Title:

Climate change and Vulnerability: A Comparison of Perspectives from Indian Sundarbans Delta

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Abstract

An understanding of how climate events influence potential harm to livelihoods may depend on perspective. When perspectives on climate-change vulnerability diverge, policies aimed at reducing vulnerability may be perceived as unjust or unproductive by intended beneficiaries. Using household-level data from an island in the Indian Sundarbans, vulnerability is assessed from three perspectives, represented by science, the public sector, and local resource users. A comparison of household vulnerability across perspectives reveals a general lack of association. This lack of association reflects ambiguities that may arise through the coexistence of different knowledge regimes. Ambiguity relates to fundamental dichotomies that pose challenges to the application and usefulness of numerical vulnerability indices.

Key words

Climate change, vulnerability, sensitivity, adaptation, Sundarbans, ambiguity.

1. Introduction

Vulnerability to climate change has spawned vigorous debate. The purpose of this paper is not to establish *the* distribution of vulnerability to climate change within a given context, but to compare different perspectives on vulnerability. Disparate perspectives may raise questions about, and undermine, public policy on climate-change vulnerability.

The idea that conceptions of vulnerability may diverge between groups of people whose viewpoints differ is recognized in recent literature on climate change, but largely through conceptual writings (see e.g. Kelly and Adger 2000, Adger 2006, Eriksen and Kelly 2006, O'Brien et al. 2007, Ribot 2009).

The three perspectives represented here are science, the public sector, and resource users; the shorthand of "above," "middle," and "below" is applied to the three perspectives (Mehta et al. 2019a). Vulnerability to climate change is, from each perspective, assessed in relation to a sample of household from an island in the Indian Sundarbans where sea-level rise, subsidence, and erosion all pose challenges to local livelihoods.

Unlike Naskar et al. (2022), whose methods combine different perspectives, the objective here is to explore divergence. Research questions can be articulated as follows. First, what is the nature and extent of disparities in vulnerability assessment between the three perspectives? Second, what are the consequences and potential causes of observed discrepancies?

2. Climate Change, Vulnerability, and Perspective

2.1 Climate Change and Vulnerability

The concept of vulnerability has received attention across a broad array of academic fields, including moral philosophy and feminist critique. Economic approaches to vulnerability often centre around the risk of becoming or remaining poor, employing standard techniques such as poverty lines and established methods of aggregation, but the literature also raises interesting questions about the poverty-vulnerability relationship and potential correlates such as food security (e.g. Stephen and Downing 2001, Chaudhuri et al. 2002, Hoddinot and Quisumbing 2003, Bourguignon et al. 2004, Calvo and Dercon 2005).

Also within the context of climate change, conceptualizations of vulnerability are diverse (Füssel and Klein 2006, Füssel 2007). Reviewing these, Hinkel (2011: 199) found little to unite them, beyond the observation that "All definitions and methodologies analysed follow a common form in that vulnerability is *a measure of possible future harm*." In this literature, the nominal cause of the potential harm is climate change; the potential harm may itself take many different forms, including morbidity, food insecurity, poverty, loss of natural capital, or loss of livelihoods – or some combination thereof. In this simple articulation, a "system" – typically a population and its natural environment – is vulnerable *to* climate change, and vulnerable *in the sense of* some specified dimension of potential harm. Vulnerability is the concept that links current circumstance with some possible hazard and its adverse consequences.

In the conventional IPCC approach, the hazard itself is quantified via the concept of *exposure* – the risk, for example, of a given extreme event, of a certain magnitude, affecting a given location within some specified future timeframe. Consequences are handled through estimates of *sensitivity* to immediate impacts and through *adaptive capacity*, denoting ability to adjust to those impacts. Objections to this approach include the normativity and ambiguity of the underlying concepts that feed into the IPCC terms (Hinkel 2011), as well as its reduction of vulnerability to an "end-point" or "residual" arithmetic – vulnerability equals exposure plus impacts minus adaptations (Kelly and Adger 2000). An issue with the conventional IPCC approach is thus its implied claims to knowledge about future impacts and adaptation; knowledge sufficiently detailed and reliable to warrant estimation of a vulnerability index.

Füssel and Klein (2006) dub this an integrated approach, since it considers both an external, natural hazard and the internal elements – both natural and social – that affect sensitivity and adaptive capacity. A perceived bias towards natural elements is nevertheless a recurring objection; a bias that may be attended by a preoccupation with proximate causes and individual correlates of vulnerability rather than underlying social processes (Eriksen and Kelly 2006, Ribot 2009). Indicator-based studies true to the early IPCC definitions tend to conceptualize climate-related hazards as triggers, while the socio-economic circumstances of affected populations serve mainly to determine measures of sensitivity and adaptive capacity. The political and economic processes of empowerment, marginalization, or differentiation that contributed to those circumstances are suppressed, in part because they are not easily reduced to observable indicators. O'Brien et al (2007), distinguishing between "outcome vulnerability" and "contextual vulnerability," view the different approaches as difficult to combine – and therefore as complementary – due to fundamental differences in models of causality and questions addressed.

Among the many dimensions of harm that one might focus on in vulnerability assessments, livelihoods – their loss or impairment – have become a popular choice. There may be several reasons for this (Blaikie et al. 1994, , Stephen and Downing 2001, Hahn et al. 2009, Ribot 2009): livelihoods in rural settings link natural and social elements; the sustainable livelihoods approach employs vulnerability context as a starting point, into which climate change fits well; the approach draws attention to the diversity of activities in which most populations are engaged and invites consideration of linkages to other dimensions of harm – from resource destruction to food insecurity – whose integration is often unproblematic.

2.2 Perspective and Ambiguity

Indicator-based approaches generally rely on conceptions of vulnerability that are pre-defined by researchers. The vulnerability index emerges via a process of selection of relevant indicators, the score for each indicator – derived from existing registers or measured via surveys – established for each observation (e.g. household or region), and an overall index score determined by methods of weighting and aggregation. In household-level studies of vulnerability, the contribution of the local population is mostly limited to supplying the information necessary to establish the scores for the various indicators.

As Mehta et al. (2019b: 1534) note, "theorising about climate-related uncertainty from 'above' by experts, natural scientists and modellers may have very little to do with how men and women … live with, understand and cope with uncertainty in everyday settings." Differences in perspective go beyond common descriptive dichotomies such as scientific/intuitive, objective/subjective, or universal/situated. According to Jasanoff (2010: 233), by separating knowledge from meaning, climate science "cuts against the grain of common sense and undermines existing social institutions and ethical commitments at four levels: communal, political, spatial and temporal." Heymann (2019) observes how historical changes in climatology dislodged it from its local roots, leading to a "dehumanized" science. Adger et al. (2011) stress the experience gained by people living in marginal natural environments, and how traditional institutions may serve to cushion shocks.

This paper engages with the ways in which vulnerability is articulated across perspectives, and the variety of associations between a given understanding of vulnerability and its nominal sources. From such variety, ambiguity emerges. Ambiguity is normally understood as something expressive of more than one possible meaning or being open to more than one interpretation. Within the above perspective, climate-change ambiguity has been construed as the uncertainties that "arise when experts disagree over the framing of possible options, contexts, outcomes, benefits or harms" (Sterling 2010: 1030), or uncertainty related to outcomes "for which we are not in a position to make probability statements" (Smith and Stern 2011: 4821). The ambiguity of relevance here, however, stems from inter-perspective differences in understandings of context and vulnerability.

2.3 Climate Change and its Impacts in the Sundarbans

The Sundarbans is the largest mangrove delta in the world, spread over the southern end of India's state of West Bengal and neighbouring Bangladesh; 40,000 km^2 that include mainland, inhabited and uninhabited islands, water and fisheries, protected areas, mangroves, forests, and tillable land. Inhabitants of the Sundarbans delta face climate-related vulnerabilities that operate across different temporal and geographical scales.

The delta has always been in flux – in terms of changing currents and their confluence, fluctuations in water temperatures and salinity, subsidence and sea level rise, the erosion of existing lands and the formation of new ones. However, the rate of change has increased in recent decades, an acceleration possibly connected to anthropogenic emissions of greenhouse gasses (Mitra et al. 2009, Raha et al. 2013), although changes have also been traced to tectonic movements in the upper Ganges (Chakrabarti 2001). The area is exposed to major natural shocks such as cyclones and floods (Hazra et al. 2002). These temporal dynamics entail vulnerabilities, and adaptive responses, with a range of physical and social implications.

The southern inhabited islands, as a part of the active delta, are particularly susceptible to environmental and geo-morphological changes of terrain. There are earth embankments running to 3,500 km in length, which help to prevent the cultivable land from flooding by saline rivers and to hold back the high tides. A recent study of the Ganga-Bramhaputra-Meghna delta, which contains the Sundarbans mangrove forest, found a high risk of long-term flooding, even if temperatures remain stable (Brown and Nicholls 2018). Sea-level rise in and near the Sundarbans is higher than the global average and is also resulting in thermal expansion of sea water, which has further impacts on erosion (Mukhopadhya 2015, Payo et al. 2016). The Indian part of the Sundarbans is vulnerable to erosion also because its mangrove cover is rapidly diminishing (Giri et al. 2007).

Accretion and erosion dynamics in the Bay of Bengal have resulted in substantial change to islands like Ghoramara, Nayachar, New Moore, and Sagar (Ghosh et al. 2003, Mukhopadhya et. al. 2015). On Ghoramara, the island where field work was conducted, change has been ongoing since 1967 (Ghosh and Sengupta 1997; Ghosh et al. 2003). While the western part of the island has undergone extensive erosion, the eastern part is gaining land mass; the net loss of land amounts to 3.19 km^2 over a 28-year period (Mukhopadhya et. al. 2015).

Impacts on local livelihoods include loss of land and buildings, inundation and salinization of crop fields and ponds, and reduced fish stocks (Hazra et al. 2002). Beyond permanent or seasonal migration, and construction and maintenance of embankments, adaptation options are limited. And as Harms (2015: 70) notes, "Processual erosions, cyclical collapses, partial flooding and the destruction of large areas during or after tropical storms undercut and erode not only the land, but also the social worlds."

3. Methodology

3.1 Focus, Methods, and Sampling

The objective is to compare and explore different perspectives on vulnerability to climate change in the context of a vanishing island. The strategy involved articulation of three indices – one for each of the perspectives considered. The methods of data gathering involved for the different indices must by necessity be different. In the "above" perspective, judgements involve selection and weighting of vulnerability indicators; in the "middle" perspective, the identities of the islanders – the objects of vulnerability assessment – are known to the assessors (public servants working on the island); for the "below" perspective, assessment consists in a subjective self-assessment.

As an initial step in pursuit of numerical indicators, a household survey was developed and a questionnaire administered to a sample of the island's population. Because location was perceived as a potentially important factor in vulnerability, a stratified sampling plan was chosen. The island is administratively divided into seven hamlets, and stratification ensured a minimum representation from each. In the interest of retaining a probability sample, the number of respondents from each hamlet was proportional to its share of the overall population. Subject to this constraint, respondents were selected randomly. From an overall population of 1225 households, 202 households were selected.

3.2 Vulnerability in the "Above" Perspective

In this local-scale study, exposure plays no part. The cyclone or sea-level rise that affects one resident of the island is the same that affects all others. Differentiation in vulnerability stems only from variation in sensitivity to these events, and in adaptive capacity.

A numerical index favours certain types of indicator (Howe et al. 2008). Continuous indicators that display significant variability, for example, are preferable to categorical indicators or indicators that display little or no variability. The survey questionnaire used here included sections on household structure and demographics, household capital (broadly understood), household income and its sources, and various aspects of vulnerability. On this foundation, 22 possible vulnerability indicators were identified; from these, 12 were selected for the initial numerical index, based on indicator type, relevance, and avoidance of overlap.

The focus is on vulnerability to climate change, in the sense of how such change affects people's livelihoods. A central element of livelihood studies over the past two or three decades has been the pentagon of capitals; the household endowment of human, social, physical, natural, and financial capital. In vulnerability assessments, these are normally construed as indicators of adaptive capacity (Brooks et al. 2005, Nelson et al. 2010, Williamson et al. 2012), but lines are sometimes blurred. This is obvious with respect to natural capital, but boats and lives may also be lost to a cyclone or a flood, thus immediately impacting physical, human, and social capital. Further elements of the livelihood approach include diversity of income sources and dependency on a given source. The 12 indicators selected for the initial numerical index were as follows: dependence on primary livelihood sources; number of income sources; impact count 2009-2015; consumer-worker ratio; public benefit schemes enjoyed; land lost last five years; human capital; social capital; physical capital; natural capital; financial capital; and net income.

Selection of indicators for the numerical index was guided by prior literature and context (Masud-All-Kamal 2013, Ghosh et al. 2014, Sebesvari et al. 2016, Samanta et al. 2017, Ghosh et al. 2018), as well as practical concerns. On the practical side, categorical variables are ill-suited to numerical indices. This is most obvious for multi-category variables, such as hamlet. But binary variables such as sex also pose problems. The logical foundation for their inclusion in a numerical index, as extremes of 0 or 1, is debatable; their tendency to pull distributions towards either extreme can be countered via weighting (of the numerical variables), but such weighting should itself require some logical justification. Further to the practical side, some variables display distributions that make their inclusion dubious – either because of insufficient variability or small subsamples, or a combination of these.

The exclusion from the numerical index of any indicator related to gender seems problematic. The gender indicators entail issues associated with either a binary distribution or moderate variability. But the underlying issue is that gender and vulnerability produce complex associations, whose nuances are difficult to capture through crude binaries or ratios. The mean wage for women in the sample amounted to just 53 percent of wages for men, and wage labour overall accounted for 63 percent of net income. Variability in the income indicator may thus subsume – and disguise – important aspects of gendered vulnerability. Variables excluded from the initial numerical index – including categorical variables such as gender – are included in the subsequent stepwise analysis. Categorical variables and skewed distributions do not pose problems for the ordered regressions.

Those subsequent analyses also involve a comparison of vulnerability indices with two conventional poverty indicators; wealth and income. Income was described above; wealth is simply the aggregate value of three of the five capitals (physical, natural, financial). Some degree of association is thus already built into the comparison between the numerical index and poverty, since each poverty indicator (or some of its components) are constitutive elements in the index.

Nominally, among the 12 indicators included in the index, half might be categorized as sensitivity indicators and the other half as indicators of adaptive capacity. By initially assigning no weights, the analysis began from an implicit assumption that each indicator possesses equal weight, and the subsequent weighting method is motivated by a comparative mission rather than by other concerns.

3.3 Vulnerability in the "Middle" and "Below" Perspectives

The "middle" vulnerability index was established via a vulnerability ranking exercise. The panel consisted of individuals who live or work on the island, each of who is therefore familiar with a large proportion of Ghoramara's population, and whose position makes him or her representative of a perspective located within local politics, bureaucracy, and public services. The eight key informants included Panchayat officials, school teachers, health workers and community leaders.

The group met in a plenary to discuss and evaluate each of the 202 households in the sample, according to a vulnerability ladder with five different rungs. Each category was given a brief description, minimalistic enough to avoid strong links with underlying drivers and sufficiently broad to allow capture of all sample households:

1. *Invulnerable*. Households whose livelihood is immune – or virtually immune – to the effects of natural hazards such as cyclones, floods, and rising sea levels, at least in the short term.
2. *Slightly vulnerable*. Households who are likely to suffer some inconveniences from the effects of natural hazards, but who are expected to recover and whose livelihood is not seriously threatened by these effects.
3. *Vulnerable*. Households who possess some livelihood sources that may be in jeopardy from the effects of natural hazards, but might also be able to recover from these effects; the fate of the household may depend on the severity and specific nature of the natural hazards.
4. *Highly vulnerable*. Households whose livelihood is under serious threat from the effects of natural hazards. Unlikely to recover completely from these effects, at least in the short term.
5. *Extremely vulnerable*. Effects of natural hazards are likely to have devastating effects on the livelihood of the household, and may even be a threat to the lives of household members. Should a natural disaster occur in the near future, migration may be the only survival option.

The "below" vulnerability index is based on a simple inquiry, included in the initial household survey. Respondents were asked to evaluate the following statement: "The livelihood of my household is at risk due to the effects of natural shocks such as cyclones, floods, and rising sea levels." Evaluation involved a standard five-point Likert scale – strongly disagree, disagree, neither agree nor disagree, agree, and strongly agree. Perspective here entails some obvious implications with regard to subjectivity and bias, but also sources of error related to respondents' knowledge and experience, which may affect their evaluation of this statement. Associations between human capital and vulnerability, for example, may reflect not just self-awareness but also awareness of climate events and their consequences.

3.4 Assumptions, Hypotheses, Data Analysis, and Ethics

First, indices for the three perspectives are constructed and compared. Next follows an examination of whether indicators included in, and excluded from, the numerical index are relevant to the middle and below indices. While the indicators – and their inclusion or exclusion – represent *assumptions* about vulnerability in the above-perspective numerical index, they represent *hypotheses* about vulnerability for the alternative perspectives. Thus, for example, it is *assumed* that natural capital is a relevant and influential indicator when constructing the numerical index; but when its influence on the middle and below indices is examined, that influence represents merely an expectation.

Each of the vulnerability indices implies an association between climate events and potential harm to households' livelihoods. Each describes a unique distribution, and a comparison of these distributions involves an assessment of the degree to which household vulnerability is consistent across perspectives.

Discrepancies between perspectives may arise not only from diverging views about the causal links between concepts, but also from how the concepts are defined. Thus, although the vulnerability indices share a fundamental concern with climate events, harm to livelihoods, and the association between them, social construction of the concepts themselves may account for some of the ambiguity observed. Statistical tests, however, rest on the assumption that differences in conceptualization are trivial.

It is legitimate to abstract from exposure in the above and middle indices because climate events will not be differentiated at the household level; only impacts and adaptability will vary between households. For the below vulnerability distribution, however, differentiated perceptions may have caused a redistribution of household ranks compared to a situation where perceptions were identical across the sample. In consequence, although the tests employed in the comparison of perspectives primarily engage with relative elements of the distributional association, they cannot control for differentiated within-sample perceptions of exposure. The extent to which this is a problem depends on how uniform perceptions are.

Missing observation for a given variable may arise from a lack of knowledge or recall. Missing observations were omitted from statistical tests. The number of observations employed for any given test may vary, with a maximum of 202. Because middle and below indices are ranked variables, comparisons and exploration involved nonparametric tests.

The methodology was approved by the Institutional Committee for Ethics and Review of Research at the Indian Institute of Health Management Research (February 2017:1). Written informed consent was obtained from all participants as per the guideline of the Committee. Consent was obtained in vernacular language for the better understanding of the respondents.

4. Results

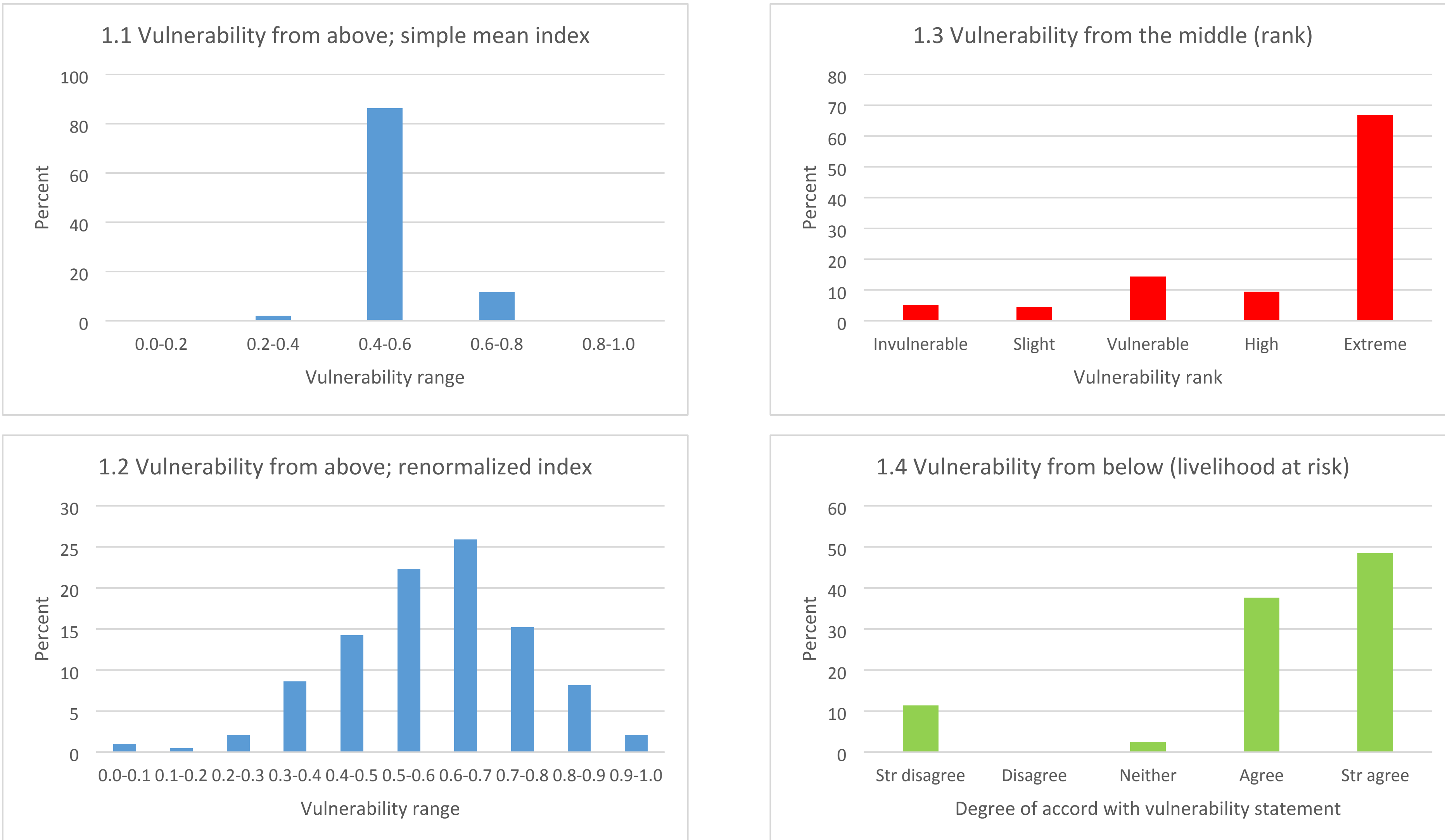
4.1 Vulnerability Distributions and Comparisons

Distributions for the three vulnerability indices are displayed in Figure 1. The first diagram, 1.1, depicts the numerical, composite “above” vulnerability index (V_A) in terms of the simple mean of the set of 12 normalized and unweighted indicators. The horizontal axis is divided into quintiles within the zero-to-one range, with the vertical bars indicating percentage frequencies. Apparent here is the bunching of scores into the central quintile. The distribution can be stretched horizontally – and compressed vertically – by re-normalizing, to produce the diagram in 1.2.

The diagram in 1.3 represents vulnerability according to the “middle” perspective (V_M), based on the vulnerability ranking by local officials and service-sector employees, with each rank reflecting a qualitative description. What is immediately apparent is the very skewed distribution, with two thirds of the sample ranked as extremely vulnerable. The diagram in 1.4 represents the “below” perspective (V_B). This displays a distribution broadly similar to that in 1.3; skewed towards the high-vulnerability end, but to a lesser extent than the middle perspective.

The bunching of scores and quasi-normal shape exhibited by the numerical index is expected from a composite index based on normalized values, even when some of the constitutive indicators are highly skewed. This distribution is strictly relative. On its own, it can only tell us something about the concentration of vulnerabilities but says nothing about absolute vulnerability; the distribution displayed in 1.1 and 1.2 might equally well be descriptive of a wealthy resort town (see also Biswas and Nautiyal, 2021).

Figure 1: Vulnerability distributions according to different perspectives



In contrast, the vulnerability ranking displayed in 1.3 is clearly of an absolute nature. The categorization of two thirds of the sample as extremely vulnerable is a reflection of the precarious situation faced by people living on a vanishing island. As with the middle perspective, the below perspective shown in 1.4 is skewed towards the vulnerable end and reflects absolute elements of vulnerability. Unlike the above and middle perspectives, this distribution reflects a purely subjective self-assessment. While 11.4% strongly disagree with the statement that their livelihoods are at risk, the next two rungs on the vulnerability ladder – “disagree” and “neither agree nor disagree” – are empty or virtually empty.

Of further interest is the correlation between these distributions; does someone described as vulnerable in one perspective also tend to be described as such in the other perspectives? Table 1 shows correlation coefficients for pairwise comparisons of the indices, along with coefficients also for correlation with two conventional poverty indices, income and wealth. Coefficients for pairs of numerical variables are Pearson coefficients; for the pair of ordinal variables, the Spearman coefficient. When a numerical and ordinal variable were paired, the numerical variable was converted into ranks and a Spearman coefficient computed.

The result here is clear but surprising: there is no significant correlation between any of the vulnerability indices.

Table 1: Correlation between vulnerability indices and poverty indicators

	Wealth	**Income**	**V_B**	**V_M**
V_A	-0.452***	-0.398***	-0.024	-0.012
V_M	-0.226**	0.019	-0.024	
V_B	-0.070	-0.026		
Income	0.265***			

*, **, *** denote significance at 0.05, 0.01, and 0.001 levels respectively
N = 197-202

The “above” indicator V_A is highly, significantly, and negatively correlated with wealth and income – this is expected since both income and the three capital indicators that constitute wealth form part of the index. The middle indicator V_M is negatively and significantly correlated with wealth but is not correlated with income. The below indicator V_B is correlated with neither wealth nor income.

The analysis proceeds by asking whether the indicators included in V_A can help to explain the distribution of vulnerabilities for V_M and V_B. To this end, an ordered logit regression of each of the latter two indices on the 12 indicators used to form the numerical index was applied. The logit procedure used was the proportional odds model. Results for V_M are given in Table 2.

Table 2: V_M regressed against the 12 constitutive V_A indicators.

Variable	Coeff	St error	z	Odds ratio	P>|z|	
Intercept 1	-5.717556	1.175669				
Intercept 2	-4.923537	1.139760				
Intercept 3	-3.667117	1.101362				
Intercept 4	-3.096508	1.089192				
Dependence	-0.417429	0.632642	-0.660	1.518054	0.509	
Income sources	0.323141	0.140804	2.295	0.723872	0.022	*
Impact count	-0.167467	0.113081	-1.481	1.182306	0.139	
Consumer-worker ratio	-0.889814	0.557136	-1.597	2.434678	0.110	
Public benefits	0.288510	0.135608	2.128	0.749379	0.033	*
Land lost	-0.024374	0.086726	-0.281	1.024674	0.779	
Human capital	-1.646560	0.733619	-2.244	5.189099	0.025	*
Social capital	-1.879146	0.766458	-2.452	6.547910	0.014	*
Physical capital	-0.000011	0.000003	-3.172	1.000011	0.002	**
Natural capital	-0.000005	0.000002	-2.202	1.000005	0.028	*
Financial capital	-0.000002	0.000004	-0.472	1.000002	0.637	
Income	0.000001	0.000003	0.385	0.999999	0.700	

*, **, *** denote significance at 0.05, 0.01, and 0.001 levels respectively
N = 198

At a first glance, the results are surprising, keeping in mind the absence of any significant correlation between the middle and above vulnerability indices: six of the 12 indicators significantly explain variation within the V_M index. A closer look, however, leads to yet more questions. The four significant capital indicators all push vulnerability in the expected direction. The two other significant indicators, however, influence V_M in the unexpected direction. Both the number of income sources and the number of public benefits realised by a responding household over the previous 12 months are associated with an increase, rather than a decrease, in vulnerability.

The corresponding regression for V_B is presented in Table 3. Because one of five ranked categories was empty, the regression reports only three intercepts.

Table 3: V_B regressed against the 12 constitutive V_A indicators.

Variable	Coeff	St error	z	Odds ratio	P>|z|	
Intercept 1	-0.052011					
Intercept 3	0.199552					
Intercept 4	2.293577					
Dependence	-0.764322	0.541984	-1.410	2.147539	0.158	
Income sources	0.081927	0.112596	0.728	0.921339	0.467	
Impact count	0.235482	0.105500	2.232	0.790190	0.026	*
Consumer-worker ratio	0.517285	0.496782	1.041	0.596137	0.298	
Public benefits	0.152799	0.117448	1.301	0.858302	0.193	
Land lost	0.036149	0.092942	0.389	0.964497	0.697	
Human capital	1.282267	0.644554	1.989	0.277408	0.047	*
Social capital	0.403803	0.712933	0.566	0.667776	0.571	
Physical capital	-0.000004	0.000003	-1.305	1.000004	0.192	
Natural capital	0.000002	0.000002	0.996	0.999998	0.319	
Financial capital	-0.000003	0.000004	-0.660	1.000003	0.509	
Income	-0.000003	0.000003	-0.963	1.000003	0.336	

*, **, *** denote significance at 0.05, 0.01, and 0.001 levels respectively
N = 198

Only two of the 12 V_A indicators significantly influenced the V_B index. The impact count, which records a household's history of sensitivity to earlier climate events, shows a positive association with V_B, as expected. Human capital, however – a combination of education and experience – also increases with vulnerability according to this perspective. This is unexpected. Human capital, as is normally assumed, reduced vulnerability in the other two perspectives.

The lack of correlation between V_A and the other two indices, V_M and V_B, can then in part be explained by the reversal of expected associations. The indicators employed in the numerical index also possess limited explanatory power, especially for V_B where the regression model, as measured by the log-likelihood, is barely significant at the 0.05 level, and where pseudo-R^2 values are in the 0.051-0.116 range. Model significance improves (< 0.0001), and psuedo-R^2 values are higher (0.110-0.234), for V_M.

4.2 Stepwise Procedures and Weighted Indices

As Hosmer and Lemeshow (2000: 116) note, stepwise procedures may be useful "…when the outcome studied is relatively new and the important covariates may not be known and associations with the outcome not well understood." Thus, to further explore these associations, a stepwise procedure was employed, incorporating all of the 22 indicators considered – including gender of head of household –

for both V_M and V_B. The model, as before, was ordered logit of the proportional odds variety. Forward selection was employed. Probability limits for variable entry and removal were set to 0.1 and 0.2 respectively.

Compared to the above regressions, the stepwise procedure for V_M (Table 4) produces the following results. Public benefits, human capital, and physical capital remain significant and with matching signs. Income sources and natural capital are no longer significant. The social capital indicator is also no longer significant and is indeed excluded during the procedure; but this is probably a result of the inclusion of the “relatives on the island” indicator, which is a component of social capital and which is significant here. Sex was among the indicators tested here but did not survive the stepwise procedure.

Table 4: Stepwise ordered logit regression with V_M as independent variable

Variable	Coeff	St error	z	Odds ratio	P>|z|	
Intercept 1	-3.164085	1.106743				
Intercept 2	-2.296930	1.077603				
Intercept 3	-0.884495	1.053132				
Intercept 4	-0.257306	1.051061				
Relatives on island	-0.066383	0.031158	-2.131	1.068636	0.033	*
Age, head of household	0.022914	0.012969	1.767	0.977347	0.077	
Size of cropland	0.277945	0.259959	1.069	0.757338	0.285	
Income sources	0.250953	0.144722	1.734	0.778059	0.083	
Public benefits	0.336503	0.146048	2.304	0.714264	0.021	*
Human capital	-2.071140	0.810648	-2.555	7.933864	0.011	*
Physical capital	-0.000011	0.000003	-3.360	1.000011	0.001	***
Natural capital	-0.000010	0.000005	-1.894	1.000010	0.058	

*, **, *** denote significance at 0.05, 0.01, and 0.001 levels respectively
N = 194

For the corresponding stepwise regression on V_B (Table 5), the differences from the above regressions are simple: only impact count remains significant (with matching sign).

The primary objective here is comparative and exploratory; identifying constitutive elements of the “middle” and “below” perspectives on vulnerability. Weighting of the 12 indicators used to construct V_A – using weighting methods based on principle component analysis, data envelopment analysis, or expert panels (e.g. Cutter et al. 2003, Gbetibouo et al. 2010, Sherly et al. 2015) – could potentially improve its correlation with V_M and V_B, but the foundation is not promising. It seems clear that V_B must primarily relate to factors not captured by V_A, while V_M exhibits associations with some of those indicators in an unexpected direction.

Table 5: Stepwise ordered logit regression with V_B as independent variable

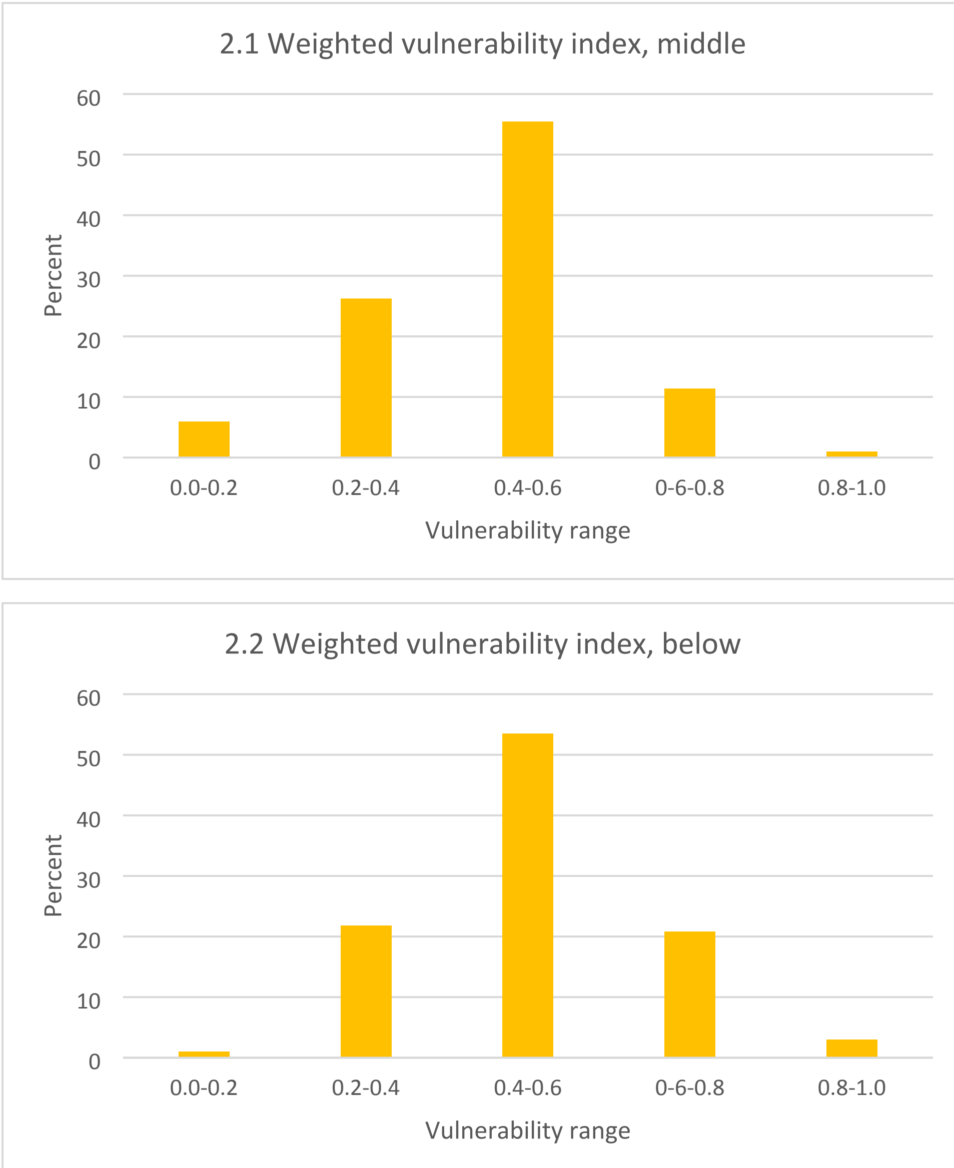
Variable	Coeff	St error	z	Odds ratio	P>|z|	
Intercept 1	-1.565052	0.665634				
Intercept 3	-1.311189	0.657710				
Intercept 4	0.747358	0.644187				
Age, head of household	-0.015164	0.009952	-1.524	1.015279	0.128	
Number of agric. plots	0.335029	0.171901	1.949	0.715317	0.051	
Dependence	-0.870197	0.537065	-1.620	2.387381	0.105	
Impact count	0.232832	0.097877	2.379	0.792287	0.017	*
Public benefits	0.164689	0.114223	1.442	0.848158	0.149	
Human capital	1.172630	0.634043	1.849	0.309552	0.064	
Physical capital	-0.000004	0.000003	-1.489	1.000004	0.136	
Financial capital	-0.000003	0.000004	-0.723	1.000003	0.470	

*, **, *** denote significance at 0.05, 0.01, and 0.001 levels respectively
N = 194

Instead, based on the stepwise procedures, two weighted vulnerability indices were constructed, labelled V_{SWM} (SWM denotes "stepwise-weighted-middle") and V_{SWB} (SWB denotes "stepwise-weighted-below"). These were developed as follows. All numerical indicators that survived the stepwise procedure were included in the index; indicators with unexpected signs (influencing vulnerability in the unexpected direction) were negated; all indicators were then weighted according to the absolute value of their standardized coefficient. Indicators requiring negation included size of cropland, income sources, and public benefits (for V_{SWM}), and number of agricultural plots, dependence, public benefits (again), human capital, and age of head-of-household (for V_{SWB}).

These indices essentially provide an answer to the question: *what would a weighted "middle" or "below" index look like if developed via vulnerability indicators from the "above" perspective*? The renormalized distributions for V_{SWM} and V_{SWB} are displayed in Fig. 2. As with the distribution for V_A, these are of a strictly relative nature.

Figure 2: Vulnerability distributions for weighted indicators based on stepwise regressions



The next task was to examine correlation – or lack thereof – between vulnerabilities in these weighted indices and those of the already established indices. The relevant coefficients are presented in Table 6, which includes also conventional poverty indicators.

Two of the significant results here are expected – V_{SWM} is strongly correlated with V_M, and V_{SWB} is strongly correlated with V_B. The new, weighted indices are after all based on indicators identified via stepwise procedures, according to their direction and magnitude of influence. Correlation between V_{SWM} and wealth is also no surprise, given earlier results.

Table 6: Correlation between weighted indices and other indices and indicators

	V_{SWM}		V_{SWB}	
V_{SWM}			-0.005	
V_A	0.143	*	-0.185	**
V_M	0.382	***	-0.047	
V_B	0.013		0.255	***
Income	-0.115		0.033	
Wealth	-0.349	***	-0.014	

*, **, *** denote significance at 0.05, 0.01, and 0.001 levels respectively

More interesting, perhaps, is the revelation that V_{SWM} is significantly correlated with both V_A and V_M, providing a link of sorts between the two. In a remarkable contrast to this result, the new “below” index, V_{SWB}, is negatively and significantly correlated with V_A. In a manner of speaking, the weighting of indicators seems to have purified the contrast between the two perspectives – recall that several indicators from the stepwise procedure influenced V_B in an unexpected direction, and therefore had to be negated.

From deliberations during the vulnerability exercise, it is known that location and migration opportunities were regarded as important by the panel that constitutes the “middle” perspective. Proximity of agricultural fields to shorelines and embankments was particularly emphasized since loss of land is permanent. While extreme events can destroy crops or granaries anywhere on the island, harm is transitory and protective measures and recovery more feasible. The distance between agricultural plots and the nearest shoreline was established. However, only 40.6 percent of the sample possessed agricultural fields, severely limiting the usefulness of this information. In the stepwise procedures, hamlet affiliation entered as a categorical variable, but it did not emerge as significant in either the “middle” ore the “below” regression. Migration prospects should be at least partially captured by capital indicators.

5. Discussion

5.1 Distributions and Association

The numerical index V_A harbours no secrets, since it was built from the ground up. Such indices are strictly relative, however, and in isolation their distributions contain little information. Internal differences in vulnerability scores may be trivial next to the precarious overall context, of which the distribution says nothing.

Vulnerability indices may contain proxies for both symptoms and causes of vulnerability – although a general complaint against such indices is that they ignore underlying social processes (Eriksen and Kelly 2007), in part because these processes may be difficult to identify and measure. In practise, the proxies included define vulnerability, and the co-existence of symptoms and causes poses problems of ambiguity, to be discussed below.

In contrast to V_A, indices for vulnerability from the other two perspectives contain absolute elements. Such indices, then, can provide information that conventional numerical indices cannot. Against this, ordinal-scale indices of this type must by necessity be of comparatively course resolution. One of the main objectives here was to examine associations between the three perspectives; and tests revealed that there was no significant correlation between any of the three indices whatsoever.

In sum, the "above" perspective on vulnerability developed here evinces a lack of overall resonance among the two other perspectives considered. A critical element in this lack of congruence is the incorporation of indicators that in the other perspectives may associate with vulnerability in the opposite of the expected direction. For the "middle" perspective, these unexpected results cancelled out the obvious resemblance to the "above" perspective in terms of incorporation of the livelihood capital categories.

Stepwise procedures and weighting allowed the construction of two new numerical indices. Since the primary task was to explore associations between different perspectives on vulnerability, weighting was designed to enhance association. As it turned out, one of the results of this exercise was a weighted index V_{SWB} – based on associations between numerical indicators and the "below" perspective on vulnerability – that exhibited significant but negative correlation with the original vulnerability index V_A. This was the culmination of an exploration where the ambiguity of indicators figured prominently.

5.2 Ambiguity

Ambiguity can most obviously arise from vagueness inherent in the concept of vulnerability itself, and the different ways in which the concept has been operationalized (Hinkel 2011, Cole 2016). In the present analysis, events (climate change), context (Ghoramara, and a sample of its population), and potential harm (to livelihoods) were elements in the framing of vulnerability that cut across perspectives. Conceptualization of events and potential harm may nevertheless differ across cultures

(Adger et al. 2013), as may the understanding of how context mediates the association between them. Ambiguity at the index level can be further traced to ambiguity also at the level of individual indicators.

A certain type of ambiguity is familiar in research where selection bias is an issue: did the new technology cause the greater wealth observed among adopters or was the technology affordable only to those already wealthy? This dilemma seems characteristic of the "public benefits" indicator, a count variable that enumerates the dimensions in which a household receives public assistance. While the assumption was that these benefits would act to reduce vulnerability, the indicator is consistently and significantly associated with greater vulnerability in the "middle" and "below" perspectives. Receiving such benefits, then, is clearly taken as a symptom of vulnerability in these two perspectives.

The association between development assistance and vulnerability may be complex (Jain and Bardhan 2023). On Ghoramara, while public benefits may serve to reduce the vulnerability of recipient households, these households still tend to remain more vulnerable than non-recipients; the targeting of public support schemes may have been successful but benefits have been insufficient to substantially reduce vulnerability.

The way in which past shocks and attendant adaptations interact with the idea of adaptive capacity also merits attention. A household's history of climate change events may be taken as evidence of chronic sensitivity but may also have provided it with valuable experience in adapting to such events. Past impacts and past adaptations – such as shifting your dwelling to a new location or pursuing new livelihoods sources – may therefore be interpreted in radically different ways.

Vulnerability was significantly influenced in an unexpected direction also by indicators related to the number of income sources, human capital, and the age of the head of household. Why more income sources should be associated with greater vulnerability is a conundrum. A greater number of income sources is normally associated with both greater security and higher incomes. Additional sources reflect an opportunistic element, and the insurance they provide does not come at the expense of a reduction in net income (e.g. Vedeld et al. 2007). There is indeed also a significant and positive correlation between income sources and net income in the data, so it seems improbable that a high number of sources could be construed as a general symptom of desperation.

The human capital indicator poses yet another problem. In the initial regressions to examine the influence of numerical indicators on V_M and V_B (Tables 2 and 3), human capital was significant for both indices – but in opposite directions. While human capital reduced vulnerability in the "middle" perspective, it increased vulnerability in the “below” perspective. The human capital indicator was a composite, combing normalized proxies for education and experience. The mystery is how such an indicator can be associated with greater vulnerability. Possibly, the method of inquiry has played a role in this; in the “below” perspective, respondent and object of inquiry generally overlap, and those with greater experience and education may take a more informed view of their own vulnerability. It is also possible that the proxy for experience – the number of years settled on the island – could be construed as a symptom of a lack of alternatives. But this is in the realm of speculation.

Vulnerability, in some conceptions, may relate to the idea that some people have more to lose than others. Perspectives that reflect absolute considerations may nevertheless incorporate relative *temporal* aspects. A vulnerability metric emphasizing the difference between a household’s pre-event and (potential) post-event states might identify also the wealthy as vulnerable, and shift attention away from adaptive capacity and towards sensitivity.

Ambiguity associated with the human capital indicator may however also resonate with much broader debates about human relations, dependence, and vulnerability. Vulnerability is not merely the regrettable consequence of human interdependence but also the wellspring of community and attendant virtues such as generosity and hospitality. Measures of “social relations” may thus be inherently ambiguous, also because relations themselves may be vulnerable (MacIntyre 1999, Laugier 2016).

Ambiguity, in its various forms, may be an important element for many of the vulnerability indicators applicable to this type of assessment. Ambiguity may attach to the interpretation of an indicator as symptom or cause, the manner in which the past is taken to signify the future, whether specific proxies are seen to reflect opportunity or necessity, and the notion that income or capital buffers can be sources of both adaptability and vulnerability.

5.3 Research and Policy Implications

According to Hinkel (2011), vulnerability assessments have generated much scepticism among researchers while still finding favour among policy makers. The reductionist nature of indicator-based vulnerability may be part of their attraction; complex processes translated into comprehensible numbers and diagrams.

It is possible to give expression to local and intermediate-level voices through the simple methods employed in this analysis. Those methods add elements of absolute vulnerability, where conventional methods permit only the relative. If local voices are to be privileged in local studies of vulnerability, however, then quantitative indices must be complemented by qualitative methods better able to capture thicker descriptions of social relations and the institutions through which they are mediated. This has been a recurring theme in social scientists’ engagement with vulnerability and climate change (e.g. Kelly and Adger 2000, O’Brien et al. 2007, Ribot 2009) and the present analysis does nothing to dispel or weaken their arguments.

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