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Seasonal and interannual dynamics of estuary connectivity along the California coast

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ARTICLE INFO

Keywords:

Intermittently closed estuaries
estuary connectivity
remote sensing
machine learning
PlanetScope
tidal attenuation
California coast

ABSTRACT

Intermittently closed estuaries are globally widespread and ecologically important, yet their mouth-state dynamics are difficult to observe simultaneously at multiple estuaries, limiting understanding of how regional forcing and local controls shape estuary-ocean connectivity. We developed a multi-year record of estuary mouth connectivity for 66 intermittently closed estuaries along the California coast using 3 m PlanetScope imagery from 2017–2025 and a machine-learning classifier trained on manually interpreted imagery. After image-quality filtering and daily aggregation, the dataset contains approximately 70,000 daily observations of predicted connectivity. Open and closed states were classified reliably, whereas partial or transitional states showed greater uncertainty, consistent with validation using higher-resolution SkySat imagery and in situ water-level observations. Satellite-derived connectivity was strongly related to tidal attenuation calculated from water-level records, indicating that the predictions capture physically meaningful differences in estuary state. Across the coast, estuary openness followed a coherent seasonal pattern consistent with seasonality of river flow, increasing from fall into winter and declining through spring and summer. Openness increased with precipitation accumulated since the start of the water year in all seasons, although the fall relationship was not statistically significant; the largest linear response occurred in spring, consistent with wetter conditions prolonging open states. Open frequency showed no simple latitudinal gradient, highlighting strong site-to-site modulation by local geomorphic, oceanic, and watershed controls. These results demonstrate that high-frequency, high-resolution satellite observations can extend estuary-connectivity analysis from individual sites to regional scales while retaining information on site-level variability.

1. Introduction

Intermittently closed estuaries are dynamic systems representative of a broader “low-inflow” estuary paradigm, in which connectivity between river and ocean emerges from the balance of wave-driven sediment transport, tidal exchange, and fluvial discharge [1–3]. Tidal exchange in these estuaries is often intermittent or strongly constrained by inlet morphology. They transition continuously between open, closed, and partially connected configurations over timescales ranging from hours to seasons [4–6]. Their outlets are often only tens of meters wide and can shift rapidly in response to transient forcing, such that even modest changes in sand berm position determine whether a system is open or closed [7, 8]. These characteristics make estuary connectivity inherently variable and difficult to observe consistently across systems. Their dynamic mouth states strongly influence hydrodynamics, salinity structure, and ecological exchange between freshwater and marine environments, with implications for habitat connectivity, water quality, and ecosystem function [9].

Despite their global prevalence and ecological importance [2, 3, 7, 10], intermittently closed estuaries remain poorly characterized beyond select individual sites. Most

existing understanding is derived from a small number of intensively monitored systems, limiting the ability to identify patterns that emerge across regions. Field observations and camera systems provide detailed records but are inherently localized. Process-based and conceptual models capture the physical drivers of inlet dynamics, emphasizing the balance between sediment transport and hydrodynamic forcing [4, 5, 11], but typically require site-specific parameterization and do not scale readily across systems. Remote sensing approaches have extended monitoring to larger regions using Landsat and Sentinel imagery [12–14], but are constrained by spatial resolution and revisit frequency, limiting their ability to resolve narrow inlet channels and short-lived opening events in small, wave-dominated systems.

Here we address this gap by constructing a multi-year dataset of estuary connectivity spanning 66 systems along the California coast over nearly a decade (2017–2025). Using high-frequency, high-resolution satellite imagery together with machine-learning classification [15], we generate a consistent time series of connectivity across a diverse set of intermittently closed estuaries. Although estuary connectivity exists on a continuum of states, we adopt a binary formulation to ensure consistency across systems, while preserving transitional behavior through probabilistic predictions and their temporal evolution in the resulting time series. This dataset enables a shift from site-specific analysis to a regional understanding of estuary dynamics, allowing connectivity to be analyzed as both a shared regional signal and a site-specific response to

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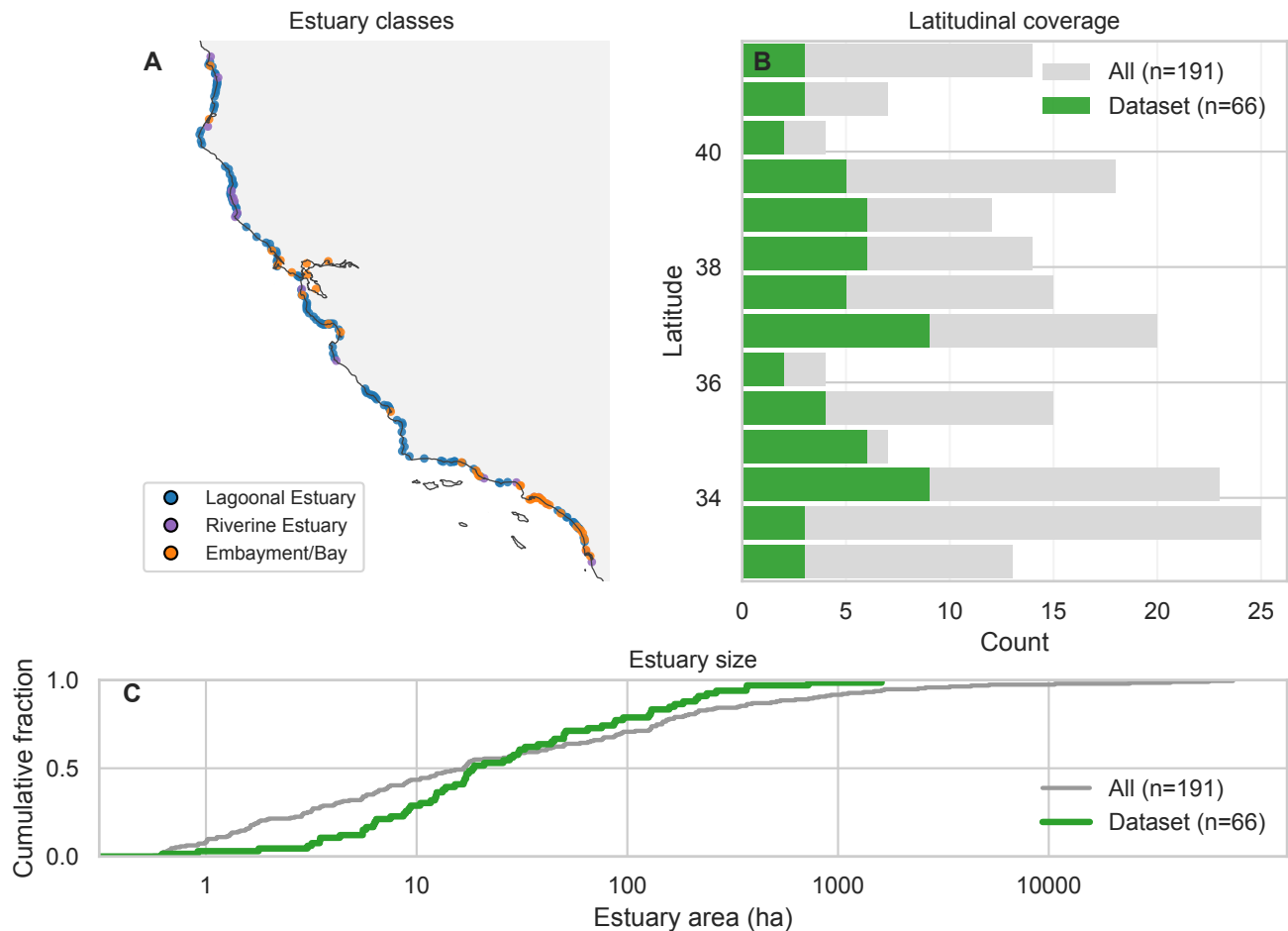


Figure 1: California estuaries and dataset coverage. (A) Locations of all identified estuaries along the California coastline, colored by the Coastal and Marine Ecological Classification Standard (CMECS). (B) Latitudinal distribution of estuaries, comparing the full set of identified estuaries ($n = 191$) with those included in the dataset ($n = 66$). (C) Cumulative distribution of estuary size (area in hectares), showing that the dataset spans a broad range of estuary sizes while underrepresenting the smallest systems.

local geomorphic and hydrologic controls. It provides a foundation for examining seasonality, interannual variability, climatic forcing, and site-to-site departures from regional patterns.

2. Methods

2.1. Site selection

Our study included 66 intermittently closed estuaries distributed along the California coast that could be mapped reliably using 3 m satellite imagery (Fig. 1). Candidate sites were compiled by combining two existing datasets: a previously published inventory of 95 intermittently closed estuaries [10] and the U.S. West Coast estuary inventory [16], accessed through the Pacific Marine and Estuarine Fish Habitat Partnership estuary points dataset.

We evaluated candidate sites using visual inspection of satellite imagery, excluding estuaries where mouth state could not be reliably determined because of occlusion, insufficient spatial resolution, or limited visible beach area. For each estuary, a single area of interest (AOI) was defined

and used consistently across the full time series. AOIs were selected by visually inspecting satellite imagery and were centered on the range of observed breach locations. Each AOI was required to encompass the full spatial extent of inlet opening across time.

Finally, sites were required to exhibit both open and closed states at least once within the observation period to ensure that connectivity dynamics could be learned and evaluated. These selection criteria were designed to ensure that connectivity could be consistently interpreted across sites, enabling comparison of estuary dynamics at a regional scale.

2.2. Imagery

We acquired satellite imagery for each estuary from Planet's PlanetScope and SkySat constellations [17, 18] spanning 2017–2025. PlanetScope provides multispectral imagery at approximately 3 m spatial resolution with near-daily coverage, whereas SkySat provides multispectral imagery at approximately 0.5 m spatial resolution with higher spatial detail but irregular temporal coverage. PlanetScope

imagery includes both four-band (blue, green, red, near-infrared) and eight-band products depending on sensor generation, whereas SkySat imagery provides four-band multispectral data. The PlanetScope constellation comprises multiple generations of sensors, including PlanetScope Classic (2016–2022), Dove-R (2019–2022), and SuperDove (2020–present), which differ in spectral response, radiometric calibration, and band configuration. These differences introduce subtle but persistent variability across acquisitions that must be accounted for when constructing consistent time series. In this study, PlanetScope imagery was used to construct connectivity time series, while SkySat imagery was used for labeling validation.

Imagery was retrieved using the Planet API for each estuary-specific area of interest (AOI) defined in the previous section. Planet imagery includes a usable data mask (UDM) with per-pixel flags for clouds, haze, shadows, and other artifacts. To ensure sufficient image quality while maintaining temporal coverage, we retained only images where at least 10% of the full scene was classified as clear and at least 90% of the AOI was free of cloud, haze, and shadow artifacts (i.e., excluding pixels flagged as shadow, light haze, heavy haze, or cloud). The UDM snow mask was not used, as wave foam is frequently misclassified as snow in coastal imagery. Additional filtering was applied at query time using Planet metadata fields. Images were required to include valid ground control points, meet standard image-quality criteria, and be in a finalized processing state. These filtering criteria were selected to retain images with sufficient usable data while maximizing temporal coverage of each estuary. We used surface reflectance products for PlanetScope imagery and orthorectified pansharpened products for SkySat imagery. In total, this process yielded 101,458 PlanetScope images and 2,237 SkySat images across all estuaries and years.

2.3. Water-level observations and tidal attenuation

We obtained in situ water-level observations for 19 of the 66 estuaries, spanning the full latitudinal range of the California coastline. Water-level data were compiled from multiple sources, including the United States Geological Survey [19], the California Estuary Monitoring Program [20], and regional monitoring programs aggregated through the UC Davis Coastal Oceanography Group. All sensors were located within the estuary lagoon. Water-level data were used to validate satellite-derived connectivity labels and interpret the physical meaning of model predictions.

Water-level time series were available at sampling intervals ranging from approximately 6 to 30 minutes and were resampled to a consistent 30-minute resolution. Basic quality control was applied by removing outliers, and only continuous segments of at least two months in duration were retained for analysis. No gap filling was performed.

To quantify ocean influence within each estuary, we calculated tidal attenuation following Heimhuber et al. [12], using it as a proxy for the degree of tidal exchange between the ocean and lagoon [9]:

$$A = 1 - \frac{R_{\text{estuary}}}{R_{\text{ocean}}} \quad (1)$$

where A is tidal attenuation, R_{estuary} is the estuary water-level range, and R_{ocean} is the ocean tidal range over the same time window. Tidal range was computed as the difference between the daily maximum and minimum water levels, producing one value per day. A three-day moving window was then applied to these daily ranges, and the minimum value within each window was retained and centered over the window. Tidal attenuation values were clipped to the range [0, 1], where values near 1 indicate little or no tidal propagation into the lagoon and values near 0 indicate strong tidal influence. This metric represents sustained tidal exchange and will not capture short-lived opening events or tidal overwash during periods of high wave activity.

Ocean tidal levels were estimated using the GOT4.10c global tide model accessed through the pyTMD library [21–23]. Tidal predictions were sampled at the centroid of each estuary AOI and interpolated from the nearest valid model grid point. Despite the relatively coarse spatial resolution of the tide model, this approach provides a sufficient approximation of offshore tidal forcing for the purposes of this analysis. These tidal predictions were combined with in situ estuary water levels to calculate tidal attenuation.

2.4. Labeling

A subset of approximately 12,000 images was labeled from the full archive of approximately 100,000 PlanetScope images. The sampling strategy provided temporal coverage and representation of challenging image conditions while keeping all labeling decisions independent of the final model. Connectivity was defined consistently across all estuaries based on observable surface channel morphology, enabling direct comparison of connectivity dynamics between systems. The labeling process was designed to support construction of a consistent time-series dataset rather than optimize performance for individual images.

Image selection was performed in two stages. First, to ensure temporal coverage, up to one image per month per estuary was selected from the available imagery (maximum of 12 images per year). When multiple images were available within a month, images coinciding with a SkySat acquisition within ± 10 hours were prioritized to support later validation; otherwise, an image was selected at random. This step ensured that the labeled dataset captured seasonal and interannual variability in estuary morphology.

Second, to enrich the dataset with difficult and lower-quality observations, additional images were selected using clustering. Image-level summary statistics derived from spectral bands and usable data mask (UDM) features were used as input to a k-means clustering procedure. Clusters associated with cloudy, hazy, noisy, and blurry imagery were identified, and up to 100 additional images per estuary were sampled from these clusters, excluding images already selected in the first stage (see Supplementary Section S1 for

Table 1
Visual classification criteria for estuary connectivity.

Closed	The estuary mouth is blocked by a sand berm with no visible surface connection to the ocean. The berm is continuous, and no channel connecting the estuary to the ocean is observed (although brief wave-driven overwash may occur before or after image capture). The estuary may appear dry or contain no visible standing water.
Open	A clear and continuous surface channel connects the estuary to the ocean. The channel is visually distinct from surrounding sand and can be traced from the estuary to the ocean. The connection is unambiguous, but may include “perched” conditions.
Partial	A partial or ambiguous connection between the estuary and ocean is present. A channel may be visible, but portions of the connection are narrow, discontinuous, or indistinguishable from surrounding wet sand. These cases include one-way drainage flow across the berm (“perched” state), brief wave-driven inflows through overwash, typically at high tide, or channels that cannot be clearly traced to the ocean.
Low-Quality	Image quality is insufficient to reliably determine estuary connectivity. This includes cases where the estuary mouth is obscured or difficult to interpret due to clouds, haze, sensor noise, blur, channel misalignment, or strong shadows. Images are labeled as low-quality only when these factors directly affect interpretation of the estuary mouth.

Satellite images were manually labeled into four classes (closed, partial, open, and low-quality) based on observable estuary mouth morphology. The definitions distinguish clear surface connections from blocked or ambiguous conditions (transitional or uncertain states). Labels are based solely on image interpretation and do not incorporate hydrodynamic data.

examples of low-quality imagery). This step ensured that challenging edge cases were included in the training dataset. On average, each estuary contributed 173 labeled images.

All images were labeled by a single analyst using false-color composites (NIR, red, green) in Label Studio. Each image was assigned one of four labels: closed, open, partial, or low-quality. The partial class represents ambiguous or weakly connected conditions, while the low-quality class captures images where connectivity cannot be reliably determined due to clouds, haze, or other artifacts. The labels describe visible surface morphology rather than hydrodynamic function; therefore, perched conditions were labeled open when the outlet appeared clear and continuous and partial when the visible connection was narrow, discontinuous, or otherwise ambiguous. Detailed label definitions are provided in Table 1. Images were reviewed sequentially by estuary and ordered temporally during labeling. The image-only labels were based solely on visible morphology; in situ water-level observations were incorporated only in the independent validation analysis described in Section 2.5.2. Multiple labeling passes were performed. After the initial pass, provisional model predictions were used to identify discrepancies with the manual labels, which were then manually re-evaluated. Model predictions were never directly used as labels, and all final labels were determined by manual inspection.

2.5. Label validation

To assess the reliability of the connectivity labels, we performed two validation analyses under different observational conditions. The first compared the original PlanetScope labels with labels generated from higher-resolution SkySat imagery. The second compared the original PlanetScope labels with labels generated using PlanetScope imagery together with in situ water-level observations. In both

analyses, the same annotator applied the same class definitions while blinded to the original labels. These analyses therefore assess within-annotator consistency across observational conditions rather than inter-annotator agreement.

2.5.1. High-resolution imagery comparison

To evaluate the effect of spatial resolution on labeling consistency, we compared labels generated from PlanetScope imagery with labels generated from higher-resolution SkySat imagery. SkySat’s approximately sixfold finer spatial resolution resolves narrow inlet channels across more pixels, making connectivity easier to interpret. We included all SkySat images acquired within ± 10 hours of a PlanetScope image, minimizing the likelihood of substantial morphological change between acquisitions. Image pairs were retained only when both images were labeled as usable, resulting in 463 pairs. Both datasets were labeled using the same false-color band combinations and labeling criteria.

2.5.2. Water-level comparison

A second validation analysis compared the original image-only labels with labels assigned using both PlanetScope imagery and in situ water-level observations. Water-level data complement the morphological evidence in satellite imagery by revealing the estuary’s hydrodynamic response to ocean connectivity. For each validation case, a two-month water-level time series centered on the image timestamp was displayed alongside the satellite image. Only images originally classified as usable were included, yielding 1,122 validation cases.

Strong ocean connectivity typically produces regular tidal oscillations, whereas closed conditions are generally associated with flat or slowly varying water levels [9]. Conditions classified as partial may include perched states characterized by one-way drainage and slowly varying water

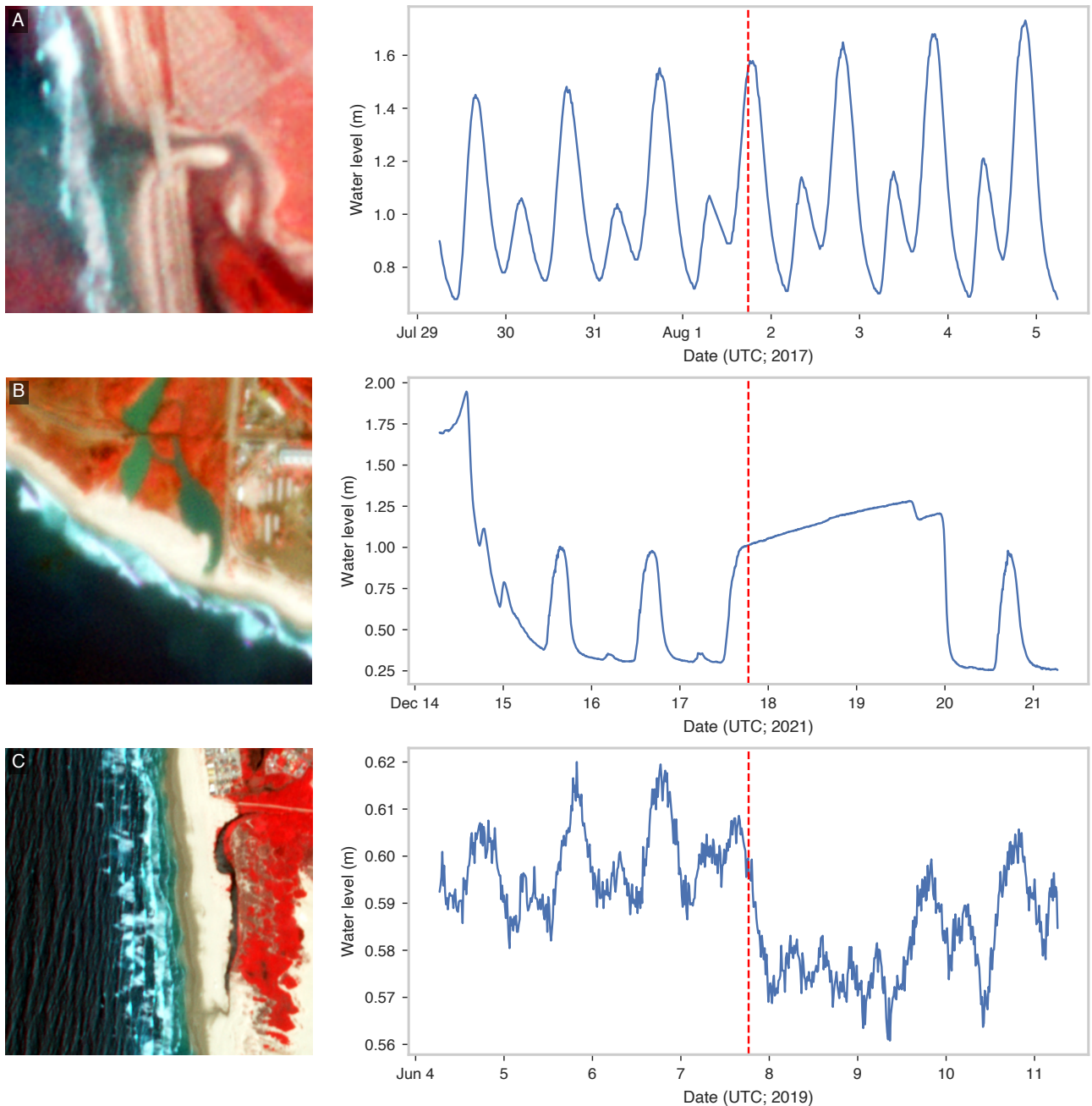


Figure 2: Examples of estuary connectivity states from satellite imagery and in situ water-level observations. Each row shows a satellite image (left) and the corresponding water-level time series (right); the vertical dashed line indicates the time of image acquisition. (A) Open conditions at Los Peñasquitos Lagoon, where a clear surface channel coincides with regular tidal oscillations in water level. (B) Closed conditions at the Ventura River estuary, where no surface connection is visible and flat or rising water levels indicate lagoon filling without tidal exchange. (C) Perched conditions at Arroyo Grande Creek, where a narrow channel coincides with weak water-level variability. PlanetScope images © 2017, 2019, and 2021 Planet Labs PBC.

levels, wave overwash of the berm at high tide producing short increases in water level, and other weak or irregular signals of reduced or intermittent ocean influence [9, 24]. Weak variability may also result from wind effects.

2.5.3. Validation summary

Across both validation analyses, agreement between labeling conditions was high for the binary classification of

open versus closed, while agreement was substantially lower for the full three-class formulation that included the intermediate partial state. For the SkySat comparison, three-class balanced accuracy was 0.76, increasing to 0.97 for two-class classification when partial was grouped with open. A similar pattern was observed for the water-level validation, with three-class balanced accuracy of 0.82, increasing to 0.98 when partial was grouped with open.

These results indicate that the distinction between open and closed estuaries is robust across differences in spatial resolution and the inclusion of hydrodynamic information, whereas the intermediate partial state represents a continuum that is more difficult to label consistently. The lower agreement for partial labels reflects a fundamental limitation of observation rather than labeling error. Although these intermediate states represent physically meaningful conditions, they are not consistently distinguishable across data sources, particularly when connections are narrow, short-lived, or sensitive to timing and resolution. In contrast, fully open and fully closed states are associated with clear and persistent morphological features, enabling more reliable classification.

Based on these results, we used a binary formulation in subsequent analyses, grouping partial and open states as surface-connected and comparing them with closed states. Intermediate and transitional states were preserved through prediction uncertainty and temporal variability rather than treated as a separate discrete class. Additional analysis of labeling agreement, including confusion matrices, is provided in Supplementary Section S2.

2.6. Connectivity classification model

We trained a convolutional neural network to classify estuary connectivity states from satellite imagery. The model architecture was based on ConvNeXt-Tiny [25] initialized with weights distilled from DINOv3 [26], a self-supervised pretraining framework for vision models (see Supplementary Section S3.1 for backbone and input comparisons). The original classification head was replaced with a newly initialized binary classification head predicting open or closed connectivity states.

The pretrained ConvNeXt-Tiny backbone expects three-channel input. To leverage the near-infrared signal available in the imagery, we instead used false-color inputs composed of NIR, red, and green bands. The NIR channel provides strong contrast between water and dark organic material, improving discrimination between water, vegetation, and debris at estuary mouths. In experiments, models trained on RGB imagery performed slightly worse than the false-color representation. Attempts to train four- or eight-band models from random initialization resulted in substantially poorer performance, indicating that pretrained initialization was important for this task given the available dataset size.

Approximately 20% of labeled images were identified as low-quality during manual labeling. These images were excluded from training the connectivity classifier and instead used to train a separate image-quality classifier described in Supplementary Section S3.3. After removing images labeled low-quality, approximately 10,000 images remained for connectivity classification.

The dataset was divided using a temporal split, with images from 2025 held out as the test set and 2021 used as the validation set. The year 2021 was selected for validation because imagery from all three PlanetScope sensor generations was available that year, providing a validation

set with substantial radiometric variability. Using a temporally separated test set ensures that evaluation reflects the model's ability to generalize across seasonal and interannual variation. After the split, the partial label was remapped to open for training the binary classifier. The resulting training set contained approximately 7,700 images. After remapping, the two classes were nearly balanced (3,771 open and 3,900 closed). To account for the slight residual class imbalance, class weights were applied to the binary cross-entropy loss.

Images were normalized using channel-wise statistics computed from the training set. All images were square crops centered on the estuary mouth and resized to 224×224 pixels. During training we applied random resized crops to introduce small variations in scale and aspect ratio, while validation images retained the original crop geometry.

The model was trained for 25 epochs using the AdamW optimizer with a learning rate of 5×10^{-5} and a backbone learning-rate scaling factor of 0.2. The batch size was 64. A cosine learning-rate schedule with a two-epoch warmup was used. To reduce overfitting, dropout, stochastic depth (drop path), and image augmentations were applied during training. Augmentations included random blur, color perturbations, sensor noise, horizontal and vertical flips, and 90° rotations. The model checkpoint that achieved the best balance between precision and recall, as measured by the validation F1 score, was selected for evaluation. The connectivity classifier was trained using binary cross-entropy with logits and entropy regularization [27], with the regularization weight set to $\lambda = 0.1$. This allowed intermediate probabilities to persist for visually ambiguous mouth states rather than forcing overly sharp predictions. Full loss-function and evaluation-metric equations are provided in Supplementary Section S3.2. A classification threshold was determined using the validation dataset to balance precision and recall and to convert predicted probabilities into binary labels during inference.

2.7. Connectivity time-series generation

Model inference was applied to approximately 100,000 PlanetScope images spanning all estuaries and years, including the labeled images used for model training. Each image was first evaluated by the image-quality classifier. Images whose predicted probability of being low-quality exceeded the validation-derived threshold were excluded, while the remaining images were processed by the connectivity classifier to estimate the probability that the estuary was open.

Some estuaries were observed multiple times on the same day, often within one to two hours. To obtain a single daily estimate for each estuary, predictions from the same day were combined using a weighted average based on estimated image quality:

$$w_i = 1 - p_{\text{low-quality},i} \quad (2)$$

where w_i is the image weight and $p_{\text{low-quality},i}$ is the predicted probability that image i was low-quality.

$$p_{\text{open,day}} = \frac{\sum_i w_i p_{\text{open},i}}{\sum_i w_i} \quad (3)$$

where $p_{\text{open,day}}$ is the daily openness probability, $p_{\text{open},i}$ is the predicted open probability for image i , and the summation is over all usable images acquired for that site on that day.

This weighting scheme reduces the influence of observations with lower predicted image quality while preserving information from multiple satellite acquisitions on the same day. If all images for a given day were classified as low-quality, the day was treated as missing in subsequent analysis.

The released dataset contains per-image and daily-aggregated predictions for each estuary. Both products include continuous probabilities and corresponding binary classifications based on the same classification threshold. These data are publicly available through Zenodo; see Section 5.

2.8. Time-series analysis

Analyses were designed to characterize estuary connectivity dynamics at the regional scale using a consistent observational framework across all sites, building on prior work demonstrating that intermittently closed estuaries exhibit strong temporal variability from daily to seasonal timescales [4, 8]. Daily estuary connectivity time series were constructed from model predictions following the inference procedure described above. All subsequent analyses were performed using these daily connectivity probabilities to ensure consistent comparison across estuaries, with binary classifications derived using fixed thresholds where noted. Although imagery is available from 2017, coverage increases substantially beginning in 2018; therefore, all time-series analyses are restricted to the period from 2018 onward.

To generate continuous daily series for regional aggregation, predicted openness was linearly interpolated between consecutive observation dates regardless of gap length. Linear interpolation preserved the observed endpoint probabilities and represented any change between them as a single gradual trajectory without introducing additional state reversals. Interpolated values estimate conditions between observed endpoints but do not identify the actual day on which an opening or closure occurred and should not be interpreted as direct daily observations. We therefore used these values for grouped regional, seasonal, and interannual analyses, not to resolve the timing of individual transitions within estuaries. For visualization, the resulting daily series were smoothed using a 7-day rolling mean.

For any specified period, site-level openness was calculated as the mean of the daily predicted openness probabilities p_{open} , including both observed and interpolated values. This metric represents the expected fraction of time that an estuary was open during that period. We refer to this mean predicted openness probability as open frequency;

full-record site means were used to characterize its spatial variation (Fig. 6).

Monthly patterns were evaluated by averaging daily predicted openness within each estuary and water-year month (October–September), then summarizing the resulting estuary-level monthly means using the median and interquartile range (IQR) across estuaries (Fig. 7). For seasonal analyses, the water year was divided into fall (October–December), winter (January–March), spring (April–June), and summer (July–September). Interannual seasonal patterns were evaluated by averaging daily predicted openness within each estuary, water year, and season, then summarizing the resulting estuary-level seasonal means using the median and interquartile range across estuaries (Fig. 8). For each season, regional median openness was compared with statewide precipitation accumulated from the start of the water year on October 1 through the end of that season: October–December for fall (3 months), October–March for winter (6 months), October–June for spring (9 months), and October–September for summer (12 months). Precipitation data were obtained from NOAA Climate at a Glance [28]. Associations were evaluated using linear regression and Spearman rank correlation. Linear slopes represent the change in regional median predicted openness per inch of cumulative precipitation, while Spearman correlation coefficients summarize monotonic relationships. All analyses used predicted probabilities rather than binary classifications to preserve information on uncertainty and transitional states.

3. Results

3.1. Model results

Model performance was evaluated separately for each original label class to assess the reliability of the connectivity estimates used in the time-series dataset. Performance was highest for images labeled as open ($F1 = 0.99$, entropy = 0.02) and closed ($F1 = 0.97$, entropy = 0.03), and lower for images labeled as partial ($F1 = 0.93$, entropy = 0.14) (Table 2). The elevated uncertainty for partial cases indicates that the model was less confident in these visually ambiguous conditions. This pattern is consistent with the labeling validation results, where intermediate connectivity states were less reliably distinguished across data sources.

Site-level performance was generally strong, with a 25th percentile $F1$ score of 0.93. Twelve sites had $F1$ scores below 0.9; however, these estimates were based on a small number of test samples per site (mean = 16), and some sites contained only one or two examples of certain conditions. Consequently, individual site $F1$ scores should be interpreted cautiously.

3.2. Validation against water-level observations

To assess the physical plausibility of the satellite-derived connectivity dataset, we examined the relationship between predicted connectivity and tidal attenuation derived from water-level observations. Estuaries predicted to be open

Table 2

Classification performance and uncertainty by connectivity label class.

Original class	F1 score	Predicted open fraction	Mean entropy	N
Closed	0.97	0.05	0.03	524
Open	0.99	0.98	0.02	440
Partial	0.93	0.86	0.14	123

For each original label class, we report the F1 score, the fraction of predictions classified as open, mean prediction entropy, and the number of samples (N).

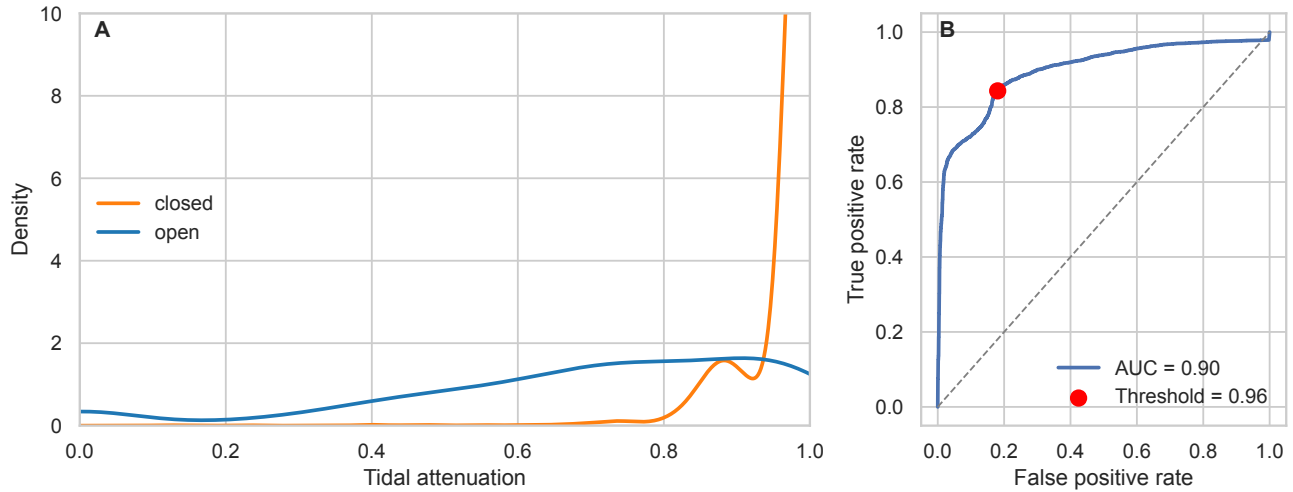


Figure 3: Relationship between predicted connectivity and tidal attenuation. (Left) Distribution of tidal attenuation values by predicted connectivity class. Estuaries predicted to be open exhibit lower tidal attenuation than those predicted to be closed. (Right) Receiver operating characteristic (ROC) curve comparing tidal attenuation to predicted connectivity (AUC = 0.90). The red point indicates a threshold of 0.96, which reproduces model predictions with an F1 score of 0.83.

exhibited substantially lower tidal attenuation than those predicted to be closed (Fig. 3), indicating stronger tidal influence when a surface connection is present. A receiver operating characteristic (ROC) analysis, which evaluates how well tidal attenuation distinguishes open from closed predictions across a range of thresholds, yielded an area under the curve (AUC) of 0.90. Applying a simple threshold classifier based on tidal attenuation (< 0.96) reproduced model predictions with an F1 score of 0.83, demonstrating strong agreement between the two measures.

3.3. Time-series dataset

The resulting dataset provides a spatially extensive, multi-year record of estuary connectivity across the California coastline. The full time-series dataset consists of approximately 70,000 daily observations after limiting to one sample per day and filtering for image quality. This corresponds to an average of 1,050 observations per estuary, with a maximum of 1,312 and a minimum of 663.

Temporal coverage varies across seasons. Valid-observation coverage was highest in spring (mean = 37.5%) and fall (mean = 36.7%), and lowest in winter (mean = 33.7%) and summer (mean = 31.9%). This pattern likely reflects greater cloud cover during winter storms and

reduced visibility from summer marine-layer clouds along the California coast [29].

Spatial variation in coverage was also evident, with coverage decreasing strongly with latitude (Spearman $\rho = -0.70$, $p < 0.001$). Southern estuaries had valid observations on approximately 30–40% of days, compared with 20–30% in northern California (Fig. 4). Inter-acquisition intervals were generally short but right-skewed, with a median of 2 days across every month and year and monthly means ranging from 2.50 to 3.42 days. Approximately 93.1% of consecutive observations had the same classified connectivity state. These same-state intervals accounted for 89.6% of all days without observations. Only 6.9% of intervals bracketed a change in state; these intervals had a median duration of 3 days, and only 2.5% exceeded 14 days. Given this distribution, linear interpolation of state probabilities provided a practical means of constructing daily time series. Most interpolated days occurred between observations with the same classified state, while interpolation across observed changes represented a gradual transition between known endpoints without assuming the exact date of the state change. Nevertheless, every estuary contained at least one gap exceeding 20 days, with the longest observed at Rodeo Lagoon (65 days during summer 2023).

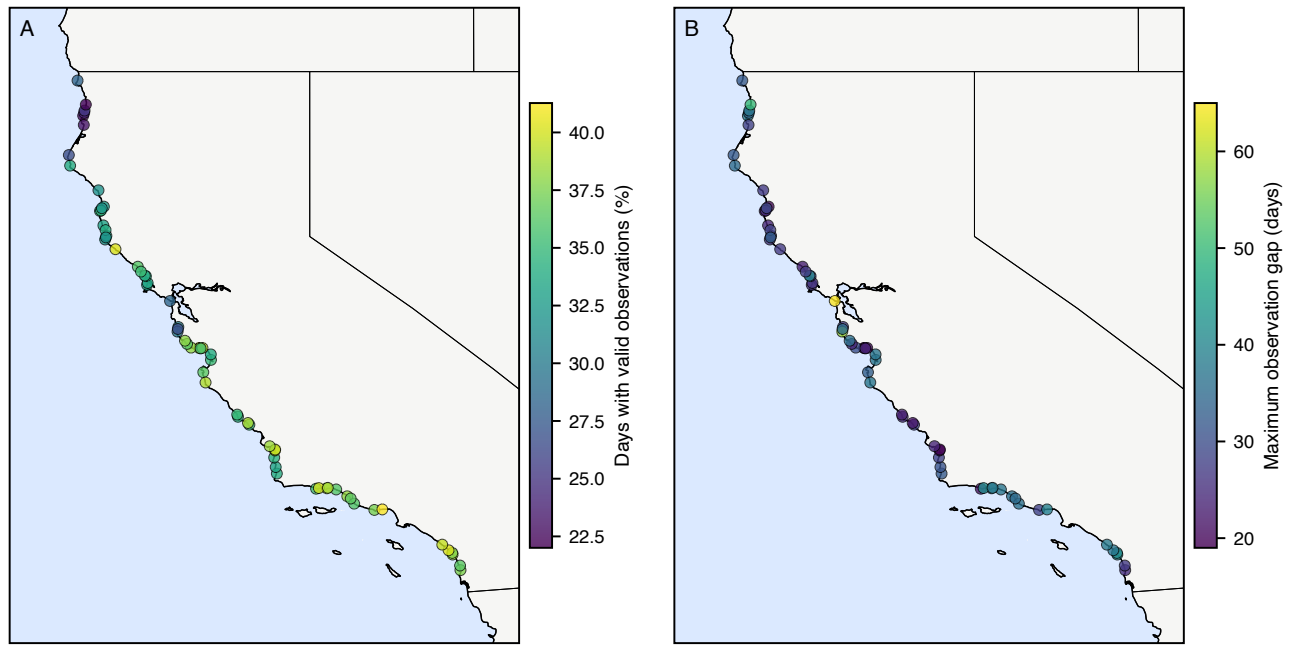


Figure 4: Spatial coverage and temporal gaps in the estuary time-series dataset. (A) Fraction of days with valid observations for each estuary, reflecting the combined effects of satellite acquisition frequency and image-quality filtering. (B) Maximum consecutive gap (in days) between valid observations.

Representative examples of estuary connectivity time series are shown in Fig. 5, illustrating the range of observed behaviors across systems, including strongly seasonal closure patterns, predominantly open systems with episodic closures, and highly variable systems with frequent transitions between states.

Malibu Lagoon (Fig. 5A) exhibits a seasonal cycle with extended summer closures and intermittent reopening events. Pajaro River (Fig. 5B) remains predominantly open but closes episodically during dry periods such as 2021. Pismo Creek Lagoon (Fig. 5C) rarely maintains a persistent tidal connection and frequently transitions between binary open and closed classifications, including during prolonged perched conditions such as those observed in 2023.

3.4. State trends

At the regional scale, the fraction of time estuaries are predicted to be open varies substantially among sites but shows no clear north–south gradient within the set of intermittently closed estuaries considered here (Fig. 6). Open frequency is not correlated with latitude (Spearman $\rho = +0.06$, $p = 0.65$), with both high and low open frequencies occurring throughout the study region. This pattern indicates that variability in estuary connectivity is not explained by broad latitudinal gradients but instead reflects strong site-to-site differences.

3.5. Seasonality

A consistent seasonal pattern in estuary mouth state emerges at the regional scale when aggregating predictions across all estuaries (Fig. 7). Median openness increases from fall into winter, peaks in January–February, and declines

through spring and summer. Variability among estuaries is greatest in midsummer, as reflected by a wider interquartile range, and lowest in October, when mouth states are relatively uniform (mostly closed). In October, most estuaries are closed following the dry summer period, when river discharge is low, while the arrival of early-season waves promotes berm formation [4].

3.6. Yearly trends

Estuary mouth state varied among years at the regional scale, although the overall seasonal structure remained consistent. Median openness across estuaries was highest in winter, ranging from 0.58 in 2021 to 0.98 in 2024 (Fig. 8). Winter coincides with high river flows that breach sandbars and help maintain the resulting openings. Winter openness was high in every year, and even in the least open winter, 2021, the median estuary was open for more than half of the season.

Interannual variability was greatest in spring, when median openness ranged from 0.08 in 2021 to 0.91 in 2024. This variability reflects differences among years in the persistence of winter openings as river flow declines and wave-driven sediment transport begins to rebuild sandbars.

Summer median openness was near zero in most years, increasing to 0.10 in 2024 and 0.27 in 2023. The wide interquartile ranges indicate that some estuaries remained open even when the regional median was low. This pattern is consistent with the seasonal decline in river flow and progressive sandbar formation, with some openings persisting into summer during wetter water years. Fall median openness was consistently low to moderate, ranging from 0.10 to 0.43, as low river flow and wave-driven sediment

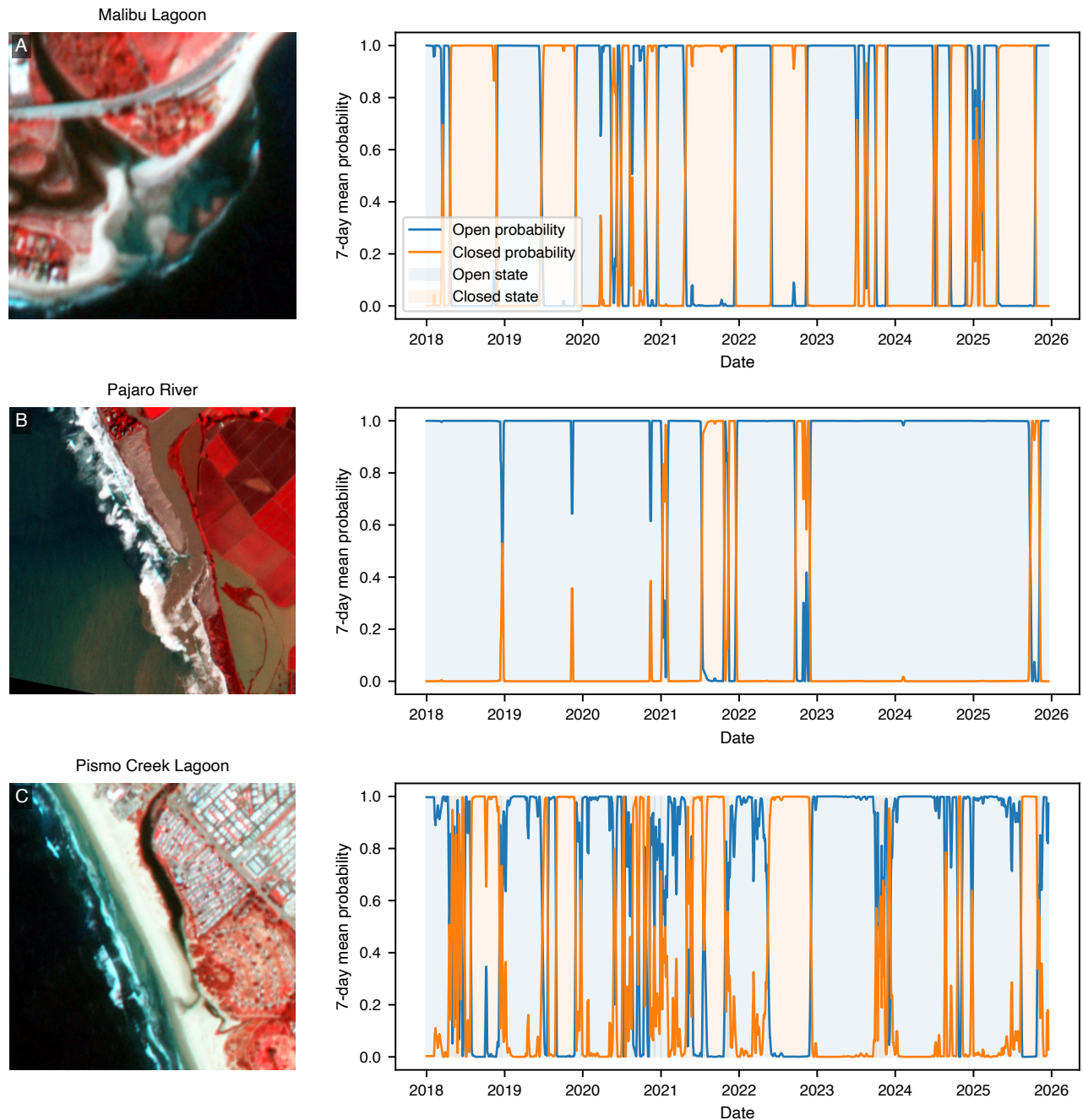


Figure 5: Example estuary connectivity time series. Each row shows a representative estuary, with a satellite image (left) and the corresponding 7-day smoothed time series of predicted connectivity from 2018–2025 (right). Blue and orange lines indicate the predicted probabilities of open and closed states, respectively, and shaded regions show the resulting binary classification. PlanetScope images © 2017 and 2018 Planet Labs PBC.

transport generally favor sandbar closure, although early wet-season rainfall can reopen estuaries.

Regional median openness was positively associated with precipitation accumulated since the start of the water year in winter ($\rho = 0.86$, $p = 0.01$), spring ($\rho = 0.86$, $p = 0.01$), and summer ($\rho = 0.79$, $p = 0.04$), while the fall relationship was positive but not statistically significant ($\rho = 0.57$, $p = 0.18$; Fig. 8). The linear slope was steepest in

spring (0.037 predicted-openness units per inch), followed by fall (0.031), winter (0.022), and summer (0.010).

4. Discussion

4.1. Scaling estuary monitoring with PlanetScope

A central challenge in studying intermittently closed estuaries is characterizing how connectivity varies across many systems over time. Efforts to observe these systems

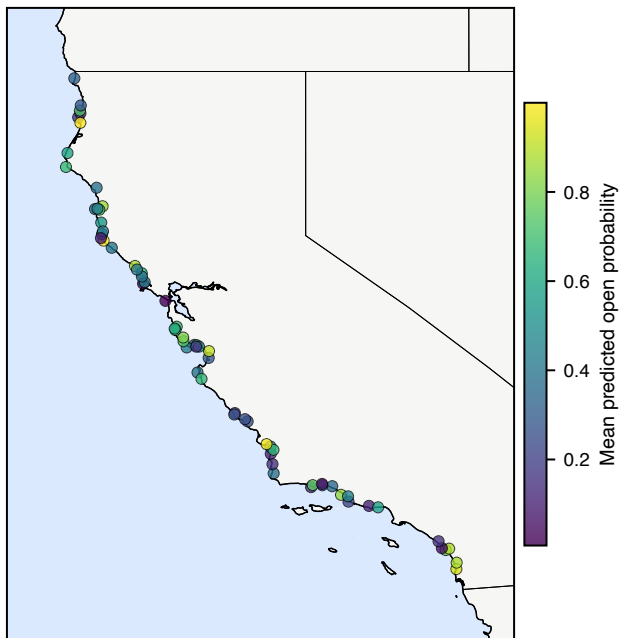


Figure 6: Spatial variability in estuary open frequency. The mean fraction of time each estuary is predicted to be open over the full time series.

consistently across the region have been limited by the difficulty of resolving narrow inlet channels and capturing short-lived opening events. Many California estuary outlets are extremely narrow, often only tens of meters wide, such that even modest changes in sand-berm position determine whether a system is open or closed [7]. At approximately 3 m resolution, PlanetScope imagery resolves these outlets with enough spatial detail for connecting channels to be visually identified (see Supplementary Section S4), whereas 10 m imagery from sensors such as Sentinel-2 often captures the outlet with only one or two pixels, producing mixed land–water signals that make interpretation ambiguous [12]. At the same time, the near-daily revisit of the PlanetScope constellation increases the likelihood of observing opening and closure events that occur on timescales of days to weeks, particularly following breach events [4, 8].

Previous satellite-based inlet-mapping tools demonstrate the value of pixel-based and pathfinding approaches for reconstructing estuary mouth dynamics from public imagery archives [12]. These methods are especially useful when the goal is to derive interpretable geomorphic quantities such as inlet width, channel position, or water-body connectivity. Our approach is complementary rather than directly equivalent. Instead of extracting a physical channel metric from segmented water pixels, we use high-frequency PlanetScope imagery and a learned classifier to estimate the probability that a surface connection is present. This formulation is useful for constructing consistent time series throughout the region because it reduces dependence on site-specific thresholds and hand-tuned polygons, while also accommodating the radiometric variability, sensor-generation differences,

band misalignment, haze, cloud contamination, and sensor noise present in a large PlanetScope archive.

4.2. Label uncertainty and site variability

Intermittently closed estuaries do not exist as strictly binary systems but instead occupy a continuum of connectivity states that vary over short temporal scales and across forcing conditions [4–6]. In addition to clearly open and clearly closed conditions, many estuaries exhibit partial or transient connections in which water exchange with the ocean may be weak, intermittent, or limited to specific tidal conditions [9]. The degree of connectivity depends on lagoon water level, channel geometry, and ocean forcing, and can change on timescales of hours to days [4, 8]. As a result, the boundary between open and closed states is not always well-defined, even from a physical perspective. This intrinsic variability makes consistent classification across many systems inherently challenging.

These ambiguities are further compounded by the limitations of satellite observation. Many estuary outlets are narrow relative to the 3 m resolution of PlanetScope imagery, such that connections may span only a few pixels. In these cases, distinguishing between shallow flow, wet sand, beach wrack, and fully closed conditions can be challenging. For example, a narrow channel may appear visually continuous in one image but indistinguishable from surrounding wet sand in another, depending on illumination, tide stage, or recent wave activity. Additional uncertainty arises from occlusion by terrain or infrastructure, as well as from image degradation due to haze, thin clouds, or sensor artifacts. These factors can obscure or distort the visual cues used to infer connectivity, particularly in systems with small beach areas or highly variable inlet morphology. Together, these observational constraints interact with the underlying physical variability to produce cases where connectivity cannot be determined unambiguously from a single image [12, 13].

This ambiguity is reflected in both the labeling process and model behavior. The partial class exhibited lower agreement across validation datasets and substantially higher predictive entropy than the open and closed classes, indicating that both human interpretation and model predictions are less certain in these cases. Rather than representing a failure of the model, this uncertainty reflects the underlying ambiguity of the system and the limits of observation, placing an upper bound on the consistency achievable when applying a common classification framework across many estuaries and observation conditions. In contrast, fully open and fully closed states are typically associated with clear morphological features and correspondingly lower model uncertainty. When comparing across sites, reduced performance was typically associated with multiple challenges rather than a single dominant geomorphic factor, including partial occlusion by headlands, narrow beach berms, low-contrast sediment backgrounds, and highly variable breach locations (see Supplementary Section S6 for examples of classification challenges). Together, these conditions reduce the clarity and consistency of the observable connectivity

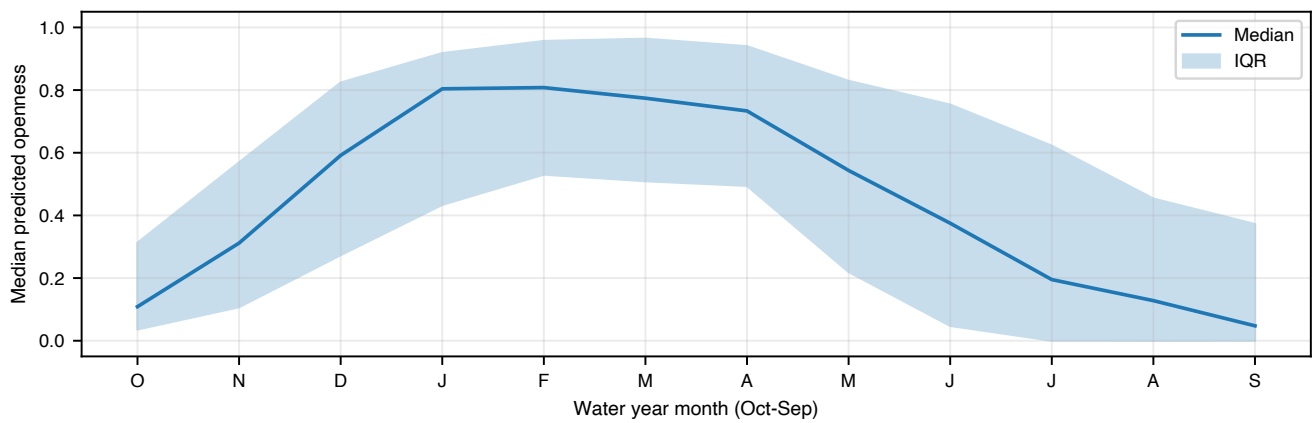


Figure 7: Regional seasonal variation in estuary openness. Median predicted openness across all estuaries by water-year month (line), with the interquartile range (IQR) shown as shading.

signal, making both manual interpretation and automated classification more difficult.

Additional experiments withholding entire estuaries from training further highlight the role of site-specific variability in determining model performance (see Supplementary Section S5). For a given estuary, performance was higher when that estuary was represented in the training dataset and lower when it was withheld. The magnitude of this decline varies across sites, indicating that model performance depends strongly on exposure to representative examples rather than on learning a universally transferable representation of connectivity. Applying this approach to larger regional or global scales will require expanding labeled observations across diverse systems and environmental conditions.

4.3. Hydrodynamic validation of predicted connectivity

Satellite-derived connectivity estimates show a strong relationship with independent hydrodynamic observations from water-level sensors. Estuaries predicted to be open were generally more tidal than those predicted to be closed (i.e., lower tidal attenuation), indicating stronger tidal influence when a surface connection is present. This relationship is reflected quantitatively by strong separation between regimes (ROC AUC = 0.90). Because tidal attenuation was not used as a model input, this agreement indicates that the connectivity estimates capture physically meaningful differences in estuary behavior.

At the same time, satellite-observed connectivity and water-level-based metrics represent fundamentally different aspects of estuary state. Satellite imagery captures the instantaneous morphological configuration of the estuary outlet, while tidal attenuation reflects the integrated hydrodynamic response of the lagoon to ocean forcing over multi-day timescales [4, 9]. These two signals are related but do not map directly onto one another, as the estuary entrance state is controlled by the balance of wave, tidal, and fluvial forcing, which can vary across short spatial and temporal scales

[24, 30]. Representative examples of these disagreement modes are shown in Supplementary Section S7.

Several processes can produce visible connections that do not correspond to strong tidal influence in the lagoon. Short-lived breaching events may create channels that allow rapid drainage of lagoon water but do not persist long enough to establish a sustained tidal signal, reflecting the sensitivity of inlet state to transient or event-driven forcing conditions [4, 14, 30]. Similarly, systems with strong river discharge may maintain an open channel while limiting tidal propagation into the lagoon [1, 3]. In other cases, estuaries may be perched, where lagoon water drains across the berm through a shallow or elevated outlet that allows outflow but restricts tidal inflow. These conditions represent real morphological connections that are readily detectable in satellite imagery but may produce weak or absent tidal signatures in water-level observations.

Conversely, water-level data can indicate tidal influence in systems that appear closed or only weakly connected in imagery. Wave overtopping or intermittent exchange across the berm can introduce ocean water into the lagoon without forming a clearly defined or persistent channel [5]. In these cases, tidal signals may be present in the lagoon water-level record even when a surface connection is not visually apparent at the time of image acquisition. These dynamics are particularly sensitive to tidal phase and recent forcing conditions, such that a system may appear closed in imagery at one moment while still exhibiting tidal influence over the course of a day [24, 31].

Together, these observations highlight the existence of intermediate connectivity states that are not fully captured by a binary open–closed classification. In practice, systems may range from fully closed to perched or draining conditions with little tidal exchange to weakly or intermittently connected states with muted tidal influence, and finally to fully open systems with strong tidal coupling. This continuum of behaviors is consistent with broader work showing that intermittently closed estuaries span a range of geomorphic and

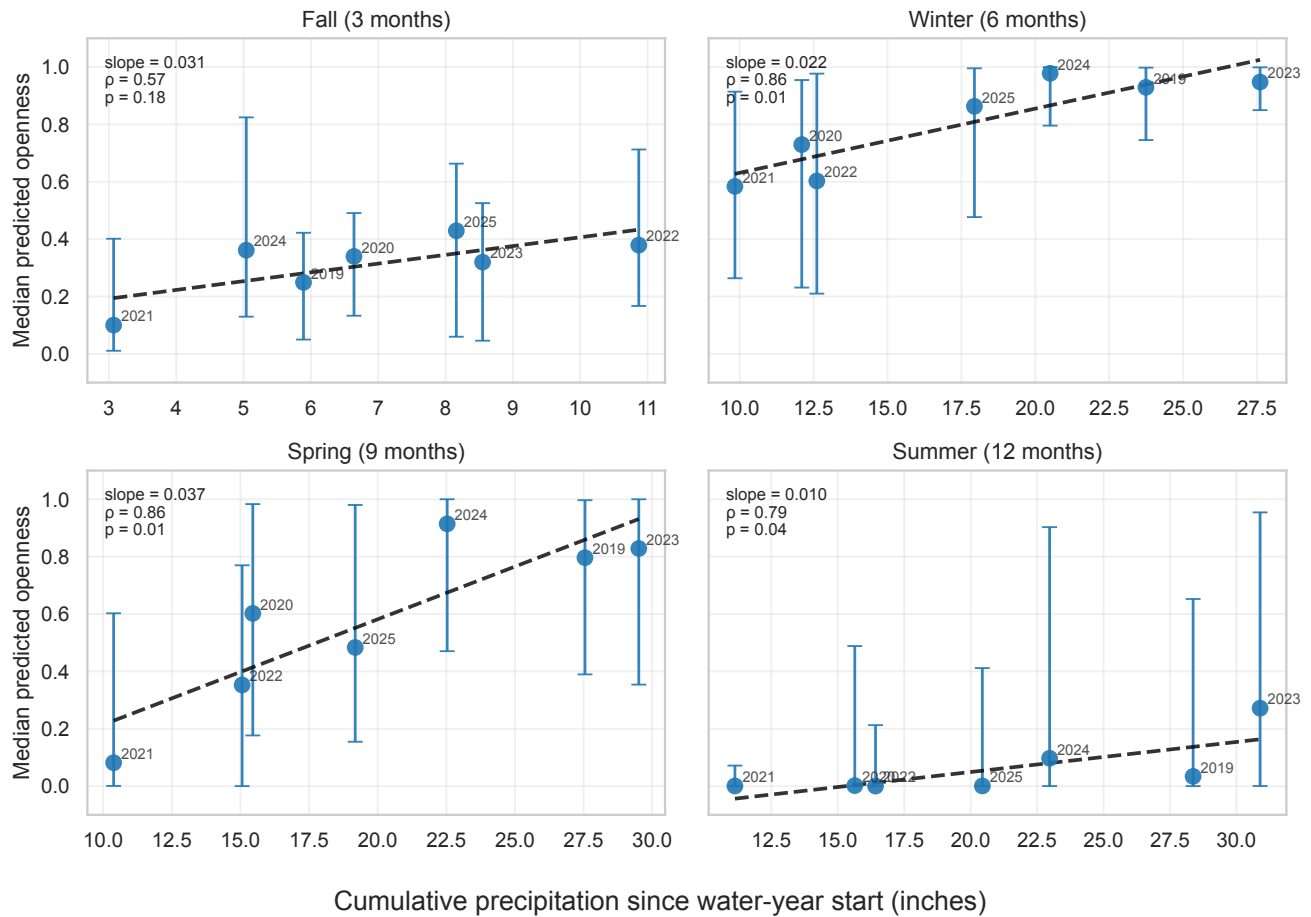


Figure 8: Relationship between cumulative California precipitation since water-year start and seasonal estuary openness. Each point shows the median across estuaries of the estuary-level seasonal mean predicted openness. Precipitation is accumulated from October 1 through the end of each season: 3 months for fall, 6 months for winter, 9 months for spring, and 12 months for summer. Error bars show the interquartile range across estuaries. Dashed lines indicate linear fits. Inset text reports the linear slope and Spearman rank correlation coefficient (ρ) with its p-value.

functional types and are governed by interacting physical processes rather than discrete states [2, 9, 32].

4.4. Regional patterns in estuary connectivity

Analysis across the California coast reveals a clear seasonal pattern in estuary connectivity, with median openness increasing from fall into winter and declining through spring and summer. This shared temporal pattern indicates a common response to seasonal hydrologic and wave forcing, even as spatial patterns remain complex. In particular, the absence of a clear north–south gradient in open frequency, despite strong latitudinal differences in climate, highlights the heterogeneous distribution and morphology of estuaries along the California coast [7] and the importance of local factors.

This contrast between shared temporal structure and spatial variability in open frequency suggests that climatic forcing influences when favorable opening conditions occur, while local controls such as inlet morphology, berm

geometry, watershed size, and discharge persistence influence how frequently and how long individual estuaries remain connected. Regional median openness was associated with precipitation accumulated since the start of the water year in winter, spring, and summer. Rank associations were equally strong in winter and spring, while spring showed the largest linear change in openness per inch of cumulative precipitation. In winter, widespread river discharge produces high openness across most estuaries, particularly in January and February. In fall, low-flow conditions and early-season waves favor closure, although regional median openness remains low to moderate rather than uniformly zero. Years following wetter water years also tended to be more open than expected from current-year cumulative precipitation alone, particularly in fall and winter, suggesting that antecedent hydrologic or geomorphic conditions may impart interannual memory to estuary connectivity. This pattern reflects the importance of the timing and balance of fluvial and marine forcing, as inlet dynamics depend not only on forcing magnitude but on the sequencing of events

and the interaction between river discharge and wave-driven sediment transport [2, 4, 14].

These regional patterns nevertheless mask strong differences among individual estuaries. Inlet geometry, watershed size, and wave exposure influence both the likelihood of opening and the persistence of open states, such that similar climatic conditions can produce different connectivity dynamics among estuaries. Previous studies have shown that intermittently closed estuaries span a range of geomorphic configurations and hydrodynamic behaviors that depend on boundary conditions [30], and that even morphologically similar systems can exhibit distinct responses because of differences in environmental forcing and basin characteristics [33]. Management intervention can further modify these dynamics. Nine of the 66 estuaries in this study have evidence of officially sanctioned recurrent or episodic breaching, and additional estuaries may have experienced historical or unauthorized breaching.

Interpretation of these regional patterns is limited by the temporal interpolation used to create continuous daily series. Because interpolation was performed across gaps of all lengths, long gaps may smooth abrupt opening or closure events and shift their apparent timing. Averaging across estuaries reduces the influence of individual gaps on regional patterns, but the interpolated series should not be interpreted as resolving short-term transitions or event timing at individual sites.

5. Conclusion

This study demonstrates that estuary connectivity can be characterized consistently across many systems using high-resolution satellite imagery, enabling a shift from site-specific observations to regional analysis. Using California as a case study, we constructed a multi-year dataset spanning 66 intermittently closed estuaries, providing the first high-frequency, satellite-derived records of estuary mouth connectivity across the California coast. This dataset reveals a coherent seasonal structure alongside strong site-level variability, highlighting the importance of understanding estuaries both as individual systems and as components of a broader coastal region.

Intermittently closed estuaries are globally widespread and ecologically important yet remain underrepresented in the literature, particularly beyond individual sites and short study periods [2, 10]. This regional, multi-year California record begins to address that gap and provides a foundation for expanding satellite-based connectivity monitoring to other regions. Withheld-estuary experiments show that broader application will require labeled examples spanning more diverse geomorphic and environmental conditions. Expanding the dataset across estuary types and regions would improve model transferability and enable comparative analysis at broader scales.

Long-term connectivity histories help move beyond this site-by-site view by identifying estuaries that respond unexpectedly to wet and dry years and by indicating where field

monitoring, restoration planning, or process-based studies may be most valuable. They also provide a baseline for tracking future change as runoff regimes, atmospheric rivers, drought intensity, sea level, and coastal sediment supply shift. Repeated observations can help evaluate how prolonged closure or frequent opening affects lagoon residence time, salinity structure, nutrient export, and habitat suitability. By resolving when and where estuaries are open, closed, or partially open, these records can also support analysis of ecological connectivity among systems, including implications for metapopulations, dispersal, and species movement. The value of the dataset is therefore not only retrospective: it provides a basis for identifying vulnerable systems, detecting departures from expected behavior, and targeting monitoring and management across the coast.

Acknowledgements

This research was supported by the California Ocean Protection Council and California State Parks (JLL). We thank Kevin O'Connor and Eric Stein for reviewing an earlier version of the manuscript and providing helpful feedback. We thank Brooke Fulkerson for sharing water-level data and Christina Toms for early feedback on the project. We acknowledge Planet Labs PBC for access to PlanetScope and SkySat imagery and metadata used in this analysis. We also acknowledge the data providers and monitoring programs that made water-level and climate records available, including the U.S. Geological Survey, the California Estuary Monitoring Program/Southern California Coastal Water Research Project, the UC Davis Coastal Oceanography Group, and NOAA National Centers for Environmental Information.

CRedit authorship contribution statement

Kyle Dorman: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Visualization, Writing – original draft, Writing – review and editing. **John L. Largier:** Conceptualization, Methodology, Writing – review and editing. **Kyle C. Cavanaugh:** Conceptualization, Methodology, Resources, Supervision, Funding acquisition, Project administration, Writing – review and editing.

Funding

This work was supported by the California Ocean Protection Council and California State Parks. The funders had no role in study design; data collection, analysis, or interpretation; preparation of the manuscript; or the decision to submit the article for publication.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Declaration of generative AI and AI-assisted technologies in the manuscript preparation process

During the preparation of this work, the authors used ChatGPT and OpenAI Codex to support code troubleshooting and to improve manuscript clarity, organization, and readability. After using these tools, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article. Generative AI tools were not used to create or alter the underlying data, results, satellite imagery, or submitted figures.

Data availability

The cleaned data products underlying this study, including estuary site metadata, area-of-interest polygons, manual labels, image-level predictions, and daily connectivity predictions, are available from Zenodo [34] at <https://doi.org/10.5281/zenodo.20753031>. PlanetScope and SkySat imagery are not redistributed; image records include Planet asset identifiers (asset_id) to identify source scenes. The analysis code is available at <https://github.com/kyle-dorman/estuary>.

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Supplementary material for Seasonal and interannual dynamics of estuary connectivity along the California coast

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Description

This supplementary material provides additional examples of imagery excluded because of inadequate image quality; detailed validation of labeling consistency using higher-resolution SkySat imagery and in situ water-level observations; additional information on classifier architecture, training, and evaluation; an assessment of spatial-resolution effects; tests of model generalization to estuaries withheld from training; examples of common classification challenges; and examples of disagreement between morphological connectivity inferred from satellite imagery and hydrodynamic connectivity inferred from water-level records. The supplement contains Supplementary Sections S1–S7, one supplementary table, and eight supplementary figures.

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S1. Low-quality image examples

Images with severe visual artifacts were excluded before mouth-state classification because these conditions obscured the estuary mouth or distorted the image features used to interpret connectivity.

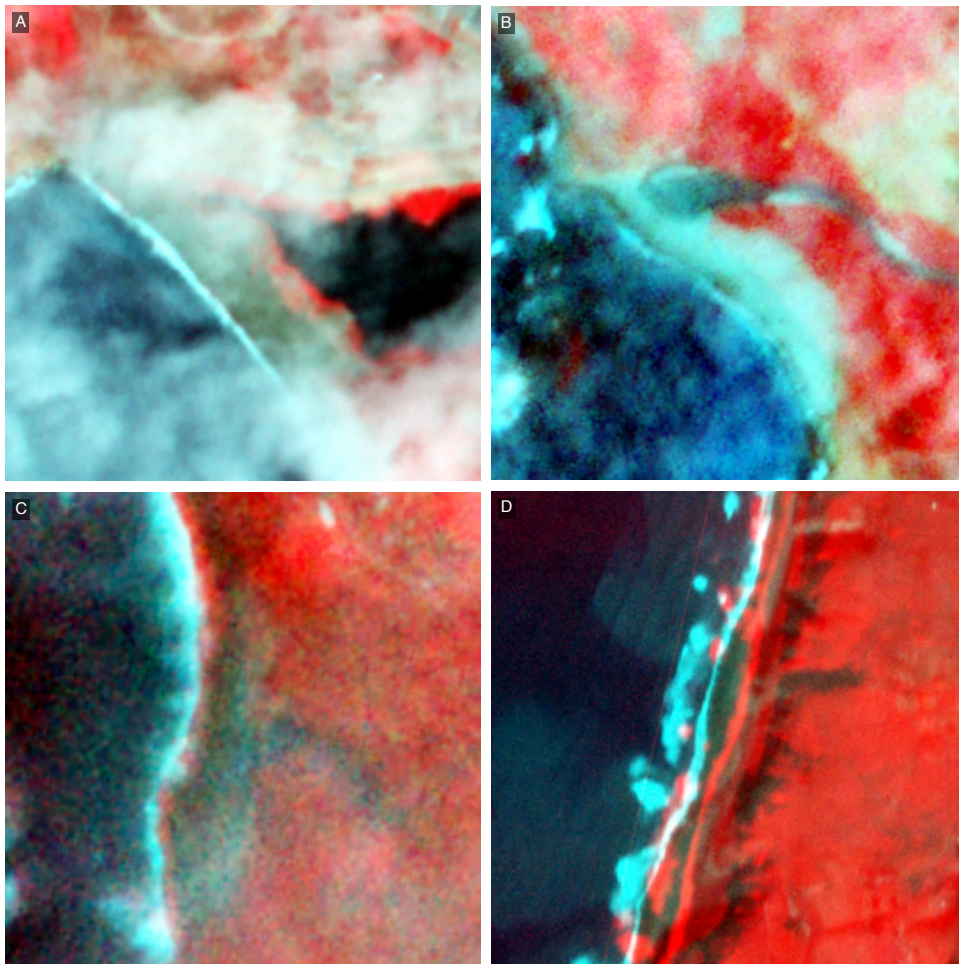


Figure S1: Examples of imagery identified by the image-quality classifier and excluded before mouth-state classification. Panels show representative failure modes at (A) Rodeo Lagoon: cloud contamination; (B) Arroyo de la Cruz: haze or low-contrast atmospheric contamination; (C) Greenwood Creek: sensor noise; and (D) Alder Creek: band misregistration. PlanetScope images © 2017, 2018, and 2022 Planet Labs PBC.

S2. Detailed validation of labeling consistency

Here we provide a detailed summary of labeling agreement for the two validation datasets described in the main text: (1) comparison with higher-resolution SkySat imagery and (2) comparison with labels generated using PlanetScope imagery together with in situ water-level observations. These analyses focus on the full three-class labeling scheme (closed, partial, open) to characterize where disagreements occur.

Comparison between PlanetScope-based labels and SkySat-based labels yielded a balanced accuracy of 0.76 for the three-class classification (Fig. S2A). Agreement was high for the closed and open classes, while the partial class showed substantially lower agreement ($F1 \approx 0.37$). Approximately 14% of images were labeled as partial in at least one dataset. Most disagreements occurred between the open and partial classes, often in cases where narrow or low-contrast channels are more clearly resolved in SkySat imagery than in PlanetScope (Fig. S3).

Comparison between PlanetScope-only labels and labels informed by water-level data yielded a balanced accuracy of 0.82 for the three-class classification (Fig. S2B). Agreement was again high for the closed and open classes, while the partial class showed lower agreement ($F1 \approx 0.58$). Approximately 7% of images were labeled as partial in at least one dataset. In this comparison, the inclusion of water-level data increased the frequency of partial labels in cases where hydrodynamic signals indicated limited or intermittent exchange despite ambiguous visual connections in the imagery.

Across both validation approaches, disagreements were concentrated in the distinction between open and partial states. These disagreements were associated with narrow or indistinct channels, differences in spatial resolution between sensors, and short-term changes in inlet morphology within the matching window. In the water-level comparison, disagreement also arose when hydrodynamic signals indicated weak or attenuated exchange despite visible or partial connections in the imagery.

Taken together, these results indicate that the partial class represents a range of intermediate conditions that are difficult to label consistently across data sources, while the distinction between open and closed states is robust. This supports the use of a binary connectivity classification in the main analysis, where consistency across systems is required.

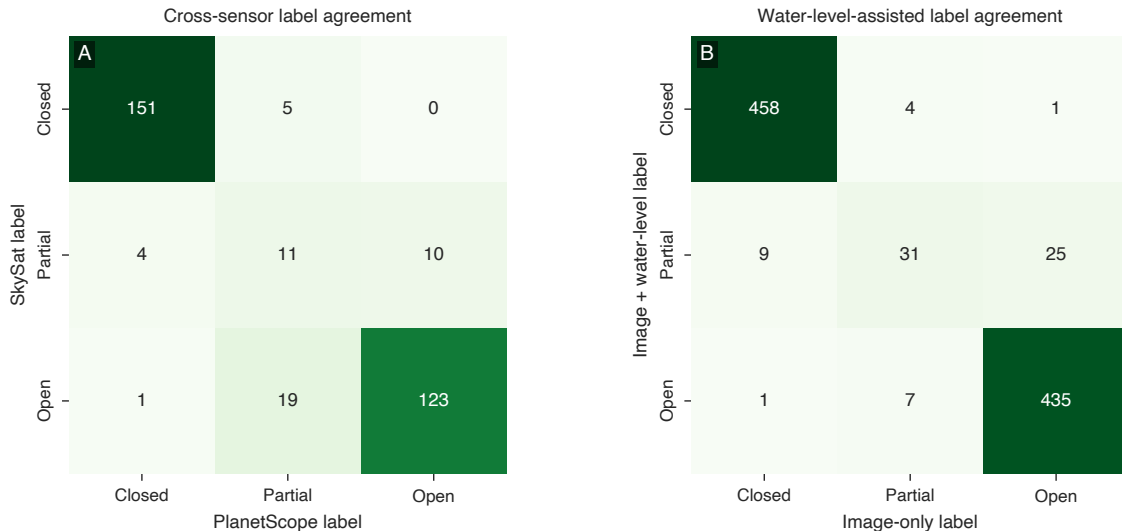


Figure S2: Detailed validation of three-class labeling consistency. (A) Cross-sensor label agreement between labels derived from PlanetScope imagery and higher-resolution SkySat imagery. (B) Water-level-assisted label agreement between labels derived from PlanetScope imagery alone (image-only) and labels generated using PlanetScope imagery together with in situ water-level observations (image plus water level).

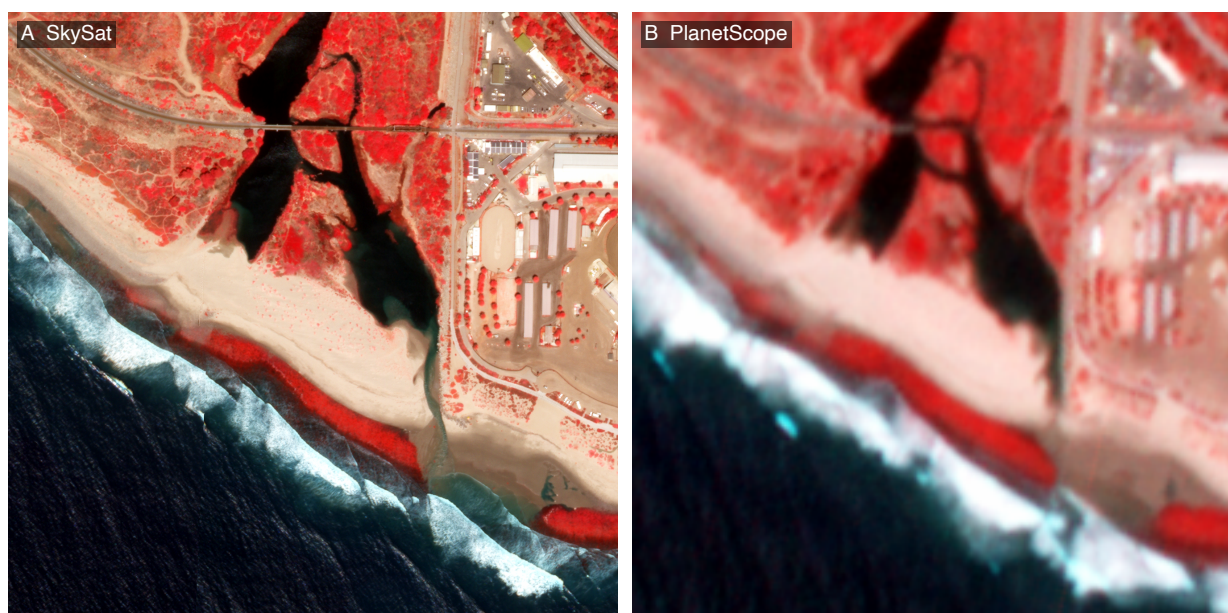


Figure S3: Disagreement between PlanetScope- and SkySat-based labeling at the Ventura River. The estuary was labeled partial in PlanetScope imagery but open in higher-resolution SkySat imagery. The narrow outlet channel in the lower-right portion of the image is difficult to distinguish from surrounding wet sand at 3 m resolution but is clearly resolved at 0.5 m resolution. PlanetScope and SkySat images © 2019 Planet Labs PBC.

Table S1

Backbone architecture, pretraining strategy, and spectral band comparison. Model performance across backbone architectures, pretraining strategies, and spectral band combinations.

Model	Pretraining	Bands	F1
ConvNeXt-Tiny	dinov3_lvd1689m	NIR-R-G	0.95
ConvNeXt-Tiny	dinov3_lvd1689m	RGB	0.94
ConvNeXt-Tiny	ImageNet-22K	NIR-R-G	0.94
ConvNeXtV2-Tiny	FCMAE and ImageNet-22K	NIR-R-G	0.93
ConvNeXtV2-Tiny	FCMAE	NIR-R-G	0.91

S3. Classifier implementation and evaluation

S3.1. Connectivity classifier backbone and inputs

To assess how model architecture and input representation affect connectivity classification in this dataset, we evaluated several backbone networks and input channel configurations under comparable training conditions (Table S1).

Among the tested models, ConvNeXt-Tiny initialized with DINOv3 weights achieved the highest performance ($F1 = 0.95$). Using RGB inputs instead of the false-color NIR–Red–Green combination reduced the F1 score by 0.014, indicating that the near-infrared channel provides useful information for distinguishing water from dark vegetation or organic material in some situations, consistent with the visual cues used during manual labeling. This highlights the importance of spectral representation for resolving ambiguous water–land boundaries in high-resolution coastal imagery.

Alternative pretraining schemes performed consistently worse. A ConvNeXt-Tiny model initialized with ImageNet-22K supervised pretraining achieved lower performance ($F1 = 0.94$), while ConvNeXtV2-Tiny models with FCMAE pretraining performed worse still ($F1 = 0.93$ and 0.91 depending on initialization). Together, these results indicate that DINOv3 provides representations better suited to capturing the spatial structure of estuary connectivity, where classification depends on relationships between landscape features rather than simple spectral thresholds.

Increasing model capacity did not improve performance. ConvNeXt-Small consistently overfit despite extensive regularization, suggesting that additional capacity is not beneficial given the dataset size and inherent label ambiguity. Vision Transformer (ViT) architectures using DINOv3 initialization also did not outperform ConvNeXt-Tiny, likely reflecting the importance of strong inductive biases for capturing fine-scale spatial structure in this setting.

For backbone comparisons, all models were trained using the same dataset and data augmentation pipeline described in the main methods, with hyperparameters adjusted as needed for each architecture. ConvNeXt-Tiny was therefore selected as the backbone for the experiments presented in the main paper because it balanced strong performance with robustness to dataset size and label ambiguity.

S3.2. Training objective, thresholding, and evaluation metrics

The connectivity classifier was trained using binary cross-entropy with logits, combined with an entropy regularization term applied to the predicted class probabilities [1]. For a batch of N images, the loss function was defined as

$$\mathcal{L} = \mathcal{L}_{\text{BCE}} - \lambda \mathcal{L}_{\text{ent}}, \quad (1)$$

where $\mathcal{L}_{\text{BCE}}$ is the binary cross-entropy loss, $\mathcal{L}_{\text{ent}}$ is the entropy regularization term, and $\lambda = 0.1$. The binary cross-entropy term was

$$\mathcal{L}_{\text{BCE}} = -\frac{1}{N} \sum_{i=1}^N [y_i \log \sigma(z_i) + (1 - y_i) \log (1 - \sigma(z_i))], \quad (2)$$

where z_i is the model output logit, $\sigma(\cdot)$ is the sigmoid function, and $y_i \in \{0, 1\}$ is the binary ground-truth label. The entropy regularization term was

$$\mathcal{L}_{\text{ent}} = -\frac{1}{N} \sum_{i=1}^N [p_i \log p_i + (1 - p_i) \log(1 - p_i)], \quad (3)$$

where $p_i = \sigma(z_i)$ is the predicted probability of surface connectivity. Because the entropy term is subtracted from the loss, it discourages overly sharp predictions when the image signal is ambiguous. The binary cross-entropy term drives separation between open and closed states, while the entropy regularization allows intermediate probabilities to persist for transitional or visually uncertain mouth states.

Model performance was evaluated using the F1 score,

$$F1 = 2 \frac{\text{precision} \times \text{recall}}{\text{precision} + \text{recall}}, \quad (4)$$

with

$$\text{precision} = \frac{TP}{TP + FP}, \quad \text{recall} = \frac{TP}{TP + FN}, \quad (5)$$

where TP , FP , and FN denote true positives, false positives, and false negatives, respectively. A classification threshold was selected using the validation dataset to balance precision and recall, and this threshold was used to convert predicted probabilities into binary open or closed labels during inference.

S3.3. Image-quality classifier

Variation in image quality is a well-documented challenge in PlanetScope data, arising from differences in sensor calibration, viewing conditions, and atmospheric effects [2]. Although Planet imagery was filtered using metadata and usable data mask criteria, some degraded images remained in the dataset, including scenes affected by thin cloud, haze, sensor noise, blur, strong shadowing, or band misalignment. Because these conditions can produce unreliable connectivity predictions, we trained a separate image-quality classifier to distinguish usable imagery from low-quality observations prior to generating estuary connectivity time series.

The image-quality classifier used the same ConvNeXt-Tiny backbone and image inputs as the connectivity classifier. The network was initialized using the trained weights from the connectivity classifier, with the final classification head replaced by a new binary head predicting low-quality versus usable imagery.

Training proceeded in two stages. In the first stage, the backbone was frozen and the newly initialized classification head was trained for five epochs using simulated image degradations applied to known high-quality images. These augmentations included fog and haze simulation, ISO-style sensor noise, and channel misalignment, designed to approximate common degradation modes observed in the satellite imagery. This stage increased the diversity of degraded examples and reduced overfitting to the relatively small manually labeled low-quality dataset. During this stage, the model was trained using the AdamW optimizer with a learning rate of 3×10^{-5} and a batch size of 128.

In the second stage, the backbone was unfrozen and the full network was trained for an additional ten epochs using only the manually labeled dataset, allowing the model to adapt to real degradation patterns present in the imagery. During this stage, the learning rate was reduced to 1×10^{-5} , with the same optimizer and batch size.

The labeled dataset contained approximately 2,500 images marked as low-quality, with all other labeled images treated as the negative class. Class imbalance was addressed using class weights in the binary cross-entropy loss. Minor color augmentations and spatial flips were applied during training. The final model was selected based on validation F1 score, and a separate classification threshold was determined using the same validation-based procedure described for the connectivity classifier.

S4. Effect of spatial resolution on estuary mouth interpretation

To illustrate how spatial resolution affects visual interpretation of estuary mouth state, we compared false-color imagery from SkySat (approximately 0.5 m), PlanetScope (approximately 3 m), and Sentinel-2 (approximately 10 m) acquired over the same estuary on 12 April 2019 within approximately two hours of one another (Fig. S4). At SkySat and PlanetScope resolution, the inlet morphology appears narrow and discontinuous, consistent with a partial or ambiguous surface connection. In the Sentinel-2 image, the same outlet appears more continuous because land, water, and wet sand are mixed within coarser pixels. This example illustrates how lower-resolution imagery can bias visual interpretation toward more open states and highlights the importance of meter-scale imagery for resolving narrow inlet channels in intermittently closed estuaries.

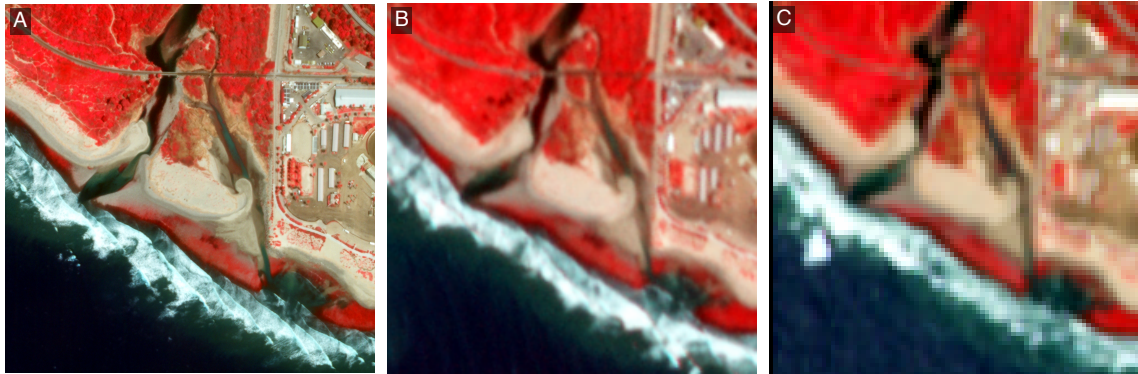


Figure S4: Effect of spatial resolution on interpretation of estuary mouth connectivity at the Ventura River. False-color images acquired by SkySat, PlanetScope, and Sentinel-2 on 12 April 2019, within approximately two hours of one another. The larger opening at the bottom left is clearly visible in all three images. The comparison focuses on the narrower secondary opening at the bottom right, which belongs to the same river system. SkySat clearly resolves the channel and its restricted connection to the ocean, whereas coarser pixels increasingly merge water, wet sand, and channel margins, making the secondary opening appear more continuous. PlanetScope and SkySat images © 2019 Planet Labs PBC.

S5. Generalizing to unseen estuaries

To evaluate the model's ability to generalize to previously unseen geomorphic settings, we performed six-fold stratified group cross-validation in which entire estuaries were withheld from training. Estuaries were assigned to folds using mouth-state class as the stratification variable and estuary identity as the grouping variable, with shuffling and a fixed random seed of 42. Thus, all observations from a given estuary remained in the same fold. In each iteration, 10–12 estuaries were held out for evaluation. Among the remaining estuaries, observations acquired in 2021 were used for validation and observations from all other years were used for training. The held-out evaluation set contained all PlanetScope observations labeled closed or open from the withheld estuaries across 2017–2025. Across the six folds, each of the 9,742 labeled observations from 66 estuaries was evaluated exactly once. Model architecture and training hyperparameters were held constant across folds, while class weights were recalculated using only the training observations in each fold.

Estuary-level model performance declined for held-out sites, although the magnitude of the decline varied among estuaries (Fig. S5). Most estuaries exhibited modest reductions in F1 score, but a subset showed substantially larger generalization gaps. These sites also exhibited increased predictive entropy, indicating greater model uncertainty for unfamiliar morphologies.

Inspection of these outlier estuaries suggested that larger generalization gaps occurred at sites with narrow or visually ambiguous inlet connections, where the open–closed signal occupies only a small number of pixels or is easily obscured by sediment, shadow, or surf. Because the training dataset includes only 66 estuaries, it may not represent the full range of geomorphic configurations needed for consistent generalization to unseen sites.

These results indicate that model performance depends strongly on exposure to representative geomorphic configurations, rather than on learning a universally transferable representation of connectivity. Expanding the labeled dataset to include additional estuary types and observational conditions will therefore be essential for improving model robustness and reducing generalization gaps in large-scale applications.

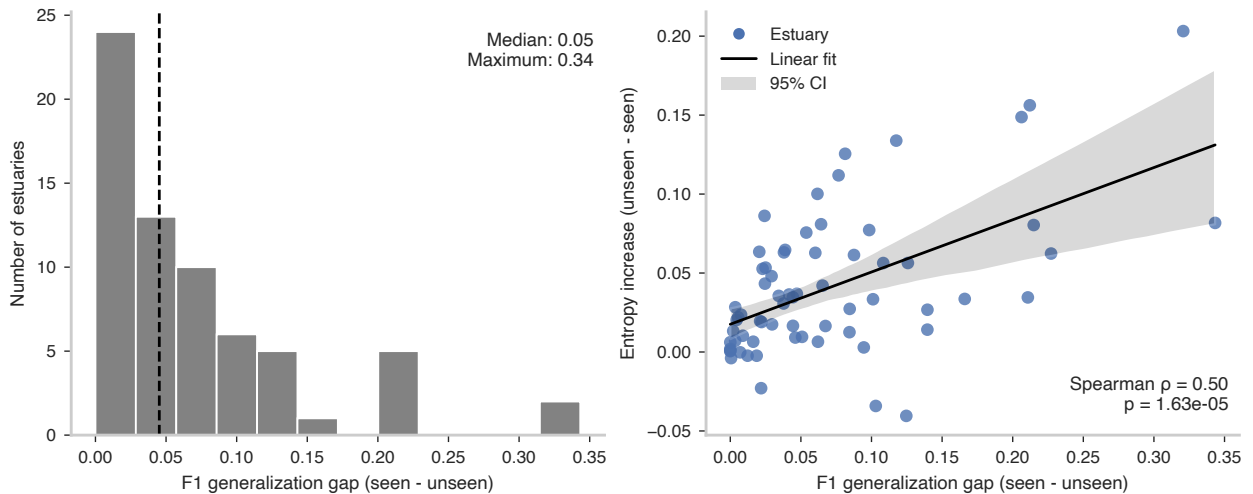


Figure S5: Generalization to unseen estuaries. The left plot shows the distribution of F1 performance differences between estuaries represented in training and estuaries held out from training, with the median and maximum annotated. The right plot shows the F1 generalization gap versus the increase in predictive entropy for held-out estuaries; points represent estuaries, the line shows the linear fit, and the shading shows the 95% confidence interval.

S6. Challenges in satellite-based classification of estuary connectivity

In addition to general data quality limitations associated with PlanetScope imagery and the inherent ambiguity of some estuary mouth-state labels, several challenges were observed during training and evaluation that reflect the interaction between estuary morphology, image resolution, and the distribution of training data.

First, large estuary areas of interest (AOIs) with relatively narrow inlet connections can be difficult to resolve after image resizing (Fig. S6A). Because model inputs are rescaled to a fixed spatial resolution, narrow connections between the ocean and lagoon may occupy only a few pixels or disappear entirely after resampling, reducing the strength of the connectivity signal used to distinguish open from closed states.

Second, some estuaries exhibit substantial shifts in label distributions between training and testing datasets (Fig. S6B). In several cases, the training set contains very few examples of one mouth state, while the held-out test set contains a higher proportion of that state. Such distribution shifts limit the ability of the model to learn representative features and can lead to larger generalization errors.

Third, highly turbid water associated with runoff or suspended sediment can resemble exposed land in spectral appearance (Fig. S6C). Because such conditions occur relatively infrequently in the training dataset, they can lead to confusion between open and closed states.

Finally, some estuaries occasionally appear completely dry or are obscured by strong shadowing or cloud cover (Fig. S6D). In these cases, the lagoon may not be visible in the imagery, either due to the absence of surface water or because it is masked by shadow or clouds. These conditions remove a key spatial cue used by the model to identify the estuary system, making it more difficult to determine where to focus within the scene. As a result, the model may produce incorrect predictions even in otherwise straightforward cases.

Taken together, these examples highlight that many classification challenges arise from the combination of limited spatial resolution and the diversity of estuary morphologies. Improving performance is therefore likely to depend more on expanding the diversity of labeled training data than on increasing model complexity.

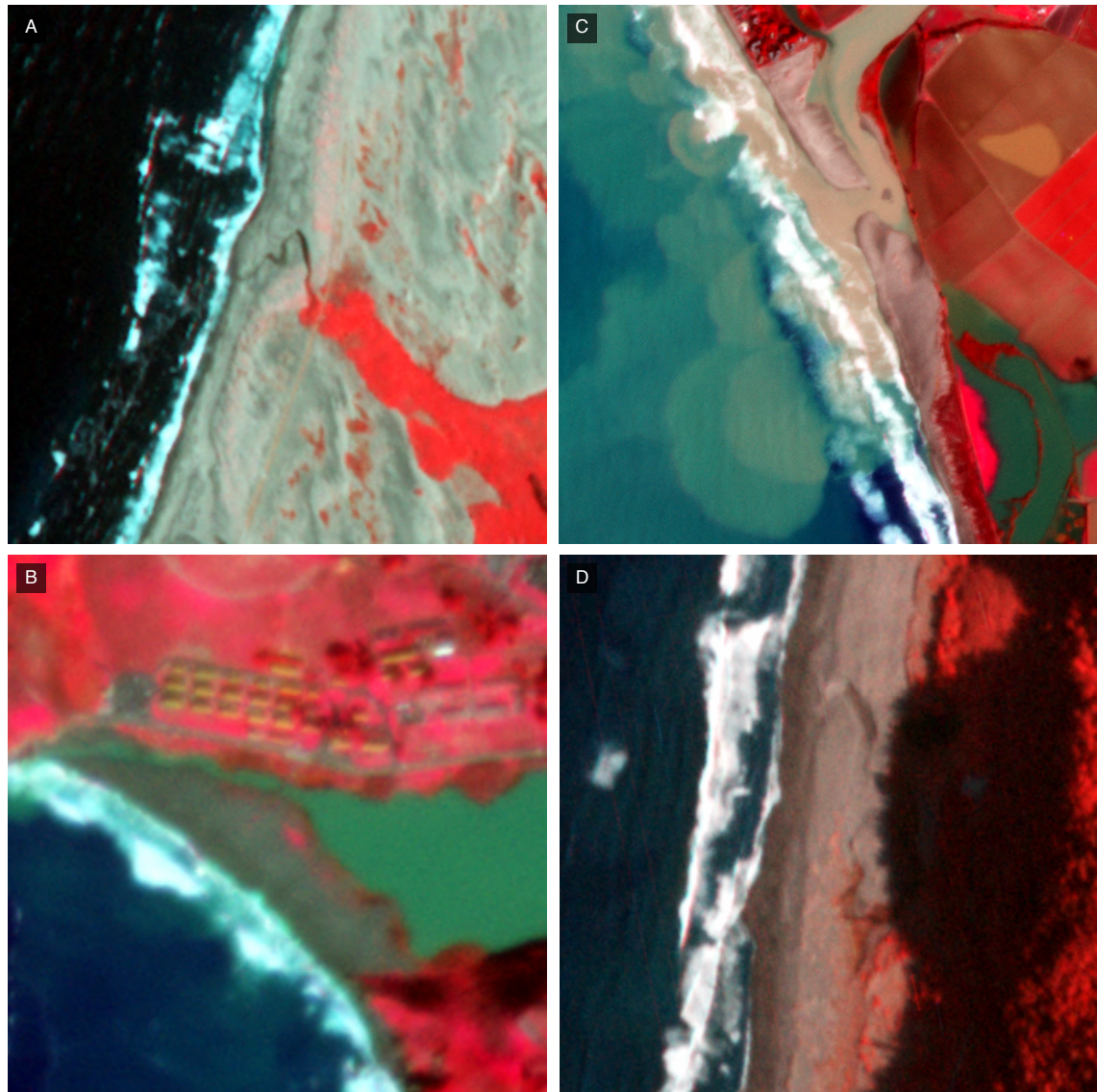


Figure S6: Examples of challenges in satellite-based estuary classification. Panels show (A) Inglenook Fen: large estuaries with narrow inlet connections can lose visible connectivity after image resizing, making open states difficult to detect; (B) Rodeo Lagoon: distribution shifts and class imbalance between training and testing datasets can occur when an estuary has very few labeled examples of one mouth state; (C) Pajaro River: highly turbid water associated with runoff or suspended sediment may be confused with exposed land; and (D) Fern Canyon: dry lagoons, strong shadowing, or cloud cover can obscure the lagoon entirely, removing key spatial cues and leading to misclassification even in otherwise clear cases. PlanetScope images © 2019, 2021, 2024, and 2025 Planet Labs PBC.

S7. Morphological and hydrological disagreements

Satellite imagery and water-level observations provide complementary but distinct views of the estuary state. Image-based predictions reflect the instantaneous morphology of the mouth at the time of acquisition, while water-level records capture the hydrodynamic response of the system over tidal timescales. As a result, disagreements between the two arise during periods when morphology and hydrodynamics evolve on different timescales.

Figures S7 and S8 show representative examples of two common disagreement modes. In each case, the satellite image is shown on the left and its corresponding time series on the right. Blue points show daily aggregated open-probability predictions plotted at the mean acquisition time of the contributing imagery; the dotted line marks the exact acquisition time of the displayed image. Estuary water level, predicted ocean tide height, and tidal attenuation use the real UTC sensor timestamps and are shown as hourly medians.

Figure S7 shows examples in which the model predicts closed conditions based on the visible absence of a continuous surface channel, while the water-level record retains a clear tidal signal. In these cases, the classification is visually consistent with the imagery: the mouth appears closed or blocked at the time of acquisition. However, tidal oscillations indicate that exchange with the ocean persisted. These cases most likely reflect wave-driven overwash of a continuous sand barrier during higher high tides.

These cases typically occur during transition periods when the mouth is actively closing. The recently constructed barrier remains low enough to permit wave-driven exchange, even as the surface connection becomes visually indistinct or fully obscured in imagery. This is reflected in rapid changes in predicted openness over consecutive image acquisitions, with classifications flipping over short time windows. The disagreement therefore reflects a temporal offset between morphological closure and the loss of hydrodynamic connectivity.

Figure S8 shows the converse case, in which a visible outlet channel leads to high predicted openness, but the water-level record shows weak tidal variability and high tidal attenuation. In these examples, the mouth appears morphologically open, but the lagoon is not strongly coupled to ocean tides. This most commonly reflects a perched state in which a positive water balance and high estuary water level maintain continuous overflow without eroding the sand barrier—that is, a one-way outflow channel with no tidal variability in lagoon water level.

These cases commonly occur when the system is non-tidal but a flow channel is visible. A shallow, perched, or recently evolving outlet may remain visible while its bed elevation lies above the ocean water level, allowing seaward flow but preventing tidal inflow. As a result, morphology indicates the presence of a pathway, but flow through that channel is only seaward. This mismatch is particularly evident during closure events, when the estuary water balance is positive, necessitating an outflow channel that may persist visually for days or weeks after tidal exchange has ceased.

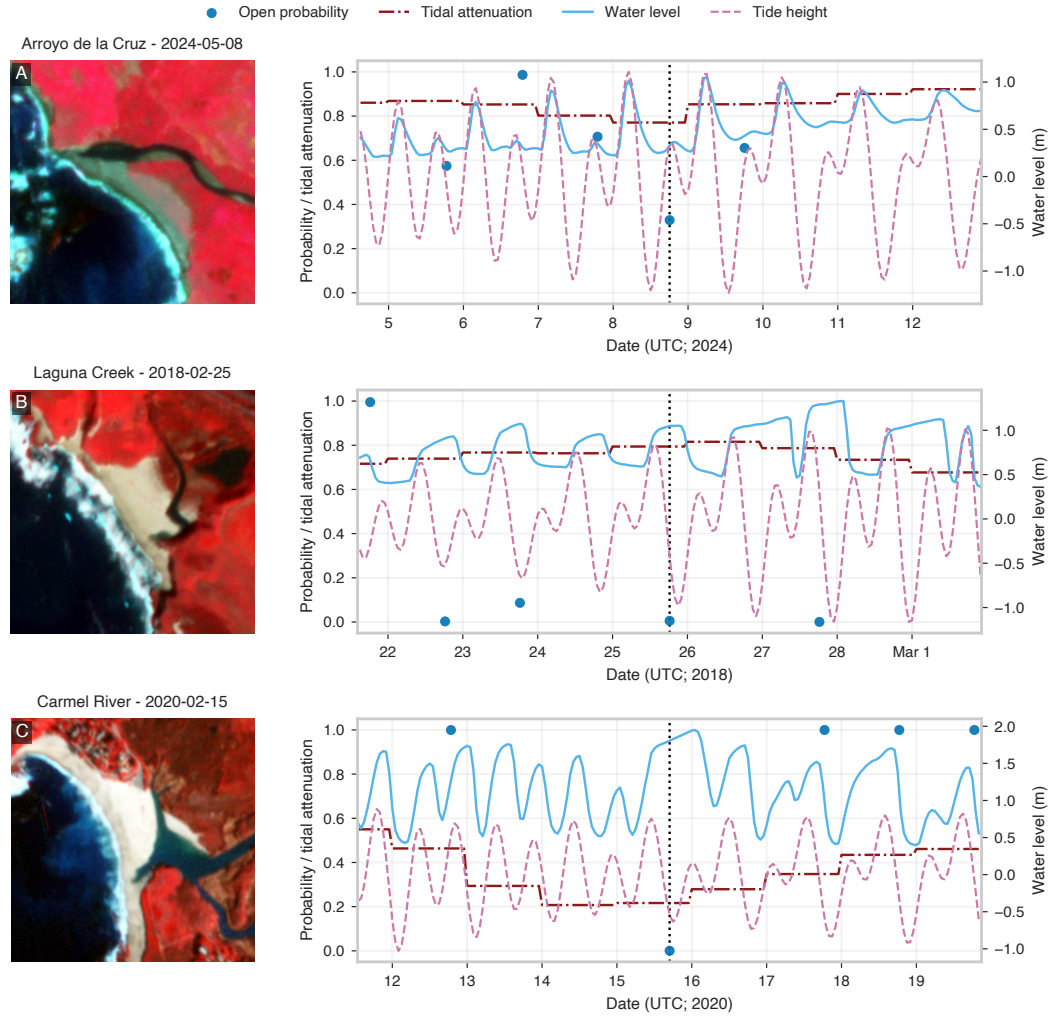


Figure S7: Morphologically closed imagery with persistent tidal behavior. Examples in which the satellite image appears closed or weakly connected and model-predicted openness is low, but the estuary water-level record retains a tidal signal. Blue points show daily aggregated open-probability predictions plotted at the mean acquisition time of the contributing imagery; the dotted line marks the exact acquisition time of the displayed image. Estuary water level, predicted ocean tide height, and tidal attenuation use the real UTC sensor timestamps and are shown as hourly medians. Because the estuary and ocean records use different vertical references, their absolute water levels should not be compared directly; tidal behavior is inferred from similarities in the timing and shape of their fluctuations. PlanetScope images © 2018, 2020, and 2024 Planet Labs PBC.

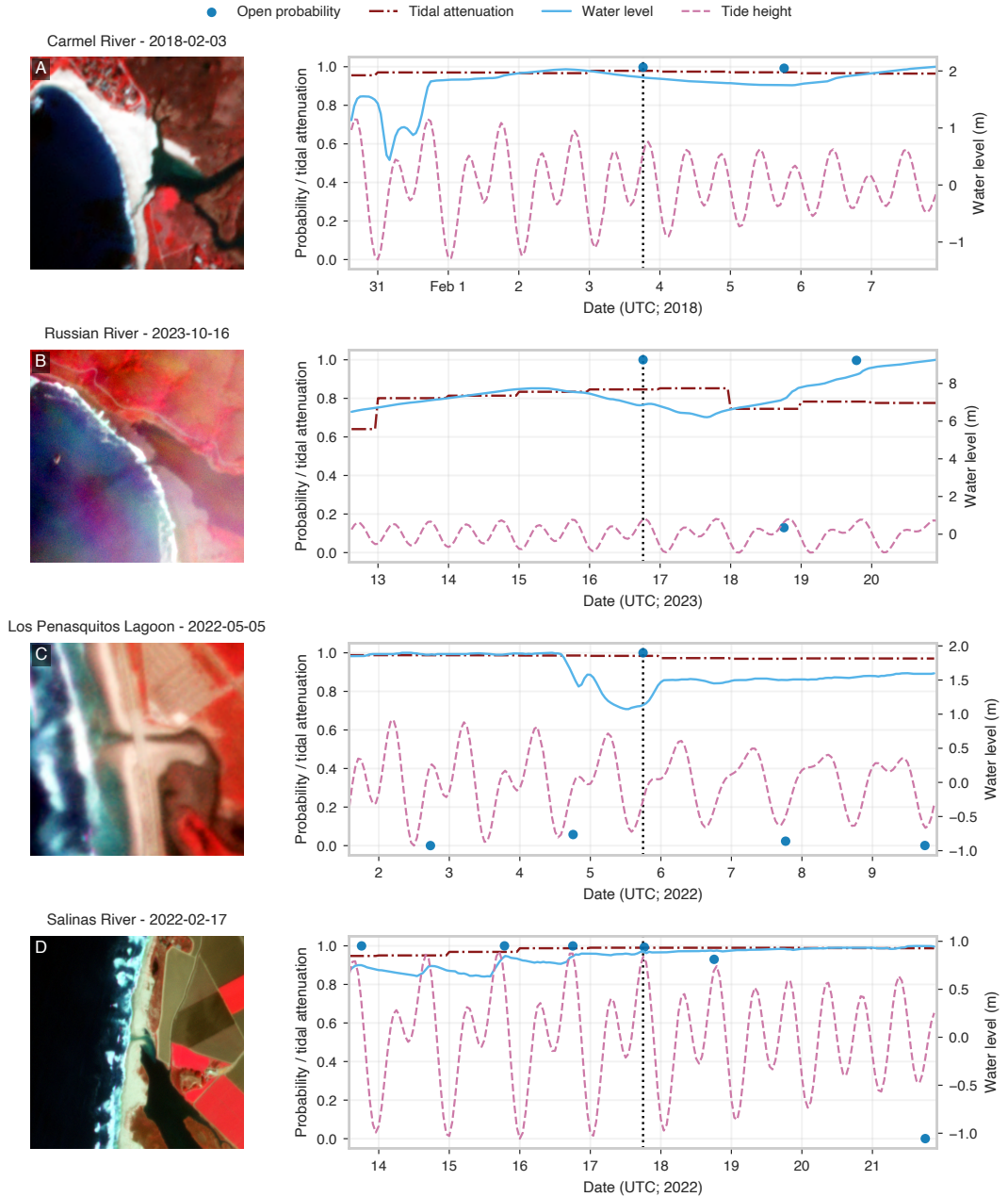


Figure S8: Morphologically open imagery with weak hydrodynamic exchange. Four examples in which a visible outlet channel yields high model-predicted openness, but the water-level record shows weak tidal variability and high tidal attenuation. Blue points show daily aggregated open-probability predictions plotted at the mean acquisition time of the contributing imagery; the dotted line marks the exact acquisition time of the displayed image. Estuary water level, predicted ocean tide height, and tidal attenuation use the real UTC sensor timestamps and are shown as hourly medians. PlanetScope images © 2018, 2022, and 2023 Planet Labs PBC.

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