

Original Article

Evaluation of Smartphone-Based Turbidity Monitoring in Two Philippine Rivers Using Normalized RGB Values

Taishi Yazawa¹ , Serbelle Juanites² , Kylla Jane E. Ramo³, Toshiyuki Shimizu⁴ 

Author Information:

¹Institute of Industrial Science, The University of Tokyo, Tokyo, Japan

²Barbaza National High School, Barbaza, Antique, Philippines

³Bachelor of Secondary Education, University of Antique, Tibiao, Antique, Philippines

⁴Faculty of Urban Management, Fukuyama City University, Hiroshima, Japan

Corresponding Author:

Taishi Yazawa
yazawa@iis.u-tokyo.ac.jp

Article History:

Date received: August 7, 2026

Date revised: September 7, 2026

Date accepted: September 18, 2026

Recommended citation:

Yazawa, T., Juanites, S., Ramo, K.J.E., & Shimizu, T. (2026). Evaluation of smartphone-based turbidity monitoring in two Philippine rivers using normalized RGB values. *Journal of Interdisciplinary Perspectives*, 4(10), 385-395.
<https://doi.org/10.69569/jip.2026.384>

Abstract. River turbidity is an important water quality indicator, but frequent and spatially distributed monitoring remains difficult in resource-limited regions because conventional instruments are costly and require calibration and technical capacity. This study evaluated the applicability and limitations of smartphone-derived turbidity monitoring in two tropical coastal rivers, the Dalanas River and the Nalupa River, located in Barbaza, Antique Province, Philippines. A total of 50 paired observations were collected during dry-season low-flow conditions within a limited turbidity range of less than 30 NTU. Smartphone-derived turbidity information, field turbidimeter measurements, and laboratory-measured operational reference turbidity were compared, and supplementary event-level analyses were conducted using 10 river-day means. The field turbidimeter closely tracked laboratory-measured turbidity but showed systematic underestimation, particularly at higher turbidity levels. At the event level, the field turbidimeter had a mean bias of -3.09 NTU, MAE of 3.22 NTU, RMSE of 4.07 NTU, and Bland-Altman limits of agreement of -8.56 to 2.39 NTU. The smartphone-derived turbidity estimate showed a compressed response, with overestimation in the low-turbidity range and underestimation in the higher-turbidity range. Its event-level mean bias was close to zero, but the MAE and RMSE were 4.90 NTU and 5.23 NTU, respectively, with wider limits of agreement of -10.78 to 10.82 NTU. Normalized RGB values obtained from the HydroColor-derived output were also analyzed using log-ratio indices. The exploratory RGB log-ratio model explained approximately 77% of the observed variation in log-transformed laboratory turbidity ($R^2 = 0.77$, $r = 0.88$), but this represents an internal log-scale fit rather than validated NTU-scale prediction. These findings suggest that smartphone-derived RGB information can reflect relative changes in river turbidity under field conditions. Although the method cannot replace laboratory or field turbidimeter measurements, it may serve as a low-cost supplementary tool for rapid turbidity screening, citizen science, and STEM education in data-scarce regions.

Keywords: Low-cost monitoring; Philippines; RGB; Smartphone; Turbidity.

River turbidity is an important indicator of water quality and has significant implications for aquatic ecosystems and water treatment processes (Bilotta & Brazier, 2008). The spatiotemporal variability of river turbidity is complex and is strongly influenced by both anthropogenic activities and climatic factors (Dethier et al., 2022). In many major Asian river systems, suspended sediment loads have declined due to dam

construction and land management practices (Syvitski et al., 2005; Dethier et al., 2022). In contrast, sediment loads may increase in rapidly developing areas or in catchments with high runoff and disturbance (Walling & Fang, 2003). In addition, river turbidity can increase rapidly during high-flow events associated with heavy rainfall and typhoons, and turbidity often rises sharply following sediment-related disasters such as landslides. As rainfall intensity is expected to increase under climate change, monitoring these short-term high-turbidity events is becoming increasingly important (Göransson et al., 2013; Lu et al., 2023; Al Sawaf et al., 2024).

River turbidity is also affected by a range of socioeconomic and land-use factors (Dethier et al., 2022). Deforestation and agricultural expansion can accelerate soil erosion, while slope development and road construction increase exposed soil surfaces and surface runoff. Human activities such as mining and dredging can also temporarily increase turbidity and contribute to riverbank erosion (Narayanan et al., 2024; Mersha et al., 2025). Because turbidity is influenced by combined natural and human factors, high-frequency and spatially extensive monitoring is needed to better understand river water quality dynamics (Droujko & Molnar, 2022).

However, frequent and spatially distributed turbidity monitoring remains challenging, particularly in resource-limited settings (Bilotta & Brazier, 2008). In rural areas of the Philippines, including the study area, the high cost of turbidity meters makes it difficult for local governments and educational institutions to install and maintain monitoring equipment. This limitation is particularly relevant in tropical river systems, where rainfall-driven runoff, typhoons, and land-use activities can cause rapid and spatially variable changes in turbidity. In the Philippines, many local rivers are closely connected to agricultural use, domestic water use, and community livelihoods, but limited equipment, personnel, and institutional capacity often constrain regular water quality monitoring (Lasco & Hardon, 2024; Melad et al., 2024; Yazawa et al., 2024a). In addition, the cost of calibration standards, limited opportunities for regular calibration, and a shortage of trained personnel restrict monitoring's spatial and temporal coverage. As a result, turbidity observations are often limited to fixed-point and low-frequency measurements, making it difficult to capture short-term turbidity changes during events such as heavy rainfall.

In recent years, smartphone-based water quality monitoring methods have been proposed as a potential supplementary approach to address these challenges (Yazawa et al., 2024b; Yazawa et al., 2025). Smartphones are low-cost, widely available, and suitable for citizen science and educational applications (Hussain et al., 2016; Ceylan Koydemir et al., 2019). Previous studies have demonstrated the potential of using smartphone images and red-green-blue (RGB) values to estimate turbidity (Malthus et al., 2020). However, many of these studies were conducted under controlled laboratory conditions or used artificial samples, and validation under natural river conditions with field-based environmental variability remains limited. Furthermore, the applicability of smartphone-based turbidity estimation in tropical rivers, where turbidity can vary substantially, has not been sufficiently examined. Systematic evaluations comparing smartphone-derived estimates with field turbidimeter measurements and laboratory turbidimeter measurements remain limited. To apply citizen science-based methods in real river environments, it is necessary to quantitatively evaluate the reliability of simplified measurement approaches and clarify the range of conditions under which they can be applied using quantitative error metrics such as bias, mean absolute error (MAE), root mean square error (RMSE), and relative error.

Unlike previous studies that mainly evaluated smartphone-derived turbidity estimation under controlled laboratory conditions or focused on application-derived turbidity outputs, this study provides a field-based comparison of three turbidity-related measurements in two tropical Philippine rivers: smartphone-derived turbidity information, field turbidimeter measurements, and laboratory-measured operational reference turbidity. This study's methodological contribution is combining two-river field validation with normalized RGB analysis and a log-ratio transformation that accounts for the compositional nature of RGB data. This approach allows evaluation of the reliability and limitations of smartphone-derived turbidity estimation under real river conditions.

Based on this background, the present study aims to evaluate the agreement and internal model fit among three types of turbidity-related measurements: (a) a smartphone-derived turbidity estimate, (b) measurements obtained using a field turbidimeter, and (c) laboratory-measured operational reference turbidity. Specifically, this study addresses the following research questions: (a) How closely do field turbidimeter measurements correspond to laboratory-measured operational reference turbidity when evaluated using association, bias, and error-based agreement metrics? To what extent can smartphone-derived turbidity information estimate laboratory-measured

operational reference turbidity under dry-season field conditions? Can normalized RGB values obtained from smartphone images, particularly log-ratio indices, be used to develop an exploratory RGB log-ratio regression model for laboratory-measured turbidity?

By demonstrating the potential effectiveness of low-cost, on-site turbidity measurement methods, this study is expected to improve water quality monitoring in resource-limited regions. In addition, the approach may support STEM education and citizen science by promoting local understanding of water quality and expanding monitoring capacity in data-scarce regions. Ultimately, this study contributes to the development of decentralized environmental monitoring and more effective water resource management.

Methodology

Study Area

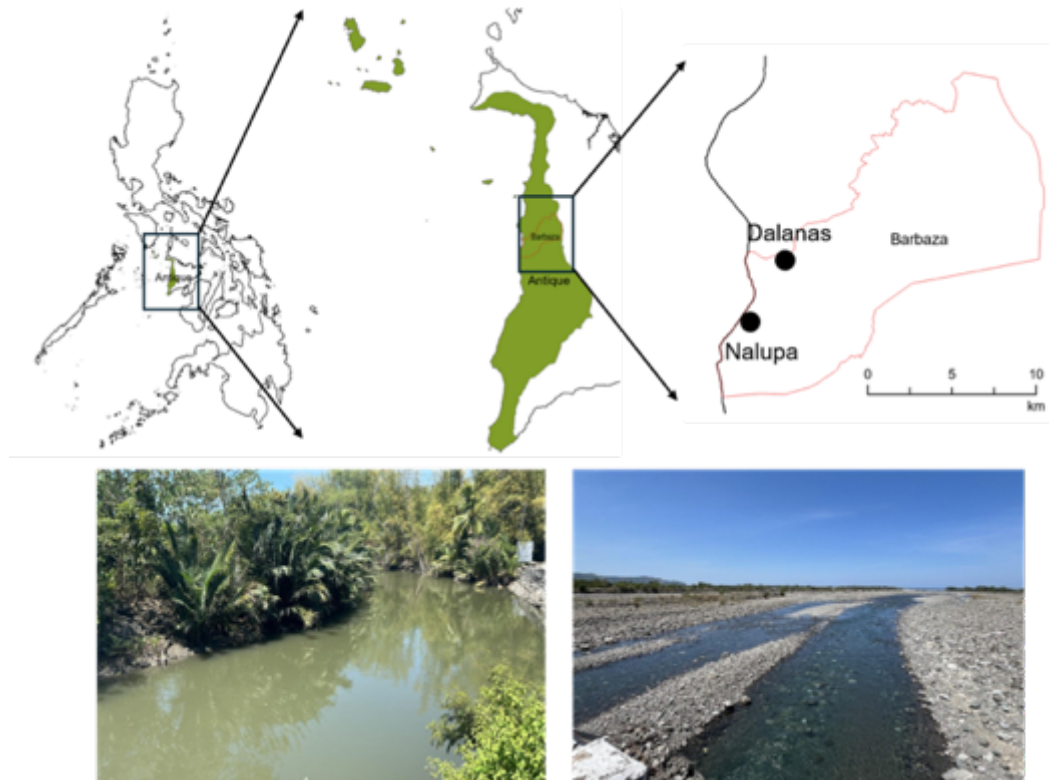


Figure 1. Study Rivers: Nalupa River (bottom-left photo) and Dalanas River (bottom-right photo) in Antique, Philippines

This study was conducted in two rivers, the Dalanas River and the Nalupa River, located in the Municipality of Barbaza, Antique Province, Philippines (Figure 1). Table 1 summarizes the coordinates, sampling dates, approximate sampling times, weather conditions, recent rainfall information, flow conditions, water surface conditions, and site-access conditions. Both rivers are tropical lowland coastal rivers that flow through coastal areas and eventually discharge into the Sulu Sea. We selected these rivers as study sites because they represent coastal river systems where turbidity may vary in response to local environmental and hydrological conditions. We collected five water samples from each river on each sampling day over five days, for a total of 50 samples. Because samples collected from the same river on the same day shared the same general hydrological and meteorological conditions, we did not treat them as fully independent river-day observations. Therefore, the dataset consisted of 50 sample-level observations nested within 10 river-day sampling events. The Nalupa River is a relatively small, calm river flowing through Barangay Jinalinan. It is characterized by shallow water and low flow velocity. The surrounding area contains natural vegetation, particularly nipa palms, forming a lowland coastal environment near the river mouth. In contrast, the Dalanas River is larger and more dynamic than the Nalupa River, with greater flow increases during rainfall events. Agricultural land is widely distributed in its catchment, and the river is closely associated with agricultural water use and irrigation.

Table 1. *Information on the Two Study Rivers in Antique, Philippines*

Item	Dalanas River	Nalupa River
Sampling site	Bridge nearest to the river mouth	Bridge nearest to the river mouth
Coordinates	11.24770,122.06767	11.22364,122.05321
Sampling dates	March 16-20, 2026	March 16-20, 2026
Sampling time	9:00-10:00 local time	10:00-11:00 local time
Season	Dry season	Dry season
Weather during sampling	Generally fair; no rainfall observed	Generally fair; no rainfall observed
Recent rainfall	Data unavailable	Data unavailable
Flow condition	Low-flow dry-season condition	Low-flow dry -season condition
Water surface condition	Slight ripples	Calm
Permission/access	Public bridge; no specific permit required	Public bridge; no specific permit required

Both rivers are closely connected to local communities' daily lives and livelihoods. Small-scale fishing and shell gathering are practiced along the Nalupa River, while the Dalanas River is used for irrigation and fishing activities. Both rivers are also susceptible to flooding and turbid runoff during heavy rainfall and typhoon events. In the Nalupa River, local cleanup activities respond to debris and pollutant inflows during flooding. In the Dalanas River, flooding and riverbank erosion are recognized as environmental concerns. These characteristics make both rivers suitable sites for evaluating real-river turbidity monitoring in tropical coastal environments. The study area is in a tropical climate region, where rainfall events can cause substantial changes in river turbidity. However, all sampling in this study was conducted during the dry season. Therefore, the measurements were obtained under conditions with limited direct influence from rainfall events.

Sampling and Measurement Procedure

Sampling sites were established on the bridge closest to the river mouth in each river. Water samples were collected, as far as possible, near the center of the river channel, targeting surface water at a depth of approximately 10–30 cm. We used a plastic bucket and cleaned polyethylene bottles (250 mL) for water collection. Immediately after collection, the samples were gently mixed to minimize the settling and separation of suspended particles.

We paired smartphone observations with physical water samples by sampling location and time. At each sampling point, we first used the HydroColor application (Leeuw & Boss, 2018) to photograph the river surface at the same location where we collected the water sample. Immediately after smartphone imaging, we collected surface water from approximately 10–30 cm depth using a plastic bucket and polyethylene bottle. We then used the collected water sample for field turbidimeter and laboratory turbidity measurements. Thus, we treated smartphone-derived values and turbidimeter measurements as paired observations matched by river, sampling day, sampling point, and sampling sequence, rather than as measurements from the exact same bottle sample. Before each measurement, we gently mixed the samples again to keep suspended particles as uniformly distributed as possible. Measurements were conducted consecutively within the shortest possible time, in the order of smartphone imaging, field turbidimeter measurement, and laboratory turbidity measurement. This procedure minimized differences among measurement methods caused by elapsed time or particle settling. For each method, we conducted three replicate measurements for each sample and used the mean value for subsequent analysis.

On-site Turbidity Measurement Using a Smartphone

Smartphone-based observations were conducted using the HydroColor application version 2.4 (Leeuw & Boss, 2018) installed on an iPhone 17 Pro Max. At each sampling point, we followed the standard HydroColor above-water measurement procedure. This procedure involved sequentially acquiring images of an 18% reflectance gray card, the river water surface, and the sky, as required by the application. We used the same smartphone, application version, and gray card throughout the field survey.

In this study, Turb_phone was defined as the turbidity estimate generated by the HydroColor application through its standard above-water measurement procedure. The application recorded the value in NTU (Nephelometric Turbidity Unit). We applied no additional equation or user-defined calibration to calculate Turb_phone. Therefore, Turb_phone represents the application-derived turbidity estimate, whereas the RGB log-ratio model described later was developed separately in this study.

The R, G, and B values used for normalized RGB and log-ratio analysis were obtained from the HydroColor-derived output following the application procedure. We did not manually extract them from raw images or

independently process photographs. Thus, the RGB-based analysis in this study used application-derived color-channel information, while Turb_phone used the HydroColor turbidity output.

Camera-specific parameters, including the exact operating system version, selected lens metadata, image format, exposure settings, HDR status, and exact viewing azimuth relative to the sun, were not independently recorded during the field survey. These parameters were not manually fixed; the iPhone camera system and the HydroColor application determined them. To reduce variability, we conducted all observations using the same device and application, the same 18% reflectance gray card, and the same measurement sequence. We adjusted the camera angle and viewing direction in the field according to the HydroColor procedure to reduce direct sun glint from the water surface.

Three HydroColor image-acquisition sequences were conducted for each sampling point, and the mean value was used for subsequent analysis. All smartphone observations were conducted within the same morning sampling period to minimize temporal variation in light conditions.

On-site Turbidity Measurement Using a Field Turbidimeter

River water collected in a bucket was mixed 10 times using a fixed procedure before measurement to homogenize suspended particles in the sample. We applied the same mixing procedure to all samples to minimize variation in mixing conditions. We measured on-site turbidity using a portable turbidimeter, TB-31 (TOA DKK, Japan). This instrument measures turbidity using a 90-degree scattered-light method with near-infrared light, and results were recorded in NTU.

We calibrated the field turbidimeter on the first day of the field survey using standard solutions of 0, 20, and 100 NTU. Because the field measurements were conducted during a short survey campaign under the same field protocol, we did not perform daily field calibration. In contrast, we calibrated the laboratory turbidimeter each day following the laboratory measurement protocol, using standard solutions of 20, 100, 400, and 800 NTU. Therefore, the field turbidimeter results should be interpreted as on-site comparator measurements rather than as fully traceable reference measurements. The survey did not independently conduct daily calibration verification, blank measurements, or standard recovery tests for the field turbidimeter. Instrument ranges and detection limits were based on the manufacturer specifications where available. This limitation is acknowledged in the Discussion.

We conducted three replicate readings for each sample and used the mean value for analysis. However, we did not retain the individual replicate readings in a form that allowed retrospective calculation of within-sample standard deviation or coefficient of variation. Therefore, this study could not quantitatively evaluate within-sample repeatability. We used replicate averaging to reduce the influence of occasional abnormal readings, but we did not interpret it as a substitute for reporting measurement precision.

Laboratory Turbidity Measurement

We used the same water samples collected in the field for laboratory turbidity measurements. During transport, the samples were stored in the dark, and analysis was conducted within 1 hour after sample collection. Before measurement, the samples were gently inverted to homogenize suspended particles while avoiding air bubbles. Measurements were conducted at room temperature.

We measured laboratory turbidity using a TBD700 laboratory turbidimeter (AS ONE, Japan). This instrument measures turbidity using a 90-degree nephelometric method compliant with ISO 7027, and results were recorded in NTU. We calibrated the instrument each day before turbidity analysis using standard solutions of 20, 100, 400, and 800 NTU. We conducted three measurements for each sample and used the mean as the representative value for subsequent analysis.

In this study, laboratory-measured turbidity was used as an operational reference for comparison because the laboratory turbidimeter was calibrated daily using 20, 100, 400, and 800 NTU standard solutions, and measurements were conducted under controlled laboratory conditions using an ISO 7027-compliant nephelometric method. However, this laboratory value should not be interpreted as an absolute reference standard, because turbidity is an operational optical measurement that depends on the instrument, calibration material, particle characteristics, and measurement conditions.

Data analysis

This study was designed as a method-comparison and exploratory prediction-model study. We compared smartphone-derived turbidity information, field turbidimeter measurements, and laboratory-measured operational reference turbidity to evaluate their associations, systematic differences, and error characteristics under dry-season field conditions. We developed the RGB log-ratio model as an exploratory calibration model using the available field dataset. Because no independent external validation dataset was available, we interpreted model performance as an internal exploratory assessment.

Associations among the HydroColor-derived turbidity estimate, field turbidimeter measurements, and laboratory-measured operational reference turbidity were evaluated using scatter plots, correlation coefficients, and regression analysis. We evaluated agreement separately using error-based and agreement-based metrics, including paired differences, mean bias, MAE, RMSE, relative error, and Bland-Altman limits of agreement. Paired differences were calculated as the method value minus the laboratory-measured operational reference value. We defined the limits of agreement as the mean bias $\pm$ 1.96 times the standard deviation of the paired differences. Relative error was calculated as the absolute paired difference divided by the laboratory-measured operational reference value and expressed as a percentage.

For RGB analysis, we used normalized RGB indices to reduce the effects of exposure conditions and variations in light intensity during image acquisition. We calculated the normalized RGB values using equations 1, 2, and 3.

$$r = R / (R + G + B) \quad (\text{Eq 1})$$

$$g = G / (R + G + B) \quad (\text{Eq 2})$$

$$b = B / (R + G + B) \quad (\text{Eq 3})$$

where R, G, and B represent the red, green, and blue color-channel values obtained from the HydroColor-derived output. The normalized RGB values are compositional data because they are constrained by ($r + g + b = 1$). Therefore, the three components are not statistically independent. Following the compositional-data framework of Aitchison (1982), we used log-ratio indices to represent the relative relationships among color components.

We defined the log-ratio predictors as $[\log(r/b)]$ and $[\log(g/b)]$. Natural logarithms were used for all logarithmic transformations. The RGB log-ratio model estimated log-transformed laboratory-measured operational reference turbidity. We retained model outputs on the logarithmic scale and did not back-transform them to NTU. Therefore, we did not apply retransformation-bias correction, such as a smearing correction. We used the RGB log-ratio model to evaluate the exploratory relationship between normalized RGB log-ratio indices and turbidity, not to provide direct NTU-scale predictions for practical monitoring. No zero values were observed in r , g , b , or turbidity values; therefore, zero replacement was not required. In addition, the relationship between RGB values and turbidity may be nonlinear due to the optical scattering characteristics of suspended particles. Therefore, we logarithmically transformed laboratory-measured turbidity values to linearize the relationship and stabilize variance. We then developed a linear regression model using log-transformed laboratory-measured turbidity as the response variable and the RGB log-ratio indices as explanatory variables.

To examine whether the RGB-turbidity relationships were influenced by river- or sampling-day-specific clustering, river-stratified correlation and regression analyses were also conducted for each normalized RGB component. We did not conduct formal multilevel modeling because the dataset included only two rivers and 10 river-day sampling events, which was insufficient for stable random-effects estimation. For the RGB analysis, we used 49 observations with complete normalized RGB and laboratory turbidity data.

We used the coefficient of determination (R^2) only to describe the internal fit of the exploratory RGB log-ratio calibration model to the available dataset. It was not interpreted as evidence of predictive validation. Because no independent validation dataset was available and the number of river-day sampling events was limited, we did not conduct external validation or robust grouped cross-validation. We avoided random splitting of individual samples because samples from the same river-day event were not fully independent, and such splitting could lead to information leakage. Therefore, interpret the model as an exploratory internal calibration model rather than a validated predictive model.

We examined regression diagnostics where possible to assess the exploratory RGB log-ratio model. Because of the

limited number of field observations, we interpreted diagnostic results cautiously and did not use them to support formal predictive validation. To reduce the risk of pseudo-replication, we conducted supplementary event-level analyses by averaging the five sample-level observations within each river-day event. Laboratory-measured operational reference turbidity, field turbidity, and smartphone-derived turbidity were summarized at the event level, resulting in 10 river-day means. We then recalculated agreement metrics using the 10 river-day means.

Ethical Considerations and Permissions

This study did not involve human participants, personal data, animal subjects, or animal experiments. Field activities consisted only of non-destructive river-surface imaging and small-volume surface-water sampling from publicly accessible bridge sites. No private land, protected area, or restricted facility was accessed. Therefore, ethics approval for human or animal subjects was not required. Because the sampling locations were publicly accessible and the water sampling was non-destructive and small-volume, this study did not require a specific municipal, environmental, site-access, or water-sampling permit. Table 1 summarizes the site-access conditions.

Results and Discussion

Smartphone-Based Turbidity vs. Laboratory Turbidity and Field Turbidimeter vs. Laboratory Turbidity

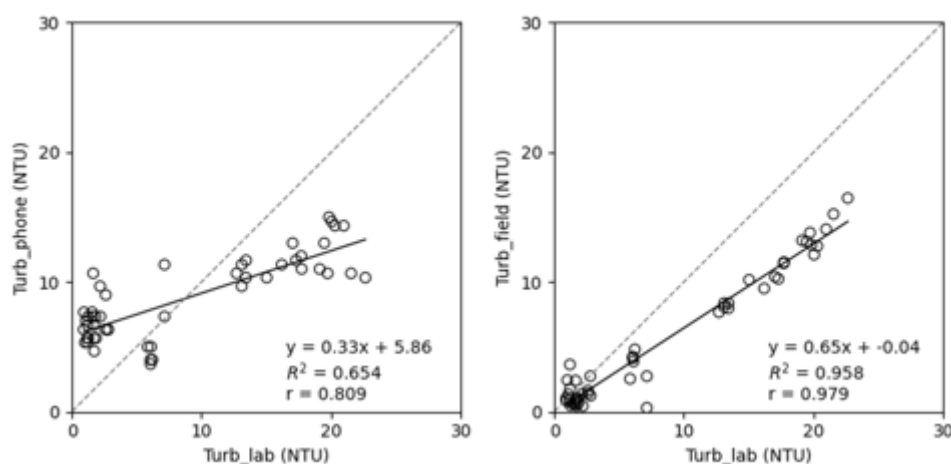


Figure 2. Comparison of Laboratory Turbidity with Smartphone-Derived Turbidity Estimates (left) and Field Turbidimeter Measurements (right)

Figure 2 shows the relationships between laboratory-measured operational reference turbidity and smartphone-derived turbidity estimate, and between laboratory-measured operational reference turbidity and field turbidimeter measurements. Smartphone-derived turbidity estimate showed a positive correlation with laboratory turbidity ($r = 0.81$, $R^2 = 0.65$), indicating that the smartphone-derived values generally increased as laboratory turbidity increased. However, the regression slope was relatively low (0.33), suggesting a compressed response compared with laboratory measurements. Specifically, smartphone-derived turbidity estimates tended to overestimate in the low-turbidity range (0–10 NTU) and underestimate in the higher turbidity range (10–30 NTU). In contrast, field turbidimeter measurements showed a very strong correlation with laboratory turbidity ($r = 0.98$, $R^2 = 0.96$). However, the regression slope was 0.65, indicating that field turbidimeter values were generally lower than laboratory turbidity values. This underestimation became more pronounced at higher turbidity levels.

These results indicate that correlation alone did not demonstrate agreement between methods. The field turbidimeter closely tracked changes in laboratory-measured operational reference turbidity, but the slope below 1 and negative mean bias indicate systematic, proportional underestimation. In contrast, the HydroColor-derived turbidity estimate showed a compressed response, with overestimation in the low-turbidity range and underestimation in the higher-turbidity range. Therefore, interpret both methods as operational comparators rather than interchangeable substitutes for laboratory-measured turbidity.

Table 2. Statistical Results of Event-Based Comparison of Laboratory Turbidity with Smartphone-Derived Turbidity Estimates and Field Turbidimeter Measurements

Comparison	<i>n</i>	<i>r</i>	<i>R</i> ²	Regression slope	Intercept	Bias	MAE	RMSE	Mean absolute relative error	Bland-Altman limits of agreement
Field and Laboratory	10	0.99	0.99	0.66	-0.09	-3.09	3.22	4.07	0.43	-8.56 to 2.39
Smartphone and Laboratory	10	0.86	0.74	0.33	5.82	0.02	4.90	5.23	1.49	-10.78 to 10.82

To account for the nested sampling structure, we conducted supplementary event-level analyses using the 10 river-day means. The event-level analysis showed that field turbidimeter measurements remained strongly associated with laboratory turbidity ($r = 0.99$, $R^2 = 0.99$). However, the regression slope was 0.66, and the mean bias was -3.09 NTU, indicating systematic underestimation by the field turbidimeter. The Bland-Altman limits of agreement were -8.56 to 2.39 NTU. The MAE and RMSE were 3.22 NTU and 4.07 NTU, respectively. Smartphone-derived turbidity also showed a positive relationship with laboratory turbidity at the event level ($r = 0.86$, $R^2 = 0.74$), but the regression slope was low (0.33), indicating a compressed response. The mean bias was close to zero (0.02 NTU). However, this near-zero bias should be interpreted cautiously because overestimation in the low-turbidity range and underestimation in the higher-turbidity range tended to cancel each other. The MAE and RMSE were 4.90 NTU and 5.23 NTU, respectively, and the limits of agreement were wider (-10.78 to 10.82 NTU), indicating weaker agreement than the field turbidimeter.

Exploratory RGB Log-Ratio Analysis

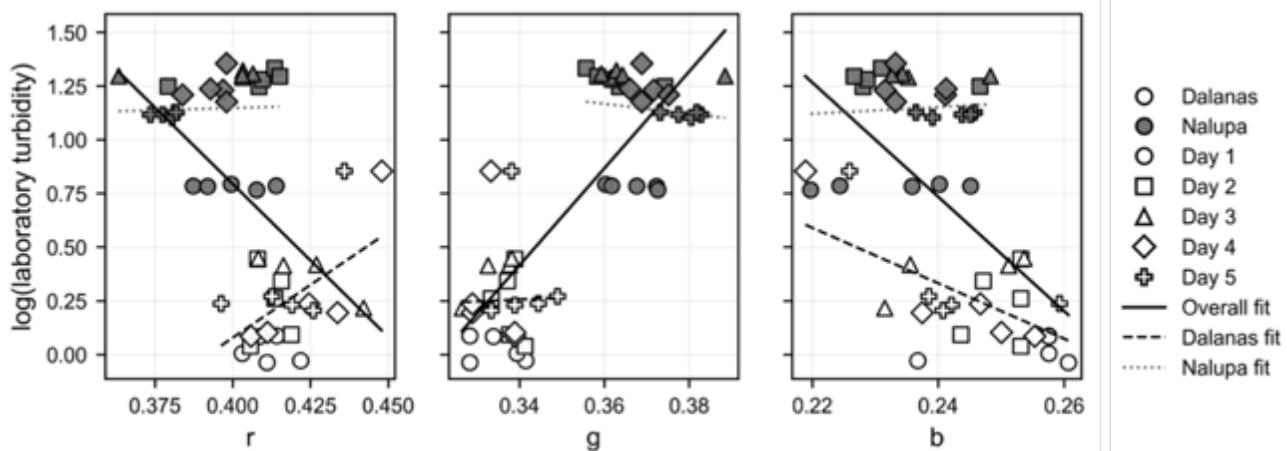


Figure 3. Relationships between normalized RGB components and log-transformed laboratory-measured operational reference turbidity. Hollow and filled symbols indicate the Dalanas and Nalupa Rivers, respectively, and marker shapes indicate sampling days. Solid lines show overall linear fits, while dashed and dotted lines show river-specific fits for Dalanas and Nalupa, respectively.

Figure 3 shows the relationships between each normalized RGB component (*r*, *g*, and *b*) and log-transformed laboratory-measured operational reference turbidity. Hollow and filled symbols indicate the Dalanas and Nalupa Rivers, respectively, and marker shapes indicate sampling days. The plotted points clustered distinctly by river, suggesting that between-river differences partly influenced the overall RGB-turbidity relationships. For example, the overall relationship between the normalized green component and log-transformed laboratory-measured turbidity was strong ($r = 0.82$, $R^2 = 0.67$), whereas the corresponding within-river relationships were weak for both Dalanas ($r = 0.02$, $R^2 < 0.01$) and Nalupa ($r = -0.10$, $R^2 = 0.01$). Therefore, interpret the overall correlations as relationships across the observed dry-season river conditions, rather than as evidence of uniform within-condition sensitivity. Because normalized RGB values are compositional data constrained by ($r + g + b = 1$), this study applied log-ratio transformations to RGB ratios and developed an exploratory RGB log-ratio regression model.

The scatter plot of observed log-transformed turbidity and fitted log-transformed turbidity showed a clear positive relationship overall. The developed log-ratio regression model explained approximately 77% of the observed variation in turbidity ($R^2 = 0.77$) and showed a high correlation coefficient ($r = 0.88$), as shown in Figure 4. These values reflect the model fit to log-transformed, laboratory-measured turbidity and should not be interpreted as NTU-scale predictive validation. Because the model outputs were retained on the logarithmic scale and not back-

transformed to NTU, we did not calculate original-scale prediction errors for this exploratory RGB log-ratio model. This result indicates that normalized RGB information from smartphone images reflected variations in river turbidity to some extent. The exploratory RGB log-ratio regression model used in this study was expressed as follows:

$$\log(T_{\text{lab}}) = \beta_0 + \beta_1 \log(r/b) + \beta_2 \log(g/b) \quad (\text{Eq 4})$$

The fitted model was represented as:

$$\log \log (T_{\text{lab}}) = -0.79 - 3.13 \log(r/b) + 13.29 \log(g/b) \quad (\text{Eq 5})$$

where T_{lab} represents laboratory-measured operational reference turbidity, and $\log$ denotes the natural logarithm. In this model, the coefficient of $\log(g/b)$ was positive and relatively large, strongly reflecting the tendency for the green component to increase relative to the blue component as turbidity increased. In contrast, the coefficient of $\log(r/b)$ was negative, indicating that, under the same $\log(g/b)$ conditions, a relative increase in the red component acted to decrease the fitted turbidity. These results suggest that the smartphone-derived turbidity signal in the study rivers was not explained simply by an increase in the red component, but rather by relative changes between the green and blue components. This result supports using normalized RGB log-ratio information as an exploratory indicator of relative turbidity variation under the observed dry-season conditions. However, because the model was internally fitted, retained on the logarithmic scale, and not externally validated, it should not be interpreted as a practical NTU-scale prediction model.

Overall, the fitted values were distributed along the 1:1 line, indicating that the model broadly distinguished turbidity levels from low to high. However, some points deviated from the 1:1 line. In particular, the model slightly underestimated or overestimated turbidity in the medium- to high-turbidity range, indicating that RGB information alone cannot fully explain turbidity. This may be because site-specific factors in real river environments, such as water surface reflection, camera angle, cloud cover, solar elevation, surface waves, particle color and size, and the presence of organic matter, affected the RGB values obtained from the images. Because the model was developed and evaluated using the same dataset, interpret the internal model fit as exploratory. Future studies should validate the model using independent datasets.

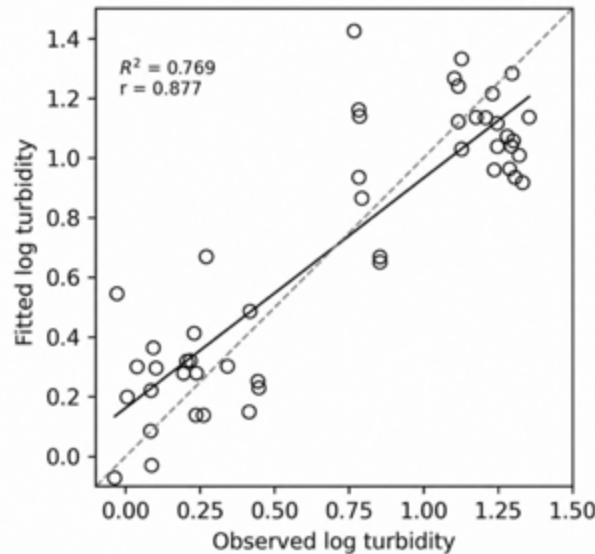


Figure 4. Relationship Between Observed and Fitted Log-Transformed Turbidity Using the Log-Ratio RGB Regression Model

General Limitations and Implications

In this study, we adopted a log-ratio model using $\log(r/b)$ and $\log(g/b)$ as explanatory variables instead of directly using normalized RGB values. Normalized RGB values are constrained by the compositional relationship ($r + g +$

$b = 1$). Because of this constraint, the individual components (r), (g), and (b) are not independent of one another. Therefore, directly applying normalized RGB values in a multiple regression model may lead to spurious correlations or unstable regression coefficients. The log-ratio transformation used in this study represents the relative relationships among RGB components and is considered an appropriate analytical approach for accounting for the compositional nature of normalized RGB data.

In the model developed in this study, the $\log(g/b)$ coefficient was large and positive. This indicates that the relative contribution of the green component compared with the blue component increased as turbidity increased. In general, as turbidity increases, scattering by suspended particles in the water also increases, altering the balance of color components in the reflected light from the water surface. The results suggest that the color information in smartphone images, particularly the relative change between the green and blue components, reflects the concentration of suspended particles in river water to some extent.

However, the scatter plot of observed and fitted values showed variability in the fitted values in some turbidity ranges. This may be attributed not only to imaging conditions in real river environments, such as solar elevation, cloud cover, water surface reflection, surface waves, and camera angle, but also to water quality characteristics such as particle size, particle color, organic matter content, and the reflectance properties of the riverbed and surrounding environment. Therefore, smartphone image-based turbidity estimation should be interpreted as a method influenced by both local light conditions and water quality characteristics, rather than as a method that reflects turbidity alone.

In addition, this study mainly used data obtained under dry-season conditions, and its applicability under flood conditions or extremely high-turbidity conditions has not been sufficiently validated. During rapid increases in turbidity after heavy rainfall, the particle-size composition of suspended matter and water-surface conditions may differ from those under normal flow conditions. Further validation using data collected during the rainy season and high-flow events is therefore needed.

Although we obtained 50 sample-level observations, these observations were nested within 10 river-day sampling events. Therefore, the effective number of independent hydrological conditions was smaller than the number of sample-level observations. This nested structure may inflate the apparent precision of sample-level analyses if not considered. To address this issue, we added event-level analyses using river-day means and interpreted the results cautiously as exploratory evidence. Future studies should include more independent sampling days, rivers, and hydrological conditions to support more robust multilevel modeling and external validation.

A key limitation is that we did not validate the RGB log-ratio model on an independent dataset. Although grouped cross-validation that holds out entire river-day sampling events would be preferable, this study had limited river-day events. Therefore, we did not estimate prediction intervals or cross-validated RMSE, MAE, and bias. Future studies should validate the model using independent datasets or grouped cross-validation designs with more river-day events, wider turbidity ranges, and more diverse illumination conditions. Another limitation is that replicate-level readings were not retained; therefore, within-sample repeatability, including coefficient of variation, could not be calculated retrospectively. In addition, we did not conduct daily calibration verification, blank measurements, or standard recovery tests for the field turbidimeter. These limitations may have contributed to uncertainty in comparing field and laboratory turbidity measurements. For this reason, we interpreted the field turbidimeter results as on-site comparator measurements, and treated laboratory turbidity as an operational reference rather than an absolute reference standard.

Based on these considerations, the smartphone image-based turbidity estimation method proposed in this study should be regarded not as a high-precision method that can completely replace laboratory turbidity measurements, but as a simple monitoring approach for rapidly assessing relative changes in turbidity in the field. In rural areas of the Philippines, where maintaining expensive analytical instruments and regular calibration is difficult, this method may serve as a supplementary water quality monitoring tool for local governments, schools, and citizen science activities. Furthermore, it may increase the frequency and spatial coverage of observations in data-scarce regions and support low-cost, decentralized river environmental monitoring.

Conclusion

This study evaluated smartphone-derived turbidity monitoring in two tropical coastal rivers in Barbaza, Antique Province, Philippines, by comparing HydroColor-derived turbidity estimates, field turbidimeter measurements, and laboratory-measured operational reference turbidity. This study's main contribution is a field-based evaluation of smartphone-derived turbidity information and normalized RGB log-ratio indices under real tropical river conditions. Field turbidimeter measurements closely tracked laboratory-measured turbidity but showed systematic, proportional underestimation, particularly at higher turbidity levels. Therefore, interpret the field instrument as an on-site comparator rather than an interchangeable substitute for laboratory measurement. The HydroColor-derived turbidity estimate and RGB log-ratio information reflected relative variations in river turbidity to a certain extent. However, the smartphone-derived estimate showed a compressed response, and the RGB log-ratio model was exploratory, internally fitted, and retained on the logarithmic scale. Thus, smartphone-derived turbidity monitoring should not be regarded as a direct replacement for laboratory or field turbidimeter measurements. Instead, it may serve as a low-cost supplementary approach for rapid screening, citizen science, STEM education, and expanding spatial observation opportunities in data-scarce regions. This study was limited by dry-season sampling, a small number of river-day events, the absence of independent validation, and incomplete calibration and repeatability information. Future studies should evaluate the approach across different seasons, rainfall conditions, turbidity ranges, river types, and smartphone models, and should validate practical NTU-scale performance using independent datasets or appropriate grouped validation designs.

Contributions of Authors

Taishi Yazawa: Conceptualization, methodology, investigation, formal analysis, writing – original draft, writing – review and editing, **Serbelle Juanites:** Investigation and formal analysis, **Kylla Jane Estella Ramo:** Investigation, **Toshiyuki Shimizu:** Conceptualization, supervision, and writing – review and editing.

Funding

This research was supported by Toyota Foundation Grant Number D24-HS-0069 and JSPS KAKENHI Grant Number 24K20969.

Conflict of Interests

The authors declare that they have no conflict of interest.

Acknowledgment

The authors acknowledge financial support from the Toyota Foundation and JSPS KAKENHI.

References

- Altchison, J. (1982). The statistical analysis of compositional data. *Journal of the Royal Statistical Society: Series B (Methodological)*, 44(2), 139–160. <https://doi.org/10.1111/j.2517-6161.1982.tb01195.x>
- Al Sawaf, M.B., Kawanisi, K., & Bahreinimotlagh, M. (2024). Examining the relationship between rainfall, runoff, and turbidity during the rainy season in Western Japan. *GeoHazards*, 5(1), 176–191. <https://doi.org/10.3390/geohazards5010009>
- Bilotta, G.S., & Brazier, R.E. (2008). Understanding the influence of suspended solids on water quality and aquatic biota. *Water Research*, 42(12), 2849–2861. <https://doi.org/10.1016/j.watres.2008.03.018>
- Ceylan Koydemir, H., Rajpal, S., Gumustekin, E., Karınca, D., Liang, K., Göröcs, Z., Tseng, D., & Ozcan, A. (2019). Smartphone-based turbidity reader. *Scientific Reports*, 9(1), 19901. <https://doi.org/10.1038/s41598-019-56474-z>
- Dethier, E., Renshaw, C., & Magilligan, F. (2022). Rapid changes to global river suspended sediment flux by humans. *Science*, 376(6600), 1447–1452. <https://doi.org/10.1126/science.abn7980>
- Droujko, J., & Molnar, P. (2022). Open-source, low-cost, in-situ turbidity sensor for river network monitoring. *Scientific Reports*, 12(1), 10341. <https://doi.org/10.1038/s41598-022-14228-4>
- Göransson, G., Larson, M., & Bendz, D. (2013). Variation in turbidity with precipitation and flow in a regulated river system – river Göta Älv, SW Sweden. *Hydrology and Earth System Sciences*, 17(7), 2529–2542. <https://doi.org/10.5194/hess-17-2529-2013>
- Hussain, I., Ahamad, K., & Nath, P. (2016). Water turbidity sensing using a smartphone. *RSC Advances*, 6(27), 22374–22382. <https://doi.org/10.1039/C6RA02483A>
- Lasco, G., & Hardon, A. (2024). Sensing, knowing, and making water quality along Marikina River in the Philippines. *Human Organization*, 83(2), 145–158. <https://doi.org/10.1080/00187259.2024.2351372>
- Leeuw, T., & Boss, E. (2018). The HydroColor app: Above water measurements of remote sensing reflectance and turbidity using a smartphone camera. *Sensors*, 18(1), 256. <https://doi.org/10.3390/s18010256>
- Lu, Y., Chen, J., Xu, Q., Han, Z., Peart, M., Ng, C.-N., Lee, F.Y.S., Hau, B.C.H., & Law, W.W.Y. (2023). Spatiotemporal variations of river water turbidity in responding to rainstorm-streamflow processes and farming activities in a mountainous catchment, Lai Chi Wo, Hong Kong, China. *Science of the Total Environment*, 863, 160759. <https://doi.org/10.1016/j.scitotenv.2022.160759>
- Malthus, T.J., Ohmsen, R., & van der Woerd, H. (2020). An evaluation of citizen science smartphone apps for inland water quality assessment. *Remote Sensing*, 12(10), 1578. <https://doi.org/10.3390/rs12101578>
- Melad, R., Nonato, R.L., Salazar, D.J., Ligaray, M., & Choi, A.E.S. (2024). Spatial assessment of water quality in Mananga River in Talisay City, Cebu, Philippines. *Results in Engineering*, 24, 103030. <https://doi.org/10.1016/j.rineng.2024.103030>
- Mersha, E., Degafa, S., Argaw, M., & Mengist, W. (2025). Spatiotemporal modeling of soil loss and sediment yield due to land use and land cover changes: Implications for watershed management. *Journal of Water and Climate Change*, 16(4), 1310–1335. <https://doi.org/10.2166/wcc.2025.467>
- Narayanan, A., Cohen, S., & Gardner, J. (2024). Riverine sediment response to deforestation in the Amazon basin. *Earth Surface Dynamics*, 12(2), 581–599. <https://doi.org/10.5194/esurf-12-581-2024>
- Syvitski, J.P.M., Vörösmarty, C., Kettner, A., & Green, P. (2005). Impact of humans on the flux of terrestrial sediment to the global coastal ocean. *Science*, 308(5720), 376–380. <https://doi.org/10.1126/science.1109454>
- Walling, D.E., & Fang, D. (2003). Recent trends in the suspended sediment loads of the world's rivers. *Global and Planetary Change*, 39(1–2), 111–126. [https://doi.org/10.1016/S0921-8181\(03\)00020-1](https://doi.org/10.1016/S0921-8181(03)00020-1)
- Yazawa, T., Rubite, K.J.G., & Macabata-Rubite, P.E. (2024a). How does the citizens' choice of water use actions based on their empirical knowledge affect the water quality in a rural community of the Philippines? *Journal of Water and Health*, 22(8), 1541–1555. <https://doi.org/10.2166/wh.2024.177>
- Yazawa, T., Rubite, K.J.G., & Macabata-Rubite, P.E. (2024b). Identifying potential concerns on surface water resources usage through citizen scientific field investigation in the Province of Antique, Philippines. *Water Policy*, 26(4), 429–440. <https://doi.org/10.2166/wp.2024.046>
- Yazawa, T., Hasid, A.S., & Carré-Poussin, V.M. (2025). Validating smartphone-based water quality monitoring for rapid environmental assessment. *Water Practice & Technology*, 20(3), 653–660. <https://doi.org/10.2166/wpt.2025.031>