

1 **A novel water pollution index for domestic water quality assessment in acid mine**
2 **drainage-impacted mining areas**

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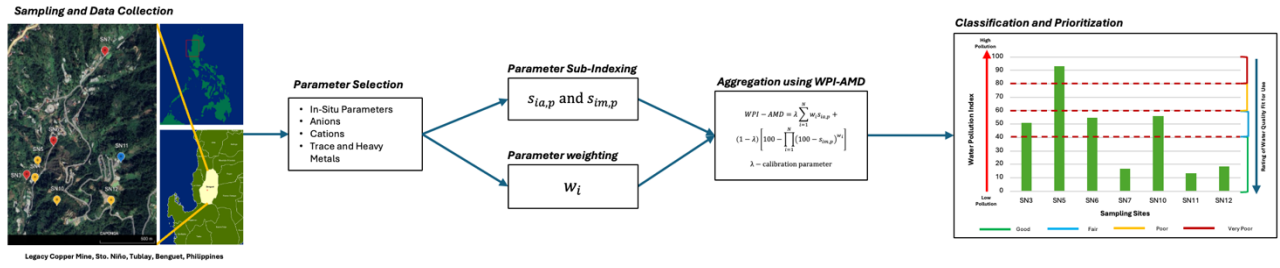
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1 Graphical Abstract



3 Abstract

4 A legacy copper mine in Sto. Niño, Barangay Ambassador, Tublay, Benguet, Philippines generating
5 acid mine drainage (AMD), posing environmental and social challenges affecting access to clean water
6 for domestic use in mine-impacted areas. With multiple water sources in the area, classification and
7 prioritization of use as well as treatment intervention are necessary. This study presents and develops
8 a novel water pollution index (WPI-AMD) designed to assess domestic water quality in AMD-impacted
9 mining areas. The WPI-AMD utilizes a multi-criteria decision-making (MCDM) tool called the
10 weighted aggregated sum product assessment (WASPAS) approach, integrating both additive and
11 multiplicative functions to overcome shortcomings of existing water quality and pollution indices
12 (WQPI). WPI-AMD includes careful selection, categorization, weighting, normalization, calibration,
13 and aggregation of relevant geochemical parameters. Sampling was conducted in the legacy mine to
14 determine the geochemistry of the identified water sources. The results show that the WPI-AMD
15 effectively evaluates AMD-impacted bodies for domestic use, providing more accurate assessment than
16 other WQPI in terms of eclipsing percentage, agreement with expert judgement, and classification
17 accuracy. Thus, WPI-AMD is a promising tool for water resource management in mining-affected
18 areas, in facilitating the classification of water bodies according to their suitability for domestic use and
19 in identifying critically polluted water bodies that require intervention. The ability of WPI-AMD to
20 integrate multiple geochemical parameters into a single, easily interpretable score makes it particularly

1 useful for community members, policymakers, and environmental managers in addressing water
2 quality issues in AMD-impacted regions.

3 **Keywords:** acid mine drainage (AMD), water pollution index (WPI), water quality index (WQI),
4 legacy mine, WASPAS, additive function, multiplicative function

1 Nomenclature

w_i	Weight sub-index of parameter, i
s_{ia}	Additive sub-index of parameter, i
N	Geochemical Parameter
λ	Calibration Parameter
ρ	Spearman's Rank Correlation Coefficient
AMDI	Gray Acid Mine Drainage Index
CCMEWQI	Canadian Council of Ministers of the Environment Water Quality Index
CWQI	Chemical Water Quality Index
EC	Electrical Conductivity
IC	Ion Chromatography
ICP-OES	Inductively Coupled Plasma Optical Emission Spectroscopy (ICP-OES)
MAMDI	Modified Gray Acid Mine Drainage Index
MCDM	Multi-criteria decision-making
NSFWQI	National Sanitation Foundation Water Quality Index
PES	Polyethersulfone
PNSDW	Philippine National Standards for Drinking Water
SMEWW	Standard Methods for the Examination of Water and Wastewater
TSS	Total Suspended Solids
US EPA	United States Environmental Protection Agency
VQI	Vasanthavigar water quality index
WASPAS	Weighted Aggregated Sum Product Assessment
WGM	Weighted Geometric Mean Method
WHO	World Health Organization
WPI	Water Pollution Index
WPI-AMD	Water Pollution Index for AMD-impacted areas
WQI	Water Quality Index
WQPI	Water Quality or Water Pollution Index
WSM	Weighted Sum Method

2 1. Introduction

Assessment of a water source involves determining of important geochemical parameters, including pH, electrical conductivity (EC), and concentrations of metals and anions. Typically, these are compared to existing water quality standards, and the degree to which parameters exceed these standards can be a metric to identify water bodies that will be prioritized for treatment. Unfortunately, the analyses and data interpretation of assessment results remain a significant issue because their expert

1 knowledge, experience, and high-level understanding of chemistry, which hindering the participatory
2 citizen science, including regional municipalities and policymakers.

3 To address this issue, water indices have been developed to inform the community about the status
4 of water bodies in an accessible format (Uddin et al., 2021; Sutadian et al., 2018). A water index
5 combines all parameter measurements of a particular water source into a single score. This score
6 indicates overall quality (referred to as water quality index (WQI) (Uddin et al., 2021)) or the degree
7 of pollution (referred to as water pollution index (WPI) (Hossain & Patra, 2020)). The single score
8 provided by the water quality/pollution index (WQPI) simplifies the understanding of water quality and
9 its suitability for various uses, including drinking, domestic purposes, and agriculture (Aljanabi et al.,
10 2021).

11 In many cases, WQPIs are applied in areas where water bodies are prone to contamination such as
12 in legacy mines which that have been closed and abandoned with little or incomplete rehabilitation
13 (Alonzo et al., 2023; Herrington et al., 2023; Promentilla et al., 2021). Legacy mines are notorious for
14 having mine-impacted waters, rocks, and soils contaminated with heavy metals like copper (Cu), lead
15 (Pb), zinc (Zn), cadmium (Cd), and manganese (Mn), and metalloids such as arsenic (As) and selenium
16 (Se) that have been left unmanaged, which could potentially cause health problems and environmental
17 degradation. In particular, the Sto. Niño legacy mine in Barangay Ambassador, Tublay, Benguet,
18 Philippines is a legacy copper mine that has been used by indigenous communities for agricultural
19 purposes since its closure and abandonment in 1982 (Alonzo et al., 2023). Having a lack of
20 understanding of the potential hazards that the site poses, the development of a WPI in mine-impacted
21 waters (i.e., a single and easily interpretable score for domestic use in their environmental context) is
22 necessary to provide ease of assessment and for community members, policymakers, and
23 environmental managers to adequately address the water quality concerns.

24 The development of a WQPI for a specific application typically involves four steps: (i) parameter
25 selection, (ii) parameter weighting, (iii) parameter sub-indexing, and (iv) aggregation procedure

1 (Abbasi & Abbasi, 2012; Uddin et al., 2021; Syeed et al., 2023). The parameter selection is usually
2 based on data availability, expert judgment, or the environmental significance of a parameter in a given
3 scenario (Uddin et al., 2021; Sutadian et al., 2016). The relative weights of importance of these
4 parameters are determined, i.e., called parameter weighting, based on expert judgment (Abbasi &
5 Abbasi, 2012; Uddin et al., 2021; Chidiac et al., 2023). The values of the parameters are then normalized
6 to a specific range of scores or sub-indices (e.g., 0 to 1), a process known as parameter-sub-indexing.
7 The sub-index obtained for each parameter indicates the measurement of the acceptability or
8 unacceptability of the value of a parameter with the local or international standard values for water
9 quality (Abbasi & Abbasi, 2012; Sutadian et al., 2016). The final method is the aggregation process,
10 which involves combining the sub-indices of the parameters into a single overall water index score.
11 The calculated overall score will indicate the overall water quality or degree of pollution of a given site.

12 For example, several water indices have been developed specifically for acid mine drainage (AMD)
13 and AMD-impacted water bodies, such as the Gray AMD Index (AMDI) (Gray, 1996) and the Modified
14 Gray AMD Index (MAMDI) (Kuma et al., 2011). These existing indices, however, focus on general
15 contamination assessment rather than evaluating water suitability for specific purposes such as
16 domestic use. AMD remains one of the most intractable post-mining legacies, producing waters of low
17 pH, elevated sulfates, and high concentrations of Fe, Mn, and toxic trace metals that can persist for
18 decades after mine closure. In many rural and peri-urban settings, these waters directly or indirectly
19 supply domestic needs. Robust and defensible assessment tools are therefore required to prioritize
20 mitigation and safeguard public health.

21 This study develops a novel approach to measuring the water pollution index for acid mine drainage-
22 impacted areas (WPI-AMD). This metric is designed to minimize the eclipsing effect wherein one
23 severely non-compliant parameter can be obscured by several parameters with high sub-index values,
24 yielding an inappropriate overall rating (Uddin et al., 2022; Sutadian et al., 2016). For example, indices
25 such as the Horton index (Horton, 1965) and the National Sanitation Foundation Water Quality Index

1 (NSFWQI) (Brown et al., 1970) that use additive aggregation or weighted sum formulations are
2 vulnerable to such an eclipsing problem. Alternatively, our proposed method is underpinned by the
3 Weighted Aggregated Sum–Product Assessment (WASPAS) framework (Zavadskas et al., 2012),
4 which integrates the Weighted Sum Method (WSM) and the Weighted Geometric Mean (WGM) via a
5 tunable parameter, λ , to resist eclipsing while retaining the communicative clarity of weighted sum
6 model and imposing a multiplicative penalty sufficient to preclude the masking of guideline
7 exceedance. Moreover, the computation can be implemented in a spreadsheet, rendering every step
8 transparent and auditable to users for easier adoption. WPI-AMD is designed to preserve the familiarity
9 with the 0-100 scale used in practice according to WHO or national drinking water criteria, affording
10 direct regulatory interpretation of the overall score.

11 This paper is organized into five main sections. Section 2 describes the Sto. Niño legacy mine in the
12 Philippines, which serves as our case study location for demonstrating the WPI-AMD application.
13 Section 3 presents the methodology, covering both the field sampling procedures used to collect water
14 quality data and the computational algorithm developed for the WPI-AMD. Section 4 analyzes the
15 results, presenting the geochemical characteristics of the water sources, calculating WPI-AMD scores,
16 and validating the new index through comparison with existing water quality indices using both
17 quantitative metrics and expert evaluation. Section 5 concludes with key findings and recommendations
18 for future research.

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2. Study Area

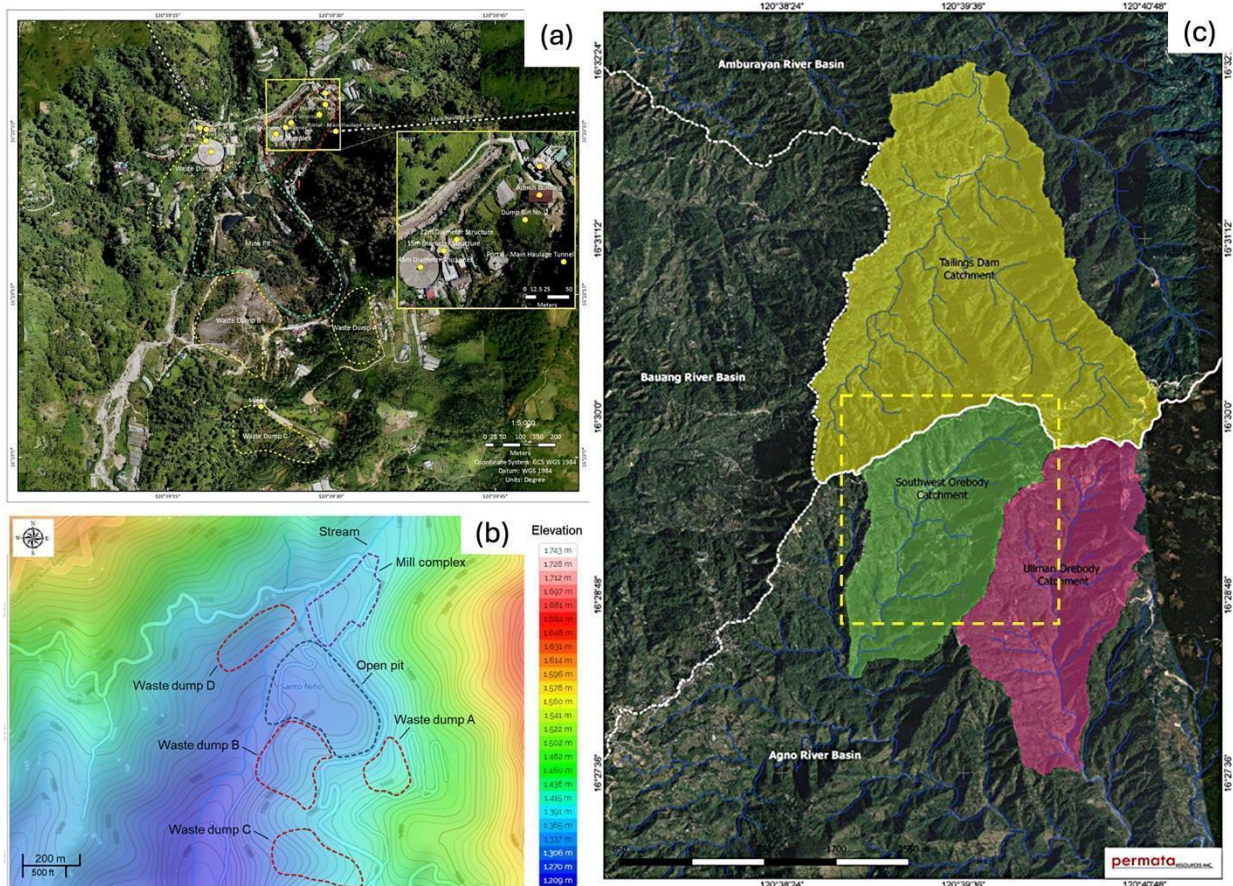


Figure 1. Sto. Niño legacy mine. a) mine pit and waste dumps; b) corresponding elevation map (Mines and Geosciences Bureau, 2019); c) water catchment areas (Mines and Geosciences Bureau, 2019)

The Sto. Niño legacy mine was first operated in 1907 by the Baguio Gold Mining Company. Imai (2002) reported that the Sto. Niño deposits consisted of two orebodies: the “Southwest orebody” (120°19’00” E, 16°29’15” N) and the “Ullmann” or the “Northeast orebody” (120°40’30” E and 16°26’40” N). Both orebodies were mined for copper and gold intermittently over a period of 75 years, with the bulk of mining occurring in the final 10 years leading up to mine abandonment in 1982.

Mines and Geosciences Bureau (2019) reported that the Southwest orebody houses the abandoned open pit and most of the mine structures. The abandoned open pit is approximately 99,650 m² and is surrounded by four waste dumps as illustrated in Figure 1. The ore minerals found include pyrite, chalcopyrite, malachite, sphalerite, and galena, while waste samples from different parts of the site

1 were dominated by quartz, plagioclase, chlorite, vermiculite, and muscovite/illite (Hammarstrom et al.,
2 2014, Herrington et al., 2023).

3 Two major river systems were have been identified within and near the abandoned mine site. The
4 first system, the Agno River, serves as the drainage for both the southwest orebody and the Ullmann
5 orebody runoff, eventually discharging into the Lingayen Gulf in Pangasinan. The second system is the
6 Amburayan River, which receives the water flowing from Fortuna Creek, located in the tailings dam
7 area. The Sto. Niño mine was permanently abandoned, and the area is utilized by the local indigenous
8 community for agricultural purposes.

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3. Methodology

3.1. Sampling in Sto. Niño Legacy Mine

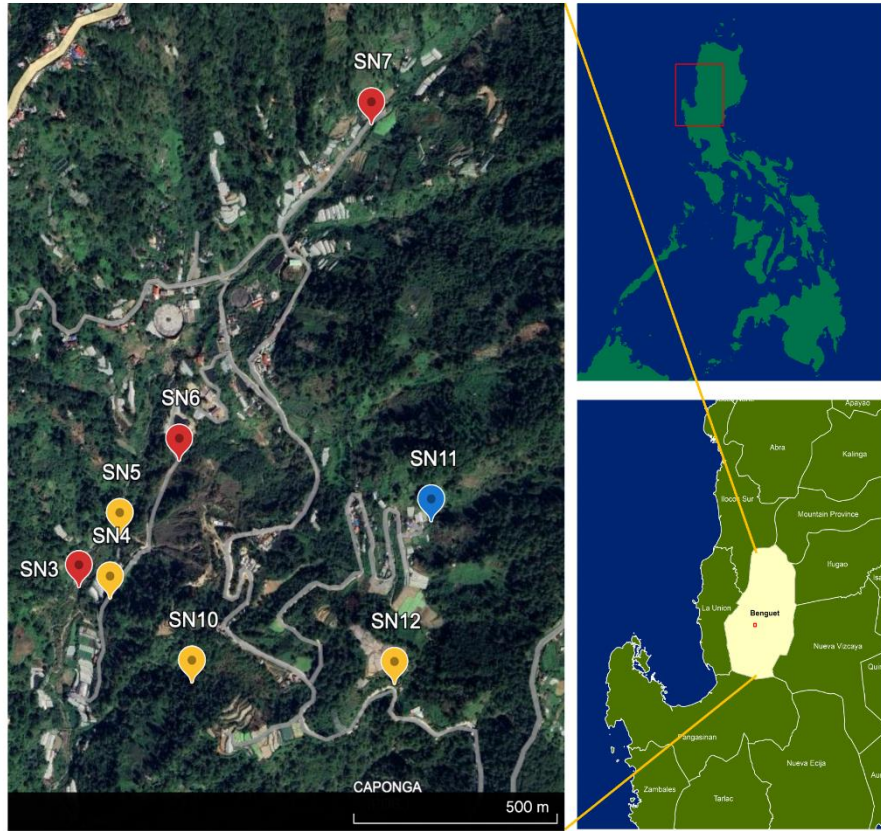


Figure 2. Water sampling sites in Sto. Niño legacy mine in Tublay, Benguet, Philippines. SN3 - Sto. Niño River Downstream (16°29'05.71" N 120°39'11.14" E), SN5 - Sto. Niño Green Wall Seepage (16°29'11.34" N 120°39'15.91" E), SN6 - Sto. Niño Waste Dump Stream (16°29'17.25" N 120°39'20.08" E), SN7 - Sto. Niño River Upstream (16°29'43.14" N 120°39'35.71" E), SN10 - Sto. Niño Green Water Stream (16°29'00.97" N 120°39'21.91" E), SN11 - Local Village Stream (16°29'13.74" N 120°39'40.42" E), SN12 - Small Scale Tunnel Stream (16°29'01.33" N 120°39'37.67" E). Satellite imagery data © 2025 Google.

A water sampling campaign was conducted in selected water bodies in the Sto. Niño legacy mine based on interviews with the local community (Figure 2). Sampling was performed at three different times: wet season in November 2022, dry season in April 2023, and wet season in November 2023, gathering a total of three (3) geochemical datasets. The samples were filtered using a 0.45 μm polyethersulfone (PES) membrane to remove the undissolved solids. Physicochemical and geochemical properties were determined from the water samples such as pH, EC, metal concentration (Cu, Fe, Mn, Al, Zn, Cd, As, Pb, Co, Ni, Cr, Se, Hg, Sb, Ba, B, Na, K, Ca, Mg), anion concentration (SO_4^{2-} , Cl^- , NO_3^- , PO_4^{3-}), alkalinity, and total suspended solids (TSS). Dissolved metals were analyzed using

inductively coupled plasma optical emission spectroscopy (ICP-OES), anions using ion chromatography (IC), alkalinity through titration with 0.02 N sulfuric acid, and TSS by gravimetric oven drying at 103-105°C. The samples for metal analysis were acidified to pH < 2 using concentrated HNO₃ and stored at <2°C before analysis. Concentrated H₂SO₄ was used and stored at <2°C to preserve the samples for analysis of NO₃²⁻ and Cl⁻. Samples for analysis of SO₄²⁻ were stored at 4°C while those for analysis of PO₄³⁻ were frozen. Protocols for the analysis were followed as stated in the Standard Methods for the Examination of Water and Wastewater (SMEWW) (American Public Health Association, 2017).

3.2. Calculation of Water Pollution Index for AMD-impacted area (WPI-AMD)

A WPI rather than a WQI was developed in this study since AMD-impacted waters are to be considered. In this environmental context, the degree of pollution is more suitable to be measured than water quality. Thus, the parameters considered are pH, metals and anions which contribute to AMD. Additionally, alkalinity was included as it is the measure of buffering capacity – it prevents the significant decrease in pH which slows down the dissolution of metals, thereby preventing or minimizing the occurrence of AMD. Different sources suggest an alkalinity level beyond 200 mg CaCO₃/L – the maximum recommended value by US EPA – to be acceptable for surface waters within the range of 30 to 400 mg CaCO₃/L (Health Canada, 2015; Illinois Department of Public Health, n.d.; United States Geological Survey, 2018). A detailed methodology on how the WPI-AMD is calculated, including the weighting and sub-indexing of the parameters mentioned, can be found in Supplementary Data A.

In summary, the WPI-AMD is calculated using the following equation (Eq. (1)).

$$WPI - AMD = \lambda \sum_{i=1}^N w_i s_{ia,p} + (1 - \lambda) \left[100 - \prod_{i=1}^N (100 - s_{im,p})^{w_i} \right] \quad (1)$$

Through the λ parameter, the WPI-AMD can be calibrated to reflect the specific decision context of domestic water safety evaluation, where complete compensatory effect between critical parameters

should be limited while maintaining sensitivity to the level of pollution. The classification of the water body based on the calculated WPI-AMD score will follow the rule illustrated in Table 1. Corresponding to the quality status classifications are descriptions of usage based on the study of Chemeri et al. (2023), which developed a new chemical water quality index (CWQI) for domestic use.

Table 1. WPI-AMD Classification Rule

WPI-AMD Score Range	Number of Standards Exceeded	Water Quality Status*	CWQI Description of Usage
$0 \leq \text{WPI-AMD} < 40$	0	Good	For drinking, upon microbiological analysis, mild treatment may be necessary.
$40 \leq \text{WPI-AMD} < 60$	1-2	Fair	For drinking, upon microbiological analysis, treatment is a necessity.
$60 \leq \text{WPI-AMD} \leq 80$	3-4	Poor	Not suitable for drinking, other uses may be identified (e.g., irrigation, industrial).
$\text{WPI-AMD} > 80$	5 and above	Very Poor	Use is not recommended.

*For a water body, for every increase in any of its parameter by 3 times the quality standard, the water quality status should be one class lower than the usual. For example, a water with a “Fair” quality based on usual rules, if it contains a parameter equal to 6 times the quality standard, should be classified two classes lower, or “Very Poor”.

3.3. Calibration of WPI-AMD Model and Development of WPI-AMD Classification Rule

In the development of the WPI-AMD classification rule, the following are considered: (i) the number of standards exceeded by the water body, and (ii) the degree to which the standards are exceeded. To validate the WPI classification rule, it was applied to the geochemical datasets of the November 2022 wet season and the April 2023 dry season (available in Supplementary Data B), where the quality status of all water bodies was obtained. The resulting quality status from the classification rule was compared to experts’ opinions, and it must demonstrate consistency with the responses of the experts before it is accepted.

Then, the WPI-AMD model was calibrated by fine-tuning it to eliminate eclipsing issues. This was done using the geochemical datasets of the November 2022 wet season and the April 2023 dry season, which served as calibration datasets. The model must be fine-tuned in such a way that it properly classifies the water bodies in the calibration datasets according to the number of water quality standards exceeded. Uddin et al. (2022) provide a guideline for proper classification, as shown in Table 2, which

is also a method of identifying the presence of eclipsing issues in water quality indices in general. This guideline or method was used for calibrating the model.

Table 2. Guidelines for Proper Classification in Water Indices and for Identification of Eclipsing Issues (Uddin et al., 2022)

Water Quality Status	Allowable Number of Standards Exceeded
Good	0
Fair	1-2
Marginal	3
Poor	> 3

3.4. Validation and Comparative Analysis of WPI-AMD Model

The calibrated WPI-AMD model was validated by applying it to the November 2023 wet season dataset, which serves as the validation dataset, for the following purposes: a) to determine whether it classifies the water bodies properly without causing any eclipsing issues and b) to identify if it has the ability to rank the water bodies according to priority for remediation. The first stage of validation involves examining the consistency of the water quality classification of the sites using the WPI-AMD model with the desired classification according to the experts' assessment. The selected experts are familiar with the local standards for drinking water and are knowledgeable about AMD-impacted sites. If the results are consistent with the experts' judgment, then the WPI-AMD can be proved useful in the evaluation of AMD-impacted sites for domestic use in the local setting.

The second stage of the validation is the comparison of the WPI-AMD with other commonly used models, particularly those applied in AMD and AMD-impacted water bodies, using the same validation dataset. First, the tendency of the models towards eclipsing, which is important for the proper classification of the water bodies, was measured by adopting the method of eclipsing identification by Uddin et al. (2022). Then, for each model, the eclipsing percentage was calculated using the formula shown in Eq. (2).

$$\text{Eclipsing percentage} = \frac{\text{number of sites eclipsed using the model}}{\text{total number of sites in validation dataset}} \times 100\% \quad (2)$$

1 Moreover, using the same validation dataset, the rankings of the sites according to priority for
2 remediation were determined using the models and compared using a nonparametric Spearman
3 correlation test. More importantly, a Spearman's rank-order correlation was also conducted between the
4 site rankings predicted by the water indices and the rankings for site remediation suggested by the
5 experts. This is to determine whether the developed WPI-AMD is more applicable specifically to AMD-
6 impacted sites for domestic use as compared to other models.

4. Results and Discussion

4.1. The Geochemical Data of the Water Sources of the Sto. Niño Legacy Mine

The average geochemical data corresponding to the water sampling sites of Sto. Niño legacy mine for November 2022, April 2023, and November 2023 sampling is shown in Figures 3 through 5 (Raw data available in Supplementary Data B), which provides context for the water sites of Sto. Niño legacy mine, where the developed WPI-AMD formula is applied and validated.

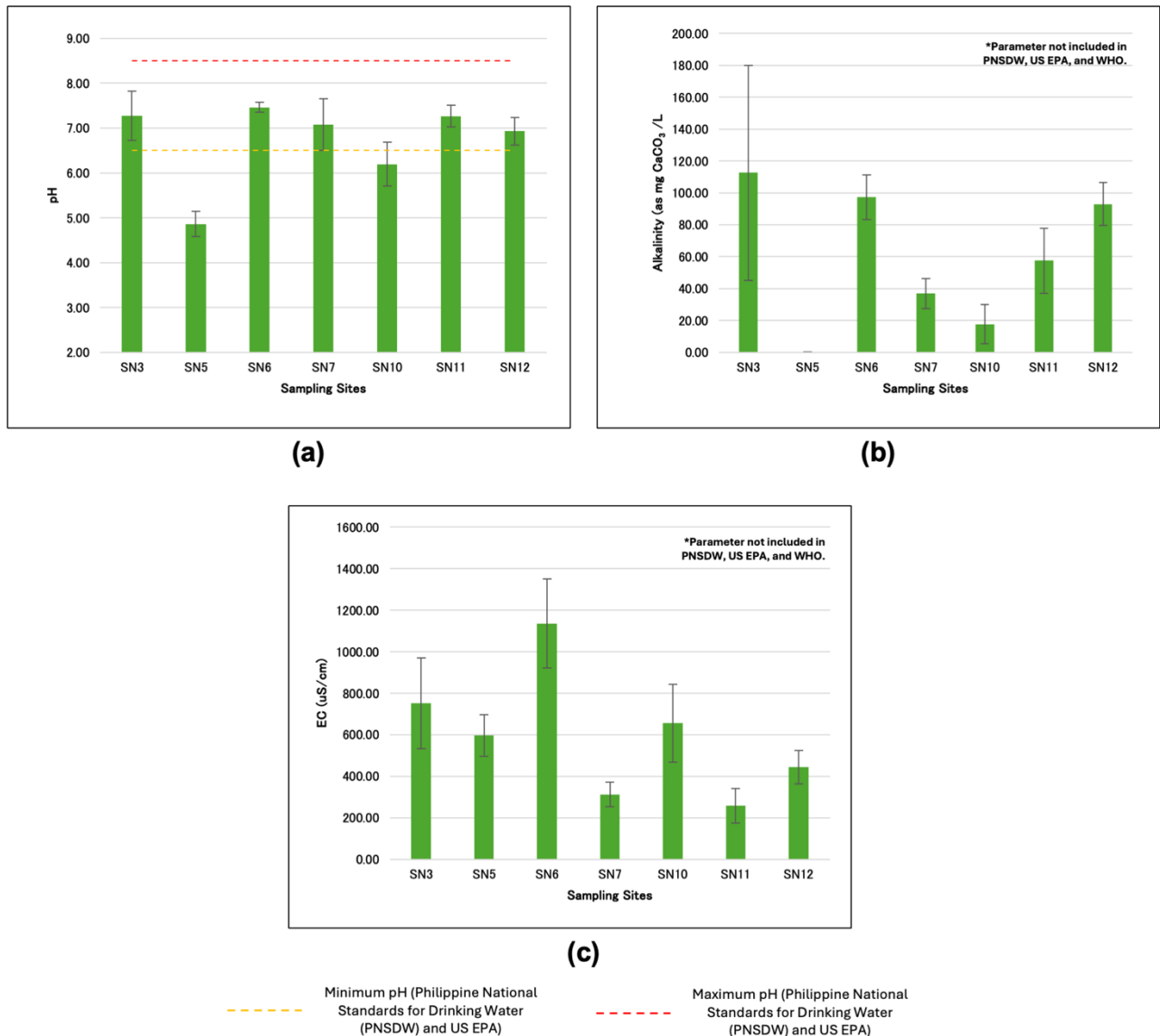
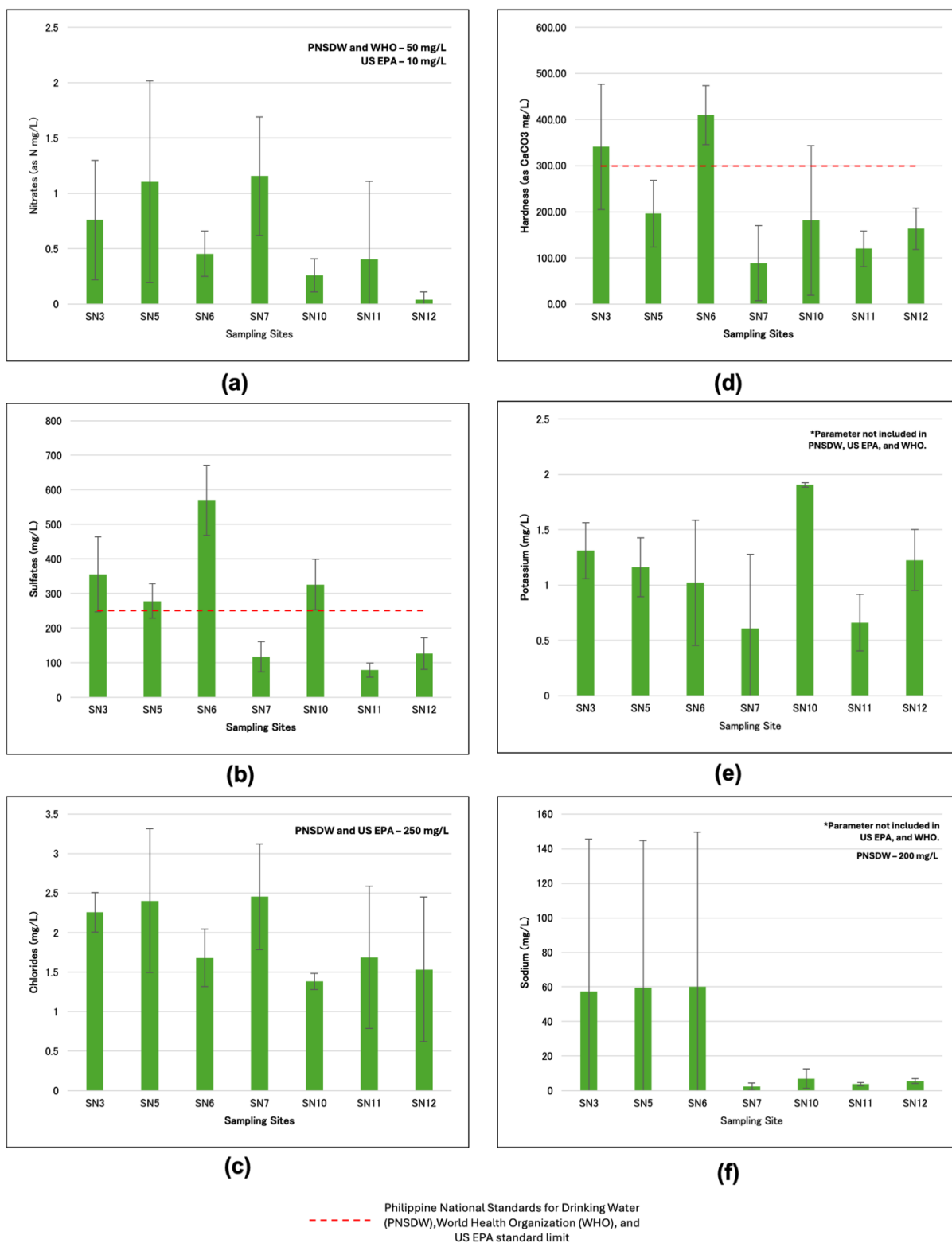


Figure 3. Average geochemical data of the water sampling sites of Sto. Niño legacy mine for November 2022, April 2023, and November 2023 sampling: in-situ parameters a-b) acceptable values for pH and alkalinity except in the cases of SN5 and SN10; c) comparing the conductivities, SN6 is consistently the highest for both seasons

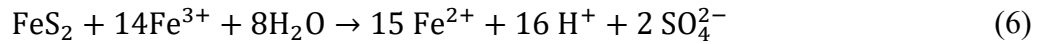
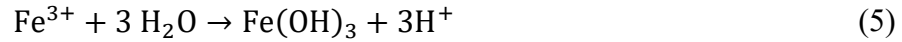
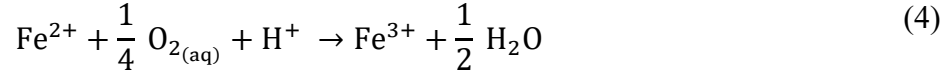
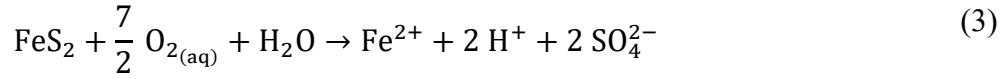
1 Illustrated in Figure 3, the average pH values of all water bodies are within the Philippine National
2 Standards for Drinking Water (PNSDW) of the Department of Health (DOH) (2017), World Health
3 Organization (WHO) (2017), and the United States Environmental Protection Agency (US EPA)
4 (2023a, 2023b) (see Supplementary Data A, Table 1) except SN5 (4.86) and SN10 (6.20), which are
5 found to be acidic. For alkalinity, although there is no official standard, when compared to the
6 recommended value of 20-200 mg/L for drinking water (Naseem et al., 2022), all sites have acceptable
7 values except SN5 (0.19 mg CaCO₃/L) and SN10 (10.63 mg CaCO₃/L) having a low buffering capacity.
8 For EC, SN6 has the highest average value which may be because of its high SO₄²⁻ concentration
9 (424.33 mg/L).



1

2 **Figure 4.** Average geochemical data of the water sampling sites of Sto. Niño legacy mine for November
3 2022, April 2023, and November 2023 sampling: major anions and cations a) and c) acceptable values
4 for Cl^- and NO_3^- for all sites; b) exceeded SO_4^{2-} standard for some sites especially SN3, SN5, and SN6.
5 d) acceptable values for hardness except SN3 and SN6; e-f) acceptable values for K and Na for all sites

1 In Figure 4, sites SN5 and SN10 are also observed to have high SO_4^{2-} concentrations (250-400
2 mg/L), which were likely produced through the chemical reactions illustrated in the following equations
3 (Eq. 3 to Eq. 6) (Moses et al., 1987; Kefeni et al., 2017; Tomiyama et al., 2019).



4 In these reactions, the formation of protons occurs simultaneously, which can explain the low pH of
5 these sites. However, this is not the case for SN3 and SN6, which have an acceptable pH despite high
6 levels of SO_4^{2-} (pH = 7.3-7.5). This could be attributed to the high alkalinity or buffering capacity (>
7 90 mg CaCO_3/L) of the sites which neutralizes the excess protons. This prevents the sharp decrease in
8 pH and in turn, maintains the low concentration of metals in these sites. This can be seen in Figure 5
9 where the concentration of metals in SN3 and SN6 is mostly within the quality standards. Hence, the
10 alkalinity minimized the occurrence of AMD in these sites. For the cations, all sites have acceptable
11 levels for hardness except SN3 (340.78 mg CaCO_3/L) and SN6 (409.99 mg CaCO_3/L) in the dry season.
12 Since the same sites also have higher alkalinity values than the other sites, it is suspected that the local
13 geology may contain CaCO_3 or MgCO_3 -rich mineral phases. Other metals, such as K and Na, were not
14 found to be significantly present at all sites.

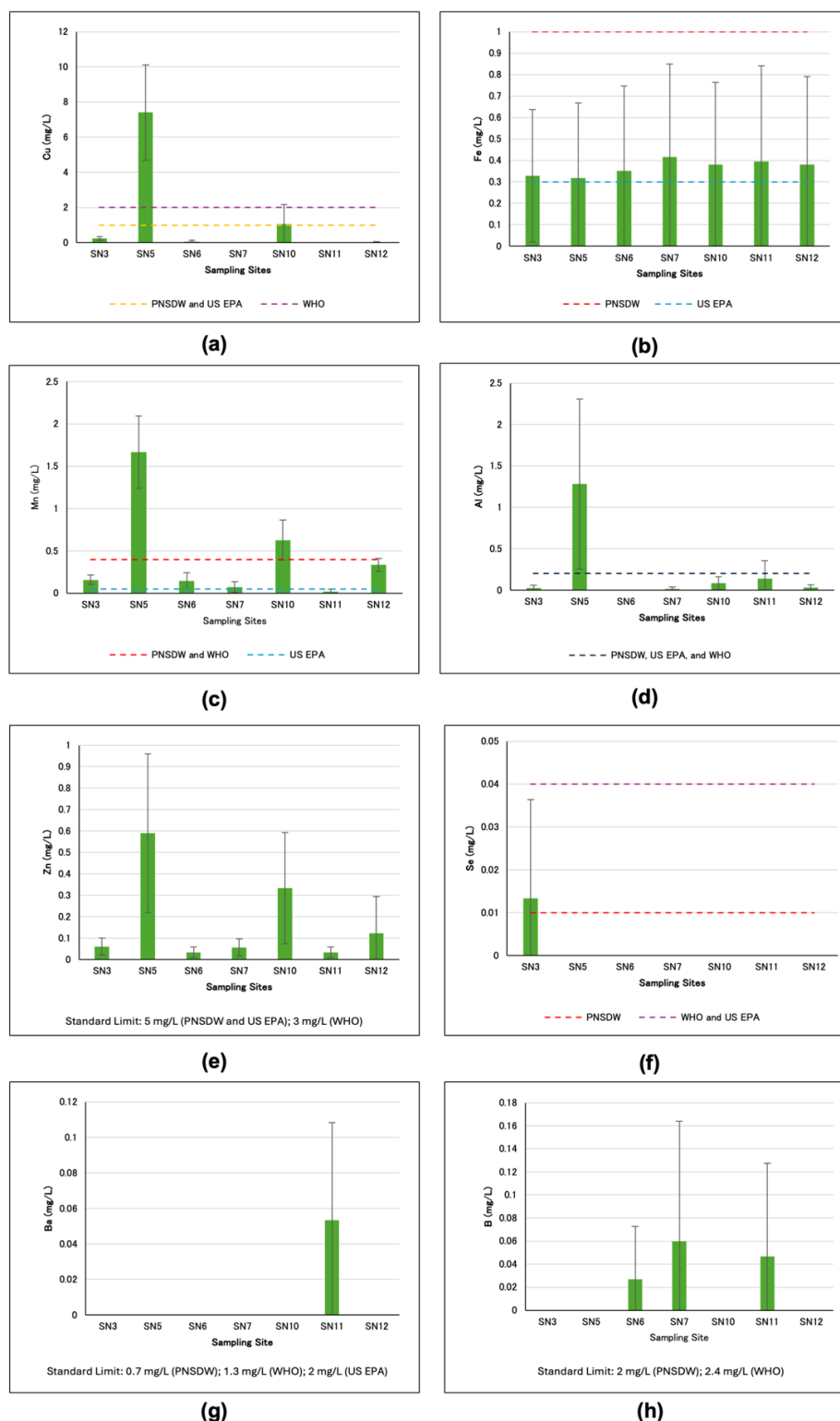


Figure 5. Average geochemical data of the water sampling sites of Sto. Niño legacy mine for November 2022, April 2023, and November 2023 sampling: trace and heavy metals. a) low Cu for most sites but significantly high Cu for SN5; b) acceptable Fe for all sites based on local standards; c-d) low Mn and Al for most sites but significantly high Mn and Al for SN5; e-h) acceptable values for Zn, Se, Ba and B for all sites

For the metals in Figure 5, SN5 and SN10 exceeded the PNSDW standards for Cu (>1 mg/L) and Mn (> 0.4 mg/L), with SN5 containing significant amounts of Al (2.31 mg/L), possibly due to their low pH, which allows further dissolution of metals. For all sites, the concentrations of Zn and Se are within acceptable levels, while As, Pb, Ni, Cr, Cd, Co, and Hg are below the detection limits (Supplementary Data B). For potential drinking water sites such as SN7 and SN11, which consistently showed low concentrations of cations and anions, Sb, Ba, and B were also measured and determined to be within the acceptable levels, with Sb being below the detection limit for all sampling campaigns.

Variability in the geochemical data is observed, suggesting the conditions vary in wet or dry season. Thus, the proposed WPI-AMD was applied for each season to classify the AMD-impacted bodies according to their potential domestic use and rank them according to priority for treatment or intervention.

4.2. WPI-AMD Score Calculation – Calibration, Validation, and Application to Sto. Niño Legacy Mine

Using the data gathered from the legacy mine, the calibration and validation of the WPI-AMD were conducted based on the proposed classification rule in Table 1. Classification of the AMD-impacted bodies using WPI-AMD should not only consider the number of standards exceeded, but also the degree to which these standards are exceeded. Therefore, a water body that strongly exceeded the quality standards should be assigned to a lower classification based on the number of standards exceeded.

The WPI-AMD classification system includes a penalty mechanism for severely polluted water bodies. When any parameter exceeds its quality standard by more than three times the limit, the water body receives an additional downgrade in classification. This means that every three-fold increase in contamination level results in a drop in classification by one additional category. To understand how this works, consider a practical example. Imagine a water body that exceeds just one quality standard. Typically, this would earn a "Fair" classification. However, if that single parameter is not just slightly over the limit but dramatically elevated, e.g., six times the allowable standard, then the classification

becomes much more severe, which represents two three-fold increases beyond the limit. Therefore, the classification drops two additional categories below "Fair," landing at "Very Poor."

This penalty system addresses a critical flaw identified by Chemeri et al. (2023) in traditional water quality indices. They found that some water sources appeared deceptively acceptable when only a few parameters exceeded standards, even though those same parameters were severely elevated posing serious health risks. By implementing this graduated penalty system, the WPI-AMD ensures that dangerously high contamination levels cannot be masked or eclipsed by technically low counts of exceeded standards.

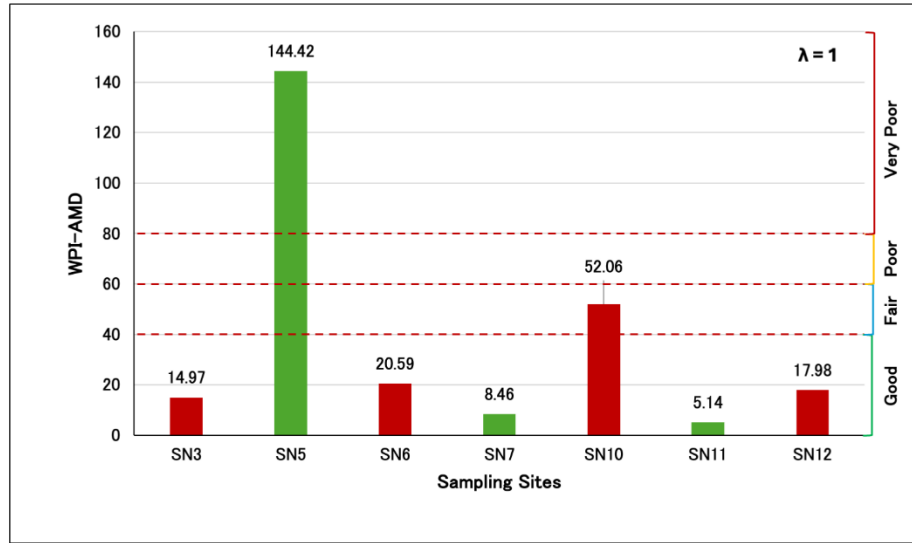
Table 3 summarizes the results of the water quality classification of the sites in the calibration dataset (November 2022 and April 2023) using WPI-AMD. The classification of all sites is consistent with that of the experts' classification, successfully demonstrating the validity of the WPI-AMD classification rule.

Table 3. Desired WPI-AMD Classes and Scores of the Water Sampling Sites in the Sto. Niño Legacy Mine Area for Wet (November 2022) and Dry (April 2023) Seasons

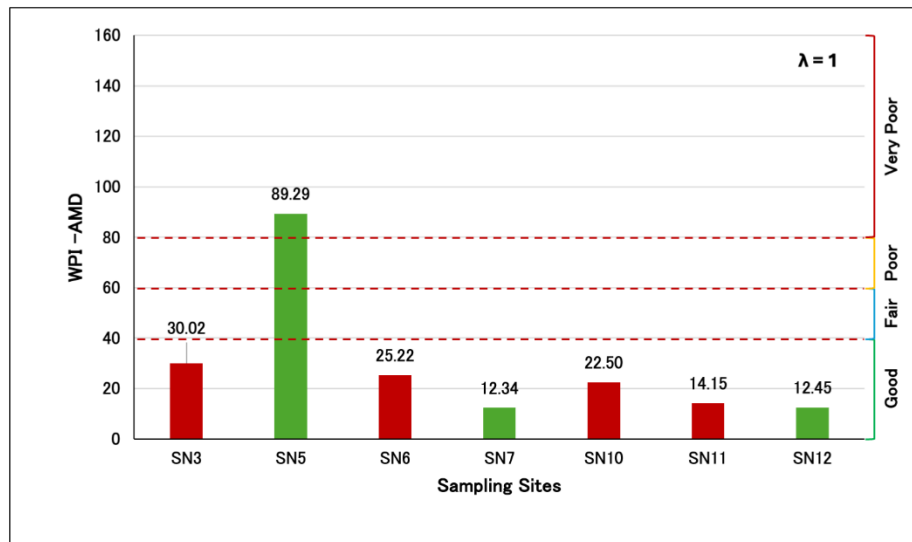
Site	Wet Season (November 2022)			Dry Season (April 2023)		
	Standards Exceeded	Quality Status	Quality Status from Experts	Standards Exceeded	Quality Status	Quality Status from Experts
SN3	SO ₄ ²⁻	Fair	Fair	SO ₄ ²⁻ , Hardness	Fair	Fair
SN5	Mn, pH, Cu, Alkalinity, SO ₄ ²⁻ , Al	Very Poor	Very Poor	Mn, pH, Cu, Alkalinity, SO ₄ ²⁻ , Al	Very Poor	Very Poor
SN6	SO ₄ ²⁻ , Hardness	Fair	Fair	SO ₄ ²⁻ , Hardness	Fair	Fair
SN7	-	Good	Good	-	Good	Good
SN10	Mn, pH, Cu, Alkalinity, SO ₄ ²⁻ , Hardness	Poor	Poor	Mn, SO ₄ ²⁻	Fair	Fair
SN11	-	Good	Good	Al	Fair	Fair
SN12	Mn	Fair	Fair	-	Good	Good

4.2.1. WPI-AMD Calibration

To illustrate the need for calibrating the WPI-AMD model, its additive (WPI-WSM) and multiplicative (WPI-WGM) aggregation components were applied to the calibration datasets, i.e., the λ value is set to 1 and 0, respectively. The results are shown in Figures 6 and 7.



(a)

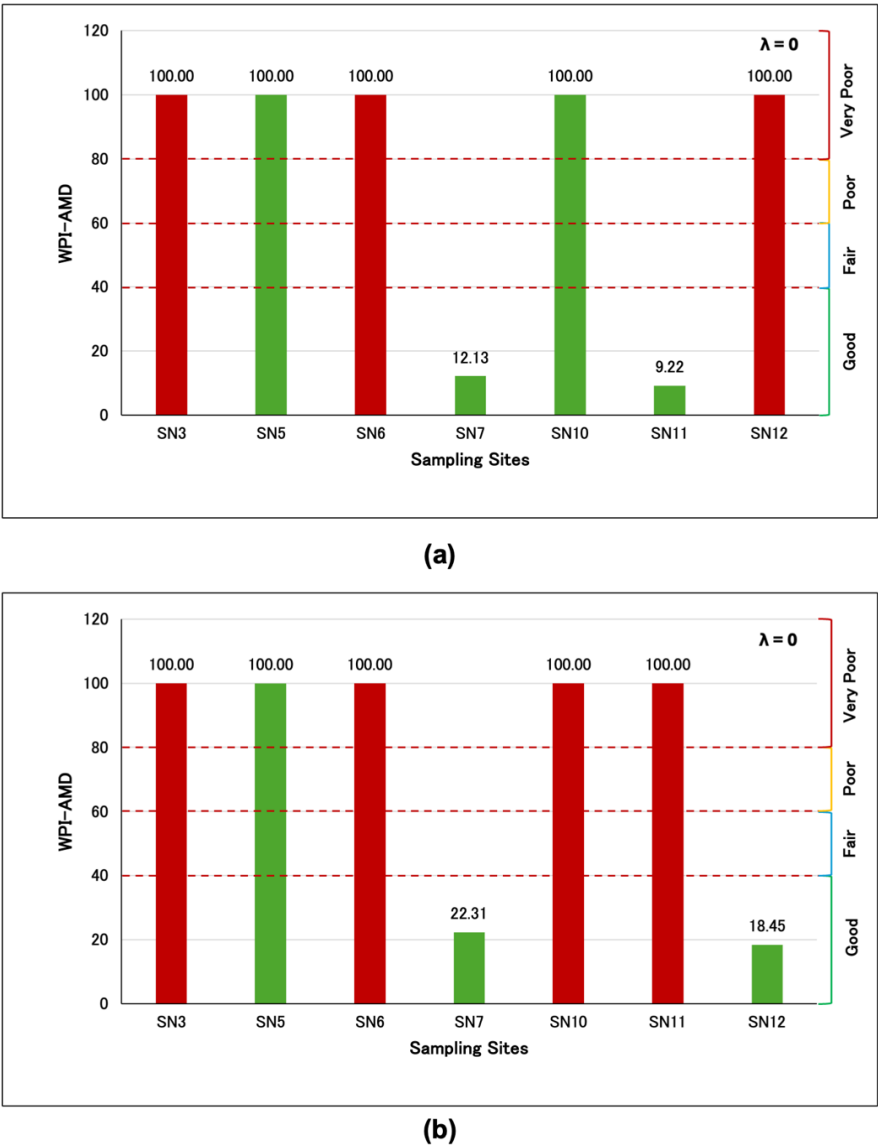


(b)

Figure 6. WPI-AMD scores of the sites in the Sto. Niño legacy mine during (a) November 2022 wet season and (b) April 2023 dry season as a purely additive function ($\lambda = 1$, WPI-WSM) (■ WPI-AMD score provides appropriate water quality classification; ■ WPI-AMD score provides incorrect water quality classification)

Illustrated in Figure 6, WPI-WSM showed that some sites have scores that do not reflect their true quality. Sites SN3, SN6, and SN10 in the November 2022 dataset and sites SN3, SN6, SN10, and SN11 in the April 2023 dataset should be classified as “Fair”, but their WPI-AMD scores fall under “Good” quality based on the graphs. Site SN10 in the November 2022 dataset should be under “Poor” quality, but its WPI-AMD score indicates “Fair”. From the application of the additive function, the presence of

1 the underestimate type of eclipsing can be seen, which has been reported in the literature (Uddin et al.,
2 2022).



3 **Figure 7.** WPI-AMD scores of the sites in the Sto. Niño legacy mine during (a) November 2022 wet
4 season and (b) April 2023 dry season as a purely multiplicative function ($\lambda = 0$) or as WPI-WGM (■
5 WPI-AMD score provides appropriate water quality classification; ■ WPI-AMD score provides
6 incorrect water quality classification).

8 On one hand, Figure 7 demonstrates that the multiplicative function (WPI-WGM) could result in
9 overestimate eclipsing. Sites SN3, SN6, and SN12 from November 2022, along with sites SN3, SN6,
10 SN10, and SN11 from April 2023, were incorrectly classified as "Very Poor" when they should have
11 received classifications ranging from "Fair" to "Poor" according to Table 3. This overestimate bias
12 occurs because the multiplicative function disproportionately penalizes any parameter exceedance,

regardless of severity. This finding aligns with previous research by Sutadian et al. (2016), who documented similar multiplicative function limitations in water quality indices.

Given that WPI-WSM ($\lambda = 1$) produces underestimate eclipsing and WPI-WGM ($\lambda = 0$) produces overestimate eclipsing, the optimal WPI-AMD configuration requires an intermediate λ value. Since eclipsing decreases at one extreme and increases at the other, an optimal λ value must exist within the range $0 < \lambda < 1$ where eclipsing is minimized. Model calibration, therefore, involves determining this λ value through systematic analysis.

Modifying the methodology of Uddin et al. (2022), allowable WPI-AMD score ranges were established for each water quality classification to prevent eclipsing as illustrated in Table 4. Compliance with these ranges ensures a more reliable classification for practical water management decisions. For example, the original classification system distinguishes between "Marginal" and "Poor" categories; however, these were consolidated into a single "Poor" classification in the WPI-AMD framework for domestic water applications. Model calibration requires determining the λ value that produces scores consistently within these established ranges.

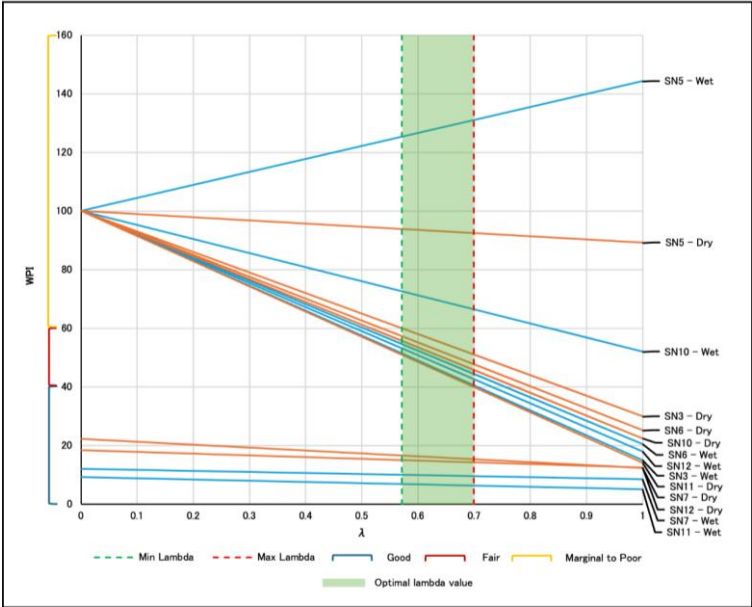
Table 4. Application of Guideline for Proper Classification of Water Indices to WPI-AMD Model for the Prevention of Eclipsing

Water Quality Status	Allowable Number of Standards Exceeded (Uddin et al., 2022)	Allowable WPI-AMD Score Range (Using Table 1)
Good	0	$0 \leq \text{WPI-AMD} < 40$
Fair	1-2	$40 \leq \text{WPI-AMD} < 60$
Marginal to Poor	3 and above	$\text{WPI-AMD} > 60$

Table 5 summarizes the allowable WPI-AMD score range for all sites in November 2022 and April 2023 calibration datasets. For all sites in the calibration datasets, the linear variation of their WPI-AMD score with respect to λ was drawn in a WPI-AMD vs. λ plane as plotted in Figure 8.

1 **Table 5.** Allowable WPI-AMD Scores for All Sites in the Calibration Dataset and the Calibration of λ

Site	No. of Standards Exceeded	Quality Status (Using Table 4)	WPI-AMD Scores (Using Table 1)	Allowable λ Range
Wet Season (November 2022)				
SN3	SO ₄ ²⁻	Fair	$40 \leq \text{WPI-AMD} < 60$	0.47-0.71
SN5	Mn, pH, Cu, Alkalinity, SO ₄ ²⁻ , Al	Marginal to Poor	WPI-AMD > 60	0.00-1.00
SN6	SO ₄ ²⁻ , Hardness	Fair	$40 \leq \text{WPI-AMD} < 60$	0.50-0.76
SN7	-	Good	$0 \leq \text{WPI-AMD} < 40$	0.00-1.00
SN10	Mn, pH, Cu, Alkalinity, SO ₄ ²⁻ , Hardness	Marginal to Poor	WPI-AMD > 60	0.00-0.83
SN11	-	Good	$0 \leq \text{WPI-AMD} < 40$	0.00-1.00
SN12	Mn	Fair	$40 \leq \text{WPI-AMD} < 60$	0.49-0.73
Dry Season (April 2023)				
SN3	SO ₄ ²⁻ , Hardness	Fair	$40 \leq \text{WPI-AMD} < 60$	0.57-0.86
SN5	Mn, pH, Cu, Alkalinity, SO ₄ ²⁻ , Al	Marginal to Poor	WPI-AMD > 60	0.00-1.00
SN6	SO ₄ ²⁻ , Hardness	Fair	$40 \leq \text{WPI-AMD} < 60$	0.53-0.80
SN7	-	Good	$0 \leq \text{WPI-AMD} < 40$	0.00-1.00
SN10	Mn, SO ₄ ²⁻	Fair	$40 \leq \text{WPI-AMD} < 60$	0.52-0.77
SN11	Al	Fair	$40 \leq \text{WPI-AMD} < 60$	0.47-0.70
SN12	-	Good	$0 \leq \text{WPI-AMD} < 40$	0.00-1.00
OVERALL RANGE				0.57-0.70



3 **Figure 8.** Graphical Calibration of λ Using the Calibration Dataset

4
5 It is desired to obtain the range of λ values that will provide an allowable WPI-AMD score range to
6 all the sites provided in Table 5. It was found out that the value of λ is between 0.57 and 0.70, so that
7 the WPI-AMD model will minimize the eclipsing effect. Alternatively, to solve for the range of λ values,

its allowable range can be calculated individually for all sites in Table 5, where the common range of λ for all sites is obtained.

Given that the tuning parameter $\lambda = 0.60$ is used, the WPI-AMD model in Eq. 1 can be formulated as the following equation (Eq. 7)

$$WPI - AMD = 0.60 \sum_{i=1}^N w_i s_{ia,p} + 0.40 \left[100 - \prod_{i=1}^N (100 - s_{im,p})^{w_i} \right] \quad (7)$$

This calibrated λ value ensures that water bodies meeting all quality standards receive WPI-AMD scores below 40 (classified as "Good"), while those exceeding one or more standards score 40 or above (classified as "Fair" or worse). This threshold behavior maintains consistency with the classification framework presented in Table 1.

4.2.2. Validation of WPI-AMD model

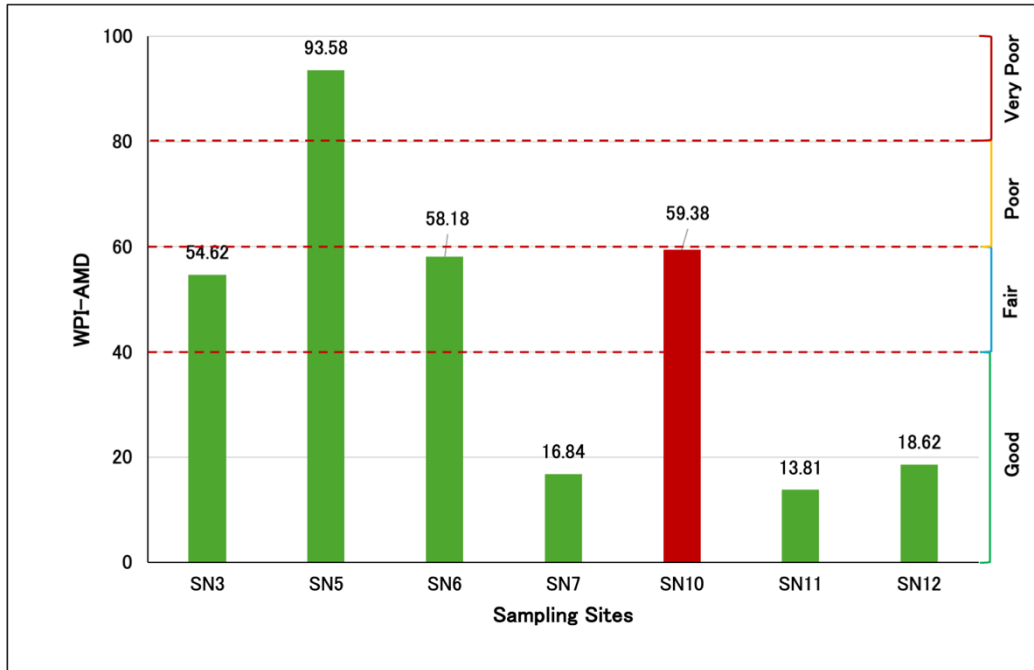


Figure 9. WPI-AMD scores of the water sampling sites in Sto. Niño legacy mine during the November 2023 wet season (■ WPI-AMD score provides appropriate water quality classification; ■ WPI-AMD score provides incorrect water quality classification).

The calibrated WPI-AMD model was validated using the November 2023 dataset. Figure 9 presents the WPI-AMD scores for all validation sites, demonstrating that the model correctly classified the

majority of sites according to established water quality standards. These results confirm the model's effectiveness for classifying AMD-impacted water bodies in domestic use applications. However, one notable exception occurred at site SN10, where the WPI-AMD produced a "Fair" classification despite expert consensus and classification rules indicating "Poor" quality. This eclipsing effect resulted from the site's unique contamination profile. While SN10 exceeded four quality standards (pH: 6.29 vs. 6.5 limit; sulfate: 319 vs. 250 mg/L; manganese: 0.6 vs. 0.4 mg/L), all exceedances were relatively modest. The mathematical aggregation of these minor violations produced a score inconsistent with expert judgment. Note that other established water quality models exhibited similar classification difficulties with this site, suggesting that SN10 represents a challenging case to demonstrate the limitation of current mathematical models for computing water quality indices.

The presence of eclipsing in the WPI-AMD model in the validation dataset was also determined using the method of Uddin et al. (2022). Using the same dataset, the performance of the WPI-AMD against the eclipsing effect was systematically compared with established and similar water quality indices (CWQI, CCME-WQI, MAMDI, WPI-WSM, and WPI-WGM). These indices employ different mathematical functions for aggregation. For example, CWQI uses multiplicative aggregation, MAMDI applies squared summation with parameter weighting, and CCMEWQI employs fixed mathematical functions without parameter weighting (Canadian Council of Ministers of the Environment, 2017).

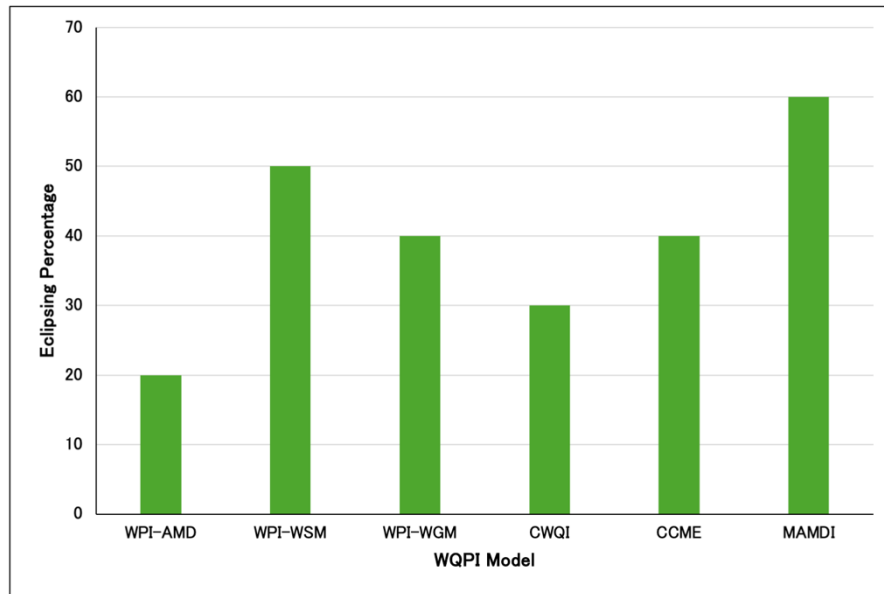


Figure 10. Eclipsing Percentage of Commonly Used and Recent Water Indices from the Validation Dataset

Table 6. Guidelines for Proper Classification of Water for Identification of Eclipsing Issues

Water Quality Status	Number of Standards Exceeded	WPI-AMD Score Range	CWQI Score Range (Chemer et al., 2023)	CCMEWQI Score Range (Canadian Council of Ministers of the Environment, 2017)	MAMDI Score Range (Kuma et al., 2011)
Good	0	< 40	< 2	> 80	> 90
Fair	1-2	40-60	2-4	45-80	20-90
Marginal to Poor	3 and above	> 60	> 4	< 45	< 20

Table 7. Identification of Eclipsing of Water Indices and the Type of Eclipsing in the Validation Dataset

Site	Standards Exceeded	Water Quality Status (based on Uddin et al., 2022)	Water Quality Status Based on Models					
			WPI-AMD (This Study)	WPI-WSM	WPI-WGM	CWQI	CCMEWQI	MAMDI
SN3	SO ₄ ²⁻	Fair	Fair	Good	Marginal to Poor	Fair	Fair	Good
SN5	Mn, pH, Cu, Alkalinity, Al	Marginal to Poor	Marginal to Poor	Marginal to Poor	Marginal to Poor	Marginal to Poor	Marginal to Poor	Fair
SN6	SO ₄ ²⁻ , Hardness	Fair	Fair	Good	Marginal to Poor	Fair	Fair	Good
SN7	-	Good	Good	Good	Good	Good	Good	Good
SN10	Mn, pH, Alkalinity, SO ₄ ²⁻	Marginal to Poor	Fair	Good	Marginal to Poor	Marginal to Poor	Fair	Good
SN11	-	Good	Good	Good	Good	Good	Good	Good
SN12	-	Good	Good	Good	Good	Good	Good	Good
SNa	Pb, Cr, As	Marginal to Poor	Marginal to Poor	Fair	Marginal to Poor	Fair	Fair	Fair
SNb	Pb	Fair	Fair	Good	Marginal to Poor	Good	Good	Good
SNe	-	Good	Fair	Good	Fair	Fair	Good	Good

■ underestimate eclipsing; ■ overestimate eclipsing

1 Table 6 presents the classification score ranges for each model, enabling systematic identification of
2 eclipsing occurrences. Figure 10 compares eclipsing percentages across all models when applied to the
3 validation dataset, while Table 7 details specific sites and eclipsing types observed. To evaluate model
4 performance under challenging conditions typical of AMD-impacted areas, three hypothetical scenarios
5 were added and analyzed in the dataset: SNa represents moderate contamination with three slightly
6 exceeded standards (similar to observed site SN10); SNb represents minimal contamination with one
7 slightly exceeded standard; and SNc represents near-threshold conditions where three parameters
8 approach but do not exceed quality standards. These scenarios simulate contamination patterns
9 commonly encountered when acid mine drainage affects otherwise clean water sources, conditions
10 particularly susceptible to eclipsing effects.

11 Indication suggests that the WPI-AMD model has lower eclipsing percentage than its purely additive
12 and purely multiplicative versions, with WPI-WSM and WPI-WGM being known to cause
13 underestimate and overestimate eclipsing issues, respectively. As compared to MAMDI, which is
14 applied specifically for AMD and AMD-impacted bodies, WPI-AMD has a lower eclipsing percentage
15 for specific use, better than MAMDI. MAMDI does not classify any water body as being “Poor” in
16 quality, but rates them as either “Good” or “Fair”. For this to be possible, it must be applied to cases
17 where the pollution of AMDs and AMD-impacted bodies is more severe than that of the sites in the
18 validation dataset. Thus, the high eclipsing percentage of MAMDI indicates that it is applied specifically
19 to evaluate the severity of pollution of AMDs rather than for general water quality and specific usage.

20 Performance analysis also reveals essential distinctions between apparent model accuracy and actual
21 robustness. Among actual validation sites, WPI-AMD demonstrated superior performance compared to
22 the established CCMEWQI, exhibiting eclipsing at only one site (SN10) instead of two. The CWQI
23 appeared optimal, correctly classifying all actual sites including SN10 where multiple minor standard
24 exceedances were observed. However, analysis of hypothetical scenarios reveals that CWQI's apparent
25 superiority may be circumstantial rather than systematic. When tested against SNa, a site with

1 geochemical characteristics similar to SN10 but representing a more challenging contamination pattern,
2 CWQI exhibited eclipsing behavior. Furthermore, CWQI failed to properly classify SNb, which
3 represents the relatively simple case of a single minor standard exceedance.

4 These findings highlight a critical advantage of the WPI-AMD approach. The model's calibration
5 process ensures accurate classification for any site exceeding one quality standard, regardless of its
6 magnitude. This systematic approach to handling single-standard violations provides greater reliability
7 across the range of contamination patterns typically encountered in AMD contexts, rather than achieving
8 good performance only under specific circumstances.

9 Note that the proposed method, like other indices, operates most reliably when contamination patterns
10 involve clear standard exceedance. For example, despite meeting all individual quality criteria, SNc
11 exhibited eclipsing behavior, receiving a classification that failed to reflect the cumulative risk posed by
12 multiple near-threshold parameters. Recognition of this limitation is essential for proper model
13 application and thus suggests guidance on when to rely on expert judgment for proper interpretation in
14 water management contexts.

15 Table 8 presents site rankings for the validation dataset, ordered from most to least critical to facilitate
16 remediation prioritization. The Spearman correlation analysis summarized in Table 9 reveals that WPI-
17 AMD, WPI-WSM, and CWQI produce identical rankings that perfectly match expert opinions. MAMDI
18 demonstrates the next-highest correlation, followed by CCMEWQI and WPI-WGM. This ranking
19 performance reflects fundamental differences in model architecture. WPI-AMD and CWQI employ
20 continuous sub-indexing functions (linear and sigmoidal, respectively), enabling fine discrimination
21 between contamination levels and eliminating ranking ties. In contrast, MAMDI's discrete sub-indexing
22 creates artificial ties by assigning identical scores to different parameter values within predetermined
23 ranges. For example, sulfate concentrations of 250 mg/L and 290 mg/L both receive the same sub-index
24 score despite their meaningful difference for water quality assessment.

CCME-WQI exhibits a different limitation. For example, it assigns default scores of 100 to all sites meeting water quality standards, preventing prioritization among these sites when preventive treatment might be warranted. This scoring behavior, also observed in WPI-WGM for four validation sites, eliminates the discriminatory power needed for effective remediation planning.

These findings demonstrate that continuous sub-indexing approaches provide superior ranking capabilities for practical water management applications, where clear prioritization guidance proves essential for resource allocation decisions.

Table 8. Rankings of Sites in the Validation Dataset Based on Common and Recent Water Indices

Site	Expert Ranking	Rankings Based on Models					
		WPI-AMD	WPI-WSM	WPI-WGM	CWQI	CCMEWQI	MAMDI
SN3	4	4	4	2.5	4	4	4
SN5	1	1	1	2.5	1	1	1
SN6	3	3	3	2.5	3	3	2.5
SN7	6	6	6	6	6	6	5.5
SN10	2	2	2	2.5	2	6	2.5
SN11	7	7	7	7	7	7	7
SN12	5	5	5	5	5	6	5.5

Table 9. Spearman Correlation Matrix of Common and Recent Water Indices from the Validation Dataset

Method	WPI-AMD	WPI-WSM	WPI-WGM	CWQI	CCMEWQI	MAMDI	Expert
WPI-AMD	1.0000						
WPI-WSM	1.0000	1.0000					
WPI-WGM	0.9107	0.9107	1.0000				
CWQI	1.0000	1.0000	0.9107	1.0000			
CCMEWQI	0.9643	0.9643	0.8750	0.9643	1.0000		
MAMDI	0.9821	0.9821	0.9107	0.9821	0.9643	1.0000	
Expert	1.0000	1.0000	0.9107	1.0000	0.9643	0.9821	1.0000

0  1
ρ

4.3. Comparative Analysis of Water Quality and Water Pollution Indices

Table 10 presents a comprehensive comparison of the WPI-AMD with established water quality indices, revealing systematic limitations in existing approaches. As demonstrated throughout this analysis, water indices employing purely additive or multiplicative aggregation functions exhibit characteristic eclipsing patterns that compromise classification accuracy.

1 **Table 10.** Comparison of WQPIs

Water Quality Index	Application	Intended Use	Types of Parameters	No. of Parameters	Weighting?	Sub-Index Weighting?	Aggregation Function	Advantages	Disadvantages	References
Horton Index	Surface waters	Evaluation of fresh surface waters	Fixed (DO, pH, coliforms, TDS, carbon chloroforms extract, alkalinity, chlorides)	8	Yes	Yes	Additive	A pioneer and structured approach assessing water quality.	Does not consider toxic parameters such as Cu, Mn, Fe, and other metals that might be of a concern in mine-impacted areas.	Horton (1965)
National Sanitation Foundation Water Quality Index (NSF WQI)	Surface waters	General surface water quality evaluation	Fixed (dissolved oxygen, fecal coliform, pH, BOD, temperature, total phosphorus, nitrates, turbidity, total solids, pesticides and toxic compounds)	11	Yes	Yes	1st version additive, 2nd version multiplicative	The index indicates water use potential and a straightforward calculation of index similar to other WQPIs.	Index is prone to eclipsing due to parameter selection.	Brown et al. (1970); Brown et al. (1973)
Canadian Council of Ministers of the Environment (CCMEWQI)	River, lakes, Wells and reservoir	Evaluate general water quality	Open	At least 4	Equal	None	Uses fixed mathematical function	Flexible and versatile index. Consider an approach in handling parameters that are below detection limits.	Index does not work well when too few parameters are considered. Categorization of parameters are subjective. All parameters are of equal importance, risking eclipsing of parameters.	Canadian Council of Ministers of the Environment (2017)
Liou Index	River	General water quality assessment	Fixed (Temperature, turbidity, SS, pH, DO, BOD, NH ₃ -N, fecal coliforms, Cd, Zn, Cu, Hg)	13	Yes (Equal)	Yes	Combination of additive and multiplicative functions	Geometric mean aggregation mitigates ambiguity from weighting, uncertainty unrelated to lowest sub-index and includes toxicity/heavy metals that are typically found in mine-impacted waters.	Parameter is fixed, which can lead to eclipsing.	Liou et al. (2004)
Dojlido Index	River	General water quality assessment	Fixed (BOD, SS, phosphate, ammonia, DO, COD-Mn, dissolved solids, Fe, phenols, organic nitrogen, hardness, Mn, SO ₄ ²⁻ , Cl, COD-Cr, nitrate, Pb, Hg, Cu Cr (IV), total Cr, Zn, Cd, Ni, and free cyanides)	26	None	None	Square root of harmonic function	Potentially a comprehensive WQPI as it can consider up to 26 parameters in assessing the water quality.	The parameters considered are fixed, which can lead to eclipsing especially if an important parameter is missing. Prone to ambiguity as it provides the worst score even when the parameters are within standard.	Dojlido et al. (1994)
Vasanthavigar Water Quality Index (VQI)	Groundwater	Drinking and irrigation	Fixed (TDS, bicarbonate, chloride, sulfate, phosphate, nitrate, fluoride, Ca, Mg, Na, K, silicate)	12	Yes	Yes	Additive	Multiparameter and standard-based, similar to NSF WQI.	Subjectivity in weight assignment while not considering other common ions that are present in AMD. Prone to underestimate eclipsing.	Vasanthavigar et al. (2010)

Water Quality Index	Application	Intended Use	Types of Parameters	No. of Parameters	Weighting?	Sub-Index Weighting?	Aggregation Function	Advantages	Disadvantages	References
Gray Acid Mine Drainage Index (AMD _I)	Acid mine drainage	Measure AMD contamination	Fixed (pH, Zn, Fe, Cu, Cd, Al, sulfate)	7	Yes	Yes	Square of total sum	Parameters selected are typically found in AMD, which may be representative for assessing water quality. Other modifications of the AMD _I used invertebrate biota as an indicator.	Can only be applied to extreme cases of AMD and does not consider other heavy metals such as As, Cr, Pb, Mn, and Hg making it prone to eclipsing. Mostly tested in coal mine sites, making its use to be more site-specific than other indices. Selection of the indices were limited to the detection limits of the available analytical techniques.	Gray (1996) Gray and Harding (2012)
Modified Gray Acid Mine Drainage Index (MAMD _I)	Acid mine drainage, acid rock drainage	Measure AMD/ARD contamination	Open	Any	Yes	None	Square of total sum	Builds on the AMD _I by incorporating other heavy metals that are typically present in AMD such as As, Pb, CN ⁻ , Hg, and Cd. Considers regulatory standards for assessment of water quality.	Complex scoring system, uses a range of value for each parameter considered which is prone to eclipsing.	Kuma et al. (2011)
Chemical Water Quality Index (CWQI)	Bottled waters, tap waters, springs, rivers, groundwaters, and thermal waters	Drinking purposes, irrigation or industrial usage	Open	Any	Yes	Yes	Multiplicative	Avoids eclipsing by not providing a worst score when the quality of the parameter deviates from the standard.	Eclipsing occurs when parameters of less importance occur in high values even in the presence of other critical parameters.	Chemeri et al. (2023)
Water Pollution Index for AMD-Impacted Bodies (WPI-AMD)	Surface water and groundwater impacted by AMD	Drinking purposes, irrigation or industrial usage	Fixed	19	Yes	Yes	Additive + Multiplicative	Used to assess and classify water bodies in mining areas that can be treated and potentially be used for domestic use.	Limited to classification of water bodies for the purpose of domestic use. Requires recalibration when applied to other environmental contexts.	This study

Additive function limitations are well-documented in multiple indices. The Horton Index demonstrates underestimate eclipsing in sensitivity analysis (Bhargava, 1985), with additive aggregation identified as the primary cause (Uddin et al., 2021; Brown et al., 1970). The NSF WQI, developed to address Horton Index limitations, retained additive aggregation and continues to exhibit eclipsing behavior (Akhtar et al., 2021). This persistent problem stems from both the additive function and parameter selection methodology (Uddin et al., 2021). Similarly, the VQI suffers from underestimate eclipsing attributed to its additive function and weighting approach (Chemeri et al., 2023).

Some index developers respond by introducing a multiplicative or WGM aggregation process, such as the multiplicative version of NSF WQI and the CWQI. The aggregation in NSF was revised to a multiplicative function by Brown et al. (1973), which reduced the eclipsing issues in the additive function. However, when a single parameter has a low water quality, the overall final score is close to the worst possible score (Sutadian et al., 2016) with the final score automatically becoming equal to the worst score when only one quality standard is exceeded.

The CWQI addresses to this issue by using a sigmoidal sub-index function, where the deviation from the quality standard does not automatically provide the worst score (which is 10), but only approaches it asymptotically (Chemeri et al., 2023). This successfully improved the multiplicative function from eclipsing problems. However, the problem with CWQI lies in its parameter weights being proportional to the sub-indices and the values of the parameters. In this case, the parameters of less importance when present in high values have high weights of importance which leads to a higher final score that indicates lower water quality. It is desired that a good water quality rating should be maintained even if the values of less important parameters increase. This is especially true if these parameters are those that only affect the aesthetic qualities of water. Our comparative analysis further revealed that CWQI exhibits poor sensitivity to multi-parameter contamination patterns characteristic of acid mine drainage. Sites with multiple minor standard exceedances were systematically misclassified, demonstrating inadequate response to the cumulative contamination effects typical of mining-impacted water bodies.

1 Since eclipsing issues are encountered in water indices that apply either additive or multiplicative
2 aggregation methods, some apply a totally different aggregation technique, such as the Dojlido index
3 and CCMEWQI. Dojlido index uses a square root of the harmonic mean of squares as its aggregation
4 procedure, where the parameters with the lowest quality can have the greatest effect on the overall score
5 (Dojlido et al., 1994). However, the overall score using this model is near the worst score, even if the
6 parameters are within the standards, which is referred to as an ambiguity (Sutadian et al., 2016). On the
7 other hand, CCMEWQI considers a different aggregation that considers the number of parameters that
8 exceeded the standards and the extent to which the standards are exceeded (Canadian Council of
9 Ministers of the Environment, 2017). It was mentioned that its aggregation does not work well when too
10 few parameters are considered (Tyagi et al., 2013; Sutadian et al., 2016). Furthermore, the parameters
11 are treated equally, which causes eclipsing problems (Uddin et al., 2021). All of these show that even
12 aggregation techniques other than the additive and multiplicative can encounter eclipsing issues.

13 Other models, instead of using a different aggregation technique, simply combine the additive and
14 multiplicative functions in the aggregation process such as the Liou index and the WPI presented in this
15 study. Liou index involves two aggregation methods: parameters of the same category are combined
16 additively, then the geometric mean of the categories (organics, particulates, and fecal coliform) is
17 obtained (Liou et al., 2004). This index can overcome the problems of both eclipsing and ambiguity
18 (Abbasi and Abbasi, 2012), although eclipsing still occurs due to the lack of important parameters
19 (Uddin et al., 2021). On the other hand, the WPI in this study integrates the additive and multiplicative
20 functions but calculates the supposed contribution of these two functions in the aggregation process. It
21 was demonstrated that the model is not prone to eclipsing as compared to the commonly used and recent
22 water indices once properly calibrated. However, some sites that have multiple parameters which are
23 already very close to the quality standards are not provided with proper water quality classification in
24 some cases, which is a problem not only by the WPI-AMD alone but also by the commonly used and
25 recent models.

1 On the application of the models, most are commonly used for surface water and groundwater for
2 general water quality assessment. Only a few models reported their application to AMD or AMD-
3 impacted bodies, which are AMDI, MAMDI, and the WPI-AMD. AMDI is the first model to be used
4 for AMD, which only includes pH, SO_4^{2-} , Zn, Fe, Cu, Cd, and Al as the important AMD parameters.
5 However, Kuma et al. (2011) showed that more parameters should be included for improved assessment
6 of AMD, leading to the development of MAMDI. The model has the same intended use as the original
7 AMDI, which is to evaluate the physicochemical quality of AMD and AMD-impacted bodies. However,
8 neither model mentioned about the assessment of these water bodies for specific use, such as drinking
9 or irrigation, but are only concerned about the measurement of the severity of pollution of these bodies.
10 It is for this reason that the WPI-AMD was developed in this paper to determine the possible intended
11 use of the AMD-impacted bodies so that they can be treated or remediated to achieve this objective. This
12 has been demonstrated, where the WPI-AMD was used to classify AMD-impacted bodies according to
13 their potential domestic use and to rank them according to priority for remediation.

14 The majority of the models include major physicochemical and biological parameters such as
15 suspended solids, fecal coliforms, and organic nitrogen, among others. Both AMDI and MAMDI did not
16 consider these parameters in their evaluation of AMD and AMD-impacted bodies, as they prioritized the
17 parameters that have a significant influence on AMD, such as heavy metals and trace elements. This is
18 the problem of most models as they do not usually consider these parameters (Uddin et al., 2021), which
19 are known to be toxic and pose a danger to the health of organisms in just a small concentration, as
20 pointed out by Chemeri et al. (2023). This is especially true if the water index is applied for domestic
21 use. To address this issue, the WPI-AMD considered these parameters in the assessment and, at the same
22 time, provided larger weights for them, as they are considered in the literature to be the most important
23 in the classification and ranking of the bodies for domestic use. Prioritizing the heavy metals and trace
24 elements in the WPI-AMD will then change its purpose, which is to identify the critical sites specifically

for remediation prior to biological treatment, as has also been done by Chemeri et al. (2023) for the CWQI.

Hence, the importance of the WPI-AMD developed in this study can be highlighted: it is applicable to AMD-impacted water bodies for domestic use, where it is possible to classify and rank the sites according to this purpose, with performance that is also comparable to the commonly used and recent water indices. The model is found to be limited in its application as it can only be used in the context of domestic use for AMD-impacted bodies. If its application will be extended to other environmental contexts, such as the evaluation of the most polluted AMDs, the recalibration of the model may be necessary, and a new WPI-AMD classification rule should be designed. Another limitation in the context of its current application has already been mentioned and demonstrated, i.e., its weakness in providing proper water quality classification to water bodies with multiple parameters that are very close to the quality standards, which is also the problem of the most commonly used water indices.

5. Conclusions

A novel WPI was formulated in this study, which can be applied to evaluate AMD-impacted water bodies for domestic use. The WPI-AMD was developed based on the WASPAS multi-criteria decision tool, which integrates the additive and multiplicative functions. The WPI-AMD was calibrated and validated by applying it to the water sites of Sto. Niño legacy mine in the Philippines, an AMD-impacted mining area with a limited domestic water supply. The formulated WPI-AMD was validated successfully, where it was found that the additive and multiplicative functions should contribute to the aggregation function by 60% and 40%, respectively. The WPI-AMD was able to resolve most of the eclipsing problems usually encountered in commonly used and recent water indices. Moreover, it can rank the water bodies properly than most of the water indices according to priority for remediation. Therefore, the WPI proved to be a useful tool towards an effective management of the issues in the AMD-impacted areas for the community and policymakers. The limitations of the WPI-AMD include the dependency of its calibration parameter to the environmental context being studied, where it must

1 be recalibrated if to be applied in a different context, and its weakness in providing proper water
2 quality classification to water bodies with multiple parameters that are very close to the quality
3 standards, which is a problem even of the most commonly known water indices.

4 Future research would focus on applying the WPI-AMD to a broader range of environmental
5 contexts, thereby recalibrating the model, further refining its parameters through principal component
6 analysis, and potentially integrating it with real-time monitoring systems for more dynamic water
7 quality assessments.

1 **CRedit Author Statement**

2 The authors contributed to the manuscript as follows: **Christian Jay P. Balboa**: conceptualization,
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5 review and editing. **Ronben M. Baute**: methodology, writing – original draft. **Aileen H. Orbecido** and
6 **Arnel B. Beltran**: conceptualization, investigation supervision, writing – review and editing, resources.
7 **Ana Santos, Anne Jungblut, Yves Plancherel, Pablo Brito-Parada, Carlito Baltazar Tabelin,**
8 **Vannie Joy Resabal, Mylah Villacorte-Tabelin, Irish Mae Dalona-Fernandez, Dennis Alonzo,**
9 **Richard Herrington, Robin Armstrong, Paul F Schofield, Agnieszka Dybowska, Maria Magliulo,**
10 and **Mahsa Baniasadi**: data curation and investigation, writing – review and editing, project
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12 analysis, supervision, investigation, project administration, writing – original draft, writing – review
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19 Co-author Pablo R. Brito-Parada is Editor-in-Chief of Minerals Engineering and was not involved in
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21 **Data Availability**

22 The corresponding author will provide the spreadsheet used in the WPI formulation upon request.

23

24

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