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Assessing Community Resilience to Climate-related Disasters: Examining the Relative Importance of Indicators

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Abstract. Selecting indicators for assessing community resilience to disasters has been a key challenge faced by practitioners specially who employs inductive assessment methods. As an aid to overcome the challenge, this study attempted to explain the usefulness of the relative importance of indicators within an index. The discussion of this paper is based on community resilience levels computed for 40 disaster-prone localities in Sri Lanka by two assessment methods: Resilience Index Measurement and Analysis (RIMA) and Resilience Capacity Index (RCI). Zero order correlation, partial correlation and semi-partial correlation measures were used in explaining and comparing the relative importance of indicators to the aggregated resilience level of each locality. The findings recommend the relative importance of indicators as an imperative criterion to be considered in selecting indicators to assess community disaster resilience.

Keywords: climate-related disasters, community resilience, Socio-ecological systems, resilience assessment methods.

1. Introduction

"Abrupt changes in performance of social systems occur in the case of disastrous events which can lead systems to be failed, leading to a major reduction or complete loss in performance with respect to some or all measures" [1]. Assessing community resilience in the aftermath of a disaster is an explicit task, which can be undertaken by recording the observations made throughout the recovery process. Such observations provide a detailed overview of how long it has been taken a system to be re-organized, which changes were irreversible and which could have been done to expedite the recovery process. Lessons-learnt are undoubtedly important in decision-making process for building community resilience. Yet decision makers such as urban engineers, spatial planners and policy makers who facilitate socio-ecological systems to build the resilience levels prior to a disaster need proactive resilience assessment methods. Further, resilience assessment cannot completely be relying on the evidenced-risk because in some cases the possible future risk can be far higher. Therefore, disaster resilience assessment has to be based on long-term predictions, which anticipate uncertainties under a range of possible scenarios. In this context, measuring the community disaster resilience for a given futuristic state becomes hypothetical and assumption-based.

"Measuring the resilience of a system is a complex undertaking, but promoting resilience-oriented adaptation will require the development of tools and metrics that will allow decision makers to assess progress and implement sustainable governance structures to facilitate adaptation" [2]. Climate-related disasters are increasing in many parts of the world making people more vulnerable. Rapid urbanization which causes human settlements to be densely concentrated at disaster-prone localities also triggers the increasing vulnerability. In this backdrop, facilitating community resilience has become a vital task. Scholars working in multiple domains have been developing methods to assess community resilience. This has lead a range of inductive approaches –"whereby one establishes a set of characteristics 'inductive' which are

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judged to be relevant to resilience, and attempts to measure these" [3]– to be emerged targeting to measure community resilience in complex socio-ecological systems. The common assumption among these inductive measures is "the degree of resilience of a particular household, community or population can also be determined partially by assessing the extent to which they can maintain general wellbeing in the event of a disaster" [3].

In spite of the complexity, several inductive resilience assessment methods have been developed in last decade. The characteristics approach which has been published in Hyogo Framework Convention is one such method that has provided an integrated measure. "The Hyogo Framework is generally accepted by international agencies, governments and many NGOs [Non-Governmental Organizations] – it is the only DRR [Disaster Risk Reduction] framework agreed internationally – so it makes sense to align the characteristics with its five priorities for action in order to draw relevant comparisons and present analysis to policy makers and other practitioners" [4]. In this method, all aspects of community resilience to disasters have been attributed to five thematic areas such as governance, risk assessment, knowledge and education, risk management and vulnerability reduction, disaster preparedness and response. As the thematic areas are very broad, each thematic area has been sub divided into three such as components of resilience, characteristics of a disaster-resilient community and characteristics of an enabling environment [4]. Capital-based approach to measure community resilience has introduced a five-fold classification based on social capital, economic capital, physical capital, human capital and natural capital [5]. Climate Disaster Resilience Index (CDRI) has also presented an alternative five-fold classification of resilience indicators based on physical, social, economic, institutional, and natural dimensions [6]. In 2010, Sherrieb et al. have explained community resilience to disasters as a function of economic development and social capital [7], [8]. In this model, economic development has been attributed to resource level, resource equity and resource diversity; and social capital was attributed to social support, participation and community bonds. The notion of resilience within the BRIC framework has been understood as a multifaceted concept that includes social, economic, institutional, infrastructural, ecological and community-based elements of the DROP model [8]. Accordingly, inductive resilience assessment methods which attributed to the disaster resilience of community groups who live in disaster-prone localities have generated a large set of indicators altogether.

In a milieu where such alternative, overlapping indicators that measure community resilience to climate-related disasters have been emerging, some authors [8] have developed consolidated matrices after comprehensively reviewing the existing literature. In related to this, many consolidated matrices are mere combinations yet some matrices have been formed with special reference to the once which have been frequently utilized by many. Meyer has categorized community resilience indicators into two groups as commonly measured aspects and less measured aspects [9]. According to the findings, many of the commonly measured indicators are the once which referred to the socio-economic status of people. Less measured indicators are mostly related to institutional, cultural and ecological aspects. Ostadtaghizadeh et al have also made a comprehensive review on the existing methods and proposed that "there are at least five defined and measureable domains of community disaster resilience including social, economic, institutional, physical and natural" [10].

In the given complex theoretical basis, practitioners who employ these assessment methods in decision-making process find it is challenging to make choices on the best indicators that measure the community resilience at a given context. "While community disaster resilience is a culture-bound concept and also related to the kind of hazards any attempt for assessment should be based on both location and hazard… community disaster indicators differ from a community to another one. So, it seems that the first step for community disaster resilience is determining community resilience indicators" [10]. Some of the indicator-based frameworks consist of a guide for practitioners to systematically customize indices. Customizing of includes modifying indicators, removing indicators, and adding new indicators referring to the characteristics of community resilience in a given context. "Such 'customizing' is to be encouraged, because it makes the characteristics more relevant to the particular needs and capacities of communities, the hazard threats those communities face, the type of DRR work implementing organizations are expert in and their capacities to deliver, and the wider operational and policy environment. It is important not to adopt individual characteristics without questioning their accuracy and relevance to a given situation" [4]. Identifying the most suitable indicators which represents the community resilience in the particular context is crucial. “This should be a thoughtful process of decision making, in which, first, the characteristics are reviewed to identify and select potentially relevant indicators, and then those selected are amended where necessary to provide the precise indicators required by the project. Often this requires extensive discussion by project stakeholders” [4]. There are several factors to be considered in selecting the mix of indicators. An empirical study conducted among Sri Lankan disaster management professionals revealed that many of them do not consider the relative importance of indicators as a criterion to be utilized in selecting the best indicators to measure community resilience in a given context. The relative importance of indicators refers to the extent as how much each indicator represents the community resilience. It can be measured by (i) the degree that each indicator contributes to the aggregated resilient level and (ii) the relatedness of each indicator to the aggregated resilience level. So far very limited attention has been paid on the relative importance of indicators but recently Ostadtaghizadeh et al have emphasised this point such as “need to use appropriate and effective methods to quantify and weigh them with regards to their relative contribution is identified, as is a need to consider how these level interrelates to influence resilience” [10]. The study attempted to stress upon this point and the main objective of this paper was to explain the prominence of ‘relative importance of indicator’ as a criterion in selection of indicators to measure community resilience to disasters. This paper attempts to explain the relative importance of indicators with reference to two inductive methods which assess community resilience to climate-related disasters.

The results explained the relative importance of 24 indicators in assessing community resilience to climatic disasters with reference to 40 disaster prone localities in Sri Lanka. Findings of the study are envisaged to bring theoretical insights to the current practice of selecting indicators for measuring community resilience to climate-related disasters. Having known the difference of relative contributions made by indicators can lead practitioners to improve the practice of customizing and localizing the existing inductive approaches used in disaster resilience assessments. “Sri Lanka being an island nation is highly vulnerable to the negative consequences of hydro-meteorological disasters. In response, there is a strong need of urban communities to be coped-up, adopted and bounced back after a disaster” [11]. Therefore, the study will positively contribute to meet the current resilience building needs of Sri Lanka as well. In overall, the findings of the study will improve the resilience assessment methods and practices. The improved assessment methods will guide the resilience building initiatives of socio-ecological systems to be better conceptualized in the decision-making processes.

The paper is structured into four sections. Section two described the method adopted including the selected case studies, indicators and statistical measures utilised for measuring the relative importance. Section three presents the results revealed and discussed how the relative importance of indicators infers. Section four summarizes the study with recommendations on utilizing the relative importance of indicators as a criterion for selecting indicators to measure community. It further describes how future research can contribute to improve the resilience assessment practice.

2. Method of Study

This study attempted to identify the relative importance of indicators by assessing the relatedness and contribution of each indicator to the aggregated value computed by resilience index. In this regard, the study was designed with two selected resilience assessment methods. The resilience values were computed for 40 localities, which are located in climate-related disaster prone areas in Sri Lanka.

Climate-related disasters – hydro-meteorological disasters mostly exacerbated by climate change – create a series of negative impacts on community life. Yet many of the existing assessment methods have been focused on one or few specific impacts which can be considered as prominent the particular context. When selecting two assessment methods, this study looked for the methods which cover a broader range of impacts addressing a range of climate-related disasters. Accordingly, two selected resilience assessment methods were (i) Resilience Capacity Index (RCI) developed by MacArthur Foundation Research Network on Building Resilient Regions with assistants from State University of New York and (ii) Resilience Index Measurement and Analysis (RIMA) model developed by Food & Agricultural Organization (FAO). RCI is an index which measures people’s conditions hypothesized to a region… recovering from disturbances such as disaster shocks" [12]. RIMA is a framework developed to measure "food and nutrition security resilience" [13]. RCI and RIMA cover broad impacts of climate-related disasters. RCI assesses "the people's recovery from a stress caused by acute blow such as natural disasters" [12]. RIMA assesses "households' resilience to food security shocks such as droughts" [13]. RCI consists of 12 indicators which are attributed to community resilience. In this study, only 11 indicators were used due to the availability of data (Refer table 1). RIMA consists of five dimensions such as productive assets, access to basic services, social safety nets, adaptive capacity and sensitivity. The study has considered 13 indicators which attributed to the above dimensions (Refer table 2).

The computation of community resilience levels by RIMA and RCI was based on secondary data collected for 40 Divisional Secretariat (DS) divisions in Sri Lanka. DS division is a local level administrative unit with a defined geographic boundary, which is above the village level and below the district level. Once the community resilience levels of each DS division were computed, the relative importance of selected indicators was explained through a multiple linier regression model. In the model, the aggregated resilience level of each index was considered as the dependent variable whereas all indicators as independent variables. The relative importance of indicators was explained by zero order correlation, partial and semi-partial correlation values. "Zero-order correlation measures only the direct effect of each predictor, they are unable to partition the variance shared by two or more correlated predictors into the variance attributable to each predictor" [14]. Zero-order correlation only gives a straightforward value of the relatedness between aggregated resilience levels. It ignores the association of other indicators within the index. Therefore, partial correlation -which "measures the predictive efficacy of an explanatory variable in the presence of a specific subset of the remaining regressors" [14]- was used as the second measure. Semi-partial correlation, which is "generally considered a more appropriate measure for regression analysis than partial correlations" [14] was used as the third measure. However, all three methods have a common limitation that "they cannot partition the variance shared between multiple correlated predictors and the dependent variable" [14]. Therefore, collinearity statistics were computed and verified that the results through Variance Inflation Factor (VFS >10) ensuring that the results have relatively insignificant level of multi-collinearity.

The test after assessing the relative contribution of indicators to the aggregated resilience level was to assess the relatedness of each indicator to the aggregated resilience level. Spearmen's correlation coefficient was calculated to assess the strength of relationship of each indicator to the aggregated resilience levels of both indices respectively. Indicators were ranked to show the relative importance of each indicator to the overall index based on the average of two correlation-coefficient values. Accordingly, the indicator with the highest Spearmen's correlation coefficient was obtained the top most rank of each index. As the distribution of two indices was different, the ranks were normalized by rescaling to the range between 0 to1. Where "X" the original is rank and "X^1" is the normalized rank, the rescaling formula is given follows.

$$X^1 = (X - X_{min}) / (X_{max} - X_{min}) \quad (1)$$

Normalized ranks of indicators of both indices were compared to identify the relative importance of indicators between indices.

3. Results & Discussion

The main objective of this paper was to explain the prominence of 'relative importance of indicator' as a criterion in selection of indicators to measure community resilience to disasters. As described in the method section, the indicators which have strong correlations with the aggregated resilience level have contributed more in determining the aggregated resilience level. Therefore, such indicators are more important in representing the community resilience in the given context. Table 1 and table 2 show the relative contribution of each indicator to the aggregated resilience level of RCI and RIMA, respectively. When compare three correlation coefficient values, the relative importance could better interpret by semi-partial correlation.

In RCI, zero-order correlation revealed no strong relationships ($r > 0.7$) but partial correlation coefficient revealed that all indicators have strongly contributed in determining overall index value ($r > 0.992$, sig.= 0.000). Therefore, all indicators are important in representing the community resilience in the given context. However a semi-partial correlation value indicates that, the unique contribution of some indicators such as access to health services (r = 0.278, sig. = 0.000), Poverty Head Count Index (r = 0.239, sig.= 0.000) is higher than the other indicators. In RIMA, zero-order correlation revealed a strong negative relationship with one indicator i.e. number of evacuated, dead, affected and relocated people during climatic disasters occurred in last 50 years (r = -0.801, sig.= 0.000). Partial correlation coefficient also revealed that this is not a spurious correlation (r = -0.950, sig. = 0.000). Partial correlation coefficient values further disclosed that average monthly income also has significantly contributed (r = 0.767, sig. = 0.000) in determining overall index value. Semi-partial correlation values of the above mentioned two indicators showed a relatively high unique contribution to the overall index such as number of evacuated, dead, affected and relocated people during climatic disasters occurred in last 50 years (r = -0.554, sig.= 0.000); average monthly income (r = -0.218, sig.= 0.000). The results clearly conclude these two as the most important indicators and others are less significant in determining the overall resilience index value.

Table 1: The relative importance of indicators within the Resilience Capacity Index (RCI)

Indicators	Sig.	Correlations			Collinearity Statistics (VIF)
		Zero-order	Partial	Semi Part	
(Constant)	.777				
1. Gini coefficient for income inequality	.000	-.016	.994	.075	5.611
2. Degree to which a local economy differs from the national economy by the proportion of its jobs in service, industrial and agricultural sectors	.000	-.042	.996	.090	3.761
3. Percentage of households in the local area spending less than 35 percent of their income on house rent	.000	.422	.994	.079	4.608
4. Number of small & medium business, access to electricity, banking density, road accessibility	.000	.628	.999	.170	4.304
5. Literacy rate	.000	.280	.995	.084	4.466
6. Prevalence of chronic illnesses and disabilities	.000	.003	.992	.067	6.549
7. Poverty Head Count Index	.000	.231	.999	.239	2.189
8. Access to health service	.000	.576	1.000	.278	1.612
9. Annual average percentage over a five-year period of a local area population that lived within the same local area a year prior.	.000	.693	.994	.075	5.514
10. Number of owner-occupied housing units as a percentage of total occupied housing units	.000	.149	.996	.090	4.004
11. Number of voters participating in the 2008 general election as a percentage of population age above 18	.000	.654	.999	.169	4.363

Table 2: the relative importance of indicators within the Resilience Index Measurement and Analysis (RIMA)

Indicators	Sig.	Correlations			Collinearity Statistics (VIF)
		Zero-order	Partial	Semi Part	
(Constant)	.336				
1. Percentage of people live in own-house	.134	.007	.302	.058	2.893
2. Percentage of families own Television, Radio, Laptop, Personal Computer	.008	.094	.511	.109	3.065
3. Percentage of population above 2030 Kcal level of dietary energy consumption	.118	-.490	-.315	-.061	1.879
4. Access to safe drinking water	.511	-.283	-.135	-.025	2.292
5. Access to electricity	.831	.482	.044	.008	4.699
6. Access to sanitation	.014	.511	.475	.099	3.005
7. Access to health services	.075	.090	-.355	-.069	1.305
8. Percentage of people live in the DS Division since birth	.021	.472	.450	.092	3.317
9. Bank density	.039	-.458	-.408	-.082	1.928
10. Average monthly income	.000	.252	.767	.218	1.775
11. Employment to population ratio	.023	.335	-.444	-.091	2.675
12. Literacy rate	.067	.308	.365	.072	1.742
13. Number of evacuated, dead, affected and relocated people during climatic disasters occurred in last 50 years	.000	-.801	-.950	-.554	1.973

The less-significance of other indicators tells that the amount in which R-squared decreases by removing any of those indicators from the index is not significant. Accordingly, in case of RCI removing an indicator except the two indicators mentioned above, do not affect the R-squared. Nevertheless in the case of RIMA, removing any of the indicators could decrease the R-squared. The results suggested that some indicators contribute more in determining the aggregated resilience level of the index. Removing such indicators can significantly decrease the R-squared value. Therefore, during the process of customizing indices, if such indicators are removed then community resilience levels represented by the index can be significantly affected. Therefore, the relative importance of indicators attributing the community resilience needs to be carefully accounted in the indicator screening stage of resilience assessment process.

Second measure utilized to assess the relative importance indicators was the relatedness of each indicator to the aggregated resilience value. Table 3 indicates the set of indicators by the normalized rank where higher the rank more related to the aggregate resilience level and therefore better represents the community resilience. Accordingly, Access to electricity, Poverty Head Count Index, Annual average percentage over a five-year period of a local area population that lived within the same local area a year prior, Number of voters participating in the 2008 general election as a percentage of population age above 18 and Access to sanitation can be considered as the most important (Rank =>.68) indicators with reference to RIMA and RCI.

Table 3: The relative importance of indicators by Normalized Rank

Index	**Indicator**	**Normalized rank (1-0)**
RIMA	Access to electricity	0.74
RCI	Poverty Head Count Index	0.71
RCI	Annual average percentage over a five-year period of a local area population that lived within the same local area a year prior.	0.71
RCI	Number of voters participating in the 2008 general election as a percentage of population age above 18	0.68
RIMA	Access to sanitation	0.68
RIMA	Average monthly income	0.63
RIMA	Percentage of people live in the DS Division since birth	0.57
RCI	Number of small & medium business, access to electricity, banking density, road accessibility	0.54
RIMA	Employment to population ratio	0.52
RIMA	Number of evacuated, dead, affected and relocated people during climatic disasters occurred in last 50 years	0.51
RCI	Literacy rate	0.43
RIMA	Bank density	0.43
RIMA	Literacy rate	0.43
RIMA	Percentage of population above 2030 Kcal level of dietary energy consumption	0.40
RCI	Access to health service	0.38
RCI	Degree to which a local economy differs from the national economy by the proportion of its jobs in service, industrial and agricultural sectors	0.29
RIMA	Percentage of families own Television, Radio, Laptop, Personal Computer	0.28
RIMA	Access to safe drinking water	0.24
RCI	Number of owner-occupied housing units as a percentage of total occupied housing units	0.18
RCI	Gini coefficient for income inequality	0.17
RIMA	Percentage of people live in own-house	0.18
RIMA	Distance to primary school, public transport, market, health centre	0.06
RCI	Prevalence of chronic illnesses and disabilities	0.06
RCI	Percentage of households in the local area spending less than 35 percent of their income on house rent	0.06

Indicators such as access to safe drinking water; number of owner-occupied housing units as a percentage of total occupied housing units; Gini coefficient for income inequality; percentage of people live in own-house; distance to primary school, public transport, market, health centre; prevalence of chronic illnesses and disabilities; percentage of households in the local area spending less than 35 percent of their income on house rent have revealed insignificant relative importance in assessing the community resilience in the given context.

In overall, Poverty Head Count Index and average monthly income can be considered as the top most important indicators among the considered set of indicators with reference to Sri Lankan context. Further, number of evacuated, dead, affected and relocated people during climatic disasters occurred in last 50 years; and access to electricity are also important in assessing community resilience in Sri Lankan context.

4. Conclusion and Way Forward

The selection of indicators has become a challenging task in assessing community resilience to climate-related disasters. This study attempted to emphasize the 'relative importance of indicators' as an imperative criterion in the indicator screening process with emphasise on a Sri Lankan case study. Resilience levels computed for 40 disaster-prone localities in Sri Lanka by RIMA and RCI methods were utilized to explain how some indicators contribute better to the aggregated value of the index; therefore become more important in determining the computed community resilience level. Indicators such as Poverty Head Count Index and average monthly income were revealed as highly important whereas some other the indicators such as distance to primary school, public transport, market, health centre; prevalence of chronic illnesses and disabilities; percentage of households in the local area spending less than 35 percent of their income on house rent were not much important in assessing community resilience in Sri Lankan context.

The findings provide useful information for practitioners who involves in assessing community resilience to climate-related disasters. Indicators have different levels of relative importance to represent community resilience level. Therefore the most important indicators require a higher priority in consolidation as well as special considerations in customizing. Omitting the indicators with insignificant importance is useful to manage the number of indicators in consolidation process specially, in circumstances where the total number of indicators is reasonably high. Further, the indicators that have strong contribution are more fragile to omit or modify when customizing. Therefore, Relative importance of indicator can be recommended as a prominent criterion in selection of indicators to measure resilience. Future works on improving assessment methods need to pay more attention on developing comprehensive tools to assess the relative importance of indicators with special reference to the methods explaining the reasons of relative importance an analytical methods that can assess the non-linier relationships in socio-ecological systems.

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