

Article

Spatiotemporal Dynamics and Climatic Associations of a Reed-Dominated Wetland in the Yongding River Basin: A Two-Stage Framework Combining Field Surveys and Remote Sensing

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Abstract

Wetlands sustain biodiversity and regulate hydrology, yet their internal functional heterogeneity is still poorly understood. Using a two-stage approach, we surveyed ten plots along the upper, middle, and lower reaches for plant communities, aboveground biomass, and environmental variables, and then monitored a selected site monthly with GF-1 and Sentinel-2 imagery (June 2023–June 2025). Ward clustering grouped the plots into three clusters; Dongzhangwu Wetland (LF10) was separated as a provisional singleton in the six-variable clustering and had the highest cluster-mean aboveground biomass (816.5 ± 426.2 g/m²; reed-dominated quadrats exceeded 900 g/m²) and a distinct soil–water profile. At LF10, NDVI peaked at 0.55 in summer and fell below 0.2 in winter, while NDWI-derived exposed water surfaces varied by more than 1 km², peaking in winter and reaching their lowest point in spring and summer; these extrema may partly reflect masking by emergent vegetation and, in winter, reduced evapotranspiration and possible water supplementation. Air temperature was most strongly correlated with NDVI and negatively correlated with water extent; both relationships persisted after deseasonalization ($r = 0.45$ for NDVI and -0.42 for water extent), while precipitation was unrelated to water extent. Given the short record, these associations should not be read as causal. The relatively high productivity of LF10 appears associated with its dominant reed community, seasonal hydrological regime, and favorable downstream hydrothermal conditions. The two-stage approach could provide a practical framework for basin-scale wetland monitoring, pending validation at additional sites.

Keywords: wetland; NDVI; NDWI; remote sensing monitoring; cluster analysis; SDGs

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1. Introduction

Wetlands are transitional ecosystems between terrestrial and aquatic environments, and are among the most productive ecosystems on Earth. They provide irreplaceable ecosystem services, including biodiversity maintenance, flood regulation, water purification, and carbon sequestration [Error! Unknown switch argument.,Error! Unknown switch argument.]. Although wetlands cover only about 4–9% of the global land surface, they store nearly one-third of the global soil carbon pool and support more than 40% of all flora and fauna [Error! Unknown switch argument.]. Yet under the combined pressure of climate change and anthropogenic activities, global wetlands have experienced unprecedented degradation over the past few centuries. Davidson [Error! Unknown switch argument.] estimated that global natural wetland loss rates average 54–57% over the long term, with losses potentially reaching 87% since 1700. A recent global assessment further revealed that at least 3.4 million km² of inland wetlands have disappeared over the past 300 years, with losses concentrated in Europe, the United States, and China during the mid-20th century [Error! Unknown switch argument.]. Agriculture (25%), urbanization (16.8%), aquaculture (10.7%), and industrial development (7.6%) stand out as the primary drivers of this loss [Error! Unknown switch argument.]. China, which holds the fourth-largest wetland area in the world (53.42 million hectares) and encompasses all wetland types defined by the Ramsar Convention, has lost approximately 54% of its wetland area since 1980 [Error! Unknown switch argument.,Error! Unknown switch argument.]. Although the Chinese government has invested over USD 4.24 billion in wetland conservation since 2000 [Error! Unknown switch argument.] and currently protects approximately 49.03% of its national wetland area [Error! Unknown switch argument.], ongoing degradation remains a critical challenge.

Although wetland extent and its drivers are increasingly well documented [Error! Unknown switch argument.–6], the internal functional heterogeneity of the remaining wetlands remains poorly understood, even though such heterogeneity is critical for targeted conservation and restoration. Current wetland monitoring has traditionally relied on two complementary yet disconnected approaches. Field-based investigation employs fixed plots and quadrat surveys to obtain high-precision ecological parameters such as plant community composition, aboveground biomass, and soil physicochemical properties [Error! Unknown switch argument.]. However, this approach is inherently limited in spatial coverage and labor-intensive, and typically yields discrete snapshot observations that fail to capture continuous spatiotemporal dynamics. Remote sensing, by contrast, uses multispectral or hyperspectral satellite imagery to extract spectral indices such as the Normalized Difference Vegetation Index (NDVI) and Normalized Difference Water Index (NDWI), enabling large-scale, periodic ecosystem monitoring [Error! Unknown switch argument.–Error! Unknown switch argument.]. Recent advances in cloud-computing platforms such as Google Earth Engine have further facilitated basin-scale wetland monitoring [Error! Unknown switch argument.–Error! Unknown switch argument.]. Nevertheless, conventional remote sensing treats all areas uniformly [Error! Unknown switch argument.,Error! Unknown switch argument.]. It cannot pinpoint ecologically critical patches or reveal the fine-scale biophysical factors—such as soil moisture and community composition—that drive ecosystem processes [Error! Unknown switch argument.]. The result is a persistent disconnect: field data lack spatial and temporal continuity, while satellite imagery lacks the biological and environmental detail needed to explain the observed spectral patterns [Error! Unknown switch argument.]. Bridging this divide calls for an integrated framework that uses field surveys to locate functional hotspots and remote sensing to track their dynamics over time [Error! Unknown switch argument.]. Yet, despite repeated calls for such integration, few studies have operationalized it as a sequential, two-stage workflow.

These methodological limitations are particularly acute in the Yongding River Basin. The basin serves as a vital ecological corridor and water-conservation area across Shanxi, Hebei, Beijing, and Tianjin, with its lower reaches lying in the Beijing–Tianjin–Hebei region. Upstream reservoir regulation, growing agricultural and industrial water demand, and increasing hydro-climatic variability have together destabilized wetland hydrology across the basin [Error! Unknown switch argument.,Error! Unknown switch argument.]. Systematic assessment of wetland status, distribution, and dynamics is therefore essential for regional ecological security and for meeting the UN Sustainable Development Goals, particularly SDG 6.6 (protection and restoration of water-related ecosystems) and SDG 15.1 (conservation and sustainable use of terrestrial ecosystems) [Error! Unknown switch argument.]. Such assessments, however, remain scarce in this basin. In particular, long-term, plot-level monitoring linked to satellite observations has yet to be established, and to our knowledge, studies that combine basin-scale functional screening with high-frequency remote-sensing monitoring of a selected wetland patch in the Yongding River Basin remain lacking.

To bridge this methodological divide, we propose a two-stage framework. In Stage 1 (broad screening), we combine basin-wide field surveys with hierarchical clustering of multidimensional environmental and biomass data to identify functionally distinct wetland patches [Error! Unknown switch argument.]. In Stage 2 (focused monitoring and correlation analysis), we use monthly, high-resolution remote-sensing time series for the selected wetland to quantify the spatiotemporal dynamics of vegetation cover and water area [Error! Unknown switch argument.,Error! Unknown switch argument.] and integrate meteorological records to examine potential climatic associations [Error! Unknown switch argument.–Error! Unknown switch argument.]. The core principle is to conduct low-cost screening across the basin, rather than dense monitoring at every site, and then to target high-frequency remote sensing on critical patches. This strategy balances broad spatial coverage with in-depth process understanding. Methodologically, our approach draws on recent work demonstrating the robustness of satellite-based long-term wetland monitoring using NDVI time series across contrasting climatic regions [Error! Unknown switch argument.], as well as studies characterizing landscape-pattern dynamics and their driving forces in the wetlands of the North China Plain [Error! Unknown switch argument.]. The novelty of this study lies not in the individual application of NDVI, NDWI, or cluster analysis, but in coupling a low-cost basin-scale screening step with a high-frequency, single-site remote-sensing monitoring step, thereby providing a practical framework for data-sparse basins.

Specifically, this study has three objectives: (1) to identify between-site functional differentiation and locate functionally distinct sites through field surveys and cluster analysis of ten wetland plots across the Yongding River Basin; (2) to quantify the spatiotemporal dynamics of NDVI and NDWI for the identified critical wetland (Dongzhangwu Wetland) using a two-year monthly remote-sensing time series; and (3) to examine the relationships between vegetation greenness, NDWI-derived water extent, and climatic factors, so as to identify the potential factors associated with this relatively high-productivity wetland. The central scientific questions guiding this investigation are as follows: What distinguishes Dongzhangwu Wetland from the other surveyed plots in the basin? What factors are associated with its relatively high productivity over time? What is the statistical association between seasonal hydrological dynamics and vegetation cover? This study develops and provides an initial test of the framework, coupling plot-level functional screening with high-frequency remote-sensing monitoring in the Yongding River Basin; the two components are applied sequentially in this first application. We expect the approach to be replicable in similar river basins where ground networks are sparse but conservation urgency is high. By linking plot-level functional screening with satellite-

based monitoring, this framework can support SDG 6.6 and SDG 15.1 reporting in basins where dense field networks are not feasible.

2. Materials and Methods

2.1. Study Area

The Yongding River Basin (112–117° E, 39–41° N) originates in Ningwu County, Shanxi Province, and flows through Shanxi, Hebei, Beijing, and Tianjin before emptying into the Bohai Sea. The river stretches approximately 740 km and drains an area of about 47,016 km², forming one of the seven major river systems of the Haihe River Basin. The region has a temperate continental monsoon climate. Mean annual temperature ranges from 6 to 14 °C, and annual precipitation ranges from 400 to 600 mm, with over 70% falling in the summer months (June–September). Topographically, the basin descends from the mountainous northwest to the southeastern plains, and includes riverine, marsh, reservoir, and constructed wetlands.

Dongzhangwu Wetland (site LF10) lies on the alluvial plain of the lower Yongding River in Langfang City, Hebei Province, at approximately 116.79° E, 39.40° N (Table 1). It is a natural reed marsh with considerable ecological value in the lower basin. The wetland is fed mainly by flood-season runoff from the Yongding River and lateral groundwater recharge. The vegetation is dominated by *Phragmites australis*, with typical hygrophytes such as *Typha orientalis* and *Bolboschoenus planiculmis* also present. Because the terrain is low-lying and drainage is poor, water area may fluctuate markedly through the year, and may be controlled mainly by the seasonally varying balance between water supply and evapotranspiration rather than by rainfall alone. This makes Dongzhangwu a hydrologically distinctive system within the basin.

The basin configuration, distribution of the ten sampling sites, and landscape of Dongzhangwu Wetland are shown in Figure 1a. The overall workflow, from field investigation and remote sensing monitoring to statistical analysis, is illustrated in Figure 1b.

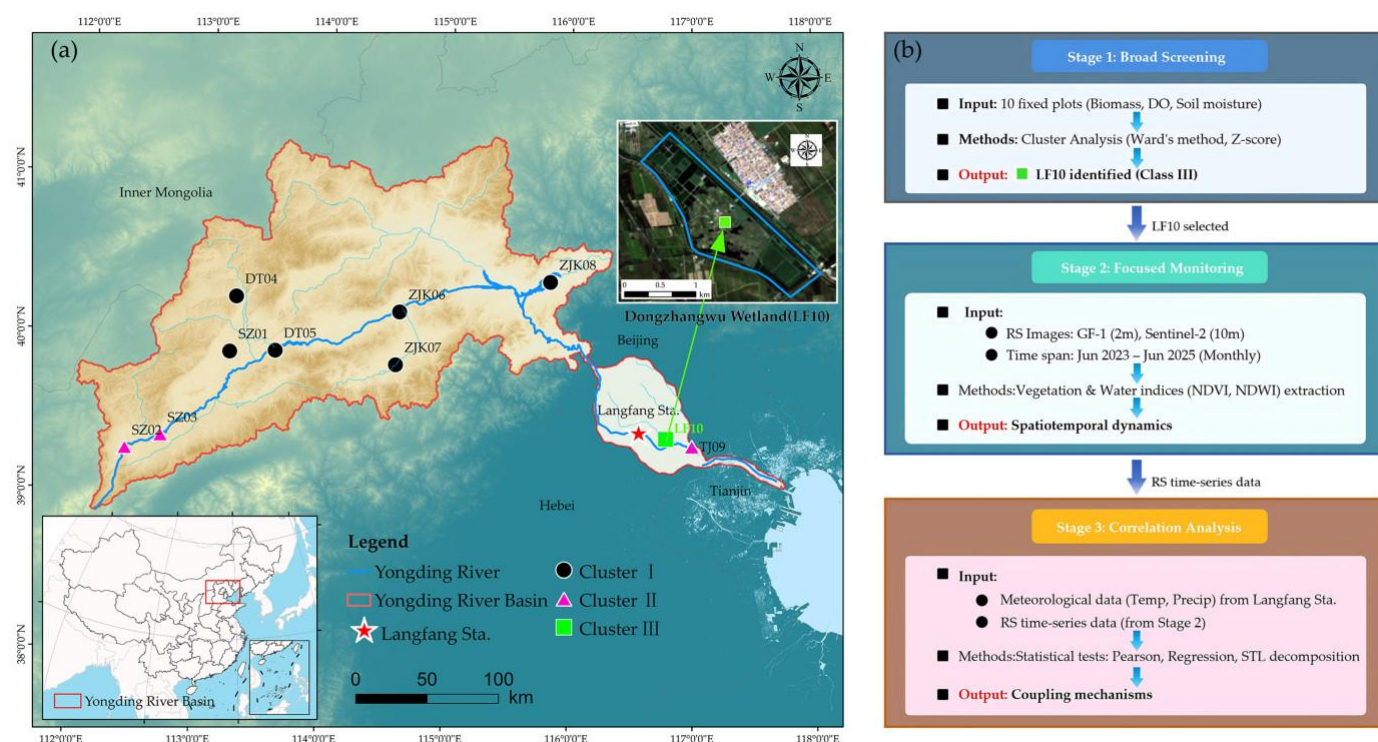


Figure 1. (a) Location of the Yongding River Basin and spatial distribution of the ten wetland survey plots across Shanxi, Hebei, and Tianjin. All ten plots are labeled with their site codes (SZ01–LF10)

to facilitate cross-referencing with Table 1. Sampling sites are classified into three groups based on Ward clustering of biomass and environmental factors: Type I (low biomass, black circles), Type II (high biomass, purple triangles), and Type III (Dongzhangwu Wetland, LF10), a provisional singleton, highlighted by a green square. The upper-right inset shows an enlarged view of Dongzhangwu Wetland; the lower-left inset shows the basin's location within China. Deep blue lines represent the main stream of the Yongding River, and light blue lines represent its tributaries. **(b)** Methodological framework of this study, consisting of two stages: Broad Screening (field survey + cluster analysis) → Focused Monitoring and Correlation Analysis (monthly remote sensing NDVI/NDWI plus meteorological correlation).

Table 1. Basic information of the ten wetland sampling plots in the Yongding River Basin.

Plot Code	Wetland Name	Administrative Region	Longitude (°E)	Latitude (°N)	Elevation (m)	Wetland Type
SZ01	Kouquan Wetland	Shuozhou, Shanxi	113.21	39.91	990	Riverine
SZ02	Huihe Wetland	Shuozhou, Shanxi	112.39	39.27	1075	Marsh
SZ03	Sanggan River Wetland	Shuozhou, Shanxi	112.68	39.36	1020	Riverine
DT04	Zhaojiayao Reservoir	Datong, Shanxi	113.25	40.26	1140	Reservoir
DT05	Sanggan River Wetland	Datong, Shanxi	113.58	39.92	941	Riverine
ZJK06	Yangyuan Sanggan River	Zhangjiakou, Hebei	114.59	40.19	804	Riverine
ZJK07	Huliu River	Zhangjiakou, Hebei	114.57	39.86	891	Riverine
ZJK08	Guanting Reservoir Wetland Park	Zhangjiakou, Hebei	115.83	40.40	463	Reservoir
TJ09	Yongding River Wetland	Tianjin	117.00	39.36	−5	Riverine
LF10	Dongzhangwu Wetland	Langfang, Hebei	116.79	39.40	9	Marsh

2.2. Field Survey and Cluster Analysis

2.2.1. Plot Establishment and Vegetation Sampling

Between June and September 2024, we established ten permanent wetland plots along the upper, middle, and lower reaches of the Yongding River Basin. Five plots were located in Shanxi Province (three in Shuozhou City and two in Datong City), four were in Hebei Province (three in Zhangjiakou City and one in Langfang City), and one was in Tianjin Municipality (Table 1). Sites were selected to capture the longitudinal gradient of the basin, the range of wetland types, and practical accessibility for fieldwork. All fieldwork was conducted in accordance with the National Technical Specification for Forest, Grassland, and Wetland Investigation and Monitoring (2022).

At each plot, we established three 1 m × 1 m quadrats for herbaceous community surveys, giving 30 quadrats in total. For each quadrat, we recorded more than 20 environmental and biological variables, including geographic coordinates, landform, elevation, wetland type, soil properties, hydrological regime, vegetation characteristics, and anthropogenic disturbance intensity. Aboveground biomass was measured by the oven-drying method. Soil moisture was determined gravimetrically at 10, 30, and 60 cm depths. Dissolved oxygen was measured in situ with a portable meter.

2.2.2. Cluster Analysis

We selected six variables for clustering: aboveground biomass, plant species richness, dissolved oxygen, and soil moisture at 10, 30, and 60 cm. The purpose of this step is exploratory rather than confirmatory: clustering is a low-cost screening tool that groups the ten plots by their measured functional attributes and flags sites departing from the main body of the data, so that subsequent high-frequency monitoring can be targeted. It is not intended to delimit wetland types or to test hypotheses about community assembly. All

variables were standardized using Z-score transformation to remove scale effects. Hierarchical cluster analysis was performed using Ward's minimum variance method. To determine the optimal number of clusters, we computed the average silhouette score for $k = 2$ to 5 and assessed stability by bootstrap resampling (1000 iterations). All analyses were run in R 4.3.0.

Collinearity among the six variables was assessed using Pearson correlations and variance inflation factors. Because the three soil-moisture layers were strongly collinear, the clustering was repeated on principal-component scores as a dimension-reduced check, once using components with eigenvalues greater than 1 and once with the three soil-moisture layers replaced by their first principal component. Two additional sensitivity checks were also performed, one excluding dissolved oxygen and one based on resampling the variable set (500 draws).

2.3. Time-Series Remote Sensing Monitoring

2.3.1. Satellite Data Acquisition

Remote sensing monitoring focused on Dongzhangwu Wetland. We acquired a time series of satellite images covering 25 months from June 2023 to June 2025. The 25-month window was chosen to match the 2024 field survey and the availability of GF-1 2 m imagery. The primary source was GF-1 (Gaofen-1) multispectral imagery at 2 m spatial resolution, obtained from the Geological Cloud Platform (geocloud.cgs.gov.cn). For months when GF-1 data were missing (July 2024, December 2024, and April 2025), we used Sentinel-2 multispectral imagery at 10 m resolution to maintain continuity. The analysis area of interest (AOI) was delineated as the wetland extent shown in Figure 1a, covering approximately 1.97 km². This AOI contains the 1200 m² ground plot (LF10, Section 3.2), so the two scales differ by about three orders of magnitude and must not be treated as directly comparable.

2.3.2. Image Preprocessing

All images were preprocessed following a standard workflow: radiometric calibration, atmospheric correction, geometric correction, and orthorectification. Radiometric calibration converted digital numbers (DN) to top-of-atmosphere reflectance. Atmospheric correction was carried out with FLAASH for GF-1 images and Sen2Cor for Sentinel-2 images to remove scattering and absorption effects. Geometric correction kept the root-mean-square error within one pixel. The preprocessed images were compiled into a monthly time-series dataset at 2 m resolution for the two-year period. All processing followed the Chinese national standards Specifications for Photogrammetric Mapping of Remote Sensing Images (GB/T 15968-2008)[34] and Specifications for Dynamic Remote Sensing Monitoring of Land Use (TD/T 1010-2015)[35]. Because GF-1 and Sentinel-2 differ in band settings, spatial resolution, and atmospheric-correction chains, the three Sentinel-2-substituted months (July 2024, December 2024, and April 2025) may carry small systematic offsets. No cross-sensor calibration was performed, but both sensors were reduced to the same physical quantity (top-of-atmosphere reflectance after atmospheric correction) and to a common 2 m grid, and both indices are normalized band ratios in which first-order radiometric offsets partially cancel.

2.3.3. Spectral Indices Calculation

(1) Normalized Difference Vegetation Index (NDVI)

NDVI was computed from the near-infrared (NIR) and red bands:

$$NDVI = \frac{\rho_{NIR} - \rho_{Red}}{\rho_{NIR} + \rho_{Red}} \quad (1)$$

where ρ_{NIR} and ρ_{Red} are reflectance in the NIR and red bands, respectively. NDVI ranges from -1 to 1 , with higher positive values indicating denser vegetation cover. Because NDVI can lose sensitivity over very dense canopies, EVI was also considered a less saturation-prone alternative, but it was not needed for this record.

(2) Normalized Difference Water Index (NDWI)

NDWI was calculated from the green and NIR bands [Error! Unknown switch argument.,Error! Unknown switch argument.]:

$$NDWI = \frac{\rho_{Green} - \rho_{NIR}}{\rho_{Green} + \rho_{NIR}} \quad (2)$$

where ρ_{Green} is reflectance in the green band. NDWI is positive for water bodies and negative for non-water features such as vegetation or bare soil. This index exploits the strong NIR absorption by water and the relatively high green-band reflectance to extract water effectively.

2.3.4. Water Area Extraction

We extracted the exposed water surface on a monthly basis using an NDWI thresholding approach [Error! Unknown switch argument.,Error! Unknown switch argument.]; NDWI rather than the SWIR-based MNDWI was used because the primary GF-1 archive lacks a shortwave-infrared band. The classification threshold was set at $NDWI > 0$, with the reference value of the index under its original definition [36]. Otsu's method was used to confirm that this fixed value was appropriate for the imagery, and every monthly mask was visually inspected. A single fixed threshold was retained for the whole 25-month series so that month-to-month differences in water area reflect surface change rather than threshold drift. Throughout this paper the mapped variable is therefore defined as the exposed (optically visible) water surface—open water that is not obscured by emergent vegetation—rather than the total inundated or flooded area. The resulting binary water masks were post-processed to remove isolated small patches and fill small holes. Water pixels were then counted and converted to surface area (km^2). This workflow followed the Technical Guidelines for Remote Sensing Monitoring of Water Bodies (T/CSGPC 003-2021). A full confusion matrix was not constructed, because the dense reed canopy produces many mixed water–vegetation–ice pixels that cannot be reliably assigned even with higher-resolution imagery. The resulting exposed water-surface estimates should therefore be regarded as approximate, especially in heavily vegetated months.

2.4. Meteorological Data

To assess climatic effects on wetland dynamics, we collected monthly mean temperature and monthly total precipitation from June 2023 to June 2025. The data were obtained from the Northern Haihe River Basin Field Scientific Observation and Research Station for Natural Resource Elements (116.5601°E , 39.4512°N ; hereafter referred to as “Langfang Station”), located in Yongqing County, Langfang City, Hebei Province. The station lies 21 km from Dongzhangwu Wetland (LF10), the only site used in the correlation analysis. The station is equipped with standard meteorological instruments and is maintained in accordance with national observation protocols. All data were quality controlled and aggregated to monthly values. The complete dataset is available from the corresponding author upon reasonable request.

2.5. Statistical Analyses

2.5.1. Time-Series Analysis

Monthly mean NDVI and monthly NDWI-derived water area were examined for seasonal structure. Because the record spans only 25 months (two growing seasons), it is too short for formal trend inference; the analysis is therefore limited to describing the seasonal cycle, and no trend slopes or significance tests are reported.

2.5.2. Correlation and Regression Analysis

We computed Pearson correlation coefficients between monthly NDVI (or water area) and monthly temperature and precipitation, with significance tested at $\alpha = 0.05$. Because the residuals of the linear models met the assumptions of normality, Pearson correlation was used as the parametric measure throughout the analysis. We then built multiple linear regression models with monthly mean NDVI (or water area) as the response variable and monthly temperature and precipitation as predictors. Standardized regression coefficients (β) were used to gauge the relative contribution of each climatic factor. Because vegetation response to climate may be delayed, we also tested 1-month and 2-month lags. To reduce the influence of shared seasonality, all correlations and regressions were additionally recomputed on deseasonalized series: (i) month-of-year anomalies, in which each observation is replaced by its deviation from the mean of the same calendar month, and (ii) year-over-year differences, in which each month is replaced by its difference from the same month one year earlier. Because the 25-month monthly series exhibits strong seasonal autocorrelation, the reported significance levels should be interpreted with caution, and all results are reported as statistical associations rather than causal effects.

2.5.3. Software

All statistical analyses were performed in R 4.3.0. Cluster analysis used the stats and cluster packages. Correlation and regression analyses used the cor.test and lm functions. Time-series decomposition used the stl function from the stats package. Remote sensing data were processed in ENVI 5.6 and ArcGIS 10.8.

3. Results

3.1. Functional Differentiation Among Wetland Sites Across the Basin

Ward's hierarchical clustering of the ten surveyed wetlands, based on six z-score standardized indicators (aboveground biomass, plant species richness, dissolved oxygen, and soil moisture at 10, 30, and 60 cm depths), yielded a three-cluster partition: two multi-site groups and one provisional singleton (Figure 2, Table 2).

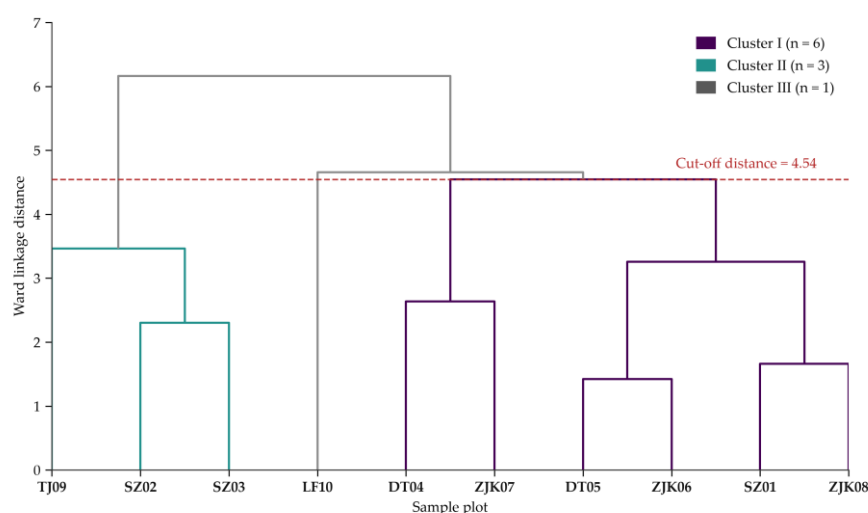


Figure 2. Dendrogram of Ward’s hierarchical clustering of the ten wetland sites. Note: Gray lines indicate the hierarchical merging of clusters above the cut-off distance (including the terminal branch for LF10 and the link between Clusters I and II). The red dashed line marks the cut-off at a Euclidean distance of 4.54, corresponding to the second-largest increase in the agglomeration schedule (from 3.46 to 4.54, $\Delta = 1.08$), which supports a three-cluster partition. The other two increases ($\Delta = 0.48$ and $\Delta = 0.61$) were comparatively smaller, making the selected cut-off the clearest elbow. The resulting three clusters (I, low biomass; II, high biomass; and III, LF10 provisional singleton) are described in Table 2. Silhouette analysis indicated a slightly higher average score for the two-cluster solution (0.198 at $k = 2$ vs. 0.160 at $k = 3$); however, the three-cluster partition was retained to preserve the separation of site LF10, which separated from all other sites in the dendrogram (bootstrap isolation frequency 44.1%).

Table 2. Cluster membership and provisional functional classification of the ten surveyed wetlands.

Cluster	Site Group	Site Codes	Mean Aboveground Biomass (g/m ²)	Key Traits
I	Low biomass	SZ01, DT04, DT05, ZJK06, ZJK07, ZJK08	364.25 ± 200.69	Most widespread type; low biomass; moderate-to-high soil moisture
II	High biomass	SZ02, SZ03, TJ09	654.49 ± 375.31	Higher biomass; stable oxygen regime
III	LF10 singleton	LF10	816.48	Provisional singleton; highest cluster-mean biomass (site-level second to TJ09); dissolved oxygen not temperature-normalized

Note: Values of aboveground biomass are presented as mean ± SD ($n = 6, 3$, and 1 for clusters I, II, and III, respectively). Cluster III contains only LF10; the site-level highest aboveground biomass was recorded at TJ09.

The low-biomass group (Type I) is the most widespread category in the basin, comprising six of the ten sites: Kouquan Wetland (SZ01), Zhaojiayao Reservoir (DT04), the Datong reach of the Sanggan River Wetland (DT05), Yangyuan Sanggan River Wetland (ZJK06), Huli River Wetland (ZJK07), and Guanting Reservoir Wetland Park (ZJK08). This group has the lowest average aboveground biomass (364.25 ± 200.69 g/m²; Figure 3a) and the lowest species richness (9.00 ± 3.58 species; Figure 3b), along with moderate-to-high soil water content at all three depths (0.67 ± 0.36, 0.54 ± 0.12, and 0.58 ± 0.09 at 10, 30, and 60 cm, respectively; Figure 3d–f) and comparatively high dissolved oxygen (7.18 ± 2.82 mg/L; Figure 3c). The high-biomass group (Type II) comprises the remaining three sites: Hui River Wetland (SZ02), the Shuozhou reach of the Sanggan River Wetland (SZ03), and Yongding River Wetland (TJ09). It is distinguished by nearly twice the aboveground biomass of Type I (654.49 ± 375.31 g/m²; Figure 3a), a slightly richer plant community (11.00 ± 5.57 species; Figure 3b), and the most stable oxygen regime of the three types (6.04 ± 0.54 mg/L; Figure 3c); however, it has the lowest soil water content throughout the profile (0.28 ± 0.06, 0.20 ± 0.06, and 0.29 ± 0.08 at 10, 30, and 60 cm, respectively; Figure 3d–f), which provides the clearest separation between Type I and Type II in Figure 3. Across all ten plots, species richness and aboveground biomass were only weakly and non-significantly related (Pearson $r = 0.546$, $R^2 = 0.298$, $p = 0.103$, $n = 10$). Because Cluster III contains only LF10, groupwise significance testing was restricted to Types I and II, and LF10 is shown for visual reference only.

Dongzhangwu Wetland (LF10) stands apart from both groups, isolated at the highest linkage distance in the dendrogram as a singleton. It is the second most productive site in the basin (816.48 ± 426.2 g/m² aboveground biomass, second only to TJ09 at 1044.67 ± 340.2 g/m²; Figure 3a), has a species richness close to the basin maximum (13 species in the plot-level census, second only to the 16 species at TJ09, of which 11 were recorded within the

three sampling quadrats; Figure 3b; Section 3.2), and exhibits the most divergent environmental profile: dissolved oxygen reaches 12.63 mg/L, which is nearly twice the average of the remaining nine sites (6.80 mg/L; Figure 3c; not temperature-normalized), and soil water content increases monotonically with depth (0.78, 0.86, and 0.90 at 10, 30, and 60 cm; Figure 3d–f). This separation therefore does not rest on biomass alone, and an independent reading of the raw variables is at least consistent with the separation of LF10, although its singleton status remains dependent on dissolved oxygen and is therefore treated as provisional. LF10 therefore separates as a third cluster, and we accordingly treat LF10 as a candidate functional hotspot—the highest-priority monitoring target under the screening step—rather than a confirmed distinct functional type. A sensitivity re-clustering excluding dissolved oxygen further qualifies this designation; both caveats are acknowledged in the Discussion.

The dimension-reduced PCA solutions reproduced the same three-cluster partition, with LF10 again separating as a singleton, and a plot-level bootstrap (2000 resamples) recovering LF10 as a singleton in 69.5% of the resamples in which it appeared. This indicates that the separation of LF10 is not an artefact of the collinear soil-moisture variables.

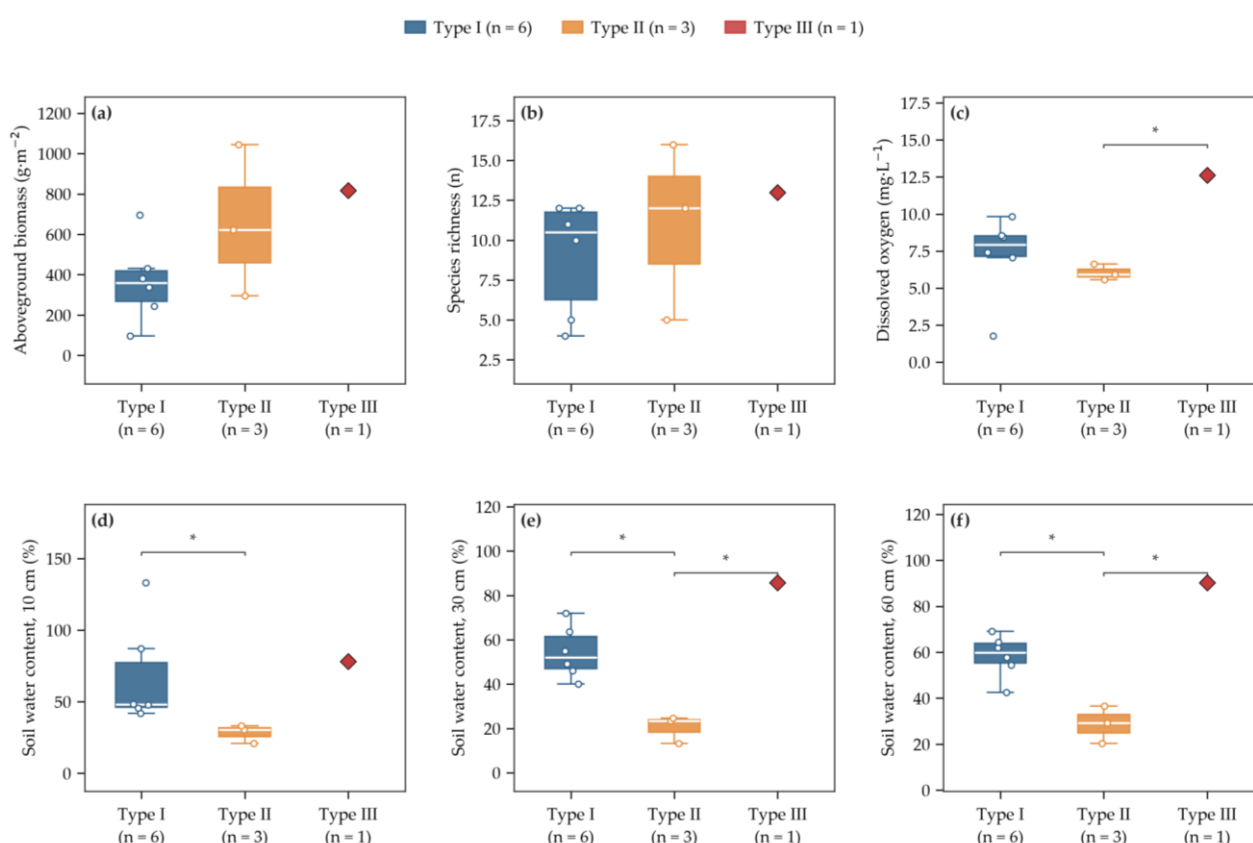


Figure 3. Distributions of the six clustering variables across the three site groups identified by Ward’s hierarchical clustering ($n = 10$ sites). (a) Aboveground biomass; (b) Species richness; (c) Dissolved oxygen; (d) Soil water content at 10 cm; (e) Soil water content at 30 cm; (f) Soil water content at 60 cm. Note: Boxes represent interquartile ranges (IQRs); whiskers extend to 1.5 × IQR from the hinges; horizontal lines indicate medians. Individual sites are shown as open circles (white fill, colored edge); the singleton Type III site (LF10) is shown as a red diamond because the box-and-whisker geometry is undefined for a single observation. The y-axis of each panel reports the original measurement unit, and soil water content is expressed as a percent (volumetric fraction × 100). Significance tests (Kruskal–Wallis followed by Dunn’s post-hoc test) were applied only between the two multi-site groups (Types I and II); the singleton Type III (LF10) was excluded from groupwise

testing because a single observation cannot be ranked, and is shown for visual reference. Significance levels: * $p < 0.05$.

3.2. Ground-Based Survey Characteristics of Dongzhangwu Wetland

Dongzhangwu Wetland (plot LF10) is located on the floodplain of the lower Yongding River in Yongqing County, Langfang City, Hebei Province (elevation 9 m; Table 1). The 1200 m² plot, established in July 2024 on flat alluvial marsh soil (gleysol), is seasonally inundated and has a reliable water source; surface water quality was classified as “excellent”.

Vegetation was dominated by a reed (*Phragmites australis*) stand covering approximately 1080 m² (>90% of the vegetated area), with a seepweed (*Suaeda glauca*) patch at the plot margin (Table 3). Canopy height and cover of the reed quadrats averaged 206 cm and 88.5%, respectively, whereas the seepweed quadrat reached 94% cover but only 13 cm in height. This indicates a marked structural contrast within the plot. A total of 11 vascular plant species were recorded within the three quadrats (Table S1), whereas the plot-level census recorded 13 species (Section 3.1); *P. australis* was the clear dominant species.

Table 3. Community structure and aboveground biomass of quadrats at Dongzhangwu Wetland.

Quadrat	Community Type (Formation)	Dominant Species	Cover (%)	Mean Height (cm)	Fresh Weight (g)	Dry Weight (g/m ²)
Q1	Reed (4201)	<i>Phragmites australis</i>	91	215	2197	1000.61
Q2	Reed (4201)	<i>Phragmites australis</i>	86	198	2493	1119.67
Q3	Seepweed (4315)	<i>Suaeda glauca</i>	94	13	2392	329.17
Mean ± SD	—	—	90.3 ± 3.6	142 ± 114	2361 ± 150	816.5 ± 426.2

Aboveground biomass averaged 816.5 ± 426.2 g/m² across the three quadrats (range: 329.2–1119.7 g/m²), with the second-highest site-level mean, behind only TJ09 (Figure 4a). The two reed quadrats contributed 1000.6 and 1119.7 g/m², while the seepweed quadrat yielded only 329.2 g/m², suggesting that the relatively high productivity of LF10 is largely attributable to the reed community.

Dissolved oxygen in surface water averaged 12.63 mg/L, nearly twice the mean of the other nine sites (6.80 mg/L; Figure 4b); because dissolved oxygen depends strongly on water temperature, flow velocity, and algal activity, this cross-site comparison is not temperature-normalized and should be treated as indicative rather than definitive. Soil water content increased monotonically with depth, averaging 0.78, 0.86, and 0.90 at 10, 30, and 60 cm, respectively (Figure 4c). Two of the three sampling points were saturated below 30 cm (SWC $\approx$ 1.0). These attributes provide the ground-truth reference for interpreting the satellite-derived NDVI/NDWI dynamics.

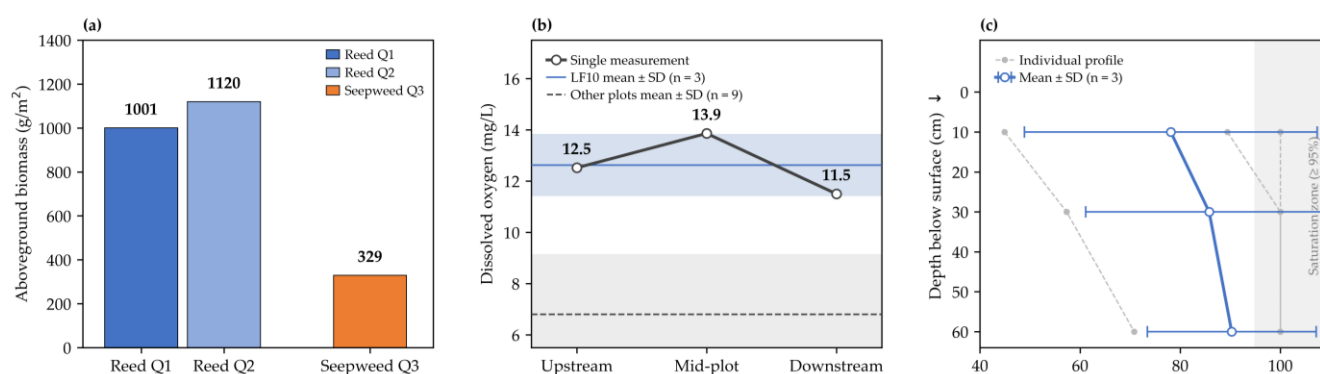


Figure 4. Patterns of aboveground biomass, dissolved oxygen, and soil water content across different vegetation communities in the Dongzhangwu wetland. (a) Aboveground biomass (g/m²) of the

three individual quadrats (Q1 and Q2: Reed community; Q3: Seepweed community). (b) Spatial variations in dissolved oxygen (mg/L). (c) Vertical profiles of soil water content (%). The y-axis is inverted (pointing downwards); the grey shaded area denotes the saturation zone ($\geq 95\%$). Note: Solid lines with error bars/shaded areas indicate mean $\pm$ SD; dashed grey lines indicate single measurements or profiles; SD represents the standard deviation; LF10 is the field plot code (Table 1)..

3.3. Spatiotemporal Dynamics of NDVI in the Dongzhangwu Wetland

3.3.1. Monthly Variation Trends

Monthly remote sensing observations from June 2023 to June 2025 revealed a distinct temperate-zone phenology in Dongzhangwu Wetland (Figure 5a). NDVI remained elevated throughout the growing season (June–September), reaching maxima of approximately 0.47 in July 2023 and 0.55 in August 2024. Values declined markedly after September and fell below 0.2 by December, remaining low through March. The minimum NDVI (0.02) occurred in December 2023, aligning with winter dormancy; by comparison, the December 2024 low was higher at 0.10. Spring green-up was evident from the pronounced NDVI rebound during April and May. The modest difference between the two summer peaks (0.47 versus 0.55) suggests relatively stable interannual greenness over the monitoring period.

Seasonal NDVI dynamics corresponded closely with concurrent air temperature (Figure 5b): both variables tracked parallel seasonal courses, reaching minima during winter (December–January) and maxima in July–August. Precipitation showed a similarly strong seasonality, peaking in July 2023 and August 2024 (Figure 5c) and broadly overlapping the high-NDVI growing season. December 2024 displayed high spatial heterogeneity ($SD = 0.37$), as shown by the wide shaded envelope in Figure 5a. This likely stemmed from mixed pixels comprising water bodies, ice, and senescent vegetation. Despite this spatial heterogeneity, the overall temporal pattern remained clear and consistent.

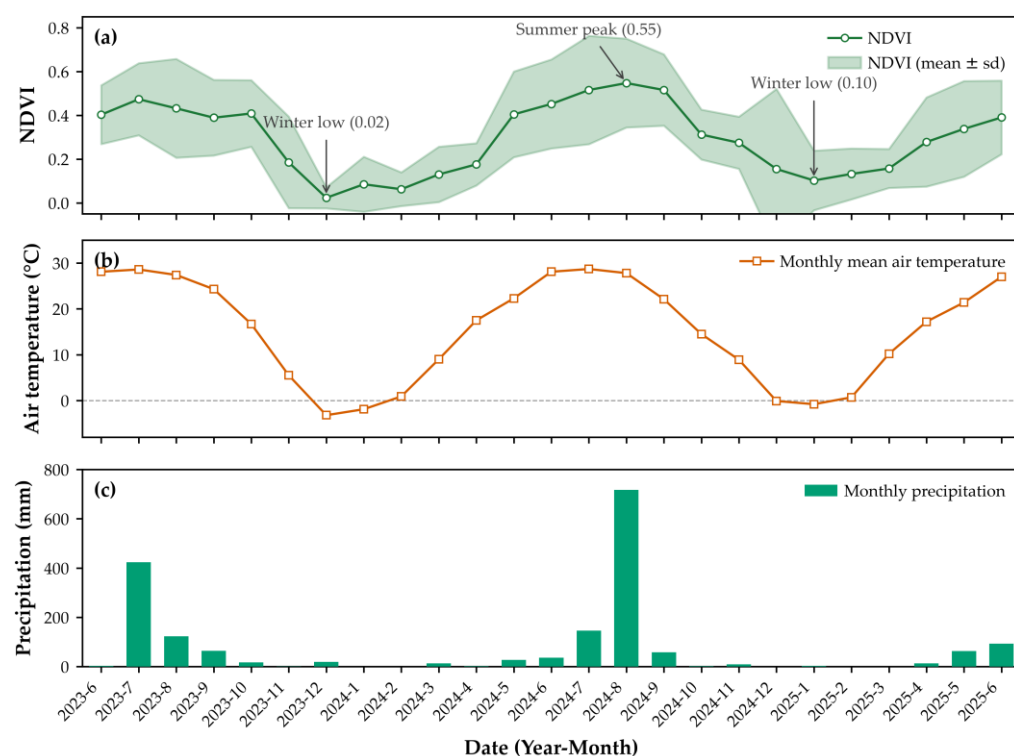


Figure 5. Temporal dynamics of the Normalized Difference Vegetation Index (NDVI) and climatic drivers at Dongzhangwu Wetland (June 2023–June 2025). (a) Monthly mean NDVI (green line with

open circles) and the spatial standard deviation (shaded green envelope). Annotated key points include the summer peak (0.55, August 2024) and winter lows (0.02, December 2023; 0.10, December 2024). (b) Monthly mean air temperature (orange line with open squares). (c) Monthly total precipitation (green bars). Note: SD, standard deviation.

3.3.2. Spatial Heterogeneity of NDVI Across Seasons

Spatial analysis identified the central wetland as the ecological core of the system. This zone had the highest NDVI, the densest vegetation cover, and the strongest interannual stability (Figure 6). Marginal and transitional areas, subject to frequent human disturbance, showed scattered low-NDVI patches and more pronounced fluctuations.

Seasonal comparisons across four representative stages—the summer peak (August 2024), autumn senescence (October 2024), winter dormancy (January 2025), and spring green-up (May 2025)—revealed clear spatial shifts. In summer, NDVI in the central zone typically exceeded 0.6, whereas marginal zones ranged between 0.3 and 0.5. In winter, values across the entire wetland declined sharply to 0.1–0.2, markedly reducing spatial heterogeneity. The two-year record further indicates that ecological stability varies spatially: central areas, supported by more favorable hydrological conditions, showed greater apparent stability.

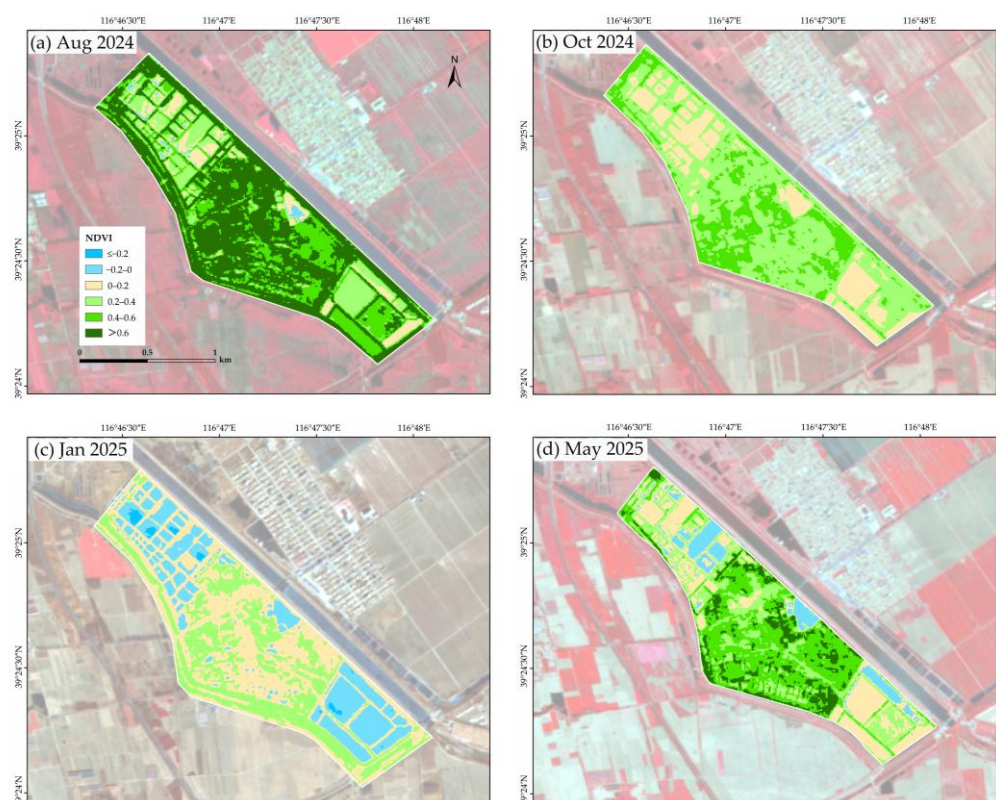


Figure 6. Spatial heterogeneity of NDVI across representative seasons in the Dongzhangwu Wetland. (a) Summer peak (August 2024); (b) autumn senescence (October 2024); (c) winter dormancy (January 2025); and (d) spring green-up (May 2025). NDVI maps were derived from GF-1 (2 m) and Sentinel-2 (10 m) imagery, overlaid on a high-resolution false-color composite background at 60% transparency. A uniform classification scheme and color scale were applied across all panels to facilitate direct seasonal comparisons. Map elements (scale bar and north arrow) are provided in panel (a) and apply to all panels.

3.4. Spatiotemporal Dynamics of NDWI in the Dongzhangwu Wetland

3.4.1. Monthly Variations in NDWI-Derived Water Surface Area

The NDWI-derived exposed water surface area in Dongzhangwu Wetland showed a seasonal cycle broadly inverse to that of NDVI (Figure 7a); this is the visible open-water surface rather than the total inundated area. Water area remained high in winter, reaching a maximum of 1.36 km² in December 2023, before contracting to a summer minimum of 0.39 km² in June 2024. It further declined to a seasonal low of 0.18 km² in September 2024. A second winter peak of 0.67 km² occurred in January 2025, a marked decline from the previous winter. During the 2024 growing season (June–September), the NDWI-derived water area ranged between 0.18 and 0.39 km², consistently lower than in the corresponding months of 2023 (~0.6–0.7 km²). This seasonal expansion and contraction closely mirrored the inverse trajectory of air temperature (Figure 7b): winter water maxima coincided with below-freezing temperatures, whereas the summer minimum aligned with the annual temperature peak. Precipitation showed strong seasonality, with maxima in July 2023 and August 2024 (Figure 7c). Notably, the 716.8 mm of rainfall in August 2024, the wettest month of the record, did not produce an immediate rise in water area, suggesting that the NDWI-indicated water extent is not directly controlled by local rainfall at the monthly scale, although the mechanism cannot be identified without water-balance data. Winter peaks were accompanied by relatively wide standard deviation envelopes (Figure 7a), likely reflecting dynamic ice–water–vegetation boundaries at the pixel scale.

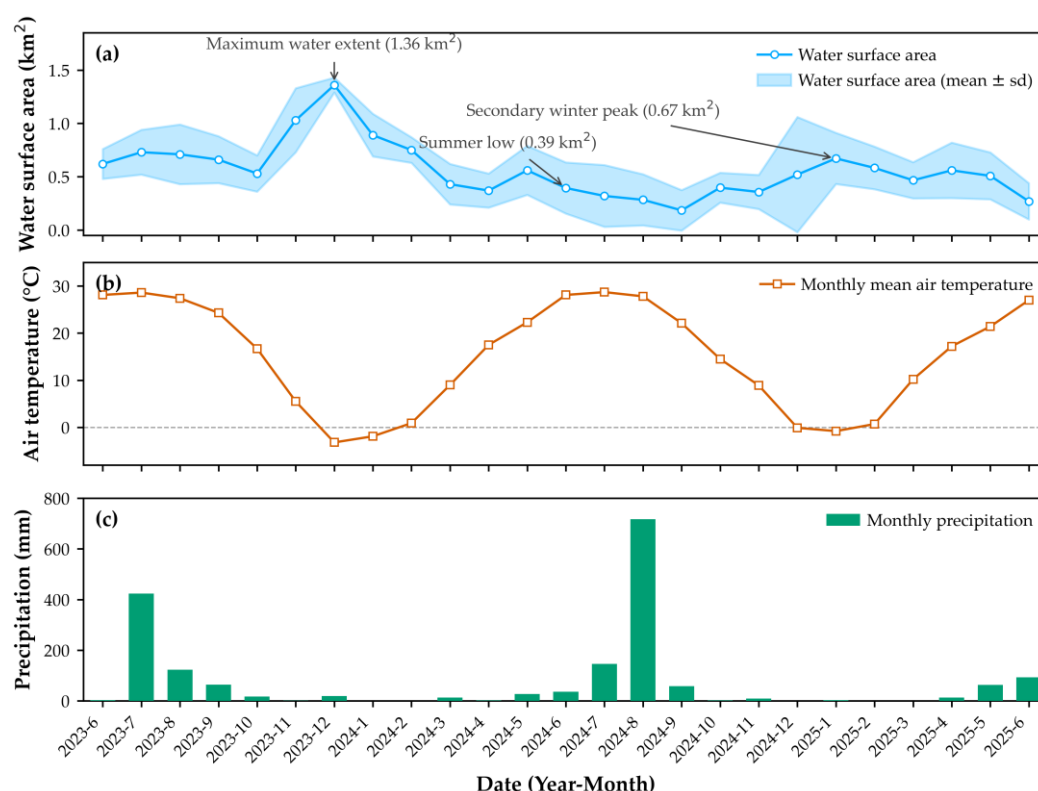


Figure 7. Temporal dynamics of water surface area and climatic drivers in the Dongzhangwu Wetland (June 2023–June 2025). (a) Monthly mean water surface area (blue line with open circles) and its spatial variability (mean $\pm$ standard deviation (SD); light blue shaded area). Key annotations include the maximum water extent (1.36 km² in December 2023), the secondary winter peak (0.67 km² in January 2025), and the summer minimum (0.39 km² in June 2024). Note that the water area further declined to a seasonal minimum of 0.18 km² in September 2024 (autumn). (b) Monthly mean air temperature and (c) monthly total precipitation. These climatic data are identical to those in Figure 5 and are reproduced here to facilitate direct comparison with water surface dynamics.

3.4.2. Spatiotemporal Variations in Water Surface Area

Over the two-year monitoring period, the NDWI-derived water extent in Dongzhangwu Wetland fluctuated markedly on a monthly basis, with seasonal extremes differing by more than 1 km² (Figure 7). The water area peaked in winter, reaching 1.36 km² in December 2023 and 0.67 km² in January 2025. By contrast, the lowest values occurred during summer and early autumn: 0.39 km² in June 2024 and a minimum of 0.18 km² in September 2024.

This pronounced seasonality was evident in the spatial distribution of water bodies across the four representative seasons (Figure 8). In August 2024 (summer), water bodies were highly fragmented, appearing mainly as small patches along the eastern margins. By October 2024 (autumn), water expanded rapidly, and by January 2025 (winter), these patches had coalesced into continuous coverage across the central wetland. As temperatures rose in May 2025 (spring), water area contracted sharply and reverted to a fragmented state.

This recurrent regime, in which the NDWI-indicated water extent increased in winter and contracted in spring and summer, ran counter to the air temperature trajectory (Figure 7b), suggesting that temperature-related evapotranspiration may be one factor controlling water extent. Notably, the extreme rainfall event in August 2024 did not trigger an immediate increase in water area, suggesting that surface water extent is not directly controlled by local rainfall at the monthly scale; possible contributors include vegetation masking of the NDWI signal, uneven spatial distribution of rainfall, and lagged storage, which cannot be separated without water-balance data. However, in the North China Plain, winter water-level maxima may also reflect enhanced recharge from ecological water supplementation, reclaimed-water release, irrigation return flow, and a sharp reduction in evapotranspiration; in the absence of water-balance or groundwater data, the attribution to evapotranspiration alone should be regarded as provisional.

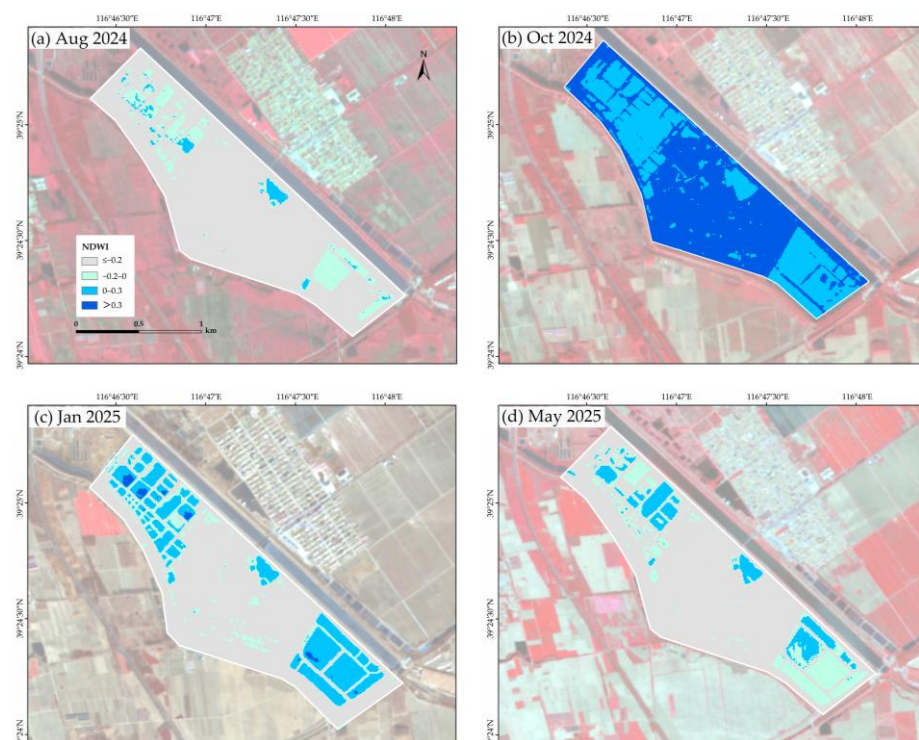


Figure 8. Spatial distribution of NDWI-derived exposed water areas across four representative seasons in the Dongzhangwu Wetland: (a) August 2024; (b) October 2024; (c) January 2025; and (d) May 2025. Water bodies (NDWI > 0) are highlighted in blue, overlaid on a high-resolution false-color

composite background. All panels use the same classification threshold ($\text{NDWI} > 0$) to enable direct seasonal comparison. Map elements (scale bar and north arrow) are provided in panel (a) and apply to all panels.

3.5. Correlation Analysis of Vegetation, Water Bodies, and Climatic Factors

Pearson correlation showed that the monthly mean NDVI was strongly positively correlated with air temperature ($r = 0.921$, $p < 0.001$) and weakly correlated with precipitation ($r = 0.550$, $p = 0.004$). Because both NDVI and temperature follow strong seasonal cycles, correlations were also computed on deseasonalized series. The NDVI–temperature association remained significant on month-of-year anomalies ($r = 0.451$, $p = 0.024$) and marginally non-significant on year-over-year differences ($r = 0.465$, $p = 0.109$), whereas NDVI–precipitation correlations were non-significant in both variants ($p = 0.208$ and 0.506).

Multiple linear regression indicated that air temperature was the strongest statistical correlate of NDVI ($\beta = 0.852$, $p < 0.001$, model $R^2 = 0.864$) and of water surface area ($\beta = -0.546$, $p = 0.032$, model $R^2 = 0.269$), while precipitation was non-significant in both models ($\beta = 0.145$ and 0.064 , ns). Deseasonalized regressions reduced explained variance but retained the temperature terms (NDVI: $\beta = 0.447$, $p = 0.023$; water area: $\beta = -0.420$, $p = 0.038$); precipitation remained non-significant in all variants ($p \geq 0.18$). These relationships are visualized as scatter plots with least-squares fits and 95% confidence bands in Figure 9. NDWI-derived water extent was negatively correlated with NDVI in both raw ($r = -0.543$, $p = 0.005$) and deseasonalized series ($r = -0.648$, $p < 0.001$), consistent with, but not independent evidence for, summer canopy masking of open-water signals. Lag analysis showed a near-synchronous NDVI–temperature response ($r = 0.928$ at 1-month lag vs. 0.921 concurrent), whereas the NDVI–precipitation response was contemporaneous ($r = 0.550$ vs. 0.478 lagged).

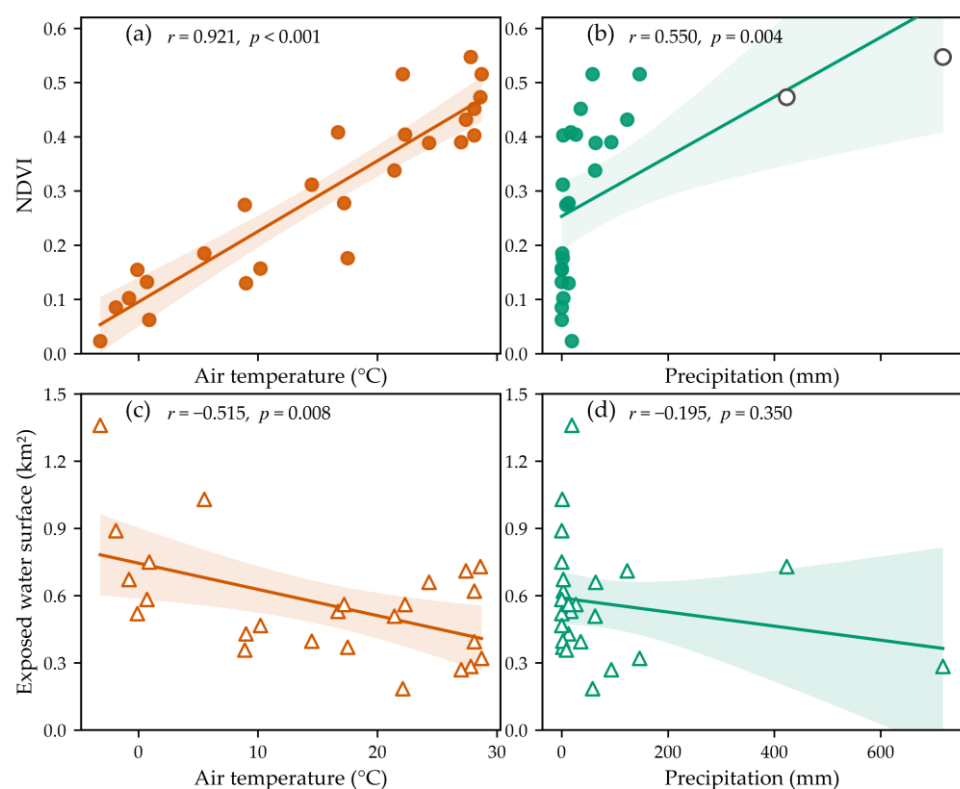


Figure 9. Relationships between monthly NDVI (a,b) or NDWI-derived exposed water surface (c,d) and air temperature (a,c) or precipitation (b,d) in Dongzhangwu Wetland (June 2023–June 2025; $n = 25$ months). (a) NDVI vs. air temperature; (b) NDVI vs. precipitation; (c) Water surface area vs. air

temperature; (d) Water surface area vs. precipitation. Solid lines are least-squares fits with 95% confidence bands; r and p are Pearson coefficients. In (b), the two open circles mark the months with precipitation above 400 mm (July 2023 and August 2024), the influence of which is discussed in the text. All coefficients describe statistical associations and do not imply causality.

4. Discussion

4.1. Factors Associated with the Relatively High Productivity at Dongzhangwu Wetland

The high productivity of Dongzhangwu Wetland cannot be attributed to any single factor. Species richness and aboveground biomass were only weakly correlated across the ten plots, suggesting that biodiversity alone is unlikely to drive productivity at the basin scale [Error! Unknown switch argument.,Error! Unknown switch argument.]. Three interacting factors—a monodominant reed community, a distinct seasonal hydrological regime, and favorable downstream hydrothermal conditions—appear to be jointly associated with the wetland’s relatively high ecosystem functioning. A similar multi-factor synergy has been reported for Baiyangdian Wetland in North China, where reed productivity was driven by climate and groundwater depth rather than by any single variable [Error! Unknown switch argument.,Error! Unknown switch argument.].

At the community level, *Phragmites australis* dominated the vegetation (86–91% cover) and accounted for nearly all standing biomass (1001–1120 g/m² in reed quadrats). Reported aboveground biomass of temperate *P. australis* stands ranges from 300 to 3000 g/m², so values above 900 g/m² are relatively high [Error! Unknown switch argument.]. Dongzhangwu’s reed biomass therefore represents a high-productivity endpoint for temperate reed wetlands. The species’ clonal growth, high photosynthetic efficiency, and ability to exploit flood-driven nutrient pulses may contribute to its dominance under favorable conditions [Error! Unknown switch argument.].

At the hydrological level, the NDWI-indicated water extent peaked in winter and contracted in spring and summer, fluctuating by more than 1 km². This contrasts with the summer-inundated regime typical of many temperate wetlands. Winter and early-spring flooding may protect rhizomes from frost damage and promote bud activation before the growing season [Error! Unknown switch argument.,Error! Unknown switch argument.], whereas the spring–summer drawdown exposes sediments to aerobic conditions, accelerating organic matter mineralization and nutrient release [Error! Unknown switch argument.], which support subsequent biomass accumulation. Similar flood-pulse mechanisms have been reported in other marsh and floodplain systems [Error! Unknown switch argument.,Error! Unknown switch argument.]. The strong negative correlation between NDWI-derived water extent and NDVI (raw $r = -0.543$, $p = 0.005$; deseasonalized $r = -0.648$, $p < 0.001$) is consistent with the interpretation that part of the apparent summer water contraction reflects canopy masking of the open-water signal, although this correlation is partly attributable to the structural coupling of the two indices.

At the climatic level, air temperature was the strongest correlate of NDVI, consistent with the dominant role of temperature in wetland vegetation phenology across mid- and high-latitude China [Error! Unknown switch argument.–Error! Unknown switch argument.]. The association persisted after deseasonalization, and the near-synchronous NDVI–temperature response indicates that reed growth follows thermal accumulation closely. Precipitation, by contrast, was not significantly related to water surface area, and its raw correlation with NDVI largely reflected the shared seasonal cycle rather than an independent rainfall effect. The wettest month of the record, August 2024 (716.8 mm), did not produce an immediate rise in water extent, and the precipitation association remained non-significant after deseasonalization. These results are statistical associations; with 25 monthly observations and no groundwater record, causality cannot be firmly established.

These factors are unlikely to operate in isolation. The reed community's high water and nutrient demand is sustained by the seasonal hydrological regime, which is in turn modulated by the downstream hydrothermal setting. Disentangling these direct and indirect pathways will require structural equation modeling supported by continuous groundwater records.

4.2. Methodological Assessment of the “Broad Screening–Focused Monitoring” Framework

The two-stage framework addresses a persistent problem in wetland ecology: reconciling the spatial coverage of remote sensing with the biological detail of field surveys. By using low-cost field screening to identify a functionally anomalous patch and then concentrating high-frequency remote sensing on that patch, the approach allocates monitoring resources where they yield the most ecological information. This logic aligns with tiered, multi-scale wetland monitoring frameworks developed in the United States, which combine landscape-level assessment with intensive site-specific condition assessment [56–58]. The specific contribution here is the pairing of a low-cost basin-wide screening step with a high-frequency, single-site monitoring step, making the framework applicable in basins where neither dense field networks nor continuous satellite coverage is available. Boundary conditions should nevertheless be noted: where wetlands are highly fragmented or persistent cloud cover constrains optical remote sensing, the screening stage may require more plots, and radar data should be incorporated from the outset.

4.3. Comparison with Existing Wetland Monitoring Studies

The seasonal amplitude of NDVI at Dongzhangwu—monthly means peaking at 0.55 in summer and falling below 0.2 in winter—falls within the range reported for temperate reed wetlands elsewhere. Demarquet et al. [Error! Unknown switch argument.] documented long-term wetland functioning in four contrasting Ramsar wetlands using Landsat archives, with annual NDVI integrals positively correlated with mean temperature. The winter water-area maximum observed here (1.36 km² in December 2023) is less common in the literature, as most temperate wetlands experience peak inundation during spring snowmelt or the summer monsoon [Error! Unknown switch argument.]. This pattern is consistent with the region's temperate continental monsoon climate, where summer evapotranspiration exceeds precipitation and low winter temperatures suppress evaporative losses.

The use of NDWI for water extraction in a wetland with substantial emergent vegetation presents a known challenge. Because the McFeeters NDWI combines green and near-infrared bands, it is less robust than the modified NDWI (MNDWI; [Error! Unknown switch argument.]) in marsh pixels where emergent vegetation raises near-infrared reflectance [Error! Unknown switch argument.]. At Dongzhangwu, the reed canopy reached 88.5% cover and approximately 2 m in height, so the summer water-area minima may partly reflect vegetation phenology rather than hydrological change. A related concern is whether NDVI saturates over this dense canopy. In this record, monthly mean NDVI peaked at 0.55, and values above 0.6 occurred only in a few central pixels, so the index remained well below its typical saturation range. EVI would be more informative at sites with denser or more persistent canopies, but it was not necessary here. NDWI was nevertheless retained because the primary GF-1 archive lacks a shortwave-infrared band and cannot support MNDWI at the native 2 m resolution [Error! Unknown switch argument., Error! Unknown switch argument.]; re-extracting the full 25-month series with MNDWI would require coarser SWIR imagery (10–30 m) and break the consistency of the high-resolution record. The degree to which vegetation phenology co-varies with the NDWI signal can be quantified: the NDWI-derived water area was strongly negatively

correlated with NDVI ($r = -0.543$ for raw monthly series and -0.648 after deseasonalization), indicating that part of the apparent summer water contraction coincides with canopy development. Mixed pixels containing water, ice, and senescent vegetation can produce spurious NDWI values, as reflected in the wide standard-deviation envelopes during winter. Otsu thresholding mitigated but did not eliminate this issue; a radar-based alternative would be more robust but was beyond the scope of this study.

4.4. Management Implications and Links to the SDGs

The Yongding River Basin has undergone substantial hydrological modification over recent decades, including upstream reservoir regulation and ecological water supplementation since 2019 [63, **Error! Reference source not found.**]. These interventions have stabilized river flow and improved riparian vegetation, but their effects on downstream wetlands such as Dongzhangwu remain poorly understood; the winter water-level maxima observed here may therefore partly reflect managed recharge as well as temperature-suppressed evaporation. The results suggest that Dongzhangwu's ecological function appears to depend on seasonal water-level fluctuation, and that management actions dampening this fluctuation—whether through channel hardening, dry-season water abstraction, or permanent inundation—may disrupt the flood–drawdown cycle associated with reed productivity. A differentiated strategy for the three site groups may be warranted: the six Type I (low-biomass) wetlands could be prioritized for restoration aimed at re-establishing hydrological connectivity and reducing anthropogenic disturbance, whereas the three Type II (high-biomass) wetlands may merit protection focused on maintaining their existing hydrological regimes. Dongzhangwu Wetland, as the site that separated from the others in the six-variable clustering, may warrant priority monitoring for early detection of functional change, although any formal conservation designation should await multi-season confirmation of its separation.

These recommendations connect directly to SDG 6.6 and SDG 15.1 [**Error! Unknown switch argument.**]. This initial application suggests that reporting on wetland extent—a key requirement of SDG indicator 6.6.1—may be achievable with freely available Sentinel-2 and GF-1 imagery supplemented by periodic field validation [**Error! Unknown switch argument.**,67]. Because the framework has so far been tested at a single site, its broader application to national SDG reporting will require validation across additional wetlands. In basins where ground observation networks are sparse, such an approach may nonetheless offer a practical starting point for generating the data needed for SDG reporting.

4.5. Limitations and Future Directions

Several limitations should be acknowledged. The clustering was based on a single survey season (summer 2024) and only ten field plots, which constrains statistical power throughout the analysis. The singleton status of LF10, although supported by the dendrogram and by bootstrap resampling (44.1% isolation frequency), should be regarded as provisional until confirmed by multi-season surveys. The three-cluster solution also had a lower mean silhouette score (0.160) than the two-cluster solution (0.198), and cluster stability was assessed only by bootstrap resampling; cross-validation against alternative algorithms and additional validity indices would be required before the classification is used operationally. The six clustering variables were intercorrelated: the three soil-moisture layers were strongly collinear (Pearson $r = 0.79$ – 0.93 ; variance inflation factors of 11.2, 60.1, and 32.8), so the soil-moisture profile effectively contributes a single dimension of information. A sensitivity re-clustering excluding dissolved oxygen no longer separated LF10 as a singleton: at $k = 3$, LF10 joined the moderate-soil-moisture sites, and it emerged as a singleton in only 15.8% of 500 resampled variable sets. Its singleton status therefore depends, at least in part, on the exceptionally high dissolved-oxygen reading, which was not temperature-normalized. The three-cluster classification should accordingly be treated as provisional and sensitive to variable selection.

Remote-sensing monitoring covered only Dongzhangwu, precluding synchronous comparison with other wetland types, and the temporal mismatch between the remote-sensing record (June 2023–June 2025) and the ground survey (June–September 2024) introduces uncertainty into any satellite–ground comparison. Meteorological forcing was represented by a single station (Langfang Station), which lies 21 km from Dongzhangwu

Wetland. The station therefore describes the lower-reach climate well, but it cannot capture spatial heterogeneity in temperature and precipitation across the basin. Micro-meteorological measurements co-located with the study plot are therefore planned for future campaigns. Groundwater depth—a key control on reed productivity in other North China wetlands—was not monitored, which limits the causal interpretation of the NDVI–temperature relationship. No cross-sensor calibration was performed between GF-1 and Sentinel-2, so the three substituted months may carry systematic offsets. As a check on the sensor substitution, all correlations were recomputed with these months excluded; the coefficients changed only marginally, so the conclusions are not affected. A full confusion matrix for the water masks also remains to be carried out, ideally using drone or high-resolution satellite imagery acquired close to the satellite overpasses. Otsu thresholding mitigated but did not eliminate this issue; a radar-based alternative would be more robust but was beyond the scope of this study. Dissolved oxygen was compared across sites without temperature normalization. Finally, the two framework components were applied sequentially in this study: field clustering identified LF10 as a candidate site, and remote sensing then characterized its dynamics. Full quantitative integration—including spatial upscaling of the functional types and an NDVI–biomass inversion model—remains for future work.

Future work could proceed along three lines. The plot network should be expanded to cover the lower basin's coastal wetlands, which are currently absent from the sampling design, to allow a more complete characterization of the inland-to-coastal functional gradient. Structural equation modeling could be applied to partition the direct and indirect effects of climate, hydrology, and community composition on wetland productivity, ideally supported by continuous groundwater records. Finally, an MNDWI-based re-extraction of water extent over the Sentinel-2 subperiod should be combined with radar remote sensing (e.g., Sentinel-1) for all-weather water mapping [**Error! Unknown switch argument.**] and thermal infrared data for evapotranspiration estimation, to strengthen both the accuracy and the mechanistic basis of the monitoring framework. EVI should also be tested alongside NDVI at sites with denser canopies.

5. Conclusions

This study combined basin-scale field screening with monthly satellite monitoring to identify and track a reed-dominated wetland with relatively high productivity in the Yongding River Basin. Ward clustering of ten plots produced a three-cluster partition—two multi-site groups and one provisional singleton. Dongzhangwu Wetland (LF10) separated provisionally from the other nine sites in the six-variable clustering, with the highest cluster-mean aboveground biomass, a species richness close to the basin maximum, and a soil–water profile that differed from all other sites. The sensitivity of this separation to variable selection is acknowledged as a limitation. These traits indicate that ecological conditions differ markedly among sites within the basin and that individual patches may carry disproportionate ecological value.

Monthly GF-1 and Sentinel-2 observations from June 2023 to June 2025 revealed clear phenological and hydrological cycles. NDVI peaked in summer and fell below 0.2 in winter, while NDWI-derived exposed water surfaces varied by more than 1 km², peaking in winter and declining in spring and summer. The summer minima may partly reflect masking of open-water signals by emergent vegetation, and the winter maxima may partly reflect reduced evapotranspiration and, potentially, managed water supplementation. Air temperature was the strongest correlate of NDVI and was negatively related to water extent; deseasonalized re-analyses confirmed that these associations persisted after removal of the shared seasonal cycle, whereas precipitation remained non-significant. The

wettest month of the record did not cause an immediate increase in water extent, suggesting that surface water extent is not directly controlled by local rainfall at the monthly scale.

The relatively high productivity of Dongzhangwu appears to be associated with a monodominant reed community, a seasonal hydrological regime, and favorable downstream hydrothermal conditions. This combination supports reed growth and nutrient cycling but also makes the wetland sensitive to hydrological simplification. These results suggest that protecting seasonal water-level fluctuations may help maintain conditions suitable for reed growth. This initial application demonstrates the two-stage approach at a single site and suggests that it may help link plot-level ecology with satellite observations in data-sparse basins. Further testing across multiple wetlands, with more plots, multi-season surveys, groundwater records, and radar or thermal data, will be needed to confirm its generality and to reduce the uncertainties identified in this study.

Supplementary Materials: The following supporting information can be downloaded at <https://www.mdpi.com/article/10.3390/su182110885/s1>. Table S1: Vascular plant species recorded at Dongzhangwu Wetland.

Author Contributions: Conceptualization, D.Z.; Methodology, X.X.; Software, X.X.; Validation, M.Y. (Mingxuan Yi) and M.Y. (Man Yuan); Formal Analysis, J.Y.; Investigation, J.Y., K.L., M.Y. (Man Yuan) and R.W.; Resources, R.W.; Data Curation, Y.S.; Writing—Original Draft Preparation, D.Z.; Writing—Review and Editing, M.Y. (Mingxuan Yi) and Y.S.; Visualization, K.L.; Supervision, M.Y. (Mingxuan Yi); Project Administration, D.Z.; Funding Acquisition, D.Z. All authors have read and agreed to the published version of the manuscript.

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