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A 41-year satellite record reveals abrupt redistribution of the Okavango Delta's flood pulse since 2012

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Abstract

The Okavango Delta is an endorheic wetland and UNESCO World Heritage site that sustains one of Africa's largest game reserves and underpins the livelihoods and ecotourism economy of northern Botswana. Its hydrology is governed by an annual flood pulse that propagates through a continually reorganizing distributary network. Yet we lack a multidecadal, multiclass, high-resolution dataset able to monitor changes to the annual flood pulse that sustains the delta. Here we present a 41-year, 30-m, monthly multiclass inundation record that distinguishes open water from vegetated or partial inundation. The record reveals a significant, system-wide reorganization of flood distribution during the mid-2010s: all three northeastern distributaries gained inundation share at the expense of southwestern distributaries, following an exceptional La Niña event and intensifying through the record-low flood of 2019. The inundation centroid has migrated to the northeast at nearly 1 km yr⁻¹

since 2012. This divergence reflects an intensifying alternation of extreme wet and dry years acting on a fan tilted northeast by long-term tectonic subsidence. Southwestern communities and ecosystems are currently experiencing a broad change in surface water delivery, and continued shifts towards the northeast support the long-term possibility that the delta's isolation from the Zambezi basin may not endure.

1. Introduction

Climate variability and human impacts are reshaping the distribution of surface water across African wetlands^{1,2}. Perhaps the most unique of these wetlands is the Okavango Delta, an expansive alluvial fan whose floodwaters never reach the sea, instead providing the foundation for a diverse wetland ecosystem that hosts one of Africa's highest concentrations of wildlife and holds UNESCO World Heritage status. Rainfall during the Austral summer (November–March) from the Cubango and Cuito watersheds, also known as the Angolan Highlands “water tower”³, supplies approximately 95% of the delta's water⁴, generating a flood wave that propagates through the Panhandle and across a broad distributary network (Fig. 1), reaching peak inundation extent in June–September, asynchronous with the local rainy season. These distributaries fall into two clusters separated by Chief's Island, a topographic high oriented parallel to the Panhandle: three southwestern (SW) distributaries —Thaoge, Xudum, and Boro — and three northeastern distributaries (NE) — Mboroga, Khwai, and Magweggana (Fig. 1). Prior studies have documented shifts in flood distribution between neighboring distributaries and debated whether they reflect permanent reorganization or transient responses^{5–7}. Distinguishing the two, and testing whether the delta reorganizes as a coherent system, requires a spatially complete, multi-decadal record that has until now been unavailable.

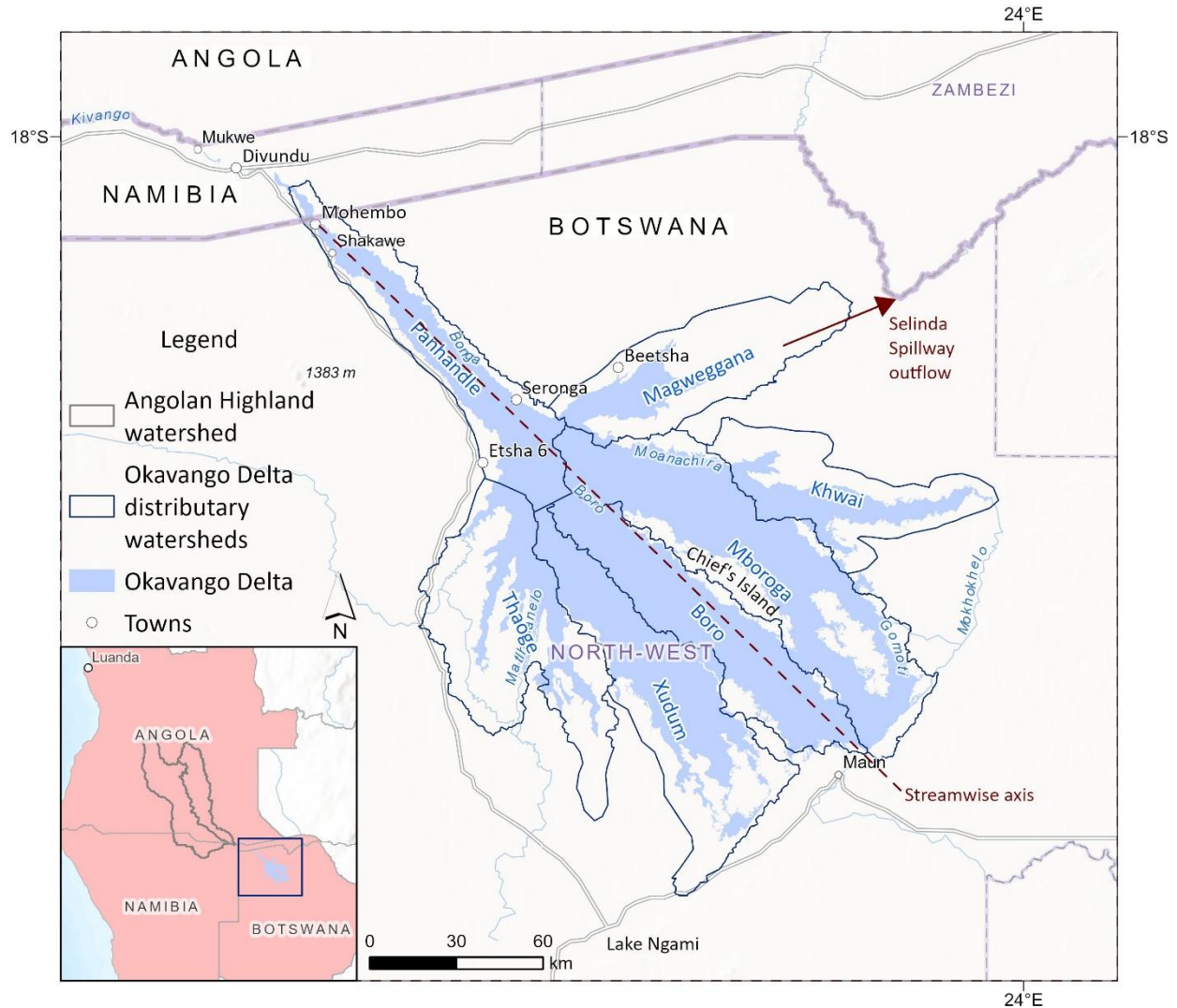


Fig. 1. The Okavango Delta system overview. Outlined are the Panhandle and the six distributary watersheds analyzed here: Thaoge, Xudum, and Boro (southwest) and Mboroga, Khwai, and Magweggana (northeast). Blue shading marks typical inundation extent within the delta, dark outlines delimit the analysis boundaries for distributaries. The dashed red line is the streamwise axis and the red arrow the Selinda Spillway outflow toward the Zambezi; the inset locates the delta within the greater Okavango basin; the gray outline delineates the upstream Angolan Highland watersheds of the Cuito and Cubango Rivers.

Flood distribution within the delta operates within a long-term tectonic framework: the delta occupies the southwestern extension of the East African Rift System, sitting atop a graben, a block of crust dropped down between two bounding faults, where differential subsidence along those faults has long been hypothesized to control flow paths^{8,9}. Recent Global Navigation Satellite System (GNSS) measurements of active crustal deformation across the graben¹⁰ corroborates

structural forcing, which may operate as a long-term influence on flood distribution direction. During larger flood years, spillover thresholds are exceeded and a greater proportion of inflow reaches SW distributaries⁷. In drier years less spillover occurs, and floodwaters concentrate in tectonically favored NE distributaries. Superimposed on this gradual tectonic influence, vegetation-mediated sedimentation feedbacks redistribute flow across the network on shorter timescales^{9,11–13}. Delta inflow via Angolan Highland precipitation is modulated by the El Niño–Southern Oscillation (ENSO); La Niña conditions bring higher summer rainfall across the Angolan watersheds, driving elevated discharge into the delta and producing larger flood extents¹⁴. The pulse’s timing and extent vary between years and across distributaries: in 2011, total inundation exceeded 11,440 km²,¹⁵ while the 2019 dry year produced a peak annual extent of just 3,408 km² (Results).

Yet the magnitude, timing, and distributary-scale structure of the flood pulse have not been quantified in nearly two decades, in large part due to a lack of remote sensing-based inundation products. Coarse-resolution products (250 m to 1 km) from MODIS and AVHRR systematically overestimate flood extent because partially wet pixels are classified as fully inundated^{16,17}, while the highest-resolution Landsat-based record¹⁶ captures only annual maxima using a binary wet/dry classification. This approach carries two fundamental limitations. Binary classification collapses the inundation continuum into a single "wet" class, obscuring ecologically meaningful differences between open water, flooded vegetation, and transitional wetland. A focus on annual flood maxima misses seasonal dynamics essential to understanding wetland function¹⁸. Flood pulse timing, propagation through the distributary network, and recession rates all carry direct implications for habitat availability^{19,20}, biogeochemical cycling^{21–23}, and human livelihoods^{24,25}.

One emerging solution to these challenges is the Dynamic Surface Water Extent (DSWE) algorithm, developed to map inundation in wetland environments, with a focus on the Florida Everglades^{26,27}, a system that shares similar hydrogeomorphic and vegetation patterns to the Okavango²⁸. DSWE's framework can be enhanced by integrating additional tests: SWIR2-based thresholding approaches have proven highly effective at detecting water beneath vegetation in the Okavango^{16,29}, suggesting that synthesis of these established methods with DSWE's multiclass structure could improve detection of vegetated inundation while maintaining confidence-based discrimination.

Here, we document a coherent, system-wide shift in the spatial distribution of the Okavango Delta's flood pulse, detected through a 41-year, monthly, multiclass inundation record at 30 m resolution. We developed an adapted version of the Dynamic Surface Water Extent algorithm (AdDSWE) that integrates dynamic shortwave-infrared thresholding with the standard DSWE confidence framework, producing monthly maps that distinguish open water from water under canopy (WUC) across most of the Landsat archive (June 1984–December 2025). Our data reveal a significant northeastward migration of the flood pulse and a decisive mid-2010s divergence in which all NE distributaries gained and two of three SW distributaries lost inundation share. The inundation centroid, which drifted slightly southwestward before 2012, reversed direction and accelerated to nearly four times its prior rate, migrating roughly 11 km toward the northeast over the following thirteen years. This pattern is consistent across both open water and total inundation extent, and emerged following the 2010–2012 La Niña high-water years, with the most extreme divergence between SW and NE distributaries occurring during and following the lowest flood on record in 2019. These findings carry direct implications for the communities, ecosystems, and carbon stores that depend on southwestern flood delivery, and reveal how compound tectonic and climatic forcing has reorganized the flood pulse across the Okavango.

2. Results

2.1. A 41-year monthly multiclass inundation record

The Landsat-derived AdDSWE dataset comprises 368 monthly inundation composites spanning June 1984 through December 2025 (Fig. 2c). We assigned each pixel to one of five confidence classes (hereafter referred to as AdDSWE classes) ranging from dry land (0) to high-confidence open water (4). Total monthly inundation extent (classes 1–4 combined) and open water extent (classes 3–4) both peak in July (Fig. 2d), with broader characterization included in supplementary materials (Supplementary Note 1). The record contains a substantial gap: no Landsat-derived composites exist from June 2010 through February 2013, owing to persistent cloud cover and the loss of Landsat observations during the 2012 sensor gap. This gap coincides with an exceptional La Niña event (Fig. 2c); water year 2011 recorded the highest total annual precipitation across the Angolan Highlands watershed³⁰, and the independent inundation records^{16,31} both document their largest inundation extents of the study period during this same interval. The maximum extents reported here therefore likely underestimate the true upper bound of inundation variability within the study period.

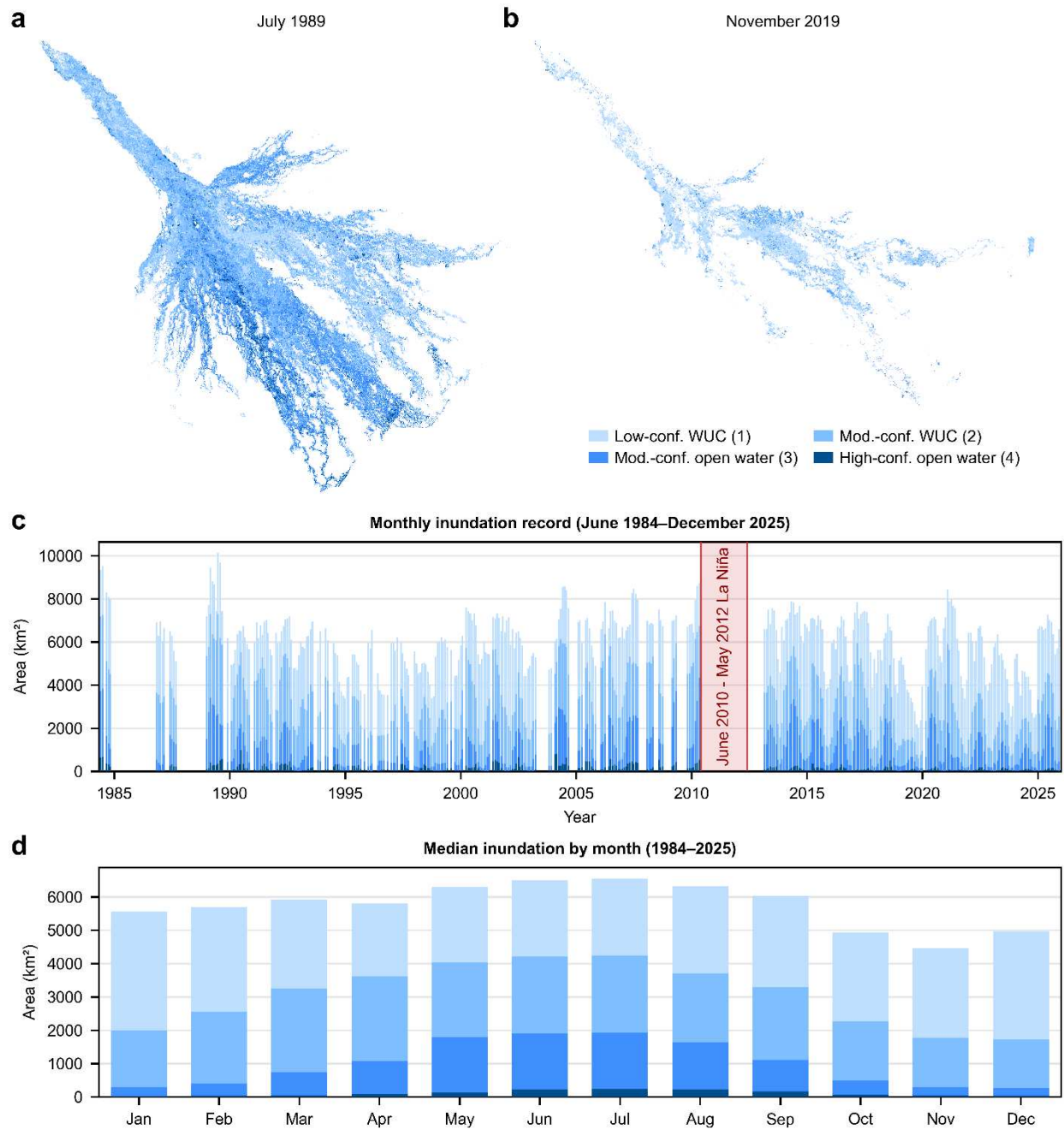


Fig. 2. The Adapted Dynamic Surface Water Extent dataset by water confidence class. Monthly inundation extent ranged from a maximum of **a** 10,136 km² in July of 1989 to a minimum of **b** 2,032 km² in November 2019. **c** Monthly inundation over the full record (June 1984–December 2025), with the exceptional 2010–2012 La Niña event denoted in red. **d** Median inundation by month.

2.2. Trends and divergence in distributary inundation share

To test whether each distributary's share of delta-wide inundation has shifted directionally across the record, we applied Mann-Kendall (MK) trend tests^{32,33} to annual mean z-scores of each distributary's monthly inundation share, conducting parallel analyses for total inundation (AdDSWE classes 1-4) and open water (AdDSWE classes 3 and 4). The z-scores express each distributary's fraction of total delta inundation as a standardized departure from its calendar-month mean fraction, so a positive value indicates an unusually large share of the flood pulse for that time of year and a negative value an unusually small share. To reduce noise inherent in monthly data, we computed annual means from all months within a calendar year, limiting observations to years with at least eight valid monthly observations. For total inundation, two SW distributaries show significant negative trends: Boro and Thaoge (Fig. 3e, f; Table 1). All three NE distributaries show significant positive trends: Magweggana, Khwai, and Mboroga (Fig. 3b-d; Table 1). Neither the Panhandle nor Xudum shows a significant trend. Open water shows the same general NE/SW contrast, with negative trends in Boro and Thaoge and positive trends in Magweggana and Mboroga (Table 1; Supplementary Fig. 1a-g). Khwai returns no significant trend in open water inundation share, and the Panhandle and Xudum remain non-significant in both datasets.

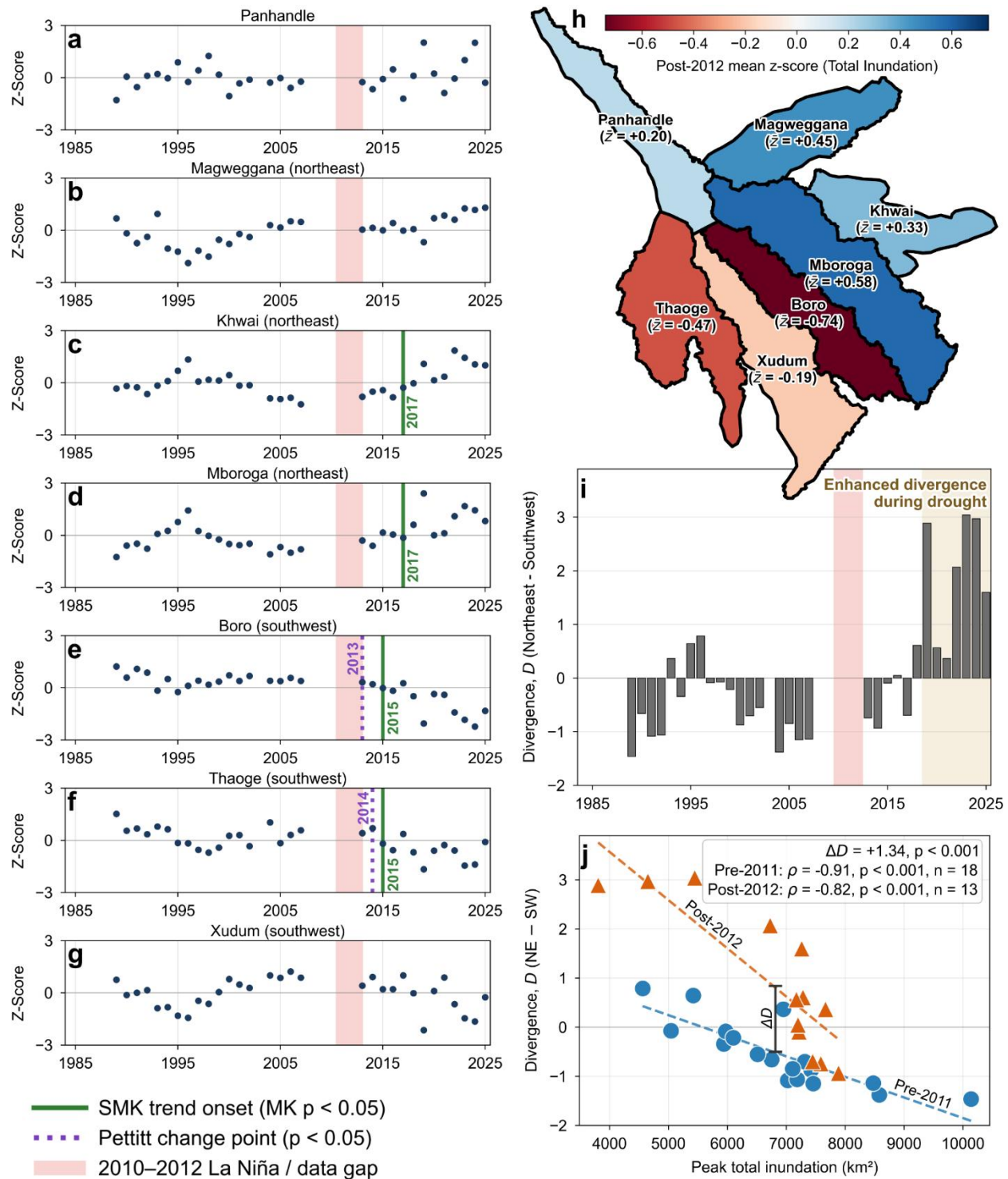


Fig. 3. Distributary-scale reorganization and divergence of total inundation area share since 2012. **a–g** Annual mean z-score time series of each distributary's share of total delta inundation area, showing significant sequential Mann-Kendall (SMK) onsets and Pettitt change points. **h** Map of the Panhandle and six distributaries colored by mean monthly z-score over the post-2012 epoch. **i** Annual northeast–southwest divergence index D . **j** D versus peak annual total inundation, by epoch, with per-epoch fits; ΔD is the ANCOVA offset at mean peak annual flood.

To localize when these trends emerged, we paired Pettitt change-point tests³⁴ with sequential Mann-Kendall (SMK) tests³⁵ to identify the year that maximally separates the pre- and post-break distributions. In total inundation, SW distributaries Boro and Thaoge show significant change-points in the early 2010s, with SMK trend onsets in 2015 (Fig. 3e, f). NE distributaries break slightly later and less sharply: Mboroga and Khwai return non-significant change-points but SMK onsets in 2017, while Magweggana's change-point is non-significant and falls earlier, in 2002, with no resolvable onset. Neither Xudum nor the Panhandle shows a significant change-point. Open-water change-points are systematically earlier than their total-inundation counterparts. Mboroga is the exception, matching its total-inundation break (2014; Supplementary Fig. 1d), as does Thaoge though short of significance (2014; Supplementary Fig. 1f). Boro and Magweggana, the two strongest movers, break markedly earlier, in 2005 and 2002 respectively (Supplementary Fig. 1e, b), with no resolvable SMK onset. Khwai and Xudum show no significant open-water change-point or trend. Full statistics are given in Table 1, and detailed SMK analyses in Supplementary Figs. 2 and 3 for total inundation and open water.

Table 1. Trend and change-point statistics for each distributary's share of delta-wide inundation, for total inundation and open water.

Dataset	Distributary	Group	Mann-Kendall τ	Pettitt change point	Sequential Mann-Kendall onset	Post-2012 $\bar{z}$
Total Inundation	Boro	SW	-0.574***	2013**	onset 2015	-0.74
	Thaoge	SW	-0.394**	2014*	onset 2015	-0.47
	Xudum	SW	+0.071	1999	-	-0.19
	Panhandle	PH	+0.075	2017	-	+0.20
	Khwai	NE	+0.29*	2017	onset 2017 established by 2014 (onset unresolvable)	+0.33
	Magweggana	NE	+0.535***	2002	onset 2017	+0.45
	Mboroga	NE	+0.351*	2014	onset 2017 established by 2010 (onset unresolvable)	+0.58
Open Water	Boro	SW	-0.824***	2005***	onset 2014	-0.77
	Thaoge	SW	-0.325*	2014	-	-0.39
	Xudum	SW	+0.015	1998	-	-0.13
	Panhandle	PH	+0.123	2017	-	+0.10
	Khwai	NE	-0.118	2000	-	-0.02

Magweggana	NE	+0.725***	2002**	-	+0.59
Mboroga	NE	+0.406**	2014*	onset 2017	+0.66

SW, southwestern; PH, Panhandle; NE, northeastern. Bold text indicates significance, * at $p < 0.05$, ** at $p < 0.01$, *** at $p < 0.001$.

In the total inundation record, both SMK trend-onset years and Pettitt change-points localize the regime transition to the mid-2010s, following the 2010–2012, the largest sustained wet anomaly in the AdDSWE record. The 33-month AdDSWE data gap from June 2010 through February 2013 prevents direct observation of the transition, but the post-gap record shows the distributary system in a new partitioning state by the time consistent observations resume. As such, we use 2010–2012 as an observationally grounded pre/post boundary for two “epochs” used in additional analyses. The more diffuse and less prevalent breaks within the open water record are expected: open water averages just 17.7% of total monthly inundation extent (Fig. 2d) and is dominated by perennial channels and lakes, which are generally more hydrologically stable across the record.

In the post-2012 epoch, mean monthly z-scores ($\bar{z}$) of inundation share are positive for the three NE distributaries and the Panhandle and negative for all three SW distributaries in the total inundation record (Fig. 3h). The open water record reproduces the same NE–SW contrast, with Mboroga, Magweggana, and Boro again experiencing the largest shifts, while Thaoge and Xudum show smaller losses and Khwai sits near zero (Supplementary Fig. 1h). The Panhandle's positive post-2012 $\bar{z}$ does not mean the Panhandle grew wetter; it reflects that floodwaters in dry years fail to propagate as far downstream, and so a larger share of whatever inundation does occur each month remains concentrated in the Panhandle rather than reaching the distal distributaries.

To quantify the NE–SW reorganization in a single annual index, we computed an annual divergence value, D , where positive values indicate that NE distributaries are capturing a disproportionate share of delta inundation for the given year relative to SW distributaries. In the total inundation record, epoch mean D ($\bar{D}$) shifted from -0.55 ($n = 18$ pre-2011) to $+0.90$ ($n = 13$

post-2012; Mann-Whitney $U = 45.0$, $p = 0.004$; Fig. 3i). D scales inversely with peak annual flood magnitude within both epochs (Spearman $\rho = -0.91$, $p < 0.001$, pre-2011; $\rho = -0.82$, $p < 0.001$, post-2012), and at mean peak annual flood magnitude the post-2012 relationship sits above the pre-2011 relationship by $\Delta D = +1.34$ (ANCOVA, $p < 0.001$; Fig. 3j), meaning a flood of a given size now drives markedly stronger northeastward divergence than the same-sized flood did before 2011. The open water record shows the same pattern ($\bar{D}$ shift from -0.53 to $+0.82$; $U = 38.0$, $p = 0.002$; Supplementary Fig. 1i), with the same inverse flood-magnitude relationship ($\rho = -0.86$, $p < 0.001$, pre-2011; $\rho = -0.55$, $p = 0.049$ post-2012) and a positive epoch offset ($\Delta D = +1.47$, $p < 0.001$; Supplementary Fig. 1j). The five highest D values on record fall in the 2019–2025 window in both datasets.

2.3. Pixel-level differencing localizes change

To visualize the spatial distribution of changes between epochs, we calculated the per-pixel difference in mean AdDSWE class between pre-2011 epoch (June 1984–May 2010) and post-2012 epoch (March 2013–December 2025), using month-stratified epoch means to avoid bias from irregular monthly sampling and partial water years (Fig. 4a; Methods), where negative values indicate a drying trend and positive values a wetting trend. NE distributaries show localized wetting post-2012 in channels leading to the Selinda Spillway in the Magweggana distributary (Fig. 4c), along the Nqoga channel system (Fig. 4f), and in distal, downstream channels within the Mboroga Distributary (Fig. 4g). Drying is concentrated in SW distributaries: lagoons and open water bodies within the Thaoge distributary and the Xudum/Boro boundary show pronounced contraction (Fig. 4e) and, in some cases, complete desiccation (Fig. 4d). Within the Panhandle, wetting along cut banks and drying along point bars (Fig. 4b) captures lateral channel migration of the meandering Okavango River.

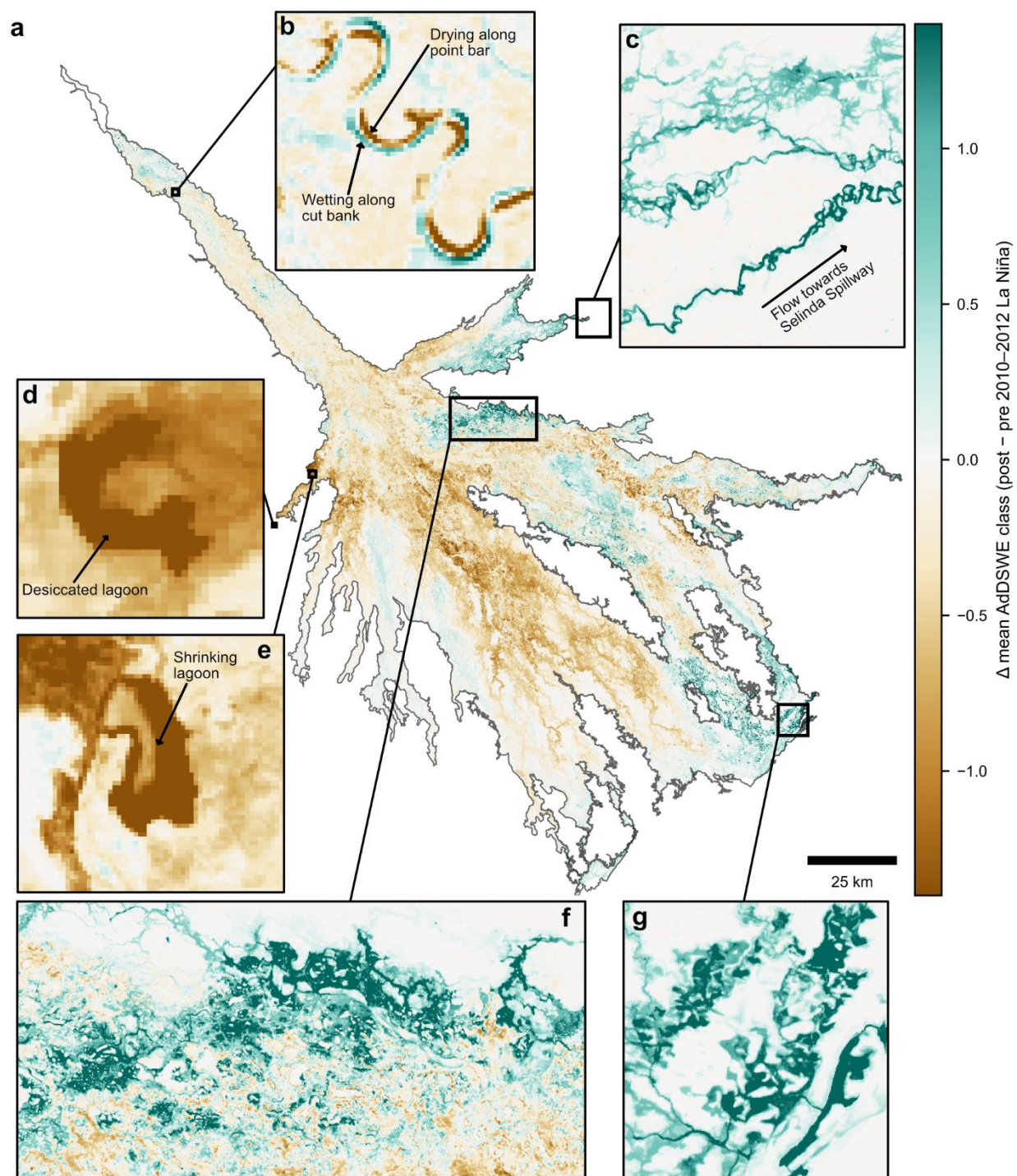


Fig. 4. Difference between mean Adapted Dynamic Surface Water Extent (AdDSWE) pixel values between epochs. The entire delta is shown in **a**. **b** Lateral channel migration along the meandering Okavango River. **c** Increased channel activation within the Magweggana distributary flowing towards the Selinda Spillway. The complete desiccation **d** and shrinking **e** of lagoons evident in the Thaoge distributary. **f** Increased inundation near the Nqoga channel system, and **g** increased downstream flood extent within the Mboroga Distributary.

2.4. Northeastward migration of the inundation centroid

To test whether the post-2012 redistribution corresponds to a fan-scale shift in inundation, we tracked the AddSWE-weighted annual inundation centroid and decomposed its annual mean position into along-fan (streamwise) and cross-fan (normal to streamwise) components relative to the principal downstream axis of the delta fan (137° from north; Fig. 1). This decomposition isolates a true directional shift from a magnitude-dependent artifact: a genuine northeastward trend should appear only in the cross-fan component, whereas a signal that merely tracks flood size would move both axes together. The cross-fan component shows a significant northeastward trend across both the post-2012 epoch and the full record (Fig. 5a). Over the full 1984–2025 record, the centroid migrated toward the northeast at 163.7 m yr^{-1} ($p = 0.005$, $R^2 = 0.25$), accumulating roughly 6 km of cross-fan displacement, but the trend is concentrated almost entirely in the post-2012 epoch. Between 1984 and 2010, cross-fan migration was slow and slightly southwestward (-223.0 m yr^{-1} , $p = 0.055$, $R^2 = 0.21$); between 2013 and 2025, it reversed and accelerated to 861.1 m yr^{-1} northeastward ($p < 0.001$, $R^2 = 0.66$), yielding approximately 11 km of cross-fan displacement in 13 years.

In contrast, the along-fan component shows no detectable trend across the full record ($+8.1 \text{ m yr}^{-1}$, $p = 0.938$, $R^2 = 0.00$; Fig. 5b) or the pre-2011 epoch ($+37.1 \text{ m yr}^{-1}$, $p = 0.872$, $R^2 = 0.00$), confirming that the cross-fan signal above is not simply an artifact of flood magnitude. The post-2012 epoch does show marginally significant upstream migration along this axis ($-1159.7 \text{ m yr}^{-1}$; $p = 0.050$, $R^2 = 0.31$), reflecting drier post-2012 conditions.

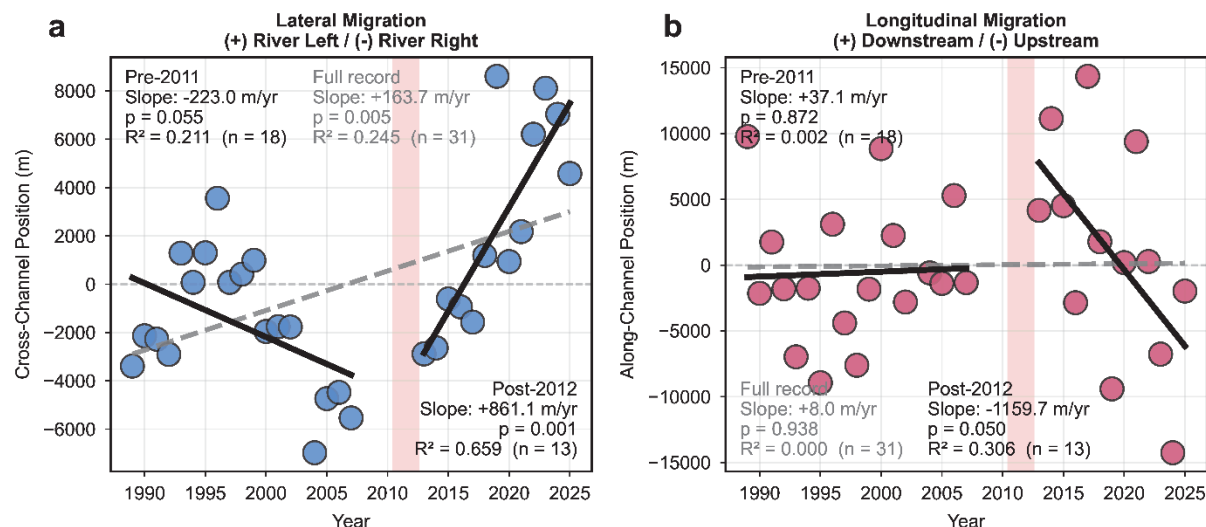


Fig. 5. Weighted annual centroid of inundation; shown along the **a** cross-channel axis and the **b** streamwise axis. Epoch best fit lines are shown as solid black lines; full record best fit lines are shown as gray dashed lines.

3. Discussion

Our results corroborate prior work documenting recurrent shifts in the spatial distribution of flooding across the delta^{5-7,29,36}. Prior to 2011, inundation trends across the six distributaries were weak and mixed in direction. During the mid-2010s, all six distributaries diverged decisively: NE distributaries gained and SW distributaries lost inundation share (Figs. 3, 4). This pattern appears consistently in both total inundation and open water extent, indicating that the shift is not merely a reorganization of where floodwaters spread across vegetated margins but a shift in the channel network itself.

This reallocation towards the northeast is broadly consistent with a body of prior work implicating neotectonic activity as a long-term driver of channel evolution and flood distribution in the Okavango Delta. Earlier studies recognized that differential subsidence along the graben's NE-trending fault arms progressively favors NE flow paths by creating a structural low toward which surface water is gradually redirected^{6,9}. At the distributary scale, permanent structural shifts in

flood distribution occurred between the Xudum and Thaoge distributaries in the late 1990s³⁷ (also observable in the AdDSWE record in Fig. 3f, g) and raised tectonic dislocation as a candidate mechanism. Dauteuil et al.¹⁰ used a network of GNSS stations across the graben to document a long-term regional tilt in which the NE portion of the delta subsides at faster rates than the SW, a deformation pattern that would cause the progressive NE migration of the annual flood. The direction and cross-channel character of the centroid displacement documented here aligns with multi-decadal drifting of the flood pulse towards the northeast (Fig. 5).

While tectonic tilt operates over long timescales and the full spatial extent of the fan, channel dynamics at the reach scale are governed by a well-documented interplay between vegetation, sedimentation, and hydrology. Continuous leakage through permeable, papyrus-lined margins drives downstream aggradation through bedload deposition; vegetation then colonizes the channel, a positive feedback that further constricts flow and promotes further deposition, until a reach is super-elevated and poised to divert flow toward a lower-gradient path^{7,11–13,36}. During a series of weak flood years, this dynamic may cause positive feedback by which flows become increasingly consolidated in NE channels, as best illustrated by the sharp increase in D during the 2019–2024 low flood sequence (Fig. 3i, j) and the positive offset in D post-2012.

The sustained high water during the 2010–2012 La Niña may have acted on an intermediate scale between long term tectonic forcing and localized ecogeomorphology. Enhanced rainfall and extended wet periods over the catchment enhance fluvial activity, including channel migration rates and the frequency of avulsions and chute cutoffs³⁸. Water year 2011 recorded the highest total water year precipitation across the Angolan Highlands in the study period, 2009–2012 the highest cumulative four-year total³⁰, and discharge at Mohembo peaked in 2010 (Supplementary Fig. 4b). Elevated stage across these years raised lateral head in channels at the fan's apex, where tectonic tilt already favors overtopping towards the northeast. This may have triggered avulsions or

a widening and increased conveyance through NE side channels and lagoons, which can be observed in the post-2012 record (Fig. 4c, f). This would account for the sharp reversal in lateral centroid migration around 2010 (Fig. 5a), and for the trend tests placing the acceleration of NE consolidation in the mid-2010s, just after the La Niña yet before the 2019 drought (Table 1). The gap in the record and the resolution of AdDSWE make this difficult to resolve directly, but ENSO-related high water acting on tectonic preconditioning has been previously recognized as enhancing avulsion frequency in other fluvial systems³⁹.

In totality, our analyses suggest that wet and dry years may play complementary roles in channel avulsion and abandonment within the Okavango. High-water years supply the energy to initiate avulsions and activate NE channels, whereas low-flood years reduce conveyance through the SW channels and create conditions for vegetation encroachment and channel abandonment. The 2010-2012 high water years, compounded by the record-low flood of 2019 that further degraded SW delivery, produced the system-scale reorganization recorded in the post-2012 AdDSWE archive. Other ecogeomorphic processes, including ecosystem engineers (e.g. hippopotamuses) and anthropogenic modification of flow paths may also have played a role in opening new flow paths towards the northeast, but represent much smaller scale forcings that are less likely to impact delta-scale flood distribution. Future work integrating higher-resolution imagery with channel-network vectorization and repeat mapping of active channel geometry could resolve how these hydrologic dynamics govern the frequency and spatial distribution of avulsions across the delta.

These finding hold implications for the future evolution of the Okavango. Projected increases in rainfall variability across the Angolan Highlands under anthropogenic climate change^{14,40} will produce more frequent extreme low-inflow years⁴¹. As documented here, such dry years disproportionately deactivate SW distributaries while NE systems maintain or gain

inundation share. Over the coming decades, this asymmetry could accelerate into increasingly irreversible consolidation of floodwater delivery into the NE distributary network. At geological timescales, this trajectory points toward a more profound reorganization: the Selinda Spillway already conveys Okavango floodwaters into the Zambezi basin during high-water years⁸, and the post-2012 wetting trend within Selinda-bound channels (Fig. 4c) and gain in inundation share (Fig. 3b, h) observed in the Magweggana Distributary suggests a decreased threshold for spillway activation in recent years. This dynamic could, in the long term, result in the loss of the delta's endorheic character and capture of its waters by the Zambezi system^{8,10}. This outcome operates at timescales far beyond the scope of water resource planning, however, and the complex hydrogeomorphic dynamics of the delta render simple extrapolation of present trends unreliable; the delta has experienced fluctuations in fluvial activity and flood distribution for thousands of years³⁸, and prior work has cautioned that the system's non-linear hydrologic responses can make transient shifts appear permanent, misinforming water management when trends are extrapolated prematurely⁷. Future flood distribution may therefore shift in directions that are difficult to anticipate from the current trajectory alone.

But communities depending on SW distributaries are impacted on management-relevant timescales, not geological ones. In the Okavango, permanent settlements sit mostly on the delta's periphery⁴² (Fig. 6), while the interior hosts ecotourism infrastructure that draw visitors to flood dependent fauna. As SW inundation declines, surface water delivery will become less reliable to settlements nearest the delta's SW margins who depend on *molapo* flood recession agriculture, fishing, and livestock^{43–45}. Flood timing and connectivity between distributary channels and adjacent wetlands determines habitat availability for fauna including migratory birds and large mammal communities^{46,47}, and declining inundation in the SW risks fragmenting habitat corridors and reducing the ecosystem's carrying capacity^{24,48}. In addition to food security, biodiversity, and

ecotourism, the flood cycle determines the magnitude and persistence of carbon-sequestering peat formations^{49,50}, while carbon and nutrient fluxes are modulated by channel–wetland connectivity and phenology^{21–23}. Abnormally dry conditions in the SW may further drive harmful algal blooms⁵¹, shift floodplain vegetation toward drought-tolerant assemblages⁵², and accelerate the ecogeomorphic feedbacks that reduce channel capacity and further diminish water delivery.

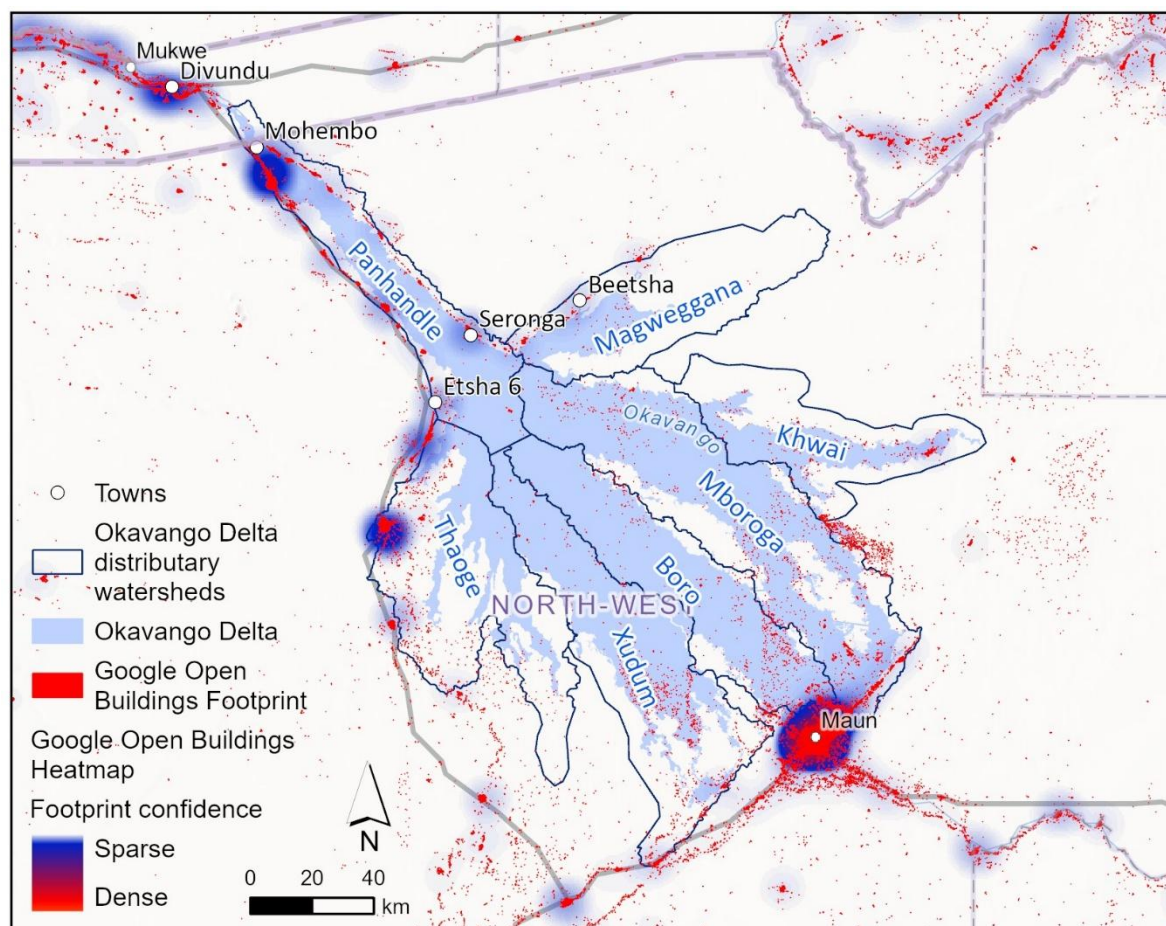


Fig. 6. Building and community distribution around the Okavango Delta. Building footprints (red) and density.

Addressing these converging risks requires not only improved scientific understanding of the delta's flood dynamics, but the development of accessible, near-real-time monitoring tools capable of tracking flood pulse arrival, spatial distribution, and recession across the delta. Products such as AdDSWE provide a foundational resource for this work, enabling the calibration

and validation of hydrological models, the construction of improved water budgets, and the benchmarking of future flood conditions against a long-term baseline. We demonstrated the utility of AdDSWE by finding that the Okavango Delta's flood pulse has undergone a coherent, system-wide redistribution toward the northeast since the mid-2010s following the 2010–2012 La Niña, and intensified during subsequent dry years. AdDSWE products applied to other flood-out wetlands in the Global South could similarly help document the extent, dynamic nature, and regional or global role of these vastly understudied systems^{53,54}.

Some interpretive caveats apply to the AdDSWE total inundation product. The lower-confidence classes (1 and 2) are designed to capture vegetated and transitional inundation; conditions where water is present but partially obscured by emergent vegetation or mixed with high-moisture soil signals. As with the binary SWIR thresholding approach of Inman and Lyons,¹⁶, these classes map broadly where surface water or saturated conditions are detectable, but may modestly misclassify high-moisture soils and dense wet vegetation as inundated. True inundation extent therefore likely falls between the open water extent (classes 3–4) and the total inundation extent (classes 1–4) reported here, with the open water product providing a conservative lower bound and the total inundation product an upper bound on total surface water area. Users working with the AdDSWE products should consider which confidence classes are appropriate for their application rather than treating total inundation as a single ground truth. Additionally, while the iterative temporal gap-filling approach (Supplementary Note 2) successfully maintained high spatial coverage across the archive, gap-filling necessarily draws on imagery from adjacent months and may introduce subtle temporal inaccuracies in areas where flood conditions change rapidly; we recommend users consult the accompanying QC mask products alongside the AdDSWE classification. Emerging SAR-based approaches, including Sentinel-1 interferometric coherence time series that can detect flood pulse arrival timing through cloud cover^{55,56}, offer a promising

complement to optical methods for resolving flood dynamics during the wet season, though such products do not yet provide the multiclass confidence structure or multi-decadal record of AdDSWE.

AdDSWE synthesizes two approaches previously applied independently in the Okavango: SWIR2-based water detection^{16,29} and the multiclass confidence framework of DSWE^{26,27}, into a single classification that discriminates open water from vegetated and transitional inundation. Practically, this results in an expansion of detected inundation extent relative to standard DSWE, concentrated in vegetated wetland margins and shallow flood zones (Fig. 7b, d). At 30 m resolution, AdDSWE resolves permanent pools, dry islands, and some distributary channels and vegetated levees (Fig. 4) that are subsumed into mixed pixels at the 250 m to 1 km resolutions of MODIS and AVHRR-based products; the lower total inundation extents reported here relative to MODIS-based estimates (Supplementary Fig. 4a) therefore reflect improved spatial fidelity rather than undercounting, consistent with Inman and Lyons,¹⁶ who found that 30 m Landsat classified systematically less area as inundated relative to comparable coarse-resolution products. Monthly compositing enables characterization of flood pulse arrival, peak, recession, and the timing of propagation amongst individual distributaries. The multiclass confidence structure distinguishes open water from WUC, interpreted here as vegetated or transitional wetland, a discrimination that is not merely taxonomic: open water and WUC or seasonally flooded land represent fundamentally different conditions for habitat connectivity, carbon flux, and channel–wetland exchange.

Our data reveal that the Okavango Delta’s flood pulse has undergone a coherent, system-wide reorganization since 2012, driven by the compound effect of tectonics, an exceptional La Niña-driven series of large annual floods, and the subsequent, equally exceptional series of dry years. This reorganization is already redirecting water away from the communities, wildlife, and carbon stores that depend on SW surface water delivery, and is unlikely to reverse to pre-2012

conditions as extreme wet and dry years become more frequent across the Angolan Highlands and the Okavango Delta.

4. Methods

4.1. Study area

The delta's endorheic, fault-controlled character precludes standard watershed delineation. Thus, we defined the study boundary by synthesizing several prior hydrologic studies of the system^{6,15,16} (Fig. 1) and applying a buffer around the resulting delta polygon to capture all active and historical distributary channels while excluding Lake Ngami and its input channels. We defined distributary boundaries within the delta by combining the HydroSHEDS framework⁵⁷ with distributary boundaries established in previous work^{36,37}. We delineated a second study area encompassing the upstream Cuito and Cubango watersheds using HydroSHEDS; this upstream catchment boundary, referred to as the Angolan Highlands Water Tower³, was used exclusively for calculating cumulative water-year precipitation totals for the basin.

4.2. Data processing and the Adapted DSWE algorithm

We mapped monthly inundation dynamics across the full study period (June 1984–December 2025) using Landsat Tier 1 Collection 2 surface reflectance products from Landsat 5 TM, 7 ETM+, 8 OLI/TIRS, and 9 OLI-2/TIRS-2 at 30 m resolution, processed in Google Earth Engine⁵⁸. Landsat 7 ETM+ was included only through May 2003, after which scan line corrector failure rendered the data unsuitable; a complete data gap also exists in 2012. We masked clouds and shadows using Landsat QA_PIXEL flags, and generated monthly cloud-free composites as pixel-wise medians of all available scenes within each calendar month. When a given month's composite fell below 95% spatial coverage of the delta, we applied iterative temporal gap-filling, incorporating imagery from progressively wider windows of adjacent months (± 1 , ± 2 , ± 3 months) until the coverage threshold was met, an adaptation of methods used in prior Okavango inundation

studies¹⁶. The temporal expansion needed for each pixel is reported in monthly QC rasters, and the overall degree of expansion needed across the AdDSWE dataset is discussed in supplementary materials (Supplementary Note 2).

We classified each monthly Landsat composite using the AdDSWE algorithm, which builds on the original DSWE decision-tree framework^{26,27}. DSWE applies five spectral tests whose binary outcomes inform a decision-tree which assigns each pixel to one of five confidence classes ranging from not water to high-confidence open water; AdDSWE applies these tests using the original DSWE²⁶ thresholds without modification but also introduces a sixth spectral test based on dynamic SWIR2 thresholding (Test 6), motivated by the sensitivity of SWIR2 reflectance to water absorption beneath dense vegetation^{59,60}, and the demonstrated effectiveness of SWIR-based approaches in the Okavango^{16,29}. For each monthly composite, we constructed a 100-bin SWIR2 reflectance histogram, smoothed the counts with a Gaussian kernel ($\sigma = 2$ bins), and set the monthly water/land threshold as the deepest local minimum between the two most prominent peaks (prominence $\geq 10\%$ of the maximum). When fewer than two prominent peaks were detected, the threshold fell back to the 30th percentile of the SWIR2 distribution. Pixels falling below this threshold were upgraded by one confidence level: class 0 promoted to class 1, class 1 to class 2, class 2 to class 3, and class 3 to class 4, with class 4 pixels unchanged. To reduce false positives from isolated misclassified vegetation, we applied morphological filtering using 8-neighbor connectivity, removing connected pixel clusters smaller than 2,000 pixels (~ 180 ha) where all pixels exhibited confidence of class 2 or below; clusters containing any pixel of class 3 or higher were retained regardless of size. We determined the 2,000-pixel cluster threshold through iterative testing to optimally suppress misclassification while remaining computationally tractable for batch processing across the 40-year Landsat archive. The final monthly products include a five-class confidence AdDSWE product and a quality control (QC) raster recording the gap-filling expansion

level applied to each pixel, and the RGB composite of the source image used to generate the AdDSWE product.

4.3. Product validation

4.3.1. Open water validation

We assessed the open water accuracy of AdDSWE through visual interpretation of 1,420 stratified validation points spanning five Landsat sensor eras and four hydrological phases. For each sensor era, 70 points (75 in the 2008 era) were independently sampled across the delta and evaluated across all four phases within that era. The four hydrological phases captured low water (January/December), rising flood (April), peak inundation (July), and recession (October); the five sensor eras represented all combinations of active Landsat missions across the archive: 1994 (Landsat 5 only), 2000 (Landsat 5 and 7, pre-scan line corrector failure), 2008 (Landsat 5 only), 2015 (Landsat 8 only), and 2024 (Landsat 8 and 9). For each point-month-year combination, an analyst visually inspected the corresponding Landsat RGB composite and independently classified the location as "open water" or "not open water," with an uncertainty flag recorded where interpretation was ambiguous.

We first constructed a class-specific error matrix to characterize how each AdDSWE confidence class distributed between the open water and not-open-water reference categories, in order to determine which confidence classes corresponded operationally to open water. The matrix showed that classes 3 and 4 best capture open water: of pixels assigned to AdDSWE classes 0, 1, and 2, 100%, 95.5%, and 92.2% were reference-confirmed as not open water respectively, while 98.3% of class 4 pixels corresponded to open water. Class 3 exhibited mixed correspondence, with 74.4% of pixels corresponding to open water. Classes 3 and 4 are therefore referred to throughout as moderate-confidence open water and high-confidence open water respectively, and we defined the binary open water product as the union of classes 3 and 4. Under

this binary definition, AdDSWE achieved an overall accuracy of 94.5% ($\kappa = 0.89$) across all 1,420 validation points, with producer's and user's accuracies for the open water class of 95.2% and 92.2% respectively. Restricting the analysis to the 1,162 points classified by the analyst with high certainty raised overall accuracy to 98.7%, indicating that the bulk of classification disagreement occurred at points where the reference interpretation was itself ambiguous. Stratifying these metrics across sensor eras and hydrological phases yielded standard deviations of 1.6% and 1.3% in overall accuracy respectively, with no sensor era nor hydrological phase falling below 92%, indicating that open water detection is robust to radiometric differences between Landsat sensors and to seasonal variation in cloud cover and flood extent. Full classification accuracy metrics are reported in supplementary materials (Supplementary Fig. 5; Supplementary Table 1).

4.3.2. Total inundation validation

To validate total inundation extent (AdDSWE classes ≥ 1) we compared AdDSWE against published annual maximum flood extent maps of Inman and Lyons¹⁶, who applied SWIR2 thresholding to Landsat composites to map annual July–October (JASO) peak inundation across the delta. Their approach closely matches the Test 6 logic in AdDSWE and achieved an overall accuracy of 91.5–98.1% against *in situ* GPS observations of standing water and high-resolution imagery. Spatial overlay of the two products across representative areas of the delta shows that AdDSWE detects flooded vegetation that the standard DSWE algorithm misses, consistent with the design of Test 6 (Fig. 7a–d). At the annual scale, we compared AdDSWE maximum JASO inundation extent against the Inman and Lyons¹⁶ record, using the JASO window to align with the Landsat compositing window of that study; the two records agreed strongly ($R^2 = 0.9$, $p < 0.001$, slope = 1.02, $n = 23$; Fig. 7e, f). We also correlated AdDSWE maximum JASO inundation extent with total water-year precipitation from the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) dataset³⁰, extracted over the upstream Angolan Highlands Water Tower catchment area.

We defined the water year as July 1 of the prior calendar year through June 30 of the year of inundation, with the annual boundary aligned to the precipitation minimum in the upstream watershed. Maximum JASO inundation scaled positively with antecedent water-year total precipitation ($R^2 = 0.55$, $p < 0.001$, $n = 34$; Fig. 7e), consistent with the well-documented upstream precipitation–inundation relationship in the delta^{17,29}. Comparisons with coarser-resolution products, including MODIS-based studies^{15,29,31}, AVHRR-based estimates^{6,61}, and the global surface water dataset of Pekel et al.⁶², are presented in the supplementary materials (Supplementary Fig. 4a) as contextual benchmarks rather than primary validation given the substantial differences in spatial resolution and detection methodology relative to AdDSWE. Additionally, we discuss the potential misclassification of burn scars as inundation in the supplementary materials (Supplementary Note 3).

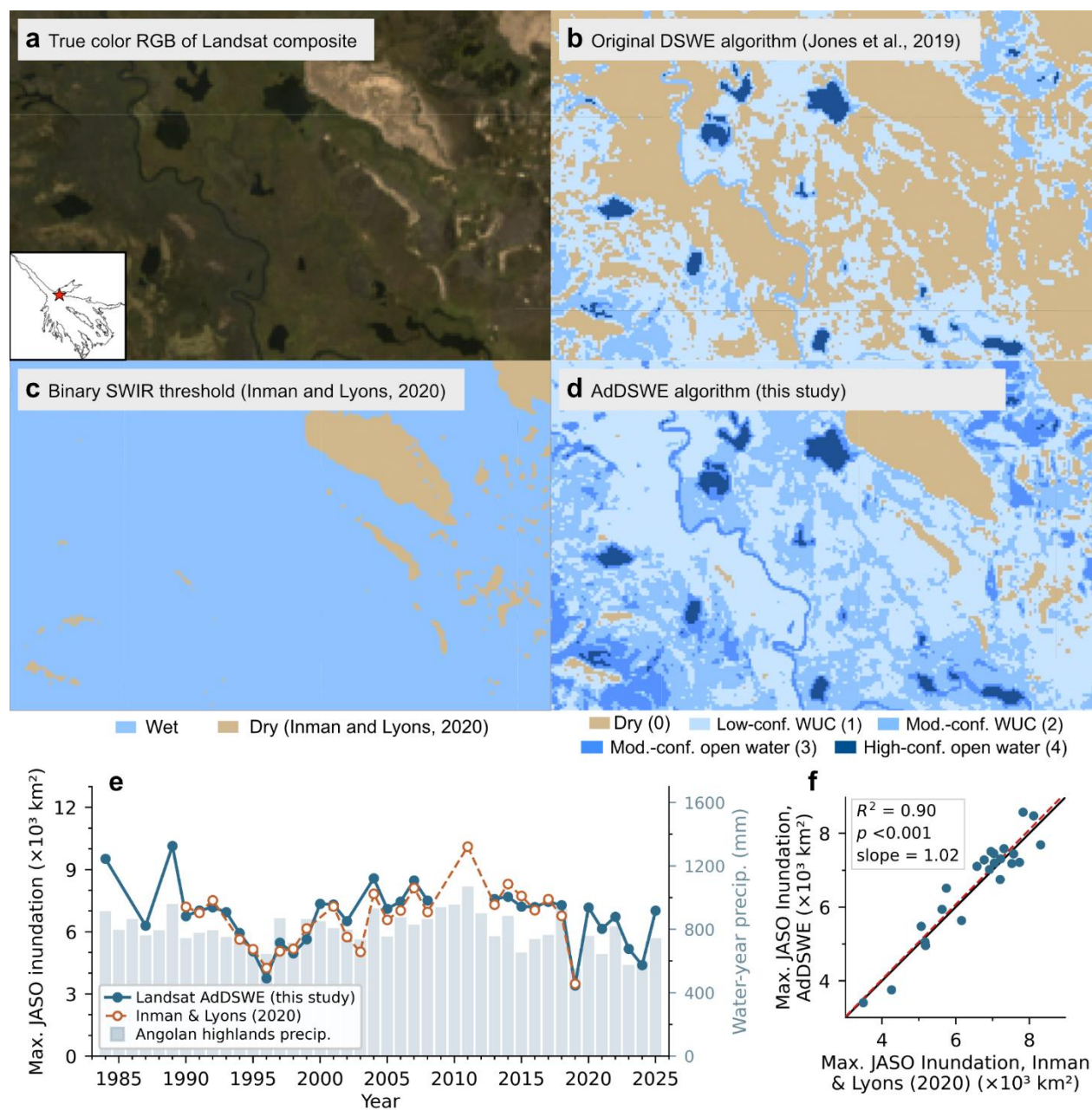


Fig. 7. Validation of the Adapted Dynamic Surface Water Extent (AdDSWE) total inundation area calculations. **a** True-color Landsat composite of a representative delta sub-region located at the red star in the inset delta map. Inundation classifications of the same scene using **b** the original DSWE algorithm²⁶, **c** the binary shortwave infrared (SWIR) threshold of Inman and Lyons⁷⁶, and **d** AdDSWE (this study). **e** Annual maximum July/August/September/October (JASO) inundation extent from AdDSWE (blue) and Inman and Lyons (orange), with total water-year precipitation over the Angolan Highlands (gray bars). **f** Scatter of annual maximum JASO inundation from AdDSWE against Inman and Lyons; 1:1 line in black, linear fit in red.

4.4. Detecting spatial redistribution in the flood pulse

We employed three complementary analyses to test whether the AdDSWE record captures significant changes in flood distribution: trend and change-point tests applied to each major distributary's share of delta-wide inundation expressed as z-scores (Fig. 3), a per-pixel difference map of sub-period means (Fig. 4), and the lateral migration of the confidence-weighted inundation centroid (Fig. 5). We perform all distributary-scale analyses for both total inundation (AdDSWE classes ≥ 1) and open water (AdDSWE classes 3 and 4).

4.4.1. Distributary-scale analysis of inundation trends

To test for systematic redistribution in the share of floodwaters among distributaries, we calculated monthly total inundation area and monthly open water area within each of the six major distributaries (Boro, Thaoge, Xudum, Mboroga, Khwai, Magweggana) and the Panhandle. Because raw inundation areas are strongly modulated by inter-annual variability in total flood magnitude, we first expressed each distributary's monthly inundation as a fraction of delta-wide inundation in that month:

$$f_{d,y,m} = \frac{A_{d,y,m}}{\sum_{d=1}^7 A_{d,y,m}} \quad (1)$$

where $A_{d,y,m}$ is the inundation area of distributary d in year y and calendar month m , and the denominator sums over all seven regions. To further remove the strong seasonal cycle in these fractions, we standardized each distributary's time series into monthly z-scores by computing the mean and standard deviation of $f_{d,y,m}$ separately for each of the twelve calendar months across all available years:

$$z_{d,y,m} = \frac{f_{d,y,m} - \mu_{d,m}}{\sigma_{d,m}} \quad (2)$$

where $\mu_{d,m}$ and $\sigma_{d,m}$ are the climatological mean and standard deviation of distributary d inundation share for calendar month m , computed across all years in the record. The resulting z-score time series represent anomalies in each distributary's share of delta inundation relative to its seasonal norm. Then we aggregated monthly z-scores into annual means, retaining only calendar years with at least eight valid monthly observations to avoid bias from sparsely sampled years. To account for serial correlation, prior to testing we applied trend-free pre-whitening⁶³ (TFPW) to series where the lag-1 autocorrelation was statistically significant⁶⁴. We then applied three tests to each of the six distributaries and the Panhandle. First, we applied the Mann-Kendall trend test^{32,33}, reporting Kendall's τ as the trend effect size. Because we tested seven regions simultaneously, we controlled the false discovery rate across each seven-test family using the Benjamini-Hochberg procedure⁶⁵ at $\alpha = 0.05$ and report FDR-adjusted p-values. Second, we applied the sequential Mann-Kendall test³⁵ to the same series to estimate trend onset years. Third, we applied the Pettitt change-point test³⁴ to the annual series without pre-whitening, identifying the year that maximally separates the pre- and post-break distribution. We tested the raw series because the detrending step within TFPW partially absorbs genuine step changes. We assessed Pettitt significance against an empirical null of 100,000 AR(1) surrogate series⁶⁶.

To quantify the delta-wide redistribution as a single annual index, we computed an annual divergence value:

$$D_t = \overline{z_{NE,t}} - \overline{z_{SW,t}} \quad (3)$$

for both total inundation and open water datasets, where $\overline{z_{NE,t}}$ is the mean of the three NE distributary monthly z-scores in year t and $\overline{z_{SW,t}}$ the mean of the three SW. The Panhandle is excluded from both groups. We compared the pre-2011 and post-2012 distributions of D using the Mann-Whitney U test⁶⁷. To test whether the divergence–flood-magnitude relationship was offset

between epochs, we fit an analysis of covariance⁶⁸ (ANCOVA), centered at the mean of peak annual flood extent. We defined peak annual flood extent as the maximum monthly inundation extent over May–October, computed from total inundation and open water, respectively. For reasoning behind the window used for peak flood inundation throughout this study, see Supplementary Note 4. We also quantified the within-epoch association between D and flood magnitude using Spearman's rank correlation.

4.4.2. *AdDSWE mean difference map*

To resolve the local features driving the regional redistribution of floodwater, we computed the mean AdDSWE class value at every 30 m pixel within each epoch using all available monthly composites, then took the post-minus-pre difference (Fig. 4). We computed epoch means by first averaging all available scenes within each calendar month and then averaging the twelve-monthly means with equal weight, ensuring uniform seasonal weighting despite irregular monthly scene availability. The 30 m resolution resolves individual channels, lakes, lagoons, and channel-margin features, allowing localized wetting (positive values) and drying (negative values) to be attributed to specific hydrologic and geomorphic processes (channel activation or abandonment, lagoon expansion or desiccation, and lateral migration of meandering river channels) that are not visible at the distributary-aggregated scale of the trend analyses presented here. The mean difference raster depicted in Fig. 4 is available alongside the AdDSWE products.

4.4.3. *AdDSWE class-weighted centroid migration*

To characterize directional shifts in the spatial distribution of inundation across the delta as a whole, we computed a monthly inundation centroid as the AdDSWE-class-weighted mean of all inundated pixel coordinates (classes ≥ 1), giving higher-confidence and open water pixels proportionally greater weight than lower-confidence and partial water pixels. We averaged the monthly centroids within each calendar year to produce annual coordinates, retaining only years

with at least eight valid monthly observations. The annual coordinates were projected into a channel-oriented reference frame aligned with the principal downstream axis of the delta fan (azimuth 137° from north; Fig. 1), decomposing displacement into streamwise (positive = distal) and cross-channel (positive = river left) components. To test for directional migration of the centroid through time, we fitted ordinary least squares regressions of each component against time over three periods: the pre-2011 epoch (1984–2010), the post-2012 epoch (2013–2025), and the full record (1984–2025). The resulting slopes characterize the rate of centroid migration along each axis in each period.

Data availability

The AdDSWE monthly inundation products and all other data supporting the findings of this study are available for download in the Dryad Digital Repository at: http://datadryad.org/share/LINK_NOT_FOR_PUBLICATION/Sru8DTYQWEGTF2qJgKucqzmbuNf52ukuR0OnyRkmY8. The monthly products and the mean difference map shown in Fig. 4 can also be viewed interactively at <https://okavango-water-mask-viewer.streamlit.app/>. Landsat Collection 2 surface reflectance imagery is publicly available through the USGS Earth Resources Observation and Science Center and Google Earth Engine. River discharge data were obtained from the Global Runoff Data Centre, 56068 Koblenz, Germany (<https://grdc.bafg.de>). CHIRPS precipitation data are publicly available from the Climate Hazards Center, University of California, Santa Barbara (<https://www.chc.ucsb.edu/data/chirps>). The Oceanic Niño Index is publicly available from the NOAA Climate Prediction Center (https://www.cpc.ncep.noaa.gov/products/analysis_monitoring/enso/oni/v6/). Google Open Buildings V3 data are publicly available from Google Research (<https://sites.research.google/gr/open-buildings/>) under Creative Commons Attribution 4.0 and Open Data Commons Open Database License v1.0.

597 **Code availability**

598 The Google Earth Engine and Python code used to generate the AdDSWE inundation record and to
 599 perform the statistical analyses is available at <https://github.com/huck-rees/Okavango>.

600 **References**

- 601 1. Garba, S. I., Ebmeier, S. K., Bastin, J.-F., Mollicone, D. & Holden, J. Wetland fragmentation
 602 associated with large populations across Africa. *Nat Commun* **16**, 5065 (2025).
- 603 2. Li, A. *et al.* African inland wetland area on the rise during the 21st century. *Nat Commun* **17**,
 604 3600 (2026).
- 605 3. Lourenço, M. & Woodborne, S. Defining the Angolan Highlands Water Tower, a 40 plus-year
 606 precipitation budget of the headwater catchments of the Okavango Delta. *Environ Monit*
 607 *Assess* **195**, 859 (2023).
- 608 4. Steudel, T. Okavango Basin - Hydrology. *Biodivers. Ecol.* **5**, 19 (2013).
- 609 5. Ellery, W. N. & McCarthy, T. S. Principles for the sustainable utilization of the Okavango Delta
 610 ecosystem, Botswana. *Biological Conservation* **70**, 159–168 (1994).
- 611 6. Gumbricht, T., Wolski, P., Frost, P. & McCarthy, T. S. Forecasting the spatial extent of the
 612 annual flood in the Okavango delta, Botswana. *Journal of Hydrology* **290**, 178–191 (2004).
- 613 7. Wolski, P. & Murray-Hudson, M. An investigation of permanent and transient changes in flood
 614 distribution and outflows in the Okavango Delta, Botswana. *Physics and Chemistry of the*
 615 *Earth, Parts A/B/C* **33**, 157–164 (2008).
- 616 8. Gumbricht, T., McCarthy, T. S. & Merry, C. L. The topography of the Okavango Delta,
 617 Botswana, and its tectonic and sedimentological implications. *South African Journal of*
 618 *Geology* **104**, 243–264 (2001).

- 619 9. Smith, N. D., McCarthy, T. S., Ellery, W. N., Merry, C. L. & R  ther, H. Avulsion and
620 anastomosis in the panhandle region of the Okavango Fan, Botswana. *Geomorphology* **20**,
621 49–65 (1997).
- 622 10. Dauteuil, O. *et al.* Present-day Deformation in the Incipient Strike-slip Basin of the Okavango
623 Delta (Botswana): Impact on the Ecosystem. *τεκτονικα* **2**, 141–157 (2024).
- 624 11. Ellery, W. N., McCarthy, T. S. & Smith, N. D. Vegetation, hydrology, and sedimentation
625 patterns on the major distributary system of the Okavango fan, Botswana. *Wetlands* **23**, 357–
626 375 (2003).
- 627 12. McCarthy, T. S., Ellery, W. N. & Stanistreet, I. G. Avulsion mechanisms on the Okavango fan,
628 Botswana: the control of a fluvial system by vegetation. *Sedimentology* **39**, 779–795 (1992).
- 629 13. McCarthy, T. S. & Ellery, W. N. The fluvial dynamics of the Maunachira channel system,
630 northeastern Okavango swamps, Botswana. *Water SA*. **23**, 115–126 (1997).
- 631 14. Gaughan, A. E. & Waylen, P. R. Spatial and temporal precipitation variability in the Okavango–
632 Kwando–Zambezi catchment, southern Africa. *Journal of Arid Environments* **82**, 19–30 (2012).
- 633 15. Thito, K., Wolski, P. & Murray-Hudson, M. Mapping inundation extent, frequency and duration
634 in the Okavango Delta from 2001 to 2012. *African Journal of Aquatic Science* **41**, 267–277
635 (2016).
- 636 16. Inman, V. L. & Lyons, M. B. Automated Inundation Mapping Over Large Areas Using Landsat
637 Data and Google Earth Engine. *Remote Sensing* **12**, 1348 (2020).
- 638 17. Milzow, C., Kgotlhang, L., Kinzelbach, W., Meier, P. & Bauer-Gottwein, P. The role of remote
639 sensing in hydrological modelling of the Okavango Delta, Botswana. *Journal of Environmental*
640 *Management* **90**, 2252–2260 (2009).

18. Ivory, S. J., McGlue, M. M., Spera, S., Silva, A. & Bergier, I. Vegetation, rainfall, and pulsing hydrology in the Pantanal, the world's largest tropical wetland. *Environ. Res. Lett.* **14**, 124017 (2019).
19. Murray-Hudson, M., Wolski, P. & Ringrose, S. Scenarios of the impact of local and upstream changes in climate and water use on hydro-ecology in the Okavango Delta, Botswana. *Journal of Hydrology* **331**, 73–84 (2006).
20. Tsheboeng, G., Bonyongo, M. & Murray-Hudson, M. Environmental factors that influence species diversity of floodplain plant communities in different flooding phases in the Okavango Delta, Botswana. *Bothalia ABC* **50**, (2020).
21. Akoko, E. River-wetland interaction and carbon cycling in a semi-arid riverine system: the Okavango Delta, Botswana. *Biogeochemistry* <https://doi.org/10.1007/S10533-012-9817-X> (2013) doi:10.1007/S10533-012-9817-X.
22. Helfter, C. *et al.* Phenology is the dominant control of methane emissions in a tropical non-forested wetland. *Nat Commun* **13**, 133 (2022).
23. Oromeng, K. V., Atekwana, E. A., Molwalefhe, L. & Ramatlapeng, G. J. Time-series variability of solute transport and processes in rivers in semi-arid endorheic basins: The Okavango Delta, Botswana. *Science of The Total Environment* **759**, 143574 (2021).
24. Kgathi, D. L. *et al.* The Okavango; a river supporting its people, environment and economic development. *Journal of Hydrology* **331**, 3–17 (2006).
25. Milzow, C., Burg, V. & Kinzelbach, W. Estimating future ecoregion distributions within the Okavango Delta Wetlands based on hydrological simulations and future climate and development scenarios. *Journal of Hydrology* **381**, 89–100 (2010).
26. Jones, J. W. Improved Automated Detection of Subpixel-Scale Inundation—Revised Dynamic Surface Water Extent (DSWE) Partial Surface Water Tests. *Remote Sensing* **11**, 374 (2019).

- 665 27. Jones, J. W. Efficient Wetland Surface Water Detection and Monitoring via Landsat:
666 Comparison with in situ Data from the Everglades Depth Estimation Network. *Remote*
667 *Sensing* **7**, 12503–12538 (2015).
- 668 28. Larsen, L. G., Harvey, J. W., null, null & null, null. How Vegetation and Sediment Transport
669 Feedbacks Drive Landscape Change in the Everglades and Wetlands Worldwide. *The*
670 *American Naturalist* **176**, E66–E79 (2010).
- 671 29. Wolski, P., Murray-Hudson, M., Thito, K. & Cassidy, L. Keeping it simple: Monitoring flood
672 extent in large data-poor wetlands using MODIS SWIR data. *International Journal of Applied*
673 *Earth Observation and Geoinformation* **57**, 224–234 (2017).
- 674 30. Funk, C. *et al.* The climate hazards infrared precipitation with stations—a new environmental
675 record for monitoring extremes. *Sci Data* **2**, 150066 (2015).
- 676 31. Hofmann, D. D., Behr, D. M., McNutt, J. W., Ozgul, A. & Cozzi, G. Dispersal and connectivity in
677 increasingly extreme climatic conditions. *Glob Chang Biol* **30**, e17299 (2024).
- 678 32. Kendall, M. G. *Rank Correlation Methods*. (Charles Griffin, 1975).
- 679 33. Mann, H. B. Nonparametric Tests Against Trend. *Econometrica* **13**, 245–259 (1945).
- 680 34. Pettitt, A. N. A Non-Parametric Approach to the Change-Point Problem. *Journal of the Royal*
681 *Statistical Society: Series C (Applied Statistics)* **28**, 126–135 (1979).
- 682 35. Sneyers, R. On the Statistical Analysis of Series of Observations. in vol. 3 192 (Geneva, 1990).
- 683 36. Wolski, P. & Murray-Hudson, M. Flooding dynamics in a large low-gradient alluvial fan, the
684 Okavango Delta, Botswana, from analysis and interpretation of a 30-year hydrometric record.
685 *Hydrology and Earth System Sciences* (2006).
- 686 37. Wolski, P. & Murray-Hudson, M. Recent changes in flooding in the Xudum distributary of the
687 Okavango Delta and Lake Ngami, Botswana : research letter. *South African Journal of*
688 *Science* **102**, 173–176 (2006).

38. Tooth, S. *et al.* Significantly enhanced mid Holocene fluvial activity in a globally important, arid-zone wetland: The Okavango Delta, Botswana. *Earth Surface Processes and Landforms* **47**, 854–871 (2022).
39. Morón, S. *et al.* Avulsion triggering by El Niño–Southern Oscillation and tectonic forcing: The case of the tropical Magdalena River, Colombia. *GSA Bulletin* **129**, 1300–1313 (2017).
40. Kusangaya, S., Warburton, M. L., Archer van Garderen, E. & Jewitt, G. P. W. Impacts of climate change on water resources in southern Africa: A review. *Physics and Chemistry of the Earth, Parts A/B/C* **67–69**, 47–54 (2014).
41. Murray-Hudson, M. Alternative futures’ of the Okavango Delta simulated by a suite of global climate and hydro-ecological models. *Water SA* <https://doi.org/10.4314/WSA.V34I5.180658> (2018) doi:10.4314/WSA.V34I5.180658.
42. Sirko, W. *et al.* Continental-Scale Building Detection from High Resolution Satellite Imagery. Preprint at <https://doi.org/10.48550/arXiv.2107.12283> (2021).
43. Mosepele, K., Kolding, J., Bokhutlo, T., Mosepele, B. Q. & Molefe, M. The Okavango Delta: Fisheries in a fluctuating floodplain system. *Front. Environ. Sci.* **10**, 854835 (2022).
44. Phonchi-Tshekiso, N. D., Sitas, N. & Selomane, O. Community perceptions on land and water acquisitions in the Okavango Delta: implications for rural livelihoods. *Ecosystems and People* **20**, 2374756 (2024).
45. Shinn, J. E. Governing for local livelihoods in transboundary river systems: insights from the Cubango-Okavango River Basin. *Reg Environ Change* **24**, 120 (2024).
46. Francis, R., Bino, G., Inman, V., Brandis, K. & Kingsford, R. T. The Okavango Delta’s waterbirds – Trends and threatening processes. *Global Ecology and Conservation* **30**, e01763 (2021).

- 711 47. Inman, V. L., Bino, G., Kingsford, R. T., Chase, M. J. & Leggett, K. E. A. Temporal and spatial
712 patterns of common hippopotamus populations in the Okavango Delta, Botswana.
713 *Freshwater Biology* **67**, 630–642 (2022).
- 714 48. Gontse, K. A livelihoods assessment of Okavango Delta communities in the villages of Tubu,
715 Habu, and Nokaneng. *GeoJournal* **90**, 13 (2024).
- 716 49. Ellery, W. N., Ellery, K., McCarthy, T. S., Cairncross, B. & Oelofse, R. A peat fire in the
717 Okavango Delta, Botswana, and its importance as an ecosystem process. *African Journal of*
718 *Ecology* **27**, 7–21 (1989).
- 719 50. Ellery, W. N. & Ellery, K. The Okavango Delta Peatlands. in *Landscapes and Landforms of*
720 *Botswana* (ed. Eckardt, F. D.) 37–56 (Springer International Publishing, Cham, 2022).
721 doi:10.1007/978-3-030-86102-5_3.
- 722 51. Veerman, J., Mishra, D. R., Kumar, A. & Karidozo, M. Environmental drivers behind the
723 exceptional increase in cyanobacterial blooms in Okavango Delta, Botswana. *Harmful Algae*
724 102677 (2024) doi:10.1016/j.hal.2024.102677.
- 725 52. Gule, T. T., Tsheboeng, G., Dlamini, W. M., Mabaso, S. D. & Cassidy, L. Change detection of
726 riparian woodland vegetation in the Okavango Delta, Botswana. *Remote Sensing*
727 *Applications: Society and Environment* **22**, 100497 (2021).
- 728 53. Grenfell, S. *et al.* Wetlands in drylands: diverse perspectives for dynamic landscapes.
729 *Wetlands Ecol Manage* **30**, 607–622 (2022).
- 730 54. Knight, J. & Lourenço, M. Wetlands of Angola. in *Wetlands of Tropical and Subtropical Asia*
731 *and Africa* 137–160 (John Wiley & Sons, Ltd, 2025). doi:10.1002/9781394235278.ch7.
- 732 55. Gaudaré, L. *et al.* Flood pulse monitoring in wetlands with multi-temporal Sentinel-1
733 interferometric coherence data: Application to the Okavango Delta (Botswana). *Remote*
734 *Sensing of Environment* **334**, 115173 (2026).

- 735 56. Hübinger, C., Fluet-Chouinard, E., Escobar, D. & Jaramillo, F. Exploring the potential of using
736 L-band InSAR for mapping flooded vegetation in tropical wetlands. *Remote Sensing of*
737 *Environment* **332**, 115086 (2026).
- 738 57. Lehner, B., Verdin, K. & Jarvis, A. New Global Hydrography Derived From Spaceborne
739 Elevation Data. *Eos, Transactions American Geophysical Union* **89**, 93–94 (2008).
- 740 58. Gorelick, N. *et al.* Google Earth Engine: Planetary-scale geospatial analysis for everyone.
741 *Remote Sensing of Environment* **202**, 18–27 (2017).
- 742 59. Brinkhoff, J., Backhouse, G., Saunders, M. E., Bower, D. S. & Hunter, J. T. Remote sensing to
743 characterize inundation and vegetation dynamics of upland lagoons. *Ecosphere* **13**, e3906
744 (2022).
- 745 60. Lefebvre, G. *et al.* Introducing WIW for Detecting the Presence of Water in Wetlands with
746 Landsat and Sentinel Satellites. *Remote Sensing* **11**, (2019).
- 747 61. McCarthy, J. M. *et al.* Flooding Patterns of the Okavango Wetland in Botswana between 1972
748 and 2000. *ambi* **32**, 453–457 (2003).
- 749 62. Pekel, J.-F., Cottam, A., Gorelick, N. & Belward, A. S. High-resolution mapping of global
750 surface water and its long-term changes. *Nature* **540**, 418–422 (2016).
- 751 63. Yue, S., Pilon, P., Phinney, B. & Cavadias, G. The influence of autocorrelation on the ability to
752 detect trend in hydrological series. *Hydrological Processes* **16**, 1807–1829 (2002).
- 753 64. Douglas, E. M., Vogel, R. M. & Kroll, C. N. Trends in floods and low flows in the United States:
754 impact of spatial correlation. *Journal of Hydrology* **240**, 90–105 (2000).
- 755 65. Benjamini, Y. & Hochberg, Y. Controlling the False Discovery Rate: A Practical and Powerful
756 Approach to Multiple Testing. *Journal of the Royal Statistical Society: Series B*
757 *(Methodological)* **57**, 289–300 (1995).

66. Serinaldi, F. & Kilsby, C. G. The importance of prewhitening in change point analysis under persistence. *Stoch Environ Res Risk Assess* **30**, 763–777 (2016).
67. Mann, H. B. & Whitney, D. R. On a Test of Whether one of Two Random Variables is Stochastically Larger than the Other. *The Annals of Mathematical Statistics* **18**, 50–60 (1947).
68. Whitbread, K., Jansen, J., Bishop, P. & Attal, M. Substrate, sediment, and slope controls on bedrock channel geometry in postglacial streams. *Journal of Geophysical Research: Earth Surface* **120**, 779–798 (2015).

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Author contributions

H.R. conceived the study, collected data, developed and refined remote sensing algorithms, performed analyses, and authored the original draft. O.C. authored sections of the original draft and assisted with data visualization and open data compliance. M.L. assisted with data collection and figure development. L.W. assisted in data curation and interpretation. V.G., K.K.C., and L.G.L. provided supervision and reviewed and edited the manuscript. All authors contributed to project conceptualization and provided manuscript feedback.

781 **Competing interests**

782 The authors declare no competing interests.

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