



**ASSESSING URBAN POOR RESILIENCE TO NATURAL DISASTERS USING ANALYTIC HIERARCHY PROCESS-BASED MODEL: A CASE STUDY ON KHULNA CITY**

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KUS: ICSTEM4IR-22/0136

Manuscript submitted: July 28, 2022

Accepted: September 28, 2022

**Abstract**

This article intends to measure the urban poor's resilience to natural disasters using an analytical hierarchy process (AHP) based model. It also explores factors affecting differentiated levels of household resilience. It is found that urban poor communities in Khulna city frequently experience urban flooding and waterlogging, caused by heavy rainfall, as a primary hazard and therefore this article emphasizes on differentiated nature of urban poor's resilience to natural hazards and the factors that shape differentiated nature of resilience. Quantitative research approach has been adopted and AHP-based indexing has been used to measure the level of resilience of the urban poor and contributing factors to their resilience level. The household questionnaire survey has been used as the data collection method and the total sample size of this research is 384 and all the primary data is collected from the six slums in Khulna city which have been selected using different vulnerability criteria like geographical location, size of the slums, and mean sea-level height of the slum. The analytical hierarchy process (AHP) model is used to determine the weight of indicators and dimensions which have been used to calculate resilience. Additionally, the principal component analysis (PCA) is also used to identify the determinant factors. The results revealed that 40.88% and 48.96% of people are low and moderately resilient respectively. The percentage of high resilient people in the low-income settlements in Khulna city is very low as only 10.16% of the households are found as highly resilient in the urban poor settlements. It identifies several factors that have the highest effect on differential level resilience, including access to formal safety nets and social assistance, income and livelihood strategy, illness, debt etc. Highlighting the factors that influence differentiated levels of resilience local government or policymakers can take different policy recommendations to improve the resilience of the urban poor that including strengthening the social security system for the urban poor, creating livelihood opportunities, public health services, etc.

**Keywords:** Resilience, urban poor, natural disasters, analytic hierarchy process, indexing, principal component analysis (PCA), Khulna city.

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DOI: <https://doi.org/10.53808/KUS.2022.ICSTEM4IR.0136-se>

## Introduction

Khulna is prone to climatic hazards due to its geospatial characteristics. The scale of climate change risk is increasing along with the increased number of people living in this city. It is always frequented by climatic hazards due to its low elevation (Haque et al., 2014) and the flat land of the city is approximately 2.5 meters above the mean sea level (Linkon & Khan, 2019). Khulna city is particularly at climate risk due to several reasons including a higher level of population density; increasing number of populations living in the urban informal settlements; spontaneous spatial growth that created natural drainage disruption; and sporadic development of urban slums particularly at risky sites (Haque et al., 2014; Pelling, 2003; Swapan et al., 2020a, 2020b). All urban residents are not vulnerable equally to climate change and climate extremes and climate change-induced shocks will disproportionately affect urban poor (Pelling, 2003; Jabeen et al., 2010; Satterthwaite et al., 2007). Climate change vulnerability of the urban poor is exacerbated by the multiple deprivations that they face living in the urban informal settlements including tenure insecurity and a high level of rent, limited access to basic service, and limited access to financial capital. Although they have a high level of climate change vulnerability, they are also active managers of their vulnerabilities by adopting adaptations which is evident in many contexts across the world (Akter & Mallick, 2013; Ha-Mim et al., 2020a; Joakim et al., 2015; Maru et al., 2014; Usamah et al., 2014). While explaining the disaster vulnerability of the urban poor, (Usamah et al., 2014) reveal a paradoxical relationship between vulnerability and resilience. They explained that residents of urban informal settlements have inbuilt resilience although they have high levels of geographical, economic, and physical vulnerability. Considering the fact, this article intends to measure the resilience of urban poor and the factors that shape their resilience.

Resilience has recently become a popular concept that helps to understand capacity of a household and a community or a system to withstand climate-induced shocks and stresses. A household or a community or a system can increase their capacity through gaining knowledge about the required capacity for a household or a community or a system to reduce their vulnerability level (Constas et al., 2020). Generally, resilience is defined as an ability to recover from any natural disturbance of any inhabitant of a certain area (Moghadas et al., 2019). In the context of urban informal settlements, resilience indicates the capability of urban informal communities to bounce back from a range of natural disturbances, shocks and stresses (Leichenko, 2011). Community resilience against climate-induced hazards requires awareness regarding climate-induced hazards, trust, social network, community cohesion, and access to government and NGOs' resources (Akter and Mallick, 2013; Ha-mim et al., 2020; Maru et al., 2014; Joakim et al., 2015; Usamah et al., 2014). Usamah et al., 2014 reveal that the strength of social relationships determines resilience of the communities against natural disasters. While measuring community resilience, it is essential to include several social, economic, physical, and institutional components. Ensuring the functionality of these components in any urban informal settlement will develop the capacity of community members to become resilient against natural disasters (Balica & Wright, 2010); (Coirolo & Rahman, 2014; Leichenko & Silva, 2014). The article answers two specific research questions: (i) how is the resilience of urban informal settlements differentiated? (ii) what are the factors that shape differentiated levels of resilience?

## Materials and Methods

### *Study area*

Khulna city is located in the southeast coastal region of Bangladesh which lies between 22° 47'16" to 22° 52'16" north latitudes and 89° 31'36" to 89° 34'35" east latitudes (see Figure 1). It is a linear city located on the bank of the Rupsha River. The city is also recognized as the divisional headquarters of the Khulna division. The Khulna district includes a portion of Sundarbans and the coast of the Bay of Bengal. Also, it is 40 kilometers far from the second largest seaport entry of the country. The population size of the Khulna city is 1.5 million and the density is 32,859 persons/square kilometers which has an area of 45.65 square kilometers (Cookey et al., 2020). There are 1138 slums where 8.14% of the households live in these slums (BBS, 2014).

However, the number of slums in the Khulna was 202 in 1997. The increasing trend of urban informal settlements in this city is evident. The average household size of urban slums in the city is 3.86 which is slightly higher than the national average.

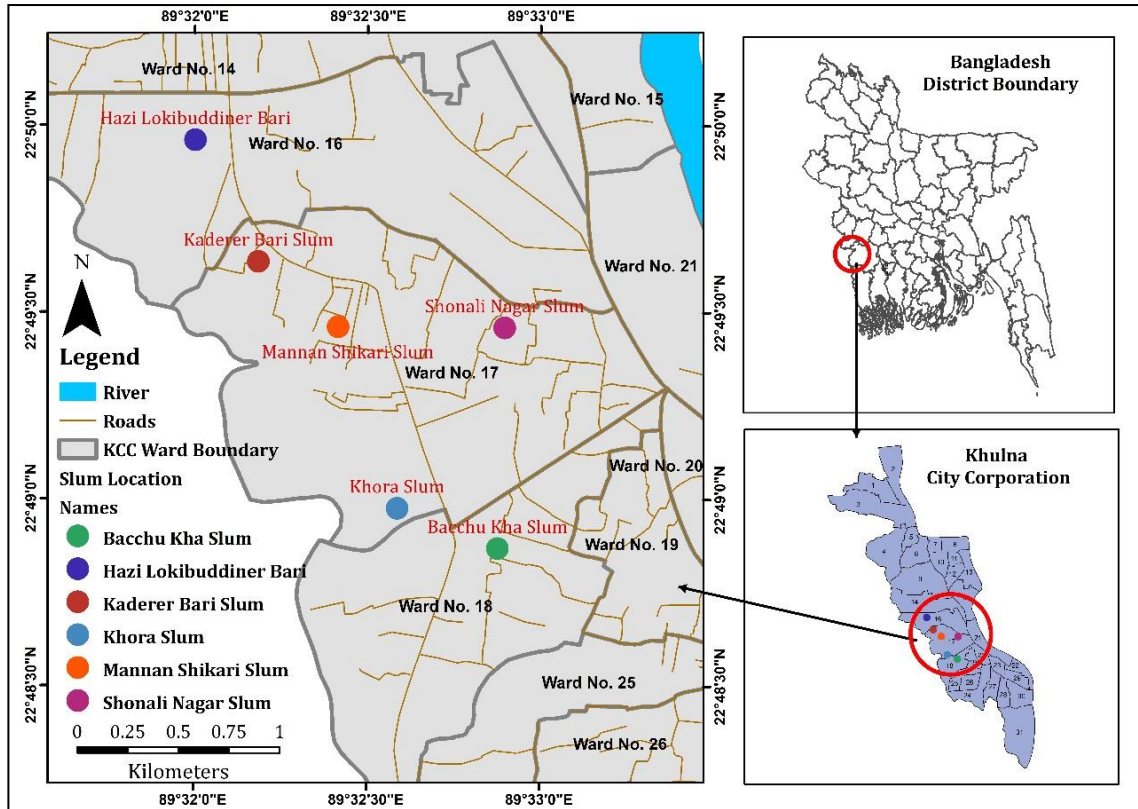


Figure 1. Study Area.

### *Sampling technique and data collection*

We follow a number of steps in order to select the slums for comparing and contrasting resilience levels of urban poor settlements and for data collection, we used a household questionnaire survey. The steps used to collate information are elaborated in the following.

### *Selection of the urban slums*

A Geographic Information System (GIS) based approach has been adopted to select the urban slums for data collection. We collected a GIS dataset of urban informal settlements from the Urban Partnerships for Poverty Reduction Project (UPPRP) and used it for further spatial analysis to explore the most physically vulnerable slums to natural disasters. In the first stage, we found a total of 85 urban poor settlements in the Khulna City Corporation (KCC) area from the spatial database of UPPRP. We adopted the following criteria to explore desired slum settlements for measuring community resilience (see Table 1).

Table 1. Selection of urban slums based on some criteria

Criteria	Selection
Age of the urban slums $\geq 20$ years	Aged urban slums are stable and fixed.
Area of the settlement $\geq 450$ m <sup>2</sup>	Large settlements are not disappearing over time.
Number of households $\geq 50$	Highly populated slums are static and durable.
Elevation of the settlement from mean sea level $\leq 1$ m	Low elevated slums are frequently attacked by natural disasters like floods, waterlogging etc.

After using above mentioned criteria we found 6 settlements in the KCC area. (see Figure 1)

### **Sample size determination**

We adopted the formula proposed by Daniel (1983) to determine the desired sample size for this research. Note that, after applying that formula the total sample size became 384. We followed a proportionate allocation method for deriving sample size from the selected slums. Therefore, samples are distributed among the six slums according to the number of households in these slums. The distribution of the sample among the slums is given in Table 2.

Table 2. Distribution of the Sample among the Slums

Serial Number	Slum Name	Number of Household	Sample size
1	Hazi Lokibuddiner Bari Slum	50	33
2	Bacchu Kha slum	114	76
3	Khora slum	103	68
4	Kaderer Bari Slum	72	48
5	Shonali Nagar Slum	132	87
6	Mannan Shikari Slum	109	72
	Total	580	384

### **Data collection method**

The unit of analysis in this research is household and households who are living in the aforementioned six slums are considered for data collection. A structured questionnaire has been developed to do the household questionnaire survey. We used a systematic random sampling technique to draw samples in these six slums. The focus of the questionnaire was on four major dimensions such as social, economic, institutional, and physical dimensions of resilience.

### **Selection of the indicators**

We selected four dimensions and nineteen indicators to measure the level of resilience of the urban slums and household level indicators have been selected. The comprehensive list of the indicators has been included in Table 3.

### **Construction of climate resilience index (CRI)**

We developed AHP based climate resilience index (CRI) to measure the differentiated nature of community resilience. While measuring the Climate Resilience index (CRI), we used the approach where each indicator contributes to the overall index. As each of the indicators has been measured on a different scale, it is essential

Table 3. Dimensions and Indicators of the Resilience

Dimension	Indicator	Explanation	Relationship with resilience	Source
Social	Illness of HH head or other household members	Disability or chronically illness of breadwinner or another persons'	Negative	(Yoon et al., 2016)
	Education status	High school education	Positive	(FAO, 2016)
	Dependent member	HHs have members of >60 years and members of <15 years		(FAO, 2016)
	Social support Network	HHs who have good relationships with neighbors, relatives and employers	Positive	(TANGO International, 2018)
Economic	Manual labor-based employments	Population work as day labor, construction work, rickshaw/van pulling, street vending, small roadside business, housemaids etc.	Negative	(Smith & Frankenberger, 2018)
	Multiple income sources	Households have multiple income sources	Positive	(Smith & Frankenberger, 2018)
	Income	Total Household income	Positive	(Vaughan, 2018)
	Savings	Households have cash savings of 5000 Tk. and above or savings in the bank	Positive	(Smith & Frankenberger, 2018)
	Debt	Households have a debt of 2000 Tk. and above	Negative	(Ha-Mim et al., 2020b)
Institutional	Training on disaster preparedness	Households who had received education and skills to prepare and protect from extreme weather events	Positive	(Ha-Mim et al., 2020b)
	Microfinance Membership	Households got micro-financial membership	Positive	(Smith & Frankenberger, 2018)
	Local government and NGOs support	Households who got local government community-based support such as	Positive	(FAO, 2016; Smith & Frankenberger,

		repairing roads, drains, and houses or free health, or sanitation supports		2018)
	CDCs' existences	The existence of CDCs' in communities' level	Positive	(Smith & Frankenberger, 2018)
	Disaster warning	Households had received a warning about disaster	Positive	(TANGO International, 2018)
Physical	Type of housing	Households have a pucca house	Positive	(FAO, 2016)
	Waterlogging	Households faced waterlogging or become waterlogged when the rain comes	Negative	(Ha-Mim et al., 2020b)
	Drinking water source	Water source distance from household	Positive	(Vaughan, 2018)
	Flooding to WATSAN	Households' latrines and water taps become flooded during flooding or when erratic rainfall happened	Negative	(Vaughan, 2018)
	Fans or cooling or Green roofing facilities	Households have fans or cooling or green roofs facilities	Positive	(Clar & Steurer, 2021)

to standardize each as an index. To standardize the indicators, this research followed the following equations which was developed by UNDP (2007). Equation (1) has been used for indicators that have a positive functional relationship with resilience and Equation (2) has been used for the indicators that have a negative functional relationship with resilience.

$$Index S_{B_x} = \frac{S_{B_x} - S_{min}}{S_{max} - S_{min}} \quad (1)$$

$$Index S_{B_x} = \frac{S_{max} - S_{B_x}}{S_{max} - S_{min}} \quad (2)$$

where  $Index S_{B_x}$  is the normalized index value and  $S_{B_x}$  is the original value of the indicator for household,  $S_{max}$  and  $S_{min}$  are the maximum and minimum values of the indicator at the household level.

After normalization, the value of dimension for each household is calculated through Equation (3).

$$M_{B_x} = \frac{\sum(Index S_{B_x} \times W_{B_x})}{W_B} \quad (3)$$

where,  $M_{B_x}$  is the value of the dimensions,  $Index S_{B_x}$  is the normalized value of each indicator under each dimension,  $W_{B_x}$  is the weight of each indicator under each dimension,  $W_B$  is the total weight of each indicator under each dimension.

Once the value of the dimension for each of the households is calculated, Equations (4) is used to determine the value of the *climate resilience index* (CRI).

$$CRI = \frac{\sum(M_{B_x} \times W_{B_x})}{W_M} \quad (4)$$

where,  $CRI$  is the value of the climate resilience index,  $M_{B_x}$  is the value of each dimension,  $W_{B_x}$  is the weight of each dimension and  $W_M$  is the total weight of each dimension.

## Results

Resilience differs among the community and also within the community because of economic, social, physical, and institutional context of the urban slums in Khulna city. This article measured both the level of resilience within and among the community. The overall calculation of the climate resilience index is presented in Table 4, Table 5 and Table 6 where Table 4 and Table 5 present the status of the dimensions and the overall level of resilience within the urban slums. The level of resilience among the urban slum dwellers is presented in Table 6. The factors that affect resilience is presented in Table 7.

### *Level of resilience of urban informal settlements in Khulna city*

Table 4 shows the community resilience score of the selected slums by different dimensions. It reveals that all the slums are moderately resilient in the social dimension. Among them, Hazi Lokibuddiner Bari Slum shows the highest resilience score in the social dimension. In the economic dimension, all the slums are low resilient because of households' low income, savings, and relatively high level of debt. Only a few people have multiple income sources but most of the slum dwellers are engaged in manual labor-based employments. The overall score in the institutional dimension is relatively lower than all other dimensions' resilience scores. It is because microfinance membership for urban slum dwellers is relatively limited and they are also deprived of getting support from local government, NGOs or community-based organizations. In the institutional dimension, Mannan Shikari Slum and Hazi Lokibuddiner Bari Slum have relatively higher resilience scores than other slums which is higher than 0.5. The resilience score in the physical dimension is also low. All the slums show a very low level of resilience score in the physical dimension which is less than 0.5. Most of the people live in Katcha houses and most of the houses in the selected urban slums became waterlogged during the rainy season. In addition, latrines, and water taps within the selected slums became flooded if extreme rainfall occurs.

The resilience score is presented in the spider diagram showing dimension-wise resilience score (see Figure 2 for details). The resilience score of the diagram ranges from 0 (less resilience) at the center of the web, increasing to 0.8 (more resilience) at the outside edge in 0.2-unit increments.

Table 4. Resilience score of urban slums

Dimension	Resilience score					
	Bacchu Kha slum	Hazi Lokibuddiner Bari Slum	Kaderer Bari Slum	Khora slum	Mannan Shikari Slum	Shonali Nagar Slum
Social	0.667	0.731	0.686	0.599	0.607	0.688
Economic	0.265	0.253	0.238	0.253	0.272	0.287
Institutional	0.410	0.527	0.233	0.306	0.570	0.407
Physical	0.363	0.389	0.374	0.331	0.369	0.415

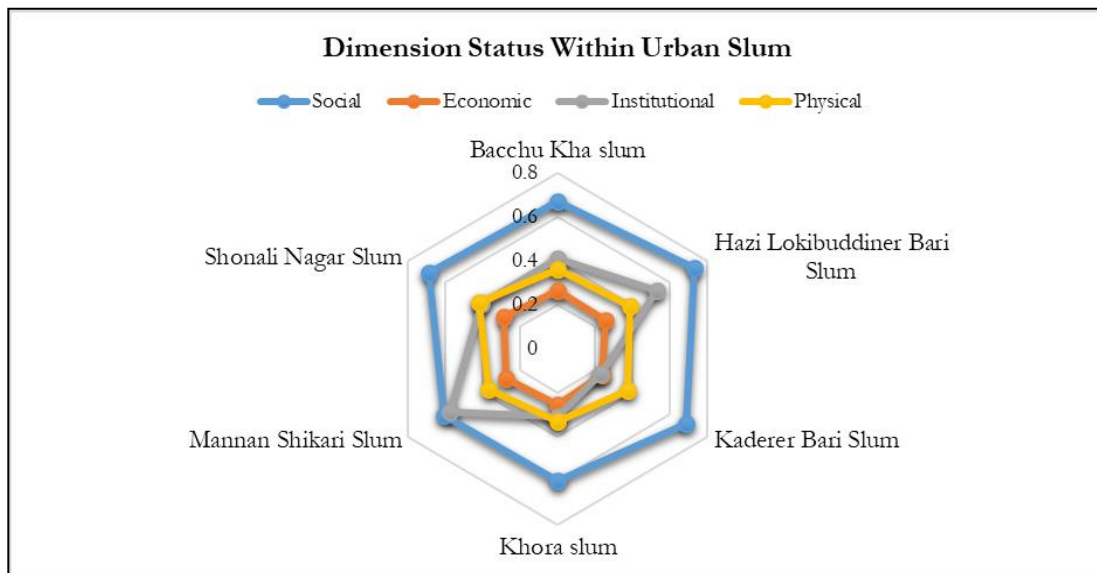


Figure 2. Spider Diagram of Resilience Index.

Table 5 represents the composite score of the resilience of the slums. The following table reveals that all the slums are within the low and moderate categories. None of the slums are found in the high category. Among the six slums, four slums were found moderately resilient, whereas two slums were found low resilient category. In addition, the moderate category slums are shown a low level value and they have just slightly higher than the cutoff moderate value (0.35). In addition, Table 5 shows that the gap among the six slums is not so high and it is lying between 0.30 to 0.45 which means all the slums are mostly in the same resilience capacity.

Table 5. Composite community resilience index score of the Slums

Slum Name	Composite CRI Value	Category
Bacchu Kha slum	0.378	Moderately Resilient
Hazi Lokibuddiner Bari Slum	0.421	Moderately Resilient
Kaderer Bari Slum	0.319	Low Resilient
Khora slum	0.327	Low Resilient
Mannan Shikari Slum	0.422	Moderately Resilient
Shonali Nagar Slum	0.398	Moderately Resilient

***Measuring household level resilience***

This article also explores level of resilience among the households living in the selected slums. Table 6 shows the distribution of households by the resilience score. It is found that the overall resilience levels of the slum households are mostly low. Around 90% of the households belong to low and moderate resilient categories. The resilience score of the slum households is not satisfactory as it represents that if any natural disturbance affects these poor communities, they have a very limited capacity of bouncing back to their present condition. The high resilience category among the households is very limited and none of these households' resilience values belongs to the fourth quartile of total resilience 1. In the slums 'Kaderer bari slum', there exist no households who have a high resilient category. It is same for the 'Khora slum'. The 'mannan shikari slum' has more percentage of the high resilient household than other slums. This is because of their linking capital. They have the highest institutional resilience which increases their ability to become resilient more than others.

Table 6. Households Registered in Different Resilience Categories

Resilience Category	Bacchu Kha slum	Hazi Lokibuddiner Bari Slum	Kaderer Bari Slum	Khora slum	Mannan Shikari Slum	Shonali Nagar Slum	Total
Low Resilient	37 (48.70%)	10 (30.30%)	30 (62.50%)	43 (63.20%)	15 20.80%	22 (25.29%)	157 (40.88%)
Moderate Resilient	31 (40.80%)	15 (45.50%)	18 (37.50%)	23 (33.80%)	46 (63.90%)	55 (63.22%)	188 (48.96%)
High Resilient	8 (10.50%)	8 (24.20%)	0 (0%)	2 (2.90%)	11 (15.30%)	10 (11.49%)	39 (10.16%)
Total	76 (100%)	33 (100%)	48 (100%)	68 (100%)	72 (100%)	87 (100%)	384 (100%)

***Factors affecting the resilience of urban slum dwellers***

To identify the factors that affect the resilience of the urban slum dwellers a "Principal Component Analysis" (PCA) has been operated. A total of 19 indicators were input into the PCA model at the beginning stage. Among them, 13 indicators have been selected and generated six blocks through the analysis (see Table 7 for details).

Table 7. Loadings of factors on the first six principal components

Principal Components	PC1	PC2	PC3	PC4	PC5	PC6
Access to Formal Safety Nets and Social Assistance (PC1)						
Microfinance Membership	.854					
Local government and NGOs support	.764					
CDCs' existences	.656					
Income and Livelihood strategy (PC2)						
Multiple income sources		.889				
Income		.674				
Savings		.700				
Illness and Debt (PC3)						
Illness of HH head or other household members			.899			
Debt			.884			
Education and Employment (PC4)						
Education status				.793		
Manual labor-based employment				.876		
Housing Condition (PC5)						
Type of housing					.779	
Waterlogging					.774	
Social Support (PC6)						
Social support Network						.965
Eigen Value	2.40	1.64	1.51	1.44	1.19	1.01
Variance (%)	18.47	12.62	11.63	11.10	9.16	7.79
Cumulative variance (%)	18.47	31.09	42.72	53.82	62.98	70.77

KMO	0.587
Bartlett's Test of Sphericity	P < 0.001

In the PCA, the Kaiser–Meyer–Olkin measure value is 0.587 which has verified the sampling adequacy for the analysis. This value is well above the acceptable limit of 0.5. Besides, the significance of Bartlett’s test of sphericity at  $p < 0.0001$  provides evidence of sufficient correlations between items. Also, the average communalities is  $> 0.500$ . Thus, factor analysis is considered statistically valid (Pituch & Stevens, 2016). The principal component analysis generated six factors using an eigenvalue cut-off of greater than 1.0 and the scree plot also provides evidence of that. These six principal components contribute to a cumulative variance of 70.77% of the original variable included in the analysis.

The share of contribution of all the main component indicators is summarized in Table 6. The first principal component (PC1), termed as “access to formal safety nets and social assistance”, includes three variables and explains 18.47% of the variance. The second principal component (PC2), termed as “income and livelihood strategy” is formed by three variables and explains 12.62% of the variance. The third principal component (PC3), termed as “illness and debt”, includes two variables, and explains 11.63% of the variance. The fourth principal component (PC4), termed as “education and employment”, includes two variables, and explains 11.10% of the variance. The fifth principal component (PC5) summarized as “housing condition”, explains 9.16% of the variance including two variables. The sixth principal component (PC6), summarized as “social support”, explains 7.79% of the variance including one variable. All these six factors have a link and influence on household resilience to natural disasters.

### Discussion

This research has measured the level of community resilience of the urban poor combined with assessing the factors that shape differentiated resilience.

The outcomes demonstrate a systematic understanding of the level and extent of the resilience of urban slums and also the households.

The result shows that the urban poor people are very less resilient in terms of the economic, institutional, and physical dimensions. But the condition of the social dimension is moderately better than other dimensions. A significant social support network has been found in these urban slums. This strong social capital assists them when a disaster occurs such as to make better evacuation decisions, searching and rescuing and providing immediate and long-term relief and recovery measures.

The composite resilience index of the urban slums revealed that there have no high resilient slums in the study area. Among the six slums, four slums were found moderately resilient, and two slums were found low resilient category. All the slums show a very lower value in most of the dimensions and indicators.

The household-level resilience analysis presented the households registered in different resilience categories. The result of the household-level resilience index revealed that most of the households are belongs to the low and moderate resilient category. The share of the high resilient category is very low. Because, the slum peoples have a very lower amount of income and savings but they have a higher amount of debt. Most of the households have no multiple income sources and usually, they are engaged in different kinds of manual labor-based employments such as day labor, construction work, rickshaw or van pulling etc. Besides, they are not getting sufficient assistance from microfinance membership, local government and NGO support. In addition, the slum peoples are mostly lived in Katcha houses and their houses, latrines and water sources become waterlogged during rainfall.

The findings of this research also contribute to investigating the determinants factors that affect the resilience of the urban poor. This study identified the six blocks of dominant factors that shape resilience. It revealed that access to formal safety nets and social assistance has the highest effect on the resilience capacity of the urban poor. It also highlighted the other dominant factors named income and livelihood strategy, illness and debt, education and employment, housing condition and social support. All these factors have a significant impact on the resilience capacity of urban slum dwellers.

## Conclusion

This article determines the resilience capacity of urban poor settlements against natural disasters. This article primarily investigates the bounce-back ability of informal households of Khulna city from climatic vagaries. In order to do so, different resilience indicator data is collected at household level.

The research finds out level of resilience both in household level and community level. Major finding from this investigation is maximum of the sample households are poorly resilient to natural disasters. At community level investigation none of the sample communities are highly resilient. Social cohesion among these communities is good but that is not helping them to lift up their resilience value. The reason behind that is their economic condition. They can help themselves and each other mentally-physically but they hardly can provide monetary support. Almost every family have increasing debt, lower income, no savings. As a result, they cannot develop the other resilience factors. Even moderate institutional support fail to enrich them economically. The study also finds out major factors that effecting resilience value among urban poor. The research found six factors including income and livelihood strategy, illness and debt, education and employment.

The study set specific indicators to develop the resilience capacity of Khulna city poor settlements. The policy should focus on these factors to up lift the living standard and bounce back capacity of informal settlements of Khulna city. The research also set up a methodical formula to find out resilience level of any city further research can be conducted in other cities to figure out their resilience level.

It is worth noting that the methods adopted for this research can be used in similar socio-economic and geographic contexts. Finally, we recommend that a similar scientific approach may be useful elsewhere to understand the level of resilience and to investigate the factors that shape the resilience to the natural disaster.

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