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Key Points:

- We conducted a 1-month laboratory experiment, recording bed morphologies and bedload transport rates every minute
- We developed an automated workflow (based on image processing, pattern recognition, dimensionality reduction, and clustering) for identifying preferred bed morphologies
- Braided river planform evolution involves transitions among a finite set of recurrent morphological states

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Braided Rivers as Morphological States: A Data-Driven Identification of Recurrent Planform Configurations

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Abstract Braided rivers reorganize their channels from time to time, featuring complex morphological dynamics and intermittent sediment transport that are difficult to describe using scalar metrics or single representative configurations. To better capture this complexity, we introduce a stochastic approach, which involves tracking the planform dynamics of channels and the associated bedload transport rates. In this approach, each state represents a given planform channel geometry, and the system can randomly transition from one state to another over time. We conducted a 1-month laboratory experiment. We identified morphological states from plan view images using an automated workflow combining several techniques (image comparison metrics, dimensionality reduction, and density clustering). The sequence of states revealed long periods of morphological stability, separated by short periods of channel reorganization. Bed morphology also showed great diversity, ranging from narrow, single-thread channels to large, braiding networks prone to sediment storage. While earlier studies have revealed the chaotic nature of modeled braided system evolution, which implies the unpredictability of exact configurations, we found that: (a) there was a limited number of recurrent states; (b) the lifetime of each morphological state was associated with a well-defined timescale; (c) there were preferential transitions from one state to another; and (d) bed morphological states were related to the variability of the sediment transport rate.

Plain Language Summary Braided rivers consist of networks of intertwined channels whose shapes change over time. A key scientific challenge is predicting changes in network geometry and associated sediment transport rates. We investigated this problem through a 1-month scaled laboratory experiment, observing how riverbed geometry evolved. The river typically remained in one configuration before rapidly reorganizing into another. Some configurations persisted, whereas others were short-lived and accompanied by major changes in overall bed geometry. Only a finite set of 16 configurations was observed. The experiment presented two challenges. The first was technical: identifying and characterizing network geometry from images containing large amounts of information. The second was theoretical: describing the temporal evolution of a river that behaves randomly. We addressed the first challenge using a workflow based on image processing and geometric shape detection to identify the most common bed geometries, revealing 16 preferred configurations. For the second, we analyzed transitions between these experimentally identified states and the duration of each state. Although bed geometry evolves with a random component, its evolution is not entirely random. Instead, transitions between configurations and their persistence indicate that the system follows a limited set of simple underlying rules, governing how the river reorganizes through time overall.

1. Introduction

Braided rivers are dynamic fluvial systems made up of intertwined channel networks that reorganize from time to time and are associated with variable sediment transport (P. E. Ashmore, 1991a; Ashworth & Ferguson, 1986): channels repeatedly divide and merge; bars form, migrate, and are reworked by the stream; bifurcations are open and closed; channels migrate or avulse; and parts of the wetted network can be abandoned and later reactivated (P. Ashmore, 2013; P. E. Ashmore, 1991b). These processes operate over a broad range of time scales, from rapid local rearrangements of bars and channels to reach-scale configurations that persist for long periods of time and that large flood events rearrange (Bertoldi et al., 2010; Hoey & Sutherland, 1991).

A large body of work has focused on reach-scale geometric descriptions of braided rivers. These include classical metrics such as braiding intensity, wetted width, active width, and entropic measures that quantify overall properties and make it possible to compare different systems and forcing conditions (P. Ashmore, 2009; P. Ashmore et al., 2011; Egozi & Ashmore, 2008; Howard et al., 1970; Tejedor et al., 2022). Data from laboratory

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scaled experiments have helped study characteristic length scales, network topology, self-affinity, dynamic scaling, self-organization, analogies with other physical systems, and graph representations of braided channel networks (Bassler et al., 1999; Connor-Streich et al., 2018; De Bartolo & De Michele, 2025; Foufoula-Georgiou & Sapozhnikov, 2001; Hundey & Ashmore, 2009; Sapozhnikov et al., 1998; Sapozhnikov & Foufoula-Georgiou, 1996, 1997, 1999). Field monitoring has also provided important observations of braided-river planform change using repeated topographic surveys, time-lapse imagery, and remote sensing (Bertoldi et al., 2010; Hicks et al., 2002; Middleton et al., 2019; Nones et al., 2018). These records are also essential for linking laboratory-scale process understanding to natural rivers, although their temporal resolution is often too coarse to resolve every ephemeral transition between reach-scale configurations. The objective of all these approaches is to identify regularity within morphodynamic variability—in other words, to extract a clear signal from the surrounding noise.

These approaches raise the question of whether filtering out fluctuations is sufficient to characterize the mean behavior of braided rivers. Here, the analogy between braided-river morphodynamics and fluid turbulence, first proposed by Paola (1996), offers a useful perspective: in turbulent flows, velocity fluctuations contribute to the bulk behavior, so ignoring them obscures how the system works. This perspective motivates four more specific questions about the role of fluctuations in braided-river dynamics.

The first of these questions concerns the nature of fluctuations. Laboratory experiments of braided rivers have revealed their sensitivity to initial and boundary conditions (Warburton & Davies, 1994), a feature that induced some authors to interpret these systems in terms of deterministic chaos rather than noise-driven dynamics (Coulthard & Van De Wiel, 2012; Lane, 2006; Stecca & Hicks, 2022); from this viewpoint, physical processes operate in a predictable (deterministic) way, but slight changes in the initial and/or boundary conditions can lead to considerable variations in the outputs, which then look random.

A complementary perspective is offered by stochastic approaches, which are well established for sediment transport. These approaches treat particle entrainment, movement, and deposition as random events (Ancey, 2010; Furbish et al., 2021), linking their fluctuations to the mean sediment transport rate (Ancey & Heyman, 2014; Furbish et al., 2012). They have also informed linear stability analyses of morphodynamic models that produce bedforms such as bars (Ancey, 2020; Bohorquez et al., 2025). However, describing stochastic sediment transport does not by itself explain how an entire braided network evolves. Recent work has begun to address this broader scale: De Bartolo and De Michele (2025) used branching-process theory to connect local channel splitting and reconnection to network-scale spatial organization. Building on the statistical description of network structure, De Bartolo and De Michele (2026) modeled channel-width partitioning with Dirichlet and logistic-normal distributions, identifying a decadal shift toward greater width concentration in the Brahmaputra–Jamuna River. These developments show how stochastic approaches can characterize network organization. Yet spatial statistics and structural changes inferred from separate surveys do not directly specify the persistence, recurrence, or transition probabilities of successive whole-planform configurations. Addressing these temporal properties requires following the sequence of configurations through time, as we do here.

A second question is related to the origins of fluctuations and patterns: when patterns or fluctuations are driven by external forcing, they are called *exogenic*. When they are produced by the system itself, they are named *endogenic* or *autogenic*. There is evidence that in braided rivers, both endogenic and exogenic processes are present. For instance, even under steady state conditions (constant water discharge and sediment feed at the flume inlet, constant flume slope, and fixed sediment properties), channels can be abandoned, former threads can be reactivated (wetted) again, bars migrate and sediment transport is intermittent (Warburton & Davies, 1994).

The third question concerns the spatial and temporal scales associated with bed patterns and channel geometries. The most obvious challenge in the modeling of braided rivers is posed by the coexistence of several length scales: grain size, channel width, bedform length, reach scale, etc. It is generally hard to cover all the spatial scales in the same model, and it is therefore usual to neglect some of them. For instance, fully deterministic morphodynamic models are able to resolve flow, sediment transport, and bed evolution at short length scales, but they rarely work on the grain scale: numerical models set to reproduce flume experiments use grid resolutions that are typically on the order of tens of centimeters (Stecca & Hicks, 2022), and applying these models to real-world rivers generally requires even coarser grids, commonly from decimeters to meters because of computational constraints (Han et al., 2023; Williams et al., 2016). When the spatial scales characterizing a physical system differ significantly from each other, it is easier to decouple scale-dependent processes in modeling; an example is provided by large

eddy simulations of turbulent flows, which remove small-scale turbulence. The problem becomes more complicated when it is no longer possible to distinguish spatial scales. This typically occurs in braided rivers (e.g., channel width or flow depth close to the coarsest grain size). The situation is even more obscure when it comes to timescales. Little is known about the temporal coupling between physical processes. For example, how long does it take for a streambed to adapt to a change in local flow? It is desirable to acquire a better understanding of the spatial and temporal scales of the dynamics of braided rivers.

The fourth question stems from the potential deterministic bias that could affect the vast majority of studies on braided rivers. Most authors use statistical tools focused on average behavior (such as scalar metrics and empirical transport capacity equations), deterministic morphodynamic models (e.g., the Saint-Venant–Exner equations), or conduct single experiments without replicating them, and all of them risk neglecting the fact that the same problem with the same initial and boundary conditions can lead to radically different channel configurations (Stecca & Hicks, 2022; Warburton & Davies, 1994). A single experiment or numerical simulation produces one realization of a possible history. If one repeats the experiment or simulation, one can create a data set that can be ensemble-averaged to show main features. However, even with this hard work, validating the numerical model or matching the laboratory test with field data will raise doubts about how well they represent a real river. Identifying the most likely configuration of the streambed or estimating the probability of observing the streambed in a given configuration may be a desirable feature, but difficult to achieve with current tools.

The ultimate question is whether there is an approach that can provide all or some of the answers to the questions above. Two factors guided our choice:

- First, we assume that a stochastic description is appropriate for the reach-scale evolution of braided-river planforms. This working assumption is supported by experimental evidence that planform geometries do not vary continuously over an unbounded range, but tend to fluctuate around characteristic configurations (Bertoldi, Ashmore, & Tubino, 2009; Bertoldi, Zanoni, & Tubino, 2009; Peirce et al., 2018, 2019). This evidence motivated a description in terms of discrete morphological states. Earlier work has also shown that braided rivers may repeatedly occupy a finite number of recurrent planform configurations (Hoffmann et al., 2019; Pirot et al., 2014, 2015), which means that part of the job involves identifying these recurrent states.
- Second, earlier experimental work has shown the significance of planform morphology in the dynamics of braided rivers and associated sediment transport (P. Ashmore et al., 2011; Ragno et al., 2021; Hundey & Ashmore, 2009), which implies that we shall work at the reach scale, ignoring the detail of the local cross-sections. Apart from identifying the channel network, we have to specify how the different states are inter-related: at which frequency does the system change state? How long it will rest in a given state i ? What is the probability that it transitions from state i to state k ?

Existing descriptions of the intermittency of bedload transport and large-scale morphological adjustments provide important context (Ancey & Recking, 2023; P. E. Ashmore, 1991b; Han et al., 2023; Paola, 2001; Schuurman et al., 2018), but they do not explicitly study the dynamics of morphological configuration changes.

Here, we address this temporal organization by analyzing high-resolution data collected over 1 month in a laboratory flume. We will demonstrate that the instantaneous plan morphologies of a braided river do not form purely random patterns, but belong to a finite set of recurrent configurations, which we will call *morphological states*. Using plan imagery as a direct representation of channel morphology at the reach scale, we will define objective measures of similarity between images and use them to identify morphological states. We will then analyze the temporal evolution of these states, focusing particularly on persistence, recurrence, and transition dynamics, under the assumption of statistical stationarity (steady-state conditions at the channel inlet). Finally, we will show that each morphological state is associated with a distinct sediment transport regime.

2. Experimental Basis and Data

2.1. Working Hypotheses and Design of Experiment

The three-dimensional geometry of a braided river, including its bed-elevation variations, influences local flow properties and sediment transport; these properties change as channels and bars reorganize. Reach-scale statistical morphometric descriptors can summarize this complex geometry, as demonstrated by analyses of bed-elevation distributions (Redolfi et al., 2016).

Table 1
Facility, Forcing, and Acquisition Settings

Working length	3.3 m
Working width	1.0 m
Bed slope	3%
Bed material	Well-sorted (unimodal) sand, $d_{10} = 0.9$ mm, $d_{50} = 1.0$ mm, $d_{90} = 1.1$ mm
Water discharge	$Q_w = 0.15$ L s ⁻¹
Sediment feed rate	$Q_s^{\text{in}} = 1.5$ g s ⁻¹
Imaging system	Overhead camera, 1 image/min
Bedload transport monitoring	50 kg load cell (0.03% FS)
Data acquisition (DAQ)	10,000 Hz averaged over 60 s
Run time	~1,200 hr

In this study, however, state identification is purely planimetric: we use images of the wetted network as a reach-scale state variable, without using bed-elevation or local water-depth data. Our first working hypothesis is that the channel planform provides an integrated signature of the current reach-scale organization of the bed. More specifically, instantaneous plan morphology records the arrangement of channels, bars, bifurcations, confluences, and abandoned threads, and the resulting image sequence contains sufficient information to identify recurrent reach-scale configurations (such as narrow single-channel states, partially braided intermediate states, and wide multi-channel states) and to track their temporal organization. The resulting states are related statistically to measured outlet sediment transport, without reconstructing local flow fields. This use of planform observations to characterize morphodynamic change is consistent with Tal and Paola (2010), who used them to examine channel mobility and reorganization in experiments with and without vegetation.

In real-world braided rivers, external controls such as flow rate, sediment input, channel slope, sediment characteristics, confinement, and vegetation set the range of channel forms and sediment-transport behavior that can occur. In our experiment, water discharge and sediment feed were constant and imposed at the channel inlet. Our second working hypothesis is that the analyzed interval was statistically stationary at the channel scale: after the initial adjustment period, the time-averaged sediment output at the flume outlet was close to the imposed sediment feed rate, so the observed planform changes were not interpreted as part of a persistent net aggradation or degradation trend.

The experimental design was guided by two essential requirements. First, the recording had to be long enough to capture rare morphodynamic events after the initial adjustment period. Second, the observations had to be collected at a sufficiently high temporal resolution to resolve the rapid transitions (reorganizations of the channel network) from one state to another. These constraints motivated a monitoring strategy combining (a) a long-duration channel experiment under steady forcing and (b) minute-resolution imaging coupled with continuous measurement of the sediment transport rate at the flume outlet.

2.2. Facility and Forcing Conditions

Experiments were carried out in a straight, fixed-bank laboratory flume with a mobile sand bed. The working section measured 3.3 m in length and 1.0 m in width, with an initial bed slope of 3%. The bed material consisted of well-sorted (unimodal) sand with median grain size $d_{50} = 1$ mm and a narrow grain-size range, with $d_{10} = 0.9$ mm and $d_{90} = 1.1$ mm. A constant water discharge $Q_w = 0.15$ L s⁻¹ and a constant sediment feed rate $Q_s^{\text{in}} = 1.5$ g s⁻¹ were imposed at the flume inlet. Sediment was delivered through a vibrator-assisted funnel connected to a water-coupled container, ensuring a continuous and uniform input. Water was dyed to enhance the visibility of the wetted corridor in overhead images. A summary of facility characteristics and forcing parameters is provided in Table 1. We selected the inflow rate, sediment feed, bed slope, and sediment grain size to maintain an active braided pattern with mobile bedload transport under constant upstream boundary conditions. The steep slope and sediment input promoted bar formation, bifurcation, and thread switching within the 1.0-m-wide working section, while the unimodal grain size distribution minimized grain sorting, allowing the analysis to focus on channel morphology reorganization rather than material texture change. Image acquisition began after an initial

adjustment period, when the time-averaged sediment transport rate at the flume outlet was sufficiently close to the imposed feed rate, so that the analyzed interval did not correspond to the initial channel formation phase.

Although the flume dimensions and forcing parameters were necessarily reduced compared to natural rivers, the experimental setup was designed to reproduce the dominant process interactions governing braided-river morphodynamics. As shown by Paola et al. (2009), small-scale stratigraphic and geomorphic experiments can capture emergent large-scale behavior when they preserve the essential feedbacks among flow, sediment transport, and morphology. In this sense, the present experiment was not intended to reproduce a specific real-world river, but rather to isolate and analyze the generic mechanisms of braided-river organization and its evolution under controlled and reproducible conditions.

2.3. Instrumentation and Acquisition

A fixed camera (Nikon D700 with a wide-angle lens) was installed 2.5 m above the flume bottom, capturing the entire submerged channels in a single 4256×2832 -pixel image at a frame rate of one image per minute. This frame rate ensured that even short-duration morphological transitions were captured.

The bedload sediment transport rate was continuously measured at the channel outlet using a 50-kg strain gauge force sensor with an accuracy of 0.03% of full scale (approximately 15 g). The sensor signal was acquired at 10,000 Hz and averaged over 60-s intervals, providing a synchronized record with the image series. The inflow rate was regulated by an inductive flow meter and a control valve, driven by a data acquisition system (DAQ), ensuring a constant flow rate throughout the experiments.

2.4. Image Processing Pipeline

Raw overhead images were converted to binary water masks using a uniform processing workflow applied consistently across all runs. Each raw frame was first cropped to the flume interior. A Hue Saturation Value (HSV) color filter, tuned to the dyed water, was then applied to isolate the wetted area as a binary mask. The mask was subsequently resized with nearest-neighbor interpolation while preserving aspect ratio, with the longest dimension set to 200 pixels, and a one-pixel-wide edge map was extracted from the processed wetted-area mask to represent water boundaries. This representation retained the essential planform geometry while reducing sensitivity to small-scale width fluctuations, and provided a compact basis for the image-similarity analysis described in the following section. The same segmentation parameters and image-processing operations were applied to the entire image sequence. After processing, each frame was represented by two binary objects: the set of wetted pixels, used to quantify areal overlap, and the set of edge pixels, used to quantify the displacement of channel boundaries and thread positions.

3. From Images to Morphological States

The central challenge of this study was to convert a continuous, high-frequency record of braided-river evolution into a discrete and interpretable set of recurrent morphological states. The experimental data set contained more than 70,000 min-resolution images, which made any form of manual classification infeasible.

Our strategy was to treat each binary water mask as a geometric object and to quantify how similar or different two planform configurations were. This approach implicitly focused on two-dimensional planform information derived from wetted-area imagery, without explicitly accounting for channel depth or bed elevation. This choice reflected our working hypothesis that reach-scale planform geometry captures dominant modes of braided-river organization observable in long-duration experiments, even though it does not resolve the full three-dimensional structure of the channel (see Section 2.1).

These pairwise similarities defined the structure of the data set in a high-dimensional composite representation. Because direct analysis or manual clustering in such a space was not practical, the information was embedded into a low-dimensional manifold that preserved neighborhood relations and temporal coherence. Within this manifold, recurrent configurations emerged as dense regions that could be identified using density-based clustering. These clusters of similar configurations provided an objective basis for defining morphological states and constructing the state-based descriptions developed subsequently.

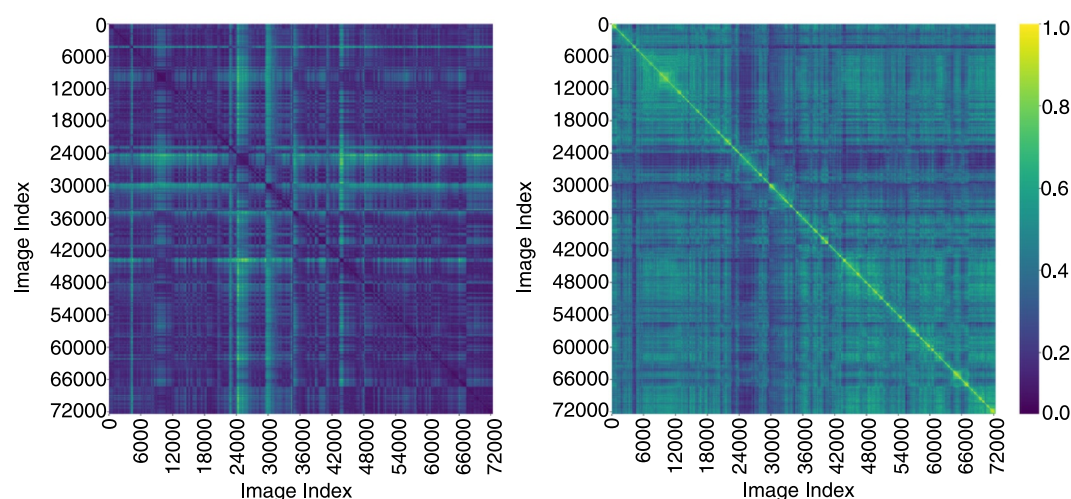


Figure 1. Pairwise morphological comparison matrices for the main experimental run. Left: normalized Modified Hausdorff Distance (MHD), for which identical frames have a diagonal value of zero. Right: normalized Dice similarity coefficient, for which identical frames have a diagonal value of one. Both matrices are symmetric by construction and compare each image pair independently of temporal order. The all-pairs comparison is used to identify recurrence: off-diagonal blocks indicate morphologies that reappear at separated times, whereas comparisons between consecutive images would only measure short-term change between adjacent frames.

We proceeded in four steps. First, we introduced a composite notion of morphological dissimilarity that captured both boundary displacement and changes in wetted area. Second, we mapped the resulting structure onto a compact, low-dimensional space using a nonlinear embedding. Third, we identified stable and recurrent clusters using density-based clustering methods. Finally, we evaluated the physical meaning of the resulting morphological states through morphometric descriptors and by examining their associated sediment-transport behavior.

3.1. Morphological Similarity

To identify recurrent planform configurations, we needed to quantify the similarity between binary water masks. Braided-river reorganization can involve lateral displacement of channel margins and internal thread boundaries, changes in wetted extent, or activation and abandonment of secondary threads. We therefore used two complementary image-based measures: the Modified Hausdorff Distance (MHD) to describe boundary displacement, and the Dice similarity coefficient to describe wetted-area overlap. The two measures were retained together because they capture different aspects of planform change, especially for intermediate cases in which two morphologies are neither identical nor completely reorganized.

The first measure was the Modified Hausdorff Distance (MHD), computed from the edge sets using the standard scikit-image implementation of the Dubuisson and Jain formulation (Dubuisson & Jain, 1994; Van der Walt et al., 2014). Conceptually, MHD compares the wetted boundaries of two masks by measuring how far the edge pixels of one planform are from the nearest edge pixels of the other. Small MHD values indicate nearly coincident bank lines and thread positions, whereas large values reflect substantial lateral displacements, avulsions, or bar-driven reorganizations. MHD was therefore suited to detecting geometric rearrangements even when the overall wetted area remained similar. The formal definitions of the distance measures are given in Appendix A.

The second measure was based on the Dice similarity coefficient, commonly used in image processing to quantify the overlap between two binary shapes (Dice, 1945). Dice similarity compares the wetted areas of two masks: high values indicate that two planforms occupy nearly the same wetted corridor, whereas low values indicate changes in wetted extent, activation or abandonment of secondary channels, or broader changes in connectivity. While MHD detects geometric displacement of the borders, the Dice coefficient captures areal overlap. Because the Dice matrix shown in Figure 1 reports similarity rather than distance, its diagonal elements are equal to one, whereas the diagonal elements of the MHD distance matrix are equal to zero. Both matrices are symmetric by construction.

Before combining the two measures, we normalized the MHD distance matrix and the Dice similarity matrix to their maximum values across the entire data set. This normalization placed both the MHD distance and Dice similarity on a common scale between 0 and 1, preventing either measure from influencing subsequent dimensionality reduction solely due to its numerical units.

The two measures were correlated but not redundant. For a sampled all-pairs comparison, the Spearman correlation between normalized MHD distance and Dice dissimilarity $1 - S_D$ was approximately $\rho = 0.82$. This positive correlation reflected the fact that large reorganizations often affected both contour position and wetted area, whereas the remaining scatter identified morphologies that differed primarily in one aspect. For example, high Dice similarity combined with high MHD indicated broadly similar wetted extent but displaced thread boundaries; conversely, lower Dice similarity with modest MHD indicated changes in wetted area or connectivity without large displacement of the main boundaries. Operationally, each frame was therefore represented by its normalized MHD distances and normalized Dice similarities to all other frames. This all-pairs descriptor was then used in the dimensionality-reduction and clustering steps.

The comparison matrices in Figure 1 exhibit a characteristic block structure: extended intervals of low MHD distance and high Dice similarity along the diagonal correspond to periods of morphological persistence, while isolated patches indicate abrupt transitions. Each matrix compares all image pairs in the record, not only consecutive frames. Thus, each column can be read as the similarity or dissimilarity of one reference morphology to every other morphology in the experiment. This full pairwise comparison was required because the objective was to identify recurrent configurations over the entire experiment. A consecutive-frame distance would describe the instantaneous rate of planform change, but it would not reveal whether a morphology observed at one time was similar to another morphology reached much later. A gradual change in color between neighboring columns indicates that the reference morphology is changing progressively relative to the rest of the data set, whereas an abrupt column-to-column color shift indicates a reorganization that changes the relationship of that image to many other planform configurations. These patterns confirmed that planform evolution alternated between long phases of quasi-stability and short phases of reconfiguration, providing the empirical foundation for the dimensionality-reduction and clustering procedures described in the next subsection.

3.2. Dimensional Reduction and Clustering of Morphological States

The pairwise comparison measures introduced in Section 3.1 define, for each image, its relationship to all other configurations in the data set. Since the record contains more than 70,000 frames, each associated with a high-dimensional composite descriptor representation, direct clustering in this space is neither computationally practical nor conceptually meaningful. Distances become less informative as dimensionality increases, and neighborhood-based methods can fail due to the so-called curse of dimensionality (Bellman, 1966). Our first task was therefore to compress the data while preserving the geometric structure that encoded morphological similarity.

3.2.1. Linear Reduction: PCA

Principal Component Analysis (PCA) identifies orthogonal directions of maximum variance in the high-dimensional similarity representation of all pairs (Maćkiewicz & Ratajczak, 1993). PCA was applied after combining the normalized MHD and Dice information to each image. The retained dimension was selected from the cumulative explained variance curve by keeping the smallest number of components that preserved at least 99% of the variance. For our data set, this criterion allowed us to retain 67 principal components, while reducing dimensionality by more than three orders of magnitude. The resulting representation was numerically stable and served as the basis for the nonlinear methods used subsequently.

3.2.2. Nonlinear Manifold Learning

Although PCA greatly reduced the dimensionality, the resulting space remained too large for visual interpretation or robust clustering. Moreover, PCA only captured linear modes of variability and could not represent the curved manifolds that naturally arise in complex morphodynamic systems. We therefore used a nonlinear manifold-learning technique that preserved neighborhood relations while projecting the data into a low-dimensional space of morphological states, called the *morpho-space*. Uniform Manifold Approximation and Projection (UMAP) was chosen because it preserved local neighborhood relations while maintaining a coherent large-scale

Table 2
Selected Parameters and Validation Metrics for the Selected UMAP HDBSCAN Configuration

Model parameters	
UMAP n_neighbors	300
UMAP min_dist	0.00
UMAP n_components	3
HDBSCAN min_cluster_size	500
HDBSCAN min_samples	250
Validation metrics	
Number of clusters	16
Noise fraction	9.93%
Silhouette score	0.55
Davies Bouldin index	0.52
Calinski Harabasz score	20,479

Note. The validation metrics report cluster compactness, separation, and the fraction of frames initially assigned to transitional noise by HDBSCAN.

organization of the manifold, making it appropriate for identifying recurrent planform configurations from high-dimensional image descriptors (McInnes et al., 2020). UMAP and clustering parameters were evaluated before defining the final state catalog, using both internal clustering metrics and physical checks on the resulting planform groups. This validation strategy is summarized here and documented in Appendix A1.

The nonlinear embedding was then applied to the 67-dimensional PCA representation, not directly to the original images. The selected UMAP embedding produced a three-dimensional morpho-space that preserved local neighborhoods while retaining a coherent large-scale arrangement of morphologically similar configurations. Table 2 lists the selected UMAP parameters, and we refer the reader to McInnes et al. (2020) for further information on their meaning.

3.2.3. Clustering in the Embedded Space

The three-dimensional UMAP embedding, as shown in Figure 2, reveals (a) dense regions corresponding to frequently visited morphologies, and (b) thin filaments associated with transitional configurations. Here, *frequently visited* means that many frames occupy the same neighborhood of the embedded morpho-space; recurrence and persistence are then quantified from the time-ordered state sequence in Section 4. To identify these groups as objectively as possible, we applied density-based clustering methods to the three-dimensional UMAP coordinates. We tested two closely related density-based clustering algorithms: DBSCAN and HDBSCAN (Ester et al., 1996; McInnes et al., 2017). DBSCAN provides a first partition but tends to merge states when point densities vary substantially across the embedding. HDBSCAN, by contrast, evaluates cluster stability across density levels and automatically labels sparse regions as noise.

The comprehensive parametric analysis revealed that the UMAP and HDBSCAN combination provided the most robust and interpretable state detection. We varied the main UMAP and HDBSCAN parameters and selected the optimal configuration using an evaluation that combined quantitative and physical consistency criteria. The quantitative assessment was based on the noise fraction and three internal validation metrics; the physical-consistency assessment involved visually inspecting the embedding, temporal ordering of points, and the cluster *medoids* (the equivalent of centroids for clusters) to verify that candidate clusters represented coherent planform configurations and not projection artifacts, compact fragments of the same morphology, or overly merged aggregates of distinct morphologies.

This visual check was therefore not used as an arbitrary manual classification step, but as a diagnostic safeguard against the known limitations of internal clustering metrics when applied to nonlinear embeddings. The algorithm rejected candidate solutions with favorable numerical scores but poor morphological coherence. The selected configuration balanced three criteria: a small number of recurrent states with clear physical interpretation, a low

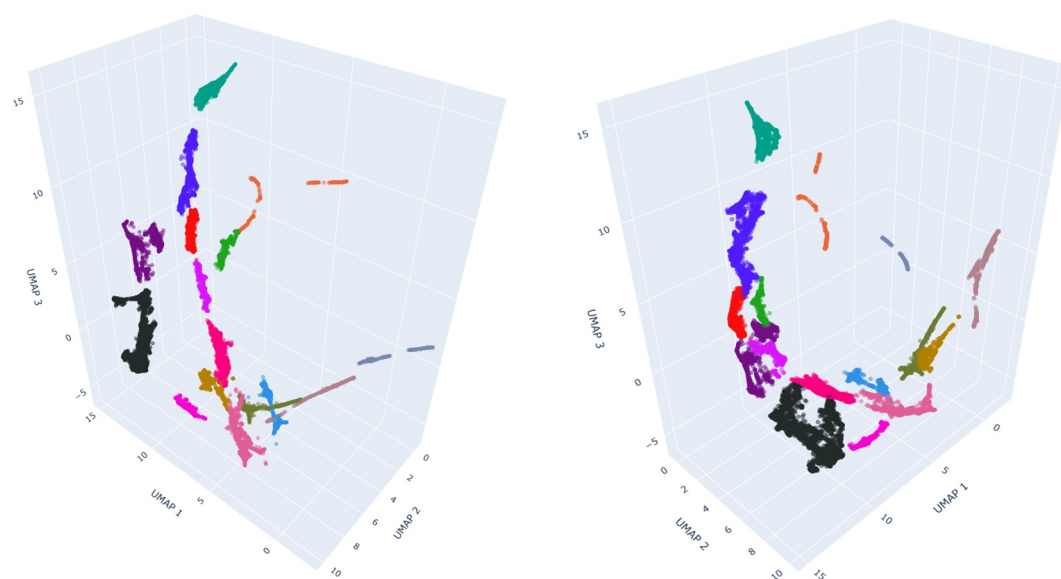


Figure 2. Three-dimensional UMAP embedding of the PCA-reduced composite descriptor representation, colored by the 16 clusters identified by HDBSCAN. Dense groups correspond to recurrent morphological states, whereas sparse filaments represent transitional configurations. Frames initially labeled as HDBSCAN noise were not used to define additional states; they were assigned to the closest recurrent cluster for the subsequent time-series analysis.

fraction of points attributed to noise, and favorable internal validation metrics. Using the parameters listed in Table 2, this approach identified 16 clusters with a noise fraction below 10%. The scattered HDBSCAN noise frames were interpreted as transient configurations, not as an additional recurrent state. For subsequent analyses of continuous time series, visit duration, transition probability, and sediment transport, each noise frame was assigned to the nearest recurrent group in the UMAP morpho-space. This nearest-cluster assignment preserved a complete one-minute state sequence and avoided introducing a poorly sampled seventeenth category, while retaining the interpretation that such frames lay between recurrent states. Internal validation indices—including the Silhouette, Davies–Bouldin, and Calinski–Harabasz scores (Calinski & Harabasz, 1974; Davies & Bouldin, 1979; Rousseeuw, 1987) reported in Table 2—indicated that the resulting clusters were compact and well separated. Moreover, the partition was consistent with the expected morphological gradient from single-thread to multi-thread geometries.

3.2.4. Resulting Morpho-Space

The resulting three-dimensional morpho-space is shown in Figure 2. Frames belonging to the same cluster form dense, compact clouds, whereas distinct morphologies appear as well-separated regions. Transitional configurations that are visited rarely and briefly occupy thin filaments and are initially labeled as noise by HDBSCAN before being assigned to the nearest recurrent state for the temporal analyses.

The dimensionality-reduction and clustering steps converted the high-dimensional image record into a compact and interpretable set of 16 recurrent morphological states altogether. A morphological state is thus defined here as a dense, temporally recurrent region of the embedded morpho-space, rather than as a prescribed value of an individual planform metric. The sparse points identified by HDBSCAN were interpreted as transition configurations and were not used to define additional recurrent states. They were, however, assigned to the nearest recurrent state when constructing the complete state sequence used for episode and transition statistics. These states defined a discrete configuration space that provided the basis for the state-based temporal analysis developed in Section 4.

3.3. Cluster Characterization

The clustering procedure described above identified 16 recurrent morphological states within the experimental record. These states were not isolated snapshots in the morpho-space, but configurations that were repeatedly

visited over time under identical external forcing. To verify that they were physically meaningful and not statistical artifacts, we characterized each cluster through three complementary properties: (a) its representative geometry, (b) its morphometric properties, and (c) its associated sediment-transport behavior. Taken together, these diagnostics showed that the clusters formed a coherent and continuous spectrum of channel morphologies with distinctive physical and dynamical signatures.

3.3.1. Representative Geometries: Medoids and Morphological Gradient

For each cluster, we selected the medoid frame, defined as the image minimizing the total composite dissimilarity with all other images within the same cluster. The medoid therefore provided a representative realization of a morphology that was recurrent throughout the experiment, rather than a simple average or idealized geometry. Figure 3 shows the medoids of the 16 clusters. The colored boxes are used as a visual reference for the grouping introduced later in the analysis of temporal organization. The cluster numbers are merely identifiers: they do not represent a temporal sequence, a ranking by visitation frequency, or a predefined progression from one morphology to another.

A consistent morphological gradient emerged within the groups, ranging from narrow, single-thread states characterized by limited channel occupancy and minimal bar development, to intermediate configurations with increased wetted width and incipient braiding. At the broad end of this gradient were states comprising multiple active threads, large bars, and complex channel networks. Medoids highlighted the main geometric features of each state, despite some variability within the clusters. This qualitative classification is quantitatively corroborated by the cluster morphometric statistics presented in Table 3. The observed morphological gradient is consistent with classical descriptions of the development of braided rivers, where bars form and migrate, channels divide and join, and the active width as well as the intensity of braiding increase with the complexity of the channel network (P. Ashmore, 2009; P. E. Ashmore, 1991a).

3.3.2. Morphometric Structure Across Clusters

To quantify the morphological differences visible in Figure 3, we computed a set of planform metrics for each cluster, including wetted width, wetted area, sinuosity, and two measures of braiding: (a) the routinely used *braiding index* (BI) (Egozi & Ashmore, 2008) and (b) the *entropy-based braiding index* (eBI), which reflects the heterogeneity of thread sizes (Tejedor et al., 2022).

The metrics summarized in Table 3 confirm that the identified states covered the dominant modes of morphological variability in the system. There was an approximate doubling of width and wetted area between the simplest and most elaborate configurations, with a marked increase in sinuosity linked to bar formation in the middle of the channel. Furthermore, both the braiding index and the entropy-based braiding index increased with braiding intensity.

Although the cluster indices did not define a strict order and non-monotonic local variations were present, the overall trend in the metric space revealed a morphological gradient ranging from single-thread to highly braided morphologies. The BI/eBI ratio increased from approximately 1.1 in narrow states to approximately 1.3 in highly braided states, highlighting the progressive emergence of threads of various sizes (Tejedor et al., 2022). These morphometric differences were also used to compare dynamic behaviors, as explained in the following sections.

3.3.3. State-Conditioned Sediment Transport

Bedload transport provided an independent and physically relevant diagnosis of the identified morphological states. Figure 4 shows the distribution of the sediment transport rate Q_s , conditioned by each cluster. Clear and systematic differences emerged across the entire morphological spectrum of Q_s . In narrow, single-thread systems, flow and thereby shear stresses were concentrated, resulting in higher transport rates and heavy-tailed distributions, indicating significant intermittency and the significant role of rare, high-magnitude events. By contrast, wide braided configurations promoted flow spreading, energy dissipation, and sediment storage, leading to lower transport rates and reduced variability.

Clusters 00, 01, 02, and 07 exhibited both high median Q_s and pronounced variability, consistent with efficient sediment conveyance and episodic sediment output. Conversely, Clusters 04, 05, 09, and 13 showed low medians and tightly clustered distributions, consistent with lower sediment output and more stable transport behavior.

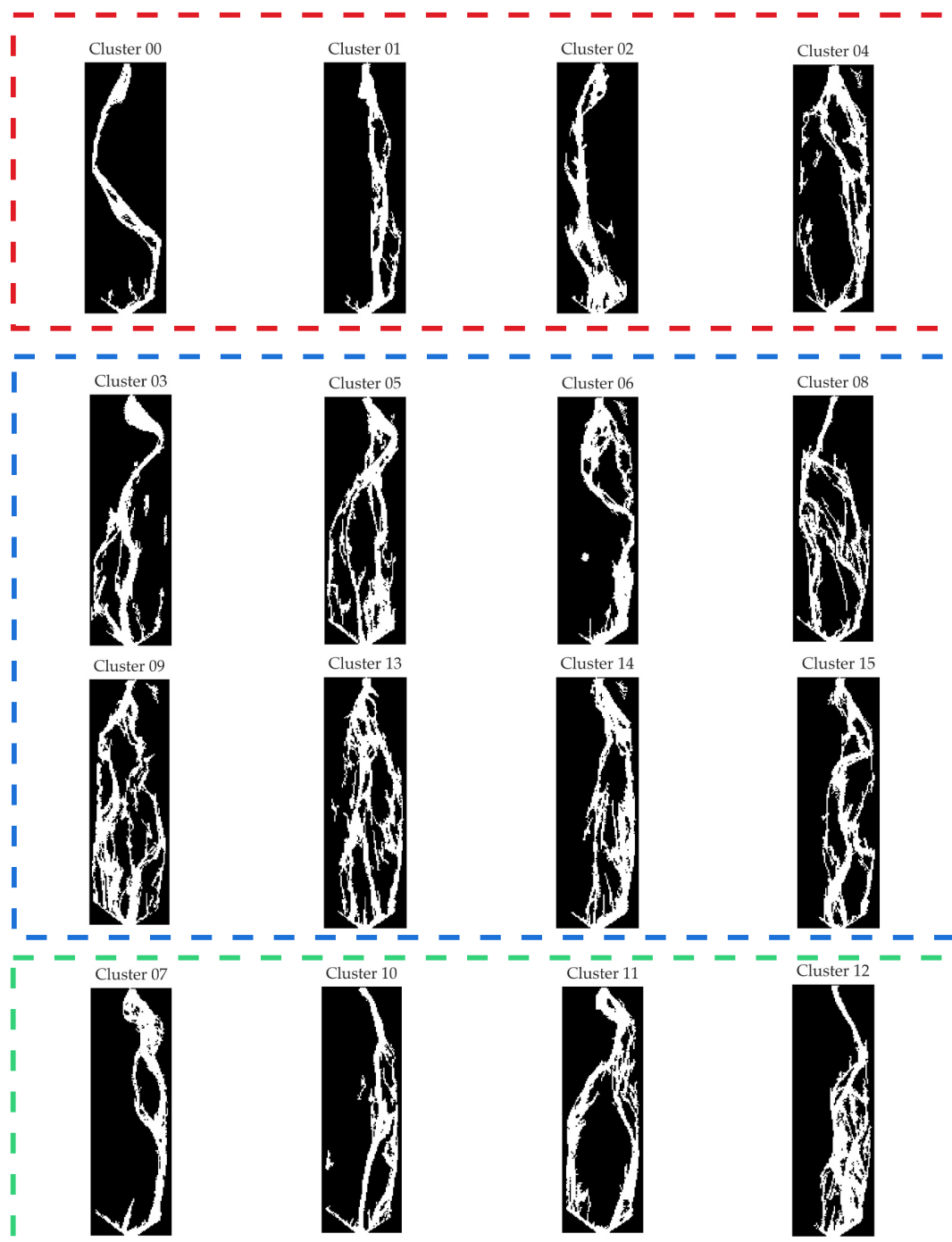


Figure 3. Representative medoids for the morphological states identified through the PCA–UMAP–HDBSCAN pipeline. The states span a morphological gradient from narrow, predominantly single-thread configurations, through transitional morphologies with partial braiding, to fully braided, multi-thread patterns with exposed bars and extensive lateral occupation of the corridor. Dashed colored boxes indicate the temporal-organization grouping. Cluster numbers are labels and do not imply temporal ordering or rank.

Importantly, these differences were not transient but persisted over long periods of time, reflecting the recurrent and long-lived nature of the underlying morphological states.

To further quantify the relationship between planform structure and sediment output, we computed Spearman rank correlations (Hauke & Kossowski, 2011) between morphometric metrics and Q_s . The results, summarized in

Table 3
Cluster-Wise Morphometric Statistics

Cluster	Width (cm)	Area (m ²)	Sinuosity	BI	eBI
00	30.9	0.93	11.79	1.77	1.53
01	19.7	0.59	11.90	1.76	1.54
02	31.3	0.94	26.98	2.85	2.36
03	41.9	1.26	30.51	3.04	2.42
04	67.2	2.02	58.51	4.32	3.38
05	66.4	1.99	73.31	5.38	4.26
06	52.4	1.57	34.02	3.28	2.66
07	34.1	1.02	20.24	2.32	1.98
08	70.2	2.11	49.25	3.71	3.05
09	68.8	2.07	76.83	5.40	4.25
10	44.8	1.35	28.73	3.07	2.51
11	64.0	1.92	47.90	3.92	3.18
12	48.8	1.46	26.00	2.89	2.37
13	68.8	2.07	52.42	4.37	3.47
14	58.8	1.76	35.48	3.62	2.94
15	50.3	1.51	39.05	3.73	3.03

Figure 5, revealed a strong and systematic pattern. Wetted width, wetted area, sinuosity, BI, and eBI were all highly correlated with one another, indicating that morphological variability was largely organized along a dominant structural axis. All these metrics were negatively correlated with the mean and variability of sediment transport rates, confirming that increased corridor occupation and braiding complexity suppressed sediment movement under constant upstream forcing.

Taken together, these results demonstrate that the 16 clusters represented physically significant morphological states. Each state occupied a distinct position along a low-dimensional morphodynamic gradient and exerted a characteristic control over sediment transport. This close coupling between geometry and process justified treating the clusters as discrete dynamic states, the persistence and transitions of which are analyzed in the following sections.

4. Temporal Organization and Transitions Among Morphological States

The morphological states characterized in Section 3.3 provided a compact representation of river planform configuration and associated sediment transport characteristics at each time step. Because the experiment was

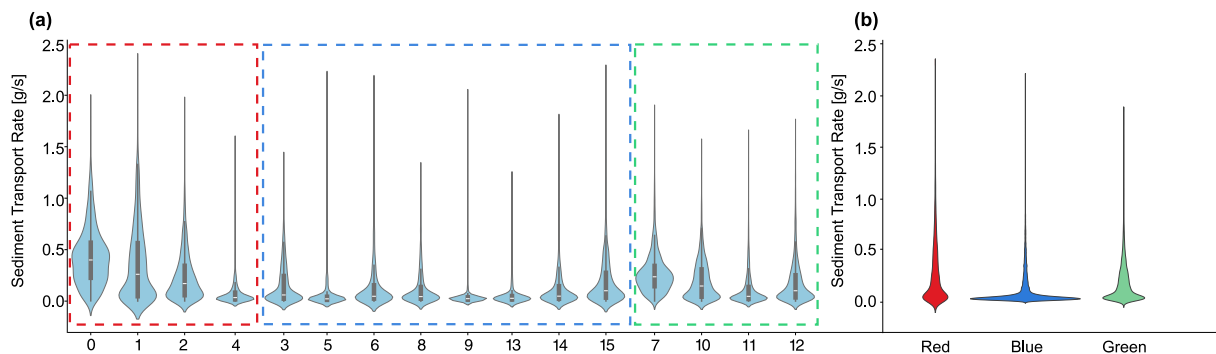


Figure 4. State-conditioned sediment-transport distributions. (a) Transport distributions for the 16 states, ordered and boxed according to the temporal-organization grouping. (b) Transport distributions pooled according to the same grouping. Single-thread states exhibit higher and more variable Q_s , whereas wide, fully braided states exhibit lower and more stable transport under identical forcing.

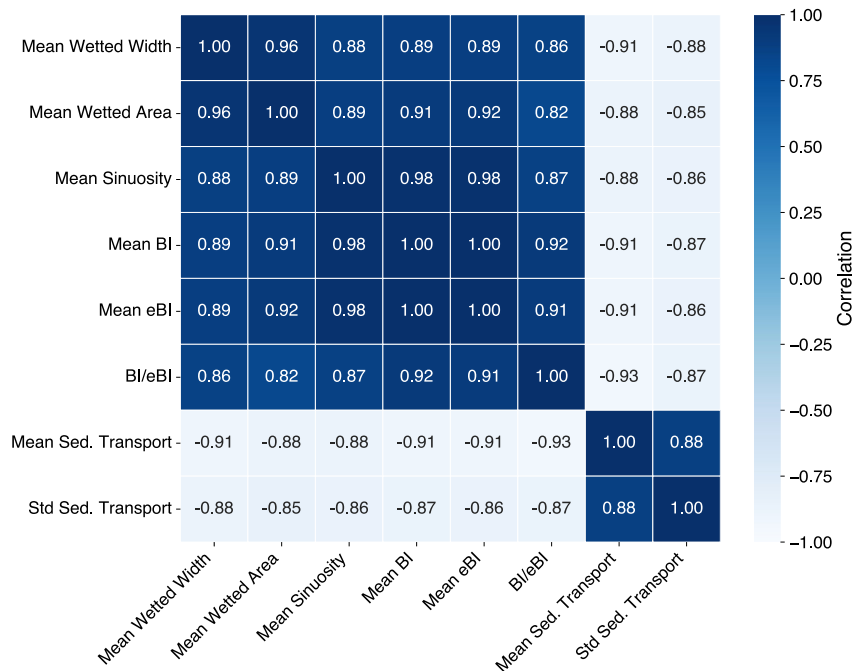


Figure 5. Correlation matrix between morphometric metrics and sediment-transport rate Q_s . Wider and more braided states correlate with reduced transport, while narrow states correlate with higher sediment output.

conducted under steady external forcing and the analysis assumed stationarity within each identified state, we interpreted the observed state sequence as reflecting the intrinsic organization of braided-channel reconfiguration at the reach scale. Any short-term readjustments arising from local mismatches between imposed boundary conditions at the flume inlet and system configuration at a given time were not explicitly resolved. They were therefore treated as part of the internal dynamics of state transitions. In this section, we describe the temporal organization of the observed states, focusing on the time-ordered sequence of states, state occupancy and persistence, as well as transitions among states.

4.1. State Occupancy and Persistence

Figure 6 shows the complete chronological sequence of observed morphological states. The evolution reveals a punctuated temporal structure, with long intervals during which the system remained in a single configuration,

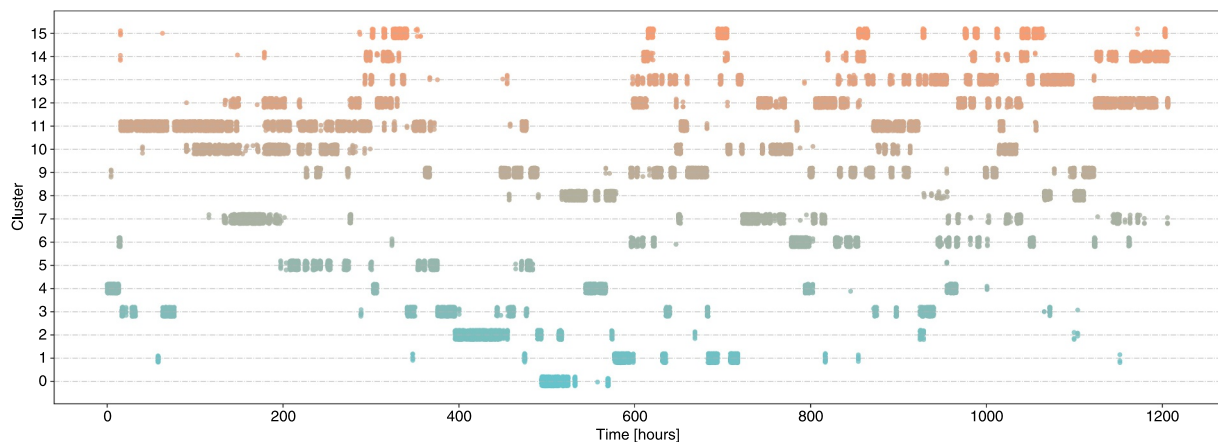


Figure 6. Time-ordered sequence of morphological states. Persistent states appear as long horizontal segments, while rapid reorganizations correspond to short excursions between configurations. Only one state is assigned at each time step; visually dense regions reflect the compression of many minute-resolution transitions into one panel.

Table 4
Empirical Persistence Metrics for the Morphological States Observed

State	Total time [min]	Number of visits	Mean episode duration [min]
00	1660	7	237.14
01	2724	16	170.25
02	3782	24	157.58
03	4278	58	73.76
04	2974	16	185.88
05	2322	58	40.03
06	2646	67	39.49
07	4760	176	27.05
08	2826	38	74.37
09	6728	63	106.79
10	5462	269	20.30
11	11,884	224	53.05
12	8072	241	33.49
13	5418	86	63.00
14	3324	91	36.53
15	3506	54	64.93

Note. For each state, total cumulative occupancy time, number of distinct visits, and mean episode duration are computed directly from the observed state sequence.

interrupted by shorter periods of rapid transition from one state to another. Persistent configurations appear in this figure as long horizontal segments in the sequence, whereas reorganization phases correspond to brief excursions through multiple states. Each time step is associated with a single morphological state; the apparent overlap of states in the dense parts of the figure results from the plotting of minute-resolution labels over the entire duration of the experiment.

The figure highlights pronounced differences in the temporal behavior of states. Most states were revisited multiple times during the experiment, but the duration of persistence at each visit varied considerably. Some states appeared only sporadically but persisted for long uninterrupted periods once established, while others reappeared frequently as short-duration episodes. For example, States 00, 01, 02, and 04 occurred in relatively few episodes but have long mean residence times, whereas States 07, 10, 11, and 12 were revisited many times in shorter episodes. Intermediate cases included States 03, 08, 09, 13, and 15. This visual organization justifies a quantitative assessment of state occupancy and persistence.

State occupancy was quantified using empirical persistence metrics computed directly from the observed state sequence. For each morphological state, we calculated: (a) the total cumulative time spent in that state during the experiment, (b) the number of distinct visits or episodes, and (c) the mean duration of an individual episode. These metrics allowed us to characterize temporal persistence without requiring assumptions about the underlying transition dynamics.

Table 4 summarizes these quantities for the 16 states. The results show substantial variability between states both in terms of total occupancy and episode structure. Some states were visited only a small number of times but had long mean episode durations, indicating a prolonged residence once entered. Other states accumulated comparable or higher total occupancy due to a large number of short visits. A third group exhibited intermediate behavior, with a moderate number of visit and episode durations.

The combined analysis of state sequences and persistence metrics revealed a heterogeneous temporal organization, where long-lasting configurations alternated with frequently visited but short-lived states. This variability allowed us to examine preferred transitions and connectivity between morphological states in the following section.

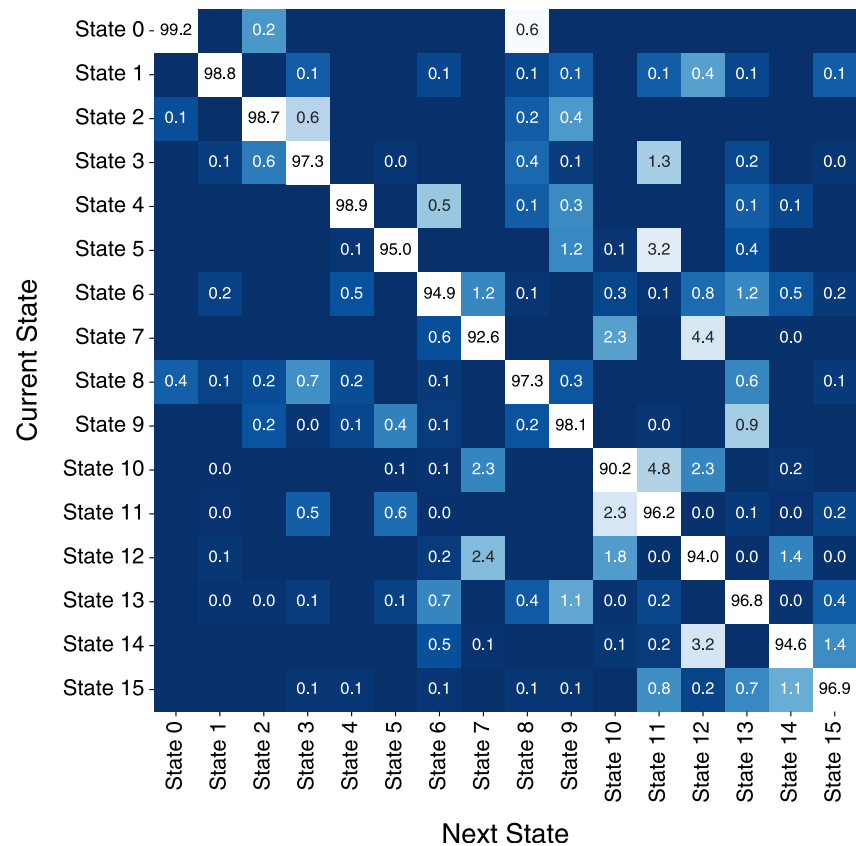


Figure 7. Empirical transition probability matrix for the 16 morphological states. Entry (i,j) gives the probability of moving from state i to state j over one time interval. Strong diagonal values indicate persistence, while the off-diagonal structure highlights preferred transitions. Axis labels are nominal cluster identifiers and do not encode morphological distance or temporal order. Values shown are in percentage.

4.2. Transition Structure and State Organization

Apart from differences in persistence, the temporal organization of planform morphological evolution was shaped by how the system transitioned between different states. Figure 7 summarizes the empirical transition probabilities deduced from the observed sequence of states. This matrix was constructed by counting the number of transitions between consecutive time steps and normalizing each row by the total number of outgoing transitions from the corresponding state, so that each element represented the conditional probability of transitioning to a given subsequent state.

The highest probabilities of transition were found on the diagonal of the resulting matrix, indicating that most consecutive time steps occurred in the same state. Off-diagonal probabilities were much lower, but not uniformly distributed across the state space. They were concentrated in a limited set of preferred paths, suggesting that state changes occurred through specific connections rather than random jumps between all configurations. Since the cluster labels were nominal identifiers, the interpretation of the transition paths depended neither on proximity to the matrix diagonal nor on the numerical adjacency of the state labels.

The strongest off-diagonal exchanges involved a small subset of recurrent states. For example, State 10 transitioned preferentially to States 11, 07, and 12, while State 11 transitioned primarily to State 10 and secondarily to States 05 and 03. State 07 transitioned primarily to States 12 and 10, and State 12 returned most often to States 07 and 10. Other repeated links included State 05 to State 11, the pair of States 12 and 14, for which the transition from State 14 to State 12 was stronger than the reverse direction, and the nearly balanced exchanges between States 03 and 02, and States 06 and 04. These probabilities were low in the row-normalized matrix due to strong persistence within states, but they allowed for the identification of recurrent paths between specific morphological configurations. Conversely, many state pairs exhibited negligible or zero transition probabilities. These examples

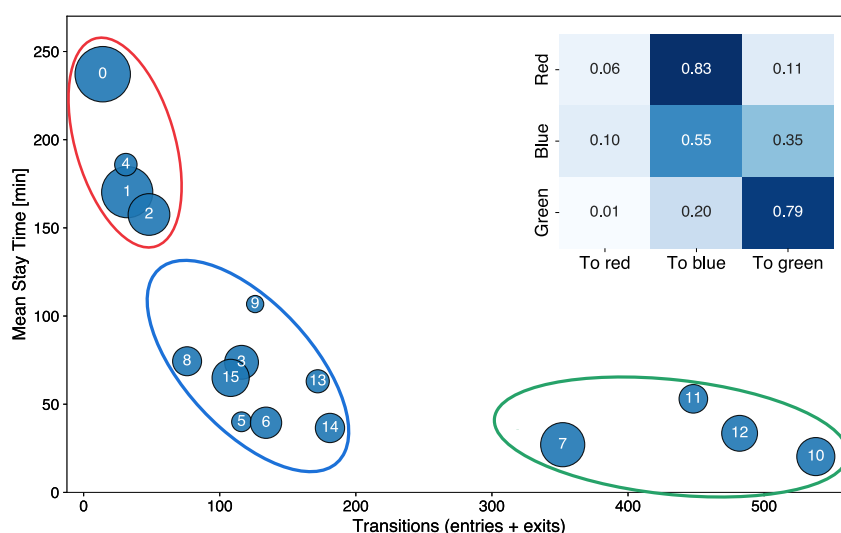


Figure 8. Relationship between transition activity and mean episode duration for all morphological states. Marker size is proportional to the mean sediment transport rate associated with each state. States cluster into three groups with distinct combinations of persistence and transition frequency, highlighted by color. Red states are long-lived and low-transition, blue states occupy an intermediate transition-corridor position, and green states are frequently revisited active-adjustment configurations. The inset summarizes transition probabilities aggregated between these three groups.

show that the transition matrix captured constrained reorganization pathways rather than a continuous temporal progression through the numbered cluster labels.

The combined effects of persistence, connectivity, and sediment transport are summarized in Figure 8. The scatter plot relates the average duration of each episode to its transition activity, defined as the total number of transitions to and from that state. The size of the markers is proportional to the average sediment transport rate associated with each state.

In this representation, the states are not uniformly distributed but are organized into three distinct groups, visually identified according to their clustering in the persistence-transition plane. We define these groups here as *dynamic macro-states*. The red macro-state contains States 00, 01, 02, and 04. This group is characterized by long mean episode durations and low transition activity, corresponding to long-lived, low-transition configurations with heterogeneous sediment-transport signatures (7–24 visits; 158–237 min). The blue macro-state contains States 03, 05, 06, 08, 09, 13, 14, and 15, which exhibited an intermediate number of visits and episode duration (38–91 visits; 39–107 min). This group occupies an intermediate region characterized by moderate persistence and transition frequency and represents transitional morphologies that favor reorganization. Several blue states are associated with comparatively low to moderate sediment output, but the group is defined primarily by its intermediate dynamical position rather than by transport magnitude alone. The green macrostate contains States 07, 10, 11, and 12, which were frequently revisited and shorter lived (176–269 visits; 20–53 min). This group is characterized by short mean episode durations and high transition activity and corresponds to highly dynamic adjustment states that were frequently visited during planform reconfiguration. These green states are also associated with relatively high or variable sediment output, which is consistent with their role as active adjustment configurations.

The same grouping was used to pool the state-conditioned sediment-transport records in Figure 4b. The red group had the largest central tendency (median $Q_s = 0.141 \text{ g s}^{-1}$; mean $Q_s = 0.254 \text{ g s}^{-1}$), the blue group had the lowest central tendency (median $Q_s = 0.034 \text{ g s}^{-1}$; mean $Q_s = 0.105 \text{ g s}^{-1}$), and the green group was intermediate (median $Q_s = 0.100 \text{ g s}^{-1}$; mean $Q_s = 0.172 \text{ g s}^{-1}$). All three macro-state distributions remained right-skewed, indicating that intermittent events of high sediment output occurred in each dynamical class even though their typical transport levels differed from each other.

The inset in Figure 8 summarizes the transition probabilities aggregated at the group level and reveals pronounced asymmetries in the transition structure. These probabilities were computed only from time steps in which the state

changed, after assigning each state to one of the three colored groups. The diagonal entries of the inset therefore indicate within-group switching between different states of the same macro-state, not persistence in the same state. States belonging to the red group showed a strong preference for transitioning to the blue group (82.5% of red-origin state changes), whereas within-red switching was comparatively rare (6.3%). Direct transitions between red and green groups occurred infrequently (11.1% from red to green and 0.9% from green to red).

The green group presents a contrasting pattern. Transitions originating from green states most often remained within the same macro-state (79.5% of green-origin state changes), reflecting frequent switching among active green configurations. When transitions out of the green group occurred, they were directed almost exclusively toward the blue group (19.7%), with direct transitions to the red group being negligible. The blue group occupied an intermediate position, with substantial within-group switching and connectivity to both red and green groups (55.3% within blue, 35.0% to green, and 9.7% to red). It therefore provided most of the cross-group connectivity, but it did not represent a uniform transport class: the transport signatures of blue states varied from configurations with low sediment output to more active links toward green states.

Taken together, these group-level transition probabilities revealed a structured temporal organization rather than random switching among all possible configurations. Planform evolution unfolded through a heterogeneous sequence of state occupations and transitions, providing a compact and interpretable description of morphological reorganization.

5. Discussion and Outlook

The results presented above indicate that the evolution of a braided channel under steady forcing can be interpreted in terms of transitions among a finite set of recurrent morphological states that differ in geometry, persistence, sediment-transport behavior, and temporal connectivity. Rather than evolving through arbitrary or continuously varying configurations, the system exhibited a tendency to organize around preferred planform states and constrained pathways of reorganization, as shown by the combined morphometric, temporal, and transition analyses. In the following, we synthesize these findings to discuss the emergence of distinct morphological states and their transport signatures, the temporal organization and dynamical roles of different classes of configurations, and the broader implications of this state-based perspective for braided-river morphodynamics and future modeling approaches.

5.1. Emergent Morphological States and Their Sediment-Transport Signatures

Clustering analysis demonstrates that the observed planform configurations can be represented by a limited number of distinct morphological states of varying complexity. Representative medoids (see Figure 3) and cluster-wise morphometric statistics (see Table 3) show strong covariation among wetted width, wetted area, sinuosity, and braiding indices, indicating that these quantities collectively describe an underlying gradient from narrow, weakly braided configurations to wide, highly braided planforms. This interpretation is further supported by the strong correlations among morphometric variables shown in Figure 5, confirming that the identified states capture coherent planform geometries rather than arbitrary combinations of metrics. This result is consistent with previous work showing that braided-river planform structure can be summarized through reach-scale descriptors such as wetted width, active width, braiding intensity, entropic braiding indices, and characteristic length scales (P. Ashmore et al., 2011; Egozi & Ashmore, 2008; Hundey & Ashmore, 2009; Tejedor et al., 2022). The present analysis broadens this perspective by treating the entire planform as an object of comparison and by examining how recurrent configurations are occupied over time.

Although the sequencing of morphological states seemed to follow a coherent logic, the timing of persistence or change was far more irregular. Persistence metrics derived from the time-ordered state sequence (see Figure 6 and Table 4) demonstrate that states with comparable morphometric properties could differ markedly in both their mean residence time (i.e., mean episode duration) and their frequency of occurrence. Some configurations were rarely visited but persisted for a long time without interruption once established, whereas others recurred frequently but only as short-duration episodes. The alternation between long-term and rapidly evolving states under constant boundary conditions indicates that no single morphology dominated the system dynamics, even in the absence of variability in external forcing. This punctuated behavior is consistent with the idea that the morphodynamics of braided rivers are internally generated, sensitive to initial and boundary conditions, and capable of producing different histories under the same imposed controls (Lane, 2006; Stecca & Hicks, 2022;

Warburton & Davies, 1994). The state sequence provides a compact empirical description of this internal variability.

Sediment transport added a nontrivial dimension to this state-based description. State-conditioned transport distributions (see Figure 4) show that the statistical properties (mean, variability) of sediment transport rates were strongly negatively correlated with measures of planform complexity. Narrow, weakly braided states exhibited the highest transport rates and the greatest variability, whereas wide, highly braided configurations were associated with lower and more stable transport. As shown by the correlation analysis, this relationship was systematic across metrics. At the same time, transport remained intermittent across all states, with right-skewed distributions indicating that rare, high-magnitude events contributed disproportionately to overall fluxes. The combination of state-dependent transport magnitude and persistent intermittency was consistent with previous observations that bed-load flux in braided systems reflects both local transport fluctuations and larger-scale sediment storage and release (Ancey & Recking, 2023; P. E. Ashmore, 1991b; Paola, 2001). Our contribution is to show that part of this variability can be conditioned on recurrent planform configurations.

It is important to note that sedimentary transport signatures did not directly correspond to state persistence. As shown by comparison of Figure 4 and Table 4, some long-lived states were associated with relatively low and stable transport, while others persisted despite greater transport variability. Conversely, frequently visited states spanned a wide range of transport intensities. This decoupling indicated that morphological persistence, transport magnitude, and its intermittency represented partially independent aspects of the system's behavior.

Taken together, these results indicate that the dynamics of braided rivers, subjected to steady forcing, were organized around a set of emergent morphological states. These states differed not only in their shape, but also in their intermittent capacity to store, release, and transport sediment. This state-based theoretical framework thus offers a concise method for combining morphological diversity, intermittent transport, and temporal persistence within the same experimental system.

5.2. Structured Reorganization Pathways and Macroscopic Dynamical Roles

Although the system had the potential to visit any morphological state, the dynamics of state changes were not entirely random, but rather favored certain states over others. The chronological sequence of states (see Figure 6) highlights an evolution punctuated by long periods of relative stability, interrupted by brief phases of rapid reorganization. During these phases, the system explored several states before stabilizing in a persistent configuration. This pattern indicated that the adjustment of the channel's planform morphology did not result in continuous drift through the configuration space, but rather in a succession of persistent occupations punctuated by short episodes of reorganization.

The empirical transition matrix (see Figure 7) shows that these reorganizations were structured. Transitions were concentrated among a limited subset of state pairs rather than being evenly distributed across all possible pairs. Because state labels were nominal, this conclusion was based on the medoids, morphometric properties, and transport signatures of the linked states rather than on numerical proximity within the transition matrix. The highest off-diagonal probabilities were observed among the frequently visited green states, especially the exchanges involving States 10, 11, 07, and 12. Smaller but repeated links connected the green and blue groups, such as States 05–11, 12–14, and 15–11, as well as the blue and red groups, such as States 03–02 and 06–04. Many other state pairs had negligible or zero transition probability.

State transitions can therefore be interpreted in relation to the established processes in braided rivers, while recognizing that a single transition can combine several mechanisms. Exchanges among active green states are consistent with repeated thread migrations, bar reworking, and local bifurcation switching within an already active multi-thread network (P. Ashmore, 2013; P. E. Ashmore, 1991b). Transitions between blue and green states likely reflected changes in the number and activity of secondary threads, including the partial abandonment of channels or their reactivation. Blue–red links connected intermediate states to long-lasting configurations and might involve larger reorganizations, but the transition matrix alone did not allow each link to be uniquely attributed to a single elementary process. We therefore interpret the clusters as recurrent reach-scale configurations and the transitions as process-informed pathways between them, rather than as direct labels for individual elementary processes.

By jointly considering persistence and transition activity (see Figure 8), we divided the morphological states into three macroscopic dynamic groups, visually identified in the persistence-transition plane. These groups correspond to the red, blue, and green classes presented in the Results section.

Red-group states exhibited long mean episode durations and low transition activity and corresponded to relatively stable configurations that persisted once established. Their transport behavior was not uniform across all the red-group states; some red-group states were associated with relatively high sediment output, whereas others had lower sediment output. The red group was therefore best interpreted as a set of long-lasting, low-transition configurations, rather than as a uniformly storage-dominated transport class of states. In particular, States 00, 01, and 02 combined long residence times with relatively high sediment output, consistent with their relatively confined, weakly braided geometries concentrating flow and transport. State 04, in contrast, belonged to the same dynamic group but had lower sediment output. By contrast, green-group states had short episode durations, high transition activity, and were revisited frequently, often coinciding with reorganization phases and higher or more variable transport. Their primary role was to facilitate adjustment rather than promote stable end-member morphologies.

The blue group occupied an intermediate position in both persistence and transition activity and covered a range of morphologies and transport behaviors. As shown by the group-level transition probabilities in Figure 8, the blue group ensured the greatest connectivity between the red and green groups. Direct transitions between red and green groups were inhibited, and transitions from both groups preferentially passed through blue states, which functioned as a transition corridor for reorganization. This corridor was not a place of uniform transport. Among blue-to-green links, State 05 and State 15 connected to State 11, while State 14 preferentially moved to State 12, connecting intermediate blue configurations to active green configurations. Among blue-to-red links, States 03–02 and 06–04 connected intermediate states to longer-lived red configurations. These examples show that the blue transition corridor contained pathways with different sediment-transport signatures rather than a single transport behavior.

Taken together, the transition matrix (see Figure 7), the persistence metrics (see Table 4) and the group-level organization (see Figure 8) reveal a well-organized arrangement in the chronology of events marking the evolution of the system: the recurrent configurations were linked by asymmetric and constrained transition paths, giving rise to distinct dynamic roles between the states.

5.3. State-Based Representations as an Intermediate Scale in Morphodynamic Modeling

A key finding of this study is that the identified morphological states differ not only in geometry but also in their functional behavior. The systematic contrasts in sediment transport between states (see Figure 4) provide evidence that planform configuration controls both the amplitude and variability of sediment flux: narrow, weakly braided states are associated with greater and more intermittent transport, whereas wider, strongly braided configurations are associated with lower and more stable fluxes. This behavior indicates that the intermittency of sediment transport is largely controlled by channel configuration.

These results also highlight the value of a state-based description at a scale that can be referred to as *mesoscopic*. Indeed, we did not attempt to resolve sediment transport and channel morphodynamics at the local scale (e.g., at the cross-section scale). Rather, we developed a theoretical framework whose central assumption is that sediment transport is conditioned by a small number of recurrent channel morphological states. In doing so, we propose an operational definition of the mesoscale and establish a link between the stochastic nature of sediment transport at the grain scale and morphological control at the reach scale. This perspective departs from the locality assumption (according to which sediment transport is controlled by local hydraulic conditions and sediment availability) by recognizing that channel configuration integrates the cumulative effects of flow, sediment storage, and bar dynamics in space and time.

From this perspective, the system's complexity is reduced to two coupled elements: (a) the transport signature associated with each morphological state and (b) the system's temporal evolution between states, two elements directly corroborated by empirical results. State-based representation thus offers a physically interpretable way to link morphology and transport without requiring the explicit resolution of all local processes.

Within the broader framework of morphodynamic modeling, the state-based approach complements existing methods. It integrates the combined effects of hydraulics, sediment storage, and bar dynamics across observed

morphology, thus offering a more parsimonious representation than deterministic models while remaining grounded in the physics of the phenomena (albeit data-driven, it is not a purely statistical approach). Apart from sediment transport, this theoretical framework also provides a quantitative basis for comparing persistence, reorganization, and variability within braided river systems, thereby reinforcing its relevance as a general tool for morphodynamic analysis. In this respect, the framework lies between (a) fully resolved deterministic morphodynamic models, which represent detailed flow-bed feedbacks but are computationally demanding (Han et al., 2023; Stecca & Hicks, 2022), (b) stochastic descriptions of sediment transport, which focus on the variability of particle entrainment and motion (Ancey, 2010; Bohorquez & Ancey, 2015; Furbish et al., 2021), but are still at the proof-of-concept stage, and (c) reach-scale approaches based on scalar metrics, which summarize the morphology but generally do not describe transitions between planform configurations (P. Ashmore et al., 2011; Tejedor et al., 2022; Connor-Streich et al., 2018).

This perspective also offers a point of comparison with observations from natural braided rivers. Field studies, based on repeated surveys, time-lapse imaging, and remote sensing, have documented planform adjustment, bar reworking, and wetted network modifications at spatial scales impossible to reproduce in the laboratory (Hicks et al., 2002; Nones et al., 2018). These surveys generally sample morphology less frequently than the present experiment and may therefore miss brief transition phases. Nevertheless, the same logic of state analysis can be applied by asking whether the images or field records recurrently occupy a limited set of channel configurations, how long these configurations persist during the available revisit interval, and whether the observed changes correspond to transitions between similar or strongly contrasting states. In this sense, laboratory results provide a frame of reference for interpreting lower-frequency field recordings: observations in natural rivers may not resolve all transitions, but they can nevertheless be used to verify whether recurring patterns, contrasts in persistence, and preferred reorganization pathways occur outside the controlled environment of the flume. This comparison is not intended to establish a direct geometric similarity between the laboratory flume and any given river. Instead, the transferable element lies in the question posed to the data, based on the morphological state. In naturally braided rivers, aerial imagery, repeated topography, or time-lapse observations could help determine whether planforms cluster into recurrent patterns, whether certain patterns persist longer than others, and whether observed changes preferentially link certain morphological classes. Field surveys with longer revisit intervals would be more likely to identify long-term states and miss brief transitions, whereas higher-frequency imaging could begin to identify the transition paths themselves. This provides a practical method for linking the current experimental framework to real-world rivers without requiring rivers to match the laboratory system in terms of scale, grain size, or boundary conditions.

5.4. Outlook: Probabilistic Evolution of Morphological States

The state-based organization highlighted in this study naturally opens the way to predictive extensions. Our results demonstrate that: (a) the evolution of the morphology of braided rivers, subjected to constant upstream boundary conditions, is organized around a finite set of recurrent morphological states; (b) these states are characterized by distinct persistence and constrained transition trajectories; and (c) the morphological states exhibit mesoscopic-scale behaviors that can be statistically predicted without requiring precise information on local hydraulic processes.

The observed patterns of persistence and switching motivate state-based probabilistic representations. The alternation among long-lasting configurations, frequently visited transition states, and asymmetric and constrained reorganization pathways suggests that the system's dynamics cannot be summarized by a single characteristic timescale or average behavior. Instead, it requires descriptions that account for heterogeneous residence times and directional transitions between states. Once the morphology is predicted at the mesoscopic scale, the strong dependence of sediment transport on the visited state makes it possible to provide realistic predictions of bedload transport rates. This extension has been implemented by Gotelli and Ancey (2026b), who used the morphological states analyzed here in a discrete-time Markov model coupled with state-conditioned transport distributions to reproduce the temporal variability of sediment transport. The present study provides the morphological characterization underlying that modeling application.

The present analysis is based on a stationarity assumption. This assumption is verified within the controlled laboratory setting and has proven essential for achieving a mesoscopic description of the system based on the concept of dynamic morphological states (each state has a strong identity and can transition to another state).

Theoretically, there is nothing preventing us from extending our approach to unsteady cases. The statistics of the steady states then depend on external factors (e.g., flow rate, sediment feed). Additional descriptors (particularly regarding bed response times relative to the rate at which boundary conditions change) are likely necessary.

6. Conclusions

In this study, we investigated the morphological evolution of braided rivers subjected to steady upstream boundary conditions. To this end, we developed a data-driven theoretical framework based on the concept of dynamic morphological states. We conducted a long-term (7 weeks) and high-frequency (one measurement per minute) laboratory experiment. The collected data showed that even with steady boundary conditions, the streambed did not remain stable but evolved continuously. This evolution was not random, but presented preferred configurations called *morphological states*. In total, we identified 16 morphological states that were visited repeatedly. The lifetime of these morphological states was randomly distributed, with characteristic durations being either short (transient states) or long (long-term states).

The experimental analysis of morphological states was based on an automated workflow combining image-based dissimilarity measurements, dimensionality reduction, and density clustering. This workflow allowed for the direct identification of morphological states from images, without requiring prior information about their geometric properties. These states covered a discontinuous range of morphologies, from narrow, efficient, single-branch channels to large, highly braided networks. Each state exhibited specific morphometric properties and sediment transport behavior. The results show that, for braided rivers, morphological evolution in configuration space does not resemble Brownian motion (a pure random walk without preferred direction or state), but rather explores and revisits a limited number of recurring patterns.

Analysis of the state chronology revealed a well-organized sequencing of morphological states, with phases of morphological persistence punctuated by events of rapid reorganization and constrained transition pathways. Taken together, these characteristics also indicate that the dynamics of braided rivers are fixed by a finite number of morphological states: for a given flume gradient, water discharge, sediment input, and grain size, the riverbed cannot adopt any shape but must necessarily conform to one of the possible states. This organization suggests that there is a scale (which we have called *mesoscopic*) that controls both channel geometry and sediment transport. From this perspective, sediment transport is not solely governed by instantaneous local hydraulics. Rather, it results from a multitude of processes conditioned by the morphological state. These morphological processes act in time and space; they include sediment storage, release, and transport, as well as bar progression.

This theoretical framework offers a data-driven representation of morphological states. It is incomplete because it can only reproduce situations for which sufficient data has already been acquired to characterize the dynamics of these morphological states. However, this framework is sufficient to answer the question posed in the article's introduction regarding the nature of the seemingly random variations in channel morphology.

Two types of questions remain to be explored. The first is whether, prior to any experiment, it is possible to determine the number of states, their geometry, or the transition probabilities that would evolve as a function of flow rate, sediment input, channel slope, grain size, vegetation, or confinement. In the absence of a suitable theory, a workaround would be to repeat the experiment we conducted to see how the input parameters influence the dynamics of the morphological states.

The second question is closely related to the working assumption of perfect stationarity of the system. What happens if, instead of fixed upstream boundary conditions, we vary the flow rate or sediment input? Since the steady state already has its own characteristic timescales (residence time, time between two transitions), the problem of interaction between external forcing and internal dynamics inevitably arises. The application of this theoretical framework still requires considerable work to clarify these questions.

Appendix A: Workflow for Identifying Morphological States

The following definitions and simplified algorithm summarize the procedure used to transform the image sequence into a time-ordered sequence of morphological states Algorithm A1. They are intended to make the workflow reproducible at the level of operations and parameter choices, while leaving implementation details such as file handling and software-specific syntax open Table A1.

Table A1

Operational Parameters Used in the Image-to-State Workflow

Workflow element	Parameter choice used in this study
Image alignment and crop	Images were rotated by 90° to align the flume, corrected by an additional 3.6°, multiplied by a fixed flume-interior mask, and cropped to the nonzero bounding box of that mask.
HSV water mask	The dyed water was isolated with fixed HSV bounds.
Mask resizing and filtering	Binary masks were resized with nearest-neighbor interpolation while preserving aspect ratio, with the longest image dimension set to 200 pixels.
Edge extraction	MHD was computed from one-pixel-wide edge maps extracted from the processed wetted-area masks. Dice similarity was computed from the processed binary masks.
Pairwise comparison	All image pairs in the record were compared. The MHD matrix and Dice similarity matrix were symmetric by construction; diagonal entries were zero for MHD and one for Dice similarity.
Dimensional reduction	PCA retained the smallest number of components explaining at least 99% of the variance, yielding 67 components. Candidate UMAP embeddings were then generated from the PCA representation.
Parameter search	UMAP used <code>n_neighbors = 50, 100, 150, 250, 300, 500</code> , <code>min_dist = 0.0, 0.1, 0.2, 0.3, 0.5, 0.75</code> , and <code>n_components = 2, 3</code> . DBSCAN used <code>ε = 0.10, 0.15, 0.20, 0.25, 0.30, 2.0</code> and minimum samples 10, 25, 50, 75, 100, 150, 200. HDBSCAN used minimum cluster size 50, 100, 150, 250, 350, 400, 500, 800 and minimum samples 15, 25, 50, 75, 100, 150, 250.
Selected state catalog	The selected embedding used UMAP with <code>n_neighbors = 300</code> , <code>min_dist = 0.00</code> , and <code>n_components = 3</code> , followed by HDBSCAN with <code>min_cluster_size = 500</code> and <code>min_samples = 250</code> . DBSCAN-noise frames were treated as transitional configurations and assigned to the closest recurrent cluster before temporal analyses.
Selection criteria	Candidate solutions were evaluated with number of clusters, noise fraction, Silhouette score, Davies–Bouldin index, Calinski–Harabasz score, and visual inspection of medoids and embedding structure for physical coherence.
Software environment	Image preparation used PIL/Pillow, OpenCV, and NumPy. Distance calculations used scikit-image routines for Dice similarity and for validation of the MHD implementation. Dimensional reduction and clustering used scikit-learn, umap-learn, and hdbscan.

W_i denote the set of wetted pixels in frame i , and let E_i denote the corresponding set of edge pixels. For two frames i and j , the directed mean nearest-neighbor distance between edge sets is:

$$h(E_i, E_j) = \frac{1}{|E_i|} \sum_{x \in E_i} \min_{y \in E_j} \|x - y\|_2.$$

The symmetric Modified Hausdorff Distance is

$$d_{\text{MHD}}(i, j) = \max[h(E_i, E_j), h(E_j, E_i)].$$

The Dice similarity coefficient and its associated distance are

$$S_D(i, j) = \frac{2|W_i \cap W_j|}{|W_i| + |W_j|}, \quad d_D(i, j) = 1 - S_D(i, j).$$

Before dimensional reduction, the MHD distance matrix and Dice similarity matrix were normalized by their respective maxima over all frame pairs,

$$\tilde{d}_{\text{MHD}}(i,j) = \frac{d_{\text{MHD}}(i,j)}{\max_{p,q} d_{\text{MHD}}(p,q)}, \quad \tilde{S}_D(i,j) = \frac{S_D(i,j)}{\max_{p,q} S_D(p,q)}.$$

Each frame was then represented by the composite descriptor vector

$$\mathbf{z}_i = \left(\tilde{d}_{\text{MHD}}(i,1), \dots, \tilde{d}_{\text{MHD}}(i,N), \tilde{S}_D(i,1), \dots, \tilde{S}_D(i,N) \right).$$

Algorithm A1: State identification from planform images.

1. Start from the ordered image sequence $I_1, \dots, I_N$ acquired at constant time interval Δt .
 2. For each image I_i , align the frame, crop it to the flume interior using the fixed mask, apply the fixed HSV threshold to isolate the water area, and obtain the binary wetted-area mask W_i .
 3. Resize W_i with nearest-neighbor interpolation to a longest dimension of 200 pixels, remove connected components smaller than 30 pixels, and extract the one-pixel-wide edge set E_i representing the wetted boundary and internal channel margins.
 4. For every pair of frames (i, j) , compute the modified Hausdorff distance $d_{\text{MHD}}(i, j)$ from E_i and E_j .
 5. For the same frame pair, compute the Dice similarity $S_D(i, j)$ from W_i and W_j .
 6. Normalize the MHD distance matrix and Dice similarity matrix by their respective maximum values over all frame pairs, producing $\tilde{d}_{\text{MHD}}$ and $\tilde{S}_D$.
 7. For each frame i , construct the composite descriptor vector $\mathbf{z}_i$ by concatenating its normalized MHD distances and normalized Dice similarities to all other frames.
 8. Assemble the matrix $\mathbf{Z}$ whose rows are the vectors $\mathbf{z}_i$. Apply PCA to $\mathbf{Z}$ and retain the smallest number of components that preserves at least 99% of the variance. In this study, this criterion retains 67 components.
 9. Generate candidate low-dimensional UMAP embeddings from the PCA representation by varying the main UMAP parameters. For each candidate embedding, cluster the points using density-based clustering over a range of parameter values.
 10. Evaluate each candidate solution using the number of clusters, the noise fraction, the Silhouette score, the Davies-Bouldin index, and the Calinski-Harabasz score.
 11. Inspect candidate embeddings and cluster medoids to verify physical coherence. This inspection checks whether clusters correspond to recognizable planform configurations and whether high-scoring solutions are affected by over-fragmentation, over-merging, or projection artifacts.
 12. Select the candidate that jointly satisfies the quantitative metrics and the physical-coherence check. In this study, the selected embedding used UMAP with $n_neighbors = 300$, $min_dist = 0.00$, and $n_components = 3$.
 13. Cluster the selected three-dimensional UMAP coordinates using HDBSCAN with $min_cluster_size = 500$ and $min_samples = 250$.
 14. Interpret dense HDBSCAN clusters as recurrent morphological states. Interpret points labeled as noise as sparse transitional configurations, not as additional recurrent states.
 15. Assign each HDBSCAN-noise frame to the closest recurrent cluster in the UMAP morpho-space, so that every image has one state label for the temporal analyses.
 16. Assign each frame its morphological-state label and preserve the original temporal order to obtain the observed state sequence $s(t_1), \dots, s(t_N)$.
-

17. For each state, compute the medoid as the frame that minimizes the total composite dissimilarity to all other frames in the same state. Use the medoids and cluster-wise morphometric statistics to verify the physical meaning of the identified states.
18. Use the observed state sequence to compute occupancy, visit duration, and empirical transition probabilities between consecutive time steps.

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Availability Statement

The image data set used in this study is publicly available through the Zenodo repository (Gotelli & Ancey, 2026a). The persistent DOI is <https://doi.org/10.5281/zenodo.18554208>.

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