial optical heterogeneity revealed by the CIELAB analysis, three representative optical proxy indices, namely the Carbonate Index (CI), Suspended Calcium Carbonate Index (SCCI), and Benthic Algae Index (BAI), were selected from the full index set for detailed investigation. These indices were selected because they capture complementary optical response characteristics related to carbonate-associated signals, suspended particle effects, and benthic contributions in alpine karst lakes. Probability density distributions of the normalized indices were subsequently analyzed to examine their spatial variability and distribution characteristics (Figure 7). The corresponding distributions of the remaining optical proxy indices are provided in the Supplementary Materials (Figure S4). To quantitatively describe distribution asymmetry and the influence of extreme values, both conventional skewness (sensitive to distribution tails) and Bowley skewness (robust to outliers and representative of the central 50% of the distribution) were calculated.

In the Five Colored Pool, most optical proxies (e.g., CI, BAI, and SI) were tightly concentrated at extremely low values. A notable feature was the stark contrast between the two skewness metrics: conventional skewness was generally high (e.g., 3.89 for the benthic algae proxy), whereas Bowley skewness remained near zero. This indicated that the majority of the lake body was highly uniform in its optical baseline, while a small fraction of outlier pixels—likely corresponding to extremely shallow near-shore margins or localized submerged structures—produced an extended high-value tail. The Suspended Carbonate Scattering Index (SCCI) was an exception, exhibiting a broader distribution and higher central tendency (Mean = 0.37), reflecting the pervasive influence of carbonate equilibrium in this pool.

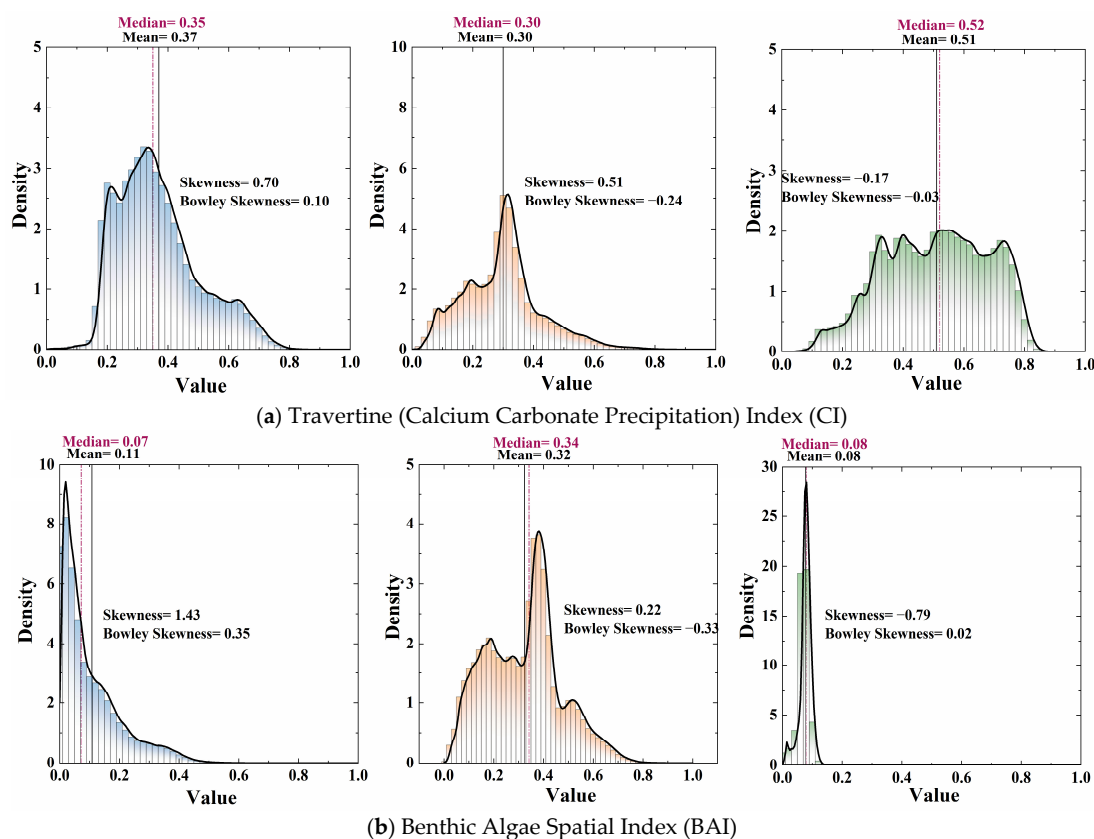


Figure 7. Cont.

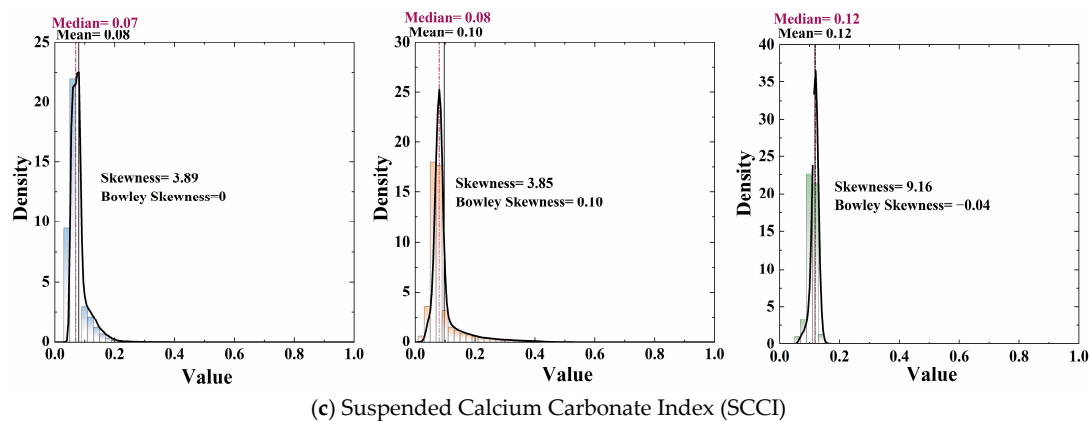


Figure 7. Comparison of representative optical proxy indices derived from UAV hyperspectral imagery across the three lake systems. From left to right, the panels correspond to the Five Colored Pool, Five Flower Lake, and Shuzheng Lakes (the largest lake). These indices characterize relative optical responses related to carbonate-related environments, suspended carbonate particles, and benthic influences, respectively.

Five Flower Lake exhibited pronounced statistical heterogeneity, with several indices showing bimodal or multimodal distributions. Probability density curves for the Water Penetration Depth Proxy Index (WPDI), and the Travertine Index (CI) displayed clearly defined dual peaks. This complex spatial structure caused notable fluctuations in quartile distributions, occasionally driving Bowley skewness negative (e.g., -0.24 for SCCI). These metrics quantitatively reflect the co-existence of disparate spatial optical regimes, strongly aligning with the visual transitions between deep absorptive basins and highly reflective shallow travertine terraces.

In the largest lake of the Shuzheng Lakes, distributions shifted toward either extreme homogeneity or bulk accumulation. The SCCI exhibited the highest mean (0.51) with a slightly left-skewed profile, indicating strong longitudinal hydrodynamic mixing. The phytoplankton pigment proxy (PPI) and travertine indices presented exceptionally sharp, leptokurtic peaks. The dual skewness metrics further highlighted extreme spatial homogenization: for example, the PPI showed near-zero Bowley skewness (0.02), indicating a uniform core water body, while the conventional skewness (-28.15) reflected isolated anomalous pixels.

Ultimately, the pronounced differences in statistical distributions and skewness metrics across these indices underscore the multi-dimensional complexity of the lakes. To seamlessly integrate these disparate optical gradients into coherent spatial maps, an unsupervised clustering model was subsequently applied.

4.3. Multi-Scale Optical Clustering and Physical Spectral Validation

To characterize the multidimensional optical heterogeneity of alpine karst lakes, a tiered unsupervised K-means clustering framework was applied to the combined feature space of normalized CIE $L^*a^*b^*$ variables and customized optical proxies.

Internal clustering validation metrics (silhouette coefficient, Calinski–Harabasz index, and within-cluster sum of squares) indicate a scale-dependent clustering behavior (See Supplementary Section S2). At the global scale, the system exhibits a dominant two-class structure ($k = 2$), representing the primary contrast between high-reflectance shallow travertine environments and low-reflectance deep basin waters. At the lake-specific scale, more complex clustering structures ($k = 3$ – 5) reflect increased intra-lake optical complexity.

To enable consistent cross-lake comparison, an intermediate and standardized configuration of $k = 3$ was adopted. This setting preserves the dominant global partitioning

structure while retaining essential intra-lake heterogeneity, allowing balanced representation across lakes with different optical complexity.

At the global scale (Tier 1), clustering results revealed distinct optical differences among the three cascade lake systems (Figure 8). The Five Colored Pool was mainly associated with high-reflectance optical clusters, whereas the Five Flower Lake and Shuzheng Lakes showed larger proportions of lower-reflectance clusters. This system-level partitioning indicates an overall optical gradient along the cascade sequence, reflecting differences in lake morphology, water depth distribution, and optical conditions among individual lake systems. However, the global clustering may mask finer-scale variability within each lake, which was further resolved through lake-specific clustering.

At the lake-specific scale (Tier 2), independent clustering reveals consistent zonation patterns characterized by a transition from Zone A to Zone C, although with varying spatial proportions among lakes (Figures 9 and 10). The Five Flower Lake exhibits the highest intra-lake heterogeneity, whereas the Five Colored Pool shows a more compact spatial distribution. The spectral characteristics of the identified optical zones were further analyzed to evaluate their differences in hyperspectral response among the three lake systems (Figure 11). Across the three lake systems, Zone A showed relatively higher spectral reflectance, particularly in the visible wavelength range, indicating stronger bottom-related optical contributions and higher reflectance conditions. Zone C exhibited lower reflectance with reduced spectral variability, representing optically darker water conditions where bottom contributions were relatively weakened. Zone B showed intermediate spectral characteristics between these two optical conditions.

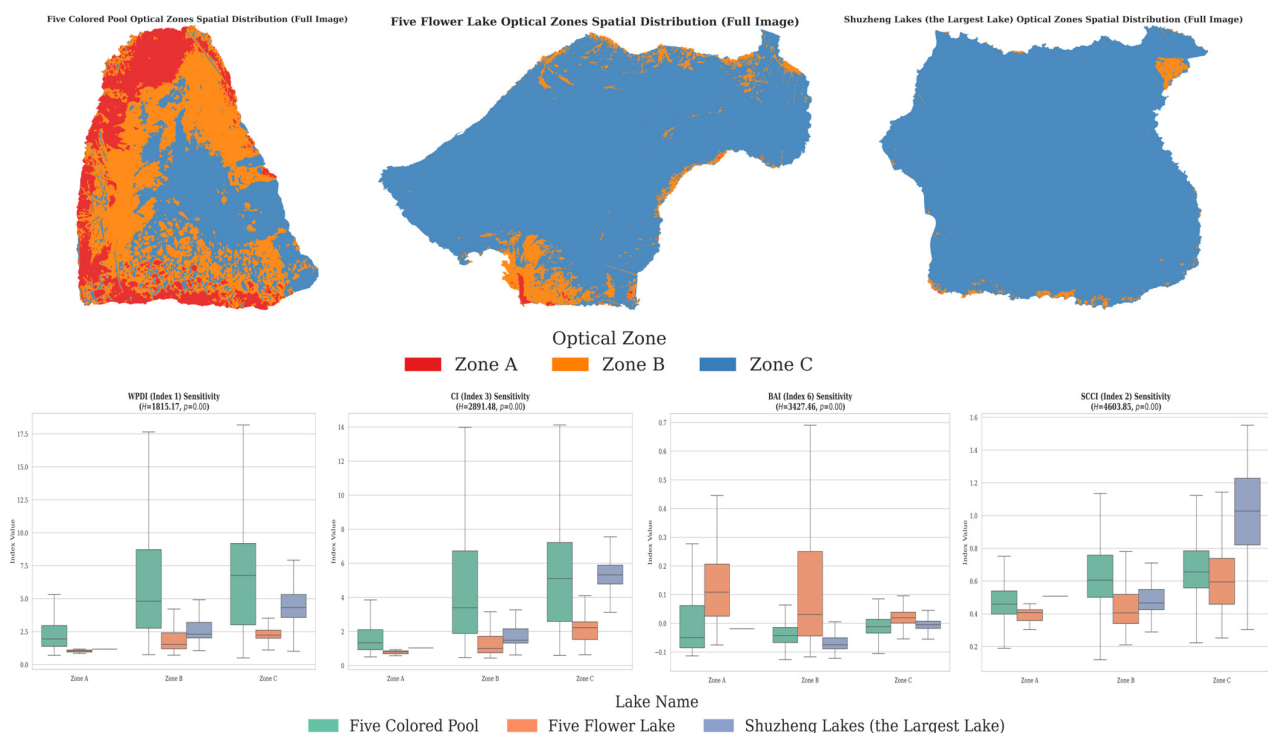


Figure 8. Tier 1 global K-Means clustering results and statistical sensitivity. The top panels illustrate the spatial configurations of the global OWTs, demonstrating a severe macro-scale “masking effect” where the high reflectance of Five Colored Pool forces the cascaded downstream lakes primarily into the deep-water category (Zone C, blue). The bottom panels present global statistical validations using a selected subset of empirical optical proxies. The extreme inter-lake baseline divergences within each global zone necessitate the subsequent implementation of localized clustering to unmix intra-lake geomorphological gradients.

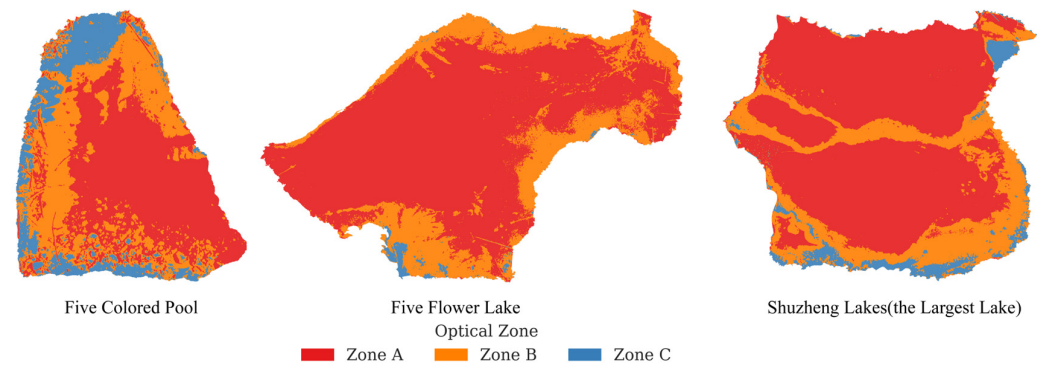


Figure 9. Spatial mapping of Optical Water Types (OWTs) derived from the Tier 2 localized K-Means clustering. Independent local K-Means clustering effectively revealed intra-lake optical heterogeneity that was previously obscured by extreme inter-lake baseline divergences. The localized clustering identified distinct optical zones, including high-reflectance optical conditions (Zone A, red) with stronger bottom-related contributions, intermediate optical conditions (Zone B, orange), and low-reflectance optical conditions (Zone C, blue) characterized by reduced spectral variability. This dual-scale approach enables hierarchical characterization of optical water types and highlights spatial patterns of optical heterogeneity across the lake systems.

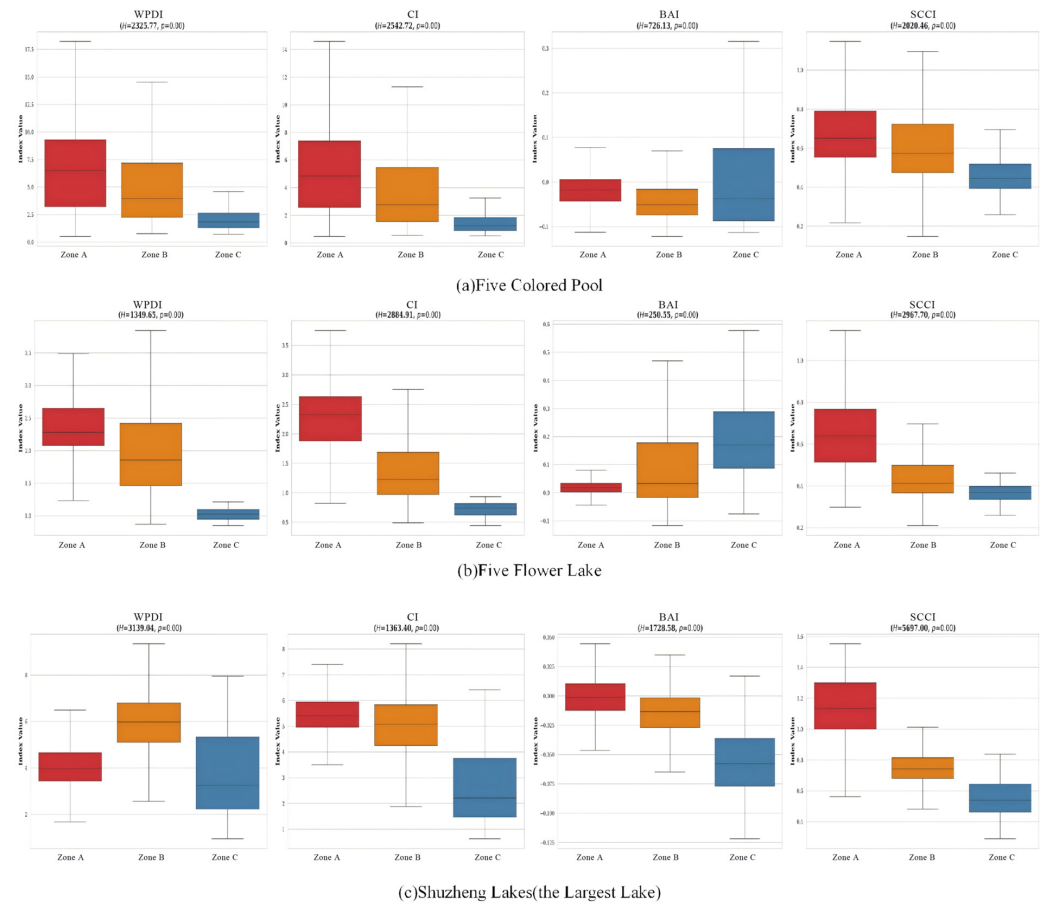


Figure 10. Intra-lake statistical distributions of selected empirical optical proxies across the localized OWTs. The 3×4 multi-panel localized boxplots (with rows corresponding sequentially to Five Colored Pool, Five Flower Lake, and the Shuzheng main lake) reveal highly significant ($p < 0.001$) spatial delineations among Zone A (red), Zone B (orange), and Zone C (blue). The emergence of clear monotonic gradients within each discrete lake validates the capability of the Tier 2 localized clustering to intra-lake distribution of Optical Water Types (OWTs), illustrating localized optical heterogeneity within each lake, overcoming the limitations of global optical thresholds.

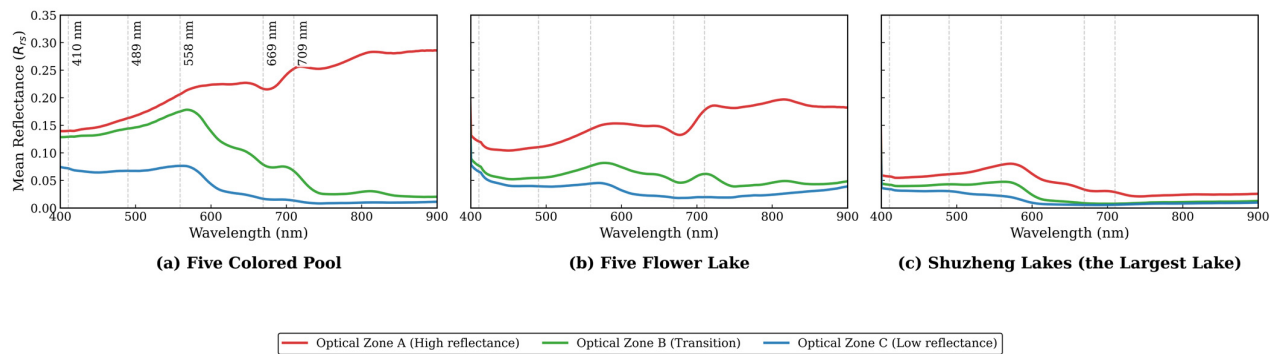


Figure 11. Mean remote sensing reflectance (R_{rs}) spectra of the cluster-derived optical zones for (a) Five Colored Pool, (b) Five Flower Lake, and (c) Shuzheng Lakes (the largest lake). Colored curves represent Zone A (high-reflectance shallow /benthic-influenced areas), Zone B (transition zones), and Zone C (low-reflectance deep /attenuation-dominated areas) derived from the clustering framework. Spectral differences among zones indicate distinct optical responses associated with variations in water-column attenuation, carbonate particle scattering, and benthic contributions. Vertical dashed lines indicate the representative wavelengths used for constructing the optical proxy indices.

4.4. Scale-Independent Sensitivity and Statistical Validation

All analyses were conducted using a baseline sample size of $N = 10,000$ pixels per lake, selected based on a sampling sensitivity analysis to achieve a balance between computational efficiency and statistical stability (see Supplementary Section S1). To evaluate potential sampling-induced bias, alternative sample sizes (5000–50,000 pixels per lake) and 100 repeated random sampling iterations were tested. The results demonstrated negligible variability in CIELAB variables (L^* , a^* , b^*) and ΔE across different sampling configurations, indicating that the extracted samples consistently captured the underlying optical characteristics of each lake.

Non-parametric Kruskal–Wallis H tests revealed statistically significant differences ($p < 0.001$) among optical zones at both global and local scales, confirming the statistical separability of the identified optical water types (OWTs). The consistent differentiation patterns across lakes further support the robustness of the proposed optical proxies and clustering framework under different spatial scales.

Importantly, the sensitivity analysis confirmed that applying an equal sampling size ($N = 10,000$ pixels per lake) did not introduce substantial bias associated with differences in lake surface area. The stable distributional characteristics observed across alternative sampling sizes indicate that the selected samples represent intrinsic lake-scale optical variability rather than merely reflecting differences in pixel abundance caused by lake size.

5. Discussion

5.1. Scale-Dependent Optical Heterogeneity of Cascade Lake Systems

The results demonstrate that optical heterogeneity in alpine karst cascade lakes is inherently scale-dependent, reflecting the coexistence of a dominant inter-lake optical gradient and more complex intra-lake spatial variability.

At the global scale, clustering analysis reveals a stable binary partitioning structure ($k = 2$), which corresponds to the primary optical contrast between high-reflectance shallow travertine environments and low-reflectance deep basin waters [40]. This first-order separation is consistent with large-scale geomorphological and hydrological controls governing optical conditions across the cascade lake system.

At the lake-specific scale, a more complex clustering structure emerges ($k = 3$ – 5), indicating enhanced intra-lake heterogeneity driven by localized bathymetric variation, benthic substrate composition, and hydrodynamic processes. These findings indicate that

optical variability within individual lakes cannot be fully captured by a single system-wide partitioning scheme.

Importantly, the observed clustering structure is robust across multiple internal validation metrics and sampling configurations (Supplementary Sections S1 and S2) [34]. No single universally optimal k value is identified across all scales; instead, the system exhibits a stable range of admissible solutions, reflecting its intrinsic multi-scale optical organization rather than algorithmic or sampling artifacts [8].

To ensure methodological consistency and enable cross-lake comparability, a standardized intermediate representation ($k = 3$) was adopted. This configuration is not interpreted as an absolute optimum, but as a scale-balanced compromise that preserves the dominant global binary structure while retaining sufficient sensitivity to intra-lake heterogeneity.

Overall, these findings highlight the importance of explicitly considering spatial hierarchy when applying unsupervised clustering methods to optically complex aquatic environments. The identified scale-dependent structure provides a physically interpretable representation of cascade lake optical organization and establishes a robust methodological basis for comparative analysis across heterogeneous lake systems.

Although the UAV observations represent a single temporal snapshot, the identified scale-dependent optical structure reflects the spatial organization observed during the acquisition period and provides a baseline reference for future multi-temporal monitoring.

5.2. Spectral Interpretation and Shallow-Water Radiative Characteristics

In highly transparent alpine karst aquatic systems, the water column generally exhibits reduced scattering compared with turbid inland waters, allowing bottom reflectance to contribute substantially under shallow conditions.

To provide a theoretical basis for interpreting the observed multi-scale optical heterogeneity, the Optically Shallow Water (OSW) radiative transfer framework is adopted as a conceptual reference. In this framework, remote sensing reflectance (R_{rs}) can be simplified as

$$R_{rs} \approx R_{\infty} + (R_b - R_{\infty}) \cdot e^{-2K_d Z}$$

where R_{∞} represents the reflectance of optically deep water, R_b is the bottom reflectance, K_d is the diffuse attenuation coefficient, and Z is water depth [48].

Although in situ measurements of K_d and Z are not available, this formulation provides a useful conceptual basis for interpreting spatial variations in optical response [65]. In shallow travertine-dominated areas (Zone A), reduced water depth leads to a stronger contribution from bottom reflectance. In contrast, in deeper basin areas (Zone C), the bottom contribution is strongly attenuated, and the optical signal is primarily controlled by water-column effects [5].

Within this framework, the observed spatial patterns of optical water types (OWTs) can be interpreted as depth-dependent optical responses shaped by combined water-column and bottom influences.

5.3. Methodological Implications and Transferability

The results provide insights into how UAV hyperspectral data and unsupervised clustering can be used to describe optical variability in alpine karst lakes.

Alpine karst lakes in Jiuzhaigou are sensitive aquatic systems in which variations in hydrological conditions, carbonate processes, sediment dynamics, and benthic environments can influence optical characteristics [28]. Long-term observations of these lakes are important for investigating how hydrological and geomorphological processes influence optical characteristics over time [66].

A key methodological challenge in optical remote sensing of alpine and protected aquatic ecosystems is the limited availability of synchronous in situ biogeochemical and bathymetric measurements [49]. Conventional bio-optical models often require field calibration, which can be difficult to obtain in protected or remote high-altitude environments [47].

Therefore, this study focuses on describing relative optical variability rather than retrieving absolute constituent concentrations. Using UAV hyperspectral imagery, empirical optical proxies were developed to describe spatial variations in water color and optical conditions without direct in situ calibration.

Although supervised classification and optical water type (OWT) approaches have been widely applied in aquatic remote sensing, their application to alpine karst cascade lakes is constrained by limited representative training datasets and the difficulty of transferring predefined spectral classes to heterogeneous carbonate-dominated environments [60]. In contrast, this study combines empirical optical proxies with unsupervised clustering to identify continuous spatial variations without requiring labeled samples or predefined spectral classes.

This approach provides a reference description of spatial optical variability in alpine karst lakes where frequent field surveys are difficult. By identifying fine-scale optical gradients and distinct optical zones, this approach helps describe spatial differences related to hydrological conditions, carbonate features, and ecosystem characteristics.

From a management perspective, the identified optical zones may help managers select representative areas for future investigation and monitoring while minimizing disturbance to protected lakes.

Due to its non-invasive nature and limited dependence on field measurements, the method may provide a useful reference for studying other shallow freshwater systems with strong spatial optical variability, but its applicability should be further evaluated using additional datasets.

5.4. Limitations and Future Perspectives

First, the proposed UAV-based empirical proxy framework does not rely on synchronous in situ biogeochemical or bathymetric measurements. Although limited-impact sampling or autonomous optical monitoring approaches may become feasible under future management frameworks, such measurements were not incorporated in the present study because the primary objective was to develop a non-invasive spatial characterization framework that can operate under current conservation constraints. The absence of such measurements also highlights the capability of UAV hyperspectral observations to provide preliminary spatial characterization without relying on site-specific calibration. While this enables application in data-scarce and protected environments, it also limits the direct conversion of dimensionless optical indices into absolute physical quantities, such as suspended particulate matter concentration, chlorophyll-a, or precise water depth. As a result, the present analysis focuses on relative spatial variability rather than absolute biogeochemical inversion.

Second, the current analysis is based on a single temporal observation, representing a spatial snapshot of optical conditions during the acquisition period. Given the strong seasonal variability of alpine karst lake systems, including hydrological fluctuations, temperature-dependent calcite precipitation, and freeze-thaw processes, the present results should be interpreted as a high-resolution spatial baseline rather than a complete representation of long-term dynamics [67]. Future investigations should integrate multi-temporal UAV observations with complementary satellite observations to quantify seasonal variations and long-term changes in optical structure.

Third, although the selected hyperspectral bands and empirical proxies demonstrate strong sensitivity to the unique optical characteristics of the study area, their direct transferability to other aquatic systems remains to be further evaluated. Variations in substrate composition, benthic structure, and water-column optical properties may affect the generalizability of the derived spectral relationships. Future studies may benefit from integrating radiative transfer modeling and limited in situ optical measurements to improve physical interpretability and cross-site robustness [68]. Furthermore, uncertainties associated with atmospheric variability and bidirectional reflectance effects may influence spectral consistency when extending the framework across different acquisition conditions or landscapes.

Overall, these limitations define the current scope of applicability of the proposed framework and provide directions for future refinement toward physically based and temporally dynamic optical modeling approaches.

6. Conclusions

This study evaluated spatial optical variability in three alpine karst lakes in Jiuzhaigou using UAV hyperspectral imagery, CIE $L^*a^*b^*$ color metrics, and empirical optical proxies. By focusing on relative spatial optical differences rather than absolute retrieval of water constituents, this study demonstrates the potential of UAV hyperspectral data for protected and data-limited lake systems. The main findings are summarized below:

Multi-scale clustering for identifying optical differences: By combining UAV hyperspectral imagery, empirical optical proxies (e.g., SCCI), CIE $L^*a^*b^*$ color coordinates, and K-means clustering, this study identified spatial differences in lake optical characteristics. The two-scale clustering strategy reduced the influence of large differences among lakes and allowed both inter-lake and within-lake optical variations to be identified.

Identification of optical zones with different spectral characteristics: The derived optical zones revealed distinct spatial patterns in the three lake systems. Zone A exhibited higher reflectance with stronger bottom-related influences, whereas Zone C showed lower reflectance and weaker bottom contributions. Zone B displayed intermediate spectral characteristics.

Statistical differentiation of optical zones: Kruskal–Wallis H tests confirmed significant differences among optical zones across the analyzed spatial scales. The proxies were able to distinguish localized optical variations within the studied lakes.

Relationships between optical patterns and lake characteristics: The multi-scale spatial patterns of the Optical Water Types correspond with differences in lake morphology, substrate exposure, and hydrological settings among the cascaded lakes (e.g., the relatively uniform optical structure of Five Colored Pool compared with the stronger spatial heterogeneity observed in Five Flower Lake.). These spatial patterns provide reference information for future studies investigating optical changes related to hydrological conditions, sediment processes, or ecosystem variations.

Overall, the combination of UAV hyperspectral imagery and spatial clustering provides a non-destructive method for evaluating optical variability in shallow-water karst lakes. By resolving fine-scale optical gradients without extensive field calibration, this approach provides a reference dataset for future comparisons of optical conditions in protected lake systems. The results should be interpreted as relative optical characterization rather than direct quantitative inversion of physical or biogeochemical parameters.

Supplementary Materials: The following supporting information can be downloaded at <https://www.mdpi.com/article/10.3390/rs18152596/s1>. Figure S1. Multi-metric evaluation of sample size sensitivity and statistical convergence (represented by ΔE in Five Flower Lake). (a) Optimization phase: Line charts illustrating the standard deviation of sampled means and sampled standard deviations as a function of sample size (N). Clear convergence ‘elbow’ points are visible at

$N = 10,000$. (b) Optimization phase: Boxplots comparing the distributions of sampled means and sampled standard deviations across varying sample sizes, demonstrating the stabilization of the distribution structure at $N = 10,000$. Note the diminishing marginal gains beyond this threshold; Figure S2. K-means clustering sensitivity analysis across global scales. The optimal number of clusters (k) was evaluated using four internal validation metrics: within-cluster sum of squares (WCSS, elbow method), silhouette coefficient, Calinski–Harabasz index, and Davies–Bouldin index; Figure S3. K-means clustering sensitivity analysis across lake-specific scales. The optimal number of clusters (k) was evaluated using four internal validation metrics: within-cluster sum of squares (WCSS, elbow method), silhouette coefficient, Calinski–Harabasz index, and Davies–Bouldin index; Figure S4. Probability density distributions of additional normalized optical proxy indices not included in the main text. From left to right, the panels correspond to the Five Colored Pool, Five Flower Lake, and Shuzheng Lakes (the largest lake); Table S1: Statistical stability verification of the 10,000-pixel sampling threshold.

Author Contributions: M.Z.: Conceptualization; Methodology; Investigation; Data curation; Formal analysis; Visualization; Writing—original draft. X.H.: Conceptualization, Methodology, Supervision, Resources, Project administration, Funding acquisition, Writing—review and editing; F.P.: Investigation, Resources; C.J.: Formal analysis, Software, Writing—review and editing; S.F.: Investigation, Data curation, and Methodology; P.L.: Investigation, Data curation. All authors have read and agreed to the published version of the manuscript.

Funding: Supported by Science and Technology Projects of Xizang Autonomous Region, China (Grant No. XZ202501ZY0004) and the National Social Science Fund Key Projects of China (Grant No. 23AZD086).

Data Availability Statement: The data presented in this study are available from the corresponding author upon reasonable request due to environmental protection restrictions.

Acknowledgments: The authors acknowledge the staff of the Jiuzhaigou Scenic Area for their assistance with field investigation and UAV data acquisition coordination. Technical and equipment support during UAV data acquisition was provided by Hi-Target Company. Additional support from team members in data processing is gratefully acknowledged. During the preparation of this manuscript, the authors used ChatGPT (OpenAI, GPT-5.5-mini) for language editing and improving manuscript readability. The authors have reviewed and edited the output and take full responsibility for the content of this publication.

Conflicts of Interest: The authors declare no competing interests.

References

1. Liu, L. Factors Affecting Tufa Degradation in Jiuzhaigou National Nature Reserve, Sichuan, China. *Water* **2017**, *9*, 702. [CrossRef]
2. Yan, H.; Liu, Z.; Deng, Z.; Sun, H.; Zhang, J. Origin of the tufa at Jiuzhaigou scenic spot in Sichuan. *Carsologica Sin.* **2013**, *32*, 15–22. [CrossRef]
3. Ye, M.; Sun, Y. Review of the Forel-Ule Index Based on In Situ and Remote Sensing Methods and Application in Water Quality Assessment. *Environ. Sci. Pollut. Res.* **2022**, *29*, 13024–13041. [CrossRef] [PubMed]
4. Wang, L.; Meng, Q.; Wang, X.; Chen, Y.; Zhao, S.; Wang, X. Forel-Ule Index Extraction and Spatiotemporal Variation from MODIS Imagery in the Bohai Sea of China. *Opt. Express* **2023**, *31*, 6180–6196. [CrossRef] [PubMed]
5. Lee, Z.; Carder, K.L.; Mobley, C.D.; Steward, R.G.; Patch, J.S. Hyperspectral remote sensing for shallow waters. 1. A semianalytical model. *Appl. Opt.* **1998**, *37*, 6329–6338. [CrossRef] [PubMed]
6. Van der Woerd, H.J.; Wernand, M.R. Hue-Angle Product for Low to Medium Spatial Resolution Optical Satellite Sensors. *Remote Sens.* **2018**, *10*, 180. [CrossRef]
7. Morel, A.; Prieur, L. Analysis of variations in ocean color. *Limnol. Oceanogr.* **1977**, *22*, 709–722. [CrossRef]
8. Bi, S.; Hieronymi, M. Holistic optical water type classification for ocean, coastal, and inland waters. *Limnol. Oceanogr.* **2024**, *69*, 1547–1561. [CrossRef]
9. Ying, H.; Wang, S.; Zhang, B.; Mao, Z.; Zhang, F.; Li, J. Earth Observation Reveals the Shifting Patterns of China’s Lake Colour Driven by Climate Change and Land Cover. *J. Environ. Manag.* **2024**, *362*, 121604. [CrossRef] [PubMed]

10. Chen, Q.; Li, Z.; Jin, Z.; Yao, S.; Zhou, Y.; Wu, H.; Liu, Y.; Zhang, G.; Liu, Y.; Yang, X.; et al. Evolution patterns, driving mechanisms, and ecological indicative effects of 730 lakes water color in the Yangtze River Basin (1984–2023). *J. Hydrol.* **2025**, *653*, 132695. [\[CrossRef\]](#)
11. Du, J.; Qiao, X.; Zhang, M.; Di, B.; Tang, Y. Wetlands in the Jiuzhaigou World Natural Heritage site of south-west China: Classification and recent changes. *Mar. Freshw. Res.* **2018**, *69*, 677–689. [\[CrossRef\]](#)
12. Lilley, S.; Hayashi, M. Hydrogeological characterization of alpine karst using the transient analysis of flow and transport. *Hydrol. Earth Syst. Sci.* **2026**, *30*, 3121–3143. [\[CrossRef\]](#)
13. He, J.; Zhang, S.; Feng, W.; Lin, J. Quantifying earthquake-induced bathymetric changes in a tufa lake using high-resolution remote sensing data. *Int. J. Appl. Earth Obs. Geoinf.* **2024**, *127*, 103680. [\[CrossRef\]](#)
14. Dang, Z.; Ren, J.; An, C.; Dai, Q.; Dong, F.; Deng, Y.; Yang, Q.; Zhuo, M. Effect of Ms 7.0 Earthquake on Travertine Landscapes and Hydrochemistry of Jiuzhaigou Core Scenic Spots. *Carsologica Sin.* **2019**, *38*, 186–192.
15. He, J.C.; Zhang, S.H.; Feng, W.; Yan, X.Y.; Jin, Z.H.; Lin, J.Y. Water Depth Retrieval of Tufa Lakes Based on Unmanned Aerial Vehicle Imagery and Machine Learning. *Natl. Remote Sens. Bull.* **2025**, *29*, 181–190. [\[CrossRef\]](#)
16. Xia, K.; Wu, T.; Li, X.; Wang, S. A New Method for Accurate Inversion of Forel-Ule Index Using MODIS Images: Revealing the Water Color Evolution in China's Large Lakes and Reservoirs Over the Past Two Decades. *Water Res.* **2024**, *255*, 121560. [\[CrossRef\]](#) [\[PubMed\]](#)
17. Yi, L.; Zhang, G.; Zhang, B. Application of UAV Push-Broom Hyperspectral Images in Water Quality Assessments for Inland Water Protection: A Case Study of Zhang Wei Xin River in Dezhou District, China. *Remote Sens.* **2023**, *15*, 2360. [\[CrossRef\]](#)
18. Bai, X.; Wang, J.; Chen, R.; Kang, Y.; Ding, Y.; Lv, Z.; Ding, D.; Feng, H. Research progress of inland river water quality monitoring technology based on unmanned aerial vehicle hyperspectral imaging technology. *Environ. Res.* **2024**, *257*, 119254. [\[CrossRef\]](#) [\[PubMed\]](#)
19. Cui, M.; Sun, Y.; Huang, C.; Li, M. Water Turbidity Retrieval Based on UAV Hyperspectral Remote Sensing. *Water* **2022**, *14*, 128. [\[CrossRef\]](#)
20. Liu, B.; Li, T. A Machine-Learning-Based Framework for Retrieving Water Quality Parameters in Urban Rivers Using UAV Hyperspectral Images. *Remote Sens.* **2024**, *16*, 905. [\[CrossRef\]](#)
21. Zhao, Y.; Wang, X.; Liu, X.; Gong, K.; Zou, L.; Lin, Z.; Yu, T.; Yu, W.; Hu, B. Application of Fine Spectral Detection and Quantitative Analysis Technology in Water Quality and Environmental Monitoring of the Yangtze River Main Stream. *Acta Geogr. Sin.* **2024**, *79*, 45–57. [\[CrossRef\]](#)
22. Hu, Y.; Zhan, W.; He, Q.; Liu, Y.; Zhan, H. A Spatially-Informed Interpretable Deep Learning Framework for High-Resolution Nutrient Monitoring in Complex Coastal Waters. *Int. J. Appl. Earth Obs. Geoinf.* **2026**, *146*, 105025. [\[CrossRef\]](#)
23. Sun, X.; Zhang, L.; Yang, H.; Wu, T.; Cen, Y.; Guo, Y. Enhancement of Spectral Resolution for Remotely Sensed Multispectral Image. *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.* **2015**, *8*, 2198–2211. [\[CrossRef\]](#)
24. Pan, X.; Wang, Z.; Ullah, H.; Chen, C.; Wang, X.; Li, X.; Li, H.; Zhuang, Q.; Xue, B.; Yu, Y. Evaluation of Eutrophication in Jiaozhou Bay via Water Color Parameters Determination with UAV-Borne Hyperspectral Imagery. *Atmosphere* **2023**, *14*, 387. [\[CrossRef\]](#)
25. Tong, X.; Zhang, B.; Zhang, L. Frontier Progress of Hyperspectral Remote Sensing in China. *J. Remote Sens.* **2016**, *20*, 689–707. [\[CrossRef\]](#)
26. Hedley, J.D.; Roelfsema, C.M.; Phinn, S.R.; Mumby, P.J. Environmental and Sensor Limitations in Optical Remote Sensing of Coral Reefs: Implications for Monitoring and Sensor Design. *Remote Sens.* **2012**, *4*, 271–302. [\[CrossRef\]](#)
27. Chang, Q.; Zwieback, S.; Berg, A. Trends and Drivers of Arctic Lake Color Change from Landsat Time Series. *Int. J. Appl. Earth Obs. Geoinf.* **2025**, *145*, 104952. [\[CrossRef\]](#)
28. Li, X.; Zhang, M.; Xiao, W.; Du, J.; Sheng, M.; Zhu, D.; Plenković-Moraj, A.; Sun, G. The Color Formation Mechanism of the Blue Karst Lakes in Jiuzhaigou Nature Reserve, Sichuan, China. *Water* **2020**, *12*, 771. [\[CrossRef\]](#)
29. Tang, Z.L.; Zhu, Z.F.; Li, X.H.; Zhong, B.; Xu, L.; Zhuo, M.; Plenkovic-Moraj, A.; Sun, G. Hyperspectral Quantitative Inversion Model for Water Quality Parameters of Lakes at the Jiuzhaigou World Natural Heritage Site. *Chin. J. Appl. Environ. Biol.* **2021**, *27*, 1256–1263. [\[CrossRef\]](#)
30. Lu, K.; Gao, X.; Liu, D.; Zhang, S.; Li, Q.; Gao, H.; Yu, H. An innovative method for identifying aquatic environmental characteristics: Construction of water quality fingerprint spectrum and combination with two-dimensional correlation spectroscopy analysis. *Environ. Res.* **2025**, *279*, 121810. [\[CrossRef\]](#) [\[PubMed\]](#)
31. Benavides-Bolaños, J.A.; Echeverri-Sánchez, A.F.; Reyes-Trujillo, A.; Del Mar Carreño-Sánchez, M.; Jaramillo-Llorente, M.F.; Rivera-Caicedo, J.P. In Situ Hyperspectral Reflectance Sensing for Mixed Water Quality Monitoring: Insights from the RUT Agricultural Irrigation District. *Water* **2025**, *17*, 1353. [\[CrossRef\]](#)
32. Lehmann, M.K.; Nguyen, U.; Allan, M.; van der Woerd, H.J. Colour classification of 1486 lakes across a wide range of optical water types. *Remote Sens.* **2018**, *10*, 1273. [\[CrossRef\]](#)
33. Kirk, J.T.O. *Light and Photosynthesis in Aquatic Ecosystems*; Cambridge University Press: Cambridge, UK, 2011.

34. Spyrakos, E.; O'Donnell, R.; Hunter, P.D.; Miller, C.; Scott, M.; Simis, S.G.H.; Neil, C.; Lambert, N.; Groom, S.B. Optical types of inland and coastal waters. *Limnol. Oceanogr.* **2018**, *63*, 846–870. [[CrossRef](#)]
35. Lv, C.; Zhao, X.; Jiang, Y.; Zhu, H.; Zhang, H.; Wang, F.; Li, Q.; Hou, K. Insights into alpine-karst-type tufa deposits in geological environmental records: A case study of the calcareous tufa profile of the Jiuzhaigou Natural Reserve on the eastern margin of the Tibetan Plateau. *Minerals* **2023**, *13*, 120. [[CrossRef](#)]
36. Robertson, A.R.; Lozano, R.D.; Alman, D.H.; Orchard, S.E.; Keitch, J.A.; Connelly, R.; Graham, L.A.; Lozano, W.; John, R.S.; Hoban, R.F.; et al. (Eds.) *CIE Recommendations on Uniform Color Spaces, Color-Difference Equations, and Metric Color Terms*; CIE: Paris, France, 2007; Volume 2, pp. 5–6.
37. Mobley, C.D. *Light and Water: Radiative Transfer in Natural Waters*; Academic Press: Cambridge, MA, USA, 1994.
38. Wyszecki, G.; Stiles, W.S. *Color Science: Concepts and Methods, Quantitative Data and Formulae*; John Wiley and Sons: Hoboken, NJ, USA, 2000.
39. Wang, S.L.; Li, J.S.; Shen, Q.; Zhang, B.; Zhang, F.F.; Lu, Z.Y. MODIS-Based Radiometric Color Extraction and Classification of Inland Water With the Forel-Ule Scale: A Case Study of Lake Taihu. *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.* **2015**, *8*, 907–918. [[CrossRef](#)]
40. Pitarch, J.; van der Woerd, H.J.; Brewin, R.J.W.; Zielinski, O. Optical properties of Forel-Ule water types deduced from 15 years of global satellite ocean color observations. *Remote Sens. Environ.* **2019**, *231*, 111249. [[CrossRef](#)]
41. *CIE 015:2004; Colorimetry*, 3rd ed. CIE Central Bureau: Vienna, Austria, 2004.
42. van der Woerd, H.J.; Wernand, M.R. True Colour Classification of Natural Waters with Medium-Spectral Resolution Satellites: SeaWiFS, MODIS, MERIS and OLCI. *Sensors* **2015**, *15*, 25663–25680. [[CrossRef](#)] [[PubMed](#)]
43. Robertson, A.R. The CIE 1976 Color-Difference Formulae. *Color Res. Appl.* **1977**, *2*, 7–11. [[CrossRef](#)]
44. *CIE 1931; Standard Colorimetric Observers*. CIE Publication S 002: Paris, France, 1986.
45. Sharma, G.; Bala, R. *Digital Color Imaging Handbook*; CRC Press: Boca Raton, FL, USA, 2002.
46. Chen, S.; Han, T.; Li, R.; Shen, M.; Zhou, C. Chromaticity-Based Discrimination of Algal Bloom from Inland and Coastal Waters Using In Situ Hyperspectral Remote Sensing Reflectance. *Water* **2024**, *16*, 2276. [[CrossRef](#)]
47. Matthews, M.W. A current review of empirical procedures of remote sensing in inland and near-coastal transitional waters. *Int. J. Remote Sens.* **2011**, *32*, 6855–6899. [[CrossRef](#)]
48. Maritorena, S.; Morel, A.; Gentili, B. Diffuse reflectance of oceanic shallow waters: Influence of water depth and bottom albedo. *Limnol. Oceanogr.* **1994**, *39*, 1689–1703. [[CrossRef](#)]
49. Topp, S.N.; Pavelsky, T.M.; Jensen, D.; Simard, M.; Ross, M.R.V. Research Trends in the Use of Remote Sensing for Inland Water Quality Science: Moving Towards Multidisciplinary Applications. *Water* **2020**, *12*, 169. [[CrossRef](#)]
50. Kutser, T.; Pierson, D.C.; Kallio, K.Y.; Reinart, A.; Sobek, S. Mapping lake CDOM by satellite remote sensing. *Remote Sens. Environ.* **2005**, *94*, 535–540. [[CrossRef](#)]
51. Gitelson, A.A.; Gao, B.-C.; Li, R.-R.; Berdnikov, S.; Saprygin, V. Remote estimation of chlorophyll-a concentration in turbid productive waters: Return to a simple two-band NIR-red model? *Remote Sens. Environ.* **2011**, *115*, 3479–3490. [[CrossRef](#)]
52. Gitelson, A.A.; Dall'Olmo, G.; Moses, W.; Rundquist, D.C.; Barrow, T.; Fisher, T.R.; Gurlin, D.; Holz, J. A simple semi-analytical model for remote estimation of chlorophyll-a in turbid waters: Validation. *Remote Sens. Environ.* **2008**, *112*, 3582–3593. [[CrossRef](#)]
53. Shi, K.; Zhang, Y.L.; Zhu, G.W.; Liu, X.H.; Zhou, Y.Q.; Xu, H.; Qin, B.Q.; Liu, G.; Li, Y.M. Long-term remote monitoring of total suspended matter concentration in Lake Taihu using 250 m MODIS-Aqua data. *Remote Sens. Environ.* **2015**, *164*, 43–56. [[CrossRef](#)]
54. Doane, D.P.; Seward, L.E. Measuring Skewness: A Forgotten Statistic? *J. Stat. Educ.* **2011**, *19*, 1–18. [[CrossRef](#)]
55. Groeneveld, R.A.; Meeden, G. Measuring Skewness and Kurtosis. *J. R. Stat. Soc. Ser. D. (Stat.)* **1984**, *33*, 391–399. [[CrossRef](#)]
56. Kruskal, W.H.; Wallis, W.A. Use of ranks in one-criterion variance analysis. *J. Am. Stat. Assoc.* **1952**, *47*, 583–621. [[CrossRef](#)]
57. Liu, X.H.; Zhang, Y.L.; Shi, K.; Zhou, Y.Q.; Tang, X.M.; Zhu, G.W.; Qin, B.Q. Mapping aquatic vegetation in a large, shallow eutrophic lake: A frequency-based approach using multiple years of MODIS data. *Remote Sens.* **2015**, *7*, 10295–10320. [[CrossRef](#)]
58. MacQueen, J. *Some Methods for Classification and Analysis of Multivariate Observations*; University of California Press: Oakland, CA, USA, 1967; Volume 1.
59. Jain, A.K. Data clustering: 50 years beyond K-means. *Pattern Recognit. Lett.* **2010**, *31*, 651–666. [[CrossRef](#)]
60. Neil, C.; Spyrakos, E.; Hunter, P.D.; Tyler, A.N. A global approach for chlorophyll-a retrieval across optically complex inland waters based on optical water types. *Remote Sens. Environ.* **2019**, *229*, 159–178. [[CrossRef](#)]
61. Guyon, I.; Elisseeff, A. An introduction to variable and feature selection. *J. Mach. Learn. Res.* **2023**, *3*, 1157–1182.
62. Xu, J.P.; Fang, C.; Gao, D.; Zhang, H.S.; Gao, C.; Xu, Z.C.; Wang, Y.Q. Optical models for remote sensing of chromophoric dissolved organic matter (CDOM) absorption in Poyang Lake. *ISPRS J. Photogramm. Remote Sens.* **2018**, *142*, 124–136. [[CrossRef](#)]
63. Rousseeuw, P.J. Silhouettes: A graphical aid to the interpretation and validation of cluster analysis. *J. Comput. Appl. Math.* **1987**, *20*, 53–65. [[CrossRef](#)]
64. Caliński, T.; Harabasz, J. A dendrite method for cluster analysis. *Commun. Stat.* **1974**, *3*, 1–27. [[CrossRef](#)]

65. McKinna, L.I.W.; Fearn, P.R.C.S.; Weeks, S.J.; Werdell, P.J.; Reichstetter, M.; Franz, B.A.; Shea, D.M.; Feldman, G.C. A semianalytical ocean color inversion algorithm with explicit water column depth and substrate reflectance parameterization. *J. Geophys. Res. Ocean.* **2015**, *120*, 1741–1770. [[CrossRef](#)]
66. Qiao, X.; Du, J.; Lugli, S.; Ren, J.; Xiao, W.; Chen, P.; Tang, Y. Are climate warming and enhanced atmospheric deposition of sulfur and nitrogen threatening tufa landscapes in Jiuzhaigou National Nature Reserve, Sichuan, China? *Sci. Total Environ.* **2016**, *562*, 724–731. [[CrossRef](#)] [[PubMed](#)]
67. Matta, E.; Bresciani, M.; Giardino, C.; Chiarle, M.; Nigrelli, G. Water Colour Changes in High-Elevation Alpine Lakes during 2017–2022: A Case Study of the Upper Orco Valley Catchment. *Water* **2024**, *16*, 1057. [[CrossRef](#)]
68. Niu, C.; Tan, K.; Wang, X.; Du, P.; Pan, C. A semi-analytical approach for estimating inland water inherent optical properties and chlorophyll a using airborne hyperspectral imagery. *Int. J. Appl. Earth Obs. Geoinf.* **2024**, *128*, 103774. [[CrossRef](#)]

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.