

Article

Surface-Water Fragmentation and Heterogeneous Responses of Dish-Shaped Sub-Lakes in Poyang Lake During the 2022 Extreme Drought

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Highlights

What are the main findings?

- A multi-source framework integrating Sentinel-1, Sentinel-2, and Dynamic World data on Google Earth Engine resolved spectral confusion among turbid water, saturated mudflats, and exposed lakebeds during extreme drought, achieving an overall accuracy of 87.44% and a Kappa of 0.80.
- The 2022 extreme drought triggered an abrupt flood-to-drought transition in Poyang Lake, in which hydrologically connected sub-lakes desiccated rapidly, whereas impounded sub-lakes retained stable core water areas as critical dry-season refugia.

What are the implications of the main findings?

- Hydrological connectivity emerges as a first-order control on the drought vulnerability of floodplain wetlands, informing conservation and water-regulation strategies under intensifying climate extremes.
- Rule-based refinement of the Dynamic World product enables accurate wetland mapping under extreme hydrological conditions, offering a transferable pipeline for other large floodplain systems.

Abstract

Extreme droughts can rapidly reshape surface-water patterns in river-connected floodplain wetlands, yet the fine-scale responses of individual dish-shaped sub-lakes remain insufficiently resolved. This study focused on the 2022 extreme drought in Poyang Lake, China's largest freshwater lake and a globally important floodplain wetland system. The objectives were to quantify wetland landscape changes during the 2022 extreme drought event and to compare the heterogeneous responses of dish-shaped sub-lakes under contrasting surface-water linkage and management-context settings. We developed a high-resolution wetland monitoring framework on the Google Earth Engine platform by integrating Sentinel-2 multispectral imagery, Sentinel-1 synthetic-aperture radar, and the Dynamic World land-cover product. This multi-source approach was designed to reduce spectral confusion among turbid water, saturated mudflats, and exposed lakebeds during extreme low-water stages. Monthly wetland maps were generated for the Poyang Lake National Nature Reserve and compared with a five-year historical baseline from 2017 to 2021. The framework achieved



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an overall accuracy of 87.44%, with a Kappa coefficient of 0.80. The results revealed a rapid wet-to-dry transition in 2022. The water area contracted by 78.1% from July to September and remained 73.6–74.7% below the historical baseline from September to November. This contraction was accompanied by extensive observable surface-water fragmentation, apparent loss of visible surface-water linkage among sub-lakes, and substantial wetland habitat contraction. Sub-lakes exhibited clearly differentiated drought responses. Sub-lakes with stronger visible surface-water linkage to the main lake generally experienced more rapid water loss during recession, whereas reserve-managed or facility-present sub-lakes retained residual water to varying degrees and may have provided important refugial habitats for waterbirds and aquatic species. These findings suggest that surface-water linkage condition, local topographic setting, and 2022 management context were jointly associated with the heterogeneous drought responses of sub-lakes. The proposed framework provides a tool for monitoring wetland landscape changes associated with extreme drought events, assessing ecological vulnerability, and supporting adaptive water-level management under intensifying climate extremes.

Keywords: extreme drought; floodplain wetlands; dish-shaped lakes; surface-water fragmentation; sub-lake heterogeneity; multi-source remote sensing; Dynamic World; Poyang Lake

1. Introduction

The global intensification of extreme hydrological events, particularly droughts, has emerged as one of the most direct manifestations of anthropogenic climate change, with mounting evidence documenting increasing frequency, duration, and spatial extent [1,2]. For river-connected floodplain lakes, rapid and anomalous water-level fluctuations reconfigure basin-scale hydrological regimes, fragment surface-water habitats, and alter wetland vegetation succession and waterbird habitat availability [3–5]. The flood pulse concept, a foundational framework in floodplain ecology, identifies periodic lateral exchange of water, nutrients, sediment, and biota between rivers and their floodplains as the primary driver sustaining wetland biodiversity and productivity [6]. Extreme drought interrupts this natural rhythm and can reduce visible surface-water linkages among floodplain water bodies [7]. These dynamics underscore the urgent need for monitoring approaches capable of accurately resolving fine-scale surface-water fragmentation and heterogeneous wetland responses under extreme conditions.

In this study, floodplain wetlands are understood as seasonally inundated river–lake floodplain systems whose hydrological, geomorphological, and ecological functions are maintained by periodic water exchange among the main lake body, floodplain depressions, shallow channels, mudflats, and wetland vegetation zones. Such systems contain both persistent and seasonal water bodies, and their ecological value depends not only on the total water area but also on the timing and spatial arrangement of shallow water, wet mudflat, and hygrophilous vegetation habitats. This definition is particularly relevant to Poyang Lake, where numerous dish-shaped sub-lakes function as fine-scale habitat units embedded within a larger river-connected floodplain.

Despite considerable methodological progress, conventional remote-sensing approaches retain significant limitations in characterizing complex wetland dynamics during extreme drought. Early and widely employed sensors such as MODIS (250 m) cannot resolve the intricate water–land mosaic within river-connected lakes [8]. Landsat imagery (30 m), though extensively used for wetland mapping [9], is frequently inadequate for

detecting rapidly shrinking and highly fragmented small water bodies or narrow sub-lake channels under pronounced drought stress [10]. A particularly critical challenge arises during rapid water recession: turbid shallow water, saturated mudflats, and exposed lakebeds exhibit spectrally similar signatures, generating substantial confusion for conventional threshold-based or shallow machine-learning classifiers and undermining mapping reliability precisely when temporal accuracy is most needed [11]. Synthetic-aperture radar (SAR), though providing all-weather observational continuity, is susceptible to wind-induced surface roughness and specular reflection from saturated mudflats, leading to systematic water omission or overestimation during transitional hydrological phases [12,13].

The recent convergence of high-resolution multi-source remote sensing and deep learning offers transformative potential to overcome these limitations. Recent dense time-series mapping studies further show that multi-temporal remote-sensing integration can reduce optical observation limitations and improve monitoring continuity under challenging atmospheric or seasonal conditions [14]. Within such synergistic frameworks, complementary sensor modalities contribute distinct advantages: Sentinel-2 provides 10 m multispectral imagery that substantially enhances spatial fidelity and enables accurate detection of small fragmented water bodies and narrow surface-water channels; Sentinel-1 SAR data afford all-weather imaging capability that compensates for optical data gaps due to convective weather and cloud cover, ensuring temporal continuity [15,16]; and deep-learning land-cover products such as Dynamic World incorporate spatiotemporal contextual information, providing contextual land-cover priors that can support boundary delineation in complex spectral environments, while still requiring local refinement and validation in water–mudflat transition zones [17]. Notwithstanding these technological advances, existing research has predominantly focused on lake-scale surface-area dynamics, while the fine-scale and spatially heterogeneous responses of numerous independent dish-shaped sub-lake systems embedded within floodplains remain poorly understood [18].

Poyang Lake, China's largest freshwater lake and a globally significant wetland, contains numerous shallow dish-shaped sub-lakes distributed across its extensive floodplain. These sub-lakes are highly sensitive to hydrological fluctuations and constitute critical overwintering habitats for internationally threatened migratory waterbirds, including the Siberian crane (*Grus leucogeranus*) [19,20]. During summer and autumn 2022, the Yangtze River Basin endured an unprecedented extreme drought driven by persistent heat and precipitation deficit [21], and independent hydrological assessments reported an abnormally protracted and early low-water condition in Poyang Lake [4,22]. Specifically, GRACE-FO and GLDAS data showed a sustained negative terrestrial water-storage anomaly in the basin from July to December 2022, accompanied by a five-year minimum SAR-derived lake surface area of 814 km² on 27 August and a Hukou-station water-level decline to only 6.4 m between June and October, while basin-wide rainfall fell to just 7.161 mm in September 2022 [4]; Concurrently, reversed zonal flow over the subtropical Tibetan Plateau was identified as the dominant dynamic driver of the unprecedented July–August 2022 heatwave along the Yangtze River Valley [21], while floodplain groundwater-flow modeling indicated a maximum groundwater-level decline of approximately 5 m and annual groundwater discharge approximately 14.5 times that in a normal year [22]. This historic event, coinciding with the maturity of high-resolution multi-source remote-sensing and deep-learning technologies, provides a unique natural experiment to examine asynchronous surface-water fragmentation and drought-response patterns of dish-shaped sub-lake systems at fine spatial scales. At a broader management scale, such hydrological-habitat changes are also relevant to ecosystem-service supply–demand and water–energy–food nexus assessments that link water availability with ecological and sustainability outcomes [23].

Against this backdrop, this study pursues three interconnected objectives: (1) to develop an operational multi-source classification framework for floodplain wetlands on the Google Earth Engine (GEE) platform, integrating Sentinel-2 optical imagery, Sentinel-1 SAR data, and the Dynamic World deep-learning land-cover product; (2) to quantitatively characterize the anomalous wet-to-dry reversal in wetland succession during the 2022 extreme drought using a 2017 to 2021 historical baseline within the Poyang Lake National Nature Reserve; and (3) to compare the heterogeneous surface-water and wetland landscape responses of dish-shaped sub-lakes under contrasting hydrological-management settings. Rather than proposing a new deep-learning algorithm, this study develops an integration framework that combines existing optical, SAR, and deep-learning products. The aim is to detect drought-induced surface-water fragmentation and differential sub-lake responses at fine spatial resolution, and to provide a transferable technical basis for the monitoring and adaptive management of floodplain wetlands under intensifying climate extremes.

2. Materials and Methods

2.1. Study Area

The study area is the Poyang Lake National Nature Reserve (29°05′–29°17′N, 115°53′–116°08′E), a protected floodplain–wetland complex within the broader Poyang Lake floodplain. It is not a purely permanent open-water lake; rather, it comprises seasonally inundated dish-shaped sub-lakes, shallow surface-water channels, exposed mudflats, and hygrophilous grasslands that alternate between aquatic and terrestrial states as water levels rise and fall. This seasonal floodplain structure supports internationally important overwintering and stopover habitats for migratory waterbirds, including the Siberian crane (*Grus leucogeranus*), and makes the reserve an appropriate model system for examining drought-induced surface-water fragmentation and habitat-state transitions [19,20].

For the purposes of this study, representative dish-shaped sub-lakes were grouped according to the management context during the 2022 drought event (Figure 1), based on updated information from the reserve-management authority and the previous literature [24]. The grouping distinguishes three information-based categories: (1) unregulated in 2022, including Dacha Lake and Bang Lake, where no artificial water-control facilities for regulation were confirmed; (2) reserve-managed in 2022, including Dahuchi Lake and Sha Lake, for which the reserve authority had management rights and documented winter water-control schemes oriented toward waterbird habitat conservation; and (3) facility-present in 2022, including Xiang Lake, Zhonghuchi Lake, Zhushi Lake, Changhuchi Lake, and Meixi Lake, where water-control facilities were present and annual regulation may have occurred, but the dominant management objective in 2022 could not be determined from the available information. This classification reflects the 2022 event context only and should not be extrapolated to later years, because management authority for additional sub-lakes was transferred to the reserve authority in 2023.

2.2. Remote-Sensing Data

All datasets were sourced from the Google Earth Engine (GEE; Google LLC, Mountain View, CA, USA; <https://earthengine.google.com/>, accessed on 30 November 2026) cloud platform (Table 1), which enables planetary-scale geospatial analysis by integrating multi-source satellite archives with high computational efficiency [5,25]. Four complementary datasets were employed to capture the full spectral and temporal complexity of wetland dynamics.

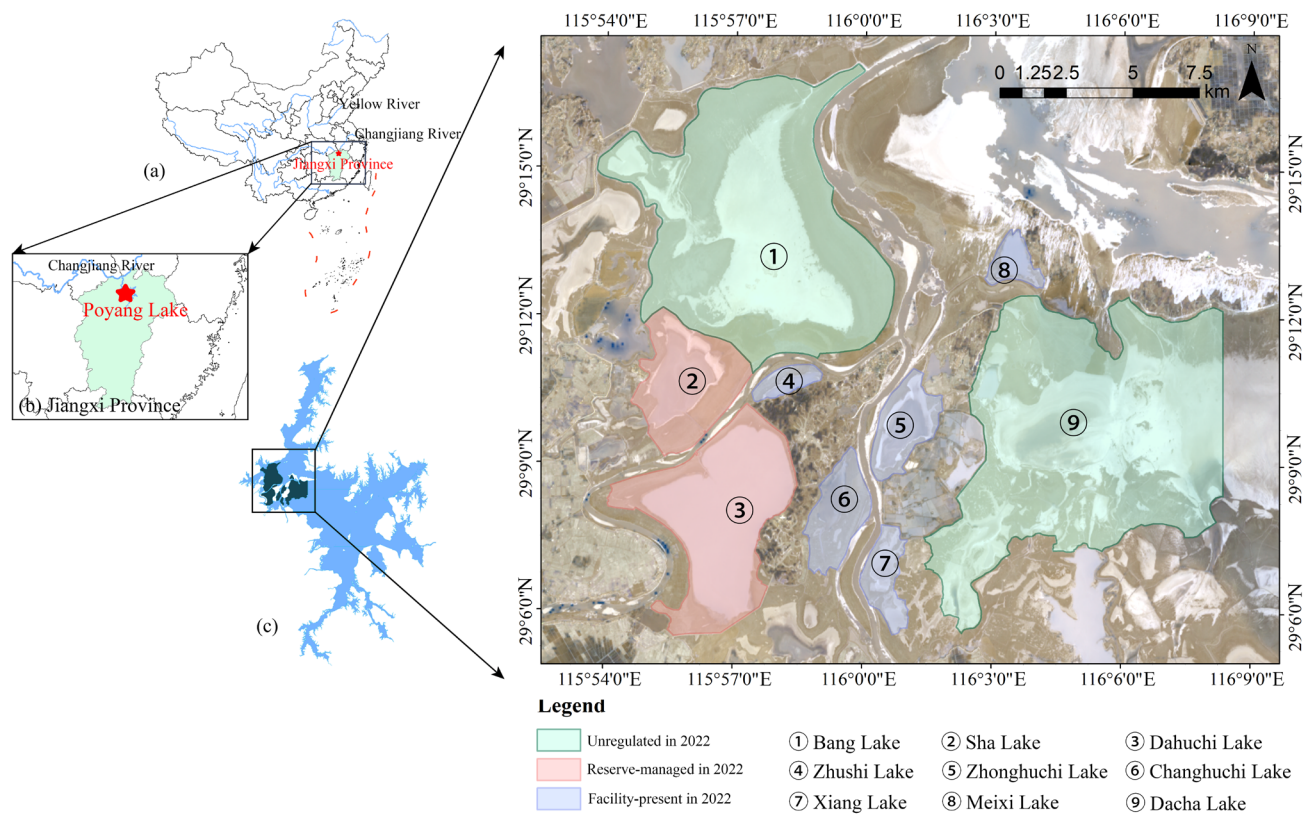


Figure 1. Location and hydrological-management context of representative dish-shaped sub-lakes in the Poyang Lake National Nature Reserve. (a) Location of Jiangxi Province and the Poyang Lake region in China. (b) Location of Poyang Lake within Jiangxi Province. (c) Extent of Poyang Lake and the Poyang Lake National Nature Reserve. The right panel shows nine representative dish-shaped sub-lakes within the reserve overlaid on a Google Earth image. Numbers denote 1, Bang Lake; 2, Sha Lake; 3, Dahuchi Lake; 4, Zhushi Lake; 5, Zhonghuchi Lake; 6, Changhuchi Lake; 7, Xiang Lake; 8, Meixi Lake; and 9, Dacha Lake. Colors indicate the 2022 drought-event management context: unregulated in 2022, sub-lakes without confirmed artificial water-control facilities; reserve-managed in 2022, sub-lakes with documented reserve authority and winter water-control schemes for waterbird habitat conservation; and facility-present in 2022, sub-lakes with water-control facilities but uncertain dominant management objectives during 2022. The map categories should not be interpreted as a permanent post-2022 management classification.

Table 1. Remote-sensing datasets used in this study.

Dataset	Sensor/Type	Resolution	Platform/Source	GEE Asset ID	Primary Application
Sentinel-2 MSI	Optical multispectral (Level-2A SR)	10 m	ESA/Copernicus	COPERNICUS/S2_SR_HARMONIZED	Primary optical features; manual validation
Sentinel-1 SAR	C-band GRD (IW mode)	10 m	ESA/Copernicus	COPERNICUS/S1_GRD	All-weather water detection; optical gap-filling
Dynamic World V1	Deep-learning land cover (probabilistic)	10 m	Google/WRI	GOOGLE/DYNAM ICWORLD/V1	Fine-grained wetland classification; spectral disambiguation
SRTM V3 DEM	Digital elevation model	30 m	NASA/USGS	USGS/SRTMGL1_003	Auxiliary regional topographic context; not used for fine-scale bathymetry or hydraulic-threshold analysis

Sentinel-2 MSI Level-2A surface reflectance imagery served as the primary optical data source (10 m spatial resolution; ~5-day revisit). Its high spatial fidelity supports the identification of small, fragmented water bodies and wetland vegetation patches that fall below the detection threshold of coarser sensors [26].

Sentinel-1 C-band SAR Ground Range Detected (GRD) data were employed to complement optical observations. Its all-weather, day-and-night acquisition capability ensures temporal continuity during persistent cloud cover associated with convective weather events, which are common across the Yangtze River Basin in summer [27].

The Dynamic World (DW) V1 land-cover product [17], a near-real-time global 10 m dataset generated by a fully convolutional neural network (FCN) applied to Sentinel-2 imagery, provides per-pixel probabilistic predictions for nine land-cover classes (including water, flooded vegetation, grass, and bare ground). These probabilistic outputs provide valuable prior information for fine-scale wetland classification under spectrally complex conditions.

The SRTM V3 digital elevation model (30 m) was used only as auxiliary regional topographic context and for broad screening of obvious terrain-related artifacts. It was not used to derive fine-scale bathymetry, sub-lake water depth, microtopographic thresholds, or hydrodynamic connectivity. Given the low relief of dish-shaped sub-lakes and exposed mudflats, the vertical accuracy of SRTM is insufficient for resolving meter- to sub-meter-scale wetland terrain variation; therefore, all water-area, landscape-transition, and fragmentation analyses were based on classified remote-sensing masks rather than DEM-derived hydraulic thresholds.

2.3. Data Preprocessing and Temporal Compositing

All data processing was implemented within GEE to ensure computational efficiency and methodological reproducibility [25]. The workflow integrates three primary remote-sensing data streams and one auxiliary topographic input within the classification framework (Figure 2): Sentinel-2 provides high-resolution optical spectral features for land-cover discrimination; Sentinel-1 SAR ensures temporal continuity under cloud cover and serves as an independent cross-validation reference for water extent; the DW deep-learning product supplies per-pixel land-cover probability priors that anchor the classification scheme and mitigate spectral confusion among visually similar surface types; and SRTM DEM provides broad topographic context without serving as a fine-scale hydraulic threshold. The integration logic follows a workflow of spectral feature extraction, all-weather observational support, and semantic-label fusion, in which each data stream compensates for a specific weakness of the others.

Formally, the monthly composite for pixel i in month t can be expressed as a multi-source feature vector:

$$X_{i,t} = [NDWI, MNDWI, NDVI, \sigma^0_{VV}, \sigma^0_{VH}, L_{DW}]_{i,t} \quad (1)$$

where the first three elements are optical spectral indices derived from Sentinel-2 median composites, σ^0_{VV} and σ^0_{VH} are SAR backscatter coefficients from Sentinel-1 median composites, and L_{DW} is the modal land-cover label from DW. The final classification C for each pixel is determined by

$$C = f(L_{DW}, MNDWI, NDVI, \sigma^0_{VV}) \quad (2)$$

where f denotes the hierarchical decision function described in Section 2.4.

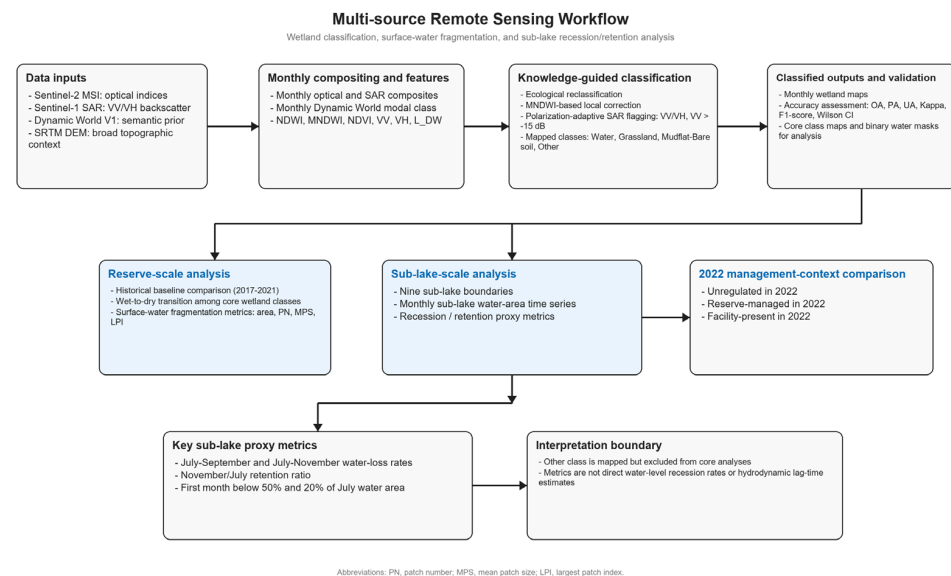


Figure 2. Multi-source methodological framework for wetland monitoring and drought-response analysis in the Poyang Lake National Nature Reserve. The workflow integrates four data sources (Sentinel-2 MSI, Sentinel-1 SAR, Dynamic World V1, and auxiliary SRTM DEM) into a unified processing chain, with SRTM used only for broad topographic context rather than fine-scale hydraulic-threshold analysis, comprising monthly compositing in Google Earth Engine, feature extraction and semantic integration, knowledge-guided wetland classification, accuracy assessment, fragmentation-metric calculation, and spatiotemporal analysis. The framework was designed to detect drought-induced surface-water fragmentation and heterogeneous responses of dish-shaped sub-lakes under contrasting hydrological-management settings.

Sentinel-2 Optical Compositing: Cloud and cloud-shadow pixels were masked using the QA60 quality assurance band. Monthly median composites were generated from all valid observations within each calendar month. The median operator suppresses outliers caused by thin residual clouds or extreme solar geometry while preserving representative surface reflectance [26]. Key spectral indices were derived from these composites (Table 2), including the Normalized Difference Water Index (NDWI), Modified NDWI (MNDWI), and Normalized Difference Vegetation Index (NDVI), which serve as primary discriminators among water, vegetation, and bare substrate.

Table 2. Spectral indices and auxiliary features used for classification.

Feature	Formula/Band	Source	Role in Classification
NDWI	$(B3 - B8)/(B3 + B8)$	Sentinel-2	Water vs. non-water discrimination
MNDWI	$(B3 - B11)/(B3 + B11)$	Sentinel-2	Enhanced water detection; turbid water correction
NDVI	$(B8 - B4)/(B8 + B4)$	Sentinel-2	Vegetation vigor; grassland identification
VV backscatter	σ^0 (VV pol.)	Sentinel-1	Open water detection (specular reflection)
VH backscatter	σ^0 (VH pol.)	Sentinel-1	Wind-roughened water correction (August)
Land-cover mode	Modal class label	Dynamic World	Semantic classification prior

The spectral indices used in this study are defined as follows:

$$NDWI = \frac{Green - NIR}{Green + NIR} \quad (3)$$

$$MNDWI = \frac{Green - SWIR_1}{Green + SWIR_1} \quad (4)$$

$$NDVI = \frac{NIR - Red}{NIR + Red} \quad (5)$$

where Green, Red, NIR, and SWIR₁ correspond to Sentinel-2 bands B3, B4, B8, and B11, respectively. NDWI and MNDWI are effective for discriminating water from non-water surfaces, with MNDWI designed to enhance open-water features and suppress built-up-area interference [28]. NDVI quantifies vegetation vigor and aids in separating actively growing hygrophilous vegetation from exposed bare substrates. A summary of all features used in the classification, including spectral indices, SAR backscatter metrics, and land-cover priors, is provided in Table 2.

Sentinel-1 SAR Compositing: A polarization-adaptive strategy was applied to maximize water detection accuracy. VV (vertical transmit–vertical receive) polarization was selected as the default because calm open water produces characteristically low backscatter through specular reflection. August was treated as an exception: persistent convective weather increased the surface roughness on open water, enhancing diffuse backscatter and causing water omission under VV. Accordingly, VH polarization was substituted for this month. Monthly median composites were generated in parallel with the optical workflow. The SAR composites provide an independent water-area estimate that enables quantitative cross-validation of optical-derived results (Section 3.1.2).

DW Monthly Mode Composite: For each pixel, the most frequently occurring DW land-cover class across all available observations within a given month was selected. This mode operator suppresses transient classification noise inherent in single-scene DW predictions and yields temporally stable monthly land-cover maps [17]. The resulting mode composite serves as the semantic backbone of the classification: its nine class labels are subsequently remapped into the four ecologically meaningful wetland categories described in Section 2.4.

2.4. Knowledge-Guided Wetland Classification Scheme

The classification framework adopts a knowledge-guided reclassification strategy, leveraging the DW product, which encodes per-pixel land-cover semantics derived from an FCN trained on a global corpus of Sentinel-2 imagery [17]. The present framework takes advantage of DW's deep-learning outputs as upstream semantic priors and applies an expert-defined reclassification ruleset, adapting the global nine-class taxonomy to the specific ecological context of Poyang Lake's floodplain wetlands (Table 3). This approach offers two advantages: (1) it inherits the spatial-contextual intelligence of the FCN, which suppresses the salt-and-pepper noise endemic to pixel-level classifiers; and (2) it enables rapid, reproducible adaptation to local wetland typologies without requiring site-specific training samples.

Table 3. Reclassification mapping table.

Dynamic World Original Class	Reclassified Category	Ecological Rationale
Water	Water	Open water bodies: lakes, channels, persistently inundated areas
Grass	Grassland	Hygrophilous wetland vegetation communities (e.g., <i>Carex</i> spp.) associated with seasonally inundated floodplain environments
Bare ground	Mudflat/Bare soil	Exposed lakebeds and desiccated sediments during water recession
Trees; crops; built area; snow/ice; shrub & scrub	Other	Non-core mapped elements; retained in classification outputs but excluded from core wetland analysis

Flooded vegetation was not treated as a terminal reclassification row in Table 3 because it was handled through rule-based reassignment using MNDWI thresholds in the subsequent decision logic. The threshold rules were used as local correction and anomaly-flagging criteria applied to ambiguous Dynamic World labels, rather than as independent

global classifiers. The $MNDWI > 0$ rule is physically interpretable because open water generally has relatively high green reflectance and strong SWIR absorption, producing positive Green-SWIR index values; this follows the MNDWI formulation proposed for enhancing open-water features [28], while subsequent threshold analysis also indicates that Green-SWIR water indices have comparatively stable but still scene-dependent thresholds [29]. Accordingly, pixels where the DW mode composite assigned bare ground but MNDWI values exceeded 0 were reassigned to water, correcting likely DW confusion between turbid shallow water and exposed substrate. Pixels initially labeled as flooded vegetation by Dynamic World were reassigned to water when $MNDWI > 0$, and to grassland otherwise. For the SAR cross-check, the $VV > -15$ dB rule was used conservatively to flag anomalous water detections rather than to automatically define water. Calm open water typically produces low C-band backscatter due to specular reflection, and previous Sentinel-1 studies in the Dongting–Poyang floodplain region have reported VV water-extraction thresholds around -15 to -16 dB [30,31]. Therefore, pixels labeled as water by DW but showing VV backscatter above -15 dB were treated as potential rough-water, mixed-pixel, or misclassification cases requiring caution. This rule-based refinement integrates the spectral, microwave, and deep-learning information streams into a unified classification decision while retaining the scene-dependent nature of threshold interpretation.

The complete classification decision process follows a hierarchical logic (Figure 3): (1) the DW monthly mode composite assigns an initial land-cover label to each pixel; (2) the nine DW classes are consolidated into four wetland categories via the reclassification ruleset (Table 3); (3) pixels with potential misclassification are identified using spectral index thresholds ($MNDWI > 0$ for bare-to-water correction); (4) SAR backscatter cross-checks are applied to flag anomalous water detections ($VV > -15$ dB); and (5) the final classified map is exported as a monthly 10 m raster for subsequent spatiotemporal analysis. This hierarchical approach ensures that the deep-learning semantic priors, optical spectral features, and microwave backscatter information are integrated in a structured and reproducible manner.

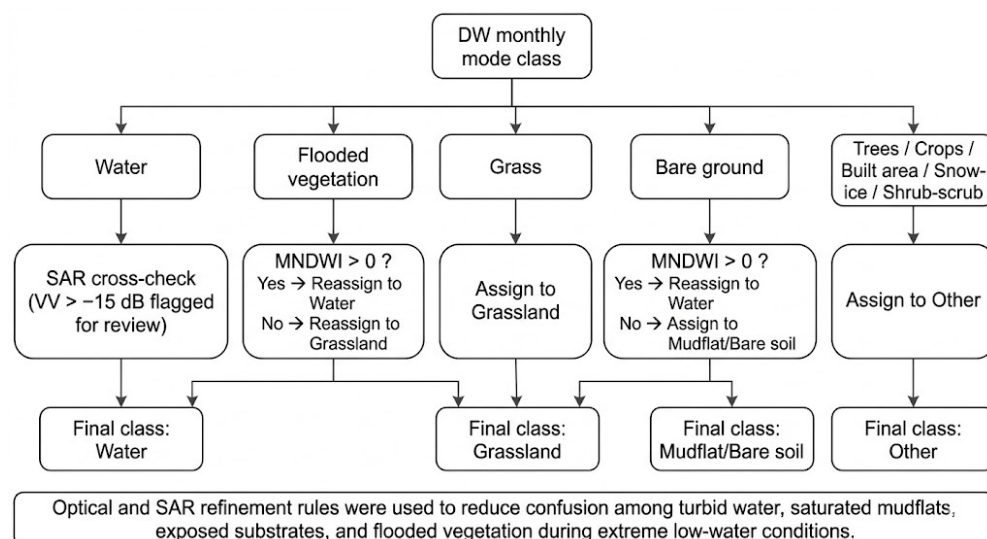


Figure 3. Hierarchical decision tree for rule-based monthly wetland classification using Dynamic World semantic priors, optical indices, and SAR backscatter. The Dynamic World monthly mode class provides the initial semantic label for each pixel, which is then refined through knowledge-guided reclassification rules tailored to the ecological context of the Poyang Lake floodplain. Pixels labeled as flooded vegetation or bare ground are reassigned according to MNDWI thresholds, while water pixels with anomalously high VV backscatter are flagged for review. The final monthly wetland classes comprise Water, Grassland, Mudflat/Bare soil, and Other.

This scheme is intended to detect broad departures from the expected sequence of wetland recession under extreme drought. Under more gradual recession, wetland landscapes would ordinarily pass through a transitional sequence from open water to wet mudflat, and then to grassland or drier exposed surfaces. In 2022, however, the water area contracted by 78.1% between July and September, indicating an exceptionally rapid high-water-to-dry transition. At the monthly compositing scale adopted here, this rapid drawdown is expressed as an apparent compression of transitional habitat states, with many pixels shifting from water or flooded vegetation to exposed substrate or grassland within a short period. The classification output retained an Other category for non-core land-cover elements, but the core wetland analysis focused on water, grassland, and mudflat/bare soil to capture these rapid landscape transitions while minimizing interference from secondary land-cover classes.

2.5. Accuracy Assessment

Classification accuracy was evaluated through stratified random sampling combined with cross-validation using multi-source high-resolution imagery, following established remote-sensing accuracy assessment protocols [32,33].

2.5.1. Validation Sample Design

To ensure that the validation samples comprehensively represented spatial heterogeneity across contrasting hydrological conditions, independent sample sets were generated for four key phenological and hydrological stages in 2022: March (near-normal water level), July (flood peak), September (rapid recession), and December (post-minimum early recovery). Stratified random sampling was applied, with sample allocation proportional to the areal extent of each core class (water, grassland, and mudflat/bare soil) in each period. In total, 987 independent validation samples were obtained across all stages, providing the statistical robustness required for spatiotemporal accuracy characterization. Although discrete validation sets were not generated for every calendar month, the four stages were chosen to span the full 2022 hydrological envelope: the September (rapid recession) and December (post-minimum early recovery) sets temporally bracket the October–November annual minimum and, therefore, validate the classifier against the same spectral conditions—fragmented residual water, exposed lakebed, and saturated mudflat—that dominate the core dry-season scenes. Because open water, the principal analytical variable of this study, is the most spectrally separable land–water transition and is validated at all four stages, the October–November water-area estimates are constrained by these bracketing samples rather than left unvalidated.

2.5.2. Reference Label Generation

Ground-truth labels were established through a hierarchical multi-source image interpretation approach. Near-date 10 m Sentinel-2 true-color and false-color composites (near-infrared–red–green band combinations, which enhance water–land boundary delineation) were used as the primary reference. For each validation sample, labels were interpreted against the closest available cloud-free or low-cloud monthly image context rather than a single universal acquisition date, so the assessment represents date-near monthly map states. For complex areas during the extreme low-water period, including highly fragmented water–land ecotones and spectrally ambiguous mixed pixels suspected to represent saturated mudflats, archived sub-meter commercial imagery available through Google Earth Pro (v7.3.6; Google LLC., Mountain View, CA, USA) was employed for supplementary verification. This hierarchical approach maximizes reference accuracy by leveraging the temporal currency of Sentinel-2 imagery alongside the spatial detail of commercial high-resolution imagery. To maintain labeling consistency, all reference

samples were interpreted by trained analysts following the same fixed evidence hierarchy, and samples that remained ambiguous after optical inspection were jointly re-examined against sub-meter imagery before a final label was assigned. Flooded vegetation was not retained as a separate accuracy class because, in the final three-class scheme, Dynamic World flooded-vegetation pixels were reassigned by rule to water ($\text{MNDWI} > 0$) or to grassland (otherwise); its classification performance is therefore embedded within the water and grassland classes rather than omitted from the assessment.

2.5.3. Accuracy Metrics

Confusion matrices were constructed for each temporal stratum, from which standard accuracy metrics were calculated: overall accuracy (OA), producer's accuracy (PA), user's accuracy (UA), F1-score, and the Kappa coefficient. F1-score was calculated for each class as the harmonic mean of PA and UA, thereby balancing omission and commission errors. The 95% confidence interval of OA was estimated using the Wilson score interval for a binomial proportion based on the 987 validation samples.

Given that the mudflat/bare category was intended primarily to capture the broad emergence of exposed substrates during rapid recession rather than to distinguish fine moisture states, the relatively lower producer's accuracy for this class does not negate the study's ability to identify major drought-induced exposure patterns at the landscape scale.

2.6. Spatiotemporal Analysis Framework

To systematically investigate the multi-scale impacts of extreme drought on Poyang Lake wetlands, a three-tier analytical framework was established. The connectivity-related evidence is defined operationally as observable surface-water fragmentation derived from monthly remote-sensing water masks. Specifically, the analysis quantifies the contraction of surface water, the subdivision of continuous water bodies into discrete patches, and the apparent loss of visible surface-water linkage between sub-lakes and the main lake body. These metrics should therefore be interpreted as reserve-scale surface-water fragmentation indicators, rather than as graph-theoretic, bathymetry-based, or hydraulic connectivity metrics.

Drought Anomaly Quantification (historical baseline comparison): Using identical data sources and processing workflows as for 2022, monthly mean water area was calculated for the period 2017–2021 to establish a historical hydrological baseline. Monthly anomalies and relative change rates for 2022 were derived by comparing observed water extent against this baseline, enabling identification of key temporal turning points in drought onset and the magnitude of extreme water-area deficits.

Wetland Landscape Transition Analysis (Markov transition matrices): To reveal drought-induced habitat transitions, a Markov transition matrix approach was applied. The 10 m wetland classification results for July (flood season peak) and September (rapid recession period) of 2022 were spatially overlaid, and transition areas and proportional flows among core classes (water, grassland, mudflat/bare soil) were quantified. This analysis provides a precise, pixel-level characterization of the "leap-type" habitat transitions induced by extreme hydrological stress.

Spatially Heterogeneous Sub-Lake Response Analysis: To isolate differential drought responses among dish-shaped sub-lakes, nine independent vector boundaries were used to extract monthly classified maps and water-area time series from the 2022 raster dataset. Sub-lakes were stratified according to the 2022 management context rather than by a simple natural-versus-artificial dichotomy: unregulated in 2022 (Dacha Lake and Bang Lake), reserve-managed in 2022 (Dahuchi Lake and Sha Lake), and facility-present in 2022 (Xiang Lake, Zhonghuchi Lake, Zhushi Lake, Changhuchi Lake, and Meixi Lake). To provide

quantitative support for this comparison, we calculated area-based surface-water recession and retention proxy metrics for each sub-lake, including July–September water-loss rate, July–November water-loss rate, November/July retention ratio, and the first month when water area declined below 50% and 20% of its July extent. These metrics quantify remotely observed surface-water recession and retention, but they are not direct water-level recession rates or hydrodynamic lag-time estimates.

Surface-Water Fragmentation Metrics: To provide quantitative evidence for the visually observed fragmentation process, binary surface-water masks were derived from the reclassified monthly wetland maps. Discrete water patches were delineated using 8-neighbor connectivity. For each monthly raster in 2022, we calculated the total water area (water_area_km²), patch number (PN), mean patch size (MPS_km²), and the largest patch index (LPI_percent), defined as the area of the largest water patch divided by total water area and expressed as a percentage. Metrics were calculated and tabulated for all 12 months. To evaluate the influence of isolated pixels on PN and related metrics, a minimum-patch filtering check was additionally conducted using 3-, 5-, and 10-pixel thresholds; these filtered estimates were used as a sensitivity check, while the reported monthly metrics retained the full mapped water mask. The interpretation emphasizes the main annual stages: July as the flood season’s maximum extent, August as rapid subdivision during the main drawdown phase, September as severe drought, November as the annual minimum surface-water extent and residual-water concentration, and December as early partial recovery with renewed proliferation of many very small water patches. Accordingly, August should not be interpreted as the annual maximum of PN across the full 12-month sequence.

3. Results

3.1. Classification Accuracy Assessment

3.1.1. Confusion Matrix Analysis

Based on 987 stratified validation samples, the integrated multi-source remote-sensing and deep-learning classification framework achieved an OA of 87.44%, with a Kappa coefficient of 0.80, indicating strong agreement between classified outputs and reference observations (Table 4). Given that the Poyang Lake National Nature Reserve is a strictly protected wetland ecosystem with minimal dryland agriculture or built-up area, non-wetland background classes in DW predictions, which were predominantly misclassified hygrophilous vegetation, were merged into the grassland category for accuracy assessment, consistent with ecological interpretation and visual validation. This merge affects only the assignment of non-core background pixels and does not alter the water or mudflat/bare soil classes that are central to the drought-response analysis; within the strictly protected reserve, dryland agriculture and built-up surfaces are essentially absent, so these background pixels represent misclassified hygrophilous vegetation rather than a distinct anthropogenic land cover, making the merge ecologically conservative rather than a source of systematic bias.

Table 4. Confusion matrix of wetland landscape classification for 2022.

Ground Truth \ Predicted	Water	Grassland	Mudflat/Bare	Total	PA (%)	F1 (%)
Water	218	36	8	262	83.21	83.52
Grassland	8	453	7	468	96.79	91.70
Mudflat/Bare	34	31	192	257	74.71	82.76
Total (Predicted)	260	520	207	987	—	—
User’s Accuracy (%)	83.85	87.12	92.75	—	OA = 87.44% (Wilson 95% CI: 85.22–89.36%); Kappa = 0.80	

The classification performance was adequate for landscape-scale drought-response interpretation, while boundary-level uncertainty remained. The overall accuracy was 87.44% (863/987), with a Wilson 95% confidence interval of 85.22–89.36%. The class-wise F1-scores were 83.52% for water, 91.70% for grassland, and 82.76% for mudflat/bare soil. Water body identification was moderately robust, with PA and UA values of 83.21% and 83.85%, respectively. The mudflat/bare soil class had a lower PA of 74.71%, indicating omission uncertainty along water–mudflat and wet–substrate boundaries, although its UA was high (92.75%). Among the 257 reference mudflat/bare validation samples, 192 were correctly classified (74.71%), while 34 (13.23%) were mapped as water, 21 (8.17%) as grassland, and 10 (3.89%) as Other/non-core. These errors indicate that uncertainty was concentrated in transitional water–mudflat–vegetation conditions, supporting the interpretation of the mudflat/bare class as a broad exposed-substrate category rather than a fine moisture-state class. Visual inspection of misclassified samples further indicated that these errors were not randomly distributed but were spatially concentrated along sub-lake margins and within rapidly desiccating water–mudflat transition zones during the September–November recession period, rather than occurring throughout the reserve. Overall, the classification accuracy is sufficient to support landscape-scale interpretation of severe water-area contraction and exposed-substrate expansion.

Because the water PA/UA values were approximately 83% and the mudflat/bare soil PA was 74.71%, the water–mudflat boundary and saturated-substrate transition zones should be interpreted with caution. A screening-level uncertainty check based on the confusion matrix indicated that the September–November 2022 water deficit remained large under alternative water-area estimates. The mapped deficits of approximately 73.6–74.7% were close to confusion-adjusted estimates of approximately 71.2–72.1%, and even the conservative upper-screening estimate retained deficits of approximately 66.4–67.5% relative to the 2017–2021 baseline. This check is not a full design-based area-adjusted accuracy assessment, but it supports the directional robustness of severe surface-water contraction during the 2022 drought.

3.1.2. Optical–SAR Cross-Validation

To independently assess data reliability, monthly water-area time series derived from Sentinel-1 SAR were cross-validated against Sentinel-2 optical estimates (Figure 4). After excluding the September outlier, which was severely affected by extensive saturated mudflat interference, the two independent sensors exhibited strong temporal consistency (Pearson $r = 0.84$; $R^2 = 0.70$; $p < 0.01$), validating the overall reliability of both monitoring streams.

Agreement was particularly strong at hydrological extremes. In August, the VH-corrected Sentinel-1-derived water area (113.52 km²) closely matched the Sentinel-2 estimate (119.23 km²), with a relative difference of only 4.8%. This corrected value should be distinguished from the uncorrected VV-based August estimate of 58.10 km² discussed in Section 4.1.2, which represents the wind-roughening-induced SAR omission case before polarization adjustment. At the annual low-water stage in November, radar-derived (30.59 km²) and optical-derived (35.35 km²) estimates differed by 4.76 km², providing independent dual confirmation of the exceptionally low water extent (<40 km²) recorded in 2022.

A pronounced divergence occurred during the rapid recession phase in September. Sentinel-2 captured an abrupt contraction of open water to 46.09 km², whereas Sentinel-1 estimates remained as high as 108.47 km². This systematic SAR overestimation is attributable to the rapid emergence of saturated mudflats, whose high moisture content and smooth surfaces produce strong specular reflection at C-band wavelengths, generating low-backscatter signals that closely mimic those of calm open water [34,35]. This divergence highlights

the fundamental limitations of SAR-only approaches during extreme drying phases and, conversely, underscores the value of the optical–DW integration framework used here for capturing wetland dynamics under extreme drought.

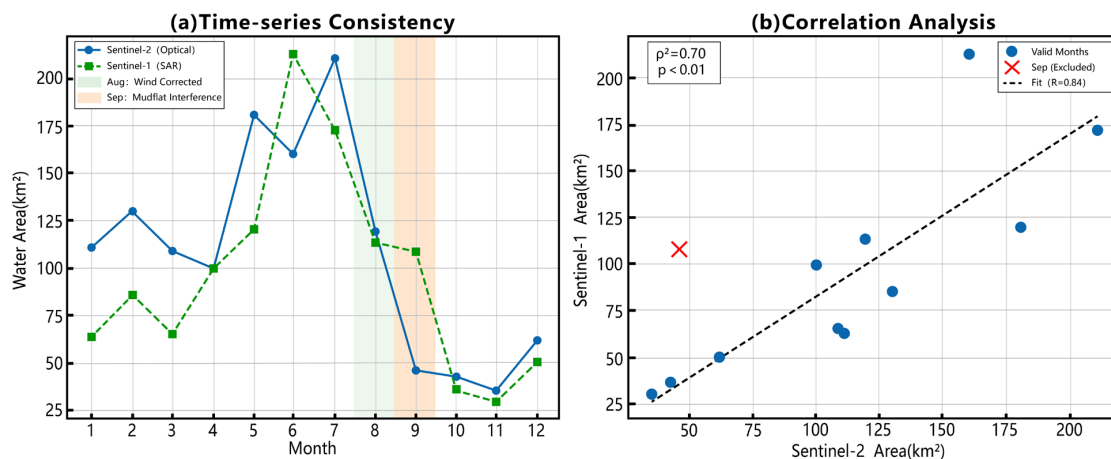


Figure 4. Optical versus SAR cross-validation of monthly water-area estimates in 2022. (a) Monthly Sentinel-2 and Sentinel-1 water-area time series, showing the August VH-based wind correction and September saturated-mudflat interference. (b) Correlation between Sentinel-2 and Sentinel-1 estimates after applying the August VH correction and excluding the September outlier. The dashed line indicates the fitted relationship, and the red cross marks the excluded September point. The correlation coefficient was $r = 0.84$, with $R^2 = 0.70$ and $p < 0.01$.

3.2. Spatiotemporal Wetland Dynamics Under Extreme Drought

3.2.1. Monthly Water-Area Dynamics

Monthly water-area dynamics in the Poyang Lake National Nature Reserve during 2022 displayed a unimodal seasonal pattern with an anomalously abrupt recession phase (Figure 5). During the first half of the year, the water area increased progressively and reached its annual maximum in July at 210.89 km², when major sub-lakes were fully hydrologically connected with the main lake body, forming a continuous “single-lake” landscape.

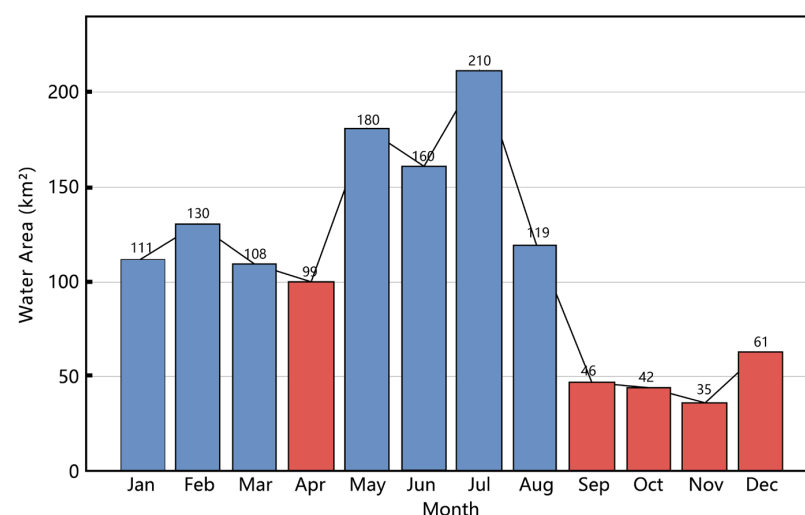


Figure 5. Monthly water-area dynamics in the Poyang Lake National Nature Reserve during 2022, highlighting the abrupt cliff-like decline from July to September. Red bars highlight the months emphasized as dry or low-water stages in the anomaly interpretation, while blue bars indicate the remaining months; the black line shows the monthly water-area trajectory in 2022.

A cliff-like recession ensued immediately following the July flood peak. Between July and August, persistent extreme heat and precipitation deficit across the Yangtze River Basin drove an abrupt water-area contraction of 91.66 km² (−43.5%), reducing the total water extent to 119.23 km². The recession intensified further between August and September, with the water area plummeting to 46.09 km². Overall, from the July flood peak to the September interim minimum, the reserve experienced a 78.1% contraction of water area within only two months, which far exceeds the typical seasonal recession rate. The annual absolute minimum was recorded in November at 35.35 km², when extensive lakebeds were exposed as mudflats and the remaining surface water was concentrated in a small number of persistent water bodies.

3.2.2. Anomalous Wetland Landscape Succession

Accompanying the rapid water contraction during late summer and autumn, wetland landscape composition underwent pronounced anomalous succession (Figure 6). During the flood peak of July, submerged grasslands and mudflats were largely inundated, with open water and flooded vegetation widely distributed, reflecting a strongly hydrologically dominated surface-water configuration and indistinct water–land boundaries.

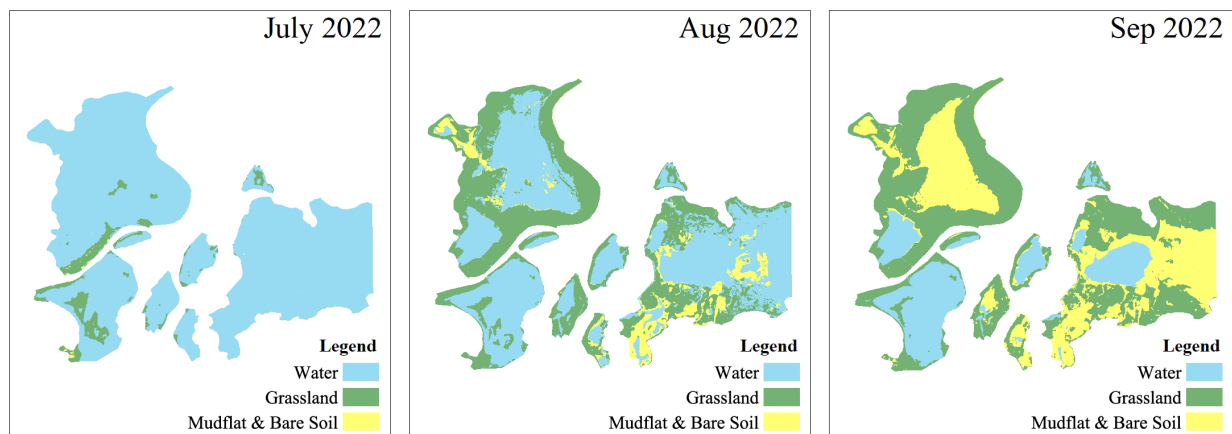


Figure 6. Spatiotemporal evolution of wetland landscape types from July to September 2022.

From August to September, an extreme recession phase, the wetland landscape was fundamentally reorganized. Markov transition matrix analysis (Figure 7) indicates that up to 69.1% of the July open-water and flooded-vegetation area (~154.48 km²) had transitioned to exposed substrate or grassland by September, suggesting that the intermediate mudflat stage was substantially compressed or not detectable at the monthly compositing scale. This apparent “leap-type” succession represents a marked departure from the more gradual recession sequence typically expected in floodplain wetlands and is consistent with the exceptional rate and magnitude of the 2022 drought-induced drawdown. By September, this anomalous habitat structure was further consolidated, with continued expansion of bare land and xerophytic grassland, along with progressive disappearance of transitional shallow-water and wet-mudflat habitats. The rapid contraction of these transitional habitats is likely to have reduced the availability of suitable foraging habitats for migratory waterbirds during their peak usage period (November–December).

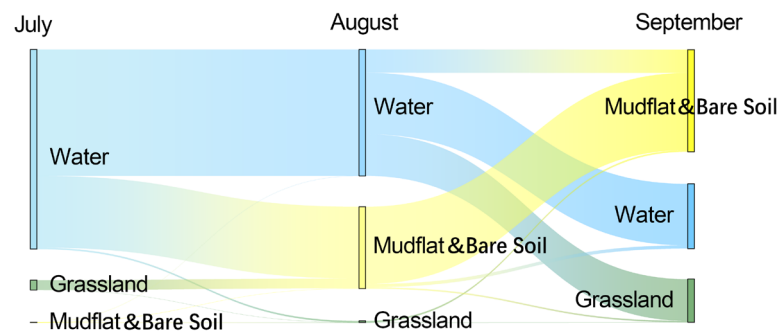


Figure 7. Sankey diagram of wetland landscape succession in the Poyang Lake National Nature Reserve from July to September 2022. The dominant transition from open water or flooded vegetation directly to exposed substrate or grassland indicates an apparent leap-type succession, in which the usual gradual sequence from open water to shallow water, wet mudflat, and then grassland was compressed at the monthly observation scale. Ecologically, this pattern implies a shortened window for shallow-water and wet-mudflat foraging habitats, reduced development time for submerged macrophytes, and potential loss of transitional feeding habitats for overwintering waterbirds.

3.3. Comparison with Historical Baseline

Comparison of 2022 monthly water areas against the 2017–2021 historical baseline reveals a pronounced two-phase hydrological pattern (Table 5; Figure 8). The first half of 2022 was characterized by a notable “wet anomaly”: from May to July, the water area consistently exceeded the long-term mean, with May reaching 180.69 km², which was 91.7% above the baseline value of 94.26 km². This demonstrates that 2022 was not defined by persistent year-round drought but, rather, by an exceptionally abrupt transition from anomalously wet to historically dry conditions.

Table 5. Monthly water area deviation from historical baseline (2017–2021) in the Poyang Lake National Nature Reserve, 2022.

Month	Baseline 2017–2021 (km ²)	Observed 2022 (km ²)	Difference (km ²)	Change Rate (%)	Hydrological Status
January	121.82	111.02	−8.80	−8.9%	Near-normal, slightly dry
February	88.84	130.09	+41.25	+46.4%	Significantly wet
March	112.96	108.83	−4.13	−3.7%	Near-normal
April	128.58	99.82	−28.76	−22.4%	Moderately dry
May	94.26	180.69	+86.43	+91.7%	Extremely wet
June	146.54	160.39	+13.85	+9.5%	Moderately wet
July	201.63	210.89	+9.26	+4.6%	Flood peak (normal)
August	198.13	119.23	−78.90	−39.8%	Drought onset (inflection point)
September	174.86	46.09	−128.77	−73.6%	Extreme drought
October	159.93	42.74	−117.19	−73.3%	Persistent extreme drought
November	139.78	35.35	−104.43	−74.7%	Annual minimum (critical habitat loss)
December	122.84	61.99	−60.85	−49.5%	Early recovery

A sharp reversal commenced in August. The water area declined to 119.23 km², representing a 39.8% deficit relative to the historical mean. This deficit intensified dramatically through September–November, the core extreme dry phase. In September, the water area contracted to 46.09 km², 73.6% below the baseline (174.86 km²). The maximum anomaly was recorded in November, when the observed water area (35.35 km²) represented only 25.3% of the long-term mean (139.78 km²), which was equivalent to the loss of approximately three-quarters of the typical water surface during the critical migratory bird overwintering period. By December, partial hydrological recovery was underway, although the water area (61.99 km²) remained 49.5% below the historical mean, confirming the persistence of drought effects well into the post-season period.

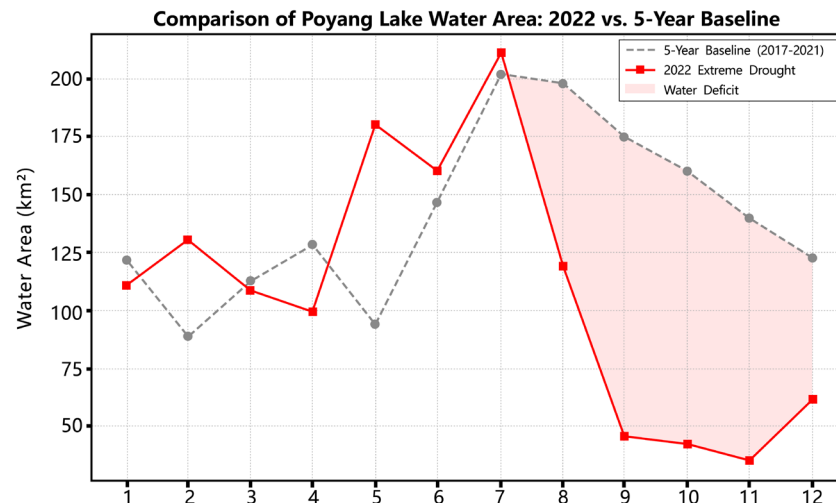


Figure 8. Deviation of observed water area from the 2017–2021 historical baseline, illustrating the pronounced wet-to-dry transition in 2022.

3.4. Fine-Scale Heterogeneous Responses of Dish-Shaped Sub-Lakes

Having established the exceptional magnitude of the 2022 wet-to-dry transition relative to both the intra-annual trajectory (Section 3.2) and the recent historical baseline (Section 3.3), the analysis now turns to the heterogeneous responses of individual dish-shaped sub-lakes that underlie this reserve-scale anomaly.

3.4.1. Reserve-Scale Surface-Water Fragmentation

The reserve-scale fragmentation metrics revealed a staged reorganization of surface water across the full 2022 sequence (Figure 9). During January–April, the water area remained moderate (99.94–130.25 km²), while PN ranged from 454 to 748, indicating a relatively dispersed but not yet drought-driven surface-water pattern. From May to July, the water area expanded markedly and reached 211.15 km² in July, while PN declined to 109 and MPS increased to 1.94 km², reflecting flood-season coalescence of water bodies. The main drawdown phase began in August, when the water area decreased to 119.38 km², PN increased sharply to 1428, and MPS fell to 0.084 km², indicating rapid subdivision of formerly continuous water surfaces. By September–November, many small patches had disappeared as the drought intensified; the water area reached the annual minimum in November (35.39 km²), with PN declining to 257 and LPI increasing to 63.09%, indicating concentration of residual water in a few persistent water bodies. December showed partial water-area recovery to 62.06 km² but the highest PN (1660) and lowest MPS (0.037 km²), suggesting renewed proliferation of numerous very small water patches during post-minimum early recovery. Thus, August is interpreted as the strongest subdivision during the main July–November drawdown phase, whereas December represents a distinct post-minimum small-patch proliferation stage across the full annual sequence.

The minimum-patch filtering check further indicated that the interpretation was not controlled by the area contribution of isolated pixels. Removing water patches smaller than 3–10 pixels substantially reduced PN in months dominated by numerous small patches, especially August and December, but changed the total water area by less than 0.5%. For example, PN decreased from 1428 to 439 in August and from 1660 to 571 in December under the 10-pixel filter, while the removed water area accounted for only 0.20% and 0.45% of the mapped water area, respectively. Thus, PN was interpreted jointly with MPS and LPI: August reflects rapid subdivision during drawdown, whereas December reflects early-recovery proliferation of many small residual or newly reconnected water patches.

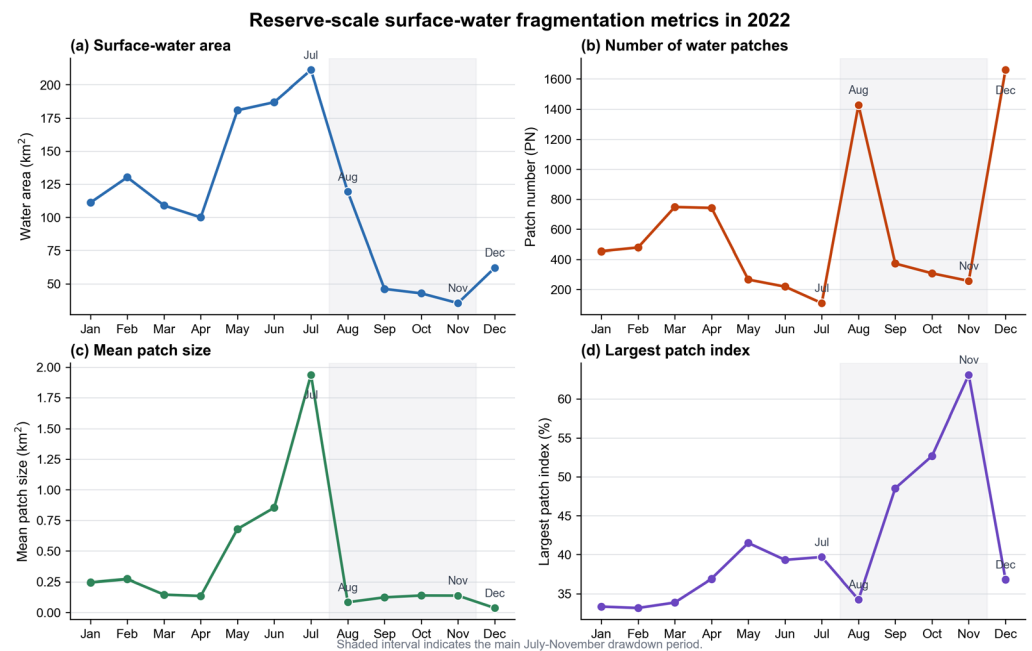


Figure 9. Monthly changes in (a) surface-water area, (b) patch number (PN), (c) mean patch size (MPS), and (d) largest patch index (LPI) derived from binary water masks. Water patches were delineated using 8-neighbor connectivity. The shaded interval indicates the main July–November drawdown period.

Following the operational definition in Section 2.6, this pattern is interpreted as observable surface-water fragmentation from remote-sensing water masks. It does not by itself identify hydraulic gradients, bathymetric thresholds, groundwater exchange, or complete hydrodynamic connectivity among sub-lakes.

3.4.2. Contrasting Response Regimes Among Sub-Lakes

Sub-lakes exhibited sharply heterogeneous surface-water recession and retention responses when evaluated with area-based proxy metrics (Figure 10). The two unregulated-in-2022 sub-lakes showed the strongest drawdown: Bang Lake declined from 72.07 km² in July to 0.32 km² in November, corresponding to a 99.6% loss and a November/July retention ratio of 0.004, while Dacha Lake declined from 83.79 km² to 1.76 km², corresponding to a 97.9% loss and a retention ratio of 0.021. These results indicate that the absence of artificial water-control facilities was associated with rapid loss of observable surface water during the 2022 extreme drought.

Sub-lakes that were reserve-managed in 2022 showed stronger water retention overall, but their responses were not identical. Dahuchi Lake retained a nearly stable core water body, with only 6.1% July–November water loss and a November/July retention ratio of 0.939. Sha Lake also retained more water than the unregulated lakes, but it still lost 54.7% of its July water area by November, with a retention ratio of 0.453. Sub-lakes that were facility-present in 2022 displayed the greatest internal variability: Meixi Lake retained 74.0% of its July water area by November, whereas Xiang Lake was almost completely dry by November. Therefore, the presence of water-control infrastructure alone did not determine drought response; operation timing, management objective, authority, and local basin morphology likely interacted with the regional drought forcing. These contrasting trajectories are also visible spatially in Figure 11, which compares the flood-peak (July) and extreme low-water (November) states of representative sub-lakes: Bang Lake transitioned almost entirely to exposed substrate by November, whereas Dahuchi Lake retained a concentrated residual core.

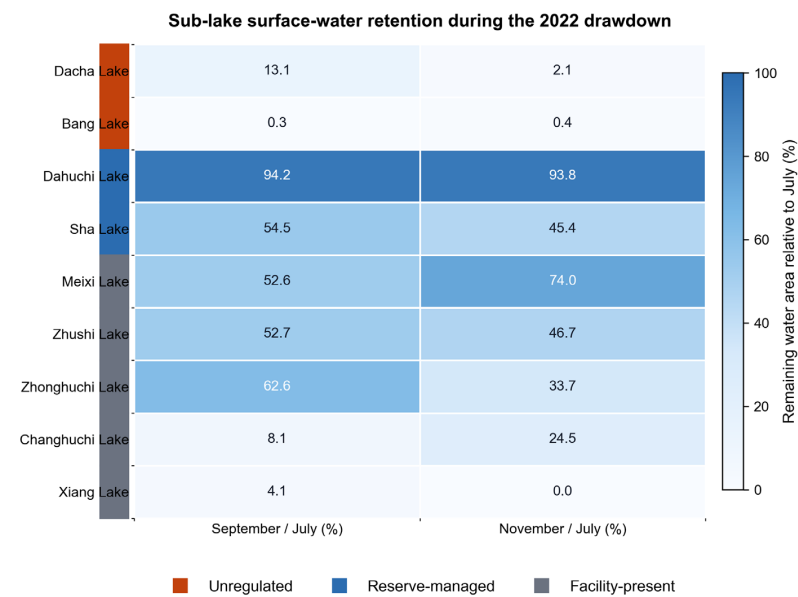


Figure 10. Sub-lake surface-water retention during the 2022 drawdown. Heatmap showing remaining surface-water area in September and November relative to July 2022 for nine representative sub-lakes. Colors indicate retention percentage, and the side bar denotes the 2022 management-context category. The Other class was excluded from this water-area analysis.

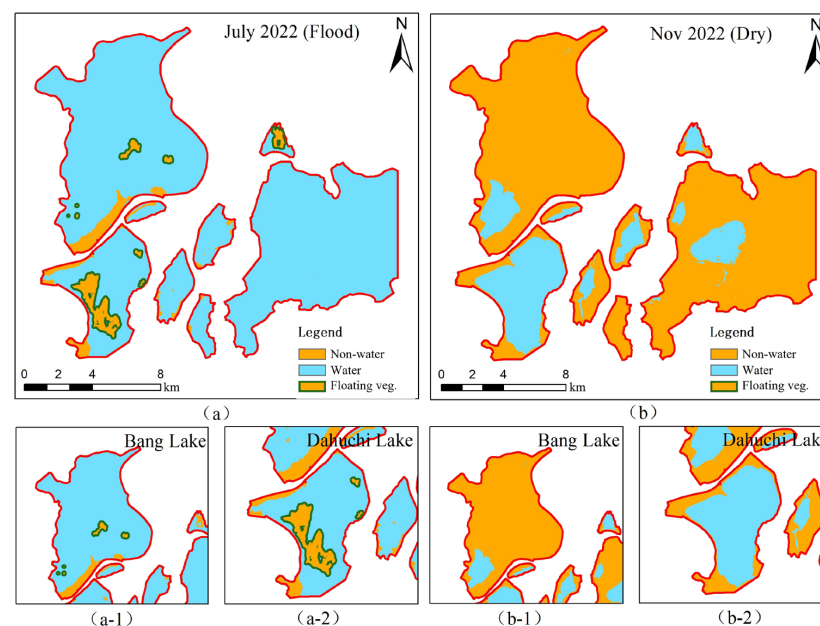


Figure 11. Spatial response of dish-shaped sub-lakes during extreme drought: comparison of flood-peak and extreme low-water conditions. **(a)** Spatial pattern of water, non-water, and floating vegetation in July 2022, representing the flood-peak condition. **(b)** Spatial pattern of water, non-water, and floating vegetation in November 2022, representing the extreme low-water condition. **(a-1)** Enlarged July view of Bang Lake. **(a-2)** Enlarged July view of Dahuchi Lake. **(b-1)** Enlarged November view of Bang Lake. **(b-2)** Enlarged November view of Dahuchi Lake. Blue denotes open water, orange denotes non-water or exposed substrate, and yellow patches with dark green outlines denote floating vegetation. The floating-vegetation category represents flood-season water surfaces covered by floating-leaved vegetation that may appear as non-water in optical imagery, clarifying that green-outlined patches are vegetation-covered water rather than bare mudflats. For this comparison, the classification is deliberately simplified to water, non-water, and floating vegetation to emphasize surface-water contraction, in contrast to the full three-class wetland scheme (water, grassland, and mudflat/bare soil) applied elsewhere in the analysis.

4. Discussion

4.1. Methodological Advances: Multi-Source Synergy and Deep Learning

4.1.1. Advantages of the Integrated Framework

The multi-source remote-sensing framework developed here offers three practical methodological strengths for extreme-drought wetland monitoring:

First, the adoption of Sentinel-2 at 10 m spatial resolution provides a threefold-finer linear spatial resolution than the widely used Landsat archive (30 m), corresponding to a ninefold reduction in pixel area. Under the extreme drought conditions of 2022, Poyang Lake experienced severe habitat fragmentation, with many dish-shaped sub-lakes and connecting channels shrinking to widths below 30 m. In such sub-pixel-fragmented environments, 30 m data are systematically susceptible to mixed-pixel effects, leading to underestimation or wholesale omission of residual water bodies [11]. The 10 m Sentinel-2 data improve detection of narrow water channels and isolated residual ponds embedded within dry mudflat substrates, which are critical hydrological features that are ecologically significant yet spectrally and spatially challenging to identify.

Second, the DW deep-learning model, based on an FCN architecture, intrinsically incorporates spatial contextual information extending beyond the single-pixel level. This contextual awareness confers a fundamental advantage over traditional single-pixel spectral thresholding (e.g., NDWI) and shallow machine-learning methods (e.g., Random Forest) during extreme recession phases, when turbid shallow water, saturated mudflats, and exposed lakebeds exhibit spectral signatures that substantially overlap. Independent evaluations of global 10 m land-cover products confirm that DW achieves competitive detection of fine-scale water features while suppressing salt-and-pepper noise in highly dynamic wetland environments [17,36].

Third, the optical–SAR integration establishes a robust cross-validation mechanism that simultaneously mitigates the two principal failure modes of single-sensor approaches: persistent cloud cover blocking optical observations, and specular reflection from saturated mudflats causing systematic SAR overestimation of water extent. The complementary strengths of Sentinel-2 optical data and the DW contextual classifier together support more reliable water delineation precisely during the extreme low-water stages, when monitoring fidelity is most critical and most difficult to achieve.

It should be noted that the classification framework does not involve independent training of a deep-learning model on site-specific samples. Instead, it strategically leverages the pre-trained DW product as an upstream semantic intelligence layer and refines its outputs through physically informed, rule-based post-processing using multi-source spectral and microwave features. The primary contribution of this work therefore lies not in algorithmic novelty per se but in the construction of a robust, cloud-based monitoring pipeline capable of generating high-quality monthly wetland landscape maps at 10 m resolution. These monthly maps, in turn, enable the discovery of fine-scale ecological processes—specifically, heterogeneous drought responses and observable surface-water fragmentation of dish-shaped sub-lakes—that were difficult to detect in previous coarser-resolution or single-sensor studies.

This contribution can be further clarified through direct comparison with the work of Liu et al. [4], who characterized the same 2022 Poyang Lake drought event using coarser-resolution satellite observations and in situ hydrological records aggregated at the whole-lake scale. Their analysis corroborates the broad timing and severity of the 2022 low-water anomaly identified here, providing independent confirmation of the overall drought timeline. However, because their approach operates at the whole-lake scale and does not resolve individual dish-shaped sub-lakes, it cannot capture the sub-lake-scale surface-water fragmentation and heterogeneous management-context responses docu-

mented in Section 3.4. The present 10 m monthly framework therefore complements rather than duplicates this prior whole-lake characterization, extending the spatial resolution of analysis from the lake scale to the scale of individual floodplain habitat units.

Recent remote-sensing studies further support this methodological direction. Boundary-refinement networks have shown that explicit treatment of object edges can improve high-precision feature extraction from remote-sensing imagery [37], while dense time-series mapping studies demonstrate the value of multi-temporal compositing for overcoming optical observation gaps in cloudy or snow-covered regions [14]. In addition, evaluations of emerging satellite data such as SDGSAT-1 GLI indicate that sensor performance should be interpreted with respect to target morphology and spatial scale [38]. These studies collectively reinforce the need for high-resolution spatial detail, multi-source temporal integration, and explicit validation when monitoring spatially complex wetland landscapes such as the Poyang Lake floodplain.

4.1.2. Sensor-Specific Limitations and Complementarity

The optical–SAR cross-validation results (Figure 4) provide mechanistic insight into the sensor-specific limitations operative during extreme hydrological transitions. Both sensors exhibited consistent overall temporal trends ($r = 0.84$, $p < 0.01$ after outlier removal) yet displayed systematic and opposing biases during critical drawdown phases, confirming that each sensor alone is insufficient for robust wetland monitoring under extreme drought.

The uncorrected VV-based Sentinel-1 estimate for August was 58.10 km², far below the Sentinel-2 estimate of 119.23 km². This underestimation is mechanistically attributable to wind-induced roughening of open-water surfaces during convective events, which enhances diffuse backscatter and causes extensive open-water surfaces to be misclassified as non-water [13]. This failure mode was effectively addressed by switching to VH polarization in August: the corrected Sentinel-1 estimate increased to 113.52 km² and the relative difference from Sentinel-2 decreased from approximately 51% to 4.8%. This comparison demonstrates that polarization-adaptive strategies are essential for SAR-based water monitoring during active convective periods.

Conversely, the pronounced Sentinel-1 overestimation during September–October (~60 km² excess) reflects the rapid emergence of extensive saturated mudflats. Their high volumetric moisture content and smooth surfaces generate very low C-band backscatter, which closely mimics the radar signature of calm open water and produces systematic specular-reflection-induced overestimation [12,34,35]. This physical mechanism represents a fundamental constraint of SAR-only monitoring approaches during extreme drying phases and is precisely the condition for which the optical–deep-learning framework provides a useful complementary advantage.

4.2. Hydrological Anomaly and Cascading Ecological Consequences

The 2022 wet-to-dry transition, from an extreme wet anomaly in May (+91.7%) to record-low water areas in September–November (−73.6% to −74.7%), demonstrates an exceptional disruption of the natural seasonal hydrological rhythm that underpins wetland ecosystem stability and service provision. This rapid transition and its ecological consequences are broadly consistent with patterns reported from other large floodplain systems experiencing extreme drought, including the Pantanal during the 2019–2020 event [39,40]. The ecological implications discussed below should be interpreted as evidence-based inferences grounded in known habitat–hydrology relationships, rather than as direct biological measurements derived from the present remote-sensing dataset.

Under normal gradual recession, water-level drawdown regulates the sequential spatial organization of vegetation belts and supports continuous biomass accumulation

in submerged macrophyte communities [20]. The accelerated drawdown between July and August 2022 is likely to have caused premature exposure and rapid desiccation of immature submerged macrophytes, including *Vallisneria spiralis*—a primary food resource for overwintering Siberian cranes (*Grus leucogeranus*). Water depth is a key determinant of reproductive allocation and tuber formation in this species [41]; the premature loss of suitable depth conditions in 2022 may therefore have suppressed tuber biomass accumulation, with likely consequences for the availability of this critical food resource during the peak overwintering period [11]. Beyond food resource availability, the rapid contraction of transitional wet substrate habitats documented here is likely to have reduced foraging opportunities for shorebirds and waders that depend on soft mudflat conditions for prey capture [42]. The temporal coincidence of this habitat collapse with the peak waterbird overwintering season (November–December) represents a critical conservation concern with potential population-level consequences for multiple IUCN-listed species.

4.3. Heterogeneous Sub-Lake Responses and Management Implications

The pronounced spatial heterogeneity in drought responses among dish-shaped sub-lakes was shaped by the interplay of local elevation, observable surface-water linkage, lake-basin morphology, and artificial water regulation. This finding has direct implications for adaptive wetland management because drought vulnerability and potential refuge capacity were unevenly distributed across sub-lake units. The interpretation avoids treating hydrodynamic connectivity as a single dominant control and instead emphasizes that remotely observed surface-water configuration interacted with topographic and management settings.

The sub-lake comparison indicates that drought vulnerability was shaped not only by geomorphic setting and observable surface-water linkage but also by the 2022 management context. The contrast between Bang Lake and Sha Lake is particularly informative after separating their boundaries: Bang Lake, where no artificial water-control facilities for regulation were confirmed, experienced nearly complete surface-water loss, whereas Sha Lake, a documented reserve-managed winter water-control lake, retained a larger fraction of its July water area. Dahuchi Lake showed the strongest buffering effect, consistent with its reserve-managed water-control status and local basin setting. These patterns support a management-context interpretation rather than a simple natural-versus-artificial dichotomy.

Facility-present sub-lakes showed heterogeneous responses, demonstrating that infrastructure presence by itself did not guarantee water retention. Some facility-present sub-lakes retained substantial residual water, whereas others underwent severe recession. This variability may reflect differences in operation timing, regulation objective, management authority, local topography, and the severity of the 2022 drought. Because the dominant operation objective for these sub-lakes could not be fully determined from the available information, they are interpreted as facility-present in 2022 rather than as uniformly fisheries-oriented or waterbird-oriented systems.

These findings suggest that adaptive wetland management during extreme drought should consider not only whether water-control infrastructure exists but also who has operational authority, what the regulation objective is, and when regulation is implemented. Reserve-managed water control in Dahuchi Lake and Sha Lake appears to have contributed to residual-water retention to varying degrees, whereas unregulated lakes rapidly lost observable surface water. For facility-present sub-lakes with uncertain 2022 management objectives, future coordination among reserve authorities, local governments, and sectoral users may be critical for aligning drought-period water management with habitat-refuge needs, subject to ecological and regulatory feasibility assessment [20,43]. This implication is

consistent with recent wetland-governance perspectives emphasizing adaptive, multi-level, and stakeholder-engaged management frameworks for sustaining wetland functions under changing environmental and institutional conditions [44].

Beyond immediate drought-response management, the observed differences in water retention among sub-lakes also have broader implications for wetland ecosystem-service assessment. Residual water bodies during severe drawdown may contribute not only to habitat refugia for migratory waterbirds but also to the capacity of floodplain wetlands to sustain ecological functions under competing water-use demands. From this perspective, future assessments could link the surface-water fragmentation and retention indicators developed here with ecosystem-service supply–demand or water–energy–food nexus frameworks [23]. Such integration would help translate event-scale remote-sensing evidence into management-relevant evaluations of habitat provision, water regulation, and sustainable wetland use.

4.4. Limitations and Future Perspectives

While the proposed framework is effective for resolving event-scale surface-water contraction and relative differences in sub-lake drought responses, its interpretive strength remains greater for broad hydrological and landscape changes than for fine substrate moisture states, sub-canopy inundation, or volumetric storage dynamics. Despite the methodological advances demonstrated here, several limitations constrain the present analysis and motivate future research directions. It should also be acknowledged that the producer's accuracy of the mudflat/bare soil class (74.71%) was lower than that of the other categories. Because this class was used here primarily to identify broad-scale exposure of substrates rather than to quantify fine moisture states, this lower producer's accuracy is unlikely to alter the direction of the principal findings, although it does constrain the precision of pixel-level habitat-state attribution. First, the DW classification scheme conflates wet mudflats and dry bare soil within a single "bare ground" category, limiting the capacity to quantitatively distinguish the successional trajectory between moist and desiccated substrates during rapid water recession—a distinction that is ecologically critical for mudflat-dependent shorebirds and invertebrate communities.

The rule-based thresholds also introduce methodological uncertainty. Although $MNDWI > 0$ and $VV > -15$ dB are supported by physical interpretation and previous optical/SAR water-mapping studies [28–31], they should not be interpreted as universally fixed decision boundaries. In this study, they were used only to refine or flag ambiguous DW-derived labels rather than to replace the multi-source classification framework. A complete perturbation-based threshold sensitivity analysis was not included because it would require reprocessing the original Sentinel-2 spectral-index composites and Sentinel-1 backscatter layers across all monthly scenes. Consequently, the reported results should be interpreted as robust for landscape-scale surface-water contraction and fragmentation patterns, but not as a full quantification of threshold-induced uncertainty. Future work should perturb key MNDWI and SAR backscatter thresholds and evaluate the resulting changes in class accuracy, water area, and surface-water fragmentation metrics. In addition, because all 987 validation samples were drawn from 2022, consistent classifier performance for the 2017–2021 baseline years was assumed, on the basis of identical data sources and processing workflows, but was not independently validated against ground-truth reference labels for those years; validating classification accuracy for at least one or two additional normal hydrological years would further strengthen confidence in temporal transferability. Although a full perturbation-based sensitivity test was beyond the scope of this revision, three lines of existing evidence constrain the influence of threshold subjectivity on the reported findings. First, $MNDWI > 0$ and $VV > -15$ dB are physically anchored decision

boundaries rather than tuned free parameters: the MNDWI zero-crossing marks the point at which strong short-wave infrared absorption by water exceeds green reflectance, and the -15 dB C-band boundary corresponds to the specular-reflection regime of calm open water, with regional optical and SAR studies converging on these values within a narrow range [28–31]. Second, the thresholds act only as refinement and anomaly-flagging rules applied to ambiguous Dynamic World pixels, so their influence is confined to the water–mudflat boundary zone rather than propagating across the entire scene. Third, and most directly, the confusion-matrix screening check in Section 3.1.1 already bounds this boundary-zone effect: even when the water area is conservatively re-estimated to absorb the full classification error, the September–November deficit remains approximately 66.4–67.5%, so any plausible threshold perturbation—which would move pixels within this same boundary zone—cannot overturn the severe-contraction conclusion. The independent convergence of MNDWI-based optical and VV-based SAR monthly water areas ($r = 0.84$; Section 3.1.2) further indicates that the results are not an artifact of a single subjectively chosen threshold.

Additional caution is required when interpreting the drivers of the 2022 event. The observed water contraction cannot be attributed solely to meteorological drought, because autumn water levels in Poyang Lake are also influenced by Yangtze River interactions, Three Gorges Reservoir autumn impoundment—which typically begins in September and, therefore, temporally coincides with the September–November recession period analyzed here—local lake-basin morphology, and sub-lake water-control structures. The present study therefore focuses on remotely observed wetland landscape responses and surface-water fragmentation, rather than decomposing the relative contributions of climate forcing, reservoir operation, groundwater processes, DEM-derived microtopographic thresholds, and bathymetric connectivity thresholds. Available bathymetric datasets were not integrated because they were not directly matched to the nine sub-lake boundaries, monthly 10 m classification grid, and event-specific water levels used here; therefore, they could not be used to derive structural connectivity thresholds for the present analysis. Future work combining water-level records, higher-resolution bathymetry or LiDAR-derived terrain information, hydrodynamic modeling, reservoir-operation records, and standardized drought indices such as SPEI, SPI, or PDSI would be needed to separate these drivers more rigorously.

The sub-lake management categories used here are restricted to the 2022 drought-event context. They should not be extrapolated to subsequent years, because management authority for additional sub-lakes was transferred to the reserve authority in 2023. Moreover, the recession and retention metrics are derived from monthly remote-sensing water-area masks and should be interpreted as area-based proxy indicators. They do not replace in situ water-level records, gate-operation records, or hydrodynamic lag-time analysis.

The historical baseline used for anomaly calculation is another source of uncertainty. The 2017–2021 reference period includes interannual hydrological variability, and 2020 may have represented an anomalous hydrological year in the wider Poyang Lake region. Including a relatively dry year in the baseline could lower the mean reference water area and thereby dampen the apparent magnitude of the 2022 negative anomaly. Consequently, the reported September–November water-area deficits should be interpreted as conservative estimates relative to this recent baseline rather than as absolute climatological extremes. Nevertheless, because the observed deficits reached approximately 73.6–74.7% relative to the baseline, the directional conclusion of exceptional surface-water contraction remains robust. Future work using longer hydrological records and explicit baseline-sensitivity tests would further strengthen anomaly attribution.

It should be emphasized, however, that the 2017–2021 window represents the maximum temporally consistent multi-source baseline available for this framework rather than an arbitrary choice. The consistent Sentinel-2 Level-2A surface-reflectance archive and the Dynamic World V1 product—both required to reproduce identical classification inputs for the baseline and for the 2022 event year—are available only from about 2015–2017 onward; extending the baseline further back would force substitution of coarser or spectrally inconsistent sensors, introducing larger cross-sensor bias than the shorter window itself. More importantly, the principal contributions of this study—the monthly surface-water fragmentation metrics (Section 3.4.1) and the heterogeneous sub-lake responses (Section 3.4.2)—are derived entirely from 2022 imagery and do not depend on the historical baseline, which serves only to provide relative anomaly context in Section 3.3. Moreover, the exceptional severity of the 2022 event is independently corroborated by baseline-free evidence, including the GRACE-FO and GLDAS terrestrial water-storage anomalies, the Hukou-station water-level decline to 6.4 m, and basin rainfall of only 7.161 mm in September 2022 [4,21,22]. Because the observed September–November deficits (73.6–74.7%) far exceed the interannual variability that a longer baseline could plausibly introduce, the direction and approximate magnitude of the 2022 surface-water anomaly are robust to the definition of the baseline period.

Error analysis reveals persistent omission errors in water detection within shallow zones along sub-lake margins where emergent or floating-leaved vegetation is densely distributed. This limitation reflects the inherent inability of passive optical sensors to penetrate dense vegetation canopies, precluding detection of sub-canopy inundation. In addition, the current analysis is restricted to surface-water extent in two dimensions; the three-dimensional aspects of drought impacts, such as water volume loss and bathymetric change, remain uncharacterized.

Future studies should address these limitations through three complementary approaches: (1) integration of L-band SAR data (e.g., ALOS-2 PALSAR-2, or forthcoming NISAR), which penetrates vegetation canopies more effectively than C-band due to longer wavelengths, enabling improved detection of sub-canopy water bodies; (2) incorporation of ICESat-2 spaceborne laser altimetry to transition from surface-area mapping to joint estimation of water volume and bathymetric change, supporting comprehensive assessment of drought impacts on water-storage capacity and ecological buffering; and (3) development of a finer-resolution multi-class mudflat differentiation scheme capable of distinguishing moist from dry exposed substrates, potentially leveraging hyperspectral data or multi-temporal moisture indices.

5. Conclusions

This study developed a multi-source remote-sensing framework integrating Sentinel-2, Sentinel-1 SAR, and the Dynamic World land-cover product on the Google Earth Engine platform to monitor fine-scale wetland landscape dynamics during the 2022 extreme drought in the Poyang Lake National Nature Reserve. The framework achieved an overall accuracy of 87.44%, with a Kappa coefficient of 0.80, and improved the mapping of spectrally complex wetland surfaces, including turbid water, saturated mudflats, and exposed lakebeds. The results showed that the reserve experienced a rapid wet-to-dry transition in 2022: the water area contracted by 78.1% from July to September and remained 73.6–74.7% below the five-year historical baseline during September–November. This rapid contraction produced an apparent compression of transitional habitat states at the monthly compositing scale, with large areas shifting from open water or flooded vegetation to exposed substrate or grassland.

The drought also exposed pronounced heterogeneity among dish-shaped sub-lakes. Sub-lakes with stronger visible surface-water linkage to the main lake generally experienced earlier and more extensive water loss during recession, whereas reserve-managed or facility-present sub-lakes retained residual water to varying degrees and may have provided important ecological refugia during the drought period. These heterogeneous responses were associated not only with observable surface-water linkage but also with local topographic characteristics and 2022 management-context settings. Therefore, the present results should be interpreted as evidence of surface-water fragmentation associated with the 2022 drought-period drawdown and heterogeneous wetland landscape responses, rather than as a complete assessment of hydrodynamic connectivity processes. The proposed framework has potential applicability to other river-connected floodplain wetlands and provides a practical approach for drought monitoring, ecological vulnerability assessment, and adaptive wetland management under increasing climate extremes.

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