Social vulnerability of coastal fish farming community to tidal (Rob) flooding: a case study from Indramayu, Indonesia

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Received: 16 July 2021 / Revised: 9 January 2022 / Accepted: 24 February 2022 / Published online: 14 March 2022
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Abstract
Climate-related disasters increasingly threaten over one-third of the global population, specific coastal communities within 100 km of coastal zones. Indonesia, the world’s largest archipelago with the second-longest coastline, faces tidal (Rob) flooding from high tides, land subsidence, and sea-level rise. This study assess fish farmers’ vulnerability to Rob flooding in Java’s Indramayu District. Our Social Vulnerability Index (SoVI) developed involved 150 questionnaires, focus group discussion, and key-informant interviews between 16 and 20 October 2019. It found a high vulnerability, a SoVI score of +1.76 comprising nine principal components (PCs): external support and government mitigation, local knowledge, income, expenditure, family size, seasonal-expenditure, education, experience, and ethnicity. Contributing to ‘vulnerability’ and ‘resilience’ concepts, it highlights community memory of repeated disasters and its impact on local adaptive capacity. Findings inform policymakers to address the PCs influencing vulnerability, including critically-needed livelihood support and early-warning systems relevant to the country’s 12,000 + coastal-villages and developing countries where over 90% of fishermen live.

Keywords Adaptive capacity · Coastal disasters · Resilience · Social vulnerability index

Introduction
Coastal disasters threaten human life, the environment, the economy and are influenced increasingly by rapid changes in the global climate system, including a temperature rise of 1.1 °C (since the pre-industrial period) and sea-level rise of 5 mm annually (2014–2019) (World-Meteorological-Organization 2019). These produce changes in the frequency, increase, and intensity of wind speed, wave height, and ocean temperature leading to coastal flooding, erosion, inundation, and land subsidence. Globally, annual climate-related disasters reached 335 (between 2005 and 2014); 90% of the 7,255 disasters (between 1998 and 2017) were floods and storms affecting over two billion, killing 124,088 (United-Nations-office-For-Disaster-Risk-Reduction and Centre-for-Research-on-the-Epidemiology-of-Disasters 2018). Global socio-economic flooding loss will increase eightfold in 2050 to around US$ 52 billion annually compared to 2005 (Hallegatte et al. 2013). Developing countries are most vulnerable due to the low social-ecological system resilience and adaptive capacity, specifically coastal communities representing over one-third of the global population (Gu 2019). As with sub-Saharan Africa, Asia including Iran, Bangladesh, India, Philippines, Vietnam, and Indonesia, face
threats of storms and floods regularly (Guleria and Edward 2012; Tran et al. 2017; Suroso and Firman 2018; Hadipour et al. 2019; Krishnan et al. 2019; Rabby et al. 2019). Our study addresses Rob flooding, i.e. tidal flooding and inundation caused by high tides, sea-level rise, and land subsidence on Java’s north coast (Buchori et al. 2018).

Indonesia, the largest archipelagic country, with a coastline of 54,716 km highly sensitive to climate conditions and anthropogenic activities, is Asia’s third most vulnerable country to floods after China and India (Marfai et al. 2008). Repeating Rob hazards pose significant challenges to communities, including life, biodiversity, and economic loss, land erosion, destruction of infrastructure, residences, and mangrove forests. Contemporaneously, communities’ livelihood activities affect environmental changes, including extensive use of groundwater causing land subsidence, uncontrolled agriculture expansion causing mangrove destruction and diminished tidal protection, land-use change of swamp-forests into residential, rice field or fish farms, narrowing of rivers, and poor drainage (Buchori et al. 2018). This loop between anthropogenic activities and environmental degradation influences communities’ adaptive capacity to disasters.

The theoretical concepts of vulnerability, resilience, and adaptive capacity inform our study (see ‘Theoretical framework: vulnerability, resilience and adaptive capacity’ section). These concepts, manifestations of the relationship amongst components within a dynamic social-ecological system (Gallopín 2006), are central to disaster management debate (Krishnan et al. 2019). Definitions of these concepts vary, although a fundamental connection can be drawn: increasing community adaptive capacity reduces pre-disaster risk (i.e. reduces vulnerability), improves during and post-disaster recovery (i.e. improves resilience), and minimizes human and economic loss. Existing literature applied these concepts to determine key factors affecting communities’ vulnerability, thereby informing governments on improved mitigation and adaptation policies (Dintwa et al. 2019; Krishnan et al. 2019; Guleria and Edward 2012; Mohanty et al. 2019). The linkage between ‘vulnerability’ and ‘resilience’ is also used in the Sendai Framework for Disaster Risk Reduction 2015–2030 (United-Nations-office-For-Disaster-Risk-Reduction and Centre-for-Research-on-the-Epidemiology-of-Disasters 2018) adopted by many United Nations members including Indonesia.

However, the application of these concepts within Indonesia’s studies are scant: a few deployed them to discern earthquake and tsunami events (Siagian et al. 2014), but not fishing communities’ vulnerability to climate-related disasters, specifically Rob flooding. The world’s leading farmed-fish producer, Indonesia has over 12,000 under-developed vulnerable coastal villages (Buchori et al. 2018). Filling this research gap, we aimed to achieve two objectives through the Indramayu District case study. Empirically, to determine key socio-economic variables affecting fish farmers’ vulnerability to Rob flooding. Theoretically, to render visible the role and extent to which repeated exposure to disasters, and the community’s collective memory of past exposure, influence local resilience and adaptive capacity. Thus, we aimed to inform policymakers on well-targeted interventions for disaster management.

Cutter’s Social Vulnerability Index (SoVI) (Cutter et al. 2003) informed our study. SoVI is a relative measure of overall community social vulnerability to environmental hazards, synthesizing socio-economic variables which contribute to reducing a community’s ability to prepare, respond, and recover from hazards (Cutter et al. 2003). In practice, numerous measurable variables exist indicating aspects of a system’s vulnerability to environmental hazards, which are often overlapping, highly correlated, and hence unsuitable for regression analysis (Holand et al. 2011). We address this by employing the Principal Component Analysis method1 to structure complex qualitative data, reduce duplicates, inconsistencies, and incomplete variables, resulting in ‘principal components’ (PCs)2 influencing the community’s vulnerability (Aksha et al. 2019). SoVI has been applied within developed and developing country studies, each researcher making it context-specific, each modification providing variables precision which better informs new studies.

For example, studies of local vulnerability to climate-related disasters revealed the following. Municipalities in North Norway showed higher socio-economic vulnerability, with variables including multi-ethnicity, population structure, and unemployment (Holand et al. 2011). Nepal’s mountain villages and municipalities are highly vulnerable, the PCs including renter, occupation, poverty, infrastructure, ethnicity, health, and education (Aksha et al. 2019). Botswana’s rural population is highly vulnerable due to the concentration of urban economic development and population concentrations under five and above 65 years (Dintwa et al. 2019). The PCs’ affecting Bangladesh’s coastal regions include household composition, ageing population, education, ethnicity, and renter (Rabby et al. 2019).

1 The PCA, a statistical dimension reduction technique, seeks to achieve a smaller number of variables which reflect a large proportion of the information contained in the original data set, creating a composite score of social vulnerability (Hair Jr et al. 2014: 146; Kirby et al. 2019; Aksha et al. 2019).

2 PCs refer to variables that can only be measured indirectly through several observable variables. During the PCA process, variables with high similarity and correlation are grouped into a smaller set of PCs summarising the relationships in given data (Rabby et al. 2019; Holand et al. 2011).
Our study extends the existing literature by assessing the SoVI of a more-specific community (coastal fish-farmers) to an equally specific hazard (Rob flooding). Thus it fills the mentioned gap in the scarcity of SoVI’s application and deployment of vulnerability, resilience, and adaptive capacity concepts within Indonesia’s studies. The rationale for selecting villages in Indramayu District is explained in the Methods section. Whilst every village is unique the study area reflects the typical socio-ecology of Indonesia’s coastal-villages concerning education, occupation, poverty, family size, expenditure, economic hardship, geographical isolation, and limited infrastructure (Statistics-Indonesia 2020a). Thus, our methodology and findings have replication and adaptation potential for Indonesia’s 12,000 + coastal-villages, and other archipelagic countries with similar social-ecological settings.

**Theoretical framework: vulnerability, resilience and adaptive capacity**

Our study is anchored on the conceptual linkage of vulnerability, resilience, and adaptive capacity which informed our conceptual-methodology framework (Fig. 2) and is relevant to hazard and disaster management discussion. Hazards are threats to a system including perturbations, i.e. major spikes such as tidal waves, severe floods, hurricanes, or earthquakes (Krishnan et al. 2019). Disasters, the consequence of severe hazards which seriously disrupt systems’ functions, results from the interaction between hazards and social conditions, impacting the social-ecological system and people’s vulnerability (Sanchez and Maldonado 2013).

Vulnerability, systems’ inherent characteristics that create the potential for harm, is assessed by exposure to perturbations and response to risks (Krishnan et al. 2019). Resilience relates to systems’ reaction during exposure, i.e. capacity to respond and rise from natural disturbances to maintain systems’ basic functions (Gallopín 2006; Wolters and Kuenzer 2015; Moreno et al. 2019.). It refers to an individual or community’s capacity to adapt, reorganize, and overcome negative experiences during environmental change, and government capacity to act with appropriate policies and strategies (Sanchez and Maldonado 2013). The ‘social-ecological system (SES) resilience’, progressed from ‘ecological resilience’ concept, enables a comprehensive assessment of how systems can reorganize, change, and learn in response to a particular threat and remain sustainable, hence reducing vulnerability (Ferro-Azcona et al. 2019).

The concept of social vulnerability constitutes three elements. Firstly ‘exposure’, meaning the degree and duration to which systems are in contact with disturbances (Gallopín 2006). Secondly ‘sensitivity’, the degree to which systems are affected by an external or internal disturbance, and thirdly systems’ coping ability and recovery potential (Gathongo and Tran 2019). Social vulnerability is also dependent upon social capital, politics, institutions, environmental, culture, economic resources, and their distribution (Gathongo and Tran 2019). Exposure to perturbations builds systems’ resilience (Ferro-Azcona et al. 2019), with communities’ memory of past events increasing their capacity to respond to future hazards. Community resilience is evident through social capacities, including social networks, participation, and organization, activated during and post disasters (Gulheria and Edward 2012; Moreno et al. 2019). Consequently, a community’s vulnerability to disasters is reduced by the activation of local resources, particularly when external support is absent (Gulheria and Edward 2012; Moreno et al. 2019).

The response capacity to long-term adjustments to SES is conceptualized as an adaptive capacity, i.e. systems’ ability to prepare for and implement measures before, during, and after hazards (Gallopín 2006; Mohanty et al. 2019). It includes the capacity to address a system’s problematic exposures and sensitivities which enable its socio-economic, institutional, and political environment to respond to overall SES changes, including the desire to learn and improve through the social learning process (Blythe et al. 2015; Mulyani and Jepson 2015). In short, adaptive capacity includes the ability to modify a system’s sensitivity and reduce its exposure to perturbations, thereby increasing its resilience.

Existing literature discussed ways to increase SES resilience by improving overall community adaptive capacity (Ferro-Azcona et al. 2019), including the need for external support and local government’s mitigation efforts (Mohanty et al. 2019). Some emphasized the need for and application of social-environmental indicators (Cutter et al. 2003) and the general impact of flood damage (Kirby et al. 2019). When measuring a system’s resilience, challenges include the qualitative nature of certain resilience variables, the vague definition of the concept (Gallopín 2006), and determining those variables most critical in influencing a community’s vulnerability (Cutter et al. 2003; Armaş and Gavriş 2013). Nonetheless, access to resources (finance, knowledge, technology, and information), social capital, beliefs, customs, age, gender, disabilities, and environmental factors are commonly accepted as attributing factors (Cutter et al. 2003; Gathongo and Tran 2019).

In summary, employing the conceptual linkage of vulnerability, resilience, and adaptive capacity we identified the following gap; the regular occurrence of Rob flooding should provide the necessary exposure for a system to learn how to absorb, respond, and adapt to disturbances, hence increasing resilience and reducing the scale of disasters’ impact (i.e. reduced vulnerability). Data previous to our research on Indramayu revealed otherwise (see Methods). We aimed to address this gap by examining the roles of the vulnerability
element of repeated ‘exposure’ and the communities’ resulting collective memory on local adaptive capacity.

**Materials and methods**

**Case study: Indramayu sub-district**

Indonesia’s 12,857 coastal villages are largely underdeveloped (Buchori et al. 2018) and climate-related disasters worsen the condition. Indramayu district is unique: its’ 1.7 million inhabitants are known as ‘orang (people) Indramayu’ speaking a ‘Javanese-Cirebon’ dialect (called ‘Dermayon’), although it is located within West-Java province whose population predominantly speak Sundanese language and are of Sundanese ethnicity (Firmansyah 2018). Our study uses the term ‘native farmers’, referring to fish-farmers who were born in, held identity cards of, and inhabited the local area for generations, and predominantly ‘orang Indramayu’. We use the word ‘fishers’ to refer to fishpond farmers.

With a land area of 2,099.42 km² and 147 km coastline (Statistics-Indonesia 2020a), the Indramayu district is one of ten areas on Java’s North coast prone to Rob and inundation hazards. Rob flooding occurs annually in July and August and can inundate fishponds over 15 days (Perdinan et al. 2014). By 2030 the district is to experience the province’ second-largest coastal inundation, affecting 10,000 ha of fishponds (Suroso and Firman 2018). It is divided into 31 sub-districts with 317 villages (Statistics-Indonesia 2020a).

Our study area, the Indramayu sub-district, is located between 108°18’-108°22’ East-Longitude and 6°18’-6°24’ South-Latitude (Fig. 1). It is the district’s largest fishpond area comprising five coastal villages (Singaraja, Singajaya, Tambak, Karangsung, and Pabeanudik).

The five villages have sixteen farmer groups, established through village-council meetings and endorsed by village heads. They work 1,810.28 ha of fishponds, producing 25,809 tons annually, and contributed US$ 10.08 million (141.1 billion Indonesian-Rupiah) to the district’s revenue in 2018 (Statistics-Indonesia 2018b). Whilst Village Economic Units (cooperatives known

![Fig. 1 The case-study area: Indramayu sub-district located between 108°18’-108°22’ East-Longitude and 6°18’-6°24’ South-Latitude. Developed by 1st author based on data from the Agency for Assessment and Application of Technology Indonesia](image)
as ‘BUMDes’) are promoted throughout the district to support livelihoods (Statistics-Indonesia 2018b), there was no evidence within our five villages. Nevertheless, a State-owned PT Pertamina Refinery company supported one village, Karangsong, to develop eco-tourism (Gunawan et al. 2017).

The district’s inhabitants mostly held either no formal or low-level education, with most villages categorized as ‘under-developed’ (Statistics Indonesia 2018b). Its revenue in 2017 resulted from government-based services (26.5%) supporting 11,608 employees, which includes education and health sectors, trades (23.58%), agriculture and fish-farming (23.19%), transportation and communication (7.72%), construction (7.5%), and mining (2.97%), the remainder includes electricity, gas and drinking water (Statistics-Indonesia 2018a). Fish farming has been an important livelihood for generations with 262,703 people (35.2% of district employment) involved in 2018, contributing US$ 957.1 million to the district’s revenue and the second-largest (19.19%) contributor (Statistics-Indonesia 2018b). With 38% of farmers concentrated within coastal areas, their activities resulted in large-scale land clearing, making the ecological system more vulnerable to flooding and negatively impacting local livelihoods (Buchori et al. 2018). Key anthropogenic activities include extensive use of groundwater exacerbating land subsidence, destruction of mangrove habitats, narrowing of rivers, poor drainage, and land-use changes of swamp-forests into residential, rice fields, or fish farms (Suroso and Firman 2018). Only one village, Karangsong, conserved its mangrove habitat for flood protection (Gunawan et al. 2017).

The district experienced 3,900.41 ha of coastline erosion (23.64 ha/year average) and 650.29 ha of sedimentation (4.81 ha/year) between 1994 and 2009 (Maryanto et al. 2018). This long-term erosion and accretion trend, increasing the frequency of Rob flooding, land subsidence, and coastal inundation events (Suroso and Firman 2018). Local people’s testimonies on the Rob increase which damaged various infrastructures were well-documented (Aldrian et al. 2011). This area is predicted to incur sea-level rise and high tides reaching 2.53 and 3.03 m in 2050 and 2100, risking between 34,600 – 42,000 ha of land to coastal inundation (Dasanto 2018). Flooding simulations between 2050 and 2100 reveal a potential loss between US$ 5.8–7.4 million (or 82.6-104.3 billion Rupiah) in non-residential lands, such as rice fields, ponds, and moorings (Dasanto 2010). Given its potential and the challenges faced, the Indramayu district provides an appropriate social-ecological setting for our research in relation to the interplay between variables determining a community’s vulnerability, resilience, and adaptive capacity.

Data collection and analysis methods

Data collection method

Data acquisition involved two phases. Firstly, the selection of key vulnerability variables of the fish farming community, including wealth, age, population density, economic dependence, housing, tenancy, ethnicity, and infrastructure (Cutter et al. 2003; Nguyen et al. 2017), as well as education, employment, family size, medical services, land ownership, and income (Aksha et al. 2019; Ferro-Azcona et al. 2019). Moreover, resilience indicators were adopted, including external support and local government’s mitigation capacity. The systems’ vulnerability elements of ‘exposure’ and ‘sensitivity’ (Nguyen et al. 2017) were considered since our study area is prone to repeated hazards. Data on population census by National Statistics was used to ascertain the socio-economic characteristics of Indramayu District against the afore-mentioned vulnerability variables. We involved an ‘expert judgement’ method to address limitations when both deductive and inductive methods were employed (Nguyen et al. 2017). The five experts familiar with Indramayu hold expertise ranging from geography, socio-economics, statistics, system-dynamics, and coastal management. This phase resulted in forty-five key-variables reflecting the socio-economic characteristics of the community, converted into forty-five questions within our semi-structured questionnaire (Table S1, Fig. 2).

In the second phase, we distributed the questionnaire to 150 respondents between 16 and 20 October 2019. Though we consider this sampling size a limitation, a sampling between 100 and 400 is considered sufficient to provide a valid basis for statistical estimation (Hair Jr et al. 2014). Moreover, we also utilized a larger data-set from the National census when selecting the initial vulnerability variables (phase-1). We selected our respondents via a purposive sampling method using the criteria, (i) fishpond farmers (ii) live in the five villages with valid identity cards, (iii) own a fishpond, and were affected by Rob flooding. Farmers fulfilling these criteria were invited to meetings by village heads: we read the questionnaire’s forty-five questions written in the National language, and translated into the local language when necessary. The completed questionnaires returned at the end of every meeting aggregated 108. To triangulate and complement the questionnaire data we conducted in-depth interviews with two government officers from local planning and disaster response agencies, and with the five village leaders.

Data analysis method

We treated the 108 completed questionnaires as valid primary data and analyzed them through the Statistical Package
for the Social Sciences (SPSS) software (Hair Jr et al. 2014). This step provides the foundation for comparing variables and reducing the risk of inaccurate results (Kirby et al. 2019). This resulted in thirty-two test/independent variables (Table 1) which presumed cause for any change in the dependent variables (depicted in Table 3) in our SoVI construction (Hair Jr et al. 2014).

The 32 independent variables were tested using ‘Kaiser-Meyer-Olkin Measure of Sampling Adequacy’ (KMO) and ‘Bartlett’s Test of Sphericity’ (Kirby et al. 2019; Rabby et al. 2019). The former analyzed the sample’s adequacy and the latter (resulted in ‘p-value’) tested the strength of the relationship between variables (Hadi et al. 2016). All 32 test variables met the minimum standard to proceed with the ‘factor analysis’ (Kirby et al. 2019), with the KMO value > 0.5 and p-value < 0.05 (Table 2). The resulting p-value of 0.000 signifies a strong correlation between all tested variables (Table 2).

The thirty-two variables explaining the relationship between the fishers’ social vulnerability and Rob flooding lacked a homogenous unit of measurement to render them comparable. To address this we employed the PCA method to reduce duplicates, inconsistencies, and incomplete variables (Cutter et al. 2003; Aksha et al. 2019). We grouped variables with high similarity and correlation into a smaller set of nine Principal Components (Table 4) consisting of seventeen dependent or outcome variables (Table 3), each capturing a dimension of fishers’ social vulnerability. The dependent/outcome variables presumed the effect of a change in the independent variable(s) (Hair Jr et al. 2014).

Furthermore, only components with eigenvalue ≥ 1.0 (Table 4) were extracted and named as PCs (Aksha et al. 2019). Each PC needs to have loading values > 0.5 to determine its reliability and meet convergent validity criteria (Dintwa et al. 2019). We measured the overall SoVI score by weighting each PC’s loading variance (%) vis-a-vis the value of the total variance of all nine PCs. The weight of each PC reflects its contribution value; the higher the value the greater its contribution to the overall SoVI score (Dintwa et al. 2019). The term

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3 KMO allows us to check the overall sampling adequacy of individual variables. The values range from 0 to 1, reaching 1 when each variable is perfectly predicted without error by the other variables; an overall value above 0.50 is required before proceeding with the factor analysis (Hair Jr et al. 2014).

4 Factor analysis, including PCA, is a statistical approach to analyse inter-relationships among a large number of variables, explained in terms of their common underlying dimensions (Hair Jr et al. 2014).

5 The ‘eigenvalue’ greater than one rule, and the scree plot, can be used to determine the number of PCs that adequately explain the correlations between the variables (Rabby et al. 2019; Aksha et al. 2019).
Table 1  Thirty-two independent variables for Social Vulnerability Index (SoVI) construction within Indramayu sub-district, Indonesia

| Vulnerability components and indicators | Independent (test) variables\(^a\) (Description by percentage) |
|----------------------------------------|-------------------------------------------------------------|
| Sensitivity                            |                                                            |
| Family size                            | Fishpond farmers (hereafter ‘farmers’) with > 4 dependants  |
|                                        | Farmers family members with a disability (pension and special needs) |
| Ethnicity                              | ‘Native farmers’\(^b\) population                           |
| Education                              | Farmers without formal education                            |
|                                        | Farmers with >2 children who are in school                  |
| Income                                 | Farmers with >10 years of working experience                |
|                                        | ‘Polyculture’ fishpond                                     |
|                                        | Farmers earning > IDR 12 million/harvest                    |
|                                        | Farmers with >twice harvest season/year                     |
|                                        | Fishponds with produce > 1 tonnes/harvest                  |
|                                        | Farmers who will remain fish farmers for the next five years |
| Renters                                | Farmers who did not rent fishponds                          |
| Infrastructure and facilities          | Fishponds without electrical power for fishpond            |
|                                        | Fishponds with water supply from seawater                  |
|                                        | Fishponds with distance <2km from fish auction market      |
| Expenditure                            | Fishpond without employee                                  |
|                                        | Fishpond without a permanent employee                      |
|                                        | Fishpond with a non-permanent employee                     |
|                                        | Farmers with expenditure from non-permanent employee        |
|                                        | Farmers without expenditure from permanent employee         |
| Exposure                               | Farmers affected by Rob flooding                           |
| Hazardous events                       | Farmers affected by economic losses due to Rob flooding     |
|                                        | Farmers who did not consider Rob flooding as a disaster     |
|                                        | Farmers with a family rescue scheme from Rob flooding      |
|                                        | Farmers without Rob flooding counseling                     |
|                                        | Farmers without received the socialization about mangrove conservation |
|                                        | Farmers who active in any coastal community organizations  |
|                                        | Fishponds without protection from Rob flooding              |
| Adaptive Capacity                      | Mitigation and external support capacity                    |
|                                        | Farmers who have an assurance/saving                       |
|                                        | Farmers without a standard operating procedure for emergency response |
|                                        | Fishpond without an evacuation route                        |
|                                        | Farmers without an early warning system                     |

Based on 150 questionnaires distributed between 16 and 20 October 2019

\(^a\)The process to achieve the thirty-two independent (test) variables is explained throughout the texts (‘Data collection method’ and ‘Data analysis method’ sections); the explanation of ‘independent variables’ is provided in section ‘Data analysis method’; and throughout the texts fishers’ refers to fishpond farmers

\(^b\) ‘Native farmers’ refers to fishpond farmers who were born in, held identity card of, and inhabited the local area for generations, and are predominantly ‘orang Indramayu’ (section ‘Case study: Indramayu sub-district’)

Table 2  Results from the KMO and Bartlett’s Test

| KMO and Bartlett’s Test | Value       |
|-------------------------|-------------|
| Kaiser-Meyer-Olkin Measure of Sampling Adequacy | 0.660       |
| Bartlett’s Test of Sphericity | Approx. Chi-Square 1830.872 |
|                           | Df 496      |
|                           | Sig (p-value) 0.000 |
‘cardinality’ relates to which PCs increase or decrease social vulnerability (Cutter et al. 2003): positive directionality (+) means the PCs increased vulnerability, negative (-) means reduced vulnerability (Table 4). When all measured PCs are scaled, positive values within the SoVI score indicate high-levels of vulnerability; negative decreased overall vulnerability (Cutter et al. 2003). An overall social vulnerability score (Box 1) is calculated by summing all the PC scores (Rabby et al. 2019).

**Box 1: formula to calculate SoVI in Indramayu sub-district.**

\[
\text{SoVI}_{\text{fishponds}} = 0.16PC1 + 0.16PC2 - 0.13PC3 - 0.12PC4 + 0.11PC5 + 0.11PC6 + 0.08PC7 - 0.07PC8 - 0.06PC9
\]

Whilst a standard range of SoVI scores is not available at the national or international level (a range from low, medium, to high), a practice accepted across the literature is that for scores above zero a positive value reflects high social vulnerability, and negative reflects a low-level of vulnerability.
Results and discussion

Our study identified nine principal components (PCs) consisting of seventeen variables that influence fishers’ social vulnerability: each has eigenvalue $> 1$ (Fig. S1), and together explained 69.44% of the data’s variance (Table 3). Their ‘cardinality’, positive or negative loadings, reflects increased or decreased vulnerability. The sum of PCs’ weights produces the SoVI score of the fishers’ community in the Indramayu sub-district, i.e. $+1.76$. The positive sign indicates the high-level of their social vulnerability to Rob flooding.

Each PC’s value (column ‘weight’) reflects its contribution to the community’s overall vulnerability: the higher the value the greater its contribution. For example, external support and local government’s mitigation capacity (weight 0.16), and local knowledge of Rob flooding (weight 0.16) are PCs with the greatest contribution to the overall SoVI. The nine PCs reflect fishers’ local characteristics: mostly held low-level education with insufficient income to afford basic livelihoods and recover from disasters, hence perpetual-poverty. Nonetheless, they insist on maintaining the farming-livelihood, becoming an intra-generational culture, and equipping them with vast experience. Poverty means they cannot afford higher education for their children, resulting in generations unable to acquire new knowledge and technology to mitigate current climate-related hazards. These characteristics influence their overall vulnerability to Rob, thereby informing government authorities on improving disaster prevention and mitigation strategies. Our key findings are discussed further below, structured around the nine PCs.

**External support and local government’s mitigation capacity and efforts (PC-1)**

This is the most significant component representing 11.21% of total variations in farmers’ social vulnerability (Table 3) comprising four variables: fishers without the ‘standard operating procedure’ (SOP) (V1 74.1%); fishponds without evacuation routes (V2 77.8%), fishers without ‘early warning system’ (EWS) (V3 83.3%), and without Rob counseling (V4 77.8%) (Table 3). All variables were positively loaded contributing to a high social vulnerability. To address this, the local community requires external support including training, technology, finance, ambulance, and labour force from State and other agencies. Our findings show the governments’ failure to provide these.

The National government and the district’s head who chairs the regional agency (‘the Agency’) are responsible for coordinating disaster relief. Interviews of local government officials confirmed that low community engagement was the main weakness within Rob mitigation and adaptation efforts, leading to insufficient new knowledge and technology transfer and weak social capital. This confirms earlier studies (Tran et al. 2017; Gathongo and Tran 2019) which highlight that when social capital, including
community organizations, is weak a disaster’s impact on the social-ecological system is severe due to the community’s inability to mobilize local resources in response. Moreover, the Agency’s limited personnel, facilities, and training resulted in personnel with low competency, only rescuing communities suffering disasters but not acting pre-emptively. Therefore the system’s sensitivity and exposure to Rob remains high for the majority of fishers. Interviews revealed that fishers responded to Rob in three ways: (i) leave to chance, (ii) harvest the fish as small tidal surges arise, and (iii) elevate the ponds with sand, together showing a short-term plan. Similar to Jozaei and Mitchell (2018)’s argument, external support and local government’s mitigation efforts are critical in building communities’ long-term adaptive capacity, including Early Warning System (EWS) availability.

The EWS development should include five inter-related aspects: (i) economic sustainability, (2) community organizations and leaders, (3) indigenous communities involvement, (4) gender and cultural diversity, and (5) effective institutional arrangements (Mohanty et al. 2019). In our study 83.3% of fishers said there is no EWS (Table S1), contributing to the community’s high vulnerability level. Interviews confirmed the lack of community organizations, local leaders, disaster management capacity building, governments’ mitigation efforts, and the Agency personnel’s knowledge on social vulnerability. Together these minimized communities’ social learning of knowledge and skills essential for building adaptive capacity.

Given the lack of external support and the government’s mitigation efforts, in agreement with Moreno et al. (2019) we suggest it is critical that the community develops its resilience by strengthening ‘activation capacity’, linking a network of local resources promptly during and post-disturbance. The community’s activation capacity is low (i.e., high vulnerability) reflected in the positive values of emergency response (V1), evacuation route (V2), EWS (V3), and local knowledge (V5) (Table 3). In this setting, the activation of local resources often requires external support (e.g., an effective government institutional organization and its mitigation and adaptation measures) resulting in a vulnerability trap loop. In this regard, the government needs to improve the adoption of the Hyogo Framework for Action (HFA) 2005–2015 (United-Nations-Office-for-Disaster-Risk-Reduction 2007) in developing an early warning system, support local livelihoods (Mohanty et al. 2019) and operations with disaster managers (Moreno et al. 2019), allow the projection of the future state of the SES system (Ferro-Azcona et al. 2019), as well as increase community awareness of the critical importance of the early warning system (Mashi et al. 2019).

**Local-knowledge of tidal (Rob) flooding (PC-2)**

This PC relates to whether fishers perceived Rob as a disaster and their knowledge and skills to respond. It comprised three positively loaded variables: inundated fishponds (V5), economic loss (V6), and farmers’ perception of Rob (V7), constituting 10.98% of SoVI’s variations, meaning high and increasing social vulnerability (Table 3). 32.4% of fishers only considered Rob as a disaster when large, as small was used as a harvesting technique (V7); 67.6% considered all scales of Rob as disasters (Table S1).

In general fishers have vast experience in fish farming with traditional harvesting systems working sufficiently well to address the re-occurrence of small-scale Rob. They used flood water as a source to provide feedstock, such as the small prawns that accompany it, and harvested fish immediately to reduce the risk of loss. To an extent, local knowledge catalyzes social resilience: since Rob has occurred for generations fishers carry memories of past events, developing the capacity to respond and adapt to hazards, including the use of the event for their benefit. However, traditional harvesting and protection systems are insufficient to address large-scale Rob. Since only modest protection for fishponds was provided by creating sand embankments severe Rob affected 68.5% of fishponds (inundated, V5) and 71.3% of farmers (economic losses, V6) (Table S1). Other forms of local knowledge and mitigation efforts by farmers were minimal: only 27.8% planted mangroves for flood protection (Table S1), 59.3% increased the pond embankment height, 12% provided pond nets, 4.6% created water tunnels, 0.9% modified their ponds, 2.8% conducted early harvests, and 20.4% made no mitigation efforts (Table S7). This data highlights the critical need for external support (PC-1) to assist local fishers to improve their mitigation capacity to respond to large-scale Rob flooding.

**Income, expenditure, family size, and seasonal expenditure (PCs 3, 4, 5, and 6)**

These four PCs are closely related. The third, comprising 8.73% of SoVI variations, includes four negatively loaded variables (Table 3): farmers earning > IDR 12 million/harvest (V8), fishpond yielding > 1 tonnes/harvest (V9), farmers who did not rent their ponds (V10), and polyculture fishponds (V11). Only 35.2% of farmers earn over 12 million Rupiah per harvest (> US$ 805, V8) (Table 3), the remainder earning less. The government places households in the Indramayu district earning below 1,899,228 Rupiah/month (under 24 Million Rupiah/year) as under the poverty line (Statistics-Indonesia 2020b). Since most fishponds are harvested twice annually, i.e. ≈ 24 M Rupiah/year, most farmers’ (64.8%) income is insufficient to meet basic needs. Moreover, 45.4% of fishponds are rented, reducing overall
harvest net income. The inundation of severe Rob and low-crop yields (75.9% farmers harvested < 1 tonnes/harvest, Table 3, S-1) led farmers further into debt. Contrary to findings from earlier studies (Cutter et al. 2003; Tran et al. 2017) where yields enabled farmers to recover from the damage. This Evidence explains income as a principal component influencing social vulnerability has also been identified by previous studies in developing countries (Tran et al. 2017).

The fourth component, expenditure, comprises 8.49% of our SoVI variations (Table 3). 65.7% of farmers (Table 3) developed their ponds themselves their income being insufficient to justify hiring additional labour. When recurring Rob either reduced profits or increased losses, farmers incurred debt to re-establish damaged ponds leading to recurring poverty.

The fifth, family size, comprises 7.77% of our SoVI variations (Table 3) with 33.3% fishers having more than four dependants (Table 3). Dependents include people less than 5 and above 65 years-old, school-age of 6–17 years, none of whom contribute to family income, i.e., the non-workforce (Statistics-Indonesia 2018a). Whilst an elderly person living alone is vulnerable to disaster (Mohanty et al. 2019), we found no evidence of a single elderly person in the study villages. A higher number of dependants reduces fishers’ financial resources and their ability to recover from disasters, and hence the low level of resilience and adaptive capacity. Whilst most fishers support less than four family members directly many support others indirectly.

The sixth PC, seasonal expenditure, explains 7.73% of our SoVI variations (Table 3). During harvest time 63.9% of fishers (Table 3) needed additional five to ten people weekly, the daily expenditure of 100,000 to 150,000 Rupiah (i.e. US$ 6.7–10) (Table S6) being a large financial burden. As most farmers incur debt when establishing ponds they have the little financial capacity to recover from Rob disasters, leading them to incur more debt, often resulting in bankruptcy and poverty. With the lens of ‘adaptive capacity’ applied to the capacity of response to long-term or adjustments to social-ecological system changes (Gallopín 2006), this situation explains a poverty trap and there is a clear indication that fish pond farming has been unable to improve the communities’ livelihood.

**Level of education and fish farmer experience (PCs 7 and 8)**

These two PCs are closely related. The level of education (PC-7) comprises 5.31% of our SoVI variance (Table 3). This finding resonates with studies in other developing countries where education was identified as a PC influencing social vulnerability (Nguyen et al. 2017; Dintwa et al. 2019; Aksha et al. 2019) but differs from the USA’s study (Cutter et al. 2003) and China (Lixin et al. 2014) where education was not identified. A 32.4% of our study’s fishers have no formal education (V15) and 25% only primary. 14.8% secondary levels, 24.1% high levels (Table S3). For instance, many farmers could neither read nor write, requiring the first author to read the questions and write the respondents’ responses. This condition constrains fishers’ ability to understand early-warning information and access recovery information during disasters.

The eighth component, fishers’ experience, comprises 5.09% of our SoVI variations (Table 3), with 63.9% having more than ten years of experience and the rest greater than five years (Table 3). Their occupation began when they were 12–15 years of age as they did not participate in formal schooling. Their techniques and methods of farming are largely informed by and acquired through experience inherited from previous generations, and hence their adaptive capacity to a tidal (Rob) flooding disaster is also formed in the same way. The memory of past events, which for generations equipped fishers with the ability to respond to repeated hazards, is challenged by contemporary environmental and climate change. With limited education, to mitigate and adapt to environmental changes fishers need external support from relevant state and non-state agencies to access external sources of information and techniques on resilient farming and technology. Moreover, the role of volunteers and environmental NGOs needs to be encouraged to enhance the local capacity to mitigate and adapt to disaster, with the latter advocated by the United Nations International Strategy for Disaster Reduction (United-Nations-Office-for-Disaster-Risk-Reduction 2007).

**Ethnicity (PC-9)**

The last PC comprises 4.09% of SoVI variations (Table 3). Small relative to other PCs, this component influences fishers’ social vulnerability less significantly. 83.3% of them are ‘native’ (Table 3), a term describing fishers born locally, holding local identity cards, inhabiting the area, and farming pond-fish for generations. Known as ‘orang Indramayu’ they speak the local ‘Dermayon’ language (ethnic population detailed in the Materials and methods section). The rest (16.7%) are migrant seasonal fishers who, when interviewed, stated that they were not local.

Similar to previous studies (Cutter et al. 2003; Aksha et al. 2019; Rabby et al. 2019), our research revealed that native fishers employed seasonal fishers which indirectly improved the overall village economy, although the ratio between the two types of fishers is different. The percentage of native fishers in our study is larger, an essential social capital that strengthens the community’s collective capacity to respond to disasters as they were more active in disaster relief activities compared with migrant fishers (Tables S1). As well as a shared language and local customs,
inhabitating the villages and sharing an occupation for generations contributed to the development of stronger bonds around shared farming activities that become culture-based. Even when experiencing harvest failure fishers return to the same livelihood with 83.3% confirming no plan to change occupation for five years, and 42.6% with intention to open new fishponds (Table S1). These findings inform the government when establishing its mitigation and adaptation plan: communities wish to continue working where they are most comfortable culturally, with valuable inter-generational experience but require protection from Rob. With a small percentage of migrant fishers, this PC did not influence local social vulnerability significantly, contrary to other studies where the components of language and cultural diversity constrained access to disaster relief resources for certain ethnic groups (Cutter et al. 2003). Nonetheless, similar to our finding, an Australia case revealed strong bonds amongst community members as a key enabling factor for the activation of local resources when disasters strike (Hanson-easy et al. 2018).

Discussion summary: theoretical contribution and policy recommendations

As discussed earlier, the phenomenon of tidal (Rob) flooding which occurs regularly, sometimes three times a year, provides the social-ecological system with regular exposure. The destruction of mangrove forests as natural tidal protection as a consequence of uncontrolled aquaculture land expansion activities toward the sea causes infiltration properties is highly impacted on coastal vulnerability to erosion rate and tidal inundation flooding. (Dasanto 2010; Suroso and Firman 2018; Maryanto et al. 2018). From the conceptual lens of vulnerability, resilience, and adaptive capacity, the repeated occurrence of Rob provides the social-ecological system with regular exposure. Government authorities should be able to anticipate and modify the system’s sensitivity, thereby increasing its resilience. However, the SoVI score of +1.76 indicates not only the high-level of fisher vulnerability but also the government’s failure to develop the community’s adaptive capacity. While our PCs of education, ethnicity, family size, and local knowledge are similar to those identified in Bangladesh, Mozambique, and Nepal (Blythe et al. 2015; Aksha et al. 2019; Rabby et al. 2019), external support and local government’s mitigation efforts, income disparity, and exposure to Rob are unique to our study. While government authorities should address all nine-identified PCs to improve future mitigation and adaptation efforts, our policy recommendations (summarised in this section’s last paragraph) focus on these uniquely-identified PCs.

Our findings contribute to the literature by highlighting the significant role of a community’s memory of past events, i.e. regular exposure to Rob flooding. This collective memory, accumulated intra-generationally, enabled community members to develop their capacity to respond and adapt to disasters. This includes their traditional knowledge to use small-scale Rob as a means of harvesting, a source of feed-stock, and to sustain the fish farming occupation. Nonetheless, these alone are insufficient to respond to severe hazards exacerbated by climate change. Therefore community experience and skills developed through the system’s repeated exposure to disasters must be complemented by the acquisition of new knowledge and technology to address the increased frequency and intensity of Rob flooding. Here external support and local government’s mitigation efforts are crucial but were largely absent in our case study.

‘Sensitivity’ to hazards, another vulnerability element besides ‘exposure’, was largely unaddressed by the government, consequently reducing the community’s overall capacity to cope with and moderate the impact of disasters. The local government’s limited human resources and finance enabled them to focus only on disaster relief. The development of the long-term capacity to modify the system’s sensitivity (including fishponds, fishers’ knowledge, and training, income, and organizational structure) is lacking. Our findings are similar to previous studies in Vietnam with Tran et al. (2017) showing the relationship between livelihood-diversity, income, and vulnerability, and Nguyen et al. (2017) which highlighted variables of poverty, income, family size, community organization, and education, as PCs influencing social vulnerability. Relevant to this is ‘activation capacity’, the ability of community members to activate and mobilize local resources to respond to hazards promptly and moderate the disaster’s impact. Activation capacity is influenced by the availability of social networks, community organizations, and local leaders, mostly missing in our study area.

In summary, related to critically needed of external support, our policy recommendations are as follows. Government authorities should improve local activation capacity by deploying sufficient resources; finance, knowledge and technology, physical, institutional, and infrastructure. Specifically, this support needs to be directed towards training local leaders and developing community organizations and cooperatives. The latter, known locally as BumDes (village economic unit) and available in many parts of the district but not within the five villages studied, are essential to building a sustainable local economy which addresses the perpetual poverty. This recommendation is in line with a Mozambique study that argued that focusing on building human capital could contribute towards minimizing the negative impact on coastal communities’ shrimp farming (Blythe et al. 2015). Utilizing our SoVI, governments should prioritize intervention on PCs with the highest contribution to overall SoVI, including the need for early warning systems and
farming standard operating procedures. Moreover, government authorities should utilize our SoVI and other relevant studies to inform government-sponsored studies across Indonesia’s coastal villages, and in particular our measured variables for adaptation to future SoVI development. This is because whilst each community is unique, coastal communities face similar socio-economic challenges. Being amongst the poorest in Indonesia, South East Asia, and Sub-Sahara Africa generally, they are continuously threatened by climate-related disasters and are heavily dependent on coastal resources where the majority of inhabitants are fish or shrimp farmers (Suroso and Firman 2018; Krishnan et al. 2019). Hence, our findings hold global policy relevance contributing empirical evidence on which PCs should be prioritized for intervention to improve relevant mitigation and adaptation strategies, and extends evidence from previous studies including those from Bangladesh, India, Iran, Mozambique, the Philippines, Vietnam, Nepal, China and Botswana (Guleria and Edward 2012; Lixin et al. 2014; Blythe et al. 2015; Tran et al. 2017; Aksha et al. 2019; Dintwa et al. 2019; Hadipour et al. 2019; Krishnan et al. 2019; Rabby et al. 2019).

Conclusions

Our study assessed the social vulnerability to Rob flooding of the fish-farming community in the Indramayu sub-district in West Java Indonesia. A context-specific Social Vulnerability Index (SoVI) was developed through questionnaires involving 150 fishpond farmers in five villages. Unique to our study is the form of hazard, Rob flooding, a regular phenomenon of the North coast of Java due to high tides, land subsidence, and a rise in sea-level. Our study filled the gaps of Indonesia-based research in the application of SoVI and the theoretical-concepts of ‘vulnerability’, ‘resilience’, and ‘adaptive capacity to climate-related hazards, and specifically Rob. Contributing to the theory our SoVI-scores of $+1.76$ show a high-level of social vulnerability, meaning that as the community’s vulnerability to recurring disaster is high (i.e. high exposure and sensitivity of the system) its capacity to absorb and moderate impacts and respond to a disaster expeditiously is low (i.e. low resilience), leading to their low competency in mitigating and adapting to social-ecological changes in the long term (i.e. low adaptive capacity).

Our SoVI comprises nine principal components (PCs): (i) external support and local government’s mitigation efforts, (ii) local knowledge, (iii) income, (iv) expenditure, (v) family size, (vi) seasonal expenditure, (vii) education, (viii) farmer experience, and (ix) ethnicity. These PCs highlight the community’s local characteristics which influence their overall vulnerability. Most fishers have insufficient income to afford basic livelihoods or recover from Rob hazards, forcing them into debt to repair ponds affected by disasters and hence perpetual poverty. Since most hold either no formal education or only primary level, they are unable to access current knowledge and technology to mitigate and adapt to severe Rob precipitated by climate change. Most fishers were born, lived, and farmed in the area for generations. Fish-farming became their culture, insisting on this means of livelihood despite harvest failures. Poverty results in them being unable to afford higher education for their children, hence low educational attainment is perpetuated.

Government should address these PCs when developing mitigation and adaptation policies for disaster risk reduction and preparedness, prioritizing those which contribute most significantly to overall social vulnerability. Noteworthy is the significance of ‘repeated exposure’ and ‘collective memory of past disasters which our study rendered visibly. However, whilst these elements enabled the community to cope with small-scale Rob, they are insufficient to address the more severe disasters influenced by contemporary climate change. Government and other agencies should provide support, including training local leaders and the community to acquire new knowledge, technology, and skills to address current climate-related disasters and to facilitate the development of a sustainable economy that breaks the poverty circle. Importantly, the government should facilitate the development of the missing early warning system. Regarding potential replication, our SoVI informs future SoVI development for Indonesia’s 12,000 disaster-prone villages located within coastal areas and other developing countries’ coastal communities where over ninety-percent of the world’s fishermen live, and which are vulnerable to climate-related disasters.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s11852-022-00854-7.

Acknowledgements The development of this article was funded by the University of Indonesia’s research grant (NKB-0333/UN2.R3.1/) HKP.05.00/2019) and Ministry of Research Technology and Higher Education. We are grateful to those who participated in the data collection activities, especially the coastal village leaders in Indramayu and Indramayu fish farming communities.

Author contributions Sepanie Putiamini: Conceptualisation (lead); formal analysis (lead); methodology (lead); writing – original draft (lead); writing – review and editing (equal). Mari Mulyani: Conceptualisation (equal); writing – original draft (equal); writing – review and editing (lead); funding acquisition (lead). Mufti Petala Patria: Formal analysis (supporting); methodology (equal); supervision (lead). Tri Edhi Budhi Soesilo: Investigation (lead); supervision (supporting). Asep Karsidi: Methodology (supporting); supervision (supporting).

Data availability All data generated or analyzed during this study are included in this published article (and its supplementary information files).
Declarations

We wish to confirm that there are no known conflicts of interest associated with this publication and there has been no significant financial support for this work that could have influenced its outcome. We confirm that the manuscript has been read and approved by all named authors and that there are no other persons who satisfied the criteria for authorship but are not listed. We further confirm that the order of authors listed in the manuscript has been approved by all of us.

Conflict of interest The authors declare no conflict of interest. The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Ethics approval All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards.

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