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Monitoring-network change reshapes long-term Water Quality Index inference: A dual-frame analysis from Ghana

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Abstract

Purpose. Long-term water-quality records are widely used to judge whether rivers and other water bodies are improving or deteriorating, but interpretation becomes difficult when the monitoring network itself changes through time. Using Ghana's national Water Quality Index (WQI) record, we investigate two sources of apparent long-term change: variation over time at consistently monitored locations and changes in the set of stations contributing to the national record.

Methods. We analysed 41 surface-water stations across 20 reported years from 2005 to 2025 using a dual-frame design that compares the changing national network with a fixed panel of 19 long-running stations. The analysis combined robust station-level trends, multiplicity control, persistence screening, endpoint sensitivity, and leave-one-station-out analysis.

Results. After 2010, the full-network median exceeded the fixed-panel median in 13 of 16 reported years, with a median difference of + 1.55 WQI units. The fixed panel itself also showed a broad low-score period from 2012 to 2018, with the strongest negative departure in 2013. Station-level trends were heterogeneous, none remained significant after multiplicity correction, and four stations met the primary persistent-poor criterion.

Conclusions. Monitoring-network change and temporal variation within a fixed station panel can coexist. We therefore propose Dual-Frame Monitoring Inference (DFMI), which reports contemporary network conditions alongside a stable sentinel panel and station-specific evidence. DFMI offers environmental agencies a practical way to make long-term monitoring records more comparable, transparent, and useful for management as observation systems evolve.

1 Introduction

Long-term surface-water monitoring gains its greatest inferential value when changes in environmental condition are interpreted alongside changes in the system used to observe that condition. Monitoring objectives, station placement, representativeness, continuity, sampling frequency, measured variables, analytical consistency, and field access all influence what a reported trend can mean (Strobl & Robillard, 2008). At regional and national scales, the composition of the monitoring network also affects representativeness and statistical power (O'Hare et al., 2020). A national indicator can therefore move because environmental conditions changed at established sites, because the monitored population changed, because the measurement protocol changed, or because several of these processes occurred together.

This inference problem is international in scope. Coordinated ambient-water-quality monitoring remains uneven globally, with persistent capacity constraints in less-resourced systems (Kirschke et al., 2020). Across Africa, data scarcity continues to complicate assessment of progress toward good ambient water quality under Sustainable Development Goal 6 (Nkwasa et al., 2024). At the same time, improving monitoring capacity often means adding stations, sensors, parameters, or sampling campaigns.

Expansion is desirable because it increases contemporary spatial coverage, yet it creates a longitudinal paradox: a national summary can become more representative of the present while becoming less directly comparable with the past if the set of contributing sites has changed.

Water Quality Indices (WQIs) make this problem especially important because they compress multiple measurements into a single management score. Ghana's adapted WQI was designed to communicate ambient condition, compare water bodies, and flag sites for investigation (Darko et al., 2013). International reviews show that WQI meaning depends on parameter selection, weighting, normalisation, and aggregation (Fortes et al., 2023; Kachroud et al., 2019; Sinha & Jain, 2026). Longitudinal inference therefore requires both population and measurement comparability. In Ghana, the original 19-station programme was sampled five times yearly during 2005–2008, whereas the current programme is described as biannual, and accessible WRC documents are not fully identical in class-boundary conventions (Darko et al., 2013; Water Resources Commission, 2025, 2026a, 2026b). Accordingly, long-term interpretation benefits from explicitly tracking both monitoring-population and measurement-context changes across the record.

Ghana provides a particularly informative empirical setting because the expansion history is explicit. The Water Resources Commission (WRC) uses ambient-water-quality monitoring to support regulation, pollution control, resource management, and sustainable water use (Water Resources Commission, 2026b). Ghana's National Integrated Water Resources Management Plan identifies reliable water-quality information, stronger monitoring and information systems, research, and decision support as national priorities and connects water management with climate resilience, food production, human welfare, economic uses, catchment protection, and transboundary cooperation (Water Resources Commission, 2012). The published WRC surface-water record began with 19 stations in 2005, expanded to 40 by 2010, and reached 41 in 2013; 2009 is absent from the annual table (Water Resources Commission, 2026b). The observed national population therefore changed substantially during the period being interpreted as a long-term record.

Ghanaian studies provide important basin-level evidence on physicochemical conditions, WQI, sediments, mining pressures, potentially toxic elements, and ecological or health risks in the Densu, Birim, Pra, Offin, Ankobra, and related systems (Amoako et al., 2010; Asare-Donkor et al., 2018; Ashong et al., 2025; Darko et al., 2023; Faseyi et al., 2022; Nunoo et al., 2022; Ofosu et al., 2021). Together, these studies provide strong local process evidence while leaving the national longitudinal-inference problem in an evolving composite-index network open. The historical WRC/CSIR WQI study covered only the original 19 stations during 2005–2008 (Darko et al., 2013). The unresolved question is which part of an apparent national trajectory reflects like-for-like change and which part is sensitive to the changing observation system.

Accordingly, the central research question is: how does explicit incorporation of monitoring-network change alter the temporal conclusions drawn from a long national WQI record? We use a reproducible dual-frame design that compares the changing observed network with a fixed sentinel panel,

complements aggregate summaries with station-specific robust trends, preserves structured missingness, respects calendar adjacency, controls multiplicity, and tests endpoint and single-station influence. The resulting Dual-Frame Monitoring Inference (DFMI) framework provides an analytical architecture that separates contemporary monitored coverage from like-for-like longitudinal comparison and complements both with station-level diagnostics and a structured pathway to mechanism-based attribution. The objectives are to audit coverage and gaps, quantify composition sensitivity, estimate within-station change with robust uncertainty control, identify persistent low-score priorities, and organise the resulting evidence for subsequent mechanism-based analysis.

2 Related work and research gap

2.1 Water Quality Index construction and longitudinal comparability

Water Quality Indices (WQIs) compress multivariate measurements into management scores. Ghana's adapted WQI was designed to communicate ambient conditions, compare water bodies, flag sites for investigation, and assess pollution-control efforts (Darko et al., 2013). International reviews show that meaning depends on parameter selection, sub-index formulation, weighting, normalisation, aggregation, and intended use (Fortes et al., 2023; Kachroud et al., 2019). The systematic review by Sinha & Jain (2026) likewise identifies subjectivity, uncertainty, aggregation bias, and weak standardisation as continuing problems. In longitudinal analysis, observed score changes may therefore reflect environmental change, index construction, or both.

Recent studies in Water Science reinforce the management value of water-quality indexing and integrated condition assessment in African waters. Kanyika-Mbewe et al. (2026) used WQI and hydrochemical indicators to support irrigation management in Malawi, while Tuffour et al. (2026) integrated water, sediment, and biological evidence to assess the ecological quality of Ghana's Keta Lagoon. These studies address condition assessment; the complementary problem examined here is whether long-term conclusions remain comparable when the monitored population itself changes.

The Ghanaian record illustrates this comparability boundary. The original 19-station programme was sampled five times yearly during 2005–2008, with annual WQI derived from seasonal values (Darko et al., 2013), whereas the current programme is described as biannual (Water Resources Commission, 2026b). WRC materials also differ slightly in class-boundary inclusivity around 25, 50, and 80 (Water Resources Commission, 2025, 2026a). These documentation differences motivate a consistent emphasis on continuous WQI for longitudinal inference, with class summaries retained as complementary descriptive evidence and a versioned method history recommended for future reporting.

2.2 Monitoring-network design, representativeness, and institutional capacity

Monitoring-network design determines the environmental population observed. Freshwater-monitoring reviews emphasise objectives, station placement, representativeness, continuity, sampling frequency, variables, analytical consistency, and logistics (Strobl & Robillard, 2008). At national scale, site retention or removal alters representativeness and trend-detection power (O'Hare et al., 2020). Expansion thus improves spatial coverage but can weaken like-for-like temporal comparability when national summaries use a changing set of sites. This tension matters internationally because monitoring capacity remains uneven (Kirschke et al., 2020) and African data gaps constrain ambient-water-quality assessment (Nkwasa et al., 2024). Expansion therefore needs an explicit comparability architecture.

2.3 Trend inference, missingness, multiplicity, and temporal robustness

Water-quality trend studies commonly use Mann–Kendall tests and Theil–Sen slopes because they are robust to non-normality and outliers (Mann, 1945; Sen, 1968). Yet trend direction and conventional significance can depend on endpoint choice, missing-year structure, temporal aggregation, serial dependence, and effect magnitude (Zhou et al., 2023). Testing many stations also creates multiplicity; false-discovery-rate control limits expected false discoveries (Benjamini & Hochberg, 1995). In evolving networks, blanks may mean sampling not started, access failure, or missing measurement, and a multi-year gap is not a one-year transition. Robust longitudinal inference therefore combines effect sizes, uncertainty, structured missingness, actual calendar spacing, multiplicity control, and sensitivity checks.

2.4 Ghanaian basin evidence, mining pressures, and emerging monitoring technologies

Ghanaian studies provide strong parameter-level basin evidence but address different questions from national longitudinal inference. Densu studies examine physicochemical conditions, trace metals, seasonality, multivariate structure, and WQI (Amoako et al., 2010; Ofosu et al., 2021). Work in the Birim, Pra, Offin, Ankobra, and related systems documents hydrochemistry, sediments, mining pressures, potentially toxic elements, and ecological or health risks (Asare-Donkor et al., 2018; Ashong et al., 2025; Darko et al., 2023; Faseyi et al., 2022; Nunoo et al., 2022). A recent Ghana review identifies continuing monitoring, treatment-evidence, speciation, integration, and policy gaps (Amidu et al., 2026), while Qian et al. (2024) shows the value of integrating field measurements, sensors, hydrology, and rainfall. These approaches broaden the monitoring toolkit and are naturally complemented by historical network-comparability analysis.

2.5 Climate, food-system, treatment, and economic significance

Reliable water-quality monitoring matters beyond environmental description. Hydroclimatic extremes and climate change can modify river-water quality through interacting hydrological and biogeochemical pathways (van Vliet et al., 2023). Water quality also intersects with irrigation, food production, and exposure pathways (Amuah et al., 2022) and drinking-water treatment costs (Price & Heberling, 2018).

These literatures establish the wider significance of water-quality monitoring and motivate a staged analytical sequence: first establish longitudinal comparability, then integrate rainfall, flow, land use, raw chemistry, treatment, food-system, and economic covariates for mechanism-based attribution.

2.6 Synthesis, research gap, and the Dual-Frame Monitoring Inference framework

Table 1 synthesises these streams. The literature establishes the usefulness and limitations of composite WQIs, the importance of monitoring-network design, the statistical demands of trend analysis, strong Ghanaian basin-level evidence, and the wider relevance of water quality to climate resilience and socioeconomic systems. What remains underdeveloped is an integrated analytical architecture for long national indicator series whose observation system changes through time. The historical WRC/CSIR study covers the original 19 stations during 2005–2008 (Darko et al., 2013), while later Ghanaian research is primarily basin-, pressure-, or technology-specific. This study extends that literature by analysing the complete 41-station WRC record through 2025 while combining an audit of network entry and structured gaps with changing-versus-fixed population comparison, multiplicity-aware station trends, genuine calendar adjacency, and endpoint and single-station sensitivity.

Table 1
Synthesis of related literature and the unresolved inferential problem.

Literature stream	Established knowledge	Unresolved issue	Role in this study
WQI construction	Composite indices support communication and screening but depend on parameters, weights, normalisation, and aggregation.	Long-term comparability benefits from versioned method and class-rule documentation.	Continuous WQI anchors longitudinal inference; class summaries provide descriptive context.
Monitoring-network design	Station placement, continuity, and representativeness affect coverage and trend power.	Network expansion changes the monitored population represented by annual summaries.	Current-network and fixed-sentinel summaries are analysed together.
Trend inference	Robust slopes and rank tests are useful, while missingness, serial dependence, endpoint choice, and multiplicity shape interpretation.	Multi-station inference benefits from multiplicity and sensitivity control.	Calendar-aware slopes, FDR control, endpoint, and influence checks are combined.
Ghanaian basin evidence	Basin studies document seasonal, mining-related, metal, sediment, and health/ecological concerns.	National longitudinal synthesis across changing monitoring populations remains underdeveloped.	Basin evidence contextualises station persistence and follow-up priorities.
Climate and socioeconomic consequences	Water quality interacts with hydroclimate, food systems, treatment costs, and economic activity.	Mechanism-based attribution benefits from external hydroclimatic, operational, and socioeconomic covariates.	DFMI structures the comparable response series for second-stage attribution.
Emerging monitoring technologies	Remote sensing and sensors can extend surveillance.	Historical comparability remains a complementary requirement as monitoring technologies evolve.	Network and technology evolution are incorporated within the observation-system perspective.

The Dual-Frame Monitoring Inference (DFMI) framework (Fig. 1) organises long-term WQI inference around two complementary network frames and station-level diagnostics. The current-network frame characterises the monitored sites represented in each reporting year, while the fixed-sentinel frame provides a like-for-like longitudinal comparison among consistently observed sites; neither frame, by itself, establishes representativeness of all Ghanaian surface waters. Station-level diagnostics resolve local trajectories, persistence, and heterogeneity that may be obscured by aggregate summaries. These perspectives are interpreted through safeguards addressing structured missingness, calendar-aware adjacency, multiplicity, endpoint sensitivity, and single-station influence, yielding information products on composition sensitivity, within-network temporal signal, and local heterogeneity. The framework then

provides a direct pathway to second-stage attribution using parameter-level measurements and mechanism-specific covariates.

The empirical contribution is to operationalise DFMI with Ghana's 2005–2025 WRC record. The analysis audits monitoring coverage and structured gaps, compares changing-network and fixed-sentinel WQI distributions, estimates within-station change with robust effect sizes and multiplicity control, and identifies persistent low-score priorities. Together, these analyses transform the national WQI archive into three complementary information products: composition sensitivity, within-network temporal signal, and station-level heterogeneity for targeted follow-up.

3 Data and methods

To structure inference from the long-run WQI archive, we operationalised the Dual-Frame Monitoring Inference (DFMI) framework shown in Fig. 1. Reported annual WQI is treated as reflecting both environmental condition and the observation system through which that condition is sampled and summarised. The current-network and fixed-sentinel frames provide complementary network-level perspectives, while station-level diagnostics resolve local trajectories, persistence, and heterogeneity. Inference safeguards address structured missingness, calendar-aware adjacency, multiplicity, endpoint sensitivity, and leave-one-station-out influence. Together, these components yield interpretable evidence on composition sensitivity, within-network temporal signal, and local heterogeneity, and provide a structured platform for subsequent mechanism-based attribution and decision analysis.

3.1 Spatial context of the monitoring network

Figure 2 places the national WQI monitoring network within Ghana's major river systems and provides the spatial counterpart to the longitudinal network audit developed in this study. The 19 long-running stations that define the fixed-sentinel panel are distinguished from the 22 stations added during network expansion. This separation is central to DFMI because the two station cohorts serve different inferential purposes: the long-running panel preserves like-for-like temporal continuity, whereas the expanded network broadens contemporary observational coverage across the national surface-water system.

The map also highlights the four locations identified by the primary persistent-poor screening rule, Ampansie–River Ankobra, Nsawam–River Densu, Lake Bosomtwe, and Dunkwa–River Offin. Their placement provides a direct geographic link between the national monitoring architecture and the station-level persistence results reported later in the manuscript. In this way, the figure connects three complementary elements of the study: the historical sentinel network, the subsequent expansion of monitoring coverage, and the locations prioritised for targeted follow-up assessment.

Read together with the station-by-year monitoring-history heatmap (Fig. 3), Fig. 2 provides a spatial–temporal view of network evolution. The map shows the geographic distribution of the two monitoring cohorts, while the heatmap shows when stations entered the annual record and how coverage changed through time. This pairing makes the central DFMI distinction tangible: broader present-day coverage

and long-term comparability are both valuable, but they answer different monitoring questions. The map is therefore used as a geographic orientation layer, while all quantitative inference remains based on the reconstructed station-year WQI record.

3.2 Monitoring record and audit structure

The source was the publicly available WRC annual surface-water WQI table containing 41 named stations and 20 reported annual columns: 2005–2008 and 2010–2025 (Water Resources Commission, 2026a). The official source is maintained by the WRC. The globally absent 2009 column was treated as a source-level gap rather than as 41 station-level missing observations. One analysis record represented one station in one reported year.

The table was reconstructed in long format, preserving source station names and separate standardised research labels. Numeric WQI values were retained exactly as reported, with no imputation. Grey source cells were coded as sampling not started, whereas orange cells denoted inaccessibility during one or both seasons. Accessibility status was stored independently of numeric observation because an orange cell could still contain an annual WQI. Two computational extraction paths agreed, and reconstructed annual minimum, maximum, and mean values reproduced the source checksums used in the reproducibility workflow.

The reconstruction contains 820 possible station-year slots, 728 numeric annual WQI observations, and 92 blanks. Of the blanks, 91 represent sampling not started and one represents inaccessibility. Nine cells carry the inaccessibility status; eight nevertheless contain numeric annual WQI values. The evidence base and analysis populations are summarised in Table 2.

Table 2
Evidence base and analysis populations.

Item	Definition or value
Reported annual columns	20: 2005–2008 and 2010–2025
Named surface-water stations	41
Possible station-year slots	820
Numeric annual WQI observations	728 (88.8%)
Structured blank cells	91 not-started; 1 inaccessible
Numeric inaccessible-status cells	8
Balanced complete panel	19 stations observed in all 20 reported columns
Primary station-trend population	41 stations with at least 12 observations spanning at least 10 calendar years
Spatial representation	Descriptive national network map for geographic context; formal basin-level inference reserved for a coordinate-verified extension

WQI = Water Quality Index. The absent year 2009 is a source-level gap, not 41 station-level missing values.

3.3 WQI classes and comparability boundary

The supplied table displays four WQI classes: Class I (80–100), Class II (50–79), Class III (25–49), and Class IV (0–24) (Water Resources Commission, 2026a). For consistent computation, these displayed ranges were operationalised as WQI ≥ 80, 50 ≤ WQI < 80, 25 ≤ WQI < 50, and 0 ≤ WQI < 25, respectively. Because accessible WRC documents vary slightly in boundary formulations (Darko et al., 2013; Water Resources Commission, 2025), continuous WQI values provide the primary longitudinal evidence and class-derived quantities provide complementary descriptive summaries.

3.4 Analysis populations and descriptive analysis

Four analysis populations were defined. The observed full network included every numeric WQI and was treated as composition-sensitive. The balanced complete panel contained stations observed in all 20 reported columns and provided the primary fixed-membership comparison. A legacy sensitivity panel required observation in 2005 and at least 18 of 20 reported years. The station-trend population required at least 12 observations spanning at least 10 calendar years, with sensitivity checks at minimum sample sizes of 10 and 15. The balanced and legacy panels both contained 19 stations; all 41 stations met the primary trend-eligibility rule.

Annual coverage was summarised by observed counts, not-started cells, inaccessible cells, and station entry year. WQI distributions were described with median, quartiles, interquartile range, minimum, maximum, mean, standard deviation, and provisional class proportions. The changing-network mean was retained only as a supplementary descriptive measure. Full-network and balanced-panel summaries were compared directly. Within the balanced panel, station-centred anomalies were calculated by subtracting each station's period median from its annual WQI.

3.5 Station-level temporal analysis

Station-specific change was estimated using Theil–Sen slopes with actual calendar year as the time variable (Sen, 1968). Slopes are reported in WQI units per decade with 95% confidence intervals. Monotonic-trend evidence was evaluated with the Mann–Kendall test (Mann, 1945), and station-level p-values were adjusted by the Benjamini–Hochberg false-discovery-rate procedure (Benjamini & Hochberg, 1995).

Serial dependence was screened using lag−1 correlation of Theil–Sen residuals only for genuinely adjacent calendar-year pairs. The 2008–2010 interval and station-specific gaps were excluded from lag−1 pairing so that serial-dependence screening reflected genuine calendar adjacency. A descriptive threshold of $1.96/\sqrt{m}$, where m is the number of adjacent residual pairs, was used to flag comparatively large absolute lag−1 correlations; the screen was treated as a diagnostic rather than a hypothesis test. As a secondary population-level sensitivity analysis, linear models with station fixed effects were estimated using station-clustered standard errors.

3.6 Persistence, transitions, and sensitivity analyses

A station was classified as persistently poor when at least 50% of its observed years were in provisional Class III or IV and at least one of its latest three observed years was also in Class III or IV. Threshold sensitivities of 40% and 60% retained the same recent-status condition.

Class transitions were calculated only when successive observations for a station were exactly one calendar year apart. The 2008–2010 gap and all station-specific missing-year gaps were excluded. Additional robustness analyses compared trend endpoints ending in 2024 and 2025 and removed each balanced-panel station in turn to quantify influence on annual medians.

3.7 Computational reproducibility

All analyses were performed in Python 3.11 using a scripted, version-controlled workflow with pinned numerical, statistical, and plotting dependencies. The workflow reconstructs the analysis-ready station-year table, executes the statistical procedures described above, regenerates the main and supplementary figures, and verifies the principal numerical results against verification checks. The reproducibility release includes the analysis-ready data representation, processed outputs, analysis and figure-generation scripts, environment specification, and verification results.

4 Results

4.1 Monitoring coverage and network expansion

The reconstructed record contained 728 numeric annual WQI values (88.8% of 820 possible reported station-year slots). Only 19 of 41 stations were observed in each of 2005–2008. Coverage increased to 40 stations in 2010–2012 and reached 41 in 2013. All 41 stations had numeric annual values thereafter except in 2023, when the inaccessible Ampansie–Ankobra station-year was blank. Station entry occurred in three cohorts: 19 stations were observed by 2005, 21 first appeared in 2010, and one first appeared in 2013. Figure 3 makes the monitoring-history change visible rather than treating it as a background property of the dataset. The broad block of grey cells before 2010 is concentrated among stations that entered when the national network expanded, so these cells represent periods before routine observation rather than conventional intermittent missingness. The later entry of the final station in 2013 produces a smaller version of the same pattern. Accessibility flags form a different type of observation-status information: they occur after a station has entered the programme and may coexist with a reported annual WQI. Distinguishing these states preserves the chronology of network development and prevents periods before station entry, access constraints, and measured annual values from being collapsed into a single missing-data category.

The heatmap also clarifies why a single national time series cannot be interpreted independently of coverage history. Before expansion, annual summaries represent the original 19-station network; from 2010 onward, they combine those long-running sites with a much larger set of additional stations. At the same time, the colour pattern shows substantial WQI variation both across stations within a year and within individual stations across years. Consequently, the visual evidence points to two simultaneous sources of change: the population of sites contributing to the annual national summary changed, and values at repeatedly observed sites also varied through time. This is the empirical reason for carrying both the changing-network and fixed-sentinel frames into the subsequent analysis rather than treating either one as sufficient on its own.

4.2 WQI distributions and composition sensitivity

Annual WQI distributions were non-monotonic. In the observed full network, the lowest median was 43.80 in 2013 and the highest was 62.49 in 2023. The balanced panel also had its lowest median in 2013 (41.60) and highest in 2023 (61.53). After network expansion, the full-network median exceeded the balanced-panel median in 13 of 16 reported years from 2010 onward and was equal in two more; 2019 was the only post–2010 year in which it was lower. The full-network mean exceeded the balanced-panel mean in 15 of 16 post–2010 years. Across those 16 years, the annual full-network minus balanced-panel median contrast had a median of + 1.55 WQI units, a mean of + 1.44, and a range from−0.73 to + 3.37 WQI units. This descriptive contrast demonstrates that the national summary is sensitive to station membership; it is not, by itself, a causal decomposition of environmental change and monitoring-network change. These annual distributions are compared in Fig. 4.

The fixed panel also contained substantial temporal variation after station membership was held constant. The median station-centred anomaly was below zero in every reported year from 2012 through 2018, with the largest negative median in 2013 (−11.45 WQI units relative to each station's period median). The same 2012–2018 low-score episode is therefore evident within the stable 19-station panel, indicating within-panel temporal variation that cannot be explained by station-entry differences alone. However, changes in sampling frequency or index computation cannot be ruled out using annual WQI scores. The positive fixed-panel median anomaly in 2023 (+ 7.74) also coexisted with wide between-station dispersion, highlighting the value of station-level diagnostics alongside national and sentinel summaries. These anomaly results are detailed in the Supplementary Information (ESM 1).

Across all 728 observed values, 515 (70.7%) were provisionally Class II, 199 (27.3%) Class III, 12 (1.6%) Class I, and 2 (0.3%) Class IV. The provisional Class III share reached 75.6% in 2013, consistent with the continuous-score trough; class distributions therefore provide useful descriptive context alongside the continuous-score analysis. Annual class proportions are provided in the Supplementary Information (ESM 1).

4.3 Station-specific trends and robustness

All 41 stations satisfied the primary trend-eligibility rule. The median Theil–Sen slope was + 2.74 WQI units per decade; 29 stations had positive slopes, 11 negative slopes, and one a zero slope. Seven original Mann–Kendall tests had $p < 0.05$; after BH-FDR adjustment, no station met $q < 0.05$, underscoring the heterogeneous and generally modest station-level monotonic signals across the network. The adjacent-year residual diagnostic flagged 7 of 41 stations (17.1%) at the sample-size-specific absolute lag−1 correlation threshold; station-level correlations, pair counts, and thresholds are reported in Supplementary Table S2. Figure 5 displays the station-specific Theil–Sen slopes and their 95% confidence intervals.

Aggregate linear estimates varied with analysis population and endpoint (Table 3). Through 2025, the all-station fixed-effects estimate was + 1.69 WQI units per decade ($p = 0.038$) and the balanced-panel estimate was−0.80 ($p = 0.247$); through 2024 the corresponding estimates were + 0.99 ($p = 0.222$) and−1.49 ($p = 0.031$). Station-level slope direction remained unchanged for 35 of 41 stations, no station met BH-FDR $q < 0.05$ under either endpoint, and leave-one-out analysis changed the balanced annual median by at most 1.50 WQI units.

Table 3
Sensitivity of aggregate within-station linear estimates to population and endpoint.

Population	Endpoint	Slope (WQI/decade)	95% CI (WQI/decade)	p
All eligible stations	2024	0.99	−0.60, 2.59	0.222
All eligible stations	2025	1.69	0.09, 3.30	0.038
Balanced complete panel	2024	−1.49	−2.85,−0.14	0.031
Balanced complete panel	2025	−0.80	−2.16, 0.55	0.247

Linear models include station fixed effects and station-clustered standard errors. The endpoint comparison quantifies sensitivity of aggregate trend estimates to the final reporting year.

4.4 Persistent poor status and adjacent-year transitions

Under the primary persistence rule, four stations were persistently poor: Ampansie–River Ankobra, Nsawam–River Densu, Lake Bosomtwe, and Dunkwa–River Offin. Their proportions of observed years in provisional Class III or IV were 80.0%, 65.0%, 62.5%, and 55.0%, respectively. The number qualifying changed to 10 stations at the 40% sensitivity threshold and three at the 60% threshold.The qualifying stations and their 2025 WQI values are presented in Table 4.

Table 4
Stations meeting the primary persistent-poor screening rule.

Station	Observed years	Class III/IV	Poor years (%)	WQI 2025	Class 2025
Ampansie–River Ankobra	15	12	80.0	29.45	III
Nsawam–River Densu	20	13	65.0	36.19	III
Lake Bosomtwe	16	10	62.5	46.56	III
Dunkwa–River Offin	20	11	55.0	49.51	III

Primary rule: at least 50% of observed years in provisional Class III/IV and at least one Class III/IV observation among the latest three observed years; the rule is used to prioritise stations for follow-up assessment.

A total of 667 valid transitions connected observations exactly one calendar year apart. Of these, 474 (71.1%) remained in the same class, 93 (13.9%) moved to a better class, and 100 (15.0%) moved to a worse class. Most movement occurred within or between Classes II and III. Figure 6 presents the corresponding transition counts and row percentages.

5 Discussion

5.1 Monitoring-network change as a general inference problem

The main scientific result is that long-term WQI inference depends materially on the monitoring population used to construct the annual indicator. After the 2010 expansion, the full-network minus fixed-panel median contrast was positive in 13 of 16 years, with median + 1.55 WQI units. Although modest on a 0–100 scale, this systematic contrast altered descriptive trajectories and, together with endpoint choice, affected aggregate trend estimates. The changing network describes sites monitored in a given year; the fixed panel provides a like-for-like longitudinal comparison.

This distinction extends beyond Ghana. Network representativeness and statistical power depend on retained sites (O'Hare et al., 2020), while station placement, continuity, frequency, variables, and logistics shape monitoring inference (Strobl & Robillard, 2008). Global capacity constraints (Kirschke et al., 2020) and African data scarcity (Nkwasa et al., 2024) make the issue especially relevant where networks are expanding. Better spatial coverage is desirable, but changing membership can confound temporal inference if it is not made explicit.

A practical implication is dual-frame reporting: publish a current-network indicator for contemporary monitored condition and a fixed-sentinel indicator for longitudinal comparability. Used together, the two frames provide complementary views of contemporary monitored condition and like-for-like longitudinal change, while station-level diagnostics reveal local heterogeneity.

5.2 Composition sensitivity coexists with a clear within-network temporal signal

The fixed-panel anomalies show that monitoring composition and within-network temporal change coexist in the record. With membership fixed, median station-centred anomalies were negative in every reported year from 2012–2018 and reached−11.45 WQI units in 2013. Leave-one-out analysis changed balanced-panel medians by at most 1.50 units and by no more than 0.47 after 2017. The record therefore contains both a composition effect and a shared within-panel temporal episode.

The 2012–2018 episode provides a focused response period for subsequent mechanism-based analysis. Hydroclimatic extremes can alter river-water quality through competing pathways (van Vliet et al., 2023), and integrated studies such as Qian et al. (2024) demonstrate the value of linking water-quality observations with hydrology and rainfall. The DFMI result therefore identifies where and when rainfall, discharge, land-cover change, mining intensity, wastewater loading, and raw WQI parameters can be integrated in a second-stage attribution analysis.

Station-level results add a third layer of evidence. The median Theil–Sen slope was positive, but none of seven nominal Mann–Kendall signals survived FDR control. Thirty-five of 41 slope directions were

unchanged when the endpoint shifted from 2025 to 2024; the six changes occurred near zero with intervals spanning zero. Aggregate fixed-effects significance also changed with endpoint. Effect sizes, uncertainty, analysis population, and endpoint sensitivity are therefore more informative than a binary national improvement/deterioration label (Zhou et al., 2023).

5.3 Station persistence in relation to Ghana's basin literature

The persistent-poor screen captures recurrence rather than monotonic trend. Ampansie–Ankobra, Nsawam–Densu, Lake Bosomtwe, and Dunkwa–Offin met the primary rule because low provisional classes recurred and remained recent. They form a transparent priority set for parameter-level, seasonal, and catchment-specific follow-up.

The screen is nevertheless consistent with earlier Ghanaian evidence. Nsawam's poor status appeared in the original WRC network (Darko et al., 2013), and Densu studies document spatial and seasonal concerns (Amoako et al., 2010; Ofosu et al., 2021). Studies of the Pra, Birim, Offin, and Ankobra identify mining-related disturbance, metals, sediments, and ecological or health concerns using measurements absent from the annual composite table (Asare-Donkor et al., 2018; Ashong et al., 2025; Darko et al., 2023; Faseyi et al., 2022; Nunoo et al., 2022). The geographic correspondence motivates targeted parameter-level, exposure, land-use, and hydrological investigation at these recurrent low-score locations; it does not establish that any specific pollutant or pressure caused their WQI histories.

Ampansie also shows why observation metadata matters. Repeated inaccessible-season flags accompany numeric annual values and 2023 is blank. If access failure is seasonally or environmentally structured, annual values may represent different sampling windows. Preserving access status and contributing seasons is therefore preferable to treating such gaps as ordinary random missingness.

5.4 Climate resilience, food systems, treatment, and economic relevance

The record matters because decisions depend on trustworthy monitoring. Ghana's IWRM framework links water resources to climate resilience, food production, welfare, economic uses, catchment protection, and transboundary management (Water Resources Commission, 2012); international evidence further demonstrates the relevance of reliable water-quality information across these domains.

For climate resilience, hydroclimatic extremes can alter water-quality constituents through interacting hydrological and biogeochemical mechanisms (van Vliet et al., 2023). The fixed-panel 2012–2018 low-score episode provides a well-defined response period for future rainfall, discharge, temperature, and land-cover analysis and establishes the comparable series needed for climate-related attribution.

For food systems, Ghanaian evidence links irrigation-water contaminants to crop and health concerns (Amuah et al., 2022). Persistent low-score locations can prioritise recovery of salinity, nutrient, microbial, metal, and other measurements needed for irrigation- and food-system-specific assessment.

For treatment planning, source-water deterioration can increase operational requirements and treatment costs (Price & Heberling, 2018). These findings can guide targeted parameter-level monitoring, source-water protection, and subsequent studies linking water-quality episodes with plant operations, treatment costs, water-use volumes, and economic outputs.

5.5 Dual-frame monitoring inference: conceptual and practical contribution

The analyses support a dual-frame interpretation that combines national coverage, fixed-sentinel comparability, and station-level diagnostics. The systematic post-expansion difference between the changing and fixed networks demonstrates observation-system dependence: aggregate summaries are sensitive to which stations constitute the monitored population. At the same time, the fixed-panel 2012–2018 anomaly demonstrates that controlling network membership does not eliminate temporal signals. These two results are complementary. One quantifies composition sensitivity; the other identifies within-panel temporal variation. The station-specific analyses add a third scale by showing heterogeneous slopes and persistent low-score histories that cannot be inferred from national medians alone.

Conceptually, DFMI extends monitoring-design reasoning from the question of where and how to sample to the additional question of what population a reported indicator represents at each time and whether that estimand is comparable through time. By making explicit the relationship between the environmental signal and the observation system through which that signal is summarised, the framework provides a transferable inference structure for long-running environmental programmes in which sites, sensors, sampling intensity, analytical protocols, or reporting rules evolve.

Practically, the Ghana case supports five principles: preserve a documented sentinel core during expansion; report current-network and fixed-sentinel summaries together; version station metadata, including entry, relocation, access, sampled seasons, and missingness; retain seasonal and parameter-level measurements where feasible because aggregation can obscure constituent-specific change (Fortes et al., 2023; Kachroud et al., 2019; Sinha & Jain, 2026); and maintain a versioned public specification of the WQI formula, weights, aggregation procedure, class rules, and method changes. Together, these practices strengthen subsequent climate, source-water, food-system, treatment, economic, and transboundary analyses and improve continuity in long-running monitoring programmes.

5.6 Study limitations and interpretive boundary

Several limitations define the scope of the findings. First, the official archive provides annual composite WQI scores rather than the original constituent concentrations, weights, sampling dates, or full method-version history. The study therefore cannot verify complete measurement comparability across 2005–2025 or attribute annual changes to particular pollutants, mining activities, climate conditions, or interventions. Second, the fixed 19-station panel removes changes in panel membership from its own time series but is not a probability sample of Ghanaian surface waters; it should not be treated as a nationally representative counterfactual. Third, the difference between full-network and fixed-panel

annual medians is a descriptive measure of composition sensitivity, not an estimate of the causal effect of adding stations. Fourth, 2009 is absent from the official record, and intermittent accessibility restrictions may make annual values based on different seasonal observations. Finally, the persistence classification depends on provisional WQI cut-points and the selected screening threshold. Accordingly, the findings are best interpreted as a robustly documented comparison of monitored indicators and a screening basis for follow-up, rather than a causal or health-risk assessment.

5.7 Research scope and next-stage analysis

The present study establishes a network-aware longitudinal evidence base at the annual composite-index level. The next analytical layer is to connect the identified temporal episodes and persistent locations with parameter-level chemistry, seasonal measurements, verified station coordinates and histories, hydroclimate, land-cover pressure, and operational metadata. This staged design turns the present WQI analysis into a structured platform for progressively richer source-water and catchment inference.

The next stage is mechanism-based attribution built on the comparable response series established here. With verified coordinates and method history, fixed-panel episodes and persistent sites can be linked to rainfall, discharge, remotely sensed land-use/mining pressure, and seasonal parameter data. Establishing comparability before drivers and consequences provides a stronger basis for climate-resilient source-water management.

6 Conclusions

Long-term water-quality trends can only be interpreted confidently when changes in the environment are considered alongside changes in the system used to observe it. Ghana's 2005–2025 WQI record illustrates why this distinction matters. The changing-network and fixed-panel summaries differed after network expansion, but their difference did not account for all temporal variation observed within the fixed panel. Even when the analysis was restricted to the same 19 long-running stations, a broad low-score period remained visible from 2012 to 2018. At the same time, station-level trajectories were highly heterogeneous, and no individual monotonic trend remained statistically significant after correction for multiple testing. The national record therefore cannot be reduced to a simple conclusion that water quality has either improved or deteriorated uniformly.

The practical lesson extends beyond Ghana. As environmental monitoring programmes expand, annual national indicators may become better descriptions of current spatial conditions while simultaneously becoming less directly comparable with earlier years. The Dual-Frame Monitoring Inference (DFMI) framework addresses this problem by keeping two questions separate: What conditions are represented by the network being monitored today? and How have conditions changed at locations observed consistently through time? Station-level diagnostics then provide the local evidence that neither national summary can capture alone.

For monitoring agencies, this leads to a straightforward reporting strategy: maintain a stable sentinel core as networks expand; report current-network and fixed-sentinel indicators together; document station entry, access, relocation, and methodological changes; preserve structured missingness rather than concealing it through imputation; and retain seasonal and parameter-level measurements for subsequent attribution. The four persistent-poor locations identified here provide priorities for follow-up assessment.

DFMI is not intended to replace basin-specific chemical, hydrological, or causal analysis. Rather, it establishes a more defensible starting point for it. Once the monitoring record has been made comparable through time, rainfall, discharge, mining and land-use pressures, raw water-quality parameters, treatment requirements, and other potential drivers can be examined against a clearer temporal baseline. The broader contribution is therefore not only a reinterpretation of Ghana's WQI history, but a transferable way of asking a fundamental question in long-running environmental programmes: are we observing a changing environment, a changing monitoring system, or both?

Declarations

Author Contribution

A.A.M. conceptualized the study, acquired and curated the data, contributed to the formal analysis and investigation, and contributed to writing the original draft and reviewing and editing the manuscript. M.N. contributed to the formal analysis and investigation and contributed to writing the original draft and reviewing and editing the manuscript. H.A.T. contributed to the investigation, validation, and review and editing of the manuscript. All authors reviewed and approved the final manuscript.

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Data Availability

The original annual Water Quality Index data used in this study are publicly available from the Ghana Water Resources Commission at https://wrc.gov.gh/ova_doc/water-quality-index/. The analysis-ready dataset, processed outputs, verification records, analysis code, and publication figures supporting the findings of this study are publicly available in Figshare at https://doi.org/10.6084/m9.figshare.33570868. The associated development repository is available at https://github.com/Adlat88/ghana-wqi-monitoring-network.

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Footnotes

1. https://wrc.gov.gh/ova_doc/water-quality-index/

Figures

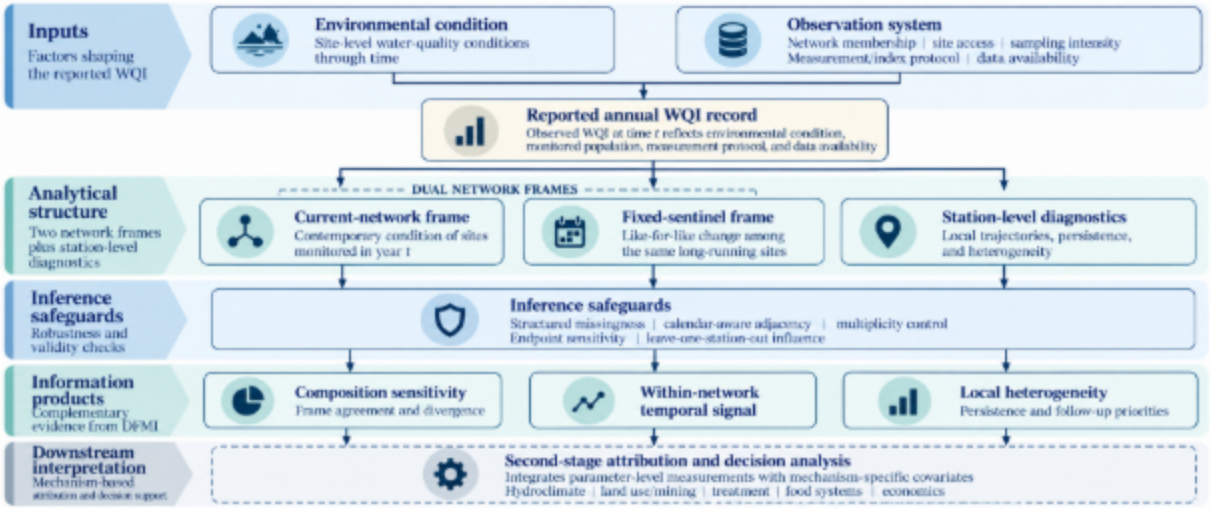


Figure 1

Dual-Frame Monitoring Inference (DFMI) framework. Reported annual WQI reflects both environmental condition and characteristics of the observation system. DFMI distinguishes a current-network frame for contemporary monitored condition from a fixed-sentinel frame for like-for-like longitudinal comparison, complemented by station-level diagnostics of trajectories, persistence, and heterogeneity. Inference safeguards strengthen interpretation of these evidence streams, which can subsequently be integrated with mechanism-specific data for attribution and decision analysis.

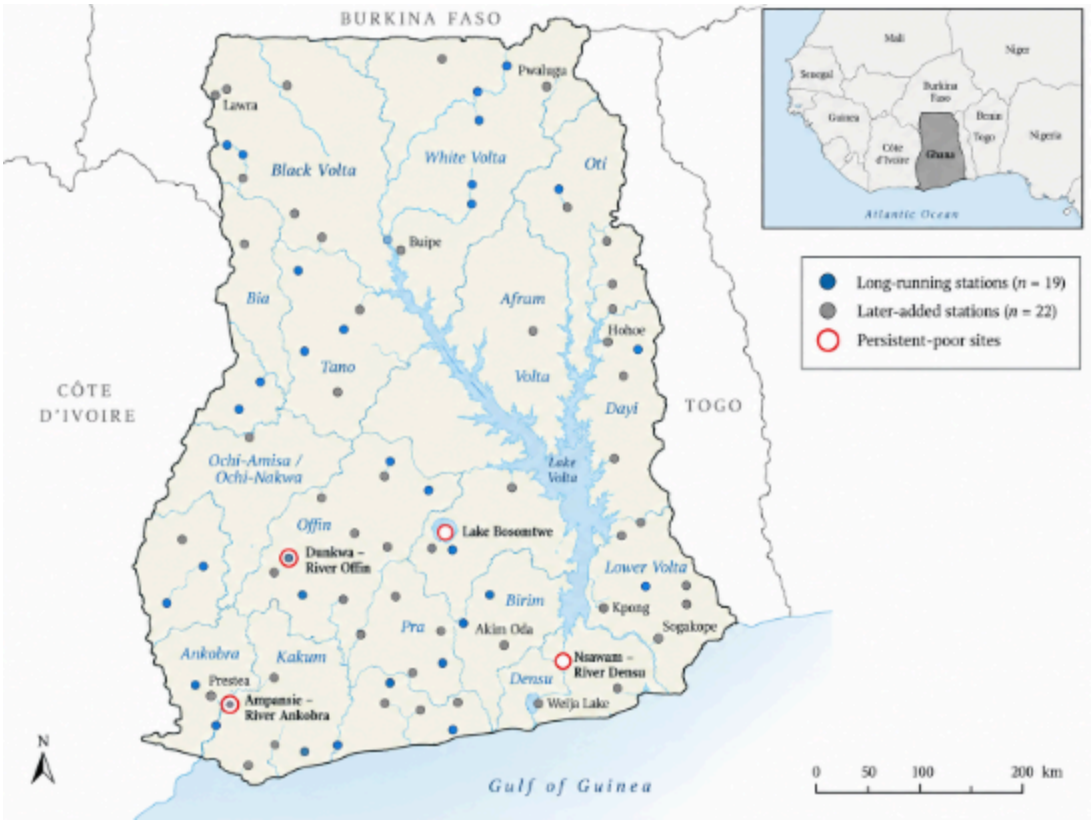


Figure 2

Geographic context of Ghana's national surface-water monitoring network. The 19 long-running stations that define the fixed-sentinel panel are distinguished from the 22 stations added during network expansion, and the four stations meeting the primary persistent-poor criterion are highlighted. Major river systems and the West Africa inset provide national and regional orientation.

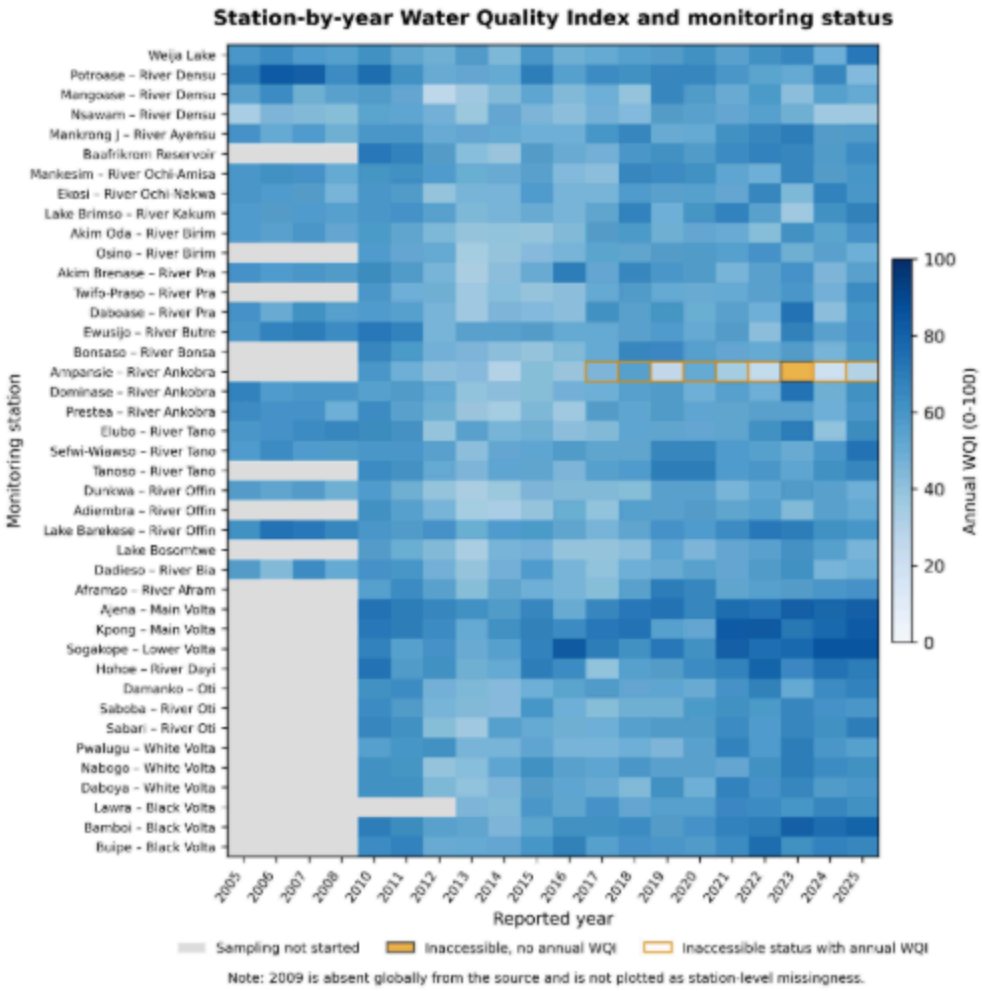


Figure 3

Station-by-year WQI record showing monitoring-network expansion and structured gaps. Grey cells indicate sampling not started; orange status is retained separately from numeric WQI because inaccessible-status cells may still contain annual values. The globally absent year 2009 is not represented as station-level missingness.

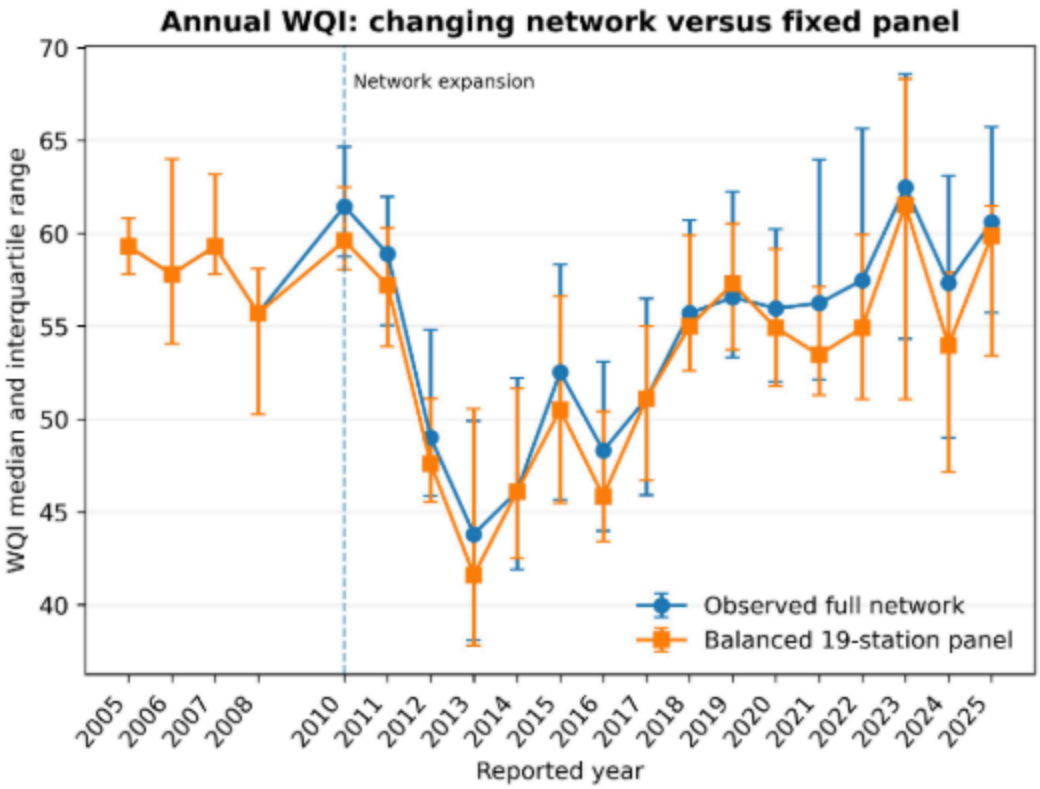


Figure 4

Annual WQI medians and interquartile ranges for the observed full network and the fixed 19-station balanced panel. Full-network annual summaries are composition-sensitive.

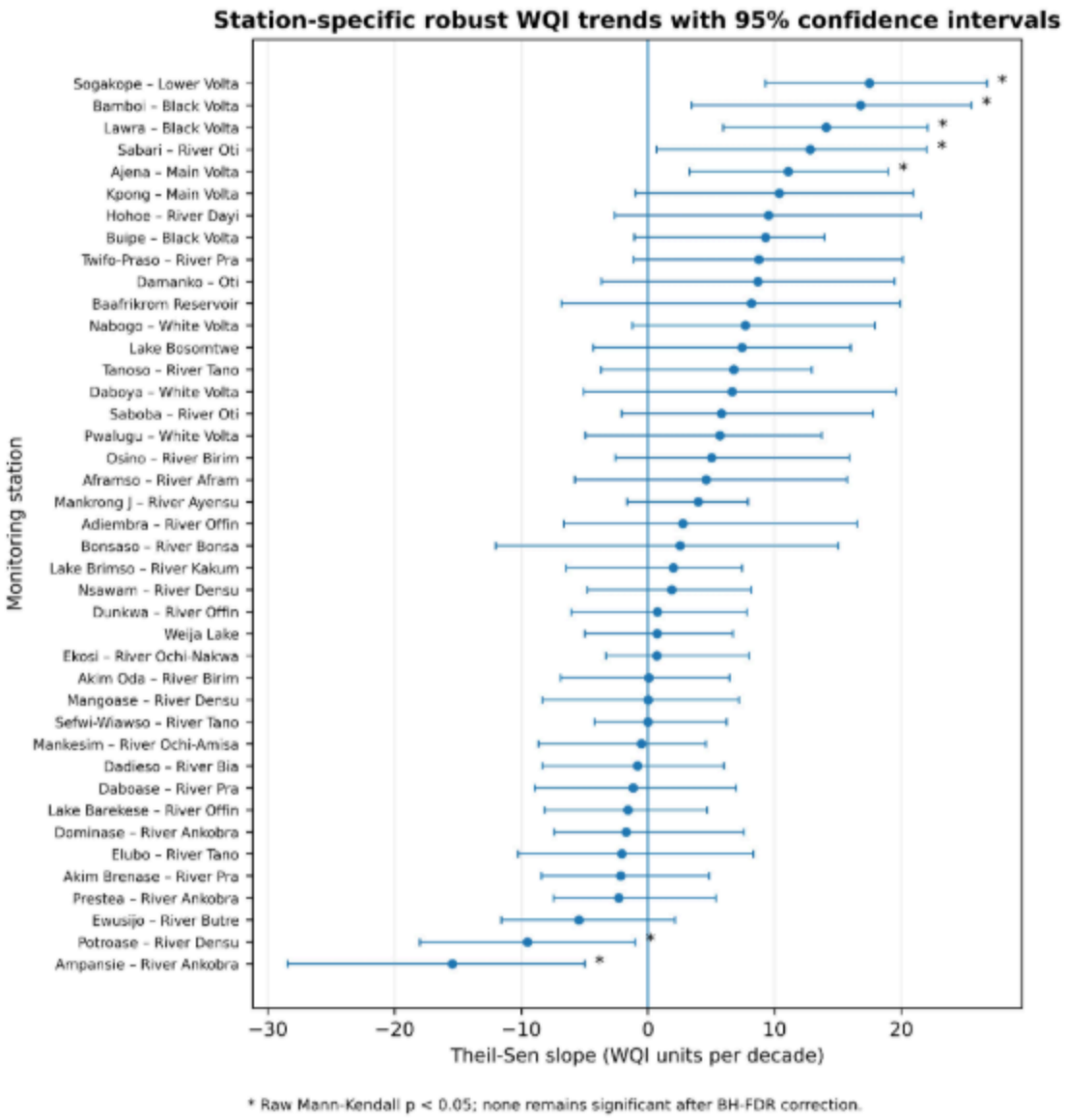


Figure 5

Station-specific Theil–Sen slopes and 95% confidence intervals. Asterisks mark original Mann–Kendall p<0.05 *signals; FDR-adjusted results are reported in the text.*

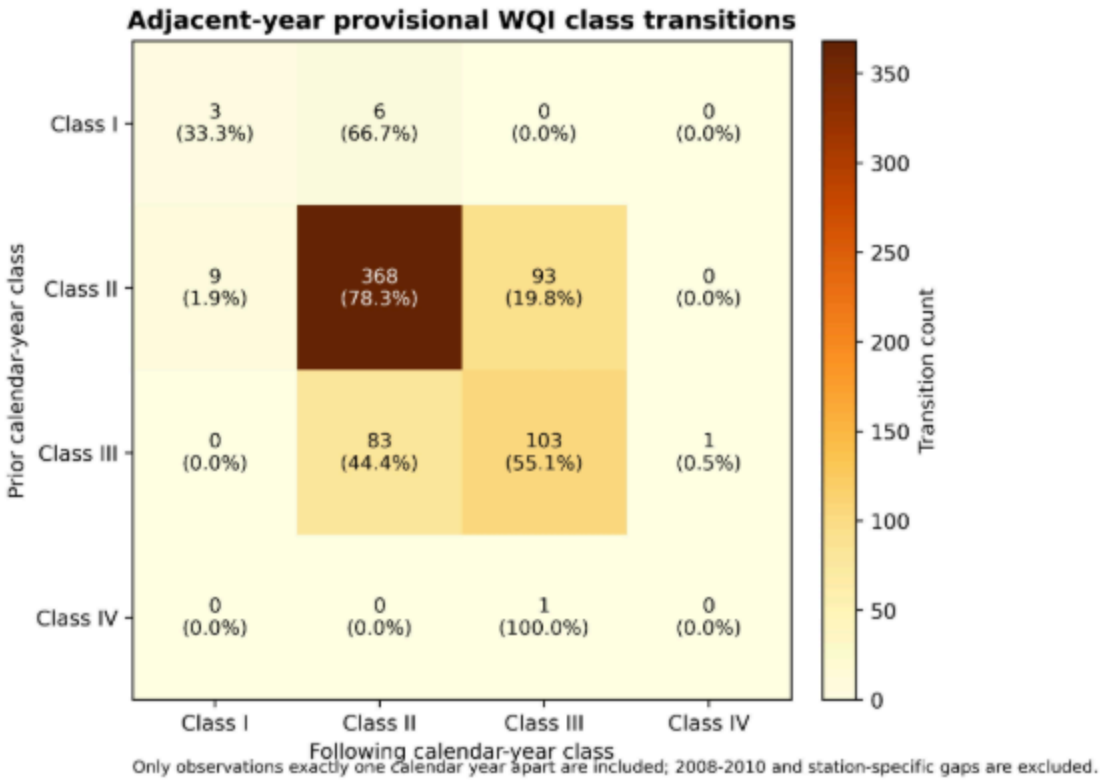


Figure 6

Counts and row percentages of genuine adjacent-calendar-year provisional WQI class transitions. The 2008–2010 gap and all station-specific missing-year gaps are excluded.

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- SupplementaryInformation.docx
- ExperimentCodeanddatafiles.zip