https://doi.org/10.51483/IJARP.2.1.2022.15-32 ISSN: 2788-5046

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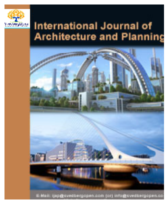

Research Paper **Open Access**

Do Community Based Urban Risk Reduction and Development Policies Converge?

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Article Info

Volume 2, Issue 1, March 2022
Received : 17 November 2021
Accepted : 19 February 2022
Published : 05 March 2022
doi: 10.51483/IJARP.2.1.2022.15-32

Abstract

United Nations Urban Sustainable Development Goal (USDG) envisages "to make cities and human settlements inclusive, safe, resilient and sustainable". For a resilient and safe city, people-oriented developmental plans and risk reduction policies exercise a significant role. To strengthen disaster risk resilience of urban communities, USDG may adopt Community Based Disaster Risk Management (CBDRM) principles for sustainable development of cities and human settlements. However, in reality, the application of CBDRM is found isolated and limited to a few sections as common people are rarely made part of development goal planning and implementation. On the contrary, the top-down approach is often adopted where only institutional policymakers, administrators and experts are involved thereby alienating people who otherwise should have been at the heart of decision making. Thus, arises the need for convergence in administrative and risk governing policies with CBDRM principles for the better attainment of urban risk reduction and development results. Millennium Development Goals foster people based development and environmental sustainability. In this paper, a case study based on CBDRM principles is reported for Silchar Town in Assam, India. Institutional urban risk reduction and administrative plans and policies of government are explored to assess their existing status and check whether there is any convergence with people based CBDRM principles at the grassroots level or are discreet. This study attempts to capture participatory opinion of target people representing several communities of the study area through concordance analysis of variables determine risk due to earthquake, flood, urban flood and fire hazards while predictive urban disaster risk analysis by ANN for two hazards viz. earthquake and urban flood only are reported to which the urban population of the town are more vulnerable and exposed.

Keywords: *Disaster, Risk, Urban, Community, Policies, Planning*

1. Introduction

Disaster Risk Reduction (DRR) approaches and frameworks purport to vulnerability reduction and resilience building of communities. But "these frameworks often fail to capture antecedent social factors that occur at local levels or

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account for vulnerability or resilience of natural environment" (Cutter *et al.*, 2008). Li-Ju Jang has report the "need to understand what helps survivors to function well during and after disasters and how to incorporate this knowledge into new practice strategies that foster survivors 'strengths and resilience" (Jang, 2009). Several national climate change adaptation plans incorporate the crucial role of local communities in DRR with the rising risk of extreme events and disasters. Meticulous implementation of existing institutional DRR plans bereft of expectations of target people on disaster resilience remains questionable. Thus, understanding and analyzing the community's perception of risk determining factors is necessary for strengthening the coping and adaptive capacity of at-risk communities.

Studies suggest that more than two-third of the world's population shall live in urban settlements by 2050, thereby adding about 2.5 billion people to the current 4 billion urban residents (United Nations, 2014a). Creating new infrastructure for the rising urban population, maintenance of critical environmental ecosystems, mitigation of climate change risk, promoting economic growth and ensuring social justice are real challenges for policymakers and administrators. Cities are locales of huge energy consumption and producers of waste. Cities are sites of bulk greenhouse gas emission which is connected to problems of urban development and sustainability. Lately, cities are hot spots of global environmental change (Fitzgerald, 2010; Hoornweg *et al.*, 2011; and Parnell, 2016). Clean energy technologies, efficient service provision and proper land use can reduce waste-related hazards (Fitzgerald, 2010). Adoption of recycling processes, green technologies, smart land-use and proper transportation planning may transform urban hubs into greener and cleaner locations (Troy, 2012; Ferrao and Fernandez, 2013). The skilled populace in cities is identified as feeders to innovation incubators that can help to mitigate the problems and challenges (Johnson, 2010; and Hoornweg *et al.*, 2011). Environmental sustainability is one of the most important components of the Millenium Development Goals (MDGs). However, challenges exist both within the framework and implementation of MDG (Fehling *et al.*, 2013). Despite the recommendations of the task force, the participation of the urban poor is rare in interventions meant for them (Hasan *et al.*, 2005). Local governments themselves do not often participate in the MDG process. Ironically, they do not have the resources and capacity necessary to achieve the MDGs at ground level.

CBDRM is significant as the impact of disaster risks on the community are increasing (Krummacher, 2014; and UNDP, 2016). Local communities are first responders in disaster risk mitigation. Research over the years reveals that the top-down model of disaster risk reduction often cannot meet the needs of at-risk communities. Involvement of communities in the CBDRM approach is of utmost importance as people are best aware of their needs and realities (Shaw *et al.*, 2012; and Krummacher, 2014). Frameworks and guidelines of government in disaster risk management are exhaustive and at times cryptic. Risk plans and programs are institutional, rigid and do not offer scope for people-centric disaster risk management. It is observed that plans at the state, district and city level in India are mainly top-down, response and relief based confined to preparedness and capacity building of institutional responders. Potential victims who are first-line responders find these institutional plans abstract and difficult to understand and have doubtful relevancy at the grass-root level. There exists a gap in the state of affairs between government-sponsored disaster risk management activities on prevention, mitigation, response, relief and rehabilitation vis-a-vis actual needs of the community. DM Act, 2005 and government guidelines there from are the legal framework of risk governance by the local authority. These frameworks are standalone and are not integrated with CBDRM principles. The disaster management policy of a country is widely influenced by community-based risk reduction approaches (Bongo, 2003), thus, the rigid institutional nature of DM policies need to be altered. The importance of community participation in formulating DM plans and programs is now acknowledged by policymakers, risk administrators and experts. Local-level risk policies when integrated with people's knowledge and experience on prevention, protection, mitigation and rehabilitation yield better outcomes in disaster risk management (Marschiavelli, 2008). Government-sponsored disaster literacy programs of people to build a disaster-resilient community (Takeuchi *et al.*, 2011). Community involvement reduces the gap between government and people while strategizing disaster risk management policies (Raungratanaamporn *et al.*, 2014). CBDRM approach enables communities to prevent and mitigate disaster risks better (Chhoun, 2016). Training of community members on systems and strategies for community-based preparedness and capacity building enables local disaster risk management programs to gain ownership among people. CBDRM approach leverage the capacity of the at-risk population in undertaking risk mitigation measures Pineda (2012).

In this paper, a case study of Silchar Town in Assam, India applying CBRDM methodology is undertaken to explore existing urban risk governing policies of the government and to examine whether there exists a convergence in risk reduction and development plans at the community level or are discreet.

2. Existing Urban Plans and Programs for Disaster Risk Reduction

This section presents both institutional and community based Disaster Risk Management plans and programs of the Government of Assam for urban areas. Data for review is scattered and is sourced from several government departments. Several documents and records of the Assam State Disaster Management Authority, District Disaster Management Authority, Cachar and Silchar Municipal Office that are online, offline, published and unpublished but available in the public domain are the source of information for review. Secondary information is collected from offline and online published government reports, documents, records, journals, booklets, repositories etc. Personal discussion with various professionals, stakeholders and line departments configured the primary data. The State Disaster Management Plan, District Disaster Management Plan (DDMP) and City Disaster Management Plan (CDMP) mention community participation as functionality but proper consolidated CBDRM compliant plans and programs of the government of Assam at the state, district and city level are missing. Government frameworks and guidelines on Disaster Risk Management is elaborate. Initiatives of the Assam State Disaster Management Authority in the domain of Disaster Risk Management are elaborative and explicable as observed from a review of pertinent documents. CBDRM approaches are observed to be tested in a few sporadic projects, studies and programs of some at-risk communities of the state involving NGOs and knowledge institutions. Three urban locales of Assam, i.e. Silchar Town, Guwahati City and Dibrugarh Town of Assam and their respective CDMP along with the Urban Risk Reduction Plan are examined. They reviewed plans and allied programs are found to be institutional with practically less focus on people based disaster risk management. It is observed that most disaster risk management plans at the state, district and city level are top-down, response and relief oriented confined to preparedness and capacity building of institutional response agencies. To create awareness on hazard-specific risk preparedness and capacity building for mitigation and prevention, a few programs and initiatives through community engagement by Community Disaster Risk Reduction (CDRR) are found to be sponsored by the government of Assam through ASDMA, respective DDMA and nodal agencies by involving disaster risk response officials, experts, knowledge institutions, NGOs, social organizations, media personnel, focal groups and community members. It is observed that in the year 2012 DDMA, Cachar performed only three programs while it was conducted about 16 programs during the period 2016 to 2019. Despite Covid-19 pandemic in the year 2020-2021, 15 such programs including community drills are planned by DDMA, Cachar. It is also observed that the majority of programs undertaken by DDMA, Cachar are directed towards building disaster risk capacity and preparedness for schools.

3. The Study Area and Methodology

The study is carried out using exploratory and inferential case-based disaster risk reduction using the participatory research technique for Silchar Town in Assam, India. Silchar in Cachar district is an emerging urban locale located in south Assam. It lies between 92°24" E and 93°15" E longitude and 24°22" and 25° 8" N latitude. The town has been inflicted by natural disasters such as earthquakes and riverine floods due to its geographical location. Moreover, it is also vulnerable to artificial hazards like urban flood road accidents and fire due to rapid unplanned urbanization, poor public infrastructure, inadequate solid waste management, improper risk governance by local authorities, high population density to name a few. The town lies in Zone V, the zone with the highest seismic risk. Silchar has a history of being affected by earthquakes since 1548 with cases of recurrent earthquakes recorded over subsequent years (Silchar Atlas, 2014-15). According to District Disaster Management Authority (DDMA), Cachar, Assam, most of the earthquakes had a magnitude of 7 and above with as high as 8.7 in 1950 with epicentre in the vicinity of Assam, thereby causing direct or indirect damage to Silchar Town. The town also suffers from the problem of urban flood due to waterlogging during rainy seasons and riverine flood due to inundation of flood plains by the river Barak and its tributaries. The intricate river system makes it suspectable to flood. The town witnessed floods in 1986, 1991 and 2004.

The target population considered in the study are people of Silchar town residing in the existing 28 municipal wards. Additional dummy ward listed as ward 29 in the study is defined as an area in the immediate periphery of 1 km of the defined municipal area. A population of 200,000 is considered the universe of the study with around 180,000 people residing within 28 municipal wards and the remaining 20,000 in the periphery of 1 km as obtained by corroborating with government census data 2010 and voter list 2015-17. 1500 people representing as an individual, member of the family, ward and the Silchar Town per se forming the urban community are targeted initially. Data collection is carried out using the participatory research technique of CBDRM through semi-structured interviews. Field Survey cum Focus Group

Interview of each member is conducted for obtaining data. Each group consisted of 30 members on average and 22 such Focus Group Interviews were conducted, thereby obtaining 660 respondents. Out of 660 respondents, 600 respondents are retained based on the missing value test. Guided Personal Interviews are carried out on 840 respondents from 29 wards. Each ward is considered as a stratum from which respondents are randomly selected with an average of 30 people from each ward. Out of these 840 respondents, 301 respondents are retained based on the missing value test. Consequently, a sample size of 901 is considered in the present study.

4. Experimental Results and Analysis

Concordance analysis is performed on responses on factors of disaster risk, capacity, environmental degradation and local weather variability. Through concordance analysis, the level of agreement/disagreement of responses on determining parameters is considered to suggest an alternative Disaster Risk Management Plan for Silchar Town. 40 variables and sub-variables are taken for ward-wise analysis to assess agreement/disagreement of responses on capacity building parameters of Silchar Town, using IBM SPSS21. These factors are: topography of ward classified into five sub-variables, expressed by variable names *Wtopo1'*, *Wtopo2'*, *Wtopo3'*, *Wtopo4'* and *Wtopo5'*, major land use of the ward classified into five sub-variables *Wlndusebld1'*, *Wlndusebld2'*, *Wlndusebld3'*, *Wlndusebld4'* and *Wlnduseoth1*, housing density of the ward expressed by variable *Whouden1*, presence of water bodies in ward by *Wwtrbod1*, which is further classified in two sub-variables given by *Wwtrbodret1'* (water bodies with retaining walls) and *Wwtrbodret2'* (water bodies without retaining walls), distance of the ward from river Barak denoted by *WdisB1*, availability of hospitals in ward categorized into five sub-variables given by *Whospy1', Whospy2', Whospy3'* and *Whospy4'* and *Whospn1*, emergency medical service providers in ward classified into seven sub-classes given by *Wemgncysp1'*, *Wemgncysp2'*, *Wemgncysp3'*, *Wemgncysp4'*, *Wemgncysp5'*, *Wemgncysp6'* and *Wemgncysp7'*, drinking and other purpose water source in ward categorized into five variables represented by *Wwtrsrc1', Wwtrsrc2'*, *Wwtrsrc3'*, *Wwtrsrc'4* and *Wwtrsrc5'*, power supply availability in all areas of ward by *Wpwrspp1*, relief camp availability in ward *Wrlfcmp1* and availability of facilities/support in ward classified into seven sub-variables *Wfacli1'*, *Wfacli2'*, *Wfacli3'*, *Wfacli4'*, *Wfacli5'*, *Wfacli6'* and *Wfacli7'*. Implications of each variable are presented in Appendix.

Tables 1(a) and 1(b) record concordance analysis result in terms of the sample, Kendall's W test, Pearson's chi-square test, degrees of freedom and asymptotic significance on capacity building factors. Concordance coefficient measured by Kendall's *W* (ranges from 0 to 1), 0 imply perfect disagreement, and 1 imply complete agreement. In the present study, 0 to 0.25 indicate very low agreement, 0.25 to 0.5 imply low agreement, 0.5 to 0.75 imply medium agreement while 0.75 to 1 imply high agreement of responses. From Table 1(a) and 1(b), moderate or medium agreement of judgements is observed in all wards except wards 6, 12, 13, 17, 20, 24, 25 which demonstrate high agreement and ward 26 shows very low agreement. Kendall's W values from the experiment reject H_0 the null hypothesis (*there is no agreement of test variables*) in all wards except ward 26 at $p < 0.05$. Chi-square values for each ward with degrees of freedom = 40 and at $\alpha = 0.05$ is observed to be above critical value rejecting the null hypothesis (*there is no association among test variables*).

Table 1(a): Ward-Wise Concordance Analysis on Capacity Factors of Silchar Town

Ward No.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
N	30	30	30	30	30	30	30	30	30	30	30	30	30	30	30	30
Kendall's W	0.697	0.661	0.566	0.678	0.597	0.794	0.736	0.827	0.735	0.661	0.724	0.794	0.810	0.741	0.729	0.721
Chi-square	278.639	264.238	226.283	271.189	238.743	317.701	294.382	330.827	294.006	264.591	289.485	285.788	324.058	296.271	291.511	288.274
df	40	40	40	40	40	40	40	40	40	40	40	40	40	40	40	40
Asymp. Sig.	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Table 1(b): Ward-Wise Concordance Analysis on Capacity Factors of Silchar Town

Ward No.	17	18	19	20	21	22	23	24	25	26	27	28	29
N	30	30	30	30	30	30	30	30	30	30	30	30	61
Kendall's W	0.789	0.697	0.633	0.805	0.670	0.739	0.715	0.754	0.754	0.212	0.735	0.785	0.576
Chi-square	315.432	278.693	253.260	322.052	267.873	295.554	286.142	301.495	301.495	264.965	293.881	314.088	484.034
df	40	40	40	40	40	40	40	40	40	40	40	40	40
Asymp. Sig.	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Variables *DWavrain3', DWavtemp3', Dwextr3h1, Dwextr3c1, Dwextr3hu1, Dwextr3rain1, Dwppleff1', Dwppleff2', Dwppleff3', Dwppleff4', Dwppleff5', Dwppleff6', Dwfldlvl1, Dwdurfld1, Dwstrngtr1, Dwpplexpf1, Dwpplexpeq1, Dwpplexpfr1, Dwpplexpuf1, Dwpplklldf1, Dwpplklldeq1, Dwpplklldfr1, Dwpplkllduf1, Dwinjrd1f, Dwinjrdeq1, Dwinjrdfr1, Dwinjrduf1, Dwrtrnprdf1, Dwrtrnprdeq1, Dwrtrnprdfr1, Dwrtrnprduf1, Dwenfaq1, Dwenfwq1, Dwenflq1, Dwenfveg1, Dweneqaq1, Dweneqwq1, Dweneqlq1, Dweneqveg1, Dwenfraq1, Dwenfrwq1, Dwenfrlq1, Dwenfrveg1, Dwenufaq1, Dwenufwq1, Dwenuflq1* and *Dwenufveg1* are used to assess agreement/disagreement of ideas of respondents on disaster risk, local weather variability and environmental degradation factors such as average annual rainfall in last three years, average annual temperature in last three years, extreme hot days in last three years, extreme cold days in last three years, extreme humid days in last three years, extreme rainy days in last three years, people affected in ward by various disasters, flood level in ward, duration of flood in ward, strength of tremor felt in house, number of people exposed to hazard in ward, number of people killed in ward, number of people injured in ward, return period per year of each considered hazard, environmental degradation in ward with respect to air quality, water quality, land quality and vegetation.

From Tables 2(a) and 2(b) medium or moderate agreement on opinions is observed in most wards with the exception in wards 2, 3, 4, 7, 8, 12, 14, 16, 17, 18 and 28 which show high agreement. The null hypothesis (*there is no agreement of test variables*) in all wards at 0.05 is rejected as per Kendall's W values. Pearson's chi-square values with degrees of freedom = 40 and at 0.05 for each ward, point to a rejection of the null hypothesis (*there is no association among test variables*).

Table 2(a): Ward-Wise Concordance Analysis on Disaster Risk and Environmental Factors

Ward No.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
N	30	30	30	30	30	30	30	30	30	30	30	30	30	30	30	30
Kendall's W	0.729	0.767	0.768	0.778	0.691	0.730	0.783	0.756	0.640	0.690	0.707	0.763	0.741	0.772	0.728	0.774
Chi-square	335.238	352.893	353.066	357.898	317.832	335.588	360.263	347.871	265.022	317.264	325.155	351.033	341.049	319.534	334.802	355.964
df	46	46	46	46	46	46	46	46	46	46	46	46	46	46	46	46
Asymp. Sig.	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Table 2(b): Ward-Wise Concordance Analysis on Disaster Risk and Environmental Factors

Ward No.	17	18	19	20	21	22	23	24	25	26	27	28	29
N	30	30	30	30	30	30	30	30	30	30	30	30	61
Kendall's W	0.777	0.792	0.671	0.710	0.677	0.606	0.696	0.698	0.562	0.574	0.681	0.757	0.527
Chi-square	357.603	364.522	308.578	294.040	311.365	278.984	320.362	289.138	206.890	263.973	313.433	348.368	509.223
df	46	46	46	46	46	46	46	46	46	46	46	46	46
Asymp. Sig.	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Further, concordance analysis is performed on parameters such as the number of people exposed, killed and return period per year for the considered hazards. Exposure to the considered hazards is measured by four variables viz. number of people exposed to flood, earthquake, fire and urban flood expressed by variables *Dwpplexpf1, Dwpplexpeq1, Dwpplexpfr1* and *Dwpplexpuf1*.

From Table 3, there is medium agreement amongst respondents on the number of people exposed to flood, earthquake, fire and urban flood. Kendall's W rejects the null hypothesis (*there is no agreement of test variables*) at 0.05. Pearson's chi-square value with degrees of freedom = 3 at 0.05, points to the rejection of the null hypothesis (*there is no association among test variables*), thereby indicating a relationship amongst test variables.

Table 3: Concordance Analysis on Several People Exposed to the Considered Hazards

Test Statistics	
N	901
Kendall's W[a]	0.648
Chi-Square	579.437
df	3
Asymp. Sig.	0.000

Note: [a] Kendall's Coefficient of Concordance.

Similarly, concordance analysis on the number of people killed by considered hazards indicated by four variables such as the number of people killed due to flood, earthquake, fire and urban flood expressed by variables *Dwpplklldf1, Dwpplklldeq1, Dwpplklldfr1* and *Dwpplkllduf1* in the experiment. From Table 4, a very low agreement is observed amongst respondents about the number of people killed due to flood, earthquake, fire and urban flood in Silchar Town. Kendall's W value from the table cannot reject the null hypothesis (*there is no agreement of test variables*) at 0.05 indicating that there is statistically no significant agreement amongst people on test variables. Chi-square value with degrees of freedom = 3 at 0.05, imply null hypothesis rejection (*there is no association among test variables*), thereby demonstrating dependence amongst test variables.

Table 4: Concordance Analysis on Number of People Killed Due to Earthquake, Flood, Urban Flood

Test Statistics	
N	901
Kendall's W[a]	0.026
Chi-Square	23.321
df	3
Asymp. Sig.	0.000

Note: [a] Kendall's Coefficient of Concordance.

Concordance analysis on return period per year for flood, earthquake, fire and urban flood for N = 901, four variables are considered labelled as *Dwrtrnprdf1, Dwrtrnprdeq1, Dwrtrnprdfr1* and *Dwrtrnprduf*1 are considered in the model. Table 5 records the result.

From Table 5, Kendall's *W* reveal a low level of agreement about the return period per year for flood, earthquake, fire and urban flood hazard, consequently not rejecting the null hypothesis (*there is no agreement of test variables*) at 0.05. Chi-square value with df = 3 at 0.05 points to a rejection of null hypothesis (*there is no association among test variables*), implying dependence amongst test variables. It can be said that there is statistically no significant agreement amongst respondents about the return period per year for flood, earthquake, fire and urban flood although the variables are correlated.

Table 5: Concordance Analysis on Return Period per Year for the Considered Hazards

Test Statistics	
N	901
Kendall's W[a]	0.499
Chi-Square	449.534
df	3
Asymp. Sig.	0.000

Note: [a] Kendall's Coefficient of Concordance.

Climate change offers immense challenges to Urban Disaster Risk Reduction (UDRR). Some schools of thought are of the view that climate change can be observed at a global level only and cannot be perceived at local levels. Others opine that global impacts of climate change bear its signature on landforms, water bodies, heat islands etc. at local levels. As per the latter school of thought, local weather variability and extremity factors are analyzed in the present case. Concordance analysis to assess the degree of agreement/disagreement of responses of respondents based on their experience, observations, acquired skills and scientific information on disaster risk reduction and local weather variability factors are carried out. The variables considered for local weather variability and extremity are average annual rainfall, average annual temperature, days of extreme heat, cold, humidity and rainfall in the last three years are labeled as *DWavrain3', DWavtemp3', Dwextr3h1, Dwextr3c1, Dwextr3hu1* and *Dwextr3rain1* respectively. From Table 6 very low agreement amongst people is observed about average annual rainfall, average annual temperature, days of extreme heat, cold, humidity and rainfall in the last three years for the majority of wards while wards 2, 6, 7, 11, 18, 19, 21, 23, 24, 25 and 26 show low-level agreement and wards 5 and 22 show medium level agreement. Kendall's W implies null hypothesis rejection (*there is no agreement of test variables*) at 0.05 concerning wards 5 and 22 while for rest of the wards cannot be rejected as it is statistically significant except forwards 3, 8, 10, 14, 20 and 27. Pearson's Chi-square values with degrees of freedom = 5 at 0.05 are found above a critical value, consequently rejecting the null hypothesis (*there is no association among test variables*) in wards 2, 4, 5, 6, 7, 11, 17, 18, 19, 21, 22, 23, 24, 25, 26 and 29 and is found significant while in remaining wards cannot be rejected demonstrating any correlation in test variables yet found statistically insignificant (Tables 6(a)and 6(b)).

Table 6(a): Ward-Wise Concordance Analysis on Local Weather Variability and Extremity

Ward No.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
N	30	30	30	30	30	30	30	30	30	30	30	30	30	30	30	30
Kendall's W	0.125	0.448	0.200	0.242	0.652	0.470	0.386	0.216	0.134	0.195	0.302	0.218	0.106	0.207	0.156	0.155
Chi-Square	6.268	22.393	10.000	12.087	32.609	23.514	19.310	10.801	6.706	9.744	15.110	10.878	5.304	10.350	7.813	7.727
df	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5
Asymp. Sig.	0.281	0.000	0.075	0.034	0.000	0.000	0.002	0.055	0.243	0.083	0.010	0.054	0.380	0.066	0.167	0.172

Table 6(b): Ward-Wise Concordance Analysis on Local Weather Variability and Extremity

Ward No.	17	18	19	20	21	22	23	24	25	26	27	28	29
N	30	30	30	30	30	30	30	30	30	30	30	30	61
Kendall's W	0.237	0.263	0.461	0.163	0.274	0.517	0.343	0.379	0.261	0.373	0.097	0.154	0.166
Chi-Square	11.849	13.128	23.050	8.175	13.690	25.870	17.158	18.926	13.065	18.649	4.864	7.692	17.448
df	5	5	5	5	5	5	5	5	5	5	5	5	5
Asymp. Sig.	0.037	0.022	0.000	0.147	0.018	0.000	0.004	0.002	0.023	0.002	0.433	0.174	0.004

Concordance analysis on local weather variability on parameters such as average rainfall and the average temperature in the last three years is represented by variable names *DWavrain3'* and *DWavtemp3'* is carried out. From Table 7, it is observed low level of agreement exists amongst people about average rainfall and temperature in the last three years in most wards with exceptions in wards 1, 3, 5, 6, 8, 9, 15, 17, 20, 22, 23,24 and 28. Wards 1, 3, 6, 8, 9, 15, 17, 20, 22, and 28 show a very low level of agreement while wards 23 and 24 demonstrate medium agreement. Ward 5 demonstrates high agreement. Kendall's W value with a degree of freedom = 1 indicates rejection of the null hypothesis (*there is no agreement of test variables*) at 0.05 forwards 5, 23 and 24. However, in the case of wards 2, 11, 12, 14, 18, 19, 21, 25, 26, 27 and 29, cannot be rejected and is found statistically significant. Forwards 2, 5, 11, 12, 14, 18, 19, 21, 23, 24, 25, 26, 27 and 29 with a degree of freedom = 1 at 0.05, Chi-square values are above the critical value, therefore, the rejecting null hypothesis (*there is no association between variables*) and found statistically significant (Tables 7(a) and 7(b)).

Table 7(a): Ward-Wise Concordance Analysis on Average Rainfall and Temperature in Last Three Years

Ward No.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
N	30	30	30	30	30	30	30	30	30	30	30	30	30	30	30	30
Kendall's W	0.100	0.450	0.200	0.300	0.900	0.100	0.300	0.200	0.100	0.300	0.400	0.400	0.033	0.400	0.000	.300
Chi-Square	1.000	4.500	2.000	3.000	9.000	1.000	3.000	2.000	1.000	3.000	4.000	4.000	3.000	4.000	0.8000	3.000
df	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Asymp. Sig.	0.317	0.034	0.157	0.083	0.003	0.317	0.083	0.157	0.317	0.083	0.046	0.046	0.564	0.046	1.000	0.083

Table 7(b): Ward-Wise Concordance Analysis on Average Rainfall and Temperature in Last Three Years

Ward No.	17	18	19	20	21	22	23	24	25	26	27	28	29
N	30	30	30	30	30	30	30	30	30	30	30	30	61
Kendall's W	0.000	0.500	0.500	0.180	0.500	0.200	0.600	0.600	0.400	0.400	0.400	0.129	0.259
Chi-Square	3.000	5.000	5.000	1.800	5.000	2.000	6.000	6.000	4.000	4.000	4.000	1.286	5.444
df	1	1	1	1	1	1	1	1	1	1	1	1	1
Asymp. Sig.	1.000	0.025	0.025	0.180	0.025	0.157	0.014	0.014	0.046	0.046	0.046	0.257	0.020

Finally, concordance analysis for measuring extreme local weather events is undertaken. Variables about extreme local weather events of heat, cold, humidity and rainfall in the last three years, are expressed by variables *Dwextr3h1, Dwextr3c1, Dwextr3hu1* and *Dwextr3rain1* in the test model. It is observed from Table 8, a very low level of agreement is observed in judgements for most wards with exceptions in wards 2, 3, 4, 5, 6, 7, 10, 11, 15, 19, 22 and 26. Wards 2, 3, 4, 5, 7, 10, 11, 15,19, 22 and 26 show a low level of agreement whereas, ward 6 shows moderate agreement. Kendall's W with degrees of freedom = 3 at 0.05 indicates that null hypothesis (*there is no agreement of test variables*) cannot be rejected for many wards with an exception for Ward 6 but is found statistically insignificant forwards 1, 8, 9, 12, 14, 16, 17, 18, 20, 22, 23, 24, 25, 27 and 28. Pearson's Chi-square values with degrees of freedom = 3 at 0.05 forwards 1, 3, 4, 5, 6, 7, 10, 11, 14, 15, 19, 26, 28 and 29, significantly reject the null hypothesis (*there is no association among test variables*) indicating dependency among test variables in these wards. Rejection of 2, 8, 9, 13, 14, 16, 17, 18, 20, 21, 22, 23, 24, 25 and 28 is ignored since it is found statistically not significant in the experiment. Forwards 12 and 27, although Chi-square results show no association among test variables but are ignored for interpretation as the values are found statistically not significant (Tables 8(a) and 8(b)).

Table 8(a): Ward-Wise Concordance Analysis on Extreme Local Weather Events

Ward No.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
N	30	30	30	30	30	30	30	30	30	30	30	30	30	30	30	30
Kendall's W	0.157	0.255	0.300	0.340	0.319	0.675	0.456	0.200	0.169	0.323	0.367	0.086	0.206	0.222	0.308	0.180
Chi-Square	4.714	7.636	9.000	10.200	9.571	20.250	13.667	6.000	5.077	9.692	11.000	2.571	6.176	6.667	9.231	5.400
df	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
Asymp. Sig.	0.194	0.054	0.029	0.017	0.023	0.000	0.003	0.112	0.166	0.021	0.012	0.463	0.103	0.083	0.026	0.145

Table 8(b): Ward-Wise Concordance Analysis on Extreme Local Weather Events

Ward No.	17	18	19	20	21	22	23	24	25	26	27	28	29
N	30	30	30	30	30	30	30	30	30	30	30	30	61
Kendall's W	0.237	0.263	0.461	0.163	0.274	0.517	0.343	0.379	0.261	0.373	0.097	0.154	0.166
Chi-Square	11.849	13.128	23.050	8.175	13.690	25.870	17.158	18.926	13.065	18.649	4.864	7.692	17.448
df	5	5	5	5	5	5	5	5	5	5	5	5	5
Asymp. Sig.	0.037	0.022	0.000	0.147	0.018	0.000	0.004	0.002	0.023	0.002	0.433	0.174	0.004

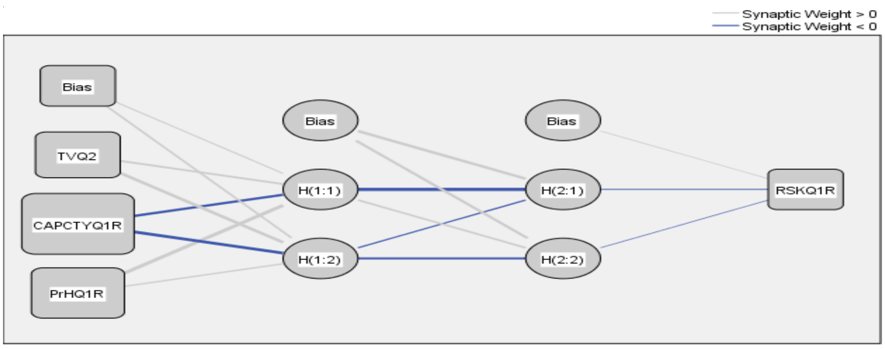
For risk prediction of the hazards considered, Artificial Neural Network (ANN) is used in the study. Feed forward Multilayer Perceptron (MLP) is used in this case. The neural network comprises an input layer, a hidden layer, and an output layer. Two hidden layers are used in the analysis with two units in each hidden layer. The respective individual units of all input variables are transformed into one common unit using standardized rescaling termed as covariates in the model. In this model, the covariates are processed using the hyperbolic tangent activation function. The output layer uses identity activation function, standardized rescaling method for scale dependents and the sum of squares as the error function. The sample size for this model is taken as 901 with no missing values. ANN is preferred to multiple linear regression analysis as data is multi-dimensional, multi-scaled, multi-layered, hybrid and complex. Moreover, the linearity assumption of multiple linear regression analysis imparts restriction to the test model and therefore imparts limitation of the study. Also, the projection of high dimensional data in low dimensional space using multiple linear regression analysis may induce bias. ANN is used on test datasets as it can handle multi-scaled, hybrid, high dimensional linear/nonlinear data, unlike multiple linear regression analysis.

For ward-wise risk prediction of the earthquake, using an ANN model comprises of training sample consisting of 625 units and a testing sample of 276 units. More precisely, 69.4% of sample units form the training set while 30.6% of sample units form the test set. The input layer comprises of three variables, viz. *TVQ2*, *CAPCTYQ1R* and *PrHQ1R* represent total vulnerability, capacity and intensity of earthquake hazard. The input layer consists of three units and the output layer consists of one dependent variable *RSKQ1R*, which denotes risk for earthquake. Table 9 depicts a model summary of risk prediction for earthquake hazards using ANN.

Table 9: Model Summary of ANN of Risk Prediction for Earthquake Hazard

Model Summary		
Training	Sum of Squares Error	104.451
	Relative Error	1.004
	Stopping Rule Used	1 consecutive step(s) with no decrease in error
	Training Time	0:00:00.03
Testing	Sum of Squares Error	0.795
	Relative Error	0.005
Dependent Variable: *RSKQ1R1*		
Note: a. Error computations are based on the testing sample.		

Figure 1 represents network mesh for risk prediction for an earthquake with three independent variables *TVQ2*, *CAPCTYQ1R* and *PrHQ1R* and one dependent variable *RSKQ1R*. The bold lines indicate close association with synaptic weights less than zero is observed between *CAPCTYQ1R*, the first unit of the first hidden layer and the first unit of the second hidden layer. A similar type of association is observed between the first unit of the second hidden layer and the second unit of the second hidden layer. Negative synaptic weights are observed from the first unit of the second hidden layer and the second unit of the second hidden layer, again indicating an association between *CAPCTYQ1R* and *RSKQ1R*. Table 10 gives parameter estimates amongst input, hidden and output layers. The normalized importance of independent variables *TVQ2*, *CAPCTYQ1R* and *PrHQ1R* are given by Figure 2.

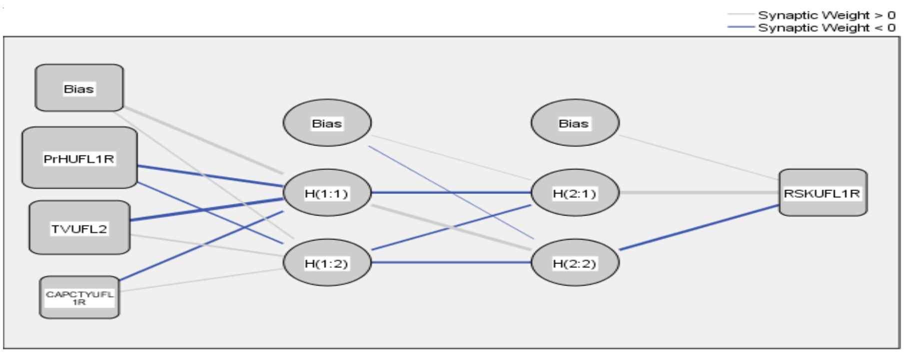


Hidden Layer Activation Function: Hyperbolic Tangent
Output Layer Activation Function: Identity

Figure 1: ANN for Predicted Risk of Earthquake

Table 10: Parameter Estimation of ANN of Risk Prediction for Earthquake

Parameter Estimates						
Predictor		**Predicted**				
		Hidden Layer 1		**Hidden Layer 2**		**Output Layer**
		H(1:1)	**H(1:2)**	**H(2:1)**	**H(2:2)**	***RSKQ1R***
Input Layer	(Bias)	0.100	0.111			
	TVQ2	0.187	0.395			
	CAPCTYQ1R	-0.362	-0.446			
	PrHQ1R	0.450	0.104			
Hidden Layer 1	(Bias)			0.390	0.296	
	H(1:1)			-0.451	0.124	
	H(1:2)			-0.100	-0.243	
Hidden Layer 2	(Bias)					0.048
	H(2:1)					-0.083
	H(2:2)					-0.043



Hidden Layer Activation Function: Hyperbolic Tangent
Output Layer Activation Function: Identity

Figure 2: Importance of Independent Variable for Risk Prediction of the Earthquake

The normalized importance of independent variables *TVQ2*, *CAPCTYQ1R* and *PrHQ1R* are given by Figure 2. It is observed that *CAPCTYQ1R* has maximum importance in risk prediction due to earthquakes for various wards of Silchar Town. Hazard intensity of earthquake *PrHQ1R* is the next most important factor followed by a total vulnerability for earthquake *TVQ2*. It can be interpreted that capacity building factors are important both in terms of resources and soft skills.

Mean and standard deviation of predicted risk for earthquake hazard with indices for various wards of Silchar Town using ANN are given in Table 11. Indices of predicted risk values for an earthquake are calibrated in the range of 5.7759 to 12.487 as low, 12.4888 to 19.1981 medium and 19.1982 to 25.9092 high. Wards 1, 3, 6, 7 and 8 show high risk value, while 2, 4, 5, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 20, 23, 24, 28 show medium risk and wards. 19, 21, 22, 25, 26, 27 and 29 show low risk (Table 11).

Table 11: Ward-Wise Risk Prediction for Earthquake Using ANN

Ward No.		Mean	Std. Deviation	Indices
1	Predicted Value for *RSKQ1R1*	25.7121	0.1305	H
2	Predicted Value for *RSKQ1R1*	18.7102	0.1251	M
3	Predicted Value for *RSKQ1R1*	25.9092	0.8685	H
4	Predicted Value for *RSKQ1R1*	19.0184	0.1124	M
5	Predicted Value for *RSKQ1R1*	13.8916	0.9367	M
6	Predicted Value for *RSKQ1R1*	22.7968	0.5228	H
7	Predicted Value for *RSKQ1R1*	19.4618	0.1158	H
8	Predicted Value for *RSKQ1R1*	23.8557	0.9071	H
9	Predicted Value for *RSKQ1R1*	14.8243	0.1815	M
10	Predicted Value for *RSKQ1R1*	13.8885	0.2762	M
11	Predicted Value for *RSKQ1R1*	16.3581	0.2593	M
12	Predicted Value for *RSKQ1R1*	16.1780	0.6227	M
13	Predicted Value for *RSKQ1R1*	18.0497	0.5507	M
14	Predicted Value for *RSKQ1R1*	19.1483	0.0915	M
15	Predicted Value for *RSKQ1R1*	17.7261	0.0353	M
16	Predicted Value for *RSKQ1R1*	12.8221	0.0797	M
17	Predicted Value for *RSKQ1R1*	17.7477	0.4234	M
18	Predicted Value for *RSKQ1R1*	15.3944	0.4746	M
19	Predicted Value for *RSKQ1R1*	11.7256	0.9170	L
20	Predicted Value for *RSKQ1R1*	14.5648	0.2451	M
21	Predicted Value for *RSKQ1R1*	8.6988	0.3509	L
22	Predicted Value for *RSKQ1R1*	5.7759	0.2181	L
23	Predicted Value for *RSKQ1R1*	12.9987	0.2164	M
24	Predicted Value for *RSKQ1R1*	17.9154	0.6319	M
25	Predicted Value for *RSKQ1R1*	6.1820	0.4411	L
26	Predicted Value for *RSKQ1R1*	11.1850	0.1901	L
27	Predicted Value for *RSKQ1R1*	9.8664	0.7805	L
28	Predicted Value for *RSKQ1R1*	17.1476	0.1081	M
29	Predicted Value for *RSKQ1R1*	11.9349	0.2670	L

ANN model for ward-wise risk prediction for urban flood consists of 624 training sample units and 277 testing sample units which are 69.3% training set and 30.7% of the test set. Three variables make up the input layer consisting of *TVUFL2*, *CAPCTYUFL1R* and *PrHUFL1R* denoting total vulnerability, capacity and intensity respectively of urban flood hazard. The output layer has one dependent variable *RSKUFL1R*, denoting risk for urban flood. Table 12 represents the model summary for risk prediction of urban flood hazards using ANN.

Table 12: Model Summary of ANN for Risk Prediction due to Urban Flood

Model Summary		
Training	Sum of Squares Error	73.490
	Relative Error	0.710
	Stopping Rule Used	1 consecutive step(s) with no decrease in error[a]
	Training Time	0:00:00.04
Testing	Sum of Squares Error	944.620
	Relative Error	0.035
Dependent Variable: *RSKUFL1R1*		
Note: [a.] Error computations are based on the testing sample.		

The network mesh for urban flood risk prediction with independent variables *TVUFL2*, *CAPCTYUFL1R* and *PrHUFL1R*, and dependent variable *RSKUFL1R* is given in Figure 3. A strong association is shown by bold lines having synaptic weights less than zero is observed between *PrHUFL1R*, the first unit of the first hidden layer and the first unit of the second hidden layer. Table 13 represents the parameter estimates between input, hidden and output layers. A similar association is seen between *PrHUFL1R*, the second unit of the first hidden layer, the first unit of the second hidden layer, the second unit of the second hidden layer and the output layer *RSKUFL1R*. *TVUFL1R* is found closely associated with the first unit of the first hidden layer and the first unit of the second hidden layer. *CAPCTYUFL1R* also shows a close association between the first unit of the first hidden layer and the first unit of the second hidden layer.

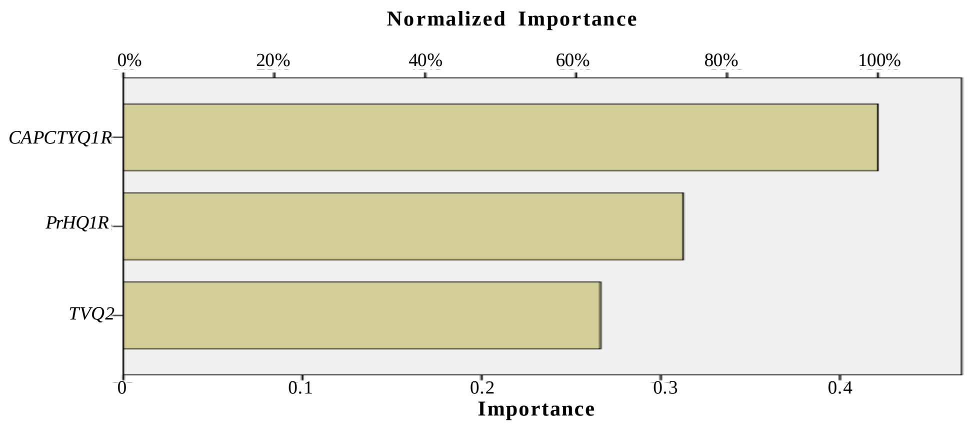


Figure 3: ANN of Predicted Risk for Urban Flood

Figure 4 gives normalized importance of independent variables *TVUFL2*, *CAPCTYUFL1R* and *PrHUFL1R*. *PrHUFL1R* is observed to have the highest importance in the prediction of risk due to urban flood *RSKUFL1R* for various wards of Silchar Town. Subsequent important factors are a total vulnerability for urban flood *TVUFL2* followed by capacity for urban flood *CAPCTYUFL1R*.

Table 13: Parameter Estimation for ANN of Risk Prediction for Urban Flood

Predictor		Parameter Estimates: Predicted				
		Hidden Layer 1		Hidden Layer 2		Output Layer
		H(1:1)	H(1:2)	H(2:1)	H(2:2)	*RSKUFL1R*
Input Layer	(Bias)	0.545	0.157			
	PrHUFL1R	-0.526	-0.225			
	TVUFL2	-0.639	0.244			
	CAPCTYUFL1R	-0.340	0.141			
Hidden Layer 1	(Bias)			0.045	-0.008	
	H(1:1)			-0.430	0.563	
	H(1:2)			-0.338	-0.369	
Hidden Layer 2	(Bias)					0.084
	H(2:1)					0.764
	H(2:2)					-0.462

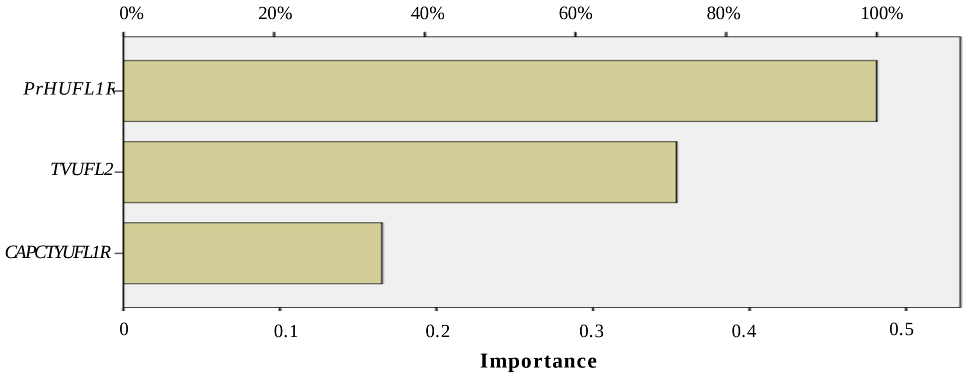


Figure 4: Importance of Independent Variable for Risk Prediction of Urban Flood

The mean value and standard deviation of predicted risk for urban flood with indices for various wards of Silchar Town using the ANN model are given in Table 14. Predicted risk values for urban flood indices are calibrated in the ranges of low, medium and high with 37.0812 to 52.4000 as low, 52.4001 to 67.7188 as medium and 67.7189 to 83.0376 as high. Wards 1, 3, 6, 7, 8, 14 and 16 fall in high risk zone, while wards 2, 9, 17, 18, 19, 20 and 28 are in medium risk zone and wards 4, 5, 10, 11, 12, 13, 15, 21, 22, 23, 24, 25, 26, 27 and 29 are in low risk zone.

Table 14: Risk Prediction of an Urban Flood Using ANN for Various Wards

Ward No.		Mean	Std. Deviation	Indices
1	Predicted Value for *RSKUFL1R1*	83.0376	0.1381	H
2	Predicted Value for *RSKUFL1R1*	58.4393	0.0970	M
3	Predicted Value for *RSKUFL1R1*	73.3121	0.6459	H
4	Predicted Value for *RSKUFL1R1*	42.9845	0.6271	L

Table 14 (Cont.)

Ward No.		Mean	Std. Deviation	Indices
5	Predicted Value for *RSKUFL1R1*	50.5078	0.8072	L
6	Predicted Value for *RSKUFL1R1*	70.0379	0.4784	H
7	Predicted Value for *RSKUFL1R1*	72.6337	0.2268	H
8	Predicted Value for *RSKUFL1R1*	69.9927	0.2320	H
9	Predicted Value for *RSKUFL1R1*	67.6655	0.3687	M
10	Predicted Value for *RSKUFL1R1*	49.8694	0.5385	L
11	Predicted Value for *RSKUFL1R1*	48.6304	0.8053	L
12	Predicted Value for *RSKUFL1R1*	48.5102	0.8651	L
13	Predicted Value for *RSKUFL1R1*	43.6988	0.1547	L
14	Predicted Value for *RSKUFL1R1*	73.4402	0.5187	H
15	Predicted Value for *RSKUFL1R1*	50.0121	0.2968	L
16	Predicted Value for *RSKUFL1R1*	68.0731	0.7801	H
17	Predicted Value for *RSKUFL1R1*	62.6560	0.9735	M
18	Predicted Value for *RSKUFL1R1*	52.6836	0.5310	M
19	Predicted Value for *RSKUFL1R1*	61.3314	0.0213	M
20	Predicted Value for *RSKUFL1R1*	59.2636	0.8921	M
21	Predicted Value for *RSKUFL1R1*	50.5954	0.9554	L
22	Predicted Value for *RSKUFL1R1*	41.0931	0.8589	L
23	Predicted Value for *RSKUFL1R1*	38.1165	0.2852	L
24	Predicted Value for *RSKUFL1R1*	49.7846	0.0003	L
25	Predicted Value for *RSKUFL1R1*	39.3474	0.6285	L
26	Predicted Value for *RSKUFL1R1*	43.9200	0.0603	L
27	Predicted Value for *RSKUFL1R1*	41.9062	0.1143	L
28	Predicted Value for *RSKUFL1R1*	59.3240	0.3179	M
29	Predicted Value for *RSKUFL1R1*	37.0812	0.5912	L

5. Conclusion

CBDRM model is primarily based on people's opinion on various aspects of disaster risk such as local disaster risk information, capacity measures, early warning systems, relief and rehabilitation procedures, search and rescue, weather variability etc. In the present study, awareness of the community on various local capacity building assets and resources are judged by the degree of agreement/disagreement of their responses using concordance analysis.

As discussed in Section 2, it is found that the existing disaster risk plans and programs under the purview of the City Disaster Management Plan (CDMP) for Silchar Town is institutional, discreet in nature, response and relief based without any provisions for community participation. Although there exists institutional level preparedness plans and programs (ASDMA, 2014-15), they are abstract to the community due to the absence of disaster literacy and awareness. From the present study, it is obvious that existing plans are hypothetical and abstract to large sections of people of the town. Moreover, a wide gap exists between needs for community preparedness and capacity building vis- a-vis obligations discharged by the Silchar Municipal Board and few assigned line departments as per guidelines of CDMP and other government disaster risk management framework. The risk-mitigating action plans of Silchar Municipality appears to be insufficient to people.

From the present study, it may be suggested that existing disaster risk management plans framed under CDMP be integrated with the CBDRM approach with the involvement of the local community. To strengthen resilience, alternative action plans with combined participation of institutional responders and local people is the need of the hour to ensure sustainable development of Silchar Town in Southern Assam. Integrated action plans involve: (a) local vulnerable community selection; (b) understanding community and rapport building; (c) hazards, vulnerability, capacity and preparedness assessment by involving local community; (d) disaster risk assessment with involvement of locals; (e) participatory mode of the local community in risk prevention, search and rescue, mitigation, relief and rehabilitation; (f) enhancing coping capacity and adaptability of locals to risks from various hazards; and (g) proper implementation of various plans with involvement of the local community. Such integration has a fair chance for a win-win situation especially when government resources are limited while disaster impacts and vulnerabilities are on the rise. Disaster management plans can be effectively accomplished only when the community, government and other stakeholders collaborate and work hand in hand.

To meet the rapid urbanization, the territorial expansion of Silchar Town by amalgamating the Gaon panchayat area with Silchar Municipal Board is suggested. The planned construction of new public infrastructure is the need of the hour. Conservation of wetlands, afforestation, rainwater harvesting, ban on single-use plastic, thermocols, desilting and cleaning of drains, stormwater channel construction etc should be the priority of the UDRR plan of Silchar Town. Risk education, training, mock drill, building awareness, dissemination of disaster risk related information, governance and transfer mechanisms are necessary to enhance community resilience. Thus, the present study indicates that urban risk reduction and administrative plans do not essentially converge with the development plans of Silchar Town.

References

Bongo, P. (2003). Community-Based Disaster Risk Reduction. In the Context of Climate Change, The case with Rural Zimbabwe.

Chhoun, N. (2016). Disaster Management in Cambodia: Community-based Disaster Risk Management in the Case of Drought. In *Foreword from the Conference Chair* (p. 12).

Cutter, S.L., Barnes, L., Berry, M., Burton, C., Evans, E., Tate, E. and Webb, J. (2008). A Place-based Model for Understanding Community Resilience to Natural Disasters. *Global Environmental Change*, 18(4), 598-606.

Fehling, M., Nelson, B. and Venkatapuram, S. (2013). Limitations of the Millennium Development Goals: A Literature Review. *Global Public Health*, 8(10), 1109-1122.

Ferrao, P. and Fernandez, J. (2013). *Sustainable Urban Metabolism*. MIT Press.

Fitzgerald, J. (2010). *Emerald Cities: Urban Sustainability and Economic Development*. Oxford University Press.

Hasan, A., Patel, S. and Satterthwaite, D. (2005). How to Meet the Millennium Development Goals in Urban Areas. *Environment and Urbanization*, 17(1), 3-19.

Hoornweg, D., Sugar, L. and Trejos Gomez, L. C. (2011). Cities and Greenhouse Gases Moving Forward. *Urbanization and Environment.*, 23(1), 207-227.

Jang, L.J. (2009). Disaster Resilience: Constructing a Disaster Resistant Community. *Fu Hsing Kang Academic J*. 96, 29-52.

Johnson, S. (2010). Where Good Ideas Come from The Natural History of Innovation. *Riverhead Books*, New York.

Krummacher, A. (2014). Community-Based Disaster Risk Management (CBDRM). Paper Presented At The Responding to Environmental Challenges to Promote Cooperation and Security in the OSCE area, Vienna.

Marschiavelli, M.I.C. (2008). Vulnerability Assessment And Coping Mechanism Related to Floods in Urban Areas: A Community-Based Case Study in Kampung Melayu, Indonesia. ITC.

Parnell, S. (2016). Defining a Global Urban Development Agenda. *World Development*, 78, 529-540.

Pineda, M.V.G. (2015). Redefining Community-Based Disaster Risk Management (CBDRM) Through Enhanced Early Warning Processes. *International Journal of Information and Education Technology*, 5(7), 543.

Raungratanaamporn, I. S., Pakdeeburee, P., Kamiko, A. and Denpaiboon, C. (2014). Government-Communities Collaboration in Disaster Management Activity: Investigation in the Current Flood Disaster Management Policy in Thailand. *Procedia Environmental Sciences*, 20, 658-667.

Shaw, R. and Krishnamurthy, R.R. (Eds.) (2012). *Disaster Management: Global Challenges and Local Solutions*, Universities Press, Hyderabad.

Takeuchi, Y., Mulyasari, F., and Shaw, R. (2011). Roles of Family and Community in Disaster Education. *Community, Environment and Disaster Risk Management*, 7, 77-94.

Troy, A. (2012). *The Very Hungry City: Urban Energy Efficiency and the Economic Fate of Cities.* Yale University Press, New Haven and London.

United Nations (2014a). World Urbanization Prospects: The 2014 Revision. Department of Economic and Social Affairs. Population Division Accessed at http://www.un.org/en/ development/desa/publications/2014-revision-world-urbanization-prospects.html

United Nations Development Programme. (2016). *Myanmar Community Based Disaster Risk Management Manual.* Naypyidaw: United Nations Development Programme.

Appendix

Implication of Variables	
People in ward affected by flood	*Dwppleff2'*
People in ward affected by urban flood	*Dwppleff3'*
People in ward affected by fire	*Dwppleff4'*
People in ward affected by these hazards	*Dwppleff5'*
People in ward not affected by any of these hazards	*Dwppleff6'*
Flood level in ward	*Dwfldlvl1*
Duration of flood in ward	*Dwdurfld1*
Strength of tremor in ward	*Dwstrngtr1*
Approx. number of people in ward exposed to flood	*Dwpplexpf1*
Approx. number of people in ward exposed to earthquake	*Dwpplexpeq1*
Approx. number of people in ward exposed to fire	*Dwpplexpfr1*
Approx. number of people in ward exposed to urban flood	*Dwpplexpuf1*
Approx. number of people killed in ward due to flood	*Dwpplklldf1*
Approx. number of people killed in ward due to earthquake	*Dwpplklldeq1*
Approx. number of people killed in ward due to fire	*Dwpplklldfr1*
Approx. number of people killed in ward due to urban flood	*Dwpplkllduf1*
Approx. number of people injured in ward due to flood	*Dwinjrdf1*
Approx. number of people injured in ward due to earthquake	*Dwinjrdeq1*
Approx. number of people injured in ward due to fire	*Dwinjrdfr1*
Approx. number of people injured in ward due to urban flood	*Dwinjrduf1*
Return period of flood	*Dwrtrnprdf1*
Return period of earthquake	*Dwrtrnprdeq1*
Return period of fire	*Dwrtrnprdfr1*
Return period of urban flood	*Dwrtrnprduf1*
Environmental degradation in air quality due to flood	*Dwenfaq*
Environmental degradation in air quality due to earthquake	*Dweneqaq*
Environmental degradation in air quality due to urban flood	*Dwenufaq*
Environmental degradation in air quality due to fire	*Dwenfaq*
Environmental degradation in water quality due to flood	*Dwenfwq*
Environmental degradation in water quality due to earthquake	*Dweneqwq*

Appendix (Cont.)

Implication of Variables	
Environmental degradation in water quality due to urban flood	*Dwenufwq*
Environmental degradation in water quality due to fire	*Dwenfrwq*
Environmental degradation in land quality due to flood	*Dwenflq*
Environmental degradation in land quality due to earthquake	*Dweneqlq*
Environmental degradation in land quality due to urban flood	*Dwenuflq*
Environmental degradation in land quality due to fire	*Dwenfrlq*
Environmental degradation in vegetation due to flood	*Dwenfveg*
Environmental degradation in vegetation due to earthquake	*Dweneqveg*
Environmental degradation in vegetation due to urban flood	*Dwenufveg*
Environmental degradation in vegetation due to fire	*Dwenfrveg*
Average annual rainfall in last three years	*DWavrain3'*
Average annual temperature in last three years	*DWavtemp3'*
Days of extreme heat in last three years	*Dwextr3h1*
Days of extreme cold in last three years	*Dwextr3c1*
Days of extreme humidity in last three years	*Dwextr3hu1*
Days of extreme rainfall in last three years	*Dwextr3rain1*
Topography of ward is hillock	*Wtopo1'*
Topography of ward is plain land	*Wtopo2'*
Topography of ward is low land	*Wtopo3'*
Topography of ward is slope	*Wtopo4'*
Topography of ward is river/canal bank	*Wtopo5'*
Major land use in ward is residential	*Wlndusebld1'*
Major land use in ward is commercial	*Wlndusebld2'*
Major land use in ward is office	*Wlndusebld3'*
Major land use in ward is social/cultural buildings	*Wlndusebld4'*
Major land use in ward fall in categories other than those stated above	*Wlnduseoth1*
Housing density of ward	*Whouden1*
Water bodies in ward	*Wwtrbod1*
Water bodies in ward with retaining wall	*Wwtrbodret1'*
Water bodies in ward without retaining wall	*Wwtrbodret2'*
Distance of the river Barak /khaal from ward	*WdisB1*
Acute care hospital in ward	*Whospy1'*
Primary care hospital in ward	*Whospy2'*
Speciality care hospital in ward	*Whospy3'*
Psychiatric care hospital in ward	*Whospy4'*
No hospital in ward	*Whospn1*
Nurse/paramedics in ward	*Wemgncysp1'*
Doctors in ward	*Wemgncysp2'*
Ambulance in ward	*Wemgncysp3'*
Chemists in ward	*Wemgncysp4'*
Medical volunteers in ward	*Wemgncysp5'*
All of these service providers in ward	*Wemgncysp6'*
None of these service providers in ward	*Wemgncysp7'*

Appendix (Cont.)

Civic supply of water is for drinking and other purpose in ward	*Wwtrsrc1'*
Deep tube wells for drinking and other purpose in ward	*Wwtrsrc2'*
Water from wells for drinking and other purpose in ward	*Wwtrsrc3'*
Water from river for drinking and other purpose in ward	*Wwtrsrc4'*
Water from pond for drinking and other purpose in ward	*Wwtrsrc5'*
Power supply in all areas of ward	*Wpwrspp1*
Engineering services in ward	*Wfacli1'*
Rescue equipment in ward	*Wfacli2'*
Skilled rescue men in ward	*Wfacli3'*
Volunteers in ward	*Wfacli4'*
Mass shelter in ward	*Wfacli5'*
All these facilities in ward	*Wfacli6'*
None of these facilities in ward	*Wfacli7'*

Cite this article as: Rajib Gupta and Arup Barman (2022). Do Community Based Urban Risk Reduction and Development Policies Converge?. *International Journalof Architecture and Planning*, 2(1), 15-32. doi: 10.51483/IJARP.2.1.2022.15-32.