Research Article

Effects of Climate Finance on Risk Appraisal: A Study in the Southwestern Coast of Bangladesh

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Utilising climate funds properly to reduce the impact of potential risks of climate change at the local level is essential for successful adaptation to climate change. Climate change has been disrupting the lives of millions of households along the coastal region of Bangladesh. The country has allocated support from its national funds and accessed international funds for the implementation of adaptation interventions. With the focus of the scientific community on climate finance mechanisms and governance at the global and the national level, there is a lacuna in empirical evidence of how climate finance affects risk appraisal and engagement in adaptation measures at the local level. This paper aims to examine how the support from climate finance affects risk appraisal in terms of the perceived probability and severity and the factors which influence risk appraisal. A field survey was conducted on 240 climate finance recipient households (CF HHs) and 120 nonclimate finance recipient households (non-CF HHs) in Galachipa Upazila of Patuakhali District in coastal Bangladesh. The results indicate that both CF and non-CF HHs experience a high probability of facing climatic events in the future; however, CF HHs anticipated a higher severity of impacts of climatic events on different dimensions of their households. With higher income and social capital, the overall risk appraisal decreases for CF HHs. CF HHs have higher engagement in adaptation measures and social groups and maintain alternative sources of income. Climate finance played a critical role in supporting households in understanding the risks that they were facing, assisting them in exploring as well as enhancing their engagement in adaptation options.

1. Introduction

Risk appraisal at the household level plays a crucial role in the adaptation pathway and towards exploring available adaptation measures. Reasons for this are manifold, recognising the centrality of the household unit in governing responses to external stimuli as cited by Jones and Tanner [1]. Risk appraisal comprises of perceived probability, which is the person's expectancy of being exposed to the threat, while perceived severity is the person's appraisal of how harmful the consequences of the threat would be to things he or she values if the threat were actually to occur [2]. Households are concerned about how climatic events may affect their livelihoods and assets based on past experiences. However, project planning and budgetary allocation for the local level are considerably done at the national level in

Bangladesh, mainly by the ministries and their subordinated departments and agencies, and do not consider the household needs. The implementation is left to the local level. Hence, the approach is rather top-down. This limits consideration of local needs and participation within the process. This is also similar for adaptation projects, although climate change is localised and needs to consider localised adaptation responses. Local governments are less involved in the planning process of the adaptation measures, which results in the local needs being insufficiently considered [3]. Furthermore, localised encounters contrast significantly with the techno-scientific accounts through which scientists, policymakers, and practitioners often conceptualise climate change risks and operationalise responses [4]. Customised adaptation interventions at the household level are also limited. In fact, households contribute from their

own resources to participate in the planned adaptation measures, increasing the overall adaptation cost for the affected households. Indeed, many of the assets, capacities, and functions required to respond to climate risk are dictated by household-level dynamics [1]. Adaptation funding is scarce and has to be used effectively [5]. External assistance facilitates, secures, and improves the process of climate risk reduction [6].

Some authors argue that the bottom-up approach prevalent in development assistance brings flexibility and innovation and that such an approach fits well with the many motivations for providing aid, with the diverse willingness and capabilities to contribute to development finance efforts [7]. Local governments are the authorities who need to react at the earliest in case of any calamities or disasters. The local governments in Bangladesh have the mandate of developing and maintaining infrastructure and basic public services such as water, sanitation, health, and educational facilities, which can be adapted to make the localities resilient. In addition, although local governments are often better informed on how to go about making development activities climate-adapted in a participatory manner with the involvement of local political leaders, communities, practitioners, and authorities, they are often unable to respond as they are provided limited funding from the central level as they have little involvement in the budgetary decisions. The insufficient funding can be followed back to the planning and budgeting done at the national level, which often does not take account of the local dimensions and cost estimates of climate change into the development planning. A more participatory bottom-up approach with the engagement of local governments and local people in the adaptation project planning, budgeting, and implementation process is needed. The challenge, however, is to channel climate finance towards adaptation measures, which fit the local context and support the most vulnerable and marginalised population.

During the Conference of Parties (COP) 15 in 2011, the Green Climate Fund was agreed upon which offers an equal funding window for adaptation and mitigation. However, almost a quarter of a century into climate change negotiations, an adequate system for defining, categorising, tracking, and evaluating climate change finance, is still absent [7]. Despite the “polluter-pays-principle” at the climate negotiations, the gap in the availability of climate finance is prevalent. The inadequacy of climate finance to meet the adaptation needs will be analysed further through this study.

At the national level, Bangladesh has taken initiatives to finance climate change interventions from national and international financial sources. By 2050, total investments of \$5,516 million and \$112 million in annual recurrent costs will be needed to protect Bangladesh against climate change [8]. The country is not helpless, therefore, against coping with sea-level rise, but it might need financial and technical assistance with providing practical mitigation measures [9]. Climate finance comes from different sources such as from the national budget, Bangladesh Climate Change Trust Fund (BCCTF), Bangladesh Climate Change Resilience Fund (BCCRF), and bilateral donors through Fast Start Finance, among others [10].

To analyse the perception of risk, a field survey was conducted in Patuakhali, on the southwestern coast of Bangladesh, on the beneficiaries of a climate finance project (referred to as CF Project) run by an international NGO. The aim of the CF Project was to support the vulnerable communities against a changing and uncertain climate. This study limits itself to the adaptation interventions at the household level due to the focus of the research on the effect of climate finance on the risk appraisal at the household level.

The paper sets out to analyse how climate financial makes a difference in the risk appraisal of households in comparison with households which do not receive support. One of the objectives of the study is to examine the influencing factors of risk appraisal, which were identified through multiple regression analysis. This research contributes to the existing literature through a comparative analysis of risk appraisal and adaptation measures of CF and non-CF households. To date, much of the adaptation literature has been theoretical, reflecting the absence of empirical data from activities on the ground [11]. Effective utilisation of climate funding requires a critical analysis of where climate finance should be focused and which factors influence the household in engaging in adaptation. Risk appraisals of climate change and influencing factors are critical to understanding adaptation behaviour [12, 13]. It has become important to adaptation strategies because the way individuals interpret their risks affects what adaptation behaviour they are likely to take [13].

2. Literature Review

Climate change is disrupting the socioeconomic conditions of people, which are difficult to overcome especially by the poor households. Natural calamities will reinforce pre-existing socioeconomic divide by damaging natural resources that support the poor’s long-term livelihood prospects and destroying their current produce, and by repeatedly rendering the poor homeless and destroying whatever little material possessions they might have [14]. Risk appraisal is derived from the premise that people comprehend their abilities and limitations. A large number of definitions, frameworks, and approaches have been proposed for explaining and quantifying risk [3, 13]. Nearly all studies on the effects of personal experience on self-protective behaviour regarding natural hazards show preparedness increasing with the severity of past damage [2].

The discourse around the provision of climate finance has been focused at the international level. Without efforts to marry adaptation theory with real-world adaptation practices, the adaptation field will continue to be siloed between theory and practice [11]. In the last 20 years, there has been an increase in bilateral and multilateral funds providing climate finance such as Global Environmental Facility (GEF), Climate Investment Fund (CIF), Fast Start Finance, Adaptation Fund, and most recently, the Green Climate Fund (GCF); each responds to needs that emerged at different times. However, the proliferation of funds has led policymakers to question whether such a diverse landscape

of funds can effectively channel climate finance to support the necessary transformation to low-emission, climate-resilient societies [15]. The IPCC special report in 2018 argued that the world only had until 2030 to keep the global temperature increase at a maximum of 1.5°C if immediate action is not taken [16]. This collates with the Paris Agreement in 2015 with the goal of keeping the temperature between 1.5°C and 2°C.

Adaptation finance is primarily allocated to multilateral entities and national governments, rather than local organisations [17]. BCCTF has allocated almost USD 400 million as of date for climate change. BCCRF, a multidonor trust fund, had committed USD188 million in grant funds to build resilience but was discontinued after 2016. The Pilot Program for Climate Resilience (PPCR) has allocated USD 110 million in grants (45%) and interest credits (55%). Until 2019, Bangladesh has received commitments of USD 88.13 million from the GCF through three approved adaptation projects. The funds are mostly in the form of loans or grants when the funding is from international sources.

The climate-relevant budget data of five key ministries for climate change from FY 2014-15 to FY 2017-18 were analysed [18]. An increase is evident for the period 2014 to 2017, with a slight decrease in the FY 2017-18, as illustrated in Table 1. One of the barriers for shifting investments' allocation to green sectors and assets is the poor understanding of the relation between climate risks, the economy, and finance [16].

An analysis of the budget allocation according to Bangladesh Climate Change Strategy and Action Plan (BCCSAP) thematic areas for the four fiscal years 2014–2018 is presented in Table 2, which indicates that the majority of the budget allocation went towards adaptation. On the contrary, the budget allocation for mitigation and low carbon development decreases from 1.74% in FY 2014-15 to 1.16% in FY 2017-18 of the total climate-relevant budget [18].

3. Theoretical and Empirical Basis of Research

For measuring risk appraisal to climate change, this paper follows the Model of Private Proactive Adaptation to Climate Change (MPPACC) to examine why some people exhibited adaptation behaviour while other people did not [2]. The MPPACC was based on the Protection Motivation Theory, which was recognised as one of the four major theories in psychological research conducted on health behaviour.

- (i) First, the perceived probability is the person's expectancy of being exposed to the threat (to use a natural-hazard example that a flood reaches the house in which a person lives).
- (ii) Second, perceived severity is the person's appraisal of how harmful the consequences of the threat would be to things he or she values if the threat were actually to occur.

Grothmann and Patt's framework was expanded further by Frank et al.'s study which identified social identity as an

important additional component of an individual's perceived risk and adaptation capacity [1]. For risk appraisal, the framework was operationalised further through quantitative analysis. The formula utilised was followed by this study as well, with some modifications explained in the succeeding section, and is as follows:

$$\text{risk appraisal} = \text{perceived probability} \times \text{perceived severity.} \quad (1)$$

The concept of threat appraisal formulated by [13] in their conceptual framework is as follows:

$$\text{risk appraisal} = \text{uncertainty} \times \text{adverse consequences,} \quad (2)$$

where $\text{uncertainty} = \text{perceived probability}$ and $\text{adverse consequences} = \text{perceived severity}$.

$$\text{Overall risk appraisal} = \sum_{i=1}^n \text{uncertainty}_i \times \text{adverse consequences}_i. \quad (3)$$

4. Materials and Methods

4.1. Study Area. In South Asia, Bangladesh is the most densely populated delta of the Ganges-Brahmaputra-Meghna (GBM) Basin [19]. The country drains out approximately 92.5% of the water that is generated in the GBM Basins (an area of 175,106 ha) [20] to the Bay of Bengal. Bangladesh has 19 coastal districts and with a coastal population of 50 million people, nearly about one-third of its total population. The coastal area represents an area of 47,211 km² equalling 32% of the country's total geographical area [21]. The coastal zone has been affected by 174 natural disasters during the period 1974–2007 [22]. Current predictions claim that this coastal area will be increasingly submerged up to 3 per cent by the 2030s, 6 per cent in the 2050s, and 13 per cent by 2080s as a result of the sea-level rise [21].

Galachipa Upazila (a subdistrict/administrative region in Bangladesh) is one of the thirteen subdistricts under the Patuakhali district in the southwestern coast of Bangladesh. Galachipa, as shown in Figure 1, has been selected as the study area as it had interventions under the CF Project concluded in 2016. Galachipa is around 925 km² large and is around 35–50 feet above the mean sea level. It has been affected by cyclones, tidal surges, coastal flooding, thunderstorms, nor'westers, heavy/irregular rainfall, and salinity. Besides these, river erosion is a severe problem in this area as the two large rivers, Agunmukha and Tetulia, flow on both sides of Galachipa and several smaller rivers flow cross-terrain through Galachipa. It has around 109 km of the embankment at different points, with around 12 door sluice gates.

4.2. Sampling. The field survey was conducted as a comparative study of the risk assessment of households who received support from the climate finance interventions (CF HHs hereafter) in relation to households who did not receive support from climate finance interventions (referred to as

TABLE 1: Climate-relevant budget allocation in selected ministries from 2014 to 2018 [18].

Budget description	Annual budget (amount in thousand taka)			
	2014-15	2015-16	2016-17	2017-18
<i>Nondevelopment budget</i>	270,827,806	300,456,768	309,209,969	358,797,697
Climate-relevant allocation	65,982,855	77,193,807	84,036,986	85,334,676
% of nondevelopment budget	24.36	25.69	27.18	23.78
<i>Development budget</i>	253,047,122	297,119,124	350,529,332	403,219,100
Climate-relevant allocation	28,066,412	46,513,505	53,701,881	61,001,430
% of development budget	11.09	15.65	15.32	15.13
<i>Total budget</i>	523,874,928	597,575,892	659,739,301	762,016,797
Climate-relevant allocation	94,049,267	123,707,312	137,738,867	146,336,106
% of total budget	17.95	20.70	20.88	19.20
% of GDP	0.62	0.71	0.70	0.66

Source: Climate Protection and Development: Budget Report, 2017-18.

TABLE 2: Allocation in BCCSAP thematic areas in the selected ministry budget [18].

BCCSAP themes	CC-relevant allocation (amount in thousand taka)			
	2014-15	2015-16	2016-17	2017-18
<i>Food security social protection and health</i>	13,304,421	16,146,944	16,678,265	17,353,924
% of total CC-relevant allocation	14.15	13.04	12.11	11.86
% of ministry budget	1.75	2.12	2.19	2.28
<i>Comprehensive disaster management</i>	20,687,257	30,318,387	29,434,227	34,671,966
% of total CC-relevant allocation	22.00	24.49	21.37	23.69
% of ministry budget	2.71	3.98	3.86	4.55
<i>Climate resilient infrastructure</i>	6,559,625	13,248,641	23,947,171	24,743,940
% of total CC-relevant allocation	6.97	10.70	17.39	16.91
% of ministry budget	0.86	1.74	3.14	3.25
<i>Research and knowledge management</i>	2,631,410	4,165,926	2,804,454	3,658,676
% of total CC-relevant allocation	2.80	3.37	2.04	2.50
% of ministry budget	0.35	0.55	0.37	0.48
<i>Mitigation and low carbon development</i>	1,639,602	1,653,730	1,613,205	1,699,220
% of total CC-relevant allocation	1.74	1.34	1.17	1.16
% of ministry budget	0.22	0.22	0.21	0.22
<i>Capacity building and institutional strengthening</i>	49,226,953	58,246,322	63,261,544	64,208,380
% of total CC-relevant allocation	52.34	47.06	45.93	43.88
% of ministry budget	6.46	7.64	8.30	8.43
<i>Total CC relevance (Tk)</i>	94,049,267	123,779,950	137,738,867	146,336,106
% of total budget for 6 ministries	17.95	20.71	20.88	19.20

Source: Climate Protection and Development, Budget Report, 2017-18.

non-CF HHs). The unit of analysis was at the household level. Crucially, household-level assessments also offer value in capturing the interactions of individual-level decisions and traits with broader social norms, behaviour, and institutions that collectively affect responses to climate hazards [1]. The CF HHs functioned as the experimental group while the non-CF HHs were the control group. Other risk assessment studies opted for an experimental and control group, allowing for comparison and reliability of results [23]. Also, both CF and non-CF HHs were of similar criteria and lived within similar geographical conditions and allowed comparison. The study employed mixed sampling methods to select households. From the 19 districts in the coast of Bangladesh, Patuakhali was chosen through purposive sampling. From within the seven subdistricts of Patuakhali, Galachipa was chosen through purposive sampling as a CF Project was implementing adaptation activities at the household level. The

beneficiaries of the CF Project had been selected by the NGO based on the criteria that the household did not have more than 10 decimal or 0.004 hectares of productive lands and had less than USD 62.5 in productive assets. Some other criteria included the nonengagement of households in microcredit programmes or projects similar to the CF Project. The last criteria were that each household had a monthly income of less than USD 62.5.

A list of 489 CF HHs supported in the Galachipa Upazila was provided by the project managers of the CF Project to the researcher. Based on the formula of Yamane (1967) for computing the size of the sample under equation (1), the sample size of 220 CF HHs was estimated. Finally, a sample of 240 CF HHs was collected through random sampling. The list of sample beneficiary households then underwent random sampling in MS Excel to determine which households should be surveyed:

FIGURE 1: Galachipa Upazila.

$$n = \frac{N}{1 + Ne^2}, \quad (4)$$

where n is the sample size in each area, N is total numbers of households in an area, and e is the precision value, set as 10% (0.10).

The CF HHs received support for adaptation measures such as plinth raising, construction of new housing, homestead gardening, agricultural support, and income diversification activities such as livestock, small businesses, small solar home systems, among others. A control group from the same study area (indicated as non-CF HHs)

which did not receive support from climate finance was also surveyed to allow the comparison and reliability of results. Unlike the CF households, there was no existing name list for the non-CF HHs. Therefore, four focus group discussions (FGDs) were conducted in the study area to identify those households, which met the same criteria for choosing CF households of the households, those who had less than 10 decimal or 0.004 hectares land, had less than USD 62.5 in productive assets, were not engaged in microcredit or similar projects, and had a monthly income below USD 62.5. Participants of the FGDs included Upazila members, members of the local disaster management committee, and local leaders who were able to identify around 240 households in the study area, which met the selection criteria. The names of the households obtained from the FGDs were then entered into an Excel sheet. However, budget constraints in conducting the survey were considered while maintaining a comparable sample size. Therefore, the number of non-CF HHs was limited to 120 households. The percentage of simulated studies with an elevated effect increases as control group size increases (30 participants: 85%; 60 participants: 92%; 100 participants: 96%; and 200 participants: 99%) [24]. Through random sampling in MS Excel, a list of non-CF households of 120 HHs was shortlisted and surveyed. In case any of the households were unwilling to be surveyed or were unavailable, the next household was chosen from the randomized list.

The field survey was conducted in April and May 2016 using a structured questionnaire. Eight interviewers were chosen based on the experience of data collection and previous knowledge of the area, and they were provided with a three-day training. Before the actual survey, the questionnaire was pretested on 15 households by the interviewers. The interviewees were read out a uniform introduction on the purpose of the survey. The interviews were conducted between one and a half hours to two hours.

4.3. Variable Measurement. The questionnaire included two main aspects of risk appraisal, namely, perceived probability and perceived severity. The variables were chosen based on previous studies on risk appraisal [13, 25] and cross-checked during pretesting. For perceived probability, the households were asked about how likely they were to experience the seven main climatic events in the future, as identified in the Patuakhali Disaster Management Plan 2014. The scale ranged from 1 to 5 (1 = not likely; 2 = less likely; 3 = likely; 4 = more likely; and 5 = very likely). For perceived severity, the households were asked about how each of the climatic events could affect different features of their lives. Perceived severity had the scales of 1 to 5 (1 = not affected; 2 = less affected; 3 = affected; 4 = more affected; and 5 = highly affected).

A number of methods, frameworks, and approaches were applied for risk assessment [13, 26–29]. For this study, it utilised the method by Le Dang et al., in which the risk appraisal was computed by multiplying perceived probability with perceived severity as given in equation (1). The

probability was based on the likelihood of the household facing these natural calamities in the future. A summation was drawn from all the perceived severity corresponding to a particular climatic event to obtain a single perceived severity. The perceived probability was then multiplied by the corresponding severity for the event to obtain the risk appraisal for that climatic event. Then, a summation was drawn to estimate an overall risk appraisal. This overall risk appraisal was used as the dependent variable for the multiple linear regression model. Le Dang followed the multiple regression model risk appraisal = f (risk experience, information, belief in climate change, trust in public adaptation, farm household characteristics, farm characteristics, and income).

Drawing on dimensions developed by Le Dang et al., the model was executed under the following function for this research and with independent variables identified for adaptation efficacy under the bivariate analysis such as x_1 = HH size, x_2 = income, and x_3 = immobile assets:

$$Y_{\text{opr}} = b_0 + b_1x_1 + \dots + b_px_p + \dots + \varepsilon, \quad (5)$$

where b_0 is the intercept, b_1 to b_p are the regression coefficients corresponding to the covariates $x_1, \dots, x_p$, ε is the error term of the model, x_1 = HH size, x_2 = income, x_3 = immobile assets, x_4 = productive assets (livestock, etc.), x_5 = mobile assets (rickshaw), x_6 = participation in social circle, x_7 = information on climate change from NGO, x_8 = support from social safety net, x_9 = monetary/in-kind support from social circle (relatives, friends, neighbours, and self-help groups) for adaptation measures, x_{10} = financial support from loans (microcredit, bank, cooperative, and mohajan) for adaptation responses, x_{11} = financial support from govt. for adaptation responses, x_{12} = financial support from NGOs (cash, materials, labour costs, and advisory services) for adaptation responses, x_{13} = self-financed adaptation responses through selling assets, and x_{14} = self-financed adaptation measures through income/savings/reducing expenditure on food, health, and education.

4.4. Data Analysis Techniques. Statistical Analysis Software (SAS) was used to analyse the household data including descriptive statistics—chi-square, Pearson's correlation coefficient, factor analysis, R^2 and adjusted R^2 , variance inflation factor, Durbin-Watson statistic, normality, and homoscedasticity were used.

To identify significant variables, bivariate analysis was conducted on all relevant independent variables which were important to the dependent variable, overall perceived risk. Those variables which had an association in the bivariate analysis were included under the independent variables for the multiple linear regression analysis in the model for this study. One regression model under equation (5) was fitted, with CF and non-CF as the independent variables. By including CF and non-CF as independent variables, we can assess the impact that CF and non-CF have on the dependent variable for the overall perceived risk.

5. Results and Discussion

Both the climate and nonclimate finance households were from Galachipa subdistrict and lived under similar conditions. This study examined the differences in the socioeconomic profile of the CF HHs and the non-CF HHs through chi-square test and corresponding *P* values, as shown in Table 3. The adaptation measures engaged in by CF and non-CF HHs are given under Table 4. As shown in Table 3, more CF HHs lived outside or on the embankment, which may have been related to the loss of land due to river erosion. Those without land inside the embankment remained outside of the embankment mainly on government land or the embankments.

Moreover, the housing structure of CF HHs was made of less durable materials. There were also a higher number of wage labourers, traders, and fishers in the CF HHs. About 18% of CF HHs pursued a secondary source of income. The average monthly income of CF households was higher at USD 59.9 in comparison with USD 54.9 for non-CF HHs. About 96.2% of the CF HHs participated in a social group such as self-help groups, producer groups, or cooperatives while only 16.7% of the non-CF HHs participated in some form of social groups. More non-CF households received support from the social safety net at 78.3% compared with 63.8% of CF HHs receiving support.

Data showed that non-CF HHs participated in most of the 26 adaptation measures on self-initiatives while the CF HHs received support in 14 adaptation measures, partially supported by the climate finance interventions. At an aggregated level, the main categories of adaptation measures all saw a higher engagement of CF HHs than non-CF HHs as shown in Table 4. Higher income levels were likely to significantly increase the likelihood of planting trees and using supplementary irrigation as adaptation choices [29]. The two highest engagements for both groups were in housing and livestock. The socioeconomic profile of the CF HHs showed that a significant number lived outside or on the embankment and needed support for housing. Livestock was perceived as an instant cash source and was the preferred option for receiving external support as they could quickly reproduce.

Furthermore, households did not need a new skill set to maintain their livestock. Both groups participated least in agriculture and fisheries. From the aggregated level, a significant difference based on the chi-square and *P* value between CF and non-CF HHs was seen for gardening, agricultural land and crops, livestock, fisheries, safe water, and access to power and fuel resources. From the socioeconomic profile and focus group discussions, support was least given to agriculture and crops as the CF HHs had lost their arable and homestead land due to river erosion. Most of the households who had lost land and could no longer do farming worked as day-labourers. About 55.4% of the CF HHs had the main source of income as day-labourers. The occupation of a day-labour is also critical as they are out of work 6 to 8 months in the whole year. This analysis is indicative of the selection bias of the climate finance project towards selecting households who had lost their land to river

erosion and who now work as day-labourers, i.e., without a stable or regular income. This bias might have caused barriers to climate finance reaching other households, who were also in dire conditions.

Engaging in adaptation measures was made possible through some households' own financial resources or external sources. Poor households, however, had fewer income sources, often had to sell assets to sustain their family's expenditure, and had limited access to financial services. There exists growing evidence of the beneficial impact of access to financial services on all aspects of social and economic outcomes at the household and firm level [30]. The absence of financial services makes diversification of income sources a livelihood strategy, as well as an adaptation response for climate-affected households. The first step is to stabilising their socioeconomic conditions. For this, it is essential to understand how the poor farmers manage their cash flows, their preferences, attitudes, and behaviours to determine the scope of diversifying income sources as an effective path out of poverty [30].

Once climate funds reach the national level, a further breakdown of the allocated amounts for hard and soft measures ensues. Studies have shown that 65% of climate funding was allocated to infrastructure investments, including coastal protection measures for flooding and erosion [11], that caused a significant portion of climate finance to be preplanned for infrastructures such as embankments. At the local level, the projects with "soft" measures, such as those related to capacity building, policy reform, and planning and management, are traditionally low cost [11] and inadequately meet the adaptation needs of the households. Data generated from this study showed that the households engaged in 24 adaptation measures whereas climate finance had 14 adaptation measures available (Table 4). Thus, it can be argued that climate finance was inadequate and the support received was beneficial to a limited extent.

The perceived probability in this study is defined as how likely households expect to face a climatic event in the future on the basis that it will affect a household's ability to rebound, i.e., overcome the effects of the climatic events. Risk experiences tend to induce people to think of the risks more often, thereby increasing their risk appraisals [13].

5.1. Perceived Probability. The perceived probability, as shown in Table 5, had the highest mean of 3.6667 and 3.9750, which ranged between likely and quite likely for both CF and non-CF HHs. The *P* value for cyclone and river erosion showed a significant correlation, however, with river erosion indicating a negative association. *T*-tests indicated that there is indeed a significant difference between the perceived probability of climate finance and nonclimate finance households. Significant differences between CF and non-CF HHs have also been observed based on the means of the CF and non-CF HHs for all climatic events as indicated by the *P* value.

5.2. Perceived Severity. The perceived severity was measured by multiple aspects of households that are affected by

TABLE 3: Summary of differences in socioeconomic profiles of climate finance (CF HHs) and nonclimate finance households (non-CF HHs).

	Findings (<i>P</i> value)	CF households	Non-CF households
Household size	No significant difference	4.07	4.27
Educational attainment	Significant difference at 10% confidence interval <i>P</i> value (0.062)	(i) The lower level of illiteracy with 69.6% (ii) Higher completion of the primary level with 26.3% (iii) Higher completion of the secondary level with 4.2%	(i) A higher level of illiteracy with 75.8% (ii) Lower completion of primary level with 25.6% (iii) No completion of secondary level
Land-holding size	No significant difference	However, more men have land than women; both CF men and CF women have more land than non-CF women	
	Significant difference at 0.01% and 0.05% confidence interval		
	Tenancy <i>P</i> value (0.049)	(i) 4.2% CF live free (ii) Only 1 CF rents (iii) 85% own housing (iv) More (10%) inherited from parents	(i) More non-CF (11.7%) live free (ii) 0 non-CF rents (iii) More non-CF (80%) own housing (iv) Less (8.3%) inherited from parents
	Location now <i>P</i> < 0.001	(i) More CF (10.4%) live outside embankment (ii) 7 CF live on embankment (iii) Less CF (74.6%) live inside embankment (iv) More CF (12.1%) live upland	(i) Less non-CF (2.5%) live outside embankment (ii) 0 non-CF live on embankment (iii) More non-CF (94.2%) live inside embankment (iv) Less non-CF (3.3%) live upland
Housing conditions		(i) More CF (3.8%) houses made of mud (ii) More CF (22.9%) houses made of leaves	(i) Fewer non-CF (0.8%) houses made of mud (ii) More non-CF (13.3%) houses made of leaves
	Household construction material <i>P</i> value (0.016)	(iii) Less CF (66.7%) houses made of corrugated tin (iv) More CF (2.9%) houses made of brick and cement (v) More CF (3.8%) houses made of others (wicker)	(iii) More non-CF (83.3%) houses made of corrugated tin (iv) Fewer non-CF (1.7%) houses made of brick and cement (v) Fewer non-CF (0.8%) houses made of others (wicker)
	Water purification methods <i>P</i> < 0.001	(i) Less CF (1.3%) use water purification tablets (ii) More CF (2.5%) use filtering systems (iii) Less CF (21.7%) use boiling (iv) More CF (62.1%) use fitkari (aluminium sulfate, also known as alum) as others (v) Less CF do not use any purification method (12.5%)	(i) More non-CF (2.5%) use water purification tablets (ii) 0 non-CF use filtering systems (iii) More non-CF (23.3%) use boiling (iv) Fewer non-CF (45%) use fitkari (aluminium sulfate, also known as alum) as others (v) More non-CF do not use any purification method (29.2%)
Primary source of income	Significant difference at 0.05% confidence interval	(i) More CF wage labourer (55.4%) (ii) Less CF in service (6.3%) (iii) More CF in trade (8.8%) (iv) More CF fishermen (7.5%)	(i) Less non-CF wage labourer (40.8%) (ii) More non-CF in service (25.5%) (iii) Fewer non-CF in trade (7.5%) (iv) Less non-CF fishermen (5.8%)
Secondary source of income	Significant difference at 0.01% confidence interval	(i) More CF as pastoralist (12.5%) and wage labourer (5.4) (ii) 71.7% CF does not have any secondary source	(i) Only 1 farmer, 1 domestic worker, 1 begging non-CF (ii) 96.7% non-CF do not have any secondary source
Average monthly income	Difference	USD 59.9	USD 54.9

TABLE 3: Continued.

	Findings (<i>P</i> value)	CF households	Non-CF households
	Significant difference at 0.01% confidence interval		
Membership in social groups	Self-help groups $P < 0.001$	More CF (64.6%) participation in self-help group	Less non-CF (1.7%) participation in self-help group
	Producer group $P < 0.001$	More CF (48.8%) participation in producer group	Less non-CF (0.8%) participation in producer group
	DMC $P < 0.001$	More CF (10.5%) participation in disaster management committee (DMC)	Less non-CF (0.8%) participation in disaster management committee (DMC)
	Cooperatives $P < 0.001$	More CF (76.3%) participating in cooperatives	Less non-CF (16.7%) participating in cooperatives
	No membership in any social group $P < 0.001$	Less CF (3.8%) not participating in any social group	More non-CF (83.3%) not participating in any social group

TABLE 4: Percentage of climate finance (CF) and nonclimate finance (non-CF) households who engaged in the adaptation measures.

Group	Adaptation measures	Groups		Chi ² (<i>P</i> value)
		CF (%)	Non-CF (%)	
Housing	Plinth raising and reinforcement of housing**	78.8	64.2	8.82 (0.003)
	Construction of new housing*	70.8	51.7	13.76 (<0.001)
	Repair of damaged housing**	28.8	31.7	0.33 (0.568)
	Homestead gardening**	55.0	42.5	5.00 (0.025)
Garden	Community nursery*	11.3	0.83	12.10 (<0.001)
	Social forestry*	19.2	12.5	2.53 (0.112)
	Changed crop varieties**	7.5	1.7	5.19 (0.023)
Agricultural land and crops	Changed crop patterns*	7.1	1.7	4.70 (0.030)
	Changed irrigation management	3.8	0	6.57 (0.037)
	Poultry farming**	85.4	72.5	8.71 (0.003)
	Duck farming**	70.8	58.3	5.63 (0.018)
Livestock	Raised poultry housing**	53.8	38.3	7.61 (0.006)
	Goat rearing**	35.8	19.2	10.53 (<0.001)
	Cow rearing**	75.8	45.8	32.01 (<0.001)
	Raised barn**	42.9	12.5	33.59 (<0.001)
	Cow fattening**	30.4	2.5	37.43 (<0.001)
Fisheries	Change in fish culture**	7.9	2.5	4.09 (0.043)
	Installation of deep tube wells*	54.6	40.8	6.05 (0.014)
Safe water	Elevated tube wells**	32.5	30	0.23 (0.631)
	Water storage tanks	4.6	0	5.67 (0.017)
Access to power and fuel sources	Solar systems*	60.8	50	3.84 (0.050)
	Rickshaw/Thela**	5.8	9.2	1.38 (0.241)
IGA	Three-wheeler*	5	3.3	0.52 (0.469)
	Trading/small business**	17.9	16.7	0.09 (0.769)

Source: Survey conducted under this study. **Adaptation measures fully supported by climate finance; *partial support from climate finance.

climatic events. To obtain a single perceived severity, all the perceived severities were aggregated corresponding to a particular climatic event such as cyclone, storm surge, and river erosion, among others. As shown in Table 6, the perceived severity to cyclones had the highest effect on the different dimensions of households such as housing, gardening, crops, and livestock and with a mean of 1.93 for the CF HHs and 1.66 for the non-CF HHs. The *P* value for all values shows a significant correlation, however, in a negative direction, derived from the *t*-test. The *t*-tests also indicated that there is indeed a significant difference between the perceived severity of climate finance and non-climate finance households. CF HHs have a higher severity on the different dimensions of the households compared to

non-CF HHs. Significant differences between CF and non-CF HHs have also been observed for the means of the CF and non-CF HHs for all climatic events as indicated by the *P* value.

5.3. Risk Appraisal and Overall Risk Appraisal. All the perceived severity for each of the climatic event was added to reach a single perceived severity, as presented in Table 7. The perceived probability was multiplied by the corresponding severity for the event to obtain the risk appraisal for that climatic event. After which, all the risk appraisals were added to estimate an overall risk appraisal which indicated a significant difference between the

TABLE 5: Mean, standard deviation, and standard error of the perceived probability, i.e., likelihood of facing the climatic events in the future.

	CF/non-CF	Mean	Std. deviation	T-test	P value
Cyclone	CF	3.667	1.541	1.963	0.051
	Non-CF	3.975	1.331		
Storm surge	CF	2.988	1.451	1.798	0.073
	Non-CF	3.242	1.160		
Flooding	CF	3.346	1.281	-0.551	0.583
	Non-CF	3.258	1.487		
River erosion	CF	2.829	1.818	-7.110	<0.001
	Non-CF	1.558	1.477		
Irregular rains	CF	2.992	1.284	0.795	0.428
	Non-CF	3.108	1.327		
Nor'wester (Kalboishakhi)	CF	4.158	1.094	0.502	0.616
	Non-CF	4.225	1.233		
Salinity	CF	1.471	1.420	-3.271	<0.001
	Non-CF	1.000	1.216		

TABLE 6: Mean, standard deviation, and standard error of the perceived severity, i.e., the effect of climatic events on different dimensions of the households.

	CF/non-CF	N	Mean	Std. deviation	Std. error	T-test	P value
Cyclone	CF	240	1.937	0.560	0.036	-4.575	<0.001
	Non-CF	120	1.663	0.522	0.048		
Storm surge	CF	240	1.692	0.630	0.041	-5.516	<0.001
	Non-CF	120	1.373	0.447	0.041		
Flooding	CF	240	1.723	0.675	0.044	-4.380	<0.001
	Non-CF	120	1.442	0.510	0.047		
River erosion	CF	240	0.892	0.697	0.045	-7.009	<0.001
	Non-CF	120	0.418	0.553	0.051		
Irregular rains	CF	240	1.021	0.458	0.030	-3.056	0.002
	Non-CF	120	0.883	0.371	0.034		
Nor'wester (Kalboishakhi)	CF	240	1.710	0.533	0.034	-4.384	<0.001
	Non-CF	120	1.466	0.465	0.043		
Salinity	CF	240	0.540	0.471	0.030	-5.011	<0.001
	Non-CF	120	0.315	0.362	0.033		

TABLE 7: Mean, standard deviation, and standard error of the risk appraisal of the households.

	CF/non-CF	N	Mean	Std. deviation	Std. error	T-test	P value
Risk appraisal_Cyclone	CF	240	7.332	3.805	0.246	-1.448	0.149
	Non-CF	120	6.773	3.259	0.296		
Risk appraisal_Storm surge	CF	240	5.340	3.539	0.229	-2.821	0.005
	Non-CF	120	4.466	2.284	0.209		
Risk appraisal_Flood	CF	240	6.114	3.408	0.220	-2.909	0.004
	Non-CF	120	5.057	3.151	0.289		
Risk appraisal_River erosion	CF	240	3.256	3.091	0.199	-8.207	<0.001
	Non-CF	120	1.142	1.784	0.163		
Risk appraisal_Irregular rains	CF	240	3.250	2.127	0.137	-2.247	0.025
	Non-CF	120	2.794	1.633	0.149		
Risk appraisal_Nor'wester	CF	240	7.165	3.097	0.200	-2.596	0.010
	Non-CF	120	6.306	2.881	0.264		
Risk appraisal_Salinity	CF	240	1.092	1.399	0.090	-5.118	<0.001
	Non-CF	120	0.501	0.791	0.072		

overall risk appraisal of CF and non-CF HHs, where the CF HHs have a higher overall risk assessment than non-CF HHs. This overall risk appraisal was used as the

dependent variable for the multiple linear regression model to assess the impact of selected independent variables on it (Table 8).

TABLE 8: Independent variables with details for the dependent variable (overall risk appraisal).

Categories	Independent variables	Measurement/ explanation	Scale	Recoded for regression analysis	Types of data
Socioeconomic factors	HH size	Numbers of household members			Continuous
	Income	Total annual income in number			Continuous
Assets	Immobile Assets (land)	Agricultural land in acre in number			Continuous
	Productive Assets (livestock, etc.)	In number			Continuous
	Mobile Assets	In number			Continuous
Involvement in social groups	Participation in self-help groups, producer group, DMC, cooperatives	Participation	1 = yes; 0 = no	1 = yes; 0 = no	Binary
Information on climate change	SISCH: information on climate change from social circle, i.e., relatives/ neighbours/friends/ community	Information received	1 = yes; 0 = no	1 = yes; 0 = no	Binary
External sources of finance	Support from social safety net	Support received from	1 = vulnerable group development (VGD) 2 = vulnerable group feeding (VGF) 3 = food for work (KABIKA) 4 = cash for work (KABITA) 5 = old age allowance 6 = allowance for the widowed, deserted, and destitute 7 = housing support 8 = test relief (TR) programme 9 = zakat in cash 10 = zakat in kindness 11 = scholarship 12 = others	1 = yes; 0 = no	Binary
	Monetary/in-kind support from Social Circle (relatives, friends, neighbours, self-help groups) for adaptation responses	Support received from	1 = relatives 2 = friends 3 = neighbours 4 = self-help groups	1 = yes for all options; 0 = no for all options	Binary
	Financial support from loans (microcredit, bank, cooperative, mohajan) for adaptation responses	Support received from	1 = microcredit 2 = bank 3 = cooperatives 4 = mohajan	1 = yes for all options; 0 = no for all options	Binary
	Financial support from govt. for adaptation responses	Support received from	1 = yes; 0 = no	1 = yes; 0 = no	Binary
	Financial support from NGOs (cash, materials, labour costs, advisory services) for adaptation responses	Support received from	1 = cash 2 = materials 3 = labour costs 4 = advisory services 5 = training	1 = yes for all options; 0 = no for all options	Binary
	Self-financed adaptation responses through selling		1 = land or building 2 = durable HH assets 3 = livestock 4 = mobile assets 5 = agricultural/fisheries equipment	1 = yes for all options; 0 = no for all options	Binary
	Self-financed adaptation responses through reduced household expenditure		1 = reduced expenditure on food, health, and education 2 = relied on savings 3 = paid from income 4 = HH members took other employment	1 = yes for all options; 0 = no for all options	Binary

6. Multiple Linear Regression Model for Overall Risk Appraisal

6.1. Regression Model for Overall Risk Appraisal for CF and Non-CF HHs. From the model for overall risk appraisal for CF HHs and non-CF HHs with 240 and 120 observations, respectively, the summary of statistical tests and the regression analysis results are given in Tables 9 and 10. The models were statistically significant at $F = 15.16$, $P < 0.01$ for CF HHs and $F = 6.30$, $P < 0.01$ for non-CF HHs, respectively. Positive auto-collinearity was observed. As shown in Table 10, a highly significant ($P < 0.01$) and negative relationship between overall risk appraisal and the independent variables was observed for income and participation in a social circle for CF HHs, while a significant and negative relationship was observed for non-CF HHs for income and information on climate change from the social circle. For CC HHs, positive and highly significant association ($P < 0.01$) between overall risk appraisal and the independent variables was seen for household size, immobile assets, and support from the social safety net. Significant relationship for CF HHs was observed between overall risk appraisal productive assets and financial support from government. On the contrary, for non-CF HHs, highly significant and positive relationship can be observed between overall risk assessment and immobile and productive assets and financial support from NGOs, while the significant and positive relationship is observed for social safety net.

7. Discussion

7.1. Climate Hazards, Risk Appraisal, and Role of the Climate Finance Project. Galachipa is vulnerable to natural hazards such as cyclones, storm surges, and river erosion, among others. It was one of the hardest hit upazilas by the 2007 super cyclone SIDR [31]. For the CF HHs, the analysis from Table 5 indicated a significant correlation between cyclone with perceived probability based on previous exposure of the households to cyclones and their perception that they will be affected by cyclones in the future. Table 5 also shows that there is a significant difference between climate finance recipient households and nonrecipients in their correlation between river erosion and perceived probability, indicating that CF HHs were severely affected by river erosion, given that the CF HHs and non-CF HHs were taken from the same study area. A possible reason is the staff of the CF Project may have had a selection bias towards selecting those households who have lost land to river erosion as beneficiaries. Loss of places is a significant risk from climate change for physical loss of land and resources [4]. Furthermore, Table 6 shows that CF HHs had a higher perceived severity than non-CF HHs, which indicates that the CF HHs were sensitised by the climate finance project towards the exposure to climatic events on their lives and livelihoods. Climate change and its risks can be understood through memories of past weather, current experience, and future imaginaries, which are attached to particular places and practices [4].

TABLE 9: Summary of results from statistical tests for CF and non-CF models for overall risk appraisal.

	CF HHs	Non-CF HHs
Number of observations	240	120
Model	10	8
Error	229	111
Corrected total	239	119
<i>F</i> value	15.16	6.30
<i>P</i> value	<.001	<.001
Root MSE	52.470	41.537
Dependent mean	142.163	112.350
Coefficient of variance	36.908	36.971
<i>R</i> -square	0.398	0.312
Adj <i>R</i> -square	0.372	0.263
Durbin-Watson <i>D</i>	1.420	1.375

The CF HHs were trained through a household adaptation plan to interpret the exposure they were facing and identify adaptation measures. The climate finance project organised exchanges between the households on the effects on climate change on their households and the precautionary measures they take, thus building awareness within the wider social circle of the households. As argued by Granderson, discourses play a significant role in how climate change and its risks are interpreted and made meaningful for communities [4]. Furthermore, climate finance supported the development of consensus and of a common understanding within the households on how to adapt. According to Granderson, responses required the adoption of a particular vision of the future, the course of action rather than another [4], and an understanding of sharing common resources and labour between the households to adapt.

7.2. Household Size. The estimated coefficient for overall risk appraisal was statistically positive and highly significant for household size, indicating that overall risk perception increases with more household members. From the household profile in Table 3, it can be seen that the average household size of the surveyed household is 4.07 and 4.27 for CF and non-CF HHs, respectively, while the Upazila average is 4.5 people per household. The possible reasons of higher risk perception may be due to the awareness that evacuated household members during climatic events leads to higher consumption costs borne by members during and after climatic effects when resources and commodities are scarce as well as adaptation costs in the future.

7.3. Income. Table 10 shows that as income increased, the overall risk perception of both the CF and non-CF households decreased. Results from this research are consistent with the findings of Alauddin and Sarker that higher-income households engaged in adaptive measures and undertook more associated risks [32]. The study also showed that risk appraisals to production, physical health, and income dimensions received greater priority while farmers paid less attention to risks to happiness and social relationships [13]. Sociodemographic characteristics like farm experience,

TABLE 10: Multiple linear regression results for CF and non-CF models for overall risk appraisal.

Independent variables	Parameter estimate	CF		Non-CF		
		Standard error	P value	Parameter estimate	Standard error	P value
HH size	6.251	2.387	0.009	—	—	—
Income	−0.003	<0.001	0.002	−0.004	0.002	0.023
Immobile assets	8.169	1.438	<0.001	8.649	2.165	<0.001
Productive assets (livestock, etc.)	1.882	0.921	0.042	3.310	1.210	0.007
Participation in self-help groups, producer group, DMC, cooperatives	−14.806	4.029	<0.001	—	—	—
SISCH: information on climate change from social circle, i.e., relatives/neighbours/friends/community	—	—	—	−7.285	2.815	0.011
Support from social safety net	23.182	7.411	0.002	21.881	8.385	0.010
Monetary/in-kind support from social circle (relatives, friends, neighbours, self-help groups) for adaptation responses	−15.206	7.325	0.039	—	—	—
Financial support from govt. for adaptation responses	18.830	7.547	0.016	—	—	—
Financial support from NGOs (cash, materials, labour costs, advisory services) for adaptation responses	—	—	—	39.503	13.963	0.006

education, and income level are the most significant factors in increasing the likelihood of farmers' adaptation practices [33]. The inverse association between income and overall risk appraisal may be due to higher income; the households perceive less risk as they engage more in adaptation measures and ascertain that they are in a better position to deal with the impacts of climate change.

Findings from the study, as seen in Table 3, also revealed that the CF HHs had a higher average income than the non-CF HHs and had an increase in assets and livestock received from the CF interventions. However, more assets expanded the risk of losing the assets they have gained through the CF intervention. Perceived probability, production, physical health, and income are the essential dimensions farmers perceive to be threatened by climate change [13]. A negative and significant association was observed between overall risk and income and involvement in social circles for overall risk appraisal. This may indicate that social circles affect the spending behaviour of households towards engaging in adaptation measures, resulting in a decrease in income and a simultaneous decrease in overall risk appraisal.

7.4. Immobile and Productive Assets. Table 10 shows that an increase in immobile assets, in terms of land, increases overall risk perception of CF and non-CF households alike. Furthermore, Table 10 also indicates a positive and highly significant association is observed between risk appraisal and productive assets in terms of livestock, poultry, agricultural equipment, and fisheries equipment for CF HHs, while for non-CF the association is highly significant. A considerable proportion of the households have been affected by river erosion and are landless; therefore, this explains the high-risk perception between overall risk perception and immobile assets. Furthermore, Vatsa argues that assets play a critical role in risk situations, and households try to resist and cope with adverse consequences of disasters and other

risks through the assets that they can mobilise in the face of shocks [34]. However, if immobile assets are affected, then the households lose their ability to cope with the effects of climatic events.

However, Islam et al. argue that a household's involvement in a diverse set of income-generating livelihood activities or strategies reduces the vulnerability of the household [25]. Income-generating activities provide households with additional income in addition to their main source of income and support in having savings and investing in building assets. Assets help in engaging in activities to address the household vulnerability. While people from different occupations are affected differently, farmers, pastoralists, and fishers are especially affected by climate change as they rely on natural resources and are, at the same time, exposed to meteorological events as well. Most decisions by farmers to adapt to climate change vary directly with livestock ownership since it serves as a store of value and encourages adaptation to climate change [32].

7.5. Participation in Social Circles. As shown in Table 10, results demonstrate increased participation in social circles causes a highly significant decrease in the overall risk appraisal of household, especially for the non-CF HHs. As hypothesised by Le Dang et al., social discourse is hypothesised to affect risk perception and adaptation assessment [13]. In fact, social capital facilitates access to a broader source of information [35]. The involvement in the social circle gives the households a better support system to gain information and even jointly face the different climatic events as social circles can act as sources of financial support and even interpersonal relationships, such as kinship networks, social obligations, trust, and reciprocity, mobilise capacity directly by enabling material responses to climate hazards or indirectly via institutional modifications [4]. Islam et al. have derived similar findings [25]. The non-CF

households' ability to cope and adapt was constrained because of their lack of participation in community organisations or the absence of community organisations as a whole, indicating that social relationships received less attention [36] from non-CF HHs.

7.6. Information on Climate Change from the Social Circle. Access to information from the social circle has a significant impact on the overall risk appraisal of non-CF HHs, as shown in Table 10. From Table 3, it is seen that around 83.3% of the non-CF HHs do not engage in any social groups. Therefore, information received from the social circle on climate change informed the households on the exposure of climate change and could have prepared accordingly, thus decreasing their risk appraisal. Information and discussion, therefore, can influence perception [13]. Information from the social circle could also have given the non-CF households a better understanding of how to interpret the information and also explore new ways of adapting from their social circle, also contributing to a decrease in the overall risk appraisal. However, other scholars have found that farmers who believe that climate change is happening and influencing their family's lives perceive higher risks in most dimensions [13].

7.7. Support from Social Safety Nets and Financial Support from Government and NGOs. The regression analysis of social safety net programmes under Table 10 illustrated a positive and highly significant relationship with overall risk appraisal for CF HHs and a positive and significant relationship for non-CF HHs. Social protection or safety net programs assist individuals, households, and communities in managing better a wide range of risks that leaves people vulnerable [34]. One of the reasons for this could be that these programs deal with both the deprivation and vulnerability of the poorest people; thus, when these programmes supported the households, they perceived themselves being at risk. Similarly, the CF HHs perceive significant and positive risk, when they received support from the government, as the assistance is aimed towards people who are at risk and need support. Furthermore, as seen in Table 10, a relationship between financial support from NGOs for adaptation measures and overall risk appraisal for non-CF HHs is evident. Possible reasons could be that when they receive the support for adaptation measures from government or NGOs, they believe that they are at risk.

7.8. Monetary/In-Kind Support from Social Circle (Relatives, Friends, Neighbours, and Self-Help Groups) for Adaptation Measures. As seen in Table 10, a negative and highly significant relationship is evident between monetary support and in-kind support from social circle for the CF HHs and overall risk appraisal. Instead of being at risk of facing the effects of climate change alone, the CF HHs could rely on getting support from their social circle. While risk appraisal played a crucial role in motivating the household to explore adaptation options which are crucial and which they can

afford, households also could share common resources within their social circle to adapt, which did not cause them to incur additional costs and yet benefit from them. Correspondingly, support from the social circle increases the effectiveness of climate finance through enhancing the utilisation of the household's own resources towards contributing towards adaptation needs of the social circle.

8. Conclusions

This study conducted a comparative analysis between CF and non-CF HHs regarding the anticipated climatic events and the severity of the events on their lives as well as factors which influenced their risk appraisal. Both CF and non-CF HHs resided in the same geographical and meteorological conditions and dealt with the same climatic events. Both groups anticipated climatic events such as river erosion and cyclones, among others, occurring in the future. However, the findings of the study indicated that CF HHs expected higher severity of climatic events on the various dimensions of their households such as housing, income, crops, equipment, among others. This result suggests that the CF HHs are more aware of the consequences of climate change and therefore engaged in more adaptation measures than non-CF HHs. Barrett had similar findings in a study in Malawi of adaptation finance-assisted villages [6]. Programs that provide technical assistance or compensation to change practices may be a positive opportunity for agricultural communities to address climate change and help offset the transaction costs associated with changing practices [25]. This analysis implies that climate finance support informed the households about the risks that they were facing, assisted them in exploring adaptation options and engaging in them. Awareness and training sessions, climate information, increased accessibility to public extensions services, and exchange within the social groups about the effects of climate change affect the potential severity or effect of climate change on the households.

Furthermore, several factors influenced the risk appraisal of the CF and non-CF HHs, respectively. The socioeconomic conditions of the households played a key role in the risk appraisal. Particularly, household size increased the risk assessment for CF HHs. While the increase in income caused a decrease in the risk assessment, increase in assets caused an increase in the risk perception of the households. These results could indicate that households do not have stable socioeconomic conditions yet.

The benefits by strengthening the social circle of the CF HHs under the climate finance project became evident as participation in the different groups and the monetary/in-kind support from the social circle resulted in a decrease in overall risk appraisal. On the contrary, Le Dang et al. argue that social circles play a significant role in facilitating decisions on using adaptation measures based on information obtained from friends, relatives, and neighbours, which increases the overall perceived risk [13].

Furthermore, awareness is not sufficient for households to engage in adaptation measures as the households were extremely poor and lacked adequate resources to adapt. In

fact, households, which intend to reduce the risks associated with climate change and have the resources or access to resources needed to make the appropriate changes, are generally more resilient and have a greater capacity to adapt [37]. Information variables can increase or decrease risk appraisals. Therefore, information from social circles is significant for non-CF HHs as they are less engaged in social circles and value the information on climate change received.

Different sources of external finance such as from the government, social safety net programmes, or financial support from NGOs, all increased the risk appraisal of the households. One of the reasons could be that finance is mainly provided to the households if they are at risk. Secondly, since the financial support is limited, the households have to examine the dimensions that are at risk from climatic events, hence making them more aware of the risks, which increases their risk appraisal correspondingly. Furthermore, this causes the households to explore adaptation options which are crucial and which they can afford to address those dimensions of the households that are at risk. Thus, risk appraisal may increase the effective utilisation of external climate finance, and the households own resources for adaptation measures.

This study tried to address the knowledge gap on the effect of climate finance on risk appraisal at the local level. The findings of this research reinforce the pattern of the inadequacy of climate finance to meet the local needs of the most vulnerable communities. At the global level, adequate funding is not provided to the developing countries by the Annex 1 countries, which include the industrialized countries and members of the OECD (Organisation for Economic Co-operation and Development) in 1992, plus countries with economies in transition (the EIT Parties), including the Russian Federation, the Baltic States, and several Central and Eastern European States. When climate finance reaches the national level, a significant proportion was allocated on hard components of adaptation such as infrastructure and recurring costs such as staff salaries. At the local level, limited climate finance remains actually to meet the adaptation needs of the households.

A dilemma remains in the pursuit of channelling climate finance support to the households. This study possibly identified a selection bias by the project team towards including people affected by river erosion as beneficiary. This could have caused other households, who were similarly vulnerable, to be not chosen as a beneficiary of the CF project as they were not affected by river erosion. In addition, some households could try to obtain more support from different projects if they have a better relationship with the project teams. Moreover, inequality could increase for the poorest and marginalised groups if climate finance does not reach them but is channelled towards the influential people who can exert more pressure to access the funding.

This research provides insights for policymakers, development partners, researchers, and practitioners that climate financing needs to be available for the exposed and marginalised households and that localised adaptation measures need to be initiated to support the affected

households. Mechanisms to locally generate and integrate customised and contextualised adaptation measures into planning processes should be studied further. How to channel the climate finance into reaching the vulnerable population in the coastal region of Bangladesh so that inequality is not increased and marginalisation is avoided was not covered under this research and may be explored further. Finally, future research may be conducted on the costs of various adaptation actions together with a cost-benefit analysis which may contribute towards the future adaptation implementation at the local level.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Disclosure

This article is an outcome of the research study of Ms Firdaus Ara Hussain for her PhD at the Asian Institute of Technology.

Conflicts of Interest

The authors declare that there are no potential conflicts of interest concerning the research, authorship, and publication of this paper.

References

- [1] L. Jones and T. Tanner, "Subjective resilience: using perceptions to quantify household resilience to climate extremes and disasters," *Regional Environmental Change*, vol. 17, no. 1, pp. 229–243, 2017.
- [2] T. Grothmann and A. Patt, "Adaptive capacity and human cognition: the process of individual adaptation to climate change," *Global Environmental Change*, vol. 15, no. 3, pp. 199–213, 2005.
- [3] I. A. Rana and J. K. Routray, "Actual vis-à-vis perceived risk of flood prone urban communities in Pakistan," *International Journal of Disaster Risk Reduction*, vol. 19, pp. 366–378, 2016.
- [4] A. A. Granderson, "Making sense of climate change risks and responses at the community level: a cultural-political lens," *Climate Risk Management*, vol. 3, pp. 55–64, 2014.
- [5] R. Barr, S. Fankhauser, and K. Hamilton, "Adaptation investments: a resource allocation framework," *Mitigation and Adaptation Strategies for Global Change*, vol. 15, no. 8, pp. 843–858, 2010.
- [6] S. Barrett, "Local level climate justice? Adaptation finance and vulnerability reduction," *Global Environmental Change*, vol. 23, no. 6, pp. 1819–1829, 2013.
- [7] J. T. Roberts and R. Weikmans, "Postface: fragmentation, failing trust and enduring tensions over what counts as climate finance," *International Environmental Agreements: Politics, Law and Economics*, vol. 17, no. 1, pp. 129–137, 2017.
- [8] M. Sarraf, S. Dasgupta, and N. Adams, *Bangladesh Development Series: The Cost of Adapting to Extreme Weather Events in a Changing Climate*, World Bank, Washington, DC, USA, 2011.
- [9] H. Brammer, "Bangladesh's dynamic coastal regions and sea-level rise," *Climate Risk Management*, vol. 1, pp. 51–62, 2014.

- [10] S. Huq, S. M. M. H. Khan, and M. Shamsuddoha, *The Bangladesh National Climate Funds—A Brief History and Description of the Bangladesh Climate Change Trust Fund and the Bangladesh Climate Change Resilience Fund*, LDC Paper Series, Bangladesh, 2012.
- [11] B. Biagini, R. Bierbaum, M. Stults, S. Dobardzic, and S. M. McNeeley, "A typology of adaptation actions: a global look at climate adaptation actions financed through the global environment facility," *Global Environmental Change*, vol. 25, no. 1, pp. 97–108, 2014.
- [12] E.-L. Sundblad, A. Biel, and T. Gärling, "Cognitive and affective risk judgements related to climate change," *Journal of Environmental Psychology*, vol. 27, no. 2, pp. 97–106, 2007.
- [13] H. Le Dang, E. Li, I. Nuberg, and J. Bruwer, "Farmers' perceived risks of climate change and influencing factors: a study in the Mekong Delta, Vietnam," *Environmental Management*, vol. 54, no. 2, pp. 331–345, 2014.
- [14] Butardo-Toribio, M. Zita, and E. R. Tenefrancia, "Land, livelihood, Poverty: assessment of selected socio-economic factors influencing community adaptive capacity to climate change," *COMCAD Arbeitspapiere Working Paper*, vol. 94, 2011.
- [15] N. Amerasinghe, J. Thwaites, G. Larsen, and A. Ballesteros, *The Future of the Funds: Exploring the Architecture of Multilateral Climate Finance*, World Resources Institute, Washington, DC, USA, 2017.
- [16] F. Lamperti, A. Mandel, M. Napoletano et al., "Towards agent-based integrated assessment models: examples, challenges, and future developments," *Regional Environmental Change*, vol. 19, no. 3, pp. 747–762, 2019.
- [17] S. Colenbrander, D. Dodman, and D. Mitlin, "Using climate finance to advance climate justice: the politics and practice of channelling resources to the local level," *Climate Policy*, vol. 18, no. 7, pp. 902–915, 2018.
- [18] Government of Bangladesh, *Climate protection and development finance division ministry of finance government of the people's republic of Bangladesh*, Government of Bangladesh, Dhaka, Bangladesh, 2017.
- [19] M. Aatur Rahman and S. Rahman, "Natural and traditional defense mechanisms to reduce climate risks in coastal zones of Bangladesh," *Weather and Climate Extremes*, vol. 7, pp. 84–95, 2015.
- [20] M. M. Q. Mirza, "Climate change, flooding in South Asia and implications," *Regional Environmental Change*, vol. 11, no. S1, pp. 95–107, 2011.
- [21] B. Mallick and J. Vogt, "Population displacement after cyclone and its consequences: empirical evidence from coastal Bangladesh," *Natural Hazards*, vol. 73, no. 2, pp. 191–212, 2014.
- [22] M. S. Hossain, J. A. Dearing, M. M. Rahman, and M. Salehin, "Recent changes in ecosystem services and human well-being in the Bangladesh coastal zone," *Regional Environmental Change*, vol. 16, no. 2, pp. 429–443, 2016.
- [23] M. R. Karim and A. Thiel, "Role of community based local institution for climate change adaptation in the Teesta riverine area of Bangladesh," *Climate Risk Management*, vol. 17, pp. 92–103, 2017.
- [24] S. S. Hutchins, C. Brown, R. Mayberry, and W. Sollecito, "Value of a small control group for estimating intervention effectiveness: results from simulations of immunization effectiveness studies," *Journal of Comparative Effectiveness Research*, vol. 4, no. 3, pp. 227–238, 2015.
- [25] M. M. Islam, S. Sallu, K. Hubacek, and J. Paavola, "Vulnerability of fishery-based livelihoods to the impacts of climate variability and change: insights from coastal Bangladesh," *Regional Environmental Change*, vol. 14, no. 1, pp. 281–294, 2014.
- [26] M. T. Niles, M. Lubell, and V. R. Haden, "Perceptions and responses to climate policy risks among California farmers," *Global Environmental Change*, vol. 23, no. 6, pp. 1752–1760, 2013.
- [27] H. B. Truelove, A. R. Carrico, and L. Thabrew, "A socio-psychological model for analyzing climate change adaptation: a case study of Sri Lankan paddy farmers," *Global Environmental Change*, vol. 31, pp. 85–97, 2015.
- [28] S. van der Linden, "The social-psychological determinants of climate change risk perceptions: towards a comprehensive model," *Journal of Environmental Psychology*, vol. 41, pp. 112–124, 2015.
- [29] J. J. Hyland, D. L. Jones, K. A. Parkhill, A. P. Barnes, and A. P. Williams, "Farmers' perceptions of climate change: identifying types," *Agriculture and Human Values*, vol. 33, no. 2, pp. 323–339, 2016.
- [30] United Nations, "Financing development gaps in the countries with special needs in the asia-pacific region," in *Proceedings of the Third International Conference on Financing for Development*, Addis Ababa, Ethiopia, July 2015.
- [31] U. Kulatunga, G. Wedawatta, D. Amaratunga, and R. Haigh, "Evaluation of vulnerability factors for cyclones: the case of Patuakhali, Bangladesh," *International Journal of Disaster Risk Reduction*, vol. 9, pp. 204–211, 2014.
- [32] M. Alauddin and M. A. R. Sarker, "Climate change and farm-level adaptation decisions and strategies in drought-prone and groundwater-depleted areas of Bangladesh: an empirical investigation," *Ecological Economics*, vol. 106, pp. 204–213, 2014.
- [33] M. N. Uddin, B. Lei, M. A. Sarker, M. Z. Rahman, and M. M. Hasan, "Role of a coastal NGO in attaining climate resilience in Bangladesh," *American Journal of Climate Change*, vol. 7, no. 2, pp. 187–203, 2018.
- [34] K. S. Vatsa, "Risk, vulnerability, and asset-based approach to disaster risk management," *International Journal of Sociology and Social Policy*, vol. 24, no. 10-11, pp. 1–48, 2004.
- [35] G. M. M. Alam, K. Alam, and S. Mushtaq, "Climate change perceptions and local adaptation strategies of hazard-prone rural households in Bangladesh," *Climate Risk Management*, vol. 17, pp. 52–63, 2017.
- [36] H. Le Dang, E. Li, I. Nuberg, and J. Bruwer, "Farmers' assessments of private adaptive measures to climate change and influential factors: a study in the Mekong Delta, Vietnam," *Natural Hazards*, vol. 71, no. 1, pp. 385–401, 2014.
- [37] W. Ullah, T. Nihei, M. Nafees, R. Zaman, and M. Ali, "Understanding climate change vulnerability, adaptation and risk perceptions at household level in Khyber Pakhtunkhwa, Pakistan," *International Journal of Climate Change Strategies and Management*, vol. 10, no. 3, pp. 359–378, 2017.