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Evaluating the Impacts of Environmental and Anthropogenic Factors on Water Quality in the Bumbu River Watershed, Papua New Guinea

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Abstract: The Bumbu River Watershed is an essential source for the drinking and sanitation needs of settlement communities within Lae, Papua New Guinea. However, poor sanitation and waste management practices have led to concerns over the safety and integrity of the watershed's resources. In this study, we explored the effect of these factors on water quality in the Bumbu river and its tributaries using water quality (22 sampling stations), geospatial (degree of urbanisation), and community survey (sanitation and hygiene practices) data. Water Quality Index (WQI) was calculated based on the Canadian Council of Ministers of Environment (CCME) template using pH, Total Dissolved Solids (TDS), conductivity, turbidity, alkalinity, calcium, magnesium, total hardness, mercury, manganese, iron, and Escherichia coli. Using geospatial techniques, principal component analysis, and forward regression analysis, we found that better water quality outcomes coincided with better community health conditions of Crime and Pollution, and better household health outcomes. Land-use itself was not significantly correlated with water quality, but distressingly, we found 19 of 22 water samples to be of "poor" quality, indicating a need for better community water regulation. The methodology and results presented can be used to inform policy decisions at the provincial/national level, and to aid future research activities in other watersheds.

Keywords: water quality; environmental factors; anthropogenic factors; Sanitation and Hygiene (WASH); urbanization; Bumbu River

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1. Introduction

The exponential growth of the world's population during the 20th century has presented challenges in a variety of ways within socioeconomic development; one of these is water scarcity, an issue that, since the 1980s, has attracted political and public attention [1]. Continued population growth during the 21st century will further increase the demand and consumption of clean water across different societal and economic sectors (e.g., industrial, energy, irrigation, domestic), as well as having a global impact [2,3]. Furthermore, with climate change rainfall as an exogenous variable, the situation will become more uncertain [4]. Even though the significance of freshwater in our world is clearly understood, 1.2 billion people globally do not have access to necessary quantities of drinking water. Human-induced climate change and the overexploitation of water resources have led to a 20% decrease in river runoff within the past half-century [5]. Whilst drinking water is a crucial component of human health worldwide, water can also be a significant source of infection if it does not meet quality standards. According to the World Health Organization (WHO), 80% of all diseases are waterborne and approximately 3.1% of all deaths occur due to unhygienic and poor-quality water [6].

Access to drinking water is a human right, and water is essential for many daily needs, such as cooking, hydration, health, and hygiene. However, we are far from achieving this universal right, with clean water and sanitation being one of the United Nations (UN) Sustainable Development Goals (Sustainable Development Goal 6 [SDG-6]) [7,8]. Therefore, although the availability of safe drinking water for human consumption is vital, some developing countries have limitations regarding clean water, especially drinking water [9].

Diarrhea is one of the best-known diseases that is entirely linked to contaminated water and food. A lack of sanitation, hand hygiene, and clean water leads to around 829,000 deaths per year globally from diarrhea, which includes 297,000 annual deaths in children under five years of age [10]. Therefore, addressing the risk factors associated with this disease could help prevent and control diarrhea-related mortalities.

In 2016, the mortality rate in Papua New Guinea (PNG) due to diarrheal diseases following exposure to unsafe WASH (Water, Sanitation and Hygiene) services was 16.3 per 100,000 of the population [11]. Within Papua New Guinea, approximately 87% of the population live in rural areas. With reduced access to clean drinking water, waterborne diseases such as dysentery, cholera, malaria, and diarrhea develop in much higher numbers, disproportionately affecting the rural population [12]. A report by World Vision Australia [13] supports this notion as they noted a diarrhea incidence of 13.3% in children under six years of age in PNG; further, the country ranks last in indicators of access to water and sanitation. The progress of urban sanitation systems in the country remains slow; in the past 15 years only 100,000 inhabitants had access to improved sanitation. Even though a higher standard of sanitation services is required to meet SDG-6, a significant percentage of the urban population still uses unimproved and basic sanitation services and face more obstacles to obtaining improved sanitation services [14]. Only 37% of the country's total population have access to drinking water, meaning Papua New Guinea ranks second-lowest in the world in terms of access to drinking water [15].

The population of Lae city in Papua New Guinea is rapidly growing as people from all over the country are migrating to the city for work and are settling. The Bumbu watercourse is one of the major streams among the Bumbu, the Busu, and the Markham Rivers that drain into the Lae district and surrounding landscape. To date, there has been no regular monitoring of water quality in the Bumbu River, and no research programs have been conducted to assess the microbial and/or physicochemical qualities of water resources within the Bumbu lower catchment area. This is despite the majority of people living in informal settlements using the river and its tributaries for drinking, washing, and recreational purposes. Factors such as growing population, illegal settlements, unsound sanitation, and waste disposal practices (such as discharging solid and liquid waste into rivers) are expected to increase the concentration of contaminants including fecal bacteria—leading to a direct harm in human health.

The purpose of this research is to explore the relationship between existing anthropogenic and environmental factors on the quality of water in the Bumbu River Watershed in Papua New Guinea. This will be achieved through analysis of river samples and the quantitative evaluation of a Water Quality Index (WQI) and the WASH community surveys.

Our research utilizes field data, water samples collected from stations along the Bumbu River were analyzed to determine the physicochemical and microbiological state of the surface waters using laboratory water analysis. Evaluation of the water quality indicators is performed using the Canadian Council of Ministers of the Environment Water Quality Index (WQI) Method CCME [16]. To identify and assess sources of pollution, we used i) geographic information system (GIS) for estimating the spatial distribution of natural processes and land-use, and ii) community surveys for estimating the spatial distribution of household practices and conditions. Finally, to determine the spatial relationship between the calculated WQI and various social, economic, and environmental (SEE) factors coming from surveys, we utilized geospatial analytic techniques (with the help of GIS), principal components analysis (PCA) and forward regression analysis.

2. Study Area

The Bumbu River basin is located in the Lae District of the Morobe Province in Papua New Guinea. It originates in the Atzera mountains and traverses over 11.76 km before emptying into the Huon Gulf of the Solomon Sea [17] Figure 1. The river runs through Taraka, Kamkumu and various urban settlements in the Lae district, and through the city of Lae, which is the second largest city in Papua New Guinea and also the capital of Morobe province. Sprawling across an area of more than 100 km^2, Lae district with a population of 148,934 inhabitants, and consists of two local-level governments (LLGs): Ahi Rural LLG and Lae Urban LLG, which have a population of 60,326 and 88,608 inhabitants, respectively [18]. Furthermore, the river is located within the Pacific Ring of Fire, a region of geologic instability that has produced numerous active faults and ongoing earthquake activity in the past.

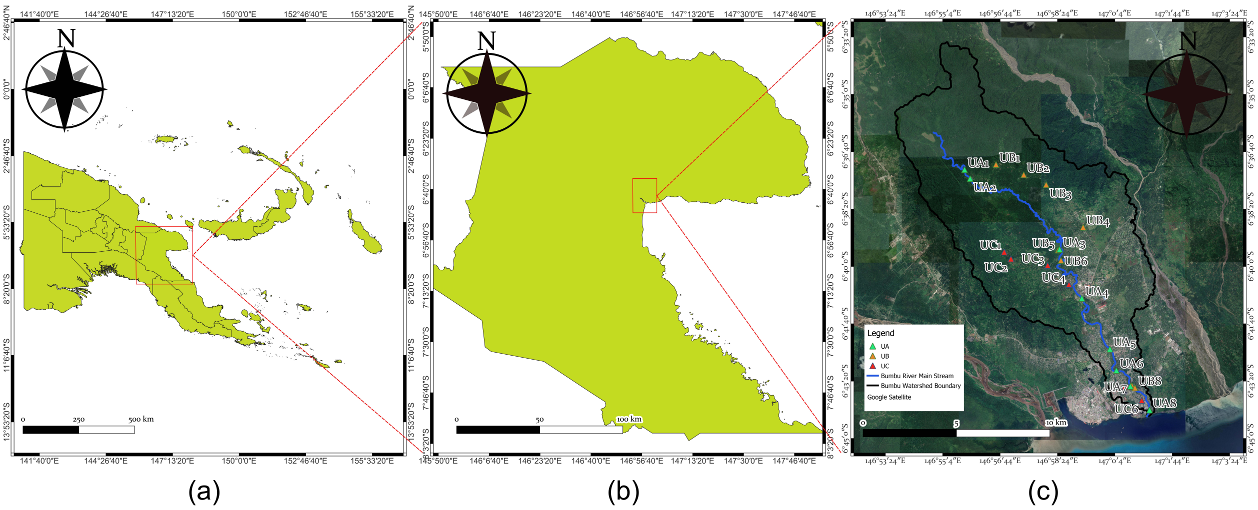

Figure 1. Map showing (**a**) Papua New Guinea, (**b**) Morobe Province and (**c**) Bumbu river basin.

3. Materials and Methods

3.1. Selection of Sampling Sites and Parameters for WQI

The 22 sampling stations utilized in this study were situated at different locations, all with varying levels of urbanization and vegetation, along the Bumbu River and its tributaries. Some of the sampling stations were situated between three major bridges (Bumbu bridge, Kamkumu bridge, and Taraka bridge), and others were located near major settlements, industrial areas, and rainforest habitats. The 22 sampling points are grouped in three main series: UA, UB, UC, corresponding to samples taken from the main stream, the right side of the stream, and the left side of the stream, respectively [19]. The environmental parameters measured were alkalinity, conductivity, total dissolved solids (TDS), turbidity, water hardness, *E. coli*, heavy metals, temperature, and pH.

3.2. Water Sample Collection

River and tributary water samples were collected from the sampling stations from March to May 2020. During this time, the average rainfall reading was 1200 mm—measured via the Papua New Guinea University of Technology (Unitech) standard rainfall gauge (SRG) [20]. The collected water samples were analyzed at the Papua New Guinea University National Analysis Laboratory and at the Environmental Laboratory of the Department of Civil Engineering, Papua New Guinea University of Technology.

The US geological survey publication "Methods for Collection and Analysis of Water Samples" [21] was used as a reference for sampling and sampling preservation techniques used in this study; further details are provided below.

GPS coordinates were recorded using the Garmin GPSMAP 64sc (Garmin, Olathe, KS, USA) and are shown in Doaemo et al. (2020b) [19]. Three water samples of 300 mL were collected near the middle of the water body at each of the 22 sampling stations. The first sample was used for microbial testing (to confirm microbial counts in terms of *E. coli*), the second sample for physicochemical tests (alkalinity, conductivity, TDS, turbidity, total hardness, and hardness from calcium and magnesium) and the third sample for trace heavy metal analysis (lead (Pb), mercury (Hg), manganese (Mn), iron (Fe), and cadmium (Cd)). On-site using a sensION156 multi-parameter field TDS, pH, conductivity, temperature, and turbidity were tested (sensIONI™156, Hach Company, Loveland, CO, USA).

The samples were collected using polyethylene bottles to prevent attachment of metals to the surface of the bottle, and 1 mL of nitric acid 0.05 M (HNO_3) was added to ensure all metals had dissolved. The samples were placed into an ice cooler and then stored at the Environment and Public Health Laboratory (Papua New Guinea University of Technology) at 0–4 °C [22] until processed within 16 h. Filtration was required for *E. coli* measurement and trace metal analysis.

3.3. Geo-Referencing of Sampling Points

The sampling points were plotted using ArcGIS mapping tools using the bearings shown on Figure 1c. The stream drainage pattern of the Bumbu River Watershed was generated using stream flow analysis with the help of Idrisi Image Analysis (runoff feature) and a 1 Arc-second Digital Elevation Model (DEM) data from US Geological Survey (USGS). The flow units were subsequently used in calculating the spatial distribution of specific parameters such as land-use and road networks.

3.4. Instrumental Analysis

3.4.1. Magnesium and Calcium Hardness, and Alkalinity

Magnesium/calcium hardness and alkalinity were determined using the American Public Health Association (APHA) standard procedure for the analysis of water and wastewater [22].

3.4.2. Calcium Hardness

Calcium hardness was determined by titration with EDTA. An EDTA concentration of 0.01M reacts with calcium, causing it to disassociate from the indicator causing it to turn back to blue when the endpoint value is reached.

3.4.3. Alkalinity

Alkalinity was measured by titration of the sample with dilute sulfuric acid (0.1 M H_2SO_4) after the addition of 0.5% phenolphthalein as an indicator. This test helped determine the concentration of hydroxides and carbonates in solutions. The concentration of bicarbonates was not determined.

3.4.4. Microbial Tests

The 300 mL sample for microbial analysis was transferred into a Pyrex glass bottle and a few drops of sodium thiosulphate 0.1 M was added for preservation. The test for *E. coli* was conducted using a membrane filtration method that involved the use of absorbent pads, Petri dishes, and a culture medium—optimized for coliform growth and identification [23]. The *E. coli* bacteria was collected on membrane filters within 6 h of sampling. The membrane filters were then placed in Petri dishes containing an agar growth medium. The Petri dishes containing the membrane samples were incubated for 22 h at 35 ± 0.5 °C. Bacterial colonies were observed after removing the Petri dishes from the incubator. Over-range samples (too numerous to count) were further diluted, and the counts were determined using the same method.

3.4.5. Trace Heavy Metals Analysis (Pb, Hg, Mn, Fe, and Cd)

Trace heavy metal analysis was performed by the Agilent ICP-MS (Inductively Coupled Plasma spectrometry) 7900 instrument (ICP-MS 7900, Agilent Technologies, Santa Clara, CA, USA).

3.5. Selection of WQI Calculation Method: The CCME Index

It is challenging to sufficiently and fully quantify water quality using a unique single variable. The Water Quality Index (WQI) is a single numeric value that is derived from measuring a series of intensive physicochemical variables (such as cation or anion concentrations) and by weighting and aggregating these analytical variables, thus providing a quantitative evaluation of water quality. Many different WQIs have been developed to evaluate the quality of water with each assessing a different set of parameters (physical, chemical, microbial, etc.). Each WQI uses different weights and calculation methods and has its own application depending on its purpose, such as recreational water, drinking water, etc. After a detailed literature review and consideration of the major factors that affect the water quality of the Bumbu River, we determined that the WQI developed by CCME was most appropriate for this study.

The primary reasons for selecting the CCME versus other WQIs include, (i) a high overlap between the parameters required by the index and the parameters we chose to monitor, (ii) its widespread use and reliability [16], and (iii) user flexibility in choosing parameters of interest so it can be adapted to local needs. This study attempts to follow the most stringent guideline available for each parameter based on a mix of water quality guidelines across different countries and regulating bodies [24–26], as provided in Table S1—Supplementary Information.

3.5.1. Overview of CCME WQI

The CCME WQI is a water quality evaluation method that gives a score to a water sample based on the combined quantification of specific chemical and physical water parameters of interest (pH, turbidity, hardness, metal content, etc.). The combination is obtained by evaluating three factors, (i) scope, the number of variables (parameters) failing to meet WQI thresholds, (ii) frequency, the number of times when such thresholds are not met, and (iii) amplitude, indicates the differential amount by which the thresholds are not met. The final score of the WQI is the square root of the sum of the squares of each factor and because each factor is represented as a percentage, the best possible score is 100 and the worst possible score is 0.

3.5.2. CCME WQI Calculation

Below is a detailed calculation used for sampling site UA1 (data in calculation taken from Table S2—Supplementary Information).

Calculation of Factor 1: Scope (F_1) shows the extent to which water quality variables failed over the period of interest. It has been adopted in the CCME directly from the British Columbia WQI:

$$F_1 = \left(\frac{\text{Number of failed variables}}{\text{Total number of variables}}\right) \times 100 = \left(\frac{4}{11}\right) \times 100 = 36.36 \tag{1}$$

The "total number of variables" represents the number of water quality variables with objectives tested during the period of time for the index calculation.

Calculation of Factor 2: Frequency (F_2) is the percentage of individual tests that do not meet the thresholds. The calculation of this factor is drawn directly from the British Columbia WQI.

$$F_2 = \left(\frac{\text{Number of failed variables}}{\text{Total number of variables}}\right) \times 100 = \left(\frac{4}{11}\right) \times 100 = 36.36 \tag{2}$$

In this study, Factor 1 = Factor 2 because there is only one set of sampling data per station (no repetitions over time).

Calculation of Factor 3: Amplitude (F_3) is the amount by which failed tests do not meet their objectives: how "far" is the failed sample value from the threshold value? The calculation of the third factor is drawn from work carried out under the auspices of the Alberta Agriculture, Food and Rural Development Programme. F_3 is calculated in three steps.

The extent to which a failed test does not meet objectives is expressed as an "excursion". When the objective is expressed as a maximum allowable value, the excursion is calculated according to:

$$\text{excursion}_i = \left(\frac{\text{Failed Test Value}_i}{\text{Objective}_j}\right) - 1 \tag{3}$$

$$\text{excursion}_{\text{iron}} = \left(\frac{0.2169}{0.1}\right) - 1 = 1.169 \tag{4}$$

$$\text{excursion}_{\text{e.coli}} = \left(\frac{40}{1}\right) - 1 = 39 \tag{5}$$

$$\text{excursion}_{\text{alkalinity}} = \left(\frac{388}{200}\right) - 1 = 0.94 \tag{6}$$

$$\text{excursion}_{\text{turbidity}} = \left(\frac{14}{5}\right) - 1 = 1.8 \tag{7}$$

Conversely, there are also objectives where the test value should not fall below a minimum allowable value. In this case, the excursion is calculated according to:

$$\text{excursion}_i = \left(\frac{\text{Objective}_j}{\text{Failed Test Value}_i}\right) - 1 \tag{8}$$

The collective amount by which the assemblies of tests are failed is calculated by adding the excursions of individual tests and dividing them by the total number of tests involved (both those meeting objectives and those not meeting objectives). This variable referred to as the normalized sum of excursions (NSE) is calculated:

$$\text{NSE} = \frac{\sum_{i=1}^{n} \text{excursions i}}{\text{number of tests}} = \frac{1.169 + 39 + 0.94 + 1.8}{11} = 3.9 \tag{9}$$

F_3 is calculated using an asymptotic function of "NSE" to scale the normalized sum of excursions to the range 0 to 100. The calculation of F_3 is as follows:

$$F_3 = \left(\frac{\text{NSE}}{0.01\text{NSE} + 0.01}\right) = 79.6 \tag{10}$$

The CCME WQI is then calculated as:

$$\text{CCME WQI} = 100 - \left(\frac{\sqrt{F_1^2 + F_2^2 + F_3^2}}{1.732}\right) = 45.28 \tag{11}$$

The factor of 1.732 arises because each of the three individual F factors can range as high as 100. This means that the vector length can reach 173.2 as a maximum. Division by 1.732 scales the vector length down to 100 as a maximum. The WQI scores were calculated using a calculator available online from CCME [16]. Table 1 shows a brief interpretive description of the quality of water samples based on the CCME WQI score [CCME 16].

Table 1. Interpretation of the scores of the CCME WQI.

Score	Category	Interpretation
Excellent	95–100	The virtual absence of threat
Good	80–94	Minor threat
Fair	65–79	Usually protected-occasional threats
Marginal	45–64	Frequently threatened
Poor	0–44	Almost always threatened or impaired

CCME, Canadian Council of Ministers of the Environment.

An important caveat is that a sample at each location in this study was only collected once. Consequently, by definition, the factor F_1 in this study will be equal to F_2. It is expected that significant variation in the WQI will be observed at each of the various sampling locations in a study that is of a longer duration. Factor F_2 is part of the statistical process that is unavailable at present and so in the current study, $F_1 = F_2$ until more data are available.

Another important caveat is the importance of each threshold value. If a WQI is formally developed for the Morobe waterways, each value must be rigorously examined, and thresholds determined based on the priorities of the Morobe population. For example, exceeding the hardness will probably not impact human health, but microbiological contamination of the water can pose significant risks to human health.

3.6. Land Use Categorisation

Following the protocol developed by Doaemo et al. (2020b) [19], relative importance values were computed for numerous runoff factors such as roads, streets, urbanized and semi-urbanized landscapes, rainfall patterns and mature and regenerating forested landscapes. Using line-vector analysis, stream and road networks were assembled for runoff compilation. Data available from Open Street Maps were used for road networks, and GIS software procedures WATERSHED and RUNOFF were used for stream network delineation. To estimate the potential impact of runoff of various land-uses, the watershed was partitioned into multiple land-use categories using aerial photography and satellite imagery. The watershed was classified into five land-use classes using "class signatures" and maximum likelihood classifiers found via the Idrisi Image Analysis. Class signatures were determined through 30 training sites (reference sites for each land cover type needed in the software in order to generate training signatures) for each class. A total of 150 training sampling points covering approximately 2.7 hectares each were utilized.

3.7. Community Surveys Analysis

A community survey was conducted to assess SEE (social, economic, and environmental) factors and trends related to water use, sanitation and waste management practices and facets of household and community health. Using a survey questionnaire that was specifically designed to be used for this research, 1100 interviews were performed with residents from randomly selected households who live in the vicinity of each sampling station (50 participants per location) within the Bumbu River Watershed. The survey questionnaire was divided into four sections:

1. Household general demographical information;
2. Basic hygiene and sanitation;
3. Major health and community concerns;
4. Perception of community issues.

It is important to note that although we refer to the questions in the survey as measures of health, they are measures of the respondents' perceptions (subjective views) of their situation and are not the result of any professional assessment of the household, community, or environmental health. Individual questionnaires were grouped for the 50 respondents at each station. The survey questionnaire contains 29 questions, among which 15 were of direct relevance to the research and so respondents' answers to these questions were only included in the analysis (Table S3—Supplementary Information). The fifteen questions of interest were divided into two sections for analysis purposes: (1) six questions reflecting on aspects of household health, water, sanitation, and hygiene, and (2) nine questions reflecting on aspects of community health, water, sanitation, and hygiene. In both sections, all questions consisted of two to four score categories, from poor outcomes to ideal outcomes. Questions with two categories were coded 0 to 1, whereas for questions with 3 categories of response from bad to ideal, coding was 0, 1, and 2. Some questions had more than three categories but with some possible answers on the same "quality level": in this case, they were coded 1 for all categories considered "ideal" and 0 for the categories considered "bad". A mean "Household health" value score was computed for the six household questions and a mean "Community health" value score was computed for the nine community health questions. The value score for both sections in each specific location was calculated as a percentage grade, the ratio between the summation of surveys response grades in each parameter and the summation of hypothetical best possible grades in each parameter. Then, the mean of all 15 questions was computed as a "Total Health" value score.

3.8. Correlation and Multivariate Analysis Methods

PCA [27] was performed using the statistical software SPSS [28], multivariate forward regression [29], correlational analyses, and geospatial analytical techniques were used to compare the physicochemical and microbiological state of surface waters (CCME WQI Indexes) with land-use, surface runoff, watershed boundaries, stream patterns, and community survey responses. Forward regression is a type of multivariate analysis used to systematically identify the independent variables explaining a significant proportion of variance in a dependent variable [30] and was used to evaluate whether a correlation exists among the different data sets.

All data were coupled with the WQ parameters and results of GIS analysis to develop a complete dataset for multivariate analysis. In combination with land-use classification and water quality data from water sampling stations, survey results were used as input for multivariate analysis.

To summarize, our research produced three main data sets: (1) water sampling results, (2) community surveys, and (3) GIS satellite, aerial, and photographic imaging. First, an initial set of results was produced from the generation of each of the three datasets. Subsequently, a correlation analysis was performed between the datasets, providing a second set of intermediate results. Finally, a comprehensive correlation analysis of all three data sets gave the final results (Figure 2).

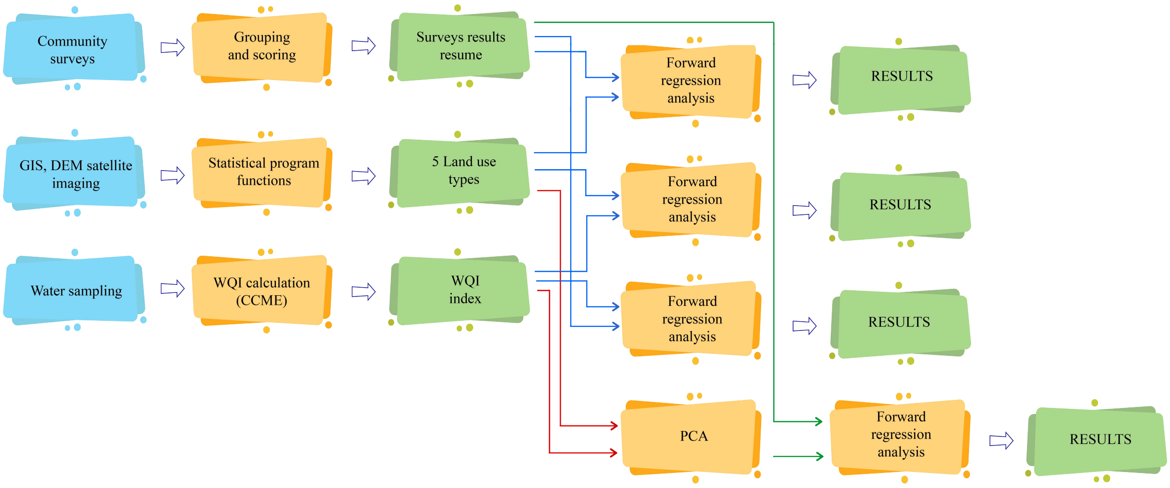

Figure 2. Flow chart showing main data sets, analysis tools used, and results from collection point. The text inside the blue boxes notes each of the three main data sets; text inside the yellow boxes represents the analysis method/s used on each of these data sets, and text inside the green boxes represent results outputs; CCME, Canadian Council of Ministers of the Environment; DEM, Digital Elevation Mode; GIS, geographic information system; PCA, principal component analysis; WQI, water quality index.

4. Results

4.1. First Data Set (Water Samples) for WQI Evaluation

Table 2 shows the WQI score for CCME for UA, UB, and UC sample series of the Bumbu River Watershed. The higher the CCME WQI value (maximum value = 100), the higher the quality of the water at the sampling point [16]. Regarding the CCME WQI, water quality may be ranked in one of the five categories (Table 1) [16]. In that sense, the lowest WQI values were observed for samples from UA7 and UA8 (WQI = 22.4), and the highest value was for the sample from UB8 (WQI = 48.6).

Table 2. CCME WQI Results, Bumbu River Watershed.

Sample ID	CCME WQI
UA1	45.2819
UA2	41.7290
UA3	38.4441
UA4	27.1740
UA5	31.4929
UA6	31.4869
UA7	22.4120
UA8	22.3921
UB1	43.8688
UB2	45.2334
UB3	40.8491
UB4	35.1272
UB5	36.7427
UB6	38.7427
UB7	40.7573
UB8	48.6383
UC1	43.8366
UC2	35.1273
UC3	38.2617
UC4	35.1272
UC5	31.4392
UC6	31.4392

CCME, Canadian Council of Ministers of the Environment; UA samples taken from the main stream, UB samples taken from the right side of the stream and UC samples taken from the left side of the stream; WQI, water quality index.

4.2. Second Data Set (Survey Analysis): Organisation into Macro-Categories

The community survey data contains resident responses on 15 aspects of health, water, sanitation, and hygiene at a household (first six questions) and community scale (last 9ninequestions). The community survey results (1100 residents who reside within the vicinity of the 22 water sampling stations) of the Bumbu River Watershed are shown in Table S4 (Supplementary Information).

4.3. Third Data Set: Land Use Categorisation

GIS software features enabled stream network delineation, which combined with aerial photography and satellite imagery, resulted in partitioning the watershed into five land-use classes: Dense forest, Regenerating forest, Green space, Semi-urban and Highly urban [19].

4.4. PCA to Estimate the Correlation between WQ and Land Use

In our water quality study, PCA revealed some interesting grouping of variates within the combined WQ and land-use environmental variables. PCA revealed that the 22 variables in the original dataset condensed to six significant dimensions that we shall call "factors" and will be explained further. These six factors together accounted for 89% of the variation in the original data. In Table 3, variates are arranged in order of importance on the extracted factors showing the variants' loading on each factor.

Table 3. Rotated component matrix showing factor loadings of 22 WQ and land-use variables on the extracted PCA components/factors.

Rotated Component Matrix (Highest Loading of a Variate on a Single Factor Is Shown in BOLD)						
	Component					
	1	2	3	4	5	6
Rainfall normalized RUNOFF	**0.900**	−0.188	−0.160	0.115	−0.046	0.272
TDS_mg_l	**0.887**	−0.137	−0.049	0.250	0.057	0.199
CCME WQI	**−0.743**	−0.266	0.065	−0.343	−0.413	−0.038
Temp	**0.684**	0.068	0.238	0.029	0.011	0.543
Fe_total_mg_l	**0.672**	0.103	−0.138	0.255	−0.117	−0.090
Turbidity_ntu	**0.669**	−0.149	0.295	0.164	−0.288	−0.324
Total_alkalinity_mg_l	**−0.628**	0.393	0.425	−0.127	−0.189	0.313
Conductivity_us_cm	**0.582**	0.042	0.272	0.133	−0.015	0.503
Road runoff IV	−0.039	**0.981**	−0.001	0.057	0.095	−0.008
Population/habitation IV	−0.038	**0.978**	0.118	0.043	0.062	0.070
Highly urban IV	−0.051	**0.973**	0.168	0.062	−0.021	0.055
pH	0.054	−0.054	**−0.877**	−0.097	0.175	0.174
Semi urban IV	−0.066	0.436	**0.740**	0.149	0.028	0.096
Green space IV	0.045	−0.235	**0.738**	−0.090	0.147	0.324
Mg_hardness	0.013	0.218	**0.692**	0.401	0.169	0.164
Ca_hardness	0.248	0.110	0.220	**0.919**	0.070	0.091
Hardness	0.229	0.131	0.298	**0.901**	0.088	0.107
Ca_total_mg_l	0.368	−0.087	−0.148	**0.861**	−0.004	0.139
E. coli	0.212	0.263	−0.151	0.147	**0.881**	0.030
Regen forest IV	−0.247	−0.423	0.161	−0.016	**0.800**	0.115
Dense forest IV	0.165	−0.377	−0.560	−0.035	**−0.649**	−0.219
Mn_total_mg_l	−0.111	−0.081	−0.075	−0.259	−0.162	**−0.725**

Ca, calcium; CCME, Canadian Council of Ministers of the Environment; TDS, total dissolved solids; IV, Relative Importance Values; Mg, magnesium; Mn, manganese; NTU, Nepthelene Turbidity unit; WQ, water quality.

Using information from Table 3, the following interpretations are possible:

- Factor 1. This factor registers as a strong indicator of water clarity due to TDS, turbidity, conductivity, Fe, and temperature all being positively linked to the factor. The CCME

WQI is also strongly negatively linked to this factor, indicating that the variations in these parameters are most highly associated with variation in the WQI. There is also a strong correlation with rainfall-runoff;

- Factor 2. This factor is mostly associated with urban conditions as reflected in the elevated loading values of variables such as highly urban, road runoff, and population/habitat;
- Factor 3. This factor is predominantly associated with semi-urban and green space variables, indicating that it is characterized by relatively less industrialized and urban conditions. Mg hardness is also positively linked to this factor. The variance of pH is negatively linked to this factor, indicating more acid conditions in these waters;
- Factor 4. This is a water hardness-related factor strongly associated to variables such as Ca hardness and Total Calcium. This is not surprising, as hardness is largely due to calcium carbonate ($CaCO_3$);
- Factor 5. This factor has a strong positive connection to *E. coli* and regenerating forest conditions while being negatively associated with dense forest conditions, suggesting that *E. coli* concentrations are highest in areas associated with regenerating forests;
- Factor 6. This factor exhibited the highest negative association with the variable pertaining to Mn presence. Temperature and conductivity showed a somewhat strong positive association with this factor, although these parameters also exhibited a strong association with the clarity factor (Factor 1 mentioned above). Conductivity will considerably increase as temperature increases, so a correlation between the two parameters is expected.

We considered the common variance of WQ and land-use variables in the PCA but not the household and community health variables. Consequently, any inferences on the correlations between the PCA factors and household and community health cannot be made and must come from outside the PCA. In other words, although the PCA can shed light on the generalized dimensions of water quality and environmental measurements assessed in this study, these do not automatically have value in determining possible inter-relationships between water quality and household/community health within the watershed. However, these dimensions from PCA were subsequently reviewed in terms of the potential inter-relationships between water quality and facets of household and community health (as revealed in the community survey results). To this end, we used forward regression analysis, which is discussed in more detail below.

4.5. Forward Regression to Estimate the Correlation between PCA and Surveys

This section investigates the aspects of community and household health surveys output as a function of the six factors identified from PCA. Given the highly correlated input variables, forward regression offers an efficient model from which other connections can be inferred in relation to the PCA results.

Regarding measures of household health, forward regression of household health score versus all six PCA factors resulted in only 1 significant relationship, with Factor 3 (Table S5—Supplementary Information). As already discussed in Section 4.4., Factor 3 is associated with semi-urban and green spaces as well as more acidic waters and greater Mg hardness. This factor accounted for 46% of the variance ($p < 0.001$) in household health measures with a positive beta = 0.694, indicating a positive relationship between higher household health outcomes (assessed through community health outcomes) and higher semi-urban and green space runoff.

In terms of measures associated with community health, forward regression of community health score versus the six PCA factors of water quality and runoff values uncovered a relationship with Factor 2 and Factor 5, accounting for 66% of the variance in the value for community health measure (Table S6—Supplementary Information). Factor 2, characterized by highly urbanized and industrialized areas, was negatively associated with improved community health outcomes ($R^2 = 0.286$, beta = -0.566, $p < 0.001$). Factor 5, characterized by elevated *E. coli* and regenerating forested areas (but not dense forest), was also negatively associated with community health outcomes (R^2 = 0.374, beta = −0.612, $p < 0.001$). Among the two factors, Factor 5 had greater relevance and extracted greater variance than Factor 2.

Forward regression analysis of the Total Health score (household and community health) versus all six factors of water quality and land-use variables, not surprisingly, showed a relationship with Factor 2, Factor 3, and Factor 5, accounting for a 70% variance in the Total Health score (Table S7—Supplementary Information): 34% negatively attributable to Factor 5 (high *E. coli*, regen forest, beta = −0.609, $p < 0.001$); 20% negatively attributable to Factor 2 (industrialized urban, beta = −0.459, $p < 0.001$) and, 16% positively attributable to Factor 3 (less urbanized but non-forested, beta = 0.404, $p < 0.003$).

4.6. Correlation between WQI and Surveys

Forward regression of CCME WQI versus household and community health perceptions showed significant relationships. Regression analysis of community health outcomes versus WQI revealed some correlation and explained variance (r = 0.589, adj. R^2 = 0.314), forward regression of WQI versus household and community health scores isolated a sequence of four variables significantly related to WQI: (1) Community crime, (2) Community pollution, (3) Community waterborne disease, and (4) Household waterborne disease; these four survey outcomes predict WQI to a significant degree, where R^2 = 0.825 at $p < 0.001$ (Table 4).

Table 4. Results of forward regression of CCME WQI versus parameters of household and community health, evaluated at all 22 sampling stations.

Model Summary—WQI vs. Health Value Scores				
Model	**r**	**R^2**	**Adj. R^2**	**Std. Error of the Estimate**
1	0.752 [a]	0.565	0.543	4.856
2	0.814 [b]	0.663	0.628	4.382
3	0.887 [c]	0.786	0.750	3.590
4	0.927 [d]	0.859	0.825	3.001

[a] Predictors: (constant), vs_Pollution_Comm; [b] Predictors: (constant), vs_Pollution_Comm, vs_Crime_Comm; [c] Predictors: (constant), vs_Pollution_Comm, vs_Crime_Comm, vs_WBD_Comm; [d] Predictors: (constant), vs_Pollution_Comm, vs_Crime_Comm, vs_WBD_Comm, vs_WBD. CCME, Canadian Council of Ministers of the Environment; Comm, community; WQI, water quality index; WBD, waterborne disease.

Inspection of the coefficients resulting from regression of WQI versus survey results (Table 5) shows that better WQI outcomes occur together with better community health scores in Crime and Pollution, and better household health outcomes occurred in areas with less waterborne disease.

Table 5. Coefficients from the results of forward regression of CCME WQI versus parameters of household and community health, evaluated at all 22 sampling stations.

Model		**Coefficients**			**t**	**Sig.**
		Unstandardized Coefficients		**Standardized Coefficients**		
		B	**Std. Error**	**Beta**		
4	(constant)	25.922	2.355		11.007	0.000
	vs_Pollution_Comm	18.279	4.818	0.548	3.794	0.001
	vs_Crime_Comm	16.218	3.706	0.459	4.376	0.000
	vs_WBD_Comm	−20.552	4.941	−0.477	−4.160	0.001
	vs_WBD	12.533	4.236	0.384	2.959	0.009
Dependent Variable: CCME WQI						

CCME, Canadian Council of Ministers of the Environment; Comm, community; WQI, water quality index; WBD, waterborne disease.

Regarding the depiction of spatial distribution, with one exception at UB8, the WQI exhibits a strong north-to-south gradient from relatively higher WQ in the upper reaches of the Bumbu to lower WQ in the lower regions of the watershed (Figure 3), comparing this result with spatial distribution of survey results, community and household health outcomes show a similar north-to-south gradient perform well in predicting WQI variance, as can be seen in Figure 3. Additionally, community crime and waterborne household disease exhibit a similar north-to-south gradient. In contrast, community pollution value scores present a more ambiguous distribution of values but contribute significantly to WQI prediction.

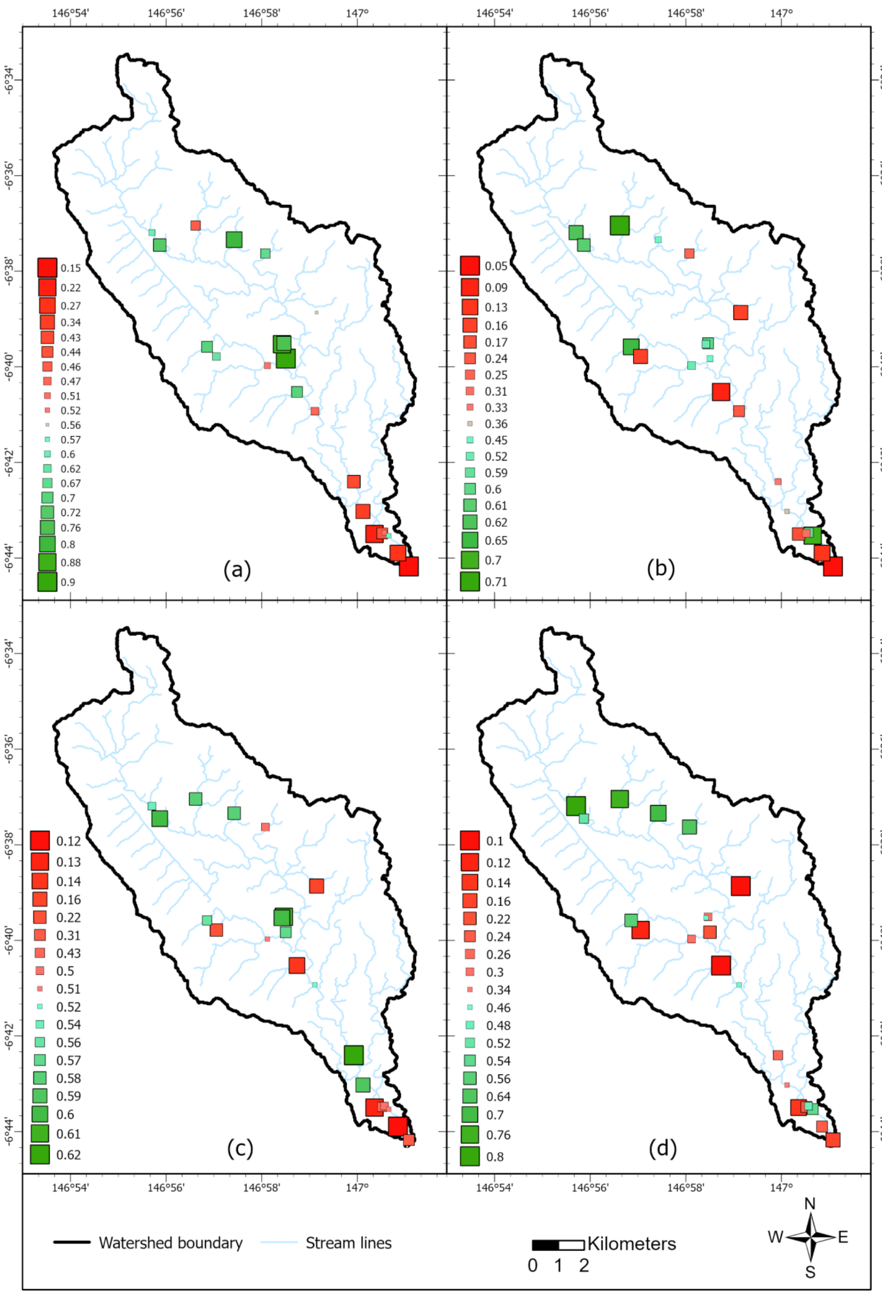

Figure 3. Depiction of spatial distribution (**a**) community crime, (**b**) community pollution, (**c**) community waterborne disease, and (**d**) household waterborne disease. Colour range is fixed and applied on survey result, from red (lowest score) to green (highest score).

4.7. Correlation between Surveys and Land Use

Figure 4 shows the standardized value scores of household health versus standardized value scores of community health plotted (with the sampling stations labelled) according to the land-use class with the highest importance value at the respective water sampling station.

Figures 1c and 3 indicate the following:

- The communities who live in the vicinity of the two highly urban stations have elevated perceptions of household health but low perceptions of community health;
- The communities who live in the vicinity of the nine dense forest stations have relatively high perceptions of community health but generally low to mid-range perceptions of household health scores;
- The communities who live in the vicinity of the four regenerating forest stations have generally low perceptions of household health but mixed results on perceptions of community health;
- The community/ies who live in the vicinity of the single semi-urban station scored high on both perceptions of community health and perceptions of household health;
- The communities who live in the vicinity of the six green space stations generally scored high in perceptions of household health but had mixed results on perceptions of community health.

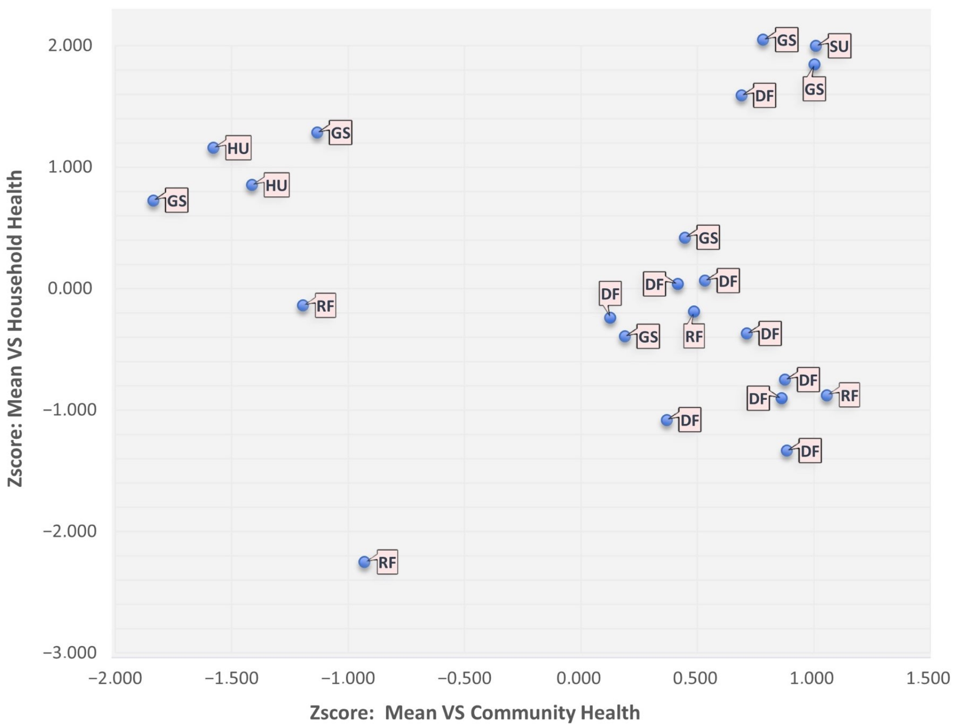

Figure 4. Scatter plot depicting standardized value scores of household health versus standardized value scores of community health at the 22 water sampling stations (HU: Highly urban; SU: Semi urban; GS: Green space; RF: Regenerating Forest; DF: dense forest).

5. Discussion and Conclusions

This study has shown how various methodological tools and techniques, such as geo-referencing, water quality surveying, community surveys and multivariate statistical analysis, can be used to explore the relationship between water quality and the various factors influencing it. It is crucial to consider the impact of different water-quality parameters on human health. Fortunately, mercury concentrations in the water collected at all sampling stations were within the thresholds [26]. However, mercury concentrations should be regularly measured because even small-scale gold mining and some industrial waste can drastically increase mercury concentrations quickly, with significant implications for human health [31]. Additionally, other parameters, particularly those relating to the microbiological activity (such as fecal bacteria) and other heavy metals, can have a considerable impact on the health of people who live near waterways and, therefore, should be regularly measured [32].

On the contrary, forward regression analysis of CCME WQI versus land use indicated that water quality is not correlated with land use as defined in this study. Correlation coefficients of WQI with land-use values varied from −0.289 to +0.222. It is thus reasonable to suggest that variation in water quality is due to or in response to factors other than land-use as defined in this study [33]. Although we found considerable variation in WQI across sampling stations, we did find that all but three of the twenty-two water samples indicated "poor" quality water according to the CCME WQI rating system; the remaining three samples (UA1, UB2, and UB8) indicated a marginal quality level.

The following impediments and difficulties were encountered during this research, (i) limited availability of testing equipment, reagents, and calibration standard, (ii) fluctuations in temperature during sampling, handling, storage, and transportation of the samples may have affected the results. For instance, dissolved oxygen (DO) and biological oxygen demand (BOD) were not analyzed though these were Parameters of Concern (POC) for the evaluation of the most currently used WQ indices, (iii) limited research funding for the high cost of testing by external laboratories, and (iv) limited accuracy in the analysis and reporting of results by the external laboratory.

Furthermore, one limitation of this study is that the number of samples collected was limited to a point in time, without considering temporal variability. Ideally, for future work, the same water sampling analysis could be performed at different time periods using better resolution DEM data, and the surveys could be geo-referenced in order to improve our confidence in the reported results.

Our research shows some correlation between health-related variables from the community survey and water quality, but questions remain about the 'common denominator' underlying these correlational relationships. For example, why and how are better community crime outcomes related to better water quality? Why are better outcomes in household waterborne disease counter outcomes for community waterborne disease? Likewise, the methodology used in this study can be extended to understanding the implications of water quality on the health of people who live near a river. Notwithstanding, further study is also recommended to explore why community waterborne disease is negatively correlated with water quality, whereas waterborne household disease is positively correlated.

Finally, the core idea of our study was to investigate the relationship between anthropogenic and environmental factors on water quality in the Bumbu River Watershed in Papua New Guinea. Authors such as Han et al. (2020) [34] and Kumar et al. (2019) [35] have studied the effects of anthropogenic activities on water quality. Nonetheless, they overlooked the likely set of environmental variables, all of which jointly may be related to water quality, as our results suggest. Likewise, the Appendix A contains the literature review we carried out around the research objective of the study, whose search results (based on a systematic approach) highlight that our research adds to the current understanding of the relationships between water quality and anthropogenic and environmental conditions in Papua New Guinea.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/w15030489/s1, Table S1: Selected Guideline Values for CCME WQI Calculation; Table S2: WQ guidelines, raw WQ data and comparison of results from spreadsheet WQI calculator vs CCME WQI calculator. UA series; Table S3: WQ guidelines, raw WQ data and comparison of results from spreadsheet WQI calculator vs CCME WQI calculator. UA series; Table S4a: Value scores for six household health variables based on 50 community responses in proximity of the 22 water quality sampling stations; Table S4b: Green space runoff IV and community overlain on green space; Table S5: Results of forward regression of household health scores versus factors of WQ parameters and runoff of land-use types, evaluated at all 22 sampling stations; Table S6: Results of forward regression of community health scores versus factors of WQ parameters and runoff of land-use types, evaluated at all 22 sampling stations; Table S7: Results of forward regression of Total Health Scores versus factors of WQ parameters and runoff of land-use types, evaluated at all 22 sampling stations.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Appendix A.1. Literature Review

The literature review incorporated some aspects of the guidelines and standards from the Collaboration for Environmental Evidence (CEE) Syntheses [36]. Two review questions were devised by the research team:

Review question 1:

- What elements are associated with water scarcity, waterborne diseases, and lack of access to clean water in populations globally and specifically in Papua New Guinea?

Review question 2:

- What are the relationships between environmental and anthropogenic factors on water quality both globally and specifically in Papua New Guinea?

Appendix A.1.1. Search Strategy

The search approach in this review was designed according to a strategy applied in different disciplines relevant to this study (e.g., environmental, ecological, public health). This allows us to retrieve all relevant data and minimize bias [37].

Scoping

Preliminary scoping searches were conducted in Scopus and in PubMed. Main search terms ("water scarcity", "water pollution", "water borne disease", "water quality", "environmental factors", and "anthropogenic factors") were established based on research questions 1 and 2 [38]. This scoping method was carried out to assess the literature size and define the terms associated with our main search terms.

Search Terms

Thesaurus functions were used to prevent errors (such as missing search terms, spelling mistakes, etc) when searching which helped identify broad or narrow concepts related to the search term thereby providing additional ways to capture articles or to discover overlooked words [36]. A total of five thesauri were applied to expand the main search terms and to identify additional terms (CAB Thesaurus, Agrovoc, General Multilingual Environmental Thesaurus (GEMET), [39], and the US National Agricultural Library's (NAL) Agricultural Thesaurus).

The searches used the main terms and their synonyms obtained from Thesaurus functions (Table A1). In addition, we adapted search strings for the different databases to allow for differing wildcards (word truncation [*]).

Table A1. Main terms and related terms according to thesaurus functions.

Main Terms					
"Water Scarcity"	**"Water Pollution"**	**"Water Borne Disease"**	**"Water Quality"**	**"Environmental Factors"**	**"Anthropogenic Factors"**
"water supply"	"polluted water"	"waterborne diseases"	"water quality control"	"climatic factors"	"anthropogenic influence"
"water availability"	"freshwater pollution"	"water-borne disease"	"water quality standards"	"site factors"	"factores antropogénicos"
"water shortage"	"brackishwater pollution"	"waterborne illness"	"calidad de agua"	"ambient conditions"	
"water deficit"	"water contamination"			"environmental conditions"	
"escasez de agua"	"clean water"			"environmental variables"	
	"stream pollution"			"factores medioambientales"	
	"contaminación del agua"				

Search String

In addition to synonyms, we considered alternative spellings and Spanish terms. Search strings were built around the main terms using Boolean operators and wildcards/truncation (where necessary) (Table A2).

Table A2. Search strings with expanded terms.

Question	Main Terms	Expanded Terms
Review question 1	water scarcity	("water scarcity" OR "water supply" OR "water availability" OR "water shortage" OR "water deficit" OR "Escasez de agua") AND ("world" OR "global" OR "developing countr*" OR "Papua New Guinea")
	water pollution	("water pollution" OR "polluted water" OR "freshwater pollution" OR "brackishwater pollution" OR "water contamination" OR "clean water" OR "Stream Pollution" OR "contaminación del agua") AND ("world" OR "global" OR "developing countr*" OR "Papua New Guinea")
	water borne disease	("water borne disease" OR "waterborne diseases" OR "water-borne disease" OR "waterborne illness") AND ("world" OR "global" OR "developing countr*" OR "Papua New Guinea")
Review question 2	Water quality, environmental factors, Anthropogenic factors	(a) ("water quality" OR "water quality control" OR "water quality standards" OR "calidad de agua") AND ("environmental factors" OR "climatic factors" OR "site factors" OR "ambient conditions" OR "environmental conditions" OR "environmental variables" OR "factores medioambientales") AND ("anthropogenic factors" OR "anthropogenic influence" OR "factores antropogénicos") (b) ("water quality" OR "water quality control" OR "water quality standards" OR "calidad de agua") AND ("environmental factors" OR "climatic factors" OR "site factors" OR "ambient conditions" OR "environmental conditions" OR "environmental variables" OR "factores medioambientales" OR "anthropogenic factors" OR "anthropogenic influence" OR "factores antropogénicos")

*truncation/wildcard searches variants of the term.

Databases

Several databases were used to source articles relevant to the literature review (within environmental, ecological, and public health fields).

- Scopus
- Web of Science
- Medline
- PubMed
- AGRICOLA
- ScienceDirect
- GreenFILE

Websites

The below websites were accessed for important governmental and organisational information relevant to the searches:

- European Environment Agency
- Stockholm International Water Institute
- Health Protection Agency, UK
- The US Environment Protection Agency
- World Health Organization
- UNICEF

Grey Literature

For the grey literature (outside of traditional publishing), ProQuest Dissertations and Theses database was used to consolidate the search.

Inclusion Criteria and Screening Process

Studies were included if they answered research questions 1 and/or 2 (Section 2, above). No limit was set on the publication year. The screening process was conducted by two researchers in two stages- (1) based on title, keywords, and abstract, and (2) in full text. A third researcher solved discrepancies.

Appendix A.1.2. Main Factors Contributing to Water Scarcity and Water Scarcity Impacts

Many factors contribute to water scarcity both in countries with sufficient water resources and in those with water deficiencies. Collapsed infrastructure and distribution systems, conflict, pollution, and mismanagement of water resources [40] are some of the determining factors in the water crisis. Agricultural activities and climate change also play important roles [2]. For example, the expansion of irrigated agriculture is one of the driving forces behind the global demand for water [41]. A study by Hess et al. [42] estimated that the average annual blue water consumption for the cultivation of potatoes in Great Britain is 61 Mm^3 (equivalent to $11m^3/t$), which means that irrigating potato fields in water-stressed regions may have a significant impact on local water scarcity. In Pakistan, the water used in the agriculture sector (the largest user of water resources) is poorly managed, and a consequence of this mismanagement is the contamination of water resources [43].

Appendix A.1.3. Factors and Impacts of Water Pollution

Water used for human consumption and use in crops must be free of contaminants. Some primary sources of contamination are untreated industrial wastewater, pesticides, sedimentation from eroded soil, human waste, agriculture, mining, sanitary landfills, urban wastewater, and fertilizers [2,25,44]. Additionally, the mitigation of chemical contamination caused by micropollutants is a complicated task since it requires methods and technical knowledge to address each of its dimensions [45]. The study developed by Xiao et al. [44] showed that the damage caused by the industrial and agricultural sectors is less when both sectors work together to mitigate water pollution by decreasing discharge levels of common pollutants. Consequently, countries should include both sectors in their environmental governance plans and direct their environmental policies to achieve common objectives to mitigate the pollution of water sources.

On the other hand, "improved" water sources will not necessarily guarantee safe drinking water unless proper monitoring techniques are in place [7]. In developing countries, it is imperative to use water treatment methods that are both economical and efficient. Pandit & Kumar [9] noted that the following treatment methods could produce drinking water: solar disinfection, filtration, hybrid filtration methods, treatment of harvested rainwater, herbal water disinfection, filtration, hybrid filtration methods, treatment of harvested rainwater, herbal water disinfection, and arsenic removal technologies.

Appendix A.1.4. A World View of Water Pollution

A study designed by Sikder et al. [46] aimed to determine if there is a difference in river pollution between developed and developing countries. The results showed that the extent of pollution in the rivers of all sampling countries was under the threshold limit.

In Africa, the countries Angola, Mozambique, Namibia, South Africa, and Lesotho have reliable water supply coverage of 23%, 32%, 63%, 63% and 66%, respectively. Regarding adequate sanitation in urban areas, the highest levels are 77% for South Africa and 76% for Botswana. In Latin America, water quality is still low and does not meet international standards for about 67% of the population, although the coverage of water supply services has increased by 50% between 1950 to 2010 [47].

In 2015, Papua New Guinea launched their National WASH policy, which seeks three goals to be attained by the year 2030 [48]:

For water supply:

- In rural areas, 70% of the population has access to a safe, convenient, and sustainable water supply.
- In urban areas, 95% of the population has access to a safe, convenient, and sustainable water supply.
- 100% of educational institutions and medical centres across the country have access to a safe, convenient, and sustainable water supply.

For sanitation:

- In rural areas, 70% of the population has access to safe, convenient, and sustainable sanitation facilities.
- In urban areas, 85% of the population has access to safe, convenient, and sustainable sanitation facilities.
- 100% of educational institutions and medical centres have access to safe, convenient, and sustainable sanitation facilities.

For hygiene:

- 100% of educational institutions and medical centres have handwashing facilities with running water and soap.
- 100% of the households that have access to an improved water supply practice total sanitation.

Additionally, other sanitation policy frameworks and plans in Papua New Guinea include: Vision 2050; National Strategy for Responsible Sustainable Development for Papua New Guinea (StaRS) 2015–2030; District Development Authorities Act; the National Water Supply and Sanitation Act, and, the Medium-Term Development Plan III (MTDP 2018–2022) [14].

Appendix A.1.5. Water Quality Versus Anthropogenic and Environmental Factors

Several anthropogenic factors heavily influence water quality. Kumar et al. [35] studied the effects of anthropogenic activities (thermal power plants and coal mining) in relation to rock-water interactions on the groundwater quality in the Singrauli industrial region of

India. Among the fifty-four groundwater samples (51 samples from hand pumps and 3 from open wells) collected, 35% and 44% of the samples during post-and-pre-monsoon seasons, respectively, had fluoride (F)-concentrations that exceeded the WHO's recommended F-limit of 1.5 mg/L [25].

Mainali and Chang [49] analyzed the seasonal trends for total nitrogen, total phosphorus, chemical oxygen demand, and total suspended solids (SS) in the Han River Basin (HRB) of South Korea using the Mann-Kendall test and explored the effects of anthropogenic (land cover and population) and natural (topography and soil) factors on concentration trends using spatial filtering regressions. Their results revealed that the water quality of the HRB improved from 1990 to 2016 with a decrease in concentrations of summer nutrients and winter SS. Around 20–70 % of the spatial variation of different water quality trends could be explained by some combination of current agricultural land cover, forest land cover, per cent area covered by water, change in land covers, and slope variations.

In a study by Zhong et al. [50] study, cluster analysis (CA) and PCA were used in order to evaluate the spatial and temporal characteristics of the surface water quality in Balihe Lake (an agricultural basin lake in China). Eleven environmental parameters (pH, water temperature, water depth, turbidity, dissolved oxygen (DO), chemical oxygen demand (COD), total nitrogen (TN), ammonium nitrogen (NH_4^+ -N), nitrate nitrogen (NO_3^- -N), total phosphorus (TP), and chlorophyll a (Chl-a)) were monitored at 45 sampling sites across four seasons (Winter 2016, Spring, Summer, and Fall 2017). The results showed that the spatial groups (less, moderately, and highly contaminated sections) of the sampling sites are exactly consistent with their geographical distribution. A study by Varanka & Hjort [51] investigated the spatio-temporal aspects of the environmental factors affecting water quality in rivers and their catchments located in Finland. The study area covered over half of Finland's land area and comprised 32 rivers and their catchments. A generalized additive model (GAMs) was used for the analysis, and water quality was evaluated using results for total phosphorus and nitrogen, pH, and water colour. Environmental factors included variables from land use/cover, climate, and other landscape characteristics. These results suggest that the nutrients present were related specifically to agriculture, water colour to lake percentage, and pH to pastures. The results showed the suitability of GAMs in water-quality studies.

This narrative literature review shows that there are currently no studies reporting on direct relationships in association between anthropogenic and environmental factors on water quality on a global basis and specifically in Papua New Guinea.

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