Assessing Water Poverty of Livelihood Groups in Peri-Urban Areas around Dhaka under a Changing Environment

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Abstract: Water poverty, measured by the Water Poverty Index (WPI), is traditionally applied at country and community levels. This study presents a livelihood-inclusive approach for measuring WPI at the livelihood group level. The specific objectives are to evaluate present and future WPIs for different livelihood groups, such as large and small male farmers, female farmers, male and female industrial workers and economically inactive women. Primary data are collected from three peri-urban areas around Dhaka using a mixed approach, including a semi-structured questionnaire survey of 260 respondents. The WPIs are calculated by using a weighted multiplicative function, and the component weights are assigned by principal component analysis. The results show that the economically inactive women are presently the most water-poor group, with a WPI value of 41, whereas the small male farmers would be the most water-poor group in the future, with a WPI value of 34. Environmental changes, such as high temperature, variability in rainfall and surface water, lowering of groundwater level, rapid population growth and unplanned urbanization, are found to be responsible for the dynamism in WPIs for different livelihood groups. The Resource and Environment components should be paid immediate attention in order to protect peri-urban livelihood groups from future water poverty.

Keywords: water poverty index; livelihood groups; principal component analysis; peri-urban areas

1. Introduction

Modern water management has emerged from a background of engineering, rather than social discourse, and it is time for “soft water paths” [1]. Hence, the concept of water poverty is introduced, which is an essential part of Integrated Water Resources Management (IWRM). IWRM embraces economic efficiency, environmental sustainability and social equity—the three E’s—and is considered as one of the main policy paradigms in water resources management [2].

Water occupies a major role in poverty alleviation, as access to water and poverty are linked [3,4]. For poverty, water management issues are related to drinking water access, cooking and sanitation through policy failure, lack of infrastructure and low capacity [4]. These factors lead to the development of indicator approaches in water resource research. Hence, the Water Poverty Index (WPI) has been developed as a holistic tool to assess water resources in an integrated manner [3]. The links between poverty, social deprivation, environmental integrity, water availability and health become clear through the underlying framework of the WPI [5].

Today, the Water Stress Index (WSI) is one of the most widely used indices for measuring water scarcity. The concept of the WSI, originally known as the “Falkenmark Indicator”, initiated the development of the present WPI framework [6,7]. Later, the WSI was combined with the Human Development Index to arrive at the Social Water Scarcity Index [8].
Thus, for the first time, the concept of water scarcity included considerations of social and economic capabilities of a population. A number of large-scale studies [9–14] highlight the need for insights into the site-specific issues of local water management [15]. Because of the inability to address different water use patterns, a situational definition of water poverty, stating that “Water poverty is a situation where a nation or region cannot afford the cost of sustainable clean water to all people at all times” was developed [16]. Thus, there is a need for a tool that moves beyond the traditional scope of water scarcity measurements and considers all the dimensions of water poverty in an inclusive, holistic format, such as the WPI. The WPI provides a solid framework for an integrated water index at the community level [17].

Caroline Sullivan was the first to introduce the concept of the WPI [3]. The WPI is a number between 0 and 100, where a low score indicates water poverty, and a high score indicates good water provision. The WPI was developed to express the complex relationship between sustainable water resource management and poverty at all levels from a community, village, district, region and nation. The community scale is considered appropriate in instances where it is possible to generate data for all the communities within a unit, so that the full complexity of the situation can be represented. This requires a simplified data collection procedure [18]. There are five components of the WPI—Resource, Access, Capacity, Use and Environment. For each component, indicators are used to evaluate index values. The indicators must be measurable, and the necessary data must be either obtainable through measurement and monitoring or be readily available [19]. The information is in the components, rather than in the final single number [20]. The indices are a statistical concept, providing an indirect way of measuring a given quantity or state, effectively a measure which allows for comparison over time [3]. The value of the WPI also varies seasonally. Seasonal differences in water poverty using WPI as a tool have also been studied [21–23].

Multiple studies have been undertaken since the WPI was first introduced. It has been applied at various scales: at grid level [12], national [24–26], river basin [4,10,27,28], regional or district as well as sub-district [27,29], a mix of basins and administrative units [30] in addition to at the local level [4,17,27,31,32]. An international comparison of 140 countries has been undertaken, producing “sensible results” [24]. A pilot study has been undertaken on a community scale in South Africa, Tanzania and Sri Lanka [18]. The WPI has been used to devise water poverty maps in South Africa [31]. A strong correlation between the WPI and Capacity has been established [25]. A new version of the WPI has been introduced for rural communities, called the Rural Water Livelihoods Index [33]. An agricultural water resource assessment tool has been used for the first time in the form of the Agricultural Water Poverty Index [34]. In Bangladesh, changes in water poverty status in the Small-Scale Water Resources Development Sector Project for two different types of subprojects have been identified [35]. The WPI has been used as a tool to monitor the progress of the water sector in a pilot site across the Bakkhali tidal river, flown through the southeastern part of Bangladesh [36]. The WPI has been used to determine the relative rankings of Bangladesh and Sri Lanka [37].

The WPI is an improved water management tool that a country’s economy can utilize to face against the climatic wrath in the years to come [38]. Changes in the global climate over the next hundred years are almost certain [39]. The changes in climate affect the spatial and temporal distributions of surface water and groundwater resources [40,41], indicating that the freshwater resources need to be managed more carefully in the future. The impact of human population growth is also a major issue when considering the future challenges for water management [42]. Additionally, rapid urbanization and industrial growth are the dominant factors behind environmental changes. Peri-urban areas face severe consequences of these environmental changes. In the peri-urban areas of Khulna, Bangladesh, water availability and access to it by communities are adversely affected by rapid urbanization and industrialization, leading to competition and conflict over water [43].
The overall impact is differently distributed among different countries, regions, income groups and men–women. Considering these scenarios, water is considered as a scarce resource in a changing environment due to urbanization and climate change, especially for the disadvantaged livelihood groups, who depend on water entirely or partially for their livelihoods. Livelihoods vary significantly within a country, from rural to urban areas and across countries. A household-level analysis is preferable for livelihood-related analyses [44]. Socio-economically and physically disadvantaged groups suffer the most due to climate-change-induced risks [45].

From the above review of the relevant literature, it appears that different studies have been conducted to assess water poverty at different scales, including at the community level. However, there has been no such study on different livelihood groups, particularly in a dynamic, peri-urban setting. Generally, high-income groups are considered to be water-secure, as they have better access to water resources and a greater capacity to withdraw, treat and use water than low-income groups. However, it is not known to what extent this holds for peri-urban livelihoods, which are being continuously reshaped by demographic, socioeconomic, urban and environmental drivers. Therefore, the hypothesis of this study is that different livelihood groups will be affected differently by environmental changes and peri-urban processes (e.g., temperature, rainfall, water level, demography and land use). This hypothesis is tested through a case study of water-related issues using the WPI in a few select peri-urban areas around Dhaka City, Bangladesh.

2. Materials and Methods

2.1. Study Area

To identify the changes in water poverty status, three different unions (the lowest tier of local administrative unit) were selected after conducting a detailed reconnaissance survey, a few focus group discussions (FGDs) and semi-structured interviews (SSIs) with local stakeholders. Two of these (the Dhalla and Saista unions) are within the Singair upazila (middle tier) of the Manikganj district, and the other (Tetuljhora union) is within the Savar upazila of the Dhaka district in Bangladesh (Figure 1). The study sites offer sufficient existence of both urban and rural characteristics, typical for peri-urban areas. The other selection criteria were accessibility, availability of different livelihood groups and the likely impact of climate change.

![Figure 1. Location of the study area (the Dhalla and Saista unions in the Singair upazila and the Tetuljhora union in the Savar upazila, Bangladesh).](image-url)
farmers, small male farmers, female farmers and economically inactive women) were selected. The small or marginalized farmers owned on average about 0.43 and 0.39 ha of land in the Dhalla and Saista unions, respectively. The large farmers had approximately 3.25 and 2.74 ha of land in the Dhalla and Saista unions, respectively. The farmers who were not actively engaged in agricultural activities are not considered in the analysis. The economically inactive women group consisted of unemployed women, adolescent girls, physically challenged and elderly women. From the Saista union, four groups (large male farmers, small male farmers, female farmers and economically inactive women) were selected.

2.2. Data

Both primary and secondary data were collected for this study.

2.2.1. Primary Data

Primary data were collected using a number of methods, such as a semi-structured questionnaire survey, FGDs with local people and SSIs with different key informants. Data collection was carried out from October 2018 to April 2019. A set of questionnaires were prepared before conducting the household survey (see Supplementary Material S1). The questionnaires were pre-tested during the reconnaissance visits to the study areas. A stratified purposive sampling technique was followed for the household survey. The total sample size for the household survey was 260 (Table 1), made up of 120 men and 140 women. Most of the studies recommend a sample size of 200−500 to represent the population. For behavioral studies, a minimum sample size of 50 per group has been recommended [46]. Small sample sizes (e.g., 40) may be used when sampling is expensive and time consuming. However, larger sample sizes are more reliable (e.g., 50–80), though there must be a trade-off between sampling effort and cost, on the one hand, and the quality of information extracted from principal component analysis (PCA), on the other hand [47]. Given the availability of time and resources, and the variability in responses, a sample size of 15–40 per group was chosen (Table 1).

Table 1. Distribution of sample size in the study area.

| Upazila | Union       | Livelihood Groups                | Sample Size |
|---------|-------------|----------------------------------|-------------|
| Savar   | Tetuljhora  | Industrial workers (male)        | 20          |
|         |             | Industrial workers (female)      | 15          |
|         |             | Industrial workers (female)      | 25          |
|         |             | Large farmers (male)             | 25          |
|         |             | Small farmers (male)             | 25          |
|         |             | Female farmers                   | 15          |
|         |             | Economically inactive women      | 30          |
| Singair |             | Large farmers (Male)             | 25          |
|         |             | Small farmers (Male)             | 25          |
|         |             | Female farmers                   | 15          |
|         |             | Economically inactive women      | 40          |
| Saista  |             | Total                            | 260         |

1 Classification of farmers is based on the amount of land they own. Farmers with 0.02–1.00 ha of land are considered as small farmers, 1.01–3.00 ha are considered as medium farmers and those with more than 3.00 ha are considered as large farmers [48]. In this study, the medium and large farmers are pooled into one category based on local perceptions, as most of the large farmers are not actively engaged in agriculture.

The questionnaire was framed in such a way that it covered all the components of present and future WPIs. Each question was designed with potential response options.
Responses against each question were recorded and converted into a numeric score. The scores ranged from 0 to 100 and were divided into a four-point scale. The highest score was 100, which is considered as fair, and the lowest score was 0, which is considered as risky. The other two scores in-between are 67 (acceptable) and 33 (poor) [49].

A total of seven FGDs were conducted in the Dhalla and Saista unions with different livelihood groups, such as male and female farmers as well as economically inactive women. The findings from the FGDs were useful in selecting the indicators for the WPI components and assessing future WPIs for the livelihood groups. SSIs were conducted with Assistant and Sub-Assistant Engineers from the Department of Public Health Engineering of the Singair upazila, a Sub-Assistant Agriculture Officer of the Singair upazila, two local school teachers and three local, large, educated farmers. These SSIs helped understand the overall situation of the location, occupation of the people, the water sources and their availability, water quality, conflicts regarding water use and other relevant aspects of the localities. The FGDs and SSIs also helped triangulate the survey results.

2.2.2. Secondary Data

Secondary data, such as climatic data (daily maximum and minimum temperatures, as well as daily total rainfall) from the years 1953 to 2017, were collected for the Dhaka station from the Bangladesh Meteorological Department (BMD). Hydrological data, such as the surface water level of the Dhaleshwari River (station name: Savar; station ID: SW69), and the groundwater level (well ID: GT5682014 and GT5682015) from the years 1975 to 2015, were collected from the Bangladesh Water Development Board (BWDB). Data for population growth in the study area were collected from the census reports of the Bangladesh Bureau of Statistics [50,51]. Landsat satellite images for 1989 and 2019 have been downloaded from the United States Geological Survey using the EarthExplorer tool (https://earthexplorer.usgs.gov/, accessed on 19 February 2019) to determine the land use changes.

2.3. Methods

There are four possible approaches to calculate the WPI—the conventional composite index approach, an alternative gap method, a matrix approach and a simple time analysis approach [3]. A composite index approach is considered useful to calculate WPI [52].

2.3.1. Methods for Evaluating the WPI

To compute the WPI using the composite index approach from a series of variables, a bottom-up approach with locally determined values and parameters was used. A conceptual framework was established for the index calculation (Figure 2). Composite indexing involves two key steps, such as the selection of indicators and the construction of the index. The first three steps in the framework are associated with selection of indicators, and the next three steps are associated with construction of the index.

Selection of Indicators

As the WPI is an indicator-based approach, the first stage consists of defining a set of relevant indicators for its five components: Resource (R), Access (A), Capacity (C), Use (U) and Environment (E). In this study, the indicators were modified as per the present scenario and relevance of the study area. The Resource component estimates physical availability of both surface water and groundwater, taking account of the variability and quality of the resource as well as the total amount of water [18]. This indicator refers to the amount of renewable freshwater available per capita, which gives an indication of population pressure on water resources [3,31]. In this study, the indicators have been modified to better represent the scenario regarding the availability of water resources based on the perceptions of local people. For example, the Resource component generally covers the availability and quality of as well as the variability in water resources. Thus, to measure the availability, perceived changes in surface water and groundwater levels were measured...
(R1 and R2 accordingly); to measure the quality, occurrence of illness from using surface water and groundwater (R4 and R6, accordingly), odor issues (R5 and R8, accordingly) and groundwater quality parameters (R7) were measured; and rainfall variability (R3), in order to measure the variability, was considered.

![Diagram](image)

**Figure 2.** Methodological framework for construction of the WPI (note: R, A, C, U and E indicate Resource, Access, Capacity, Use and Environment, respectively).

The Access component covers the extent of access to the water for human use, accounting for not only the distance to a safe source, but also the time needed for collection of a household’s water and other significant factors. Access means not simply safe water for drinking and cooking, but water for irrigating crops or for industrial use. The indicators for the Access component of female industrial workers were access to safe drinking water inside the industry (A1), daily water collection time including travel and waiting time (A2), collection of water even when sick (A3), security issues during the collection of water (A4), access to improved washroom facilities inside the industry (A5) and access to improved sanitation and medication (A6 and A7, accordingly). For male industrial workers, the indicators were A1, A6, A7 and access to safe water supply for daily use; for male farmers, they were access to irrigation, A6 and A7; and for female farmers and economically inactive women group, indicators A2, A3, A4, A6 and A7 were selected.

The capacity component denotes the effectiveness of people’s ability to manage water. This capacity is reflected as both financial and social capacity. Capacity is interpreted in the sense of income to allow purchase of improved water, and education and health which link with income and indicate a capacity to lobby for more effective management of water resources [18]. For the Capacity component, nine indicators were used—affordability (C1), financial help (C2), access to institutional loans (C3), duration of residence (C4), political or NGO linkage (C5), training in water, sanitation and hygiene issues (C6), education ratio (C7) and roles in operation and maintenance (C8 and C9 accordingly).
The ways in which water is used for different purposes, such as domestic, agricultural and industrial uses, are covered by Use component. For female industrial workers, four indicators—daily water requirement inside and outside the industry for domestic use (U1 and U2, accordingly), occurrence of violence (U3) and conflicts regarding water use (U4)—were selected for the Use component. For male workers, U3 was eliminated as it was not applicable for them. For male farmers, irrigation water requirement, daily water requirement and conflicts indicators were used; for female farmers, indicators U2, U3, U4 and water requirements for cooking for laborers as well as for post-harvesting activities were used; and for economically inactive women, indicators U2, U3 and U4 were used.

The Environment component evaluates the environmental condition and integrity related to water and ecosystem goods and services from aquatic habitats in peri-urban areas [18]. The Environment component had six indicators, including consumable fish species in surface water (E1), reduction in fish species (E2), damage and loss due to flood or drought (E3), crop loss (E4), drainage problems (E5) and reduction in vegetation cover (E6). All data for the indicators were collected through a questionnaire survey.

After selecting and classifying the indicators for R, A, C, U and E, scoring is done for all the indicators, and thus they are prepared for further analysis. For R1 and R2, responses from the questionnaires were divided into four categories: no change (100), low decrease (67), medium decrease (33) and high decrease (0). Responses for R3 were segmented as less, moderate, high and very high; R4 and R6 as no illness, minor illness, moderate illness and major or extreme illness; R5 and R8 as no odor, seasonal mild odor, seasonal extreme odor and odor throughout the year; and R7 as no water quality issue, presence of iron only, presence of arsenic only and presence of both iron and arsenic.

A1 was divided into four scores based on the distance of drinking water points from the workstation. A2 was evaluated basically by a yes–no question, but if any household has piped water connection, then the scores depended on whether the supply was continuous or intermittent. A3 scores depended on how frequent one had to collect water despite being sick. A3 and A4 were not applicable for the Tetuljhora union, as they have a piped water connection. A5 depended on the adequacy and maintenance of separate washroom facilities for females inside the industry. A6 scores were assigned based on the appearance of the latrines the households had. A7 scores were assigned based on the availability of the emergency doctors and medical facilities. The scores for access to irrigation were assigned based on whether the agricultural water-managed areas were well-equipped for irrigation or not.

C1 was measured based on the cost–income ratio in terms of percentage. C2, C3, C4 and C5 were evaluated from yes–no questions. C6 was segmented based on the number of years the households had lived in the study area. C7 denoted the ratio of educated people (primary level) to the total household number. C8 measured how frequent one operated the water source. The scores of C9 were based on the participation rate in maintenance of the water source.

Water requirement scores were divided based on the level of shortages reported by the households. The scores for the occurrence of violence were divided based on the degree of violence when demand was not fulfilled, or one could not bring water timely. The reported conflicts were scored based on the degree and level of the conflict.

E1 was evaluated based on a yes–no question. The scores for E2 were segmented based on the reduced number of fish species. E3 and E4 were scored in terms of the severity of the amount of loss and damage due to flood and/or drought, and crop loss accordingly. The scores of E5 were assigned based on the level of waterlogging due to drainage problems in the study area. E6 evaluated the level of reduction (low = 100, medium = 67, high = 33, critical = 0) in vegetation cover. While collecting information from the interviewees for the future, the same questionnaire (with changes in few cases) but reflecting a future time period was used. Additionally, the findings on changes in temperature, rainfall, surface water and groundwater levels, land use and population growth from secondary data analyses were conveyed to the respondents so that they were able to provide informed
responses. For scoring the future responses, the above segmentations of scores were used, but the responses, and hence the scores, changed depending on the future scenario and local perception.

The next step was the selection of indicators at the subindex level by conducting PCA. Before applying PCA to the dataset, it is recommended that the factorability of all the indicators collectively and individually be tested using the Kaiser–Meyer–Olkin (KMO) test, a measure of sampling adequacy (MSA) [53]. The threshold value was considered as 0.5 [54]. Another test of the strength of the relationship among the variables is done by using Bartlett’s test of sphericity [55]. Bartlett’s test for the indicators indicated that the probability should be less than 0.05 in order to reject the null hypothesis. The remaining components, which did not satisfy the conditions for factorability tests, were calculated by averaging the indicator values without applying PCA.

The next step was performing the PCA to explore whether the variables were statistically balanced at both index and subindex levels. The decision of retaining factors was based on the “variance explained criteria”, i.e., to keep enough factors to account for 80% of the variation [56]. The number of selected variables must be equal to the number of principal components that have characteristic roots in the correlation matrix greater than 0.7 [57].

After deciding the number of indicators to keep, the combination of the retained indicators was the next step. At this level, an additive aggregation was employed, since variables in the same indices can compensate the performance of each other [54]. Moreover, all variables were considered as having the same importance, and hence an equal weighting scheme was selected for the retained variables. An equal weighting scheme at the subindex level was also used in the development of a regional WPI in Tunisia [54]. The main argument for equal indicator weights is based on the premise that no objective mechanism exists to assess the relative importance of the different aspects included in the subindex structure [58]. Moreover, no weighting system is above criticism, and it is for this reason that equal weighting is often employed. A conventional practice is the selection of weights following a consultation with experts. However, this is a relatively subjective method of weighting, and it is often singled out for its arbitrariness. Alternatively, multivariate techniques, such as PCA, present an empirical and more objective option for weight assignment. This technique has the advantage of determining those set of weights which explain the largest variation in the original variables. However, PCA is usually applied at the index level with a multiplicative aggregation [54], probably to tradeoff the objectivity and complexity of a higher (index) level with the transparency and simplicity of a lower (subindex) level. Hence, this approach was chosen in the present study.

Construction of the Index

After calculation of the five subindices, PCA was performed again to assign the component weights [26]. In this study, weight calculation was only used among the components (R, A, C, U and E). A varimax orthogonal rotation was applied to each analysis in order to maximize the variance of factor loadings, and thus to enhance the interpretability of the results. To obtain the final weighting scheme, the principal component retained must be weighted with the proportion of variance calculated by dividing the square root of the eigenvalue of the corresponding principal component by the sum of the square root of the eigenvalue. After that, calculated weights were normalized in such a way that the sum of the weights were equal to 1. The following equation was used for the weight calculation:

\[
    w_i = \frac{1}{\sum_{k=1}^{n} PC_k \sqrt{\lambda_k}} \sum_{k=1}^{n} \frac{\sqrt{\lambda_k}}{\sum_{k} \sqrt{\lambda_k}},
\]

where \( w_i \) is the weight assigned to the ith component of the WPI, \( PC_k \) is the value of the characteristic vector associated with the kth principal component and \( \lambda_k \) is the eigenvalue.

The last step was the aggregation of the subindices. The most appropriate aggregation function is the weighted multiplicative function, as it does not allow compensability.
between the different components [4]. A multiplicative function tends to penalize poor performance in components more heavily [58] and more accurately identifies the hot spots of a dataset. Several factors, such as the chosen scale, the components and sub-components used, and the chosen data sources can influence the choice of calculation function [14,18,59]. A comparison between additive and multiplicative functions has shown that the latter produces lower values in each of the three cases studied [60], but the order remains unchanged. Therefore, in this study, a weighted multiplicative function was used. Numerically, the WPI can be formulated as follows:

\[
WPI = \prod_{i=R,A,C,U,E} X_i^{w_i} \quad (2)
\]

where WPI is the value of the WPI for the corresponding group and \( X_i \) is the value of component \( i \), which can be Resource, Access, Capacity, Use or Environment.

2.3.2. Methods for Evaluating Environmental Changes

Trend analysis of Hydroclimatic Variables

Two methods, namely Pearson’s \( r \) and Mann–Kendall tests, were used to detect trends in two climatic variables—temperature and rainfall, and two hydrological variables—surface water and groundwater levels [61–63].

Rainfall Variability Analysis

Rainfall variability was evaluated using the coefficient of variation (CV). A higher CV implies a higher variability in water resources, which may also reflect a higher climate-induced risk and vulnerability of resources [64,65]. A low value indicates a high degree of dependability, and a high value indicates erratic behavior. CV is calculated by the following equation:

\[
CV = \frac{\sigma}{\mu} \times 10 \quad (3)
\]

where \( \sigma \) is the standard deviation and \( \mu \) is the mean rainfall over a period of observation. CV is used to classify the degree of variability of rainfall events as less (CV < 20), moderate (20 < CV < 30), and high (CV > 30) [66].

Another analysis of rainfall variability is conducted by determining the inter-annual variability. Standardized rainfall anomaly (Z) assesses the frequency and severity of droughts. The following equation has been used for the calculation:

\[
Z = \frac{X_i - \bar{X}}{S} \quad (4)
\]

where \( X_i \) is the rainfall of a particular year, \( \bar{X} \) is the long-term mean annual rainfall over a period of observation and \( S \) is the standard deviation of annual rainfall over the period of observation. The drought severity classes are extreme drought (Z < −1.65), severe drought (−1.28 > Z > −1.65), moderate drought (−0.84 > Z > −1.28) and no drought (Z > −0.84) [67].

Environmental Factors

To assess the environmental change in the study area, two factors—population growth and land use changes—were considered. Population growth was assessed with a geometric growth function [68]. The following annual compounding formula was used for the estimation of present and future populations:

\[
P_t = P_0 (1 + r)^t \quad (5)
\]

where \( P_0 \) is the initial population, \( P_t \) is the population in \( t \)-years later and \( r \) is the annual population growth rate.
A land use or land cover dataset was generated from the digital image classification of Landsat 5 and 8 satellite images. There were two broad classification procedures: supervised and unsupervised. The supervised classification was the essential tool used for extracting quantitative information from remotely sensed image data [69]. A total of four classes were assigned (water body, bare land, settlement and urban development area in addition to agricultural land and vegetation) [70,71]. All the images used in this study were from the month of February, which is a cloud-free month in Bangladesh.

3. Results

Both present and future WPIs for different livelihood groups were calculated. The values indicate how the WPI scores varied temporally as well as by livelihood group.

3.1. Present WPIs for Different Livelihood Groups

Table 2 shows the results for factorability tests. To proceed with PCA, Bartlett’s test of sphericity for the subindices would indicate the presence of non-zero correlations if the p-values were less than 0.05 and the KMO values were greater than 0.5. For the remaining components, which do not satisfy the factorability tests, each of these subindices was calculated as an average of their indicator values.

Table 2. Factorability tests (KMO and Bartlett’s tests) for industrial workers in peri-urban areas around Dhaka.

| Union      | Group | Variable | KMO Index | Bartlett’s Test of Sphericity |
|------------|-------|----------|-----------|------------------------------|
|            |       |          |           | Approx. Chi-Square | df | p-Value |
| Tetuljhora | Male  | R        | 0.495     | 59.100 | 28 | 0.001 |
|            |       | A        | 0.559     | 4.600  | 6  | 0.000 |
|            |       | C        | 0.306     | 60.400 | 36 | 0.007 |
|            |       | U        | 0.553     | 3.950  | 3  | 0.000 |
|            |       | E        | 0.515     | 32.544 | 15 | 0.001 |
|            | Female| R        | 0.525     | 43.711 | 28 | 0.000 |
|            |       | A        | 0.515     | 11.018 | 15 | 0.001 |
|            |       | C        | 0.423     | 43.486 | 36 | 0.008 |
|            |       | U        | 0.504     | 4.772  | 3  | 0.189 |
|            |       | E        | 0.649     | 14.788 | 15 | 0.047 |
| Dhalla     | Female| R        | 0.544     | 34.414 | 28 | 0.000 |
|            |       | A        | 0.573     | 18.800 | 21 | 0.598 |
|            |       | C        | 0.445     | 38.093 | 36 | 0.374 |
|            |       | U        | 0.609     | 4.406  | 3  | 0.001 |
|            |       | E        | 0.468     | 11.456 | 15 | 0.720 |

After conducting the factorability tests, principal components associated with eigenvalues greater than 0.7 were selected. For example, four indicators (R2, R3, R5 and R8) were retained after discarding the rest of the resource components for the first group, and the cumulative variance explained for the component is about 85% (Table 3). It is seen from Table 3 that more than 80% of the data were retained for all the variables after conducting PCA. Then, the component values were calculated by applying an equal weightage to the retained indicators following the calculation of weightages by PCA for the components. Thus, the final, present WPIs for the male and female industrial workers in the Tetuljhora union were found to be 48 and 46, respectively. In the Dhalla union, the female industrial workers scored 56. For all three groups, the weightage for the Capacity component was the highest. Therefore, the social components were more dominant than the physical components in the study area.
Table 3. PCA results for industrial workers in peri-urban areas around Dhaka.

| Union | Group | Variable | Data Retained | Variable Equation | Value | Weight (after Normalization) | Present WPI |
|-------|-------|----------|---------------|-------------------|-------|----------------------------|-------------|
| Tetuljhora | Male | R | 84.947 | 0.2 * R2 + 0.2 * R3 + 0.2 * R5 + 0.2 * R8 | 38.725 | 0.13 | 48 |
| | | A | 86.741 | 0.33 * A1 + 0.33 * A2 + 0.33 * A4 | 65.488 | 0.21 |  |
| | | C | - | - | 53.360 | 0.36 |  |
| | | U | 81.902 | 0.5 * U1 + 0.5 * U2 | 68.425 | 0.17 |  |
| | | E | 91.944 | 0.25 * E2 + 0.25 * E4 + 0.25 * E5 + 0.25 * E6 | 17.025 | 0.13 |  |
| Dhalla | Female | R | 85.635 | 0.25 * R2 + 0.25 * R3 + 0.25 * R5 + 0.25 * R6 | 31.633 | 0.15 |  |
| | | A | 86.178 | 0.25 * A1 + 0.25 * A3 + 0.25 * A5 + 0.25 * A6 | 73.967 | 0.14 |  |
| | | C | - | - | 49.800 | 0.27 |  |
| | | U | - | - | 70.440 | 0.19 |  |
| | | E | 87.817 | 0.25 * E1 + 0.25 * E3 + 0.25 * E4 + 0.25 * E6 | 28.900 | 0.25 |  |

A total of 130 farmers (100 males and 30 females) were surveyed from the Dhalla and Saista unions. Female farmers participating in any kind of agricultural activity, such as cooking, carrying lunch for the workers in the field or engaging in post-harvest activities, were also surveyed as their activities also required a large portion of water each day. The detailed results of the present WPIs for other groups can be obtained upon request.

Table 4 shows the present WPI values for all the groups. The WPI scores ranged from 41 to 57 for the present condition. The WPI scores ranged from 46 to 56 for the industrial workers, 42 to 57 for the farmers and 41 to 50 for the economically inactive women.

Table 4. Present WPIs for different livelihood groups in peri-urban areas around Dhaka.

| Union | Group | R | A | C | U | E | Present WPI |
|-------|-------|---|---|---|---|---|-------------|
| Tetuljhora | Industrial workers (male) | 38.73 | 65.49 | 53.36 | 68.43 | 17.03 | 48 |
| | Industrial workers (female) | 31.63 | 73.97 | 49.80 | 70.44 | 28.90 |  |
| Dhallai | Industrial workers (female) | 52.80 | 65.07 | 51.34 | 84.66 | 50.44 |  |
| | Large farmers (male) | 48.04 | 68.78 | 61.56 | 77.40 | 44.01 |  |
| | Small farmers (male) | 37.87 | 67.50 | 43.46 | 78.80 | 35.72 |  |
| | Female farmers | 40.56 | 49.56 | 50.56 | 68.80 | 35.72 |  |
| | Economically inactive women | 41.66 | 60.20 | 39.78 | 71.33 | 45.78 |  |
| Saista | Large farmers (male) | 39.14 | 54.19 | 60.57 | 41.28 | 39.60 |  |
| | Small farmers (male) | 36.95 | 26.82 | 31.45 | 52.80 | 47.68 |  |
| | Female farmers | 29.88 | 29.94 | 45.96 | 57.60 | 50.13 |  |
| | Economically inactive women | 39.34 | 56.78 | 35.99 | 38.28 | 45.03 |  |

The bold indicate the highest and the lowest values.

The large farmers (male) group in the Dhallai union had the highest WPI value of 57, and the economically inactive women group in the Saista union had the lowest value of 41. Thus, the large farmers group in the Dhallai union was the most water-secure group, and the economically inactive women group in the Saista union was the most water-poor among all the groups. Among the three industrial workers groups, the female industrial workers group in the Dhallai union was the most water-secure group, and the same group in the Tetuljhora union was the most water-poor group. The pentagram plot (Figure 3) allows for a quick visualization and an easy comparison of the present WPI values of the three unions. In the Tetuljhora union, Resource and Environment scores were very low. In the Dhallai union, the male large farmers were the most water-secure group, whereas the economically inactive women were the most water-poor. The Resource, Environment and Capacity scores were also comparatively lower than the Access and Use scores. In the Saista union, the situation was similar to that of the Dhallai union in the cases of water-secure and
water-poor groups. In this union, the Resource and Access component scores were lower than the other component scores. In the Dhalla union, the scores were more uniformly distributed for all the groups. However, in the Saista union, the scores were scattered and nonuniform for the groups.

![Diagram of Water Poverty Index (WPI) for different livelihood groups in Tetuljhora, Dhalla, and Saista unions.](image)

**Figure 3.** Present WPI pentagrams for different livelihood groups in the (a) Tetuljhora; (b) Dhalla; and (c) Saista unions.

### 3.2. Comparison of Present WPIs for Different Groups

The WPI component scores show the underlying reasons for water poverty and their variation within the groups, as well as between the locations within the study area. The male industrial workers were more water-secure than the female workers in Tetuljhore. Both groups scored poorly in the Resource and Environment components as this area had undergone huge environmental degradation due to the establishment of tanneries and industries near the bank of the Dhaleshwari River. The score in the Resource component was higher for the male workers than that of the female workers because the occurrence of illness from using surface water and groundwater was higher in the case of female workers. In the Access component, the female group scored higher because of the higher access to improved washroom facilities inside the industry in addition to access to improved sanitation. The Capacity and Use scores were nearly similar. The male group scored poorly in the Environment component because of the low score for the indicator related to loss and damage, caused by severe floods and droughts in the last 15 years.

The industrial workers in the Dhalla union were more water-secure than that of the Tetuljhore union, as the Tetuljhore union showed excessively lower values for the Resource and Environment components. The rate of environmental degradation and pollution from the industries were higher in the Tetuljhore union. However, better access to reliable water sources, piped water connections and medications caused the industrial workers in Tetuljhore to obtain a higher value in the Access component. The Dhalla industrial workers had a slightly better score in the Capacity component than those of Tetuljhore due to the lower cost of water. The monthly average incomes of these groups currently range from USD 82 to USD 106. In the Tetuljhore union, they have to pay more than 5% of their monthly income for water, whereas in Dhalla the cost of water is about 2-3% of their monthly income.

The present WPI for the male large farmers was slightly higher (WPI = 57) than that of the male small farmers (WPI = 55) in Dhalla. The Resource and Environment scores were comparatively lower than the Access, Capacity and Use scores. For the Resource component, the score of the large farmers (WPI = 48) was higher than that of the small farmers (WPI = 38), because the rate and level of occurrence of illness for using groundwater was higher for the small farmers than for the large farmers. The reason behind this is that the small farmers do not practice any treatment method, such as boiling or filtering, for the source water before drinking it. The Access score for the large farmers was higher as the small farmers scored poorly in all three of the indicators (access to irrigation, sanitation and medication). The large farmers had a higher capacity for getting help from their relatives and neighbors during a disaster due to a longer duration of residence. For the
Water component, the small farmers had better scores than the large farmers because of the higher score for the fulfilment of demand for irrigation water.

In the Saista union, the access value (26.82) and capacity value (31.45) of the small farmers were very low compared to that of the large farmers. The cost of water for small farmers is very high compared to their income. These farmers have to pay about USD 7 per month on average, or share one-fourth of their crops, as an irrigation fee in the cropping seasons (Rabi and Kharif). Additionally, the overall cost of production for rice is very high. So, their access to irrigation and affordability was very low.

Comparison of the present WPIs for large farmers between Dhalla and Saista unions reveals that the large farmers in the Dhalla union were more water-secure than the large farmers in the Saista union due to reliable water sources, better access to irrigation facilities (access to pumps or deep tubewells, which are installed in the agricultural land under irrigation) and sanitation, more association with political clans and NGOs, less scope for conflicts regarding water use and less damage due to seasonal floods. Comparison of the present WPIs for small farmers between the Dhalla and Saista unions reveals that the small farmers in the Saista union had lower access, capacity and use scores than the small farmers in the Dhalla union, because the irrigation and production costs are higher in the Saista union and the affordability of the farmers is limited. The average monthly income of the large farmers (about USD 95) is higher than that of the small farmers (about USD 59–88).

In the Dhalla union, physically challenged and elderly women’s present WPI score (33) was the lowest amongst all the groups. The Resource, Access, Capacity and Use scores showed a gradual decrease among the three groups. The indicators which influence the value for the Resource component are the occurrence of illness for using surface water and groundwater. In the Access component, the unemployed women scored better than the other two groups due to higher scores in the access to medication. The physically challenged women usually do not prefer to go outside to visit doctors. In the Capacity component, the education ratio and the role in operation of water source were higher for the unemployed women than for the other two groups. In the case of the Use component, more violence is reported when the water demand cannot be fulfilled or the water cannot be fetched timely, and this caused the score to decrease for adolescent girls.

A comparison of the present WPIs for the economically inactive group in the Saista union shows that the physically challenged and elderly women were the most water-poor and the unemployed women were the most water-secure. Unemployed women show consistently higher values for all the components because of better access to sanitation and medication as well as their role in operating the water source.

The economically inactive group in the Dhalla union was more water-secure than that of Saista union because of better Access, Capacity and Use scores. The Dhalla group had better access to medication and sanitation than the Saista group. Additionally, the water availability in Dhalla was not as irregular as in Saista. In Saista, the education ratio was very low. The Saista group scored poorly in the Use component due to frequent incidents of physical violence, which adolescent girls and unemployed women face when they fail to bring sufficient water from a distant source.

### 3.3. Future WPIs for Different Livelihood Groups

#### 3.3.1. Assessment of Environmental Change

**Changes in Temperature**

The annual temperature (1953–2017) of Dhaka was found to be increasing at a rate of 0.03 °C per year, which is an increase of 3 °C in 100 years. Considering the data for the last 28 years (1989–2017), the increase was found to be 4.89 °C in 100 years. The annual maximum and minimum temperatures (1953–2017) also show increasing trends of 1.24 °C and 4.87 °C in 100 years, respectively. The data for the last 28 years show increasing trends of 2.97 °C and 6.81 °C in 100 years, respectively. Thus, the increasing rates of temperature are higher for the last 28 years than that of the last 64 years, which indicate that the temperature is rising rapidly in recent years in the study area. The rising temperature leads
to a rise in the rate of evaporation from water bodies and the soil surface of the study area, hence increasing the water requirements for domestic and irrigation purposes.

Changes in Rainfall

Decadal (10 years) variation in total rainfall in the pre-monsoon summer season (March to May) is shown in Figure 4. The rainfall in the first three decades (1961–1990) is found to have increased gradually, but it has decreased drastically in the last two decades (1991–2010).

The annual rainfall, considering the data for 64 years, shows an increasing trend of 0.44 mm/year. However, the recent data of 28 years shows a decreasing trend of 5.72 mm/year. Considering the total rainfall from March to May, the trend analysis is also done for the pre-monsoon summer rainfall. This is the most critical season in Bangladesh, as the temperature is high, rainfall is low and the surface water and groundwater levels deplete drastically in this season. The analysis shows a decreasing trend of 0.01 mm and 0.21 mm per year for 64 years and 28 years of data, respectively. Thus, the decreasing trend in recent data is higher than that in the overall data.

Table 5 shows that the CVs of different rainfall parameters at Dhaka vary from 20% to 48%. The annual rainfall shows a moderate variability in both long-term and recent data. The pre-monsoon summer rainfall shows erratic behavior in the long-term data, as the CV is more than 30%. The daily maximum pre-monsoon rainfall for both long term and recent data shows highly erratic behavior, indicating that there is a constant threat of prolonged drought in the dry season.

![Figure 4](image-url) Decadal variation in rainfall in the pre-monsoon summer season at Dhaka.

Table 5. Variability in different rainfalls at Dhaka.

| Parameters                          | Standard Deviation (mm) | Coefficient of Variation (%) | Degree of Variability |
|-------------------------------------|-------------------------|-----------------------------|-----------------------|
| Annual total rainfall (1953–2017)   | 418                     | 20.6                        | Moderate              |
| Annual total rainfall (1989–2017)   | 500                     | 24.9                        | Moderate              |
| Pre-monsoon total rainfall (1953–2017) | 5.5                    | 31.5                        | High                  |
| Pre-monsoon total rainfall (1989–2017) | 4.9                    | 28.5                        | Moderate              |
| Maximum daily pre-monsoon rainfall (1953–2017) | 38.8                    | 48.1                        | High                  |
| Maximum daily pre-monsoon rainfall (1989–2017) | 30.0                    | 39.2                        | High                  |

Figure 5 shows the inter-annual variability in rainfall at Dhaka. A very low value in the rainfall anomaly corresponds to a severe drought year. The anomaly value ranges from +2.04 in 1984 to −1.67 in 1992. There were six consecutive dry years from 2009 to 2014 and six consecutive wet years from 1983 to 1988.
Changes in Groundwater Level

The groundwater level in the study area was found to be reducing at an alarming rate. The trend lines (Figure 6) indicate an increase in the depth to the groundwater table below the surface of the ground. The rate of decline is found to be 2.82 cm per year at Singair village and 7.93 cm per year at Parilnoadda. The level fluctuates between 6.64 m and 4.39 m below the ground level (bgl) at Singair, and between 4.75 m and 8.19 m bgl at Parilnoadda. Thus, fluctuations in groundwater level also show a high variability.

Figure 6. Trends in groundwater levels at Singair (left) and Parilnoadda (right).

Changes in Surface Water Level

The trends in annual minimum high and low water levels (Figure 7) and the average water levels in March of the Dhaleshwari River in the Savar upazila were determined in order to understand the situation regarding the surface water availability. According to the local information, the river water level usually falls to its lowest level in March. All the parameters indicate a decreasing trend. The water level of the Dhaleshwari River is decreasing at 0.74, 0.69 and 0.33 cm per year for the annual minimum high tide, annual minimum low tide and average daily water level in March, respectively. Though the decreasing rates are not alarming, the intra- and inter-annual variability is high.

Figure 7. Trends in annual minimum high tide (left) and low tide (right) levels of the Dhaleswari River at Savar.

Population Growth

In the Tetuljhora union, the population growth rate is very high due to the shifting of tannery industries to this area from Dhaka City. The shifting has created employment opportunities for a large number of lower income people and increased inward migration.
to Tetuljhora and Dhalla at an alarming rate. Table 6 shows the projected population by 2049 in the three unions, considering 2011 as the base year. The analysis also indicates that the population density in the future would be the highest in the Tetuljhora union, followed by the Dhalla and Saista unions.

Table 6. Projected population in the selected peri-urban areas around Dhaka.

| Union      | Growth Rate * (r), % | Total Population |
|------------|----------------------|------------------|
|            | 2011 | 2019 | 2049    | 2049       |
| Tetuljhora | 8.83 | 106,929 | 210,419  | 266,4057  |
| Dhalla     | 1.44 | 36,203 | 40,590   | 62,330    |
| Saista     | 1.44 | 27,188 | 30,483   | 46,809    |

* Growth rate is obtained from upazila-level population data of BBS.

Changes in Land Use

The land use maps for the three unions were generated (not shown here) for the years 1989 and 2019. In all of the unions, the agriculture and vegetation area and the amount of water body were found to have decreased and the percentage of settlement and urban development area was found to have increased. For example, the agriculture and vegetation area decreased to 28% in 2019 from 49% in 1989 in the Tetuljhora union. The area of water body decreased from 4.2% to 3.9%, and the areas under settlement and urban development increased from 34% to 45% in the union over the same time period. It is anticipated that this pattern of land conversion will continue in the future in the study areas.

3.3.2. Future WPIs for Different Livelihood Groups

From the primary data of household surveys and a prediction of the environmental condition in the study area, future WPIs for each livelihood group were calculated. Considering the present situation, a prediction for the environmental condition by 2050 was made. As water poverty is dynamic, the hypothesis is that the present WPIs will change for all the groups, considering environmental and climatic changes. Table 7 shows the future WPIs for different livelihood groups in the study area. In the Tetuljhora union, the Resource, Environment and Use scores are very low. In the Dhalha and Saista unions, the Resource and Environment scores are very poor. The future WPIs indicate that the female industrial workers in the Dhalha union could be the most water-secure and the male small farmers in the Saista union could be the most water-poor.

Table 7. Future WPIs for different livelihood groups in peri-urban areas around Dhaka.

| Union             | Group                  | R   | A     | C      | U      | E      | Future WPI |
|-------------------|------------------------|-----|-------|--------|--------|--------|------------|
| Tetuljhora        | Industrial workers (male) | 16.27 | 66.05 | 48.92  | 45.67  | 30.84  | 41         |
|                   | Industrial workers (female) | 23.28 | 83.69 | 57.83  | 64.57  | 16.97  | 40         |
| Dhalha            | Industrial workers (female) | 42.74 | 54.26 | 52.33  | 59.88  | 39.02  | 49         |
|                   | Large farmers (male)   | 45.37 | 72.10 | 68.81  | 64.70  | 11.86  | 45         |
|                   | Small farmers (male)   | 34.90 | 44.06 | 28.80  | 59.30  | 25.86  | 36         |
|                   | Female farmers         | 37.69 | 59.31 | 49.87  | 61.05  | 24.93  | 48         |
|                   | Economically inactive women | 35.09 | 55.33 | 40.98  | 62.78  | 39.67  | 46         |
| Saista            | Large farmers (male)   | 31.83 | 45.47 | 58.46  | 36.61  | 28.89  | 39         |
|                   | Small farmers (male)   | 35.38 | 24.36 | 30.15  | 47.87  | 40.10  | 34         |
|                   | Female farmers         | 28.57 | 31.67 | 48.77  | 41.40  | 39.40  | 38         |
|                   | Economically inactive women | 25.45 | 49.02 | 40.89  | 31.94  | 19.09  | 34         |

3.3.3. Comparison of WPIs between Present and Future

The future WPI scores show a different scenario for a few groups, especially for the industrial workers in Dhalha and the small farmers in Saista. The comparison between
present and future WPIs for the male and female industrial workers in Tetuljhora is shown in Figure 8. The Capacity component would improve for the female workers, whereas it would degrade for the male workers. Because of an increasing role in operating the water source and greater interest for participation in training on water, sanitation and hygiene issues, the Capacity component would improve for the female workers. Both the groups show lower scores in the Use component as conflicts regarding water use would increase in the future due to excessive water demand. The overall future WPI scores would be lower than the present scores in both cases.

The female industrial workers in the Dhalla union would be the most water-secure group among all the groups in the future. The overall future WPI score (49) is lower than the present WPI score (56). The Capacity component could slightly improve for the increasing indicator scores in the education ratio. The rest of the component scores could decrease in the future (Figure 9).

For the three farmer groups in the Dhalla union, the Resource, Use and Environment components would decrease due to an increase in occurrence of illness from using surface water and the excessive reduction in vegetation cover (Figure 10a). For the three farmer groups in the Saista union, the Resource, Use and Environment components would decrease in the future. For the small male farmers, all the components and their indicators score poorly, and that is why this group might be the most water-poor group in the future. The Capacity component for the female farmers could increase slightly due to an increased role in operating the water source and increased NGO activities (Figure 10b).

Figure 8. Present and future WPI pentagrams for (a) male industrial workers and (b) female industrial workers in the Tetuljhora union.

Figure 9. Present and future WPI pentagrams for female industrial workers in the Dhalla union.
A uniform decrease is noticed in the comparison of the present and future WPIs for the economically inactive women in Dhalla for all the components (Figure 11a). All the component scores would decrease in the future because of the decrease in groundwater level, the increase in the cost-income ratio, limited access, lack of sufficient water, reduction in vegetation cover and improper drainage facilities. The present and future WPI pentagrams for the economically inactive women in Saista show a uniform decrease in the Resource and Environment components because of a decrease in surface water and groundwater levels in the future, increase in arsenic contamination in groundwater and increase in crop loss. However, the Capacity of this group would increase due to the increase in duration of residence and NGO activities (Figure 11b).

4. Discussion

The approach used to calculate WPIs in this study differs from the previous works based on the input data and the scale to which it was applied. The underlying framework of the WPI has similar components and sub-components but contains different indicators and a different dataset. The resultant WPIs can be used to target the most water-poor livelihood groups in the peri-urban areas at the household level. These indices can then be used to identify the areas in which development policies should be concentrated for
the greatest efficiency \cite{3,31}. It is important to note that the national analysis of water scarcity is of limited use in assessing whether individuals or communities are water-poor. Statistics in the form of aggregated information at the national level sometimes mask issues of local water scarcity \cite{30,34,71}. To address this, location- and group-specific indicators were introduced \cite{49}. The main question in terms of the choice of indicators is whether to search under the lamp (reorganizing readily available data) or to ask where the lamp should point (identifying data needs regardless of availability). The first approach has the benefit of time and cost savings. These are important advantages. However, to assess whether they are sufficient it is imperative that the second question be asked too. This is what this paper does. The method of index calculation used here requires that new data collection efforts must be undertaken. This method accurately reflects local perceptions of water poverty \cite{72}. If information can be collected in a participatory manner at the community level, local people will be empowered, both through a better understanding of their water needs and of how to communicate this information to policy makers \cite{3}.

The selected set of components and indicators have been used to discuss the spatial and temporal variation in the water scarcity situation for a 30-year assessment period. These variations suggest that different unions and groups require different policy interventions. At different spatial scales, there is no clear trend; however, analysis of the WPI components shows higher Access and Capacity metrics in peri-urban areas (Tetuljhora), and higher Resource and better Environment metrics in peri-rural areas (Saista). Such variations suggest the need of scale-specific management plans to improve the overall water poverty situation in the study area.

The application of the WPI has shown that some groups can apparently be “water poor” with a high level of access to safe drinking water, which is odd. The projected subindex value for Access of the female industrial workers in Tetuljhora is the highest of all the groups (83.69), but they apparently will be more water-poor than most of the groups. This is due to the low values of E, and to some extent R (Table 7). The poor environmental and physical factors have led to the odd index. Thus, a higher A alone cannot save a group from water poverty. Lower R, C, U and E can dominate the situation. One group may have better access in the future. However, if the group does not have better capacity for water management, available water resources, or a better environmental condition, it will eventually be water-poor. So, this paper also claims that water poverty should not be considered equivalent to a lack of access to water due to a society’s poverty.

High temperature is one of the main reasons that women prefer indoor activities more than men do. The productivity of the female farmer group would decrease in the future, as female farmers would have to work outside their homes for a considerable period of time. Female farmers in Saista would suffer the most, as most of them have to collect water from a distant source by walking and also have to carry lunch on the farms. The higher temperature would worsen the situation in the future.

The variability in rainfall could increase and the total amount of rainfall could decrease in the future due to climate change. In this situation, the farmer groups of the Dhalla and Saista unions would suffer the most for the rainfed crops. On the other hand, excessive, untimely rainfall would hamper the production of rice, for which the small farmers would suffer the most as their income would be affected.

All three unions are dependent on groundwater. The abstraction rate of groundwater would increase and the recharge rate would decrease in the future due to human developmental activities, and thus all the marginalized groups would suffer heavily. Mostly, the people living in the Saista union would be the victim of this, as the scores of the present WPIs of the livelihood groups of the Saista union are very low compared to other unions. Among all the livelihood groups in Saista, the small male farmers would suffer the most. The small farmers would suffer as the cost of production would increase, because irrigation by shallow tubewells would not be possible and they would not be able to afford deep tubewells.
The variability in surface water levels would increase in the future. In the future, if the surface water level increases due to heavy rain, floods might occur. In this case, the Tetuljhora union will be affected more than the Dhalla and Saista unions. The odor from surface water is high in the Tetuljhora union. The floodwater will affect both the male and female industrial workers. The female workers in particular will be highly affected as the rate of occurrence of illness in them is higher than in the male workers.

The future WPIs can be highly affected due to the excessive growth of population. The Tetuljhora union is already densely populated. The excessive population growth in the future would increase the water demand and also affect access to water. In Tetuljhora, the female industrial workers would suffer more than the male workers because the water supply could be intermittent due to the increasing demand, and because women workers are responsible for managing and storing water.

All three unions are facing rapid and unplanned urbanization. The Tetuljhora union has more industries, schools, colleges and other public facilities, and is already overpopulated. People from rural settings could migrate to this union because of the increased opportunities for employment and better access to modern facilities. This area is expected to be fully urban in coming years due to the increase in built-up areas. On the other hand, the Dhalla union is also a point of attraction for migrants due to lower house rents and a secure water supply. The Saista union is currently considered as a peri-rural area as it is less developed than the other two unions, and the water supply system is not well-developed. However, the degree of urbanization in the last 30 years proves that it is constantly converting into a peri-urban area.

As policy recommendations, it is suggested from this study that a consistent supply of piped water and the installation of deep tubewells will reduce water poverty for most of the livelihood groups. A uniform and equitable water distribution system will reduce the burden on female farmers and economically inactive women in the Saista union. Reuse of wastewater can be helpful for the farmer groups to grow vegetables and other crops. In order to use wastewater and to maintain the water quality of rivers, an effluent treatment plant must be operational and properly maintained. Additionally, constructing water treatment plants will reduce the occurrence of illness among the livelihood groups, especially in the Tetuljhora union. Institutional intervention is required to arrange training and awareness programs on climate change, agricultural technology, disaster risk management, water conservation strategies and water treatment methods. Water pricing policies should also be gender-inclusive [73]. Though there are many policies, plans, laws and organizations in Bangladesh to develop, manage, regulate and conserve water, the environment and allied resources in a fair and equitable manner, their actual implementation is far below the expectations of the masses. This aspect of implementations needs further attention from the policy makers and regulators of the country.

In order to meet the growing water demand of the peri-urban areas, improved water management strategies must be adopted.Dependency on groundwater should be reduced to meet the future water demands. According to the National Water Policy (1999), the reliance on groundwater needs to be reduced and the use of surface water needs to be increased [74]. The dredging of the Dhaleshwari River and the re-excavation of the existing khals, canals and other water bodies can reduce pressure on groundwater. As per BDP2100, water pollution can also be controlled by flow augmentation through dredging [73]. People can use these surface water bodies for bathing, cooking and washing purposes if restoration is possible. Managing water demand, promoting the conjunctive use of surface water and groundwater in addition to facilitating water storage in peri-urban areas can lower the pressure on groundwater [73]. The use of surface water is suggested for livestock watering, domestic use, irrigation, fishing and brick-making purposes in other countries [75–77] to reduce pressure on groundwater. Adoption of pro-poor water policies, enforcement of existing laws to protect the water bodies and planned urban development could be the keys to improve water poverty both at present and in the future.
5. Conclusions

The climatic and environmental drivers in peri-urban areas around Dhaka would deteriorate in the future. The future WPI values for different livelihood groups could decrease in physical components (Resource and Environment). However, better scores in the Access, Capacity and Use components would help groups adapt to the future water poverty. Thus, to be more water-secure, social components of water poverty must be improved. Education and different awareness programs are important to fight against water poverty, as the people in the study area are taking the peri-urbanization process as a positive feature, neglecting the environmental degradation.

Predicting water poverty continues to be a challenging task, as it is often impaired by the scale and magnitude of the problem. Different parameters have been considered in different countries to define water poverty. Due to these varied parameters, understanding water poverty remains a complex task. Therefore, a need is still there to develop a location- and group-specific framework with categorization of the parameters for a holistic understanding of water poverty. This framework can act as a base for future studies on marginalized groups. However, the weighting and aggregation technique is a major shortcoming of this framework, since these influence the coherence and interpretability of the final values [56]. Different combinations of aggregation methods and weightages should be applied and compared to find the best-suited one for this scale. The method should minimize overestimation (ambiguity) and underestimation (eclipsing). Ambiguity problems arise when the aggregate index exceeds the critical level without any of the subindices exceeding the critical levels. In contrast, eclipsing problems exist when the composite does not exceed the critical level, despite one or more of the subindices exceeding the critical levels [58]. In this case study, ambiguity and eclipsing have occurred in some cases. Some indicators do not represent the actual scenario of the study area, such as the degree of rainfall variability and conflict regarding water use. Hence, caution is needed while using existing data, selecting data and combining datasets, which provide scope for further improvement in future studies.

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