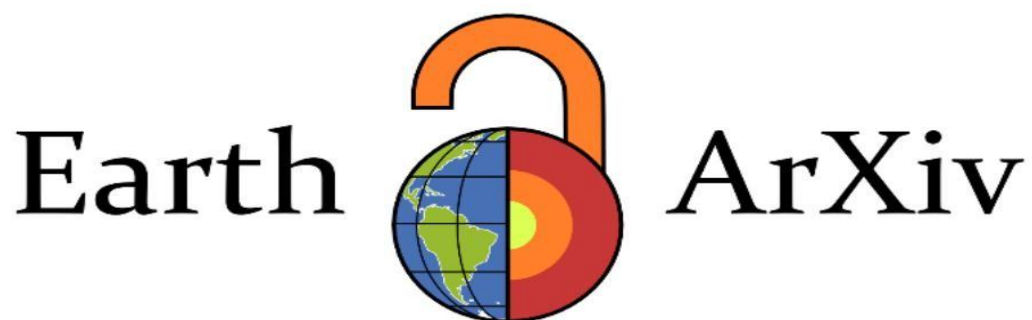




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**Temporal Synchronization Determines the Accuracy of Sentinel-2 Turbidity Retrieval:**

**Evidence from Community-Based Monitoring of the Buriganga River,  
Dhaka**

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## Abstract

Community-based environmental organizations require continuous water quality data but are constrained by the cost and labor of physical sampling. Satellite remote sensing offers a free alternative, yet validation studies of inland waters frequently report weak agreement between satellite indices and ground measurements, and the cause of that disagreement is rarely isolated. This study analyzed 28 Sentinel-2 observations across 12 dates at three sites on the Buriganga River in Dhaka, Bangladesh, between January and April 2026, alongside eight calibrated field measurements of turbidity, pH, and dissolved oxygen. Three findings emerged. First, the reach adjacent to the Hazaribagh tannery district was more turbid than the Katashur Outfall on every one of 11 valid observation dates (Wilcoxon  $p = .001$ ), establishing a persistent spatial gradient that discrete sampling campaigns had not resolved. Second, turbidity rose by 88% river-wide between January and February ( $p = .006$ ), and the cleanest site deteriorated fastest, compressing the gradient between the tannery reach and the outfall from 2.0 to 1.5. Third, repeat same-day observations established a measurement noise floor 2.6 times smaller than between-date variation, indicating that 86% of observed variance reflects genuine day-to-day change. That last result predicts, and the data confirm, that pairing protocol governs retrieval accuracy: comparing generalized field averages against satellite observations from the same approximate period yielded no significant relationship ( $R^2 = .04$ ,  $p = .46$ ), whereas matching each field measurement to a cloud-free overpass on the same calendar date yielded strong agreement ( $R^2 = .94$ , 95% CI [.71, .99],  $n = 8$ ,  $p < .001$ ), with a cross-validated retrieval error of 5.4 NTU. Sensor capability was identical under both protocols. Weak validation outcomes in dynamic inland waters may therefore reflect protocol failure rather than sensor limitation.

*Keywords:* Sentinel-2; Normalized Difference Turbidity Index; turbidity; temporal synchronization; Buriganga River; community-based monitoring; Google Earth Engine

## **Temporal Synchronization Determines the Accuracy of Sentinel-2 Turbidity Retrieval:**

### **Evidence from Community-Based Monitoring of the Buriganga River, Dhaka**

The Buriganga River is the reason Dhaka stands where it does. It carried the trade that established the city, supplied its drinking water, and sustained the fishing families settled along its banks. Within living memory, residents drank from it directly and bathed in it without consequence. (Kamal et al., 1999)

That river is now among the most degraded urban watercourses in South Asia. Untreated industrial effluent, most prominently from the tanneries historically concentrated at Hazaribagh, combines with municipal sewage discharged along its length to produce water failing nearly every standard of ecological health (Fatema et al., 2018; Majed et al., 2022). The burden falls disproportionately on those with the fewest alternatives: fishing families whose catch has collapsed, and riverside residents with no other water available to them.

Reversing this trajectory requires evidence, and evidence requires sustained measurement. It is precisely here that community-led monitoring encounters a structural constraint. Conventional water quality assessment depends on physical sample collection followed by laboratory analysis, a sequence that is costly, labor-intensive, and difficult to sustain at the frequency required to detect change. A volunteer organization can mount an excursion once or twice monthly. It cannot deploy a field team daily across several kilometers of river. The organizations with the strongest incentive to document the Buriganga's condition are therefore the least equipped to do so continuously, and the resulting record consists of isolated snapshots separated by intervals during which conditions are simply unknown.

Optical satellite remote sensing offers a structural resolution to this constraint. The European Space Agency's Sentinel-2 mission provides imagery at 10 m resolution with an

approximately five-day revisit interval, distributed without charge. If reflectance recorded from orbit corresponds reliably to conditions measurable at the water surface, a community organization could monitor an entire river system continuously without additional field deployment.

Whether that correspondence holds, however, is contested. Validation studies of inland and coastal waters report agreement ranging from strong to negligible, and the sources of disagreement are typically attributed to atmospheric correction, optical complexity, or sensor resolution. One candidate explanation receives comparatively little scrutiny: the interval between field collection and satellite overpass. Where studies pair measurements separated by days or weeks, often unavoidably given field logistics, a weak result is conventionally interpreted as evidence about the sensor. It may instead be evidence about the pairing.

This distinction carries practical consequence. If retrieval accuracy is limited by sensor capability, community organizations cannot remedy it. If it is limited by pairing protocol, they can, at no cost, by rescheduling excursions against a publicly available overpass calendar.

This study addresses two questions in sequence. The first is descriptive: what spatial and temporal structure does a continuous satellite record reveal in the Buriganga that discrete sampling has not? The second is methodological: does temporal alignment between field sampling and satellite overpass govern the accuracy with which that structure can be validated? The two are connected, because the answer to the first supplies the physical justification for the second.

## **Literature Review**

### ***Condition of the Buriganga***

Assessments of the Buriganga converge on a consistent picture of severe degradation:

depressed dissolved oxygen, elevated heavy-metal concentrations, and biochemical oxygen demand substantially exceeding national standards (Fatema et al., 2018; Majed et al., 2022). Fatema et al. (2018) documented dissolved oxygen levels well below thresholds required for aquatic survival, rendering the water ecologically hostile. Majed et al. (2022) further identified elevated levels of toxic heavy metals—including chromium, cadmium, and lead—originating prominently from industrial discharge near the Hazaribagh reach.

These studies share a methodological structure as well as a conclusion. Each rests on physical collection followed by laboratory analysis, yielding high-confidence measurements at discrete points in space and time. The approach is sound, but its resolution is inherently coarse in both dimensions. Spatially, a study reporting a river-wide average cannot attribute contamination to a particular outfall. Temporally, a record composed of monthly samples cannot distinguish a sustained deterioration from a transient episode. Both distinctions matter for regulatory action, and both are precisely what a continuous satellite record is positioned to supply.

### ***Optical Remote Sensing of Water Quality***

Optical remote sensing addresses resolution by exploiting a physical relationship: suspended particulate matter alters the spectral reflectance of water. Clear water absorbs strongly in the red portion of the visible spectrum, whereas water carrying suspended sediment scatters red wavelengths back toward the sensor. The ratio of red to green reflectance therefore encodes particulate load, a principle underlying a family of satellite turbidity indices applied across lakes, estuaries, and rivers. (Kutser et al., 2020).

Two constraints limit the approach. Optical sensors cannot observe through cloud, restricting usable imagery in monsoon climates. And the reflectance signal responds to particle scattering rather than to chemical composition, so the retrieved quantity is turbidity itself rather than the contaminants that may accompany it.

### ***The Normalized Difference Turbidity Index***

The Normalized Difference Turbidity Index (NDTI) operationalizes the red and green relationship as a single normalized ratio:

$$NDTI = (\rho_{\text{Red}} - \rho_{\text{Green}}) / (\rho_{\text{Red}} + \rho_{\text{Green}})$$

where  $\rho$  denotes surface reflectance. For Sentinel-2 this corresponds to bands B4 (red, 665 nm) and B3 (green, 560 nm). Index values increase with suspended solid concentration, and the normalized form partially compensates for scene-to-scene variation in illumination geometry (Lacaux et al., 2007).

For community monitoring the index has a decisive practical advantage: it requires two spectral bands, no atmospheric modeling beyond the standard surface reflectance product, and no proprietary software. Methodological training for this study was drawn from NASA's Applied Remote Sensing Training (ARSET) program (NASA Applied Remote Sensing Training Program [ARSET], 2024).

### ***Gaps Addressed by This Study***

Two limitations in existing work motivate this study. First, remote sensing assessments of South Asian rivers have generally operated at coarse spatial scales, treating a river as a single optical unit. The Buriganga's contamination is not uniformly distributed. It enters at identifiable outfalls, and monitoring that cannot resolve those junctions cannot support attribution to a source.

Second, validation studies routinely pair field and satellite observations collected days apart, treating the interval as negligible measurement noise. If river conditions vary on sub-daily timescales, this assumption is not conservative but systematically distorting: it would depress

reported accuracy for reasons unrelated to sensor performance, while leaving practitioners without guidance on how precisely sampling must be timed. We identified no study treating temporal synchronization as an explicit experimental variable at discharge-point scale. This study does so, and additionally quantifies the measurement noise floor against which the assumption can be tested directly.

## Method

### *Study Area*

Sampling was conducted at three sites along the Buriganga, selected to represent distinct contamination regimes (Table 1).

**Table 1**

#### *Monitoring Site Characteristics*

| Site                 | Coordinates               | Contamination regime                            | Satellite obs. | Field pairs |
|----------------------|---------------------------|-------------------------------------------------|----------------|-------------|
| Hazaribagh Reach     | 23.7314° N,<br>90.3622° E | Adjacent to the historical tannery district     | 28             | 2           |
| Buriganga Confluence | 23.7385° N,<br>90.3588° E | Downstream of both; mixed and partially diluted | 28             | 3           |
| Katashur Outfall     | 23.7432° N,<br>90.3551° E | Direct discharge point; principal KWPI site     | 28             | 3           |

*Note.* Satellite observations denote qualifying Sentinel-2 retrievals across 12 dates. Field pairs denote temporally synchronized field and satellite measurements.

### *Research Design*

The study proceeded in two stages. The first characterized spatial and temporal structure using the full satellite record of 28 observations across 12 dates. The second evaluated retrieval accuracy against ground measurement using a two-phase within-dataset design in which pairing protocol was the sole manipulated variable. Sensor, index, extraction procedure, sites,

instrument, and season were held constant, so any difference in accuracy between phases is attributable to temporal alignment.

In **Phase 1 (unsynchronized pairing)**, field measurements were aggregated into generalized period averages and compared against satellite observations from the same approximate window without date matching. This reflects the pairing available to organizations that cannot control deployment timing, and to retrospective studies drawing on archival field records.

In **Phase 2 (synchronized pairing)**, excursions were scheduled against predicted Sentinel-2 overpasses, and each measurement was matched to a cloud-free observation of the same site on the same calendar date.

### ***Ground-Based Measurement***

Field measurements were collected by the KWPI field team using a Hanna HI9829 multiparameter probe signed out from the Notre Dame College laboratory under the supervision of Md Nazmul Hassan. The instrument was calibrated against institutional standards before each excursion, and every sample was assigned a laboratory reference number (NDC-KWPI-001 through NDC-KWPI-008) linking the field record to its calibration event, establishing a chain of custody between the calibration and the measurement it supports.

Three parameters were recorded at each visit: turbidity in nephelometric turbidity units (NTU), pH, and dissolved oxygen (DO) in mg/L. Turbidity served as the validation target, being the parameter to which optical sensors respond directly. pH and DO were recorded as contextual indicators. Field conditions including flow state, visible discoloration, odor, vessel traffic, and recent rainfall were logged alongside each measurement and are reported in Appendix A. Manufacturer-specified accuracy for the instrument was  $\pm 0.2$  for pH,  $\pm 0.1$  mg/L for DO, and  $\pm 2\%$  for turbidity. Samples were collected at a standard depth of 0.5 meters below the surface

between 10:00 and 14:00 local time, with three replicate readings averaged per visit to minimize local variance.

### ***Satellite Data Acquisition***

Satellite observations were obtained through the Google Earth Engine (GEE) API, which provides programmatic access to the Sentinel-2 archive (Gorelick et al., 2017). The Surface Reflectance product was used, incorporating atmospheric correction prior to index computation. Scenes with scene-level cloud cover exceeding 20% were excluded, and retained imagery was visually inspected to confirm that the sampling coordinates themselves were unobstructed by cloud or shadow.

Reflectance was extracted from bands B4 and B3 and converted to NDTI. Extraction was performed over a small region surrounding each coordinate rather than a single pixel, reducing sensitivity to georeferencing error and to isolated anomalous pixels. Twelve dates yielded qualifying imagery, and several dates produced more than one qualifying observation. Those repeat observations are analytically valuable: because they sample the same site on the same day, the spread among them estimates observational noise independently of any real change in the river, a property exploited in the Results.

### ***Synchronization Protocol***

Phase 2 pairing required an exact calendar-date match between a field record and a qualifying satellite observation at the same site. No temporal tolerance was permitted. Eight such pairs were obtained across the study period.

### ***Statistical Analysis***

Spatial structure was assessed by paired  $t$  test and Wilcoxon signed-rank test on the perdate difference between sites, the latter included because the sample is small and the former assumes normality. Temporal change was assessed by independent-samples  $t$  test comparing

January and February site means. Observational noise was estimated as the pooled within-date standard deviation across dates yielding repeat observations, and compared against the between-date standard deviation.

Retrieval accuracy was modeled by ordinary least squares regression of NDTI on ground-measured turbidity. Model fit was assessed by the coefficient of determination ( $R^2$ ), with significance evaluated by a two-tailed  $t$  test on the slope at  $\alpha = .05$ , and a confidence interval for  $R^2$  obtained by Fisher  $z$  transformation. Because the synchronized sample is small, three robustness procedures were applied: Spearman's rank correlation, the Shapiro-Wilk test on residuals, and leave-one-out cross-validation (LOOCV) of the inverted model in its operational form. Identical procedures were applied to both phases. Analyses were conducted in Python using NumPy, SciPy, and pandas.

One observation was excluded from site comparisons. On 11 March the Hazaribagh Reach returned an NDTI of 0.010, the lowest value recorded anywhere in the study, at the most contaminated site, on a date when ground sampling recorded the season's highest turbidity elsewhere on the river. This is physically implausible and is treated as a sensor artifact. Its influence is reported explicitly in the Results rather than silently removed.

## **Results**

### ***Ground-Based Measurements***

Across the eight calibrated samples, turbidity ranged from 36.2 to 86.5 NTU ( $M = 62.5$ ,  $SD = 15.2$ ). The maximum was recorded at the Katashur Outfall on 11 March 2026, an excursion during which the field team independently logged a strong chemical odor and visible algal presence. The minimum occurred at the Buriganga Confluence on 7 April 2026 following rainfall, and reflects dilution rather than any reduction in discharge.

pH remained mildly acidic throughout (range 6.5 to 7.1,  $M = 6.8$ ,  $SD = 0.2$ ). Dissolved oxygen declined across the study period from 4.1 mg/L in early January to 2.5 mg/L in midMarch ( $M = 3.3$ ,  $SD = 0.59$ ). Every measurement fell below the 5 mg/L threshold established for aquatic life by the Bangladesh Environment Conservation Rules (Department of Environment, 1997), indicating conditions hostile to fish populations throughout.

Dissolved oxygen tracked seasonal progression more closely than it tracked turbidity ( $r = -.27$ ), consistent with declining discharge and rising temperature reducing oxygen solubility as the dry season advanced. pH and DO were strongly associated ( $r = .90$ ), suggesting a shared driver, most plausibly the concentration of organic load as flow volume fell. Because these parameters covary with season rather than with turbidity, they are reported as context and were not entered into the retrieval model.

**Table 2**

*Synchronized Field Measurements and Matched Sentinel-2 Observations, January to April 2026*

| Date (2026) | Site                 | Turbidity (NTU) | NDTI | pH  | DO (mg/L) | Lab reference |
|-------------|----------------------|-----------------|------|-----|-----------|---------------|
| 7 January   | Katashur Outfall     | 48.7            | .052 | 7.1 | 4.1       | NDC-KWPI001   |
| 20 January  | Buriganga Confluence | 60.5            | .077 | 6.9 | 3.8       | NDC-KWPI-002  |
| 30 January  | Hazaribagh Reach     | 65.6            | .079 | 7.0 | 3.9       | NDC-KWPI-003  |
| 14 February | Katashur Outfall     | 74.2            | .086 | 6.7 | 3.1       | NDC-KWPI-004  |
| 19 February | Buriganga Confluence | 63.0            | .082 | 6.8 | 3.4       | NDC-KWPI-005  |
| 6 March     | Hazaribagh Reach     | 65.4            | .086 | 6.6 | 2.9       | NDC-KWPI-006  |
| 11 March    | Katashur Outfall     | 86.5            | .106 | 6.5 | 2.5       | NDC-KWPI-007  |
| 7 April     | Buriganga Confluence | 36.2            | .029 | 6.8 | 2.7       | NDC-KWPI-008  |

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*Note.* NDTI = Normalized Difference Turbidity Index; DO = dissolved oxygen. Each row pairs a field measurement with a cloud-free Sentinel-2 observation of the same site on the same calendar date. Full field condition logs appear in Appendix A.

### ***A Persistent Spatial Gradient***

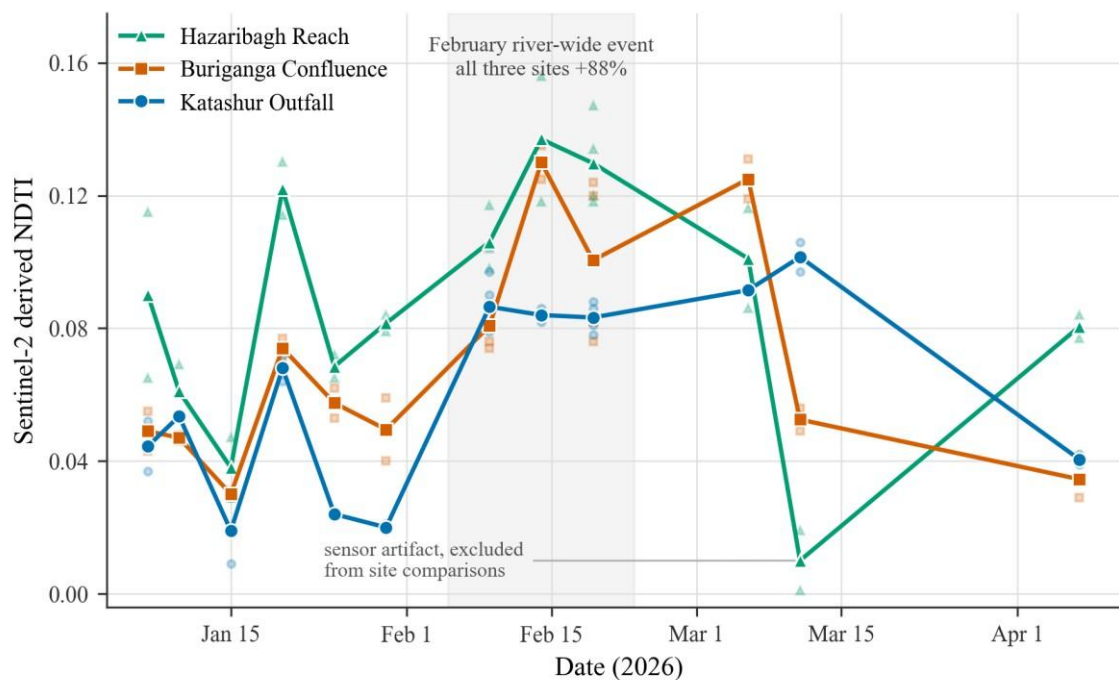
The continuous satellite record resolves a spatial structure that the eight field samples, distributed two or three per site, could not establish (Figure 1). Averaged across all valid dates, NDTI was lowest at the Katashur Outfall ( $M = .056$ ,  $SD = .028$ ), intermediate at the Buriganga Confluence ( $M = .071$ ,  $SD = .035$ ), and highest at the Hazaribagh Reach ( $M = .092$ ,  $SD = .031$ ). The tannery reach was 65% more turbid than the outfall on average.

The ordering is not an artifact of averaging. The Hazaribagh Reach exceeded the Katashur Outfall on all 11 valid observation dates, without exception (Figure 2a). The mean perdate difference was 0.036 NDTI units, paired  $t(10) = 6.34$ ,  $p < .001$ , Wilcoxon signed-rank  $p = .001$ . The Hazaribagh Reach was the most turbid of the three sites on 10 of those 11 dates.

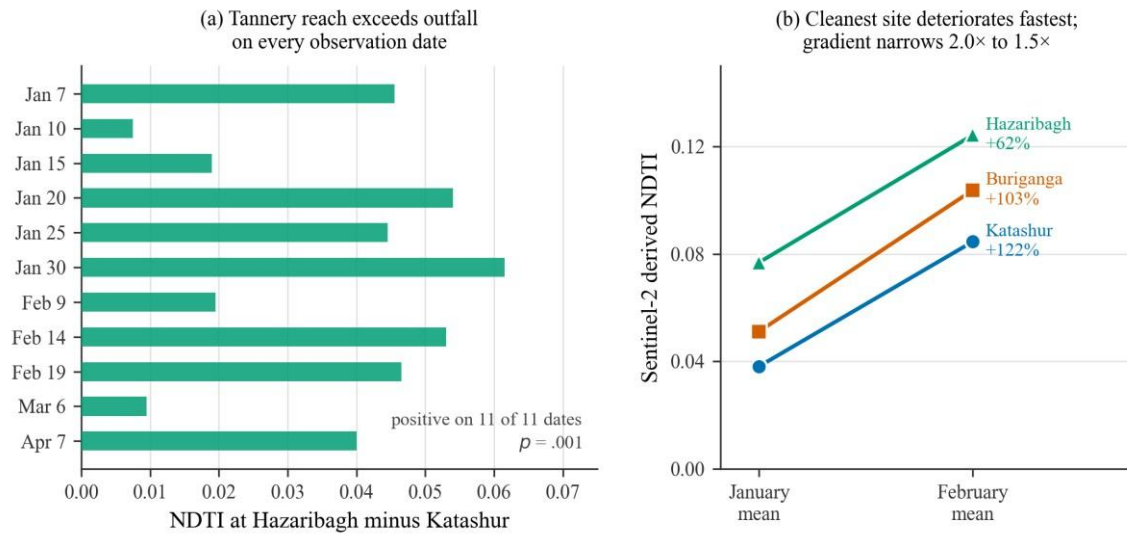
This is the kind of finding a monthly sampling program is poorly positioned to establish. Demonstrating that one reach is persistently worse than another requires repeated simultaneous observation at both, which is exactly what a field team visiting one site per excursion cannot provide, and exactly what a satellite supplies at no cost. The result also carries a specific attribution: the elevation is concentrated at the reach adjacent to the tannery district, and it persists across every observation, including dates on which the river as a whole was comparatively clear.

**Figure 1**

*Sentinel-2 NDTI at Three Buriganga Monitoring Sites, January to April 2026*



*Note.* Bold markers denote the daily mean where multiple qualifying observations were available; faint markers denote individual observations. Shaded region marks the February event described below. Derived from Sentinel-2 Surface Reflectance imagery with scene cloud cover below 20%. Higher NDTI indicates greater suspended solid concentration. The 11 March value at the Hazaribagh Reach is treated as a sensor artifact and excluded from site comparisons.

**Figure 2***Spatial Persistence and Seasonal Compression of the Turbidity Gradient*

*Note.* Panel (a) shows the per-date difference in NDTI between the Hazaribagh Reach and the Katashur Outfall; every value is positive. Panel (b) shows January and February site means, with the percentage increase for each site. The 11 March artifact is excluded from both panels.

***The February Event and Gradient Compression***

Between January and February, turbidity rose sharply and simultaneously at all three sites (Figure 2b). River-wide mean NDTI increased from .055 to .104, a rise of 88%,  $t = 3.91$ ,  $p = .006$ . The increase was significant at each site individually: Katashur Outfall +122% ( $p = .007$ ), Buriganga Confluence +103% ( $p = .004$ ), Hazaribagh Reach +62% ( $p = .034$ ).

That the rise occurred at all three sites simultaneously identifies it as a basin-scale event rather than a local discharge. Supporting this, the three sites were strongly intercorrelated across the study period once the 11 March artifact was excluded: Katashur and Confluence  $r = .85$  ( $p = .001$ ), Katashur and Hazaribagh  $r = .79$  ( $p = .004$ ), Confluence and Hazaribagh  $r = .80$  ( $p = .003$ ). The sites rise and fall together, which is the signature of a shared driver such as declining dry-

season discharge concentrating a roughly constant pollutant load, rather than of independent local inputs.

The relative magnitudes carry the more consequential implication. The cleanest site deteriorated fastest and the dirtiest site slowest, so the gradient between them narrowed: the ratio of Hazaribagh to Katashur NDTI fell from 2.01 in January to 1.47 in February. As dry-season flow declines, the comparatively cleaner reaches converge toward the condition of the worst one. The river does not merely get dirtier in the dry season; it becomes uniformly dirty, and the relative advantage of the less contaminated reaches erodes. For a community organization, this reframes the monitoring question. The relevant seasonal risk is not only that peak contamination rises, but that the stretches of river people rely on as comparatively safe stop being distinguishable from the ones they avoid.



**Figure 3.** Sentinel-2 true-color imagery of the Buriganga River on January 15, 2026 (left) and February 14, 2026 (right). Markers indicate the Hazaribagh Reach (red), Buriganga Confluence (blue), and Katashur Outfall (green). The visual darkening corresponds to an 88%

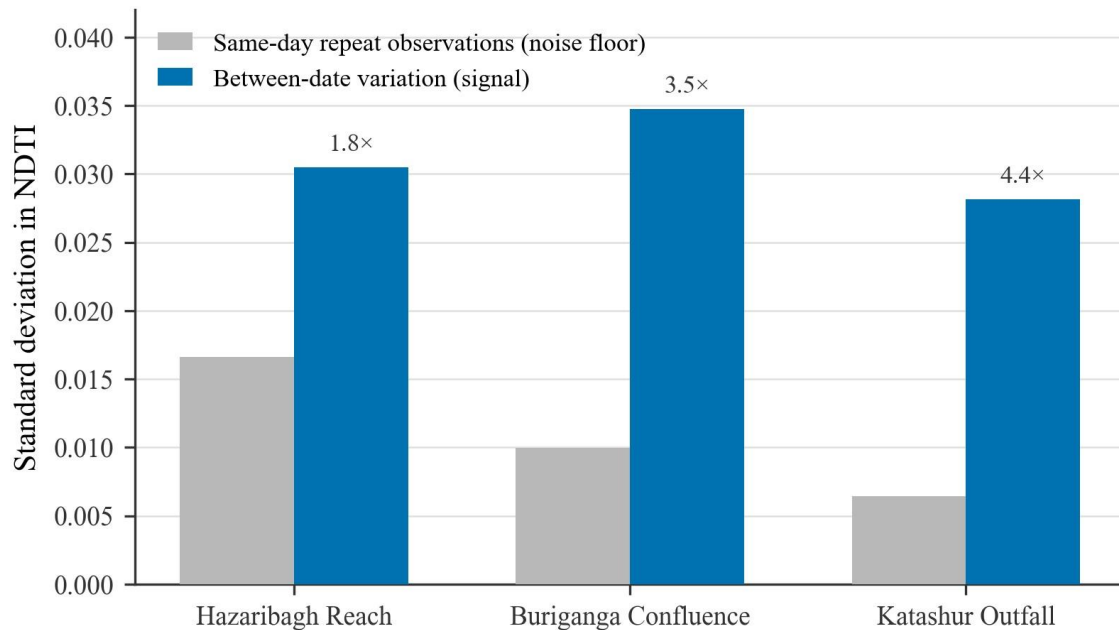
river-wide increase in measured turbidity.

### ***Observational Noise and the Rate of Real Change***

Several dates yielded more than one qualifying satellite observation of the same site. Because these observations sample identical water on an identical day, the spread among them estimates observational noise, including residual atmospheric effects, view-angle differences, and pixel-selection variability, independently of any real change in the river. This provides a noise floor against which genuine variation can be measured.

Pooled within-date standard deviation was .0118 NDTI units across all sites, against a between-date standard deviation of .0311 (Figure 4). Between-date variation therefore exceeds the noise floor by a factor of 2.6, implying that 86% of observed variance reflects genuine day-to-day change in the river rather than measurement error. The ratio varied by site: 4.4 at the Katashur Outfall, 3.5 at the Buriganga Confluence, and 1.8 at the Hazaribagh Reach. The tannery reach is both the most turbid site and the most internally heterogeneous, its higher same-day spread consistent with an actively discharging plume producing patchy conditions within a single scene.

This result is the physical premise on which the remainder of the analysis rests. The river's optical state changes substantially between one overpass and the next, and those changes are real rather than instrumental. Any protocol pairing a field sample with a satellite observation from a different date is therefore comparing two genuinely different states of the river.

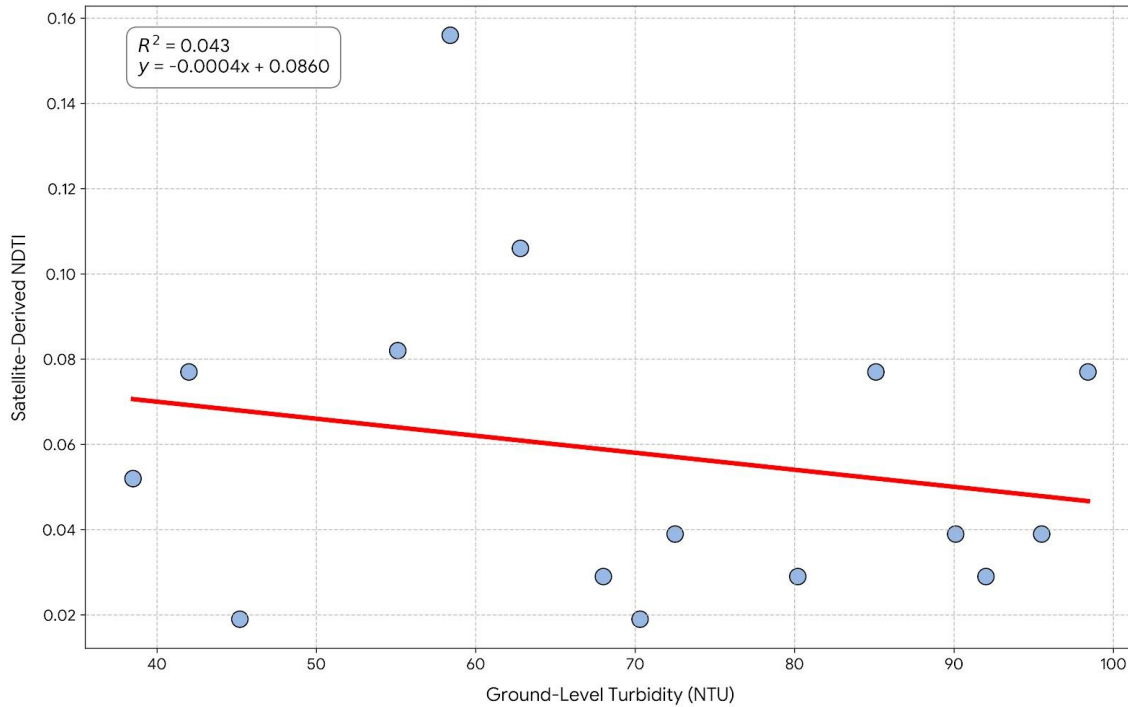
**Figure 4***Observational Noise Floor Compared With Between-Date Variation*

*Note.* Noise floor is the pooled within-date standard deviation across dates yielding repeat observations of the same site. Signal is the between-date standard deviation of daily means. Ratios above each pair give signal relative to noise. The 11 March artifact is excluded.

***Phase 1: Unsynchronized Pairing***

Under unsynchronized pairing, no meaningful relationship emerged between ground turbidity and satellite NDTI (Figure 5). The regression yielded  $R^2 = .04$  with a slightly negative slope, and the correlation was not statistically significant ( $p = .46$ ). Satellite reflectance accounted for approximately 4% of variance in ground-measured turbidity, a result indistinguishable from chance.

Read in isolation, this outcome would support the conclusion that Sentinel-2 imagery is unsuitable for monitoring the Buriganga. The negative slope would further imply, implausibly, that more turbid water appears optically clearer from orbit. Both inferences would be incorrect.

**Figure 5*****Unsynchronized Pairing of Ground Turbidity and Satellite NDTI (Phase 1)***

*Note.* Field measurements compared against satellite observations without same-date matching.  $R^2 = .04$ ,  $p = .46$ ,  $n=12$ .

***Phase 2: Synchronized Pairing***

Applying strict same-date matching transformed the result. Across the eight synchronized pairs, NDTI and ground turbidity were strongly and positively associated (Figure 6),  $R^2 = .94$ , 95% CI [.71, .99],  $n = 8$ ,  $t(6) = 9.96$ ,  $p < .001$ . The fitted model was

$$NDTI = 0.00151 \times Turbidity - 0.0198$$

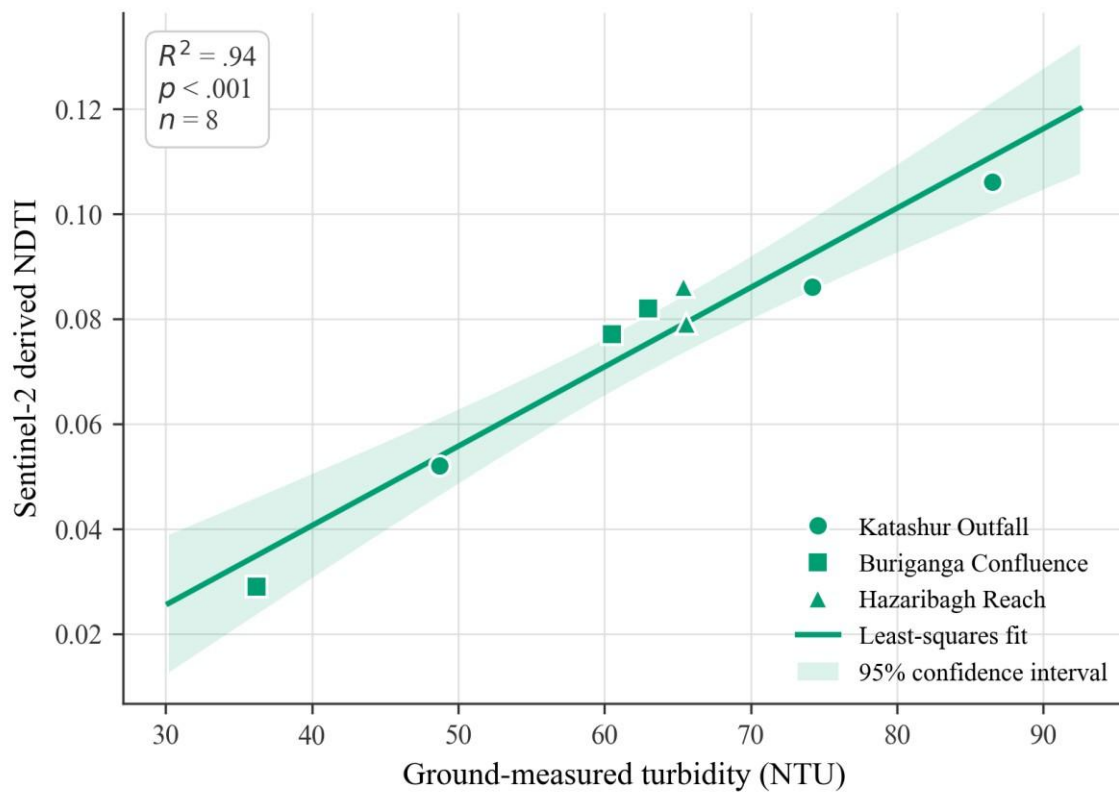
with slope 95% CI [0.00114, 0.00188] and residual standard deviation 0.0061 NDTI units (Table 3). Satellite reflectance explained 94% of variance in ground-measured turbidity, against 4% under unsynchronized pairing, a 22-fold increase attributable solely to temporal alignment.

**Table 3***Regression Coefficients for the Synchronized Retrieval Model*

| Parameter | Estimate | SE      | 95% CI             | <i>t</i> (6) | <i>p</i> |
|-----------|----------|---------|--------------------|--------------|----------|
| Slope     | 0.00151  | 0.00015 | [0.00114, 0.00188] | 9.96         | < .001   |
| Intercept | −0.0198  | 0.0097  | [−0.0436, 0.0040]  | n/a          | n/a      |

*Note.*  $n = 8$ . Response variable is NDTI; predictor is ground-measured turbidity in NTU.  $R^2 = .94$ , 95% CI [.71, .99].

Residual  $SD = 0.0061$ . **Figure 6**

*Synchronized Pairing of Ground Turbidity and Satellite NDTI (Phase 2)*

*Note.* Each point pairs a field measurement with a cloud-free Sentinel-2 observation of the same site on the same calendar date. Marker shape denotes site. Shaded band is the 95% confidence interval for the fitted mean.  $R^2 = .94$ ,  $n = 8$ ,  $p < .001$ .

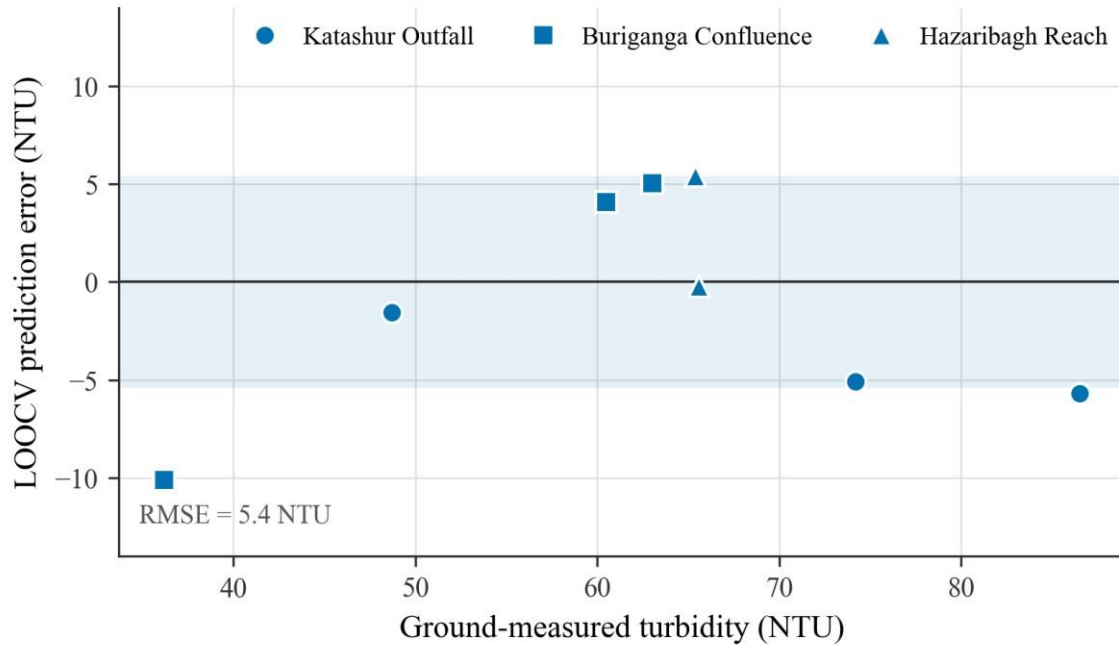
### ***Model Robustness and Predictive Validation***

Three procedures established that the Phase 2 result is not an artifact of small sample size. Spearman's rank correlation confirmed a strong monotonic relationship independent of distributional assumptions,  $r_s = .91$ ,  $p = .002$ , indicating the association is not produced by one or two influential observations. The Shapiro-Wilk test provided no evidence against residual normality,  $W = .86$ ,  $p = .13$ . Residuals showed no systematic pattern with respect to fitted values or site.

Because the operational application of the model is the reverse of its fitted form, estimating turbidity from an observed index, the inverted expression was evaluated directly:

$$\text{Turbidity (NTU)} = (\text{NDTI} + 0.0198) / 0.00151$$

Leave-one-out cross-validation returned a root-mean-square error of 5.4 NTU and a mean absolute error of 4.6 NTU, corresponding to 8.6% of mean observed turbidity (Figure 7). The largest single deviation, 10.1 NTU, occurred at the lowest observed turbidity, where the estimator is most sensitive to the intercept term. Because each fold omits the sample being predicted, these figures estimate performance on unseen observations and are a stronger indication of operational accuracy than the fit statistics alone.

**Figure 7***Leave-One-Out Cross-Validation Error for the Inverted Turbidity Estimator*

*Note.* Each point is the prediction error for one observation when the model is refitted with that observation excluded. Marker shape denotes site. The shaded band spans  $\pm 1$  RMSE (5.4 NTU). Errors show no systematic dependence on turbidity magnitude or site.

***Sensitivity to the Excluded Observation***

The 11 March Hazaribagh value materially affects the spatial results, and its exclusion is therefore reported rather than assumed. Retaining it reduces the correlation between the Katashur Outfall and the Hazaribagh Reach from  $r = .79$  ( $p = .004$ ) to  $r = .27$  ( $p = .39$ ), converting a significant association into a null one, and reduces the count of dates on which the tannery reach was most turbid from 10 of 11 to 10 of 12. A single unscreened artifact is thus sufficient to reverse a substantive conclusion about how the river behaves, which is itself a result worth reporting: automated extraction without visual screening is not a safe operating procedure. The Phase 2 retrieval model is unaffected, since 11 March at Hazaribagh was not among the synchronized pairs.

## **Discussion**

### ***What the Continuous Record Adds***

The three descriptive findings share a common property: each required repeated, simultaneous observation of multiple sites, and none could have been established by the eight field samples alone.

The spatial gradient required simultaneity. Establishing that the tannery reach is persistently more turbid than the outfall means observing both at the same moment, repeatedly. A field team visiting one site per excursion produces measurements that differ in date as well as location, leaving the two explanations confounded. The satellite record separates them, and the answer is unambiguous: the elevation appeared on every valid date, including dates when the river as a whole was comparatively clear.

The February event required continuity. A field program sampling monthly would have recorded higher February values and could reasonably have attributed them to a local discharge at whichever site happened to be visited. The satellite record shows the rise occurring at all three sites at once, with the sites strongly intercorrelated throughout, which points instead to declining dry-season flow concentrating a roughly constant load. That distinction matters directly for advocacy, because it identifies the mechanism as seasonal hydrology acting on continuous industrial input rather than a discrete polluting incident.

The compression finding required both. That the cleanest site deteriorated fastest, narrowing the gradient from 2.0 to 1.5, is a relationship between sites over time, and is visible only when both dimensions are sampled densely.

### ***Why Synchronization Governs Accuracy***

The noise floor analysis supplies the mechanism connecting the descriptive findings to the methodological one. Between-date variation in NDTI exceeds same-day observational spread

by a factor of 2.6, so 86% of the variation between one overpass and the next is real change in the river rather than measurement error. The Buriganga's optical state is genuinely different from week to week.

It follows that a field sample collected three days before an overpass is not a noisy measurement of the condition the satellite observed. It is an accurate measurement of a different condition. Averaging across such intervals does not attenuate error; it destroys the signal. The slightly negative Phase 1 slope is the expected consequence: with the true relationship severed, the fitted slope reflects nothing but the arrangement of unrelated values.

This inverts a common inferential move. A weak validation result is ordinarily read as evidence about sensor capability. These data indicate that in rapidly varying systems it may instead be evidence about the pairing protocol, and that the two are readily confused because both produce the same signature of low  $R^2$  and a non-significant slope. For such systems, temporal synchronization is not a refinement of the validation method. It is a precondition for the validation being informative at all.

We note the reciprocal implication. Because Phase 1 is a within-study comparison rather than a reanalysis of published work, these results establish that pairing interval can produce this signature, not that it explains any particular published finding. Distinguishing the two would require systematically reanalyzing validation studies against their reported pairing intervals, a tractable and, we suggest, worthwhile exercise.

### ***Operational Implications***

For KWPI, these results establish that the organization can monitor the Katashur Outfall and comparable junctions continuously, at no marginal cost, using imagery already in the public domain, with an expected error of roughly 5 NTU against its own calibrated instrument. Rather than deploying a field team to determine whether conditions have deteriorated, the organization

can consult satellite imagery and reserve physical sampling for periodic recalibration and for events the satellite flags as anomalous.

The requirement this imposes is procedural rather than financial. Sentinel-2 overpass times are published in advance, so excursions can be scheduled to coincide with them at no additional cost. What the method demands is not better equipment but better timing, a constraint a volunteer organization can satisfy more readily than a budgetary one. This is a substantive point about accessibility: the binding constraint on community-based remote sensing turns out to be one of the few such organizations are well positioned to relieve.

The consequence for advocacy is a change in the kind of claim that can be supported. A field measurement documents a moment. A validated satellite record documents a pattern, and the patterns recovered here are of the type regulatory argument depends on: a named reach that is worse than its neighbors on every observation, and a seasonal window in which the whole river deteriorates together. Evidence of that structure, anchored to instrument-calibrated ground truth, is a qualitatively different instrument of persuasion from a handful of isolated samples.

### ***Limitations***

**Sample size.** The synchronized analysis rests on eight pairs distributed across three sites. Although the relationship is highly significant and survives rank-based and cross-validated testing, the interval estimate is correspondingly wide, with the 95% CI for  $R^2$  spanning .71 to .99. The coefficients should be treated as provisional, and the design cannot establish whether calibration differs meaningfully between sites.

**Seasonal restriction.** Data collection ends in April 2026 because optical sensors cannot observe through cloud. As the pre-monsoon transition begins, persistent cloud eliminates usable imagery, and this constraint is absolute rather than incremental: during the monsoon the method is unavailable, not merely degraded. Because the monsoon is also when runoff most dramatically

alters river conditions, the method is presently blind during the period of greatest hydrological interest.

**Attribution.** The persistent elevation at the Hazaribagh Reach is consistent with tannery discharge but does not establish it. The satellite measures turbidity, not its source, and other explanations including channel morphology, depth, flow velocity, and vessel traffic could contribute. Establishing attribution would require either upstream and downstream sampling bracketing the discharge point, or contaminant-specific analysis.

**Anomalous observations.** As the sensitivity analysis shows, one unscreened artifact was sufficient to reverse a substantive conclusion. Automated extraction cannot reliably distinguish artifacts from genuine observations, and operational deployment requires visual inspection of flagged scenes rather than unsupervised ingestion.

**Single-parameter retrieval.** NDTI responds to optical scattering by suspended particles. It does not detect dissolved contaminants, heavy metals, or biochemical oxygen demand, precisely the pollutants of greatest concern in the Buriganga. Elevated turbidity frequently accompanies industrial discharge, but the association is correlational and unquantified here. The pH and DO measurements reported above, which covary with season rather than turbidity, illustrate that not all water quality parameters are recoverable through this channel.

**Instrumentation.** Measurements were collected with a single probe calibrated against institutional standards rather than by an accredited laboratory. Calibration records support internal consistency and traceability, but absolute accuracy has not been independently verified. The reported error is therefore error relative to the reference instrument, not to a certified standard.

**Generality.** These findings derive from one river across one dry season. The synchronization requirement should hold wherever the monitored quantity varies faster than the

pairing interval, but the specific calibration coefficients are local and should not be transferred without revalidation.

### ***Future Research***

The seasonal limitation is the most consequential and admits a known technical approach. Synthetic Aperture Radar sensors, including Sentinel-1, penetrate cloud and operate independently of solar illumination. SAR does not retrieve turbidity directly, but combining SAR-derived surface and flow characteristics with optical calibration established during the dry season may permit year-round monitoring. [CITE 7, see 04\_Sources, if this section is developed]

Three further extensions follow from the findings above. Extending the record across a full annual cycle would test whether the gradient compression observed between January and February continues through the late dry season and reverses with the monsoon, which would convert a two-month observation into a seasonal model. Bracketing the Hazaribagh discharge point with upstream and downstream sampling would convert the persistent elevation from an association into an attribution. And establishing whether NDTI covaries with dissolved oxygen or contaminant concentration, mediated through turbidity, would determine whether the method extends beyond suspended solids toward the pollutants that motivate the monitoring in the first place.

### **Conclusion**

Analysis of 28 Sentinel-2 observations across 12 dates resolved three features of the Buriganga that eight field samples could not. The reach adjacent to the Hazaribagh tannery district was more turbid than the Katashur Outfall on every valid observation date ( $p = .001$ ), a persistent gradient of 65%. Turbidity rose 88% river-wide between January and February ( $p = .006$ ), simultaneously at all three sites, identifying a basin-scale seasonal mechanism rather than a local discharge. And because the cleanest site deteriorated fastest, the gradient between the

tannery reach and the outfall compressed from 2.0 to 1.5, indicating that dry-season conditions erode the distinction between the river's better and worse stretches.

Repeat same-day observations established that 86% of the variation between overpasses is real change rather than measurement error. That finding predicts the study's methodological result and explains it. Matching each field measurement to a cloud-free overpass on the same calendar date yielded strong agreement with ground truth ( $R^2 = .94$ ,  $p < .001$ , cross-validated error 5.4 NTU), whereas the same data paired without same-date matching explained 4% of variance and yielded no significant relationship.

The contribution is therefore twofold. The first is substantive: a continuous, zero-cost record of a river whose degradation is well documented but sparsely measured, resolving spatial and seasonal structure that discrete sampling had not. The second is methodological: in systems varying on daily timescales, temporal synchronization between field and satellite observation is a precondition for meaningful validation rather than a refinement of it. Studies reporting weak satellite-to-ground agreement in such systems may be measuring the limits of their pairing protocol rather than the limits of the sensor.

For the Katashur Water Protection Initiative, the practical result is that a volunteer organization equipped with a calibrated probe and a published overpass schedule can now

monitor a river continuously, connecting an international satellite program to the specific discharge points affecting the communities living beside them.

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### Data Availability Statement

All underlying data, including datasets, high-resolution imagery, and Google Earth Engine scripts, are publicly available in the project's digital archive at:

<https://drive.google.com/drive/folders/1rozMw8nMSb4oE3K03Fvmw934U0Ys2qr?usp=sharing>

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## Appendix A

### Synchronized Field Dataset and Condition Logs

The complete synchronized dataset supporting Table 2 and Figures 6 and 7, comprising eight field measurements with matched Sentinel-2 observations, laboratory reference numbers, and full field condition logs.

## Appendix B

### Sentinel-2 NDTI Extraction Output

Raw Google Earth Engine export of NDTI values for all three monitoring sites across the study period, comprising 28 observations on 12 dates, from which Figures 1, 2, and 4 were constructed. Two records in the original export carried a date of 3 November 2026; the associated values correspond to the 11 March 2026 observation, and the discrepancy was identified as a transcription error and corrected. The corrected file is supplied as *Earth\_Enginechart (date-corrected).xlsx*; the original is retained unaltered for audit.

## Appendix C

### Unsynchronized Pairing Dataset (Phase 1)

| Observation Date<br>(2026) | Site             | Satellite<br>NDTI | Generalized Field Turbidity<br>(NTU) | Temporal<br>Offset |
|----------------------------|------------------|-------------------|--------------------------------------|--------------------|
| 3 January                  | Katashur Outfall | .048              | 62.5                                 | +4 days            |
| 12 January                 | Hazaribagh Reach | .071              | 65.0                                 | -5 days            |
| Buriganga                  |                  |                   |                                      |                    |

|             |                         |      |      |          |
|-------------|-------------------------|------|------|----------|
| 18 January  | Confluence              | .066 | 60.1 | +2 days  |
| 25 January  | Katashur Outfall        | .055 | 62.5 | -8 days  |
| 4 February  | Hazaribagh Reach        | .089 | 70.3 | +9 days  |
| 9 February  | Buriganga<br>Confluence | .080 | 68.4 | +6 days  |
| 22 February | Katashur Outfall        | .091 | 75.2 | -3 days  |
| 28 February | Hazaribagh Reach        | .095 | 78.0 | +4 days  |
| 8 March     | Buriganga<br>Confluence | .099 | 80.1 | -10 days |
| 15 March    | Hazaribagh Reach        | .108 | 85.4 | +6 days  |
| 26 March    | Katashur Outfall        | .085 | 70.5 | -7 days  |
| 2 April     | Buriganga Conflu.       | .041 | 40.2 | +5 days  |

## Appendix D

### Google Earth Engine Scripts

Two scripts are supplied. The second, *GEE\_Export\_TrueColor\_Imagery.js*, exports true-colour and NDTI imagery for the clearest and most turbid observed dates and is included in the project files

```
// NDTI EXTRACTION SCRIPT: Buriganga River (Jan-Apr 2026)
```

```
// 1. Define monitoring sites based on KWPI field coordinates with 30m buffer var
hazaribagh = ee.Feature(ee.Geometry.Point([90.3622, 23.7314]).buffer(30), {name:
'Hazaribagh Reach'}); var confluence = ee.Feature(ee.Geometry.Point([90.3588,
23.7385]).buffer(30), {name:
'Buriganga Confluence'}); var katashur = ee.Feature(ee.Geometry.Point([90.3551,
23.7432]).buffer(30), {name: 'Katashur Outfall'}); var sites =
ee.FeatureCollection([hazaribagh, confluence, katashur]);

// 2. Load Sentinel-2 Surface Reflectance and apply filters var s2 =
ee.ImageCollection('COPERNICUS/S2_SR_HARMONIZED')
.filterBounds(sites)
.filterDate('2026-01-01', '2026-04-30')
.filter(ee.Filter.lt('CLOUDY_PIXEL_PERCENTAGE', 20));

// 3. Function to compute NDTI and apply cloud/water masking var
computeNDTI = function(image) {
```

```

// NDTI = (Red - Green) / (Red + Green) -> (B4 - B3) / (B4 + B3)
var ndti = image.normalizedDifference(['B4', 'B3']).rename('NDTI');

// Apply QA mask for clouds and cirrus  var qa
= image.select('QA60');  var cloudBitMask = 1
<< 10;  var cirrusBitMask = 1 << 11;  var mask
= qa.bitwiseAnd(cloudBitMask).eq(0)
.and(qa.bitwiseAnd(cirrusBitMask).eq(0));

return image.addBands(ndti).updateMask(mask);
};

// 4. Map function over the collection var
s2_ndti = s2.map(computeNDTI);

```