



CCWEM and CCWIF: 10 m Datasets of Coastal Wetland Extent and Inundation-Frequency Gradients across China

Jintao Liang^a, Yong Zhang^b, Yi Wang^{a*}, Chao Chen^c, Junfan Bao^{d,e}

^a School of Geophysics and Geomatics, China University of Geosciences, Wuhan 430000, China

^b Yangtze River Basin Monitoring Center Station for Soil and Water Conservation, Changjiang
Water Resources Commission, Wuhan, Hubei 430010, China

^c School of Geography Science and Geomatics Engineering, Suzhou University of Science and
Technology, Suzhou 215009, China

^d Henan Provincial Third Geological and Mineral Survey Institute Co., Ltd., Xinyang, Henan
464000, China

^e Henan Natural Resources Science and Technology Innovation Center (Information Perception
Technology Application Research), Xinyang, Henan 464000, China

* Corresponding author: Yi Wang, cug.yi.wang@gmail.com

ABSTRACT:

Coastal wetlands are critical ecological spaces for coastal-zone management, with direct implications for wetland conservation, shoreline regulation, and nearshore spatial planning. Here, we present two complementary 10 m datasets for China's coastal wetlands in 2025: the China Coastal Wetland Extent Map (CCWEM) and the China Coastal Wetland Inundation Frequency Map (CCWIF). CCWEM delineates the maximum wetland extent along the Chinese coast, whereas CCWIF further characterizes internal inundation-frequency gradients within this extent. To generate CCWEM, we constructed a four-season semantic segmentation dataset based on multi-season Sentinel-2 observations and developed SeasonMamba, which integrates shared encoding, seasonal adaptive fusion, and pseudo-MSIC representation learning to achieve stable delineation of coastal wetlands under varying seasonal and tidal conditions. To generate CCWIF, the Chinese coast was divided into 58 tidal subregions to account for spatial heterogeneity in tidal environments, and a region-specific inundation-frequency estimation



29 workflow was developed by integrating Sentinel-2 MNDWI time series with tide gauge
30 observations. CCWEM mapped 8906.15 km² of coastal wetlands and achieved an overall
31 accuracy of 94.07%, with an F1 score of 94.83% in low-tide boundary validation. Independent
32 validation using Sentinel-1 observed water occurrence showed overall monotonic agreement
33 with the CCWIF classes across all validation regions combined (Spearman's $\rho = 0.756$),
34 supporting its ability to characterize relative inundation-frequency gradients. To our knowledge,
35 CCWIF provides the first national-scale dataset describing coastal wetland inundation-
36 frequency gradients across China. Together, CCWEM and CCWIF provide a consistent high-
37 resolution spatial dataset for characterizing both the extent and internal hydrological structure
38 of China's coastal wetlands, supporting coastal wetland monitoring, assessment, and
39 management under complex tidal conditions.

40 **Keywords:** Coastal wetland dataset; Wetland extent; Inundation-frequency gradients; Earth
41 observation; Sentinel-2; China

42 1. INTRODUCTION

43 Coastal wetlands are critical ecological interfaces between land and sea, providing
44 irreplaceable ecological and societal benefits, including the maintenance of coastal biodiversity,
45 blue carbon storage, storm-surge attenuation, and support for coastal socio-economic systems
46 (He et al., 2025a; Day et al., 2024; Hübinger et al., 2026). However, under the combined
47 pressures of global environmental change and intensive human activities, coastal wetlands are
48 undergoing substantial spatial reorganization and functional transformation, with sea-level rise
49 widely recognized as a major driver of their long-term trajectories (Schuerch et al., 2018;
50 Murray et al., 2019). Previous studies have shown that coastal wetlands may face considerable
51 loss risks under climate change, and that their future responses are strongly mediated by local
52 sediment supply, accommodation space for landward migration, and coastal management
53 regimes (Mao et al., 2025; Guimond, 2025). In China, the long and geomorphologically diverse
54 coastline, pronounced spatial variations in tidal range and tidal regime, and strong regional
55 differences in coastal landforms together give rise to highly heterogeneous wetland



distributions and tidal inundation patterns (Wen et al., 2024; Wang et al., 2023a). Such spatial and hydrological heterogeneity creates a strong demand for consistent high-resolution data that can represent not only where coastal wetlands occur, but also how tidal inundation varies within them. Therefore, a national-scale dataset that jointly characterizes the maximum wetland extent and internal inundation-frequency gradients is essential for providing a more complete spatial representation of China's coastal wetlands and for supporting analyses of coastal hydrological processes, wetland dynamics, conservation, and coastal-zone management.

In recent years, large-scale coastal wetland and related water-body products have provided an important foundation for coastal-zone mapping, although they differ substantially in target objects, spatiotemporal resolution, and methodological design (Mcowen et al., 2017; Worthington et al., 2024; Zhen et al., 2026; Li et al., 2022). The products most closely related to this study are dedicated intertidal wetland products. For example, Jia et al. (2021) automatically implemented the Maximum Spectral Index Composite (MSIC) and threshold segmentation on the Google Earth Engine (GEE) platform to process Sentinel-2 time-series imagery over China, producing a 10 m tidal flat map of China. Murray et al. (2022) used long-term Landsat observations to map the losses and gains of three types of tidal wetlands—tidal flats, salt marshes, and mangroves—at the global scale from 1999 to 2019. Zhang et al. (2022) proposed the MTWM-TP method by integrating satellite-derived tidal information and phenological features and generated a 10 m multi-class coastal wetland product for East Asia, providing a representative benchmark for regional wetland composition mapping. More recently, Li et al. (2026a) integrated Sentinel-1/2 observations, field data, and deep learning to map coastal wetland vegetation in eastern China, further enriching high-resolution coastal wetland datasets. In contrast to dedicated coastal wetland products, broader wetland dynamic products place greater emphasis on interannual monitoring continuity and comprehensive wetland typology. Representative examples include GWL_FCS30 (Zhang et al., 2023a) and GWL_FCS30D (Zhang et al., 2024). The former used 2020 as the baseline year and integrated multi-source prior products, time-series remote-sensing imagery, automatic samples, and



83 hierarchical classification strategies to produce a global 30 m fine-resolution wetland map with
84 a unified representation of eight wetland subclasses. The latter further extended this framework
85 to annual mapping from 2000 to 2022 and improved long-term mapping continuity and
86 robustness through spatiotemporal consistency constraints. In addition, several mature baseline
87 products have been widely used in wetland studies. For instance, GLWD v2 (Lehner et al.,
88 2025) integrated multi-source ground and satellite data to construct a global database of 33
89 water-body and wetland classes, while JRC Global Surface Water (Pekel et al., 2016) used
90 large-scale Landsat imagery to generate global 30 m layers of surface water occurrence,
91 seasonality, and change. These products provide important benchmarks for national-scale
92 comparison and external validation. However, several data gaps remain for the consistent
93 characterization of China's coastal wetlands. First, some products focus only on individual
94 targets, such as tidal flats, mangroves, or coastal vegetation, and therefore cannot fully capture
95 the complex salt marsh–tidal flat–shallow water transition structure within China's coastal
96 wetlands. Second, many products are designed primarily for static or annual-scale mapping and
97 are not sufficient to explicitly address the state inconsistency at the same location caused by
98 tidal fluctuations and seasonal variation. Third, existing large-scale products generally
99 emphasize wetland classification, spatial extent, or temporal change, with limited consideration
100 of the joint representation of maximum wetland extent and internal hydrological gradients.
101 Therefore, a remaining data gap is a high-resolution dataset that can consistently characterize
102 the maximum wetland extent along the entire coast of China while providing a spatial basis for
103 further describing internal inundation-frequency gradients.

104 Compared with static wetland mapping, inundation frequency provides a more direct
105 characterization of tidal hydrological processes within coastal wetlands. Existing studies have
106 therefore mainly progressed along two lines: the development of dynamic wetland products and
107 the process-oriented modelling of remote-sensing time series. On the one hand, advances in
108 long-term remote-sensing archives and cloud-computing platforms have substantially
109 improved the temporal continuity of wetland dynamic mapping (Hu et al., 2025; Liang et al.,



2025; Li et al., 2026b). For example, GWD30, built upon the global 30 m Seamless Data Cube
(Chen et al., 2024), provides a global wetland dynamic dataset from 2013 to 2024 at a 4-day
interval. Related global monitoring initiatives, including GlobWetland and Global Mangrove
Watch, have also demonstrated the value of long-term Earth observation for wetland
assessment and change monitoring (Jones et al., 2009; Bunting et al., 2022). On the other hand,
increasing efforts have attempted to link remote-sensing time series with hydrological
processes to improve the physical interpretability of inundation-frequency information (Yang
et al., 2022). For instance, WofS and its extended applications have demonstrated that long-
term water-occurrence observations can support the characterization of inundation dynamics
and recurrence patterns (Huang et al., 2018; Huang et al., 2019). More recently, WetFramework
(Liang et al., 2026) integrated water-index time series, Fourier fitting, and tide gauge
observations to characterize the pixel-level long-term mean water response and estimate
wetland inundation frequency at the regional scale. Nevertheless, a clear data gap remains for
China's coastal wetlands. Existing dynamic wetland products primarily describe wetland
distribution and temporal change, whereas available inundation-frequency studies are generally
regional and do not provide a spatially consistent national-scale dataset that explicitly
characterizes internal inundation-frequency gradients under contrasting tidal and
geomorphological conditions. Therefore, a national-scale dataset that integrates stable
maximum wetland extent with regionally calibrated inundation-frequency gradients is needed
to provide a consistent representation of the spatial and hydrological structure of China's
coastal wetlands.

To address these data gaps, this study presents two complementary 10 m datasets for coastal
wetlands along the entire coast of China: the China Coastal Wetland Extent Map (CCWEM)
and the China Coastal Wetland Inundation Frequency Map (CCWIF). The datasets follow a
sequential organization in which the maximum wetland extent is first delineated and internal
inundation-frequency gradients are then characterized within this extent. To generate CCWEM,
we constructed a four-season semantic segmentation dataset based on multi-season Sentinel-2



137 observations and used SeasonMamba to jointly model stable wetland structures, seasonally
 138 variable zones, and pseudo-MSIC representations, thereby improving the consistency of
 139 maximum wetland extent delineation under varying seasonal and tidal conditions. Building on
 140 CCWEM, we further accounted for the spatial heterogeneity of tidal environments along the
 141 Chinese coast by dividing the coastal wetlands into 58 tidal subregions and integrating Sentinel-
 142 2 MNDWI time series with tide gauge observations to generate CCWIF. Together, CCWEM
 143 and CCWIF provide a consistent national-scale representation of both the spatial extent and
 144 internal hydrological gradients of China's coastal wetlands. The main contributions of this
 145 study are summarized as follows:

- 146 (1) We constructed a four-season semantic segmentation dataset for China's coastal
 147 wetlands and developed a multi-season sample joint-modelling strategy, providing a data
 148 foundation for stable delineation of the maximum wetland extent under complex tidal
 149 and seasonal conditions.
- 150 (2) We generated the 10 m CCWEM using SeasonMamba, which integrates shared encoding,
 151 season-adaptive variable-length fusion, and pseudo-MSIC representation learning to
 152 delineate the maximum extent of natural coastal wetlands along the coast of China.
- 153 (3) We generated the 10 m CCWIF by combining tidal regionalization, Sentinel-2 MNDWI
 154 time-series analysis, and tide gauge observations across 58 tidal subregions, providing a
 155 national-scale representation of relative inundation-frequency gradients within the
 156 mapped coastal wetland extent.
- 157 (4) We evaluated the quality of CCWEM and CCWIF through complementary validation
 158 strategies, including stratified product-level validation, low-tide boundary assessment,
 159 and independent Sentinel-1 observed water occurrence validation, providing multiple
 160 lines of evidence for dataset reliability and supporting their use in coastal wetland
 161 monitoring, hydrological analysis, conservation and restoration, and coastal-zone
 162 management.



163 2. MATERIALS

164 2.1. Definition of Coastal Wetlands

165 The Ramsar Convention adopts an inclusive definition of wetlands, encompassing a wide
 166 range of natural and artificial, permanent and seasonal, inland and coastal aquatic or semi-
 167 aquatic environments. This definition has broad applicability in global wetland inventories and
 168 conservation frameworks (Rakkasagi et al., 2024). However, it remains too broad for fine-scale
 169 remote-sensing mapping of coastal wetlands. Therefore, this study adopts a more operational
 170 definition of coastal wetlands, restricting them to natural wetland systems located in the land-
 171 sea transition zone that are dominated by tidal processes and characterized by periodic
 172 inundation and exposure. Specifically, coastal wetlands in this study include tidal flats, salt
 173 marshes, and mangroves, but exclude aquaculture ponds, salt pans, and other artificial wetlands
 174 (Wang et al., 2020).

175 2.2. Study Area

176 China is located along the northwestern Pacific margin, with its coastline spanning the Bohai
 177 Sea, Yellow Sea, East China Sea, and South China Sea. Extending across multiple climatic
 178 zones from north to south, the Chinese coast exhibits pronounced differences in coastal
 179 geomorphology, sedimentary environments, and tidal dynamics (Wang et al., 2023b), as shown
 180 in Fig. 1. Under the combined influence of large river inputs, monsoon climate, and tidal
 181 processes, China's coastal wetlands show a distinct north-south spatial pattern, shifting from
 182 tidal flats and salt marshes in the north to the coexistence of tidal flats, salt marshes, and
 183 mangroves in the south (Zhao et al., 2023). The study area covers 14 coastal provincial-level
 184 administrative regions of China, including Liaoning, Hebei, Tianjin, Shandong, Jiangsu,
 185 Shanghai, Zhejiang, Fujian, Guangdong, Hong Kong, Macao, Guangxi, Hainan, and Taiwan.
 186 In addition, 200 tide gauges are distributed along the coast, providing the observational basis
 187 for characterizing tidal conditions across different coastal segments.

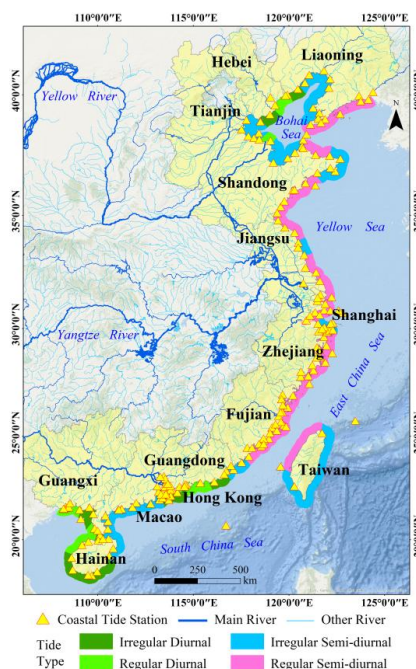


Fig. 1. Distribution of tidal types and coastal tide stations along the coast of China.

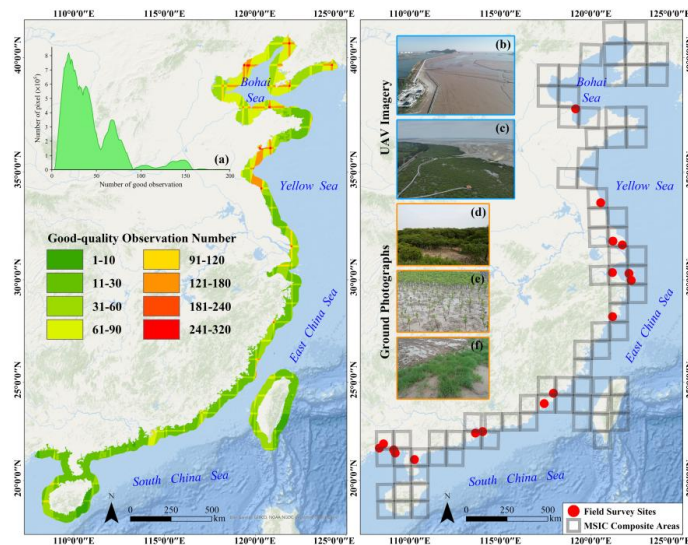
2.3. Input Data and Sample Preparation

2.3.1. Seasonal dataset construction and dataset split

To support national-scale multi-season mapping of coastal wetlands, we constructed a four-season coastal wetland sample dataset based on Sentinel-2 observations, together with field survey records and MSIC composite regions, as shown in Fig. 2. The remote-sensing data were Sentinel-2 Level-2A products available on the GEE platform. These products have an approximately 5-day revisit cycle and provide atmospherically corrected surface reflectance bands, making them suitable for monitoring vegetation, soil, and water conditions (Gahrouei et al., 2026; Wagner et al., 2026). Across the national coastal zone, the number, spatial distribution, and frequency histogram of good-quality candidate observations are shown in Fig. 2(a). To improve the reliability of sample annotation, we conducted multiple field surveys in representative coastal wetland regions of China during 2024–2025. These surveys covered typical tidal flat, salt marsh, and mangrove habitats, as shown in Fig. 2(b)–(f), and provided



203 important ground references for image interpretation, class-boundary delineation, and label
 204 refinement.



205
 206 **Fig. 2.** Observation quality, MSIC composite areas, and field survey sites for coastal wetland dataset
 207 preparation. (a) Spatial distribution and histogram of good-quality observations; (b) UAV image from
 208 Daishan Island, Zhejiang; (c) UAV image from Beibu Gulf, Guangxi; (d) Ground photograph from Longhai,
 209 Fujian; (e) Ground photograph from Yuhuan, Zhejiang; (f) Ground photograph from Hangzhou Bay,
 210 Zhejiang.

211 For seasonal sample construction, Sentinel-2 images acquired in January, April, July, and
 212 October 2025 were selected to represent winter, spring, summer, and autumn, respectively.
 213 Images with cloud cover lower than 10% were retained as candidate samples. Coastal wetland
 214 extents were then manually annotated by combining remote-sensing image interpretation with
 215 field survey information. The images were organized as three-channel inputs (NIR, Red, and
 216 Green), and both images and their corresponding labels were cropped into 512×512 pixel
 217 patches for subsequent model training and evaluation. In total, 2131, 1182, 996, and 946
 218 samples were constructed for winter, spring, summer, and autumn, respectively.

219 Considering the strong spatial autocorrelation that commonly exists among adjacent patches
 220 and the pronounced regional ecological heterogeneity along the Chinese coast, we split the
 221 dataset into training, validation, and test subsets at the Sentinel-2 tile level rather than at the
 222 patch level. This strategy was adopted to ensure both spatial independence and regional



representativeness. Specifically, all samples from the same tile were assigned to the same subset and were not split across different subsets. To ensure that the model could learn the major coastal wetland types and their regional variations along the Chinese coast, each subset included tiles from the major regional groups T49, T50, and T51, while strict independence was maintained at the tile level. Finally, the training, validation, and test sets consisted of 45, 9, and 10 tiles, respectively, and were used for parameter learning, model selection, and final generalization assessment of SeasonMamba. The complete tile list is provided in [Table S1](#).

2.3.2. MSIC composite generation

MSIC is designed to reconstruct composite observations that are closer to the maximum exposure state of intertidal zones from dense time-series imagery, thereby reducing spatial inconsistencies in single-date images caused by instantaneous tidal differences ([Wen et al., 2024](#); [Sun et al., 2024](#)). Specifically, this study used 79 Sentinel-2 tiles covering China's coastal zone as the basic processing units. For each tile, all available Sentinel-2 Level-2A images in 2025 were collected. After cloud and shadow masking, the normalized difference vegetation index (NDVI) was calculated for each image and used as a pixel-level quality metric ([Jia et al., 2021](#)). Then, for each pixel location, the observation corresponding to the maximum NDVI value along the temporal dimension was selected, while all spectral bands from the same acquisition were retained to generate a multi-band composite image. This procedure was implemented in GEE using the `qualityMosaic` function based on the quality metric. Because tidal inundation generally reduces near-infrared reflectance and suppresses NDVI, whereas wetland vegetation and exposed tidal flats tend to show higher NDVI under exposed conditions, this strategy preferentially preserves surface information closer to low-tide exposure conditions. It should be noted that the resulting composite images were not used directly as training labels. Instead, they served as model prediction inputs for extracting the national-scale maximum wetland extent.



248 3. DATASET GENERATION

249 The overall workflow of the dataset generation is shown in Fig. 3 and consists of five
 250 interlinked components: (a) constructing a four-season dataset of China's coastal wetlands,
 251 including multi-temporal remote-sensing samples and corresponding annotations for spring,
 252 summer, autumn, and winter; (b) organizing observations from the same spatial location across
 253 different seasons into seasonal groups, and further generating core masks and probability masks
 254 for model supervision; (c) developing the SeasonMamba model, which extracts the maximum
 255 wetland extent through seasonal and pseudo-MSIC branches; (d) integrating water-index time
 256 series and tide gauge records for curve fitting to estimate pixel-level wetland inundation
 257 frequency; and (e) generating the final CCWEM and CCWIF products. Sections 3.1–3.3
 258 describe the multi-season sample organization, the SeasonMamba network architecture, and the
 259 inundation-frequency estimation method, respectively.

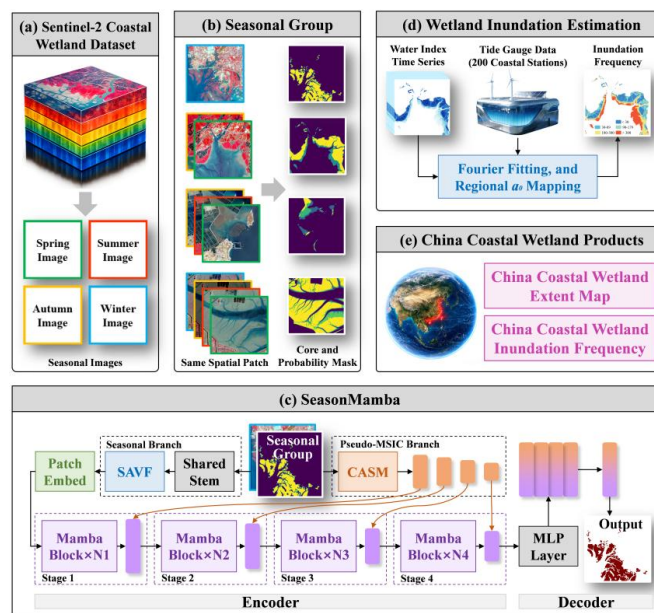


Fig. 3. Overall workflow for generating the CCWEM and CCWIF datasets.



3.1. Multi-season Sample Matching and Seasonal Group Construction

To explicitly model the seasonal appearance variability and label uncertainty of coastal wetlands, this study did not treat each single-season image patch as an independent training sample. Instead, observations acquired at the same spatial location in different seasons were organized into a seasonal group, as shown in Fig. 3(b). Specifically, image-label pairs were first matched within the winter, spring, summer, and autumn datasets, and the tile ID, acquisition date, and spatial location index were parsed from the file names. A cross-season spatial matching key was then constructed to aggregate samples from different seasons that corresponded to the same spatial location. For the i -th seasonal group, the input can be expressed as:

$$\mathcal{X}_i = \{I_i^{(1)}, I_i^{(2)}, \dots, I_i^{(N_i)}\}, \quad N_i \in \{1, 2, 3, 4\} \quad (1)$$

where $I_i^{(k)}$ denotes the three-channel image patch at the same spatial location in the k -th available season, and N_i is the number of valid seasonal observations in the group. Because of cloud contamination, observation conditions, and data availability, valid samples were not necessarily available for all four seasons at every spatial location. Therefore, a seasonal group can be regarded as a variable-length input consisting of N_i three-channel patches, conceptually organized as $N_i \times C \times H \times W$, rather than as a conventional fixed-form single-image tensor. This organization enables the model to learn more stable wetland representations from multi-season observations at the same location, rather than relying on the instantaneous appearance of a single season.

For each seasonal group, the corresponding multi-season labels were further fused into two types of supervision information: a core mask and a probability mask, which were used to describe seasonally variable zones and label-uncertain regions. Let $Y_i^{(k)}$ denote the binary label of the k -th available season in the i -th group. The core mask and probability mask are defined as:



$$M_i^{\text{core}} = \bigcap_{k=1}^{N_i} Y_i^{(k)}, \quad M_i^{\text{prob}} = \frac{1}{N_i} \sum_{k=1}^{N_i} Y_i^{(k)} \quad (2)$$

where M_i^{core} represents pixels labelled as coastal wetlands in all available seasons, emphasizing stable and high-confidence wetland areas. M_i^{prob} represents the occurrence probability of wetland labels across multiple seasons and provides soft supervision for tidal flat exposure–inundation transition zones and other seasonally variable areas.

With this construction, each training sample is no longer a single-date image, but consists of a variable number of seasonal observations $\mathcal{X}_i$ and their corresponding dual supervision masks, M_i^{core} and M_i^{prob} . This provides the input basis for the subsequent multi-season joint modelling in SeasonMamba.

3.2. SeasonMamba

3.2.1. Seasonal branch

The seasonal branch is designed to jointly model multi-temporal observations acquired at the same spatial location across different seasons, thereby extracting more stable wetland representations from temporally heterogeneous but spatially aligned inputs. Specifically, for each seasonal image $I_i^{(k)}$ in a seasonal group, a parameter-shared stem is first used to extract initial features. This design preserves spatially consistent structural information across seasons while reducing the model’s dependence on the appearance pattern of any single season. The shallow features from all available seasons are then organized as a feature set and fed into the season-adaptive variable-length fusion (SAVF) module for adaptive integration, producing the seasonal fused feature F_i^{sea} for the corresponding seasonal group. This process can be formulated as:

$$F_i^{\text{sea}} = \phi_{\text{SAVF}} \left(\left\{ \phi_{\text{stem}} \left(I_i^{(k)} \right) \right\}_{k=1}^{N_i} \right) \quad (3)$$



309 The core objective of this branch is not to fit the surface appearance of a fixed season, but to
 310 identify spatially stable wetland structural patterns from multi-season observations. Meanwhile,
 311 it suppresses short-term appearance disturbances caused by tidal-level differences, residual
 312 water, illumination changes, and phenological variation. By organizing the input as a variable-
 313 length seasonal group, the seasonal branch can also naturally accommodate missing seasons or
 314 imbalanced seasonal coverage, thereby improving the robustness of the model under complex
 315 real-world observation conditions. The detailed workflow of this branch is shown in Fig. 4(a).

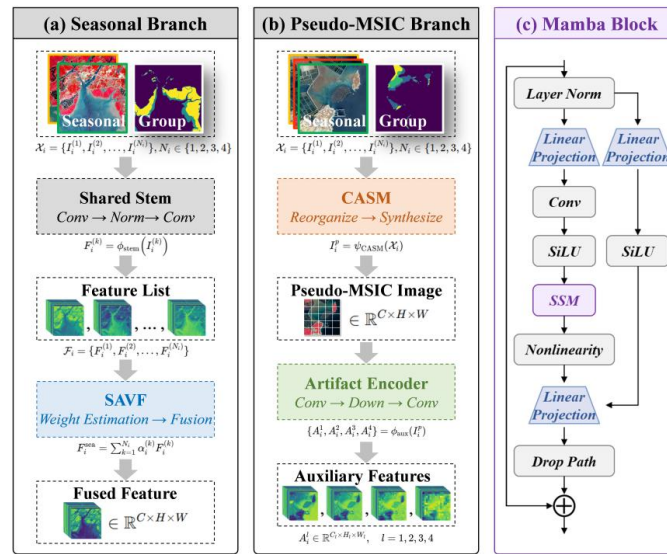


Fig. 4. Overview of the proposed SeasonMamba framework

3.2.2. Pseudo-MSIC branch

319 The pseudo-MSIC branch is designed to reduce the training–inference domain mismatch
 320 between multi-season observations used for model training and MSIC composites used for
 321 inference, enabling the model to learn wetland features that are closer to the actual prediction
 322 scenario (Ji et al., 2025). Specifically, all available seasonal observations $\mathcal{X}_i$ are first fed into
 323 the composite artifact synthesis module (CASM), which generates a pseudo-MSIC image I_i^p
 324 through cross-season reorganization and synthesis. This process does not aim to reconstruct any
 325 real single-season image. Instead, it simulates the overall appearance of the same spatial



location under composite observation conditions, so that the generated image better resembles the MSIC image used for subsequent prediction in terms of texture organization, boundary morphology, and local mixed patterns. The pseudo-MSIC image I_i^p is then fed into an artifact encoder to extract multi-scale auxiliary features $\{A_i^l\}_{l=1}^4$, which supplement the backbone network in modelling composite-image representations. The whole process can be summarized as:

$$\{A_i^l\}_{l=1}^4 = \phi_{aux}(\phi_{CASM}(\mathcal{X}_i)) \quad (4)$$

Different from the seasonal branch, which mainly focuses on modelling cross-season stable wetland structures, the pseudo-MSIC branch explicitly simulates the composite-observation style through CASM and uses the artifact encoder to learn feature patterns introduced by the compositing process. This design improves the robustness and generalization ability of wetland delineation under composite-image prediction scenarios. The detailed workflow of this branch is shown in Fig. 4(b).

3.2.3. Encoder–decoder architecture and optimization

Considering that coastal wetland targets are often characterized by narrow and elongated boundaries, fragmented patches, and broad spatial continuity, the encoder adopts a hierarchical architecture composed of multi-stage Mamba blocks (Gu et al., 2023). This design is used to model long-range spatial dependencies with relatively high computational efficiency. The internal structure of the Mamba block is not further expanded here and is shown in Fig. 4(c). In SeasonMamba, F_i^{sea} is fed into the main encoder, while $\{A_i^l\}_{l=1}^4$ are injected into corresponding encoder stages as auxiliary composite-style features. The former represents cross-season stable wetland structural information, whereas the latter provides supplementary texture, boundary, and local contextual information that is closer to the MSIC composite-observation style. During decoding, we adopt a lightweight design consistent with the SegFormer decoder (Zhang et al., 2023b), in which multi-scale features are progressively restored and fused. By combining high-level semantic information with low-level spatial details,



the decoder reconstructs more refined wetland boundaries. The overall encoder–decoder process is illustrated in Fig. 3(c).

During training, we used a joint loss function composed of core supervision, probabilistic supervision, and a feature consistency constraint. First, for the core mask, binary cross-entropy loss and Dice loss were jointly used to strengthen the model’s ability to identify stable wetland areas while maintaining consistency in both region-level classification and boundary overlap (He et al., 2025b). Second, for the probability mask, an additional binary cross-entropy loss was introduced to explicitly exploit seasonal wetland occurrence information and reduce the hard-label bias caused by transition zones and uncertain regions. Furthermore, to enhance domain consistency between the seasonal-group representation and the MSIC-style representation, we introduced a lightweight high-level feature consistency constraint. Specifically, the high-level features from the seasonal fused main branch and the corresponding high-level features from the pseudo-MSIC branch were separately processed by global average pooling, and their semantic proximity was constrained using mean squared error. This encourages CASM to learn domain-invariant wetland semantics, rather than merely generating auxiliary representations that superficially resemble composite images. The final loss is defined as:

$$\mathcal{L} = \mathcal{L}_{core} + \lambda_{prob} \mathcal{L}_{prob} + \lambda_{cons} \mathcal{L}_{cons} \quad (5)$$

where $\mathcal{L}_{core}$ denotes the supervision term based on the core mask, $\mathcal{L}_{prob}$ denotes the probabilistic supervision term based on the probability mask, and $\mathcal{L}_{cons}$ denotes the high-level feature consistency constraint. λ_{prob} and λ_{cons} are balancing coefficients for the corresponding loss terms. Because this study uses variable-length seasonal groups as input units, Group Normalization was used instead of Batch Normalization during training to improve stability under small-batch conditions. The main training configuration of SeasonMamba is summarized in Table S2.



377 3.3. Inundation Frequency Estimation

378 3.3.1. Coastal partition and MNDWI time-series construction

379 After obtaining the national-scale maximum wetland extent, namely CCWEM, we further
 380 estimated pixel-level inundation frequency within this extent. Given the pronounced spatial
 381 heterogeneity in tidal regime, tidal range, and tidal dynamics along the Chinese coast, applying
 382 a single national-scale mapping relationship would likely introduce substantial regional bias.
 383 Therefore, this study adopted a partition-based modelling strategy. The coastal wetland
 384 distribution zone of China was divided into 58 subregions, within which modified normalized
 385 difference water index (MNDWI) time series were constructed separately to support subsequent
 386 curve fitting and parameter mapping.

387 To ensure the representativeness of the time series, each month was divided into three fixed
 388 temporal windows: days 1–10, days 11–20, and day 21 to the end of the month, resulting in 36
 389 ten-day temporal units. For each temporal window, all Sentinel-2 observations acquired within
 390 the same window in the target year and the preceding year were extracted and merged, and a
 391 median composite was then generated to reduce the effects of residual clouds, anomalous
 392 observations, and short-term noise. Compared with using observations from a single year only,
 393 this cross-year same-window compositing strategy increases the number of valid observations
 394 and improves spatial coverage while maintaining consistent seasonal phases.

395 3.3.2. Temporal fitting and key parameter extraction

396 After obtaining the MNDWI time-series image stack, we applied a Savitzky–Golay (S-G)
 397 filter to reduce noise and improve data quality, as illustrated in Fig. 5(a) (Liu et al., 2024). The
 398 smoothed time series was then fitted using a Fourier function, as shown in Fig. 5(b) (Sun et al.,
 399 2023). The fitting function is defined as:

$$400 \quad y = a_0 + a_1 \cos(\omega x) + b_1 \sin(\omega x) + a_2 \cos(2\omega x) + b_2 \sin(2\omega x) \quad (6)$$



where y denotes the fitted MNDWI value, x represents the temporal position, ω is the frequency coefficient, a_0 is the constant term, and a_1 , a_2 , b_1 , b_2 characterize periodic variations at different temporal scales.

This procedure extracts the periodic water-related signal from the MNDWI time series and isolates the constant term a_0 as the stable response after smoothing and fitting. Hydrologically, a_0 can be interpreted as a pixel-level proxy for the long-term mean water-covered condition at the annual scale. Statistically, a_0 summarizes the persistent component of the MNDWI temporal signal jointly shaped by local tidal processes and microtopographic variations, thereby providing an intermediate variable for subsequent regional calibration against the tidal level–annual inundation days relationship. The main parameter settings for S-G filtering and Fourier fitting are summarized in Table S3.

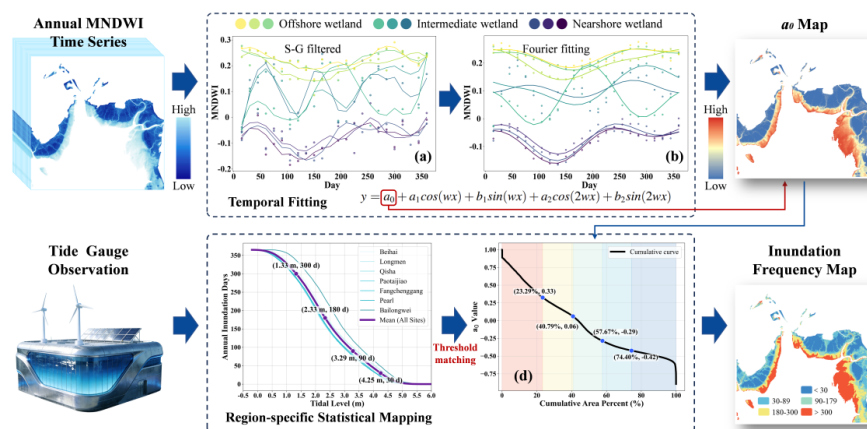


Fig. 5. Workflow of region-specific inundation frequency estimation, illustrated using Pearl Bay, Fangchenggang City as an example. (a) S-G filtering of annual MNDWI time series; (b) Fourier fitting and extraction of the key parameter a_0 ; (c) Regional tidal level–annual inundation days curve derived from tide gauge observations; (d) Cumulative area curve of a_0 .

3.3.3. Region-specific mapping from a_0 to inundation frequency

After obtaining pixel-level a_0 , we established a region-specific statistical mapping within each subregion to convert a_0 into annual inundation-frequency classes, considering the differences in tidal hydrodynamic conditions among coastal segments. This conversion does not directly retrieve instantaneous tidal level, absolute water depth, or land-surface elevation



422 from a_0 . Instead, it is based on a monotonic ranking assumption within each region: within a
 423 tidally coherent subregion, pixels with higher long-term mean water response are generally
 424 expected to experience longer annual inundation duration. Therefore, a_0 is defined in this study
 425 as a relative hydrological response indicator that characterizes the pixel-level mean inundation
 426 condition at the annual scale, serving as an intermediate variable that links remote-sensing
 427 water-index time series with tide-gauge-derived statistical information.

428 Specifically, for each subregion, tide gauge observations were first used to construct
 429 a tidal level–annual inundation days relationship, which describes the annual inundation
 430 duration associated with different tidal-level conditions. Based on the predefined annu
 431 al inundation duration thresholds of 30, 90, 180, and 300 d, the corresponding tidal-le
 432 vel nodes and temporal proportions were identified from this relationship, as shown in
 433 Fig. 5(c). The names of the subregions and their corresponding area-percentage thresh
 434 olds are provided in Table S4, and the tidal level–annual inundation days curves and
 435 threshold nodes for all 58 subregions are shown in Fig. S1. Hourly tidal-level records
 436 from 200 tide gauges along the Chinese coast were obtained from the National Marin
 437 e Data Center (<https://mds.nmdis.org.cn/pages/tidalCurrent.html>).

438 Meanwhile, all wetland pixels within each subregion were ranked according to their a_0 values,
 439 and their cumulative area percentages were calculated to construct the regional a_0 cumulative
 440 area curve, as shown in Fig. 5(d). The temporal proportions corresponding to different
 441 inundation-duration thresholds in the tidal level–annual inundation days relationship were then
 442 matched with the a_0 cumulative area curve to determine the corresponding a_0 thresholds within
 443 each subregion. In other words, tide gauge observations provide the tidal-level exceedance
 444 probabilities, or temporal proportions, associated with the annual inundation-duration
 445 thresholds, whereas the a_0 cumulative curve provides the spatial ranking of relative inundation
 446 intensity among wetland pixels. Together, these two components enable region-specific
 447 calibration from the remote-sensing-derived a_0 response to inundation-frequency classes.



Through this procedure, continuous a_0 values were divided into five annual inundation-frequency classes: <30 d, 30–90 d, 90–180 d, 180–300 d, and >300 d. Finally, the a_0 thresholds obtained for each subregion were mapped back to the spatial domain to classify all wetland pixels within that subregion, and the results were integrated to generate CCWIF. This region-specific mapping strategy avoids the systematic bias that may arise from applying a single national threshold and allows the final product to better adapt to the differences in tidal background and wetland hydrological processes among coastal segments. Therefore, the resulting inundation frequency emphasizes the relative differentiation of annual-scale inundation intensity among wetland pixels, rather than instantaneous water-level variations during individual tidal events.

4. RESULTS

4.1. Performance and Transferability of the CCWEM Generation Framework

To evaluate the performance of SeasonMamba and its multi-season learning framework for coastal wetland delineation, we first calculated semantic segmentation accuracy metrics using the independent test set. SeasonMamba achieved strong segmentation performance, with a mean intersection over union (mIoU) of 93.25% and a mean pixel accuracy (mPA) of 96.22%. For the target class of coastal wetlands, the precision, recall, and F1-score reached 93.88%, 92.97%, and 93.43%, respectively, with a corresponding IoU of 87.66%. These results indicate that the proposed multi-season joint training framework can effectively extract cross-season stable wetland structural features, thereby providing reliable support for national-scale coastal wetland mapping and inference.

To further assess the effectiveness and transferability of the multi-season learning framework in complex coastal wetland delineation, we conducted analyses from two perspectives: internal model ablation and cross-backbone transferability. The former was used to examine the contributions of the seasonal branch, pseudo-MSIC branch, and multi-season input organization to the performance improvement of SeasonMamba, whereas the latter was used to



474 verify whether the proposed multi-season learning strategy can be consistently transferred to
 475 different types of backbone networks.

476 The internal ablation results are shown in Table 1. The following observations can be made:

477 1) The complete model (E1) achieved $F1_{\text{wetland}}$ of 93.43% and mIoU of 93.25%, outperforming
 478 all other configurations. Removing either the pseudo-MSIC branch (E2) or the seasonal branch
 479 (E3) led to varying degrees of decline in both metrics, indicating that both branches contributed
 480 stable performance gains. The larger performance degradation caused by removing the seasonal
 481 branch further suggests that cross-season stable structure modelling is a more critical source of
 482 improvement. 2) When the input was reduced from four seasons to three seasons (E1 to E4),
 483 the model accuracy decreased only slightly. In contrast, when the model was degraded to the
 484 single-season baseline (E6), the performance drop became more pronounced. This indicates
 485 that the proposed framework is robust to partial seasonal missingness, while complete multi-
 486 season inputs provide the most discriminative wetland representations.

487 **Table 1. Ablation experiments on the proposed multi-season learning framework and branch design (%)**

ID	Seasonal Group	Seasonal Branch	Pseudo-MSIC Branch	Seasons used	$F1_{\text{wetland}}$	mIoU
E1	✓	✓	✓	4	93.43	93.25
E2	✓	✓	✗	4	92.78	92.63
E3	✓	✗	✓	4	92.52	92.38
E4	✓	✓	✓	3	93.27	93.09
E5	✓	✓	✓	2	92.25	92.12
E6	✗	✗	✗	1	90.64	90.60

488

489 The results of the cross-backbone transferability experiments are presented in Table 2. Two
 490 main observations can be made: 1) All backbones achieved consistent improvements after
 491 incorporating the proposed framework, indicating that the framework is not specifically
 492 dependent on SeasonMamba. CNN-based, Transformer-based, and Mamba-based hierarchical
 493 backbones all benefited from the proposed multi-season learning strategy. 2) The magnitude of
 494 improvement varied across different backbones. ConvNeXt (Woo et al., 2023) and SegFormer
 495 (Zhang et al., 2023b) showed relatively larger gains, whereas MambaVision (Hatamizadeh et



al., 2025), despite achieving higher absolute performance, exhibited a smaller relative improvement. This suggests that the proposed framework does not simply replace the representational capacity of the backbone itself, but rather complements conventional single-season training by improving cross-season information organization and adaptation to phenological and tidal-state perturbations.

Table 2. Transferability of the proposed multi-season learning framework to different backbone networks (%)

Backbone	Setting	F1 _{wetland}	mIoU	Δ F1 _{wetland}	Δ mIoU
ConvNeXt	Baseline	89.13	89.23	—	—
ConvNeXt	+ Proposed framework	91.58	91.49	2.45	2.26
SegFormer	Baseline	90.34	90.33	—	—
SegFormer	+ Proposed framework	92.70	92.55	2.36	2.22
MambaVision	Baseline	91.62	91.53	—	—
MambaVision	+ Proposed framework	93.61	93.43	1.99	1.90

Together with the ablation experiments, the transferability results further demonstrate that the core value of the proposed method lies in establishing a multi-season learning mechanism that is relatively decoupled from the specific encoder architecture. Specifically, the training organization based on seasonal groups, the seasonal branch for modelling cross-season stable structures, and the pseudo-MSIC branch for alleviating the representation gap between training and inference jointly constitute the main sources of performance improvement. Importantly, these improvements can be consistently transferred to different types of mainstream backbones.

4.2. Coastal Wetland Extent Characterized by CCWEM

Based on the national-scale inference results, CCWEM was used to characterize the spatial pattern and provincial composition of the maximum wetland extent along the Chinese coast, as shown in Fig. 6. Overall, China’s coastal wetlands exhibit a distribution pattern combining continuous and patchy forms along the coastline. Large continuous coastal wetlands are mainly distributed in Bohai Bay, the Yellow River Delta, the Jiangsu coast, the Yangtze River Estuary, Hangzhou Bay, and the Beibu Gulf. In contrast, along parts of the southeastern coast, coastal



wetlands are generally narrow, fragmented, and discontinuous due to the influence of
mountainous and hilly coasts, artificial shorelines, and fragmented bay systems.

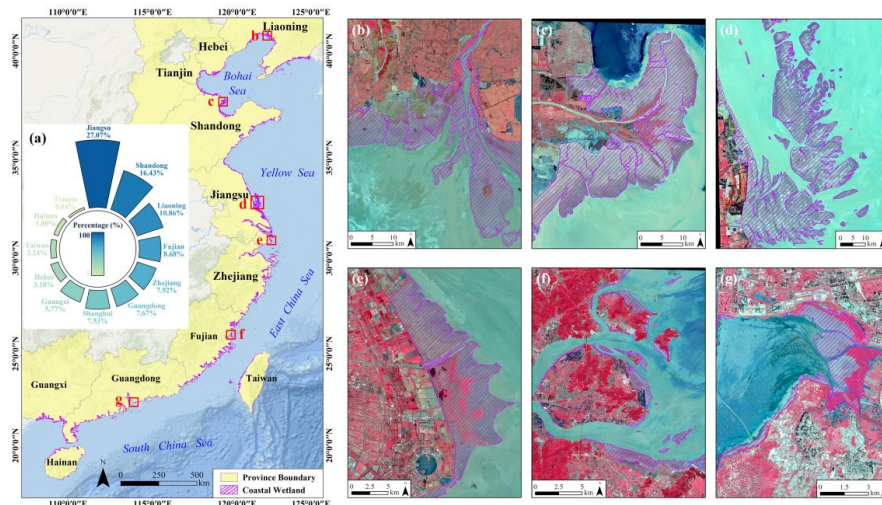


Fig. 6. Spatial distribution and provincial composition of the CCWEM. (a) National distribution of mapped coastal wetlands and provincial percentage composition; (b) Liaohe Estuary; (c) Yellow River Estuary; (d) Yancheng coastal wetland, the largest coastal wetland area in China; (e) Yangtze River Estuary; (f) Minjiang Estuary; (g) Pearl River Estuary.

The area statistics are shown in Table 3 and Fig. 6(a). The total area of China's coastal wetlands was 8906.15 km². At the provincial level, Jiangsu had the largest coastal wetland area, with 2411.07 km², accounting for 27.07% of the national total. It was followed by Shandong and Liaoning, with areas of 1463.19 km² and 967.39 km², accounting for 16.43% and 10.86%, respectively. Fujian, Zhejiang, Guangdong, and Shanghai also contained relatively large coastal wetland areas, accounting for 8.68%, 7.92%, 7.67%, and 7.53% of the national total, respectively. In contrast, Tianjin, Hainan, and Taiwan had relatively small proportions, accounting for 0.84%, 1.80%, and 2.24%, respectively. Overall, Jiangsu, Shandong, and Liaoning together accounted for more than half of China's total coastal wetland area, indicating that China's coastal wetlands are mainly concentrated in large muddy tidal flats, estuaries, and bay regions in northern and eastern China.



538 **Table 3. Provincial areas and percentage composition of the CCWEM product in China.**

Region	Coastal wetland (km ²)	Percentage (%)
China	8906.15	100.00
Liaoning	967.39	10.86
Hebei	283.14	3.18
Tianjin	74.88	0.84
Shandong	1463.19	16.43
Jiangsu	2411.07	27.07
Shanghai	670.91	7.53
Zhejiang	705.26	7.92
Fujian	772.84	8.68
Guangdong	682.99	7.67
Guangxi	514.32	5.77
Hainan	160.54	1.80
Taiwan	199.61	2.24

539 **Note:** For statistical reporting, Hong Kong and Macao were merged into the Guangdong region. The same
 540 treatment was applied to all subsequent province-level statistics.

541 4.3. Product-level Accuracy and Low-tide Boundary Reliability of CCWEM

542 To further assess the product-level reliability of CCWEM for national-scale mapping, we
 543 evaluated its accuracy from two complementary perspectives: conventional stratified random
 544 sampling and boundary-point validation under low-tide conditions. The former was used to
 545 examine the overall classification accuracy of CCWEM at both national and provincial scales,
 546 whereas the latter specifically targeted the maximum wetland extent emphasized by CCWEM
 547 and further assessed its spatial consistency along intertidal boundary zones.

548 First, a stratified random sampling strategy was adopted for product-level accuracy
 549 assessment of CCWEM. Considering the boundary uncertainty inherent in coastal wetland
 550 mapping, validation samples were divided into three strata: coastal wetland, adjacent water, and
 551 adjacent inland. The latter two strata represent neighbouring water bodies and inland non-
 552 wetland areas within 1 km of the wetland boundary on the seaward and landward sides,
 553 respectively. Within each stratum, 1000 validation points were randomly generated, which can
 554 be implemented in GEE using the stratifiedSample function. These points were then manually
 555 interpreted with reference to high-resolution Google Earth imagery. Based on the interpretation



556 results, a binary confusion matrix was constructed, and the User's Accuracy (UA), Producer's
 557 Accuracy (PA), Overall Accuracy (OA), and F1-score of the wetland class were calculated.

558 The stratified random sampling results indicate that CCWEM showed high consistency with
 559 manual interpretation at the national scale. At the national level, UA_{wetland} , PA_{wetland} , $F1_{\text{wetland}}$,
 560 and OA reached 92.50%, 90.39%, 91.43%, and 94.07%, respectively, as shown in Table 4. In
 561 terms of regional differences, provinces with extensive tidal flat distributions generally
 562 achieved higher accuracy, such as Jiangsu, Liaoning, and Shandong. By contrast, accuracy was
 563 slightly lower in Zhejiang, Guangdong, and Hainan, where coastlines are more fragmented and
 564 neighbouring water bodies and artificial surfaces are more spatially intermixed. The complete
 565 province-level confusion matrices are provided in Table S5.

566 **Table 4.** Accuracy metrics of the CCWEM product based on stratified random sampling at the national
 567 and provincial levels (%).

Region	UA_{wetland}	PA_{wetland}	$F1_{\text{wetland}}$	OA
China	92.50	90.39	91.43	94.07
Liaoning	94.53	90.98	92.72	94.60
Hebei	93.33	89.36	91.30	92.73
Tianjin	89.66	89.66	89.66	91.67
Shandong	94.41	90.48	92.40	93.47
Jiangsu	95.74	93.92	94.82	94.27
Shanghai	91.04	88.41	89.71	92.31
Zhejiang	87.32	88.57	87.94	93.95
Fujian	91.40	88.54	89.95	95.23
Guangdong	85.29	89.23	87.22	95.36
Guangxi	91.11	85.42	88.17	92.03
Hainan	89.66	83.87	86.67	92.79
Taiwan	87.88	90.63	89.23	94.85

568

569 Because CCWEM is designed to delineate the maximum wetland extent of coastal wetlands,
 570 the reliability of its boundary should be evaluated under low- or near-low-tide conditions. In
 571 this study, nine key validation regions distributed along the Chinese coastline were selected.
 572 These regions cover representative temperate, subtropical, and tropical coastal zones in China
 573 and include diverse geomorphic settings, such as estuaries, bays, and open coasts. They are also
 574 located under different tidal environments, thereby reflecting regional variations in the



intertidal wetland edge along the Chinese coast. A total of 1500 boundary sample points were selected to evaluate the ability of the product to delineate the boundary between wetlands and non-wetlands.

To ensure that the validation samples represented the maximum exposed boundary of the intertidal zone, tide-level information corresponding to Sentinel-2 overpass times was further obtained from nearby tide gauges in each region. Sentinel-2 images acquired at low or near-low tide were preferentially selected as the reference basis for boundary validation. The tide gauges, Sentinel-2 overpass times, instantaneous tide heights, and tidal states corresponding to the nine validation regions are summarized in Table 5.

For the boundary validation, Pearl Bay was used as an example to illustrate the selection of boundary points, as shown in Fig. 7(a). The boundary points were mainly distributed along the interface between wetlands and non-wetlands and were used to assess the capability of the product to characterize intertidal boundary positions. Fig. 7(b)–(j) show the tide-level variations corresponding to the Sentinel-2 overpass times for the nine validation regions.

Table 5. Selected coastal tide stations and tidal conditions at the Sentinel-2 transit times for the nine validation regions.

Region	Province	Station	Transit time	Instantaneous tide height (m)	Tide status
Liaohu Estuary	Liaoning	Yingkou	2025-06-11 10:51:51	0.82	Low tide
Haihe Estuary	Tianjin	Tangu	2025-08-11 10:55:41	0.83	Low tide
Yellow River Estuary	Shandong	Weifang	2025-09-02 10:45:29	0.86	Low tide
Yancheng	Jiangsu	Jiang Harbor	2025-03-20 10:41:40	1.06	Near low tide
Yangtze River Estuary	Shanghai	Zhongjun	2025-01-22 10:39:20	1.41	Low tide
Hangzhou Bay	Zhejiang	Ganpu	2025-03-18 10:35:51	1.03	Near low tide
Jiulong River Estuary	Fujian	Shima	2025-01-17 10:40:31	1.73	Low tide
Anpu Harbor	Guangdong	Xiabo	2025-04-21 11:05:29	1.00	Near low tide
Pearl Bay	Guangxi	Pearl Harbor	2025-10-08 11:21:51	1.43	Near low tide

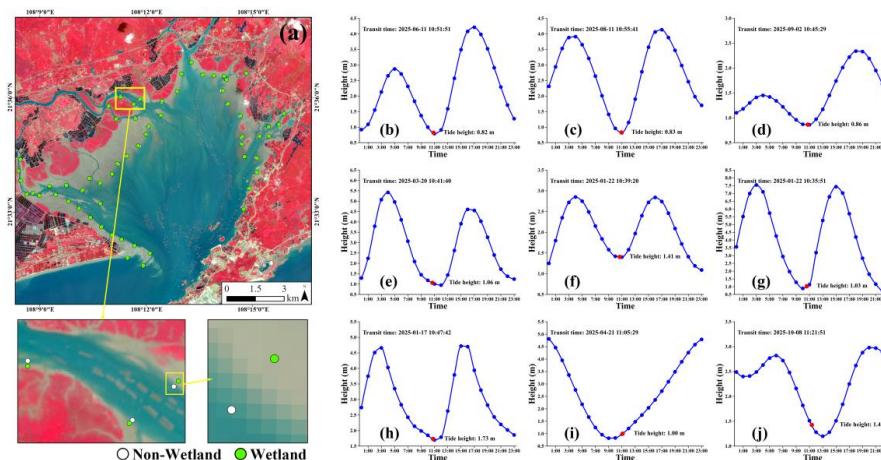


Fig. 7. Edge-point sample illustration and tidal conditions at the Sentinel-2 transit times for the nine validation regions from north to south along the coast of China. (a) Edge-point sample illustration in Pearl Bay; (b) Liaohe Estuary; (c) Haihe Estuary; (d) Yellow River Estuary; (e) Yancheng; (f) Yangtze River Estuary. (g) Hangzhou Bay; (h) Jiulong River Estuary; (i) Anpu Harbor; (j) Pearl Bay.

The point-by-point validation results based on the 1500 boundary sample points are presented in Table 6. For the wetland class, the F1 score and OA reached 94.83% and 94.67%, respectively, while the PA and UA were 97.87% and 91.98%, respectively. These boundary-point validation results indicate that the proposed CCWEM product can accurately delineate the maximum exposed boundary of the intertidal zone and shows high consistency with the observed boundary positions.

Table 6. Confusion matrix and accuracy metrics for the edge-point validation, with accuracy values reported in percent.

Class	Wetland	Non-wetland	Total	UA	F1	OA
Wetland	734	16	750	91.98	94.83	94.67
Non-wetland	64	686	750	97.72	94.49	
Total	798	702	1500			
PA	97.87	91.47				

4.4. Inundation-Frequency Gradients Characterized by CCWIF

Based on the regionalized inundation-frequency estimation results, CCWIF was used to characterize the spatial pattern and provincial composition of inundation-frequency gradients within China's coastal wetlands, as shown in Fig. 8. Overall, pronounced inundation-frequency gradients were observed within China's coastal wetlands. High-frequency inundation zones



were mainly distributed in low-lying tidal flats near the seaward side and areas adjacent to tidal channels, whereas low-frequency inundation zones were mostly located along landward margins, salt marsh vegetation zones, and relatively elevated tidal flats. This land-to-sea increasing inundation pattern was particularly evident in typical tidal flat and estuarine wetland regions, including the central Jiangsu coast, the Yellow River Estuary, the Yangtze River Estuary, Hangzhou Bay, the Minjiang River Estuary, and the Pearl River Estuary. These results indicate that CCWIF can effectively characterize the internal tidal exposure–inundation gradients of coastal wetlands.

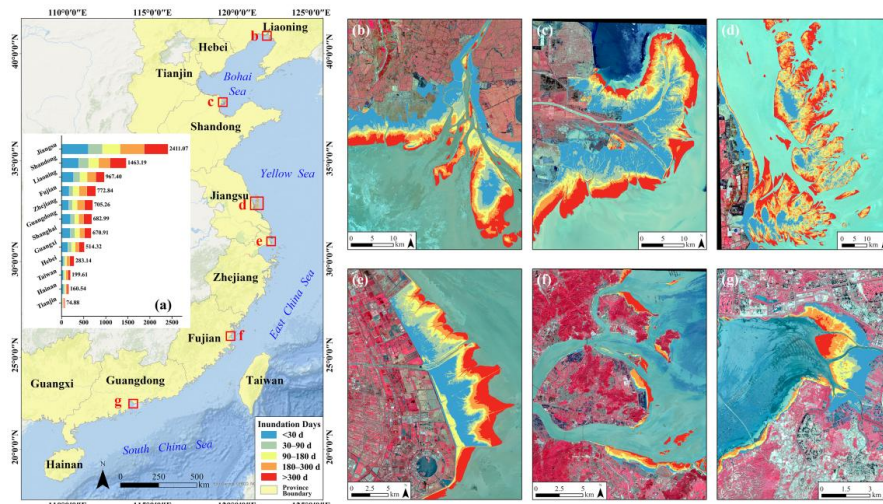


Fig. 8. Spatial distribution and provincial composition of the CCWIF. (a) National distribution of CCWIF classes and provincial area composition of five inundation-frequency classes; (b) Liaohe Estuary; (c) Yellow River Estuary; (d) Yancheng coastal wetland, the largest coastal wetland area in China; (e) Yangtze River Estuary; (f) Minjiang Estuary; (g) Pearl River Estuary.

The area statistics are shown in Table 7 and Fig. 8(a). The total area represented by CCWIF was 8906.14 km². Among the inundation-frequency classes, areas with annual inundation duration lower than 30 days occupied the largest area, reaching 2274.67 km². This was followed by high-frequency inundation zones with annual inundation duration greater than 300 days, covering 2149.80 km². At the provincial level, Jiangsu remained the province with the largest CCWIF area, with a total of 2411.07 km². The areas of its five inundation-frequency classes were 606.60, 317.64, 401.24, 545.13, and 540.46 km², respectively, indicating a relatively complete tidal-flat inundation gradient. Shandong and Liaoning had the second and third largest



632 CCWIF areas, respectively. Overall, CCWIF inherits the spatial clustering pattern of China's
 633 coastal wetlands revealed by CCWEM, while further characterizing hydrological differences
 634 within wetlands. The results also suggest that tidal inundation characteristics of coastal
 635 wetlands along the Chinese coast are jointly controlled by regional tidal dynamics, geomorphic
 636 settings, and wetland types, resulting in pronounced spatial heterogeneity.

637 **Table 7. Provincial areas of the five CCWIF classes across China (km²).**

Region	<30 d	30–90 d	90–180 d	180–300 d	>300 d	Total
China	2274.67	1227.43	1438.72	1815.52	2149.80	8906.15
Liaoning	270.69	144.38	164.08	194.57	193.68	967.40
Hebei	43.11	34.03	38.27	72.16	95.58	283.14
Tianjin	13.12	9.20	14.46	17.87	20.23	74.88
Shandong	385.68	224.95	228.03	256.22	368.31	1463.19
Jiangsu	606.60	317.64	401.24	545.13	540.46	2411.07
Shanghai	197.33	103.15	106.93	111.34	152.17	670.91
Zhejiang	162.25	80.91	110.67	165.85	185.57	705.26
Fujian	171.30	87.54	136.80	177.16	200.03	772.84
Guangdong	203.65	93.97	90.72	111.85	182.80	682.99
Guangxi	139.98	84.14	83.60	85.97	120.63	514.32
Hainan	41.79	24.85	27.92	29.94	36.04	160.54
Taiwan	39.17	22.69	36.00	47.46	54.30	199.61

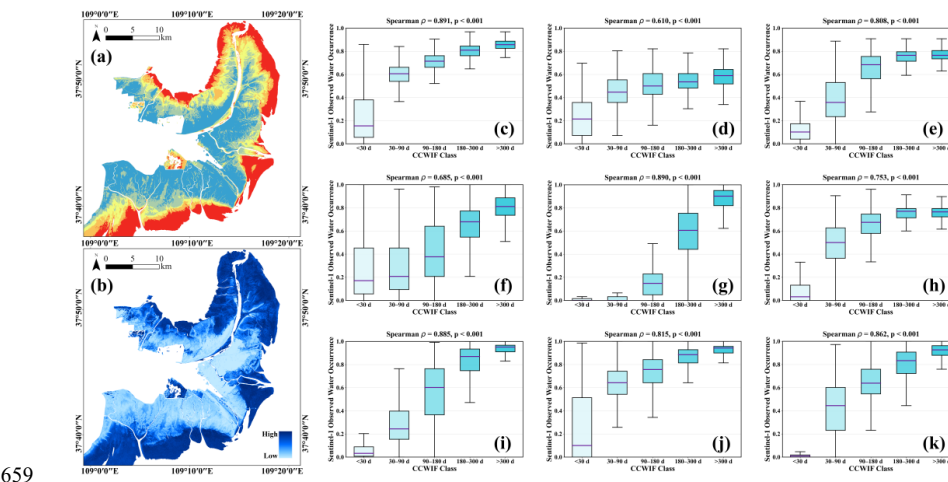
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639 4.5. Independent Validation of CCWIF Using Sentinel-1 Observations

640 Because CCWIF was generated from Sentinel-2 MNDWI time series and tide gauge
 641 observations, an independent data source is needed to evaluate its ability to characterize relative
 642 inundation-frequency gradients. In this study, Sentinel-1 SAR-derived observed water
 643 occurrence (OWO) was introduced as an independent reference in nine representative coastal
 644 wetland regions. For each validation region, Sentinel-1 GRD images acquired during 2024–
 645 2025 were collected. Within the CCWEM extent, water bodies were extracted from the VV
 646 backscatter of each image using a local Otsu thresholding method. Sentinel-1 OWO was then
 647 calculated as the ratio between the number of times a pixel was identified as water and the
 648 number of valid Sentinel-1 observations. This validation procedure is independent of the
 649 Sentinel-2 MNDWI time series used to generate CCWIF.



650 Sentinel-1 OWO was subsequently spatially overlaid with the five CCWIF classes. To reduce
651 the effects of spatial autocorrelation and differences in area among inundation-frequency
652 classes, stratified random sampling was conducted within each validation region according to
653 the CCWIF classes, with 5000 pixels randomly selected from each class. Based on these
654 samples, the distribution of Sentinel-1 OWO corresponding to each CCWIF class was
655 summarized, and Spearman's rank correlation test was used to assess the monotonic
656 consistency between CCWIF classes and Sentinel-1 OWO. This validation design primarily
657 evaluates whether higher CCWIF classes correspond to higher independent SAR-derived water
658 occurrence. The results are shown in Fig. 9 and Table 8.



660 Fig. 9. Sentinel-1 validation of CCWIF across nine regions. (a) CCWIF classes in the Yellow River
661 Estuary; (b) Sentinel-1 OWO in the same region; (c–k) boxplots of Sentinel-1 OWO across the five CCWIF
662 classes in nine validation regions: (c) Liaohu Estuary; (d) Haihe Estuary; (e) Yellow River Estuary; (f)
663 Yancheng; (g) Yangtze River Estuary; (h) Hangzhou Bay; (i) Jiulong River Estuary; (j) Anpu Harbor; (k)
664 Pearl Bay.

665 Table 8. Sentinel-1-based validation statistics for CCWIF across nine representative wetland regions.

Region	Province	Images	Spearman ρ	p-value	Median OWO trend
Liaohu Estuary	Liaoning	73	0.891	<0.001	increasing
Haihe Estuary	Tianjin	57	0.610	<0.001	increasing
Yellow River Estuary	Shandong	104	0.808	<0.001	increasing
Yancheng	Jiangsu	164	0.685	<0.001	increasing
Yangtze River Estuary	Shanghai	61	0.890	<0.001	increasing
Hangzhou Bay	Zhejiang	126	0.753	<0.001	increasing
Jiulong River Estuary	Fujian	123	0.885	<0.001	increasing



Anpu Harbor	Guangdong	71	0.815	<0.001	increasing
Pearl Bay	Guangxi	131	0.862	<0.001	increasing

666

667 As shown in Fig. 9(a-b), in the Yellow River Estuary, the spatial pattern of Sentinel-1 OWO
 668 was generally consistent with the CCWIF classes. Furthermore, Fig. 9(c-k) shows that
 669 Sentinel-1 OWO increased overall with increasing CCWIF class across the nine validation
 670 regions. The Spearman's rank correlation coefficients ranged from 0.610 to 0.891, and all
 671 correlations were statistically significant ($p < 0.001$). Among the validation regions, the Liaohe
 672 River Estuary, Yangtze River Estuary, Jiulong River Estuary, Pearl Bay, Anpu Harbor, and
 673 Yellow River Estuary showed strong monotonic agreement. Although the correlations were
 674 relatively lower in the Haihe River Estuary and Yancheng, the median OWO still increased
 675 with increasing CCWIF class, indicating that the relative inundation gradients were effectively
 676 captured.

677 These results provide independent evidence that CCWIF can characterize relative
 678 inundation-frequency gradients within coastal wetlands. They also support the rationale for
 679 using a_0 as a regionalized hydrological response proxy and provide independent evidence for
 680 the regionalized a_0 -inundation frequency mapping strategy. It should be noted that the Sentinel-
 681 1 validation mainly reflects relative consistency rather than the absolute accuracy of annual
 682 inundation days, because SAR-based water extraction may still be affected by vegetation
 683 structure, surface roughness, wind waves, and other factors.

684 5. DISCUSSION

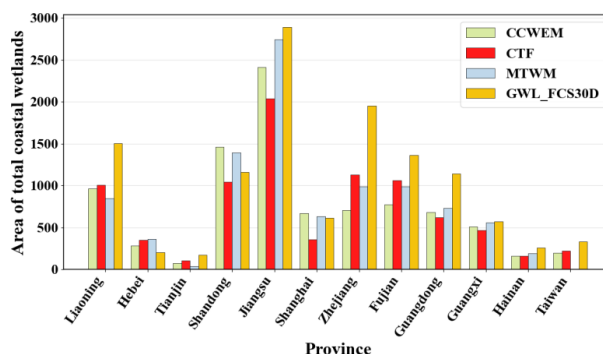
685 5.1. Added Value of CCWEM Relative to Existing Coastal Wetland Products

686 The added value of CCWEM relative to existing coastal wetland products lies not only in
 687 differences in mapped area and spatial boundaries, but also in its target definition and
 688 methodological design. Existing coastal wetland products at the Chinese or regional scale
 689 mostly rely on spectral-index thresholds, tide-assisted rules, traditional machine-learning
 690 approaches, or classification strategies designed for specific wetland types. In contrast,



691 CCWEM was generated using a multi-season deep-learning semantic segmentation framework.
 692 Through SeasonMamba, CCWEM jointly models cross-seasonally stable wetland structures,
 693 seasonally variable zones, and representation differences in MSIC composite imagery, making
 694 it better suited for delineating the maximum wetland extent of natural coastal wetlands,
 695 including tidal flats, salt marshes, and mangroves, under complex tidal conditions. To further
 696 clarify this added value, we compared CCWEM with CTF (Jia et al., 2021), MTWM (Zhang et
 697 al., 2022), and GWL_FCS30D (Zhang et al., 2024) in terms of provincial area composition and
 698 spatial details in representative regions.

699 The area comparison with existing products reveals clear differences in the total mapped area
 700 and provincial distribution of China's coastal wetlands, as shown in Fig. 10. Overall, the total
 701 coastal wetland area extracted by CTF was smaller than that of CCWEM, whereas MTWM and
 702 GWL_FCS30D both reported larger areas than CCWEM, with GWL_FCS30D showing the
 703 largest mapped area. These differences indicate that discrepancies among products are related
 704 not only to spatial resolution, but also closely to target class definitions and mapping strategies.
 705 Fig. 11 presents subset comparisons for Anpu Harbor in Guangdong, Sanmen Bay in Zhejiang,
 706 and Jiaozhou Bay in Shandong.



707

708 **Fig. 10.** Provincial area comparison of coastal wetlands derived from CCWEM, CTF, MTWM, and
 709 GWL_FCS30D across China (km²). Note that the area of Taiwan Province was not included in MTWM.

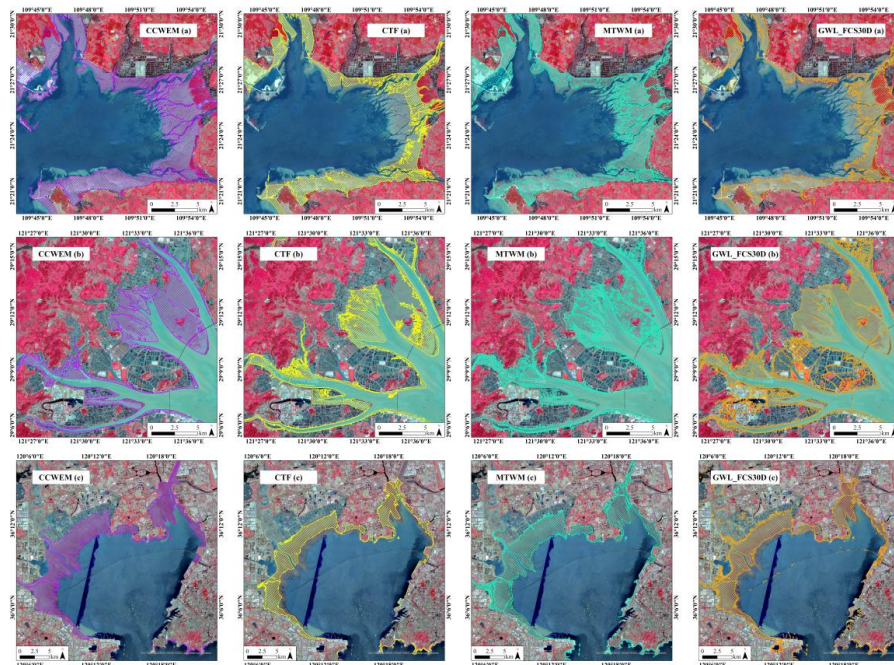


Fig. 11. Comparison of coastal wetland maps derived from CCWEM, CTF, MTWM and GWL_FCS30D in three representative coastal regions: (a) Anpu Harbor, (b) Sanmen Bay, and (c) Jiaozhou Bay.

The differences between CTF and CCWEM are first related to their target mapping objects. CTF was designed for tidal flat mapping in China. Its core methodology constructs composite images under high- and low-tide conditions from Sentinel-2 time series and extracts exposed tidal flats within the intertidal zone, but it does not separately identify mangroves or salt marshes as target classes. The differences between MTWM and CCWEM mainly arise from their classification strategies. By jointly using tidal and phenological features, MTWM identifies tidal flats, salt marshes, and mangroves simultaneously. It is therefore more likely than CTF to retain vegetated coastal wetlands, resulting in a larger mapped area than CTF and a spatial extent closer to CCWEM. GWL_FCS30D shows the largest discrepancy from the other products, mainly because it is based on a global 30 m annual wetland mapping framework. This product uses Landsat time series to generate global annual wetland maps from 2000 to 2022 and includes eight wetland subclasses, among which only mangroves, salt marshes, and tidal flats were selected for comparison in this study. Owing to its global-scale design and 30 m spatial resolution, GWL_FCS30D is more susceptible to mixed-pixel effects in China's



coastal zone, where shorelines are highly fragmented, aquaculture ponds are densely distributed, and tidal channels are complex. As a result, parts of nearshore transition zones, aquaculture-pond margins, and scattered patches may be included within the wetland extent, leading to a substantially larger total area than CCWEM. Overall, CCWEM, generated using a multi-season deep-learning framework, provides a national-scale representation of the maximum wetland extent that is more consistent with the definition of natural coastal wetlands and exhibits more coherent spatial detail.

5.2. Necessity of Coastal Tidal Regionalization for CCWIF

The tidal environment along the Chinese coast exhibits pronounced spatial heterogeneity, with substantial differences among coastal segments in tidal range, tidal-wave propagation, and tidal-regime structure. If a unified set of parameters were applied directly at the national scale to retrieve coastal wetland inundation frequency, regional differences in tidal controls would likely be overlooked, thereby affecting the stability and comparability of the results. Therefore, this study partitioned the Chinese coast according to representative tidal characteristics derived from tide gauge observations. Specifically, harmonic analysis was first performed on tide gauge water-level time series to extract major tidal parameters. The M_2 amplitude and M_2 phase represent the amplitude and phase of the principal lunar semidiurnal constituent, respectively, and were used to characterize the strength of the semidiurnal tidal component and the alongshore propagation of tidal waves. In addition, the form number F was introduced to characterize tidal-regime structure:

$$F = (K_1 + O_1) / (M_2 + S_2) \quad (7)$$

where K_1 and O_1 denote the amplitudes of the principal diurnal tidal constituents, and M_2 and S_2 denote the amplitudes of the principal semidiurnal tidal constituents. Thus, F represents the relative strength of the principal diurnal constituents to the principal semidiurnal constituents and can be used to distinguish tidal regimes. A smaller F indicates dominance of semidiurnal tides, whereas an increasing F indicates a stronger diurnal component and a gradual transition



753 toward mixed or diurnal tidal regimes. On this basis, mean tidal range was further combined
754 with these parameters to comprehensively characterize tidal intensity, the degree of semidiurnal
755 tidal control, tidal-wave propagation, and tidal-regime differences across coastal segments,
756 which were then used for tidal partitioning.

757 The necessity of this partitioning can be illustrated more clearly by the Zhejiang–Fujian
758 coastal segment. As shown in Figs. 1 and 12, this segment is generally located within a
759 continuous regular semidiurnal tidal-regime zone. If only tidal-regime categories were
760 considered, it could be treated as a single region. However, tidal characteristics along this
761 segment are not spatially uniform, but instead vary continuously from north to south. On the
762 one hand, tidal range and M2 amplitude fluctuate among different coastal sections, indicating
763 that tidal energy is not spatially homogeneous, as shown in Fig. 12(a-b). On the other hand,
764 alongshore variations in M2 phase indicate that tidal-wave propagation is not synchronous
765 across the entire segment, but instead shows phased propagation and adjustment among
766 different coastal sections, as shown in Fig. 12(c). In other words, although this continuous
767 coastal segment shares the same dominant tidal regime, its internal tidal dynamics are not
768 uniform, and the response relationships between water-index time series and tidal inundation
769 processes may differ across locations. Accordingly, this study further divided the continuous
770 Zhejiang–Fujian regular semidiurnal tidal-regime zone into 10 subregions. This example
771 demonstrates that the purpose of tidal partitioning is not only to identify broad tidal-regime
772 zones, but also to capture fine-scale alongshore differences in tidal environments under a
773 broadly consistent tidal-regime background. Following the same principle, the entire Chinese
774 coast was further partitioned at the national scale, resulting in 58 tidal subregions.

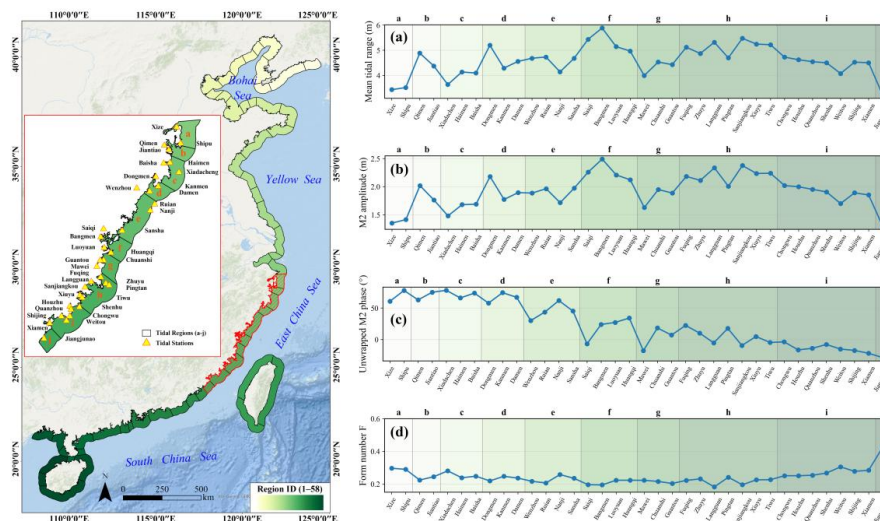


Fig. 12. Tidal regionalization of China's coastal wetlands and spatial variations in representative tidal characteristics along the coast. (a) Mean tidal range; (b) M2 amplitude; (c) Unwrapped M2 phase; (d) Form number F.

To further examine the rationale for using the fitted constant term a_0 as a stable annual-scale water-response indicator, we compared pixel-level a_0 values with the observed annual mean MNDWI within the above 10 representative subregions. It should be noted that this comparison is not intended as an independent accuracy validation. Rather, it is used to examine whether a_0 extracted from Fourier fitting can stably preserve the long-term mean water response embedded in the original MNDWI time series. As shown in Fig. 13, the two variables show high consistency across all subregions, indicating that a_0 can effectively represent the relative annual-scale water-cover status of each pixel. This supports its use as an intermediate variable linking remote-sensing-derived water responses with tide-gauge-based statistical information.

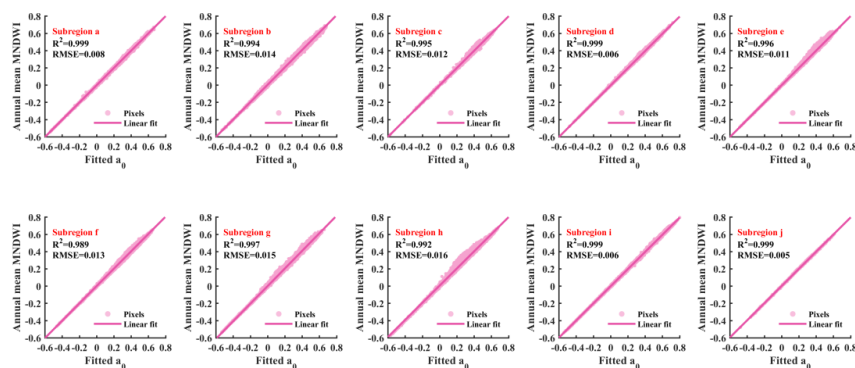


Fig. 13. Consistency between fitted a_0 and annual mean MNDWI across 10 subregions along the Zhejiang–Fujian coast.

5.3. Potential Applications of CCWEM and CCWIF

CCWEM and CCWIF provide complementary spatial information on the extent and internal hydrological structure of China’s coastal wetlands and can be used individually or jointly depending on the application. A single wetland extent map can answer the question of “where wetlands are”, but provides limited information on tidal exposure intensity and hydrological differences within wetlands. By jointly characterizing the maximum wetland extent and internal inundation-frequency gradients along the entire Chinese coast at 10 m spatial resolution, CCWEM and CCWIF extend the information provided by traditional static wetland extent maps. The two datasets can therefore support a range of applications related to coastal wetland monitoring, ecological assessment, hydrological analysis, conservation and restoration, and coastal-zone management, including needs emphasized in the 2030 Agenda for Sustainable Development (Colglazier, 2015) and the National Wetland Conservation Plan (2022–2030).

Specifically, CCWEM delineates the spatial boundaries and regional distribution of natural coastal wetlands and can provide a spatial baseline for mangrove restoration (Nie et al., 2026), monitoring and management of *Spartina alterniflora* invasion (Chen et al., 2025), carbon stock assessment, biodiversity conservation, and coastal wetland resource inventories (Liu et al., 2026). Building on this spatial extent, CCWIF further characterizes relative hydrological differences within coastal wetlands, ranging from low- to high-frequency inundation zones. It



813 can be used to describe regional inundation-frequency patterns and provide observational
 814 constraints for hydrodynamic process modelling (Kramer et al., 2026; Shen et al., 2026),
 815 including potential coupling with models such as Delft3D, FVCOM, and SCHISM. In addition,
 816 CCWIF can provide auxiliary information for exploring regional tide level–elevation
 817 relationships and can serve as prior spatial information for sediment transport, vegetation
 818 expansion, and ecological suitability modelling. Under sea-level rise and increasing coastal
 819 development pressure, the inundation-frequency gradients represented by CCWIF may also
 820 help identify spatial differences in the sensitivity of coastal wetlands to water-level changes and
 821 hydrodynamic disturbances. When used together, CCWEM and CCWIF can support
 822 assessments of enhanced inundation, tidal-flat contraction, and constrained landward wetland
 823 migration (Payandeh et al., 2026; He et al., 2026), thereby providing complementary spatial
 824 information for coastal wetland vulnerability analysis, adaptive management, and future-
 825 change assessment.

826 **5.4. Limitations and Uncertainties**

827 Although CCWEM and CCWIF provide a systematic national-scale characterization of the
 828 maximum wetland extent and inundation-frequency gradients of China’s coastal wetlands,
 829 several limitations and uncertainties remain.

830 First, for CCWEM: 1) SeasonMamba still relies on four-season samples and manual
 831 annotations. The training samples may remain imbalanced in terms of regional distribution,
 832 seasonal completeness, and label accuracy, which may affect the model’s generalization ability
 833 in complex coastal settings, especially in highly turbid estuaries, areas with dense aquaculture
 834 ponds, and regions dominated by mangroves or high-coverage salt marshes. 2) MSIC
 835 representation is inherently dependent on optical time-series compositing. Its results are still
 836 constrained by cloud contamination, observation frequency, and tidal conditions at the time of
 837 image acquisition. Therefore, the generated maximum-exposure appearance does not
 838 necessarily correspond to the absolute lowest-tide exposure state in a strict physical sense.



839 Second, for CCWIF: 1) The reliability of inundation-frequency gradient estimation is
 840 affected by wetland cover conditions. In bare tidal flats and low-vegetation-cover tidal flats,
 841 MNDWI time series can relatively directly capture transitions among open water, wet mudflats,
 842 and exposed sediments. In sparsely vegetated areas, inundation signals may be affected by
 843 mixed pixels and seasonal phenology. In densely vegetated areas, such as mangroves, reed beds,
 844 and high-coverage salt marshes, optical signals mainly reflect canopy-surface characteristics
 845 and may underestimate under-canopy inundation processes. 2) Sentinel-1 OWO provides
 846 independent validation and demonstrates good monotonic consistency between CCWIF and
 847 SAR-derived water occurrence. However, Sentinel-1 OWO may still be affected by vegetation
 848 structure, surface roughness, wind waves, and double-bounce scattering. Therefore, Sentinel-1
 849 validation mainly supports the relative inundation-frequency gradients rather than the absolute
 850 accuracy of annual inundation days. 3) The regionalized mapping of CCWIF relies on the
 851 monotonic ranking assumption between a_0 and annual inundation duration within the same tidal
 852 subregion. In areas with dense tidal channels, complex artificial shorelines, or hydrodynamic
 853 conditions altered by engineering structures, this relationship may be weakened. Therefore,
 854 CCWIF is better interpreted as a regionally calibrated product of relative inundation-frequency
 855 gradients for characterizing internal hydrological structure and tidal exposure differences
 856 within wetlands, rather than as a pixel-level retrieval of absolute annual inundation days.

857 6. CONCLUSION

858 This study presents two complementary 10 m datasets for coastal wetlands along the entire
 859 coast of China in 2025: CCWEM and CCWIF. Following a sequential strategy of first
 860 delineating the maximum wetland extent and then characterizing internal inundation-frequency
 861 gradients, CCWEM was generated from multi-season Sentinel-2 observations using a four-
 862 season coastal wetland sample dataset and the SeasonMamba model, while CCWIF was derived
 863 by integrating tidal regionalization, Sentinel-2 MNDWI time series, and tide gauge
 864 observations across 58 tidal subregions. CCWEM delineated 8906.15 km² of natural coastal
 865 wetlands and achieved an overall accuracy of 94.07%, with an F1 score of 94.83% in low-tide



866 boundary validation. Independent Sentinel-1 observed water occurrence validation further
867 showed overall monotonic agreement with the CCWIF classes (Spearman's $\rho = 0.756$),
868 supporting the capability of CCWIF to characterize relative inundation-frequency gradients
869 within coastal wetlands. To our knowledge, CCWIF provides the first national-scale dataset
870 describing coastal wetland inundation-frequency gradients across China. Together, CCWEM
871 and CCWIF provide a consistent high-resolution representation of both the spatial extent and
872 internal hydrological structure of China's coastal wetlands and can support coastal wetland
873 monitoring, ecological and hydrological analyses, conservation and restoration, and coastal-
874 zone management. Future improvements may incorporate higher-temporal-frequency remote-
875 sensing observations, longer tide gauge records, and complementary SAR, LiDAR, and
876 hydrodynamic information to further improve dataset quality in complex coastal environments
877 and densely vegetated wetlands.

878 **DISCLOSURE STATEMENT**

879 No potential conflict of interest was reported by the author(s).

880 **DATA AVAILABILITY STATEMENT**

881 The CCWEM and CCWIF datasets described in this study are openly available from Figshare
882 at <https://doi.org/10.6084/m9.figshare.32096356.v2> (Liang, 2026).

883 **AUTHOR CONTRIBUTION**

884 **JL:** Conceptualization, Data curation, Methodology, Software, Validation, Formal analysis,
885 Visualization, Writing – original draft, Writing – review & editing; **YZ:** Methodology,
886 Validation, Formal analysis, Writing – review & editing; **YW:** Conceptualization, Supervision,
887 Project administration, Funding acquisition, Writing – review & editing; **CC:** Data curation,



888 Validation, Formal analysis, Writing – review & editing; **JB**: Data curation, Investigation,
 889 Writing – review & editing.

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894 REFERENCES

- 895 Bunting, P., Rosenqvist, A., Hilarides, L., Lucas, R.M., Thomas, N., Tadono, T., Worthington, T.A., Spalding, M., Murray, N.J.,
 896 Rebelo, L.-M., 2022. Global mangrove extent change 1996–2020: Global Mangrove Watch version 3.0. *Remote Sens.*
 897 14, 3657. <https://doi.org/10.3390/rs14153657>
- 898 Chen, C., Chen, Y., Liu, Z., Xue, Z., Yang, G., Sun, W., 2025. PCSAI: a phenological characteristics-based *Spartina alterniflora*
 899 index derived from a time-series of remote sensing images. *Big Earth Data* 9, 965–993.
 900 <https://doi.org/10.1080/20964471.2025.2554043>
- 901 Chen, S., Wang, J., Liu, Q., Liang, X., Liu, R., Qin, P., Yuan, J., Wei, J., Yuan, S., Huang, H., Gong, P., 2024. Global 30 m seamless
 902 data cube (2000–2022) of land surface reflectance generated from Landsat 5, 7, 8, and 9 and MODIS Terra constellations.
 903 *Earth Syst. Sci. Data* 16, 5449–5475. <https://doi.org/10.5194/essd-16-5449-2024>
- 904 Colglazier, W., 2015. Sustainable development agenda: 2030. *Science* 349, 1048–1050. <https://doi.org/10.1126/science.aad2333>
- 905 Day, J.W., Anthony, E., Costanza, R., Edmonds, D., Gunn, J., Hopkinson, C., Mann, M.E., Morris, J., Osland, M., Quirk, T., Rovai,
 906 A., Rybczyk, J., Spencer, T., Stephens, J., Syvitski, J., Twilley, R., Visser, J., White, J.R., 2024. Coastal wetlands in the
 907 Anthropocene. *Annu. Rev. Environ. Resour.* 49, 105–135. <https://doi.org/10.1146/annurev-environ-121922-041109>
- 908 Gahrouei, O.R., Guindon, L., Perbet, P., Correia, D.L., Côté, J.-F., Bêland, M., 2026. Windthrow mapping in boreal forests using
 909 a spatio-temporal deep learning approach and Sentinel-2 imagery. *Remote Sens. Environ.* 335, 115270.
 910 <https://doi.org/10.1016/j.rse.2026.115270>
- 911 Gu, A., Dao, T., 2023. Mamba: Linear-time sequence modeling with selective state spaces. *arXiv preprint arXiv:2312.00752*.
 912 <https://doi.org/10.48550/arXiv.2312.00752>
- 913 Guimond, J.A., 2025. The overlooked role of terrestrial groundwater in coastal wetland resilience. *Nat. Water* 3, 364–366.
 914 <https://doi.org/10.1038/s44221-025-00406-x>
- 915 Hatamizadeh, A., Kautz, J., 2025. MambaVision: A hybrid Mamba-Transformer vision backbone, in: *Proceedings of the IEEE/CVF*
 916 *Conference on Computer Vision and Pattern Recognition*, pp. 25261–25270.
 917 <https://doi.org/10.1109/CVPR52734.2025.02352>
- 918 He, Q., Li, Z.A., Elphick, C.S., Sun, Y., Sutherland, W.J., Taylor, N.G., Wasson, K., 2025a. Making restoration effective for dynamic
 919 coastal wetlands. *Glob. Change Biol.* 31, e70455. <https://doi.org/10.1111/gcb.70455>
- 920 He, Y., Chen, H., Zhu, Q., Zhang, Q., Yang, W., Yang, J., Shi, W., Gao, L., Filonchik, M., 2025b. A dual-stream coding fusion
 921 network for landslide mapping based on multisource remote sensing images. *IEEE Trans. Geosci. Remote Sens.* 63, 1–
 922 21. <https://doi.org/10.1109/TGRS.2025.3637781>
- 923 He, Y., Zhang, Q., Zhu, Q., Chen, H., Huo, T., 2026. A data-knowledge-model synergistic reasoning framework for landslide



- 924 identification. *Remote Sens. Environ.* 340, 115404. <https://doi.org/10.1016/j.rse.2026.115404>
- 925 Hu, X., Chen, C., Yang, Z., Liu, Z., 2025. Reliable, large-scale, and automated remote sensing mapping of coastal aquaculture
- 926 ponds based on Sentinel-1/2 and ensemble learning algorithms. *Expert Syst. Appl.* 293, 128740.
- 927 <https://doi.org/10.1016/j.eswa.2025.128740>
- 928 Huang, C., Chen, Y., Zhang, S., Li, L., Shui, J., Liu, Q., 2019. Integrating water observation from space product and time-series
- 929 flow data for modeling spatio-temporal flood inundation dynamics. *Remote Sens.* 11, 2535.
- 930 <https://doi.org/10.3390/rs11212535>
- 931 Huang, C., Chen, Y., Zhang, S., Wu, J., 2018. Detecting, extracting, and monitoring surface water from space using optical sensors:
- 932 A review. *Rev. Geophys.* 56, 333–360. <https://doi.org/10.1029/2018RG000598>
- 933 Hübinger, C., Fluet-Chouinard, E., Escobar, D., Jaramillo, F., 2026. Exploring the potential of using L-band InSAR for mapping
- 934 flooded vegetation in tropical wetlands. *Remote Sens. Environ.* 332, 115086. <https://doi.org/10.1016/j.rse.2025.115086>
- 935 Ji, C., Tang, H., 2025. Towards reliable land cover mapping under domain shift: An overview and comprehensive comparative
- 936 study on uncertainty estimation. *Earth-Sci. Rev.* 263, 105070. <https://doi.org/10.1016/j.earscirev.2025.105070>
- 937 Jia, M., Wang, Z., Mao, D., Ren, C., Wang, C., Wang, Y., 2021. Rapid, robust, and automated mapping of tidal flats in China using
- 938 time series Sentinel-2 images and Google Earth Engine. *Remote Sens. Environ.* 255, 112285.
- 939 <https://doi.org/10.1016/j.rse.2021.112285>
- 940 Jones, K., Lanthier, Y., van der Voet, P., van Valkengoed, E., Taylor, D., Fernández-Prieto, D., 2009. Monitoring and assessment of
- 941 wetlands using Earth Observation: the GlobWetland project. *J. Environ. Manage.* 90, 2154–2169.
- 942 <https://doi.org/10.1016/j.jenvman.2007.07.037>
- 943 Kramer, M.R., Arias, M.E., Wang, P., 2026. Modeling the effects of mangrove hybrid infrastructure for coastal flood protection. *J.*
- 944 *Environ. Manage.* 404, 129594. <https://doi.org/10.1016/j.jenvman.2026.129594>
- 945 Lehner, B., Anand, M., Fluet-Chouinard, E., Tan, F., Aires, F., Allen, G.H., Bousquet, P., Canadell, J.G., Davidson, N., Ding, M.,
- 946 Finlayson, C.M., Gumbricht, T., Hilarides, L., Hugelius, G., Jackson, R.B., Korver, M.C., Liu, L., McIntyre, P.B., Nagy,
- 947 S., Olefeldt, D., Pavelsky, T.M., Pekel, J.-F., Poulter, B., Prigent, C., Wang, J., Worthington, T.A., Yamazaki, D., Zhang,
- 948 X., Thieme, M., 2025. Mapping the world's inland surface waters: an upgrade to the Global Lakes and Wetlands
- 949 Database (GLWD v2). *Earth Syst. Sci. Data* 17, 2277–2329. <https://doi.org/10.5194/essd-17-2277-2025>
- 950 Li, A., Song, K., Chen, S., Mu, Y., Xu, Z., Zeng, Q., 2022. Mapping African wetlands for 2020 using multiple spectral, geo-
- 951 ecological features and Google Earth Engine. *ISPRS J. Photogramm. Remote Sens.* 193, 252–268.
- 952 <https://doi.org/10.1016/j.isprsjprs.2022.09.009>
- 953 Li, M., Worthington, T., Chen, B., Smart, L., Spalding, M., Zhang, T., Chowdhury, S.U., Bai, Y., Yan, D., Li, S., Xu, B., 2026b.
- 954 Global mapping of tidal wetlands and adjacent environments using tidal analysis and multi-source Earth observations.
- 955 *ISPRS J. Photogramm. Remote Sens.* 234, 293–306. <https://doi.org/10.1016/j.isprsjprs.2026.02.014>
- 956 Li, Y., Yuan, L., Liu, T., Song, Z., Yang, S., Zhu, Z., and Liu, M., 2026a. CCAV-10m: an annual spatiotemporal dataset for eastern
- 957 coastal China's wetland vegetation by integrating Sentinel-1/2 observations via deep learning. *Earth Syst. Sci. Data*, 18,
- 958 2907–2927. <https://doi.org/10.5194/essd-18-2907-2026>
- 959 Liang, J., 2026. CCWEM_CCWIF, Figshare. Dataset. <https://doi.org/10.6084/m9.figshare.32096356.v2>
- 960 Liang, J., Wang, Y., Li, P., Fang, Z., 2025. Unlocking coastal wetland dynamics: a 40-year evolutionary analysis using HASX-Net
- 961 and time series insights from Yancheng, China. *Int. J. Digit. Earth* 18, 2518571.
- 962 <https://doi.org/10.1080/17538947.2025.2518571>
- 963 Liang, J., Zhang, Y., Wang, Y., Chen, C., 2026. WetFramework: A deep learning framework for coastal wetland boundary extraction
- 964 and inundation frequency estimation. *J. Hydrol.* 671, 135273. <https://doi.org/10.1016/j.jhydrol.2026.135273>
- 965 Liu, M., He, W., Zhang, H., 2024. WPS: A whole phenology-based spectral feature selection method for mapping winter crop from
- 966 time-series images. *ISPRS J. Photogramm. Remote Sens.* 210, 141–159. <https://doi.org/10.1016/j.isprsjprs.2024.03.005>
- 967 Liu, N., Cui, Y., Yang, S., Fang, Y., Ren, Y., Zhang, S., Luo, C., Zhang, X., Zhang, Y., 2026. Wetland restoration for waterbird



- 968 conservation: A framework and its application at Chongming Dongtan in China. *Biol. Conserv.* 317, 111799.
- 969 <https://doi.org/10.1016/j.biocon.2026.111799>
- 970 Mao, D., Wang, M., Wang, Y., Jiang, M., Yuan, W., Luo, L., Feng, K., Wang, D., Xiang, H., Ren, Y., Zhen, J., Jia, M., Ren, C.,
- 971 Wang, Z., 2025. The trajectory of wetland change in China between 1980 and 2020: hidden losses and restoration effects.
- 972 *Sci. Bull.* 70, 587–596. <https://doi.org/10.1016/j.scib.2024.12.016>
- 973 McOwen, C.J., Weatherdon, L.V., Van Bochove, J.W., Sullivan, E., Blyth, S., Zöckler, C., Stanwell-Smith, D., Kingston, N., Martin,
- 974 C.S., Spalding, M., Fletcher, S., 2017. A global map of saltmarshes. *Biodivers. Data J.* 5, e11764.
- 975 <https://doi.org/10.3897/BDJ.5.e11764>
- 976 Murray, N.J., Phinn, S.R., DeWitt, M., Ferrari, R., Johnston, R., Lyons, M.B., Clinton, N., Thau, D., Fuller, R.A., 2019. The global
- 977 distribution and trajectory of tidal flats. *Nature* 565, 222–225. <https://doi.org/10.1038/s41586-018-0805-8>
- 978 Murray, N.J., Worthington, T.A., Bunting, P., Duce, S., Hagger, V., Lovelock, C.E., Lucas, R., Saunders, M.I., Sheaves, M.,
- 979 Spalding, M., Waltham, N.J., Lyons, M.B., 2022. High-resolution mapping of losses and gains of Earth's tidal wetlands.
- 980 *Science* 376, 744–749. <https://doi.org/10.1126/science.abm9583>
- 981 Nie, X., Xue, Z., Li, X., 2026. Label-free mangrove mapping from temporally consistent PlanetScope imagery with interpretable
- 982 deep unfolding network. *ISPRS J. Photogramm. Remote Sens.* 235, 19–37.
- 983 <https://doi.org/10.1016/j.isprsjprs.2026.02.035>
- 984 Payandeh, A.R., Simard, M., Jones, C.E., Christensen, A., Jensen, D., Denbina, M., Oliver-Cabrera, T., 2026. Multi-sensor airborne
- 985 remote sensing for calibrating hydrodynamic and sediment transport models in coastal Louisiana wetlands
- 986 (Atchafalaya–Terrebonne). *Water Resour. Res.* 62, e2025WR042357. <https://doi.org/10.1029/2025WR042357>
- 987 Pekel, J.F., Cottam, A., Gorelick, N., Belward, A.S., 2016. High-resolution mapping of global surface water and its long-term
- 988 changes. *Nature* 540, 418–422. <https://doi.org/10.1038/nature20584>
- 989 Rakkasagi, S., Goyal, M.K., Jha, S., 2024. Evaluating the future risk of coastal Ramsar wetlands in India to extreme rainfalls using
- 990 fuzzy logic. *J. Hydrol.* 632, 130869. <https://doi.org/10.1016/j.jhydrol.2024.130869>
- 991 Schuerch, M., Spencer, T., Temmerman, S., Kirwan, M.L., Wolff, C., Lincke, D., McOwen, C.J., Pickering, M.D., Reef, R., Vafeidis,
- 992 A.T., Hinkel, J., Nicholls, R.J., Brown, S., 2018. Future response of global coastal wetlands to sea-level rise. *Nature*
- 993 561, 231–234. <https://doi.org/10.1038/s41586-018-0476-5>
- 994 Shen, J., Cai, X., Qin, Q., 2026. Machine learning prediction of saltwater intrusion to support coastal water resource management.
- 995 *J. Environ. Manage.* 401, 128811. <https://doi.org/10.1016/j.jenvman.2026.128811>
- 996 Sun, C., Li, J., Liu, Y., Zhao, S., Zheng, J., Zhang, S., 2023. Tracking annual changes in the distribution and composition of
- 997 saltmarsh vegetation on the Jiangsu coast of China using Landsat time series–based phenological parameters. *Remote*
- 998 *Sens. Environ.* 284, 113370. <https://doi.org/10.1016/j.rse.2022.113370>
- 999 Sun, J., Tang, C., Mu, K., Li, Y., Zheng, X., Zou, T., 2024. Tidal flat extraction and analysis in China based on multi-source remote
- 1000 sensing image collection and MSIC-OA algorithm. *Remote Sens.* 16, 3607. <https://doi.org/10.3390/rs16193607>
- 1001 Wagner, W., Bauer-Marschallinger, B., Roth, F., Stachl, T., Reimer, C., McCormick, N., Matgen, P., Chini, M., Li, Y., Martinis, S.,
- 1002 Wieland, M., Kraft, F., Festa, D., Hassaan, M.A.S.A., Tupas, M.E., Zhao, J., Seewald, M., Riffler, M., Molini, L., Kidd,
- 1003 R., Briese, C., Salamon, P., 2026. The fully-automatic Sentinel-1 Global Flood Monitoring service: Scientific challenges
- 1004 and future directions. *Remote Sens. Environ.* 333, 115108. <https://doi.org/10.1016/j.rse.2025.115108>
- 1005 Wang, F., Li, X., Tang, X., Sun, X., Zhang, J., Yang, D., Xu, L., Zhang, H., Yuan, H., Wang, Y., Yao, Y., Wang, C., Guo, Y., Ren,
- 1006 Q., Li, Y., Zhang, R., Wang, X., Zhang, B., Sha, Z., 2023b. The seas around China in a warming climate. *Nat. Rev. Earth*
- 1007 *Environ.* 4, 535–551. <https://doi.org/10.1038/s43017-023-00453-6>
- 1008 Wang, M., Mao, D., Wang, Y., Xiao, X., Xiang, H., Feng, K., Luo, L., Jia, M., Song, K., Wang, Z., 2023a. Wetland mapping in East
- 1009 Asia by two-stage object-based Random Forest and hierarchical decision tree algorithms on Sentinel-1/2 images.
- 1010 *Remote Sens. Environ.* 297, 113793. <https://doi.org/10.1016/j.rse.2023.113793>
- 1011 Wang, X., Xiao, X., Zou, Z., Hou, L., Qin, Y., Dong, J., Doughty, R.B., Chen, B., Zhang, X., Chen, Y., Ma, J., Zhao, B., Li, B.,



- 1012 2020. Mapping coastal wetlands of China using time series Landsat images in 2018 and Google Earth Engine. ISPRS
- 1013 J. Photogramm. Remote Sens. 163, 312–326. <https://doi.org/10.1016/j.isprsjprs.2020.03.014>
- 1014 Wen, K., Liao, P., Jiang, A., 2024. Integrating time series Sentinel-2 images and tide height to mapping tidal flats in the Chinese
- 1015 mainland. J. Hydrol. 645, 132264. <https://doi.org/10.1016/j.jhydrol.2024.132264>
- 1016 Woo, S., Debnath, S., Hu, R., Chen, X., Liu, Z., Kweon, I.S., Xie, S., 2023. ConvNeXt V2: Co-designing and scaling ConvNets
- 1017 with masked autoencoders, in: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition,
- 1018 pp. 16133–16142. <https://doi.org/10.1109/CVPR52729.2023.01548>
- 1019 Worthington, T.A., Spalding, M., Landis, E., Maxwell, T.L., Navarro, A., Smart, L.S., Murray, N.J., 2024. The distribution of global
- 1020 tidal marshes from earth observation data. Glob. Ecol. Biogeogr. 33, e13852. <https://doi.org/10.1111/geb.13852>
- 1021 Yang, X., Zhu, Z., Qiu, S., Kroeger, K.D., Zhu, Z., Covington, S., 2022. Detection and characterization of coastal tidal wetland
- 1022 change in the northeastern US using Landsat time series. Remote Sens. Environ. 276, 113047.
- 1023 <https://doi.org/10.1016/j.rse.2022.113047>
- 1024 Zhang, H., Wang, S., Zhang, Y., 2023b. A Dual-Path Multi-Scale Feature Fusion Decoder for SegFormer. Procedia Comput. Sci.
- 1025 222, 147–156. <https://doi.org/10.1016/j.procs.2023.08.152>
- 1026 Zhang, X., Liu, L., Zhao, T., Chen, X., Lin, S., Wang, J., Mi, J., Liu, W., 2023a. GWL_FCS30: a global 30 m wetland map with a
- 1027 fine classification system using multi-sourced and time-series remote sensing imagery in 2020. Earth Syst. Sci. Data
- 1028 15, 265–293. <https://doi.org/10.5194/essd-15-265-2023>
- 1029 Zhang, X., Liu, L., Zhao, T., Wang, J., Liu, W., Chen, X., 2024. Global annual wetland dataset at 30 m with a fine classification
- 1030 system from 2000 to 2022. Sci. Data 11, 310. <https://doi.org/10.1038/s41597-024-03143-0>
- 1031 Zhang, Z., Xu, N., Li, Y., Li, Y., 2022. Sub-continental-scale mapping of tidal wetland composition for East Asia: A novel algorithm
- 1032 integrating satellite tide-level and phenological features. Remote Sens. Environ. 269, 112799.
- 1033 <https://doi.org/10.1016/j.rse.2021.112799>
- 1034 Zhao, C., Jia, M., Wang, Z., Mao, D., Wang, Y., 2023. Toward a better understanding of coastal salt marsh mapping: A case from
- 1035 China using dual-temporal images. Remote Sens. Environ. 295, 113664. <https://doi.org/10.1016/j.rse.2023.113664>
- 1036 Zhen, J., Mao, D., Wang, Y., Wang, J., Nie, C., Huo, S., Xiang, H., Ren, Y., Luo, L., Wang, Z., 2026. National mapping of wetland
- 1037 vegetation leaf area index in China using hybrid model with Sentinel-2 and Landsat-8 data. ISPRS J. Photogramm.
- 1038 Remote Sens. 232, 18–33. <https://doi.org/10.1016/j.isprsjprs.2025.11.031>