Multi-hazard and risk informed system for Enhanced local and regional Disaster risk management

MEDiate

Deliverable D3.2

Integrated socio-physical vulnerability assessment methodologies for evaluating dynamic multi-hazard risk

Author(s):	Nadeeshani Wanigarathna, Ejiro Esohwode, Denise Hawkes, Mahdi Jahangard, Keith Jones, Mariantonietta Morga, Marcello Arosio, Chen Huang, Abdelghani Meslem, Pierre Gehl
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LIST OF PARTNERS

Participant	Name	Country
NOR	NORSAR	Norway
DEL	Deltares	Netherlands
IIASA	International Institute for Applied Systems Analysis	Austria
BRGM	Bureau de Recherches Géologiques et Minières	France
EUC	Fondazione Eucentre	Italy
IMO	Icelandic Meteorological Office	Iceland
IMT	Institut Mines-Telecom	France
UIce	University of Iceland	Iceland
R2M	R2M Solution	France
RINA-C	RINA Consulting	Italy
IUSS	Istituto Universitario di Studi Superiore Pavia	Italy
OSL	Oslo kommune	Norway
NICE	Metropole Nice Cote d'Azur	France
AUS	Austurbru	Iceland
UStr	University of Strathclyde	UK
UCL	University College London	UK
ARU	Anglia Ruskin University	UK
ECC	Essex County Council	UK

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1 INTRODUCTION

Disasters cause significant losses to people, assets and businesses. In 2015, (United Nations Office for Disaster Risk Reduction (UNDDR) estimated that annual economic loss from disasters such as earthquakes, tsunamis, cyclones, and flooding was in the range of 250 billion to 300 billion (USD) and predicted an increasing trend. More recently, SwissRe reported 284 billion (USD) in global economic losses from natural disasters for the year 2022 (Banerjee et al., 2023). These losses cause a significant burden on people, and this financial burden poses an existential risk, particularly to marginalised groups. In their 2015 assessment, the UN claimed that the current losses, if shared amongst the world's population, would be equivalent to an annual loss of almost US$70 for each person of working age or two months' income for people living below the poverty line (UNDDR, 2015). In addition to the financial burden, disasters significantly impact the health and well-being of the population. Existing literature reveals observed differential burdens of disaster losses on marginalised groups (e.g. Soden et al., 2023; Walsh and Hallegatte, 2019; Cutter and Finch, 2020; Hallegatte, 2020). This report presents methodologies for integrating socio-physical vulnerability assessment when assessing dynamic multi-hazard risk.

1.1 Background

Disaster loss assessment forecasts often assess direct losses associated with damage to physical assets. These assessments, therefore, neglect undervalued assets such as health, clean air and water, and a safe future for their children (UNDDR, 2022). Moreover, the impact of disasters on physical assets, as well as other non-tangible assets, are different for different social groups. Estimates produced based on traditional asset loss metrics are misleading as they underestimate the impact on the poorest population, which has few assets (generally of little value) to lose (Hallegatte et al., 2020). Approaches which integrate socio-economic dimensions would estimate the ability of affected households to cope with and recover from disaster asset losses based on their circumstances.

A number of researchers have highlighted the disaster disparity for marginalised social groups along wider axes such as income, social status, age, race, gender, disability, etc. (e.g. Soden et al., 2023; Cutter et al., 2016). Beyond individual factors, risk is also aggravated by broader socioeconomic factors such as poverty, economic inequality, gender inequality, urbanization, conflict and fragility, and human development choices that are pushing planetary boundaries further (UNDDR, 2022). UNDDR estimates that their most optimistic scenario suggests that an additional 37.6 million people will be living in conditions of extreme poverty due to the impacts of climate change by 2030 compared to 2020 living conditions.

Cutter et al. (2003, 2008, 2016) represent a set of key references to extensively investigate the socio-economic impact of disasters. The authors discussed the relationship between socio-economic factors and disaster impacts, disaster recovery trajectory, and community resilience. For example, Cutter et al. (1996) discussed vulnerability to environmental hazards and introduced the hazards-of-place vulnerability model. In a later work (Cutter et al., 2003), they highlighted the lack of consideration of socially created vulnerabilities within loss assessment, so they introduced a Social Vulnerability Index (SoVI) as an approach to measure social vulnerability at the county level for the USA. This index identified 11 independent social vulnerability factors that accounted for about 76 percent of the variance of environment-related hazard impact disparity in the USA. They were Personal wealth, Age, Density of the built environment, Single-sector economic dependence, Housing stock and tenancy, Race, Ethnicity – Hispanic, Ethnicity-Native American, , Occupation, and Infrastructure dependence. Chaplin et al. (2019) explained the intersection between people who play different roles in society, such as parents, workers and members of society and argued that they bring capacities and vulnerabilities which need to be considered in disaster risk policy formulation instead of a "one-size fits all" approach. All people play multiple roles in society, such as parents, workers, and members of social or demographic groups. Each of these roles brings capacities and vulnerabilities, and these identities intersect. This creates challenges for disaster risk policy formulation, which, therefore, cannot be based on a "one size fits all" approach (Chaplin et al., 2019). According to the Sendai Framework Terminology on Disaster Risk Reduction (UNDDR, 2016) Vulnerability *refers to 'the conditions determined by physical, social, economic* *and environmental factors or processes which increase the susceptibility of an individual, a community, assets or systems to the impacts of hazards*'. Previous researchers have considered a range of physical, social, economic and environmental vulnerability indicators applicable to the study population and the hazard studied when estimating individuals or communities' ability to prepare for, withstand and recover from natural hazards. Impacts determined by individual indicators are then summed up to present vulnerability indices. Table 1:1-1:4 comprehensively reviews vulnerability indicators related to four selected natural hazards and for different geographical contexts.

Soden et al. (2023) argued that asset-informed risk-management strategies primarily focus on protecting infrastructure. Wellbeing-informed strategies can utilize more comprehensive available measures for better-informed disaster preparedness and contingent planning. Even though these measures do not reduce asset losses, they can foster socio-economic resilience to cope and recover from asset losses and the wellbeing impact of natural disasters. (Walsh, 2019). Soden et al. (2023) developed a typology to categorise disaster risk assessment practices based on how the models attempt to consider equity.

- **Type 0 approaches:** These models do not engage with equity considerations, as is characteristic of traditional asset loss-based analyses.
- **Type 1 approaches:** Here, the discussion on equity is supported by descriptive statistics and/or qualitative understandings of group vulnerabilities, although the models omit such information.
- **Type 2 approaches**: These models are based on index-based models and employ a risk index where equity factors—such as class/income, gender, and age—are considered parameters or social indicators in a vulnerability index.
- **Type 3 and Type 4 approaches**: These models disaggregate risk by various social groups. In Type 3 models, the overall risk faced in a given geographic area is assigned according to the percent of the overall population that comprises these groups. In Type 4 models, differential potential impacts of hazards are incorporated into the model by disaggregating vulnerability.
- **Type 5 approaches**: These approaches measure the utility of the consumption loss due to a disaster event based on the welfare loss model.

1.2 Aim, objectives and structure of the report

This report presents the results of Task 3.2 of WP3 of the MEDiate project in relation to modelling the social consequences of multi-hazards, accounting for possible interactions with impacts on the built environment. The research investigated the social consequences using three modelling approaches and is presented in three parts of this research.

- The first approach, as reported in Chapter 2, considered social impacts by directly understanding and quantifying the vulnerability of socio-virtual-physical networks to natural hazard disasters, using publicly available data to construct a suitable econometric model to determine the effects of different socio-economic variables on disaster impacts. Manual data mining from a range of publicly available data sources (Census data, labour force survey data, Gross disposable household income (GDHI), labour force survey headline indicators (national and regional), the Annual Population Survey (APS), UK business; activity, size and location: 2021 and the UK House Price Index England were used to develop the .econometric model. Counterfactual analysis can be leveraged (e.g. by altering the location or changing the scale of previous events) to estimate the potential social impacts of past near misses.
- The second approach, as reported in Chapter 3, was focused on sociovirtual- physical networks. Network analysis principles and graph concepts were used to explain how to establish the impacts of vulnerabilities brought in by damage to infrastructure which connects services and communities.

- As reported in Chapter 4, the final approach demonstrated how to disaggregate the asset losses as a function of socio-economic characteristics (marked by different patterns of socio-virtual-physical connectedness) to identify any disproportionate effects of an event (or series of events). Here, we present details of how social vulnerability indices and socioeconomic status indices could be used to locate marginalised communities based on their socioeconomic circumstances, which can then be considered when quantifying risk metrics and risk mitigation planning.

Table 1:1 Vulnerability indicators for flood hazards

	Reference	Country	Study area	Socio-Economic and other vulnerability Indicators
1	Menoni et al., 2012	Italy	Sondrio	Built environment-related exposure and vulnerability Buildings structural vulnerability; Properties within flood risk zone; Resistance and resilience of structural mitigation measures; Camping facilities in hazardous areas; Vulnerability assessment of public facilities Vulnerability of the urban fabric (e.g. roads, Existence of public; Other facilities: hospitals, fire brigades, etc. Social vulnerability factors Age structure; Percentage of autonomous and healthy population; Employment rate; Annual population growth rate; Immigration index; Social networking; Criminality rate; Conflict among social/ethnic groups
2	McGrath et al., 2019	Canada	communities in southern Ontario.	Built Environmental parameters related to damage Number of Stories and Basement (one-storey single-family residence with basement; one-storey single-family residence, but without basement; Two-storey single-family residence with basement; Two-storey single-family residence without basement; Town house)
3	Nofal et al., 2020	USA	Various	Building components Vulnerability DS0 (Crawlspace Insulation Flooring Insulation) DS1 (AC Unit/ Heater Wood Flooring); DS2 (Washer/ Dryer Lower Cabinets); DS3 (Drywall ; Upper Cabinets) DS4 (Wood Framing Decking Flooring)
4	Fatmah, 2023	Indonesia	8 flood-prone urban villages of Depok City	Socio-economic indicators Flood knowledge and practices based on social demographics; Gender; Marital Status; Age (<60, >60); Last Education; Number of biology children (1-2, 3-4, >4); Total Family Income (4 subcategories)
5	Larson et al., 2021	USA	Recurrent Home Flooding in Detroit, MI 2012–2020	Economic indicators Tenure type (Own, Rent); Percent of homes owner-occupied Built Environment Indicators - Year of built (Pre 1910 through to 1958 or later); Building sq ft; Living space sq ft; Basement sq ft; Type of basement (Finished, unfinished) Housing conditions determinants (13 pre-existing conditions such as leaky roof, mould) Neighbourhood and environmental determinants - Census tract poverty (%); Census tract under 18 poverty (%); Percent African-American; Percent Hispanic ; Distance to nearest waterway (m); Elevation (m); Percent of home built before 1939
6	Sayers et al., 2017	UK	Generic	Socio-Economic Indicators

				Age (Young children (% people under 5 years); Older people (% people over 75 years); Health (Disability / people in ill-health (% people whose day- to-day activities are limited); Households with at least one person with long term limiting illness (%); Income (Unemployed (% unemployed); Long-term unemployed (% who are long-term unemployed or who have never worked); Low income occupations (% in routine or semi-routine occupations); Households with dependent children and no adults in employment (%); People income deprived (%); Information use (Recent arrivals to UK (% people with <1 year residency coming from outside UK); Level of proficiency in English); Local knowledge (New migrants from outside the local area (%); Tenure (Private renters (% Households); Social renters (% households renting from social landlords); Physical mobility (High levels of disability (% disabled); People living in medical and care establishments (%); Lack of private transport (% households with no car or van); Crime (High levels of crime) Built Environment indicators (Housing characteristics; Caravan or other mobile or temporary structures in all households (%); Direct flood experience - No. of properties exposed to significant flood risk (%) Service availability - (Emergency services exposed to flooding (%); Care homes exposed to flooding (%); GP surgeries exposed to flooding (%); Schools exposed to flooding (%); Social networks (non-flood) Single-pensioner households (%); Lone-parent households with dependent children (%); Children of primary school age (4-11) in the population (%)
7	Bhattacharya and Lamond, 2014			Memory/learning from previous flooding indicators (Social characteristics (Age, Income, Health, etc..); Environmental Memory (change in climate, etc..; Mental health impacts from previous events; Memory and learning (Memory decay, in and out of flood pane, etc..)
8	Szewranski et al., 2018	Poland	City of Wrocław,	Poverty risk index; settlement density; Presence of older people
9	Tanir et al., 2021	USA	metropolitan regions along the coast, the Washington, DC metropolitan area	Socio-Economic Indicators (41) % Female population; % age 5 years and under& 65 years and over; Median Age; % African American population % Asian population; % Native American population; % Native Hawaiian population; % Hispanic population; % Female Employment; % Adult educational attainment less than 12th Per capita income; % Unemployed; % Population under poverty level; % Households under the poverty level; % Disabled population; % Disabled population below poverty level; % Housing without vehicle; % Population earning less than 35K in the last 12 months; % Population earning less than 40K in the last 12 months; % Population without earnings; Median household income; Aggregate Income; % Population without health insurance; % Population with Food Stamp assistance; % Vacant housing; % Mobile housing; % Renters occupied; Median house value; Average home value; Median gross rent; Average cash rent; % speaking English as a second language with limited English proficiency; % Population Ratio of Income to Poverty level less than

				1.0; GINI index; % Population no social security income; % Female headed householders; % Female headed householders living alone; % Female householder with children; % Children living with family; % Population works in service industry; % Population works in extractive industry
10	Fernandez et al., 2015	Portugal	study of Vila Nova de Gaia	Population indicators - Age Structure (under 14, upper 65, 14-65); Gender (Male, female); Fmaily number (<4, >5) Building Characteristics - Building year; Floors; Function (residential, non residential) Socio economic indicators - Level of Education (Junior/high shcool, high school, university); Housing tenure type (Landlord, Tenant); Unemployment rate; Literacy rate; Exposed elements; Land use (Urban, Agricultural, Forest); Population density; Building density
11	Chakraborty et al., 2020	Canada	A micro-dataset of the 2016 Canadian census of population	Socio-Economic Indicators - Ability to cope with/ Special needs population (Female, Age, etc..); Household/Family Structure; Ethnicity; Visible Minority; Education; Access to Financial Resources/Wealth; Occupation; Employment Status; Built Environment/ Accessibility; Renterers; No private vehicle/Public transit; Population density (urban/rural); Mobility; Dwelling size Built Environmental variables (expanded) - House with major repair; Crowded home; Period of home construction; Dwelling is in apartment with 5 stories built before 1980
12	Karagiorgos et al., 2016	Greece	e regional unit of East Attica	social networks (Length of residency; Degree of solidarity; family and friends living in the communities, members of local associations or local social networks post-incident outcomes (focusing on damages and psychological effects; Security indicators (Self concern to the village, owned properties and individual life; Previous flood experiences; Individual preparedness socio-economic and demographic (Ownership; employment rate, educational background, age, savings; household incomes and Disabled persons in the household
13	Roden et al., 2015	Italy	floodplain of northern Italy	Socio-Economic Indicators Socio-economic status; Percentage of housing units without basic; sanitation installations Percentage of rent houses at family unit; Gender Percentage of female; Ethnicity Percentage of no native people Age Percentage of dependent people (,4 and .85 years old); Education; Percentage of illiterate people; Percentage of people with less than 8 years of education; Employment (Percentage of unemployed people; Percentage of retired people; Percentage of active people involved in the agriculture sector); Family structure (Percentage of single parents (both female and male headed); Percentage of family with more than six members; Population consistency Population growth index; Income Mean annual income per single inhabitant; Special needs people Percentage of people living in assistance institute
14	Fekete, 2009	Germany	Karlsruhe, Dresden, Ruhr-Area	Vulnerability for Leave home; Emergency shelter & regulation age; unemployed; gender; pensioner; high school degree residents up to 14 years; elementary school; persons per household; income very high; income low; rooms; home ownership; high qual employment; urbanity

15	Felsenstein and Lichter 2013	Israel	Coastal Communities in Israel	Individual socio-economic status (Income, % disabled, % dependednt; % car ownership) Municipal level indicators (House prices/wealth) Income distribution (Income)

Table 1:2 Vulnerability Indicators for Storm/ Extreme winds

	Reference	Country	Study area	Socio-Economic and other vulnerability Indicators
1	Zhang and Peacock, 2009	USA	Miami-Dade County	Household dislocation factors; damage to the neighbourhood; Average damage; Average home value before hurricane; % owner occupied; Median household income; % Black; % White; % Hispanic (focused only on single-family structures)
2	Hughes et al., 2022	USA - Connecticut	Fairfield Beach community	Socio-Demographic Indicators Age Child (0–9); Adolescent (10–18); Young adult (19–29); Middle-aged (30–45); Older adult (45–64); Elder (65þ); Race (Caucasian; other); Gender (Male; Female)
3	Masozeraa et al., 2007	USA	Hurricane Katrina in New Orleans	Social Vulnerability Indicators Socio Economic Status (Socio-economic status (income, political power, prestige); Gender; Race and ethnicity Age; Residential property; Renters; Education; Health status; Social dependence; Special-needs populations Ability to respond -Transportation
4	Cutter et al., 2014	USA	Hurricane Sandy NewJersey	Recovery time social vulnerability indicators - Percent White; Percent Elderly; Percent with college degree Percent Poverty; Median household income $; Percent owner occupied homes; Median value owner occupied home; Percent secondary/ vacation homes; Percent state's NFIP policies; NFIP policy value; Percent state revenue from accommodation and food services
5	Finch and Cutter et al., 2010	USA	Hurricane Katrina in New Orleans Recovery indicators	Recovery related vulnerability indicators - Race and class (% Black, Education less than high school, service occupations; poverty; unemployment; Young families (Female, females in the labor force, % kids under 5, people per housing unit); Public housing developments (Renters, housing unit density); Elderly (Social security recipients, % population over 65,median age); Hispanic immigrants (% Hispanic, % international migration); Special needs (Nursing home residents, % manufactured housing; (mobile homes);Natural resources employment (% Asian, % employed in extractive industries (fishing, farming, forestry, mining)
6	Cutter, 2003			Income, gender, race, age of people, family structure, education, population growth, occupation, the potential loss of employment following a disaster, renters and residential property

7	Mulmin, 2023		Hurricane Harvey 2017	Recovery trajectories for people with disabilities - Percentage of registrants seeking special accommodations Disability (%) ; African American(%) ; Latinx ; Homeowners(%); Limited English proficiency(%); Unemployed (%) Poverty(%); Population density; Disaster damage; Flood insurance status(%)
8	Talbot, 2021	Puerto Rico	Hurricanes Irma and Maria 2017 (municipalities of Loíza and Yabucoa)	Housing Reconstruction vulnerabilities Gender; Age; Education; Annual Income; Employment Status; Ownership of house; Number of minors in home
9	Lieberman-Cribbin et al., 2021	USA	Hurricane Sandy (New York City and Long Island	Gender; Race; Education; Existing mental health conditions; Apartment residents; Age; Median household income
10	Laska and Morrow, 2007	USA	Hurricane Katrina 2005 for New Orleans population	% residents living below poverty line; % residents who are African American; % households without a vehicle % of housing units occupied by renters; (other indices identified but not anlyased)
11	Crowley, 2020	USA	North Carolina and South Carolina that received individual assistance for Hurricane Florence	Socio economic vulnerabilities and reported post-disaster needs Per Capita Emergency Needs; Per Capita Food Needs; Per Capita Shelter Needs; Peak Gust (mph); Distance to the Coast (mi); Proportion of Homeowners with Flood Insurance ; Median Home Value; Median Household Income (US$); Proportion of the Population with a Bachelor's Degree ; Proportion of the Female Population ; Proportion of the Population Over 65 ; Proportion of the Population Aged 5 and Under ; Proportion of the Population That Does Not Speak English; Proportion of the Minority Population;
12	Griego et al., 2020	USA	Hurricane Harvey in Greater Houston, Texas	Socio economic variables affecting Disaster assitance and Recovery Near term recovery; Hispanic Foreign-born non-citizen; Hispanic Foreign-born US citizen; Hispanic US-born; Non-Hispanic Black or African American; Non-Hispanic Multiracial/Other Race; Children in Household; Unemployed; Retired; Income; Disability; PTS Symptoms; Property damage; Contents Insurance
13	Bjarnadottir and Stewert, 2011		2004–2005 Atlantic hurricane season	Race (African American) and poverty; Age and gender; Socioeconomic status (Income and housing ownership); Race (Native American and Asian) and unemployment; Hispanic

14	Burton, 2010	USA	Mississippi coastal counties Hurricane Katrina	Age and socioeconomic status (Percent of social security recipients; Per capita income; Percent of over 65 years of age; Percent of families earning $100,000 or more; Percent of females; Percent of the population living in urban areas; Percent of female labor force participation) Race (African Americans and poverty)Percent of persons 25 or older with less than 12 years education; Percent of living in poverty; Percent of Black or African American; Percent of female headed households; Median dollar value of owner occupied housingunits; Median rent) Built environment density (Housing density; Percent of population living in urban areas; Percent of female headed households; Percent of employed in service occupations; Percent of housing units as mobilehomes) Lifelines and employment (Percent civilian labor force participation; Percent of employed in transportation, communications, and public utilities; Median dollar value of owner occupied housing units; Nursing home residents per capita; Percent of renter occupied housing units) Families with dependents (Average number of persons per household; Percent of under five years of age; Nursing home residents per capita; Median age) Race (Hispanics; Percent of Hispanic populations) Race (Asian and agricultural workers) (Percent of Asian; Percent of employed in primary industry:farming, fishing, mining, forestry) Rural farm populations (Percent of rural farm populations)
15	Zachary and Wilbert, 2017	USA	Hurricane Katrina in New Orleans	State Change (3 Years) ; County Change (3 Years) ; Address Change (3 Years); Credit Score; Subprime Credit Score Homeownership; Home balance; Has Derog. Home; Has auto; Auto Balance; Has Derog. Auto; Has Consumer Debt; Consumer Balance ; Has Derog. Consumer Debt; Consumer Derog. Balance; Household Size ; Live Alone; Live with Partner

Table 1:3 Vulnerability Indicators for Extreme Heat

	Reference	**Country**	**Study area**	**Socio-Economic and other vulnerability Indicators**
1	Bélanger et al., 2015	Canada	Québec	BE related Low Rent Housing (Yes, No); Building Architype (Apartment buildings <= 4 floors; Apartment buildings > 4 floors); Parking adjacent to building (Yes, No); Elevator in Building (Yes, No); Tenure Type (Renter, Owner); Backlog repair and maintenance (Major, moderate, No); Air conditioning (Air con and Fans, Air con, Fans, Nothing) People related Age (<65 years, vs >+65 years; Sex (Woman vs Men); Long term absence from work (disease or handicap) State of health (fair , Poor); (Urban) Air pollution (Yes No); Health problems due to air quality (Yes, No)

2	Chen et al., 2022	Taiwan	Six major cities in Taiwan,	Environmental related Indicators Ratio of areas lacking water; Ratio of areas lacking green space; Ratio of developed areas; Proportion of commercial areas; Road Density Economic vulnerability indicators - Proportion of people in low-income households; Low-income households as a proportion of total Households; Number of people in low-income households; Number of low-income households Social vulnerability indicators – Age; Elderly dependency ratio; Child dependency ratio; Dependency ratio; Household size; Sex Ratio; Number of people with disabilities
3	Chow and Chuang, 2012	USA	Metropolitan Phoenix	Hazard exposure indicators - Maximum temperature exposure; Minimum mean summer temperature; Vegetation Index Socio- Economic Indicators - Population > 65 years of age; Median household income; Population of foreign-born noncitizens; Population living in different; residences from 5 years prior
4	Depietri et al., 2013	Germany	85 districts of Cologne	exposure related indicators - the number of people per city/district differently exposed to heatwaves due to the Urban Heat Island effect Social susceptibility - the percentage of the population per city district older than 65 years; the percentage of unemployed per city district; Number of immigrants is correlated with unemployment hence ignored lack of resilience - the percentage of elderly living alone per city district; the cooler micro climate and cleaner air (Proxy – The percentage of the surface of Cologne covered by urban forest per city district
5	Derakhshan et al., 2023	USA	California and Los Angeles	Set 1 - Exposure and Environment variables; Mean Tree Canopy; Projected Number Extreme heat; Percent Population without Health Insurance; Percent Population Age Below 5; Percent Pop Age 65 and more; Percent Without Car; Percent Not speaking English; Percent Less than College Education; Particulate Matter; No Air Conditioning Set 2 Social variables: Hispanic, education, linguistic isolation; Poverty, unemployment, mobile home; Race (African American); Nursing House Residents; No Health insurance, Race (Native American); Female; No automobile access Set 3 - Socio-economic; Household composition/disability; Minority status/language; Housing type/transportation
6	Dong et al., 2020	China	177 blocks covering wuhan city	Heat Stress Indicators - Human perception of heat (Universal Thermal Climate Index) Soal Vulnerability indicators - Proportion of population under 14-year old; Proportion of population over 65-year old Proportion of female population; Proportion of population with education level below high school; Employment type (Proportion of population engaged in agriculture, forestry, animal husbandry and fishery); GDP per capita Convenience to reach medical assistance facilities Human Exposure indicators - Population density

7	Eisenman et al., 2016	USA	Maricopa County	Building Vulnerability indicators - Wall materials; Insulation thickness; Window panes; attic insulation; roofing material; size of home; percent of households with air conditioning Socio-economic vulnerability - Percent Hispanic/Latino; Percent foreign born; percent uninsured; Income below poverty level; Work in construction; Female householder, no husband present Renters living alone without vehicle - Householder living alone; Percent renter households; No vehicle available older age/ female/living alone - Householder living alone <65 years old; Percent <65 years old; Percent female agriculture or extraction industry - Works in agriculture, forestry, fishing, hunting, mining
8	Grigorescu et al., 2021	Romania	Bucharest Metropolitan Area	Exposure related vulnerability - Permanent resident population; Agricultural area; Environmental indicators; Climate conditions; Impervious surfaces (grey areas); Green areas; Water resources Sensitivity related vulnerability - Age - persons aged 65 and above and the children; 0–10 years old; Roma population Population employed in agriculture, forestry and fishing; Unemployment Rate; Agricultural Income; Connectivity to the drinking water network; Cultivated environment (arable land); Inhabited environment Adaptive Capacity - Connectivity to drinking water infrastructure; Healthcare services provided by high-level medical infrastructure; Pharmacies; Early warning and intervention services; Education level, Heat management & adaptation in agriculture; Blue areas; Forest Areas; Protected Areas
9	Johnson et al., 2012	USA	1995 Chicago Extreme Heat Event	Females age 65 and up; Males age 65 and up; Females age 65 and up living alone; White Population; Females head of household; Males age 65 and up living alone; Mean family income in 1989; Per capita income in 1989; Mean household income in 1989; Population 25 and older with less than high school education; Asian population; Population age 65 and older in group living; Other race population; Hispanic population; Population 25 and older with a high school education Normalized difference built-up index; Normalized difference vegetation index; Black population; Land surface temperature
10	Lehnert et al., 2020	USA	Georgia county-level	Socio Economic vulnerability - % Below Poverty Level; % Unemployed; Per capita Income; % Age 25 or Older with No High School Diploma Household Composition & Disability indicators - % Age 65 or Older; % Age 17 and younger; % Single Parent Household Minority Status & Language related indicators - % Minority; % Age 5 or Older Speak English “Less than Well” Housing and Transportation related indicators - % Multi-Unit Structures; % Mobile Homes; % Crowding (More people than rooms); % Households without a Vehicle; % In Institutionalized Group Quarters

11	Mallen et al., 2019	USA	Heat-related deaths in Dallas in 2011	Exposure - No green space; Sensitivity Indicators - Over age 65; Living alone; Over age 65 and living alone; Diabetes prevalence; Race other than white Adaptive capacity - Living below poverty line; Less than high school education; No AC access; NO full AC access
12	Reid et al., 2009	USA	All cities of USA	Demographic variables - Percent population below the poverty line; Percent population with less than a high school diploma; Percent population of a race other than white; Percent population living alone; Percent population ≥ 65 years of age; Percent population ≥ 65 of age living alone Diabetes prevalence - Percent diabetes diagnosed population Land cover - Percent census tract area not covered in vegetation; Air Conditioning - Percent households without central AC; Percent households without any AC
13	Sabrin et al., 2020	USA	Camden, NJ	Building footprint and height data - (a) Water fraction, where the cell values with 1 (in gray) and 0 (in black) indicate cells with and without water, respectively; and (b) percent imperviousness (%). Air Quality - estimates of air toxics, ozone, particulates and acid dispositions Social Vulnerability indicators - Average of 12 months household income in dollars during 2010–2014; Population below the age of 5 and over 65; overall density (per acre) in the census block groups; Asthma; COPD; and stroke hospitalization rate
14	Shih and Mabon, 2021	Taiwan	Whole country	Exposure - Living environment (Homeless people; Living environment; Living density; Building types (eg. height, materials, quality).; Surrounding greenspaces and water bodies; Occupational type (Outdoor labouring workers; Indoor labouring workers in hot environments Sensitivity - Age (Young children; Elderly people); Health status (Disability/mobility impairment; Existing physical health; problems (excluding handicaps); Existing psychological health problems); Gender (Male, Female); Race and ethnicity (Ethnic minority (excluding indigenous people); Indigenous people) Adaptive capacity - Resources (Income; Availability of cooling devices; (e.g. fans, air conditioning); Ability to acquire information (Education level; Linguistic capability); Level of isolation (Living alone; New overseas immigrants) Social Capital (Accessibility of medical resources; Support from societies/ communities)
15	Sun et al., 2022	China	4807 grids in Hangzhou city	Heat Exposure - Daytime LST, Demographic - The older population (≥65); children (≤5); Population density Economic (Points density of Catering accommodation, Tourism, Leisure, Shopping centres and Company POIs (DECO) Infrastructure (Points density of Residential landmarks, Government institutions, Public service and Traffic service POIs (DINF) - Adaptive capacity indicators GDP per capita (GDP) (NTL); Green and blue space coverage; Night time light intensity; Waterbody rate; Availability of medical resources

16	Watkins et al., 2021	USA	Phoenix, Arizona	Adaptive Resources indicators - (Window Air Conditioner; Swamp or Evaporative Cooler; Window Fans; Floor or Ceiling Fans; Basement; Awning, Shades, and/or Shutter; Yard with Swimming Pool; Misters; Working Car) Adaptive Behaviour indicators - (22 behavioural variables such as Open Windows; Dress in Lighter, Cooler, or Less Clothing) 9 Proximate Sensitivity indicators - Cost of Electricity Limits Use; Cost of Repairs Limits AC Use Often Struggle to Afford Essentials; General Health Relative to Others; Increased Risk to Extreme Heat Often works outside; Someone Nearby You Would Ask for Help If Too Hot; Neighbour Comfortable Asking For Assistance if Too Hot; Comfortable Asking Religious or Community Organization If Too Hot
17	Weber et al., 2015		city of Philadelphia,	Exposure - Average temperature, heat days; social sensitivity indicators - the percent of the population that lives below the poverty line; the percent of households that consist of a single person over the age of 65 living alone; the percent of housing units that were built before 1960 (proxy for housing units without central air conditioning); the percent of the population that did not graduate from high school (proxy for an additional indicator of poverty and access to resources) Adaptive indicators - large-scale cooling or greening projects
18	Wilson and Chakraborty, 2019	USA	metropolitan Chicago for the years 1990, 2000, and 2010	Adaptive Capacity - Proportion of people aged 25C without H.S. diploma; Mean household income; Female-headed households; Proportion of occupied housing units with no car; Poverty rate; Proportion of renter households; Proportion of substandard housing units; Proportion of occupied housing units comprised of mobile homes Sensitivity related indicators - Proportion of elderly population; Proportion of people aged under 18 homes for the aged and dependent Both Adaptive capacity and sensitivity - Proportion of population living in group quarters; Proportion of population in nursing homes or Proportion of population identifying as Black or African-American only Proportion of population identifying as Asian, Native Hawaiian, or Pacific Islander only; Proportion of population identifying as some other race only; Proportion of population identifying as Hispanic
19	Zemtsov, 2020	Russia	Moscow, 2010-2017	Exposure indicators - Population density Susceptibility indicators - Advanced age population; Sedentary population; Migrants Adaptive capacity - High Income population; Low income population
20	Zottarelli et al., 2020	USA	Sixty-one zip codes in Texas	Social Vulnerability indicators the percentage of the population living in poverty, unemployed' 65 years of age and older, aged 17 and younger, that are civilians with disability, living in single-parent households, minority, living in multi-unit

				housing living in mobile homes, income, education, English language ability, crowding, access to transportation and group quarters.

Table 1:4 Vulnerability Indicators for Landslides

	Reference	Country	Study area	Socio-Economic and other vulnerability Indicators
1	Antronico et al., 2020	Italy	February 2010, landslide in the town of Maierato (Calabria, southern Italy)	Factors influencing in triggering landslides and floods lack of maintenance and remedial works along slopes and streams, illegal buildings, the lack of interest of local public administrators; climate changes; features of the area; farmland abandonment; and lack of citizen's awareness towards environmental issues Social Characteristics - elderly and disabled people; owned (owns) business activities or farms Economic factors - Economic hardship for the lack of or paucity of economic support; access to the town and connecting it to the surrounding area; poor economic support received from the institutions Institutional Dimensions - Lack of information and poor involvement of the local community in the actions and measures taken by local policy-makers; no information of the Civil Protection Plan (institutional dimension); Political divisions in the community and lack of social cohesion; feeling of abandonment by the central and local institutions (institutional dimension); Feeling of a part of the population of being unprepared and unsafe in case of a new emergency, because of an inefficient risks governance in the post-disaster period and until now
2	Gonçalves and Zezere, 2018	Portugal	Loures municipality (18 civil parishes)	Social Vulnerability - Population density: number of residents per square kilometre; Young population: Population younger than 13 years old; Old population: Population older than 64 years old; Female population: Number of female residents; Illiterate population: Number of residents who do not read neither write Without activity: Number of residents living without economic activity; Unemployed population: Number of unemployed residents looking for first job or for a new job. Built Environment: Number of dwellings without water, WC, sewer or bathroom; Rented dwellings: Number of classical family accommodation of usual residences which are rented Reclassified location coefficient: used to characterise the property market and the accessibility of the buildings by the Portuguese Tax Services physical vulnerability of the buildings - wood or metal (light structures); adobe, rammed earth, or loose stone walls; brick or stone masonry walls; masonry walls confined with reinforced concrete
3	Eidsvig et al., 2014	Europe	Skien, Norway Stranda, Norway Grevena, Greece Andorra la	Demographic and social indicators - Children below 5 years and people above 65 years of age; People with language and cultural barriers; Rural populations who are dependent on the surroundings; natural resources for their primary source of income; High-density populations People without a post-secondary education

			Vella, Andorra Barcelonnette, France Slaˇnic, Romania	Building and infrastructure indicators - housing type; critical infrastructure (affected/not affected) Preparedness indicators - The risk awareness of the population; The early warning capacity of the society; The stringency of regulation control and the extent of emergency response procedures; The emergency response Recovery indicators - Personal wealth; Insurance and disaster funds; Quality of medical services
4	Dias et al., 2020	Brazil	443 Brazilian municipalities	Number of children (<5 years old) and elderly (>60 years old); Number of vulnerable men; Number of vulnerable women; Number of households without adequate sanitation; Number of households without adequate water supply; Per capita income ()Number of exposed people without income or with an income per capita of less than half the minimum wage
5	Park et al., 2016	Korea	Validated for Seoul, Korea,	Physical Vulnerability - RC Frames vs Non RC frames; Social Demographic Indicators; Age distribution; Number of workers who may be exposed to disasters; Population density; Foreigner ratio; Education level; Housing type secondary-damage-triggering indicators - Number of public offices; Road area ratio; Number of electronic supply facilities; School area ratio; Commercial and industrial area ratio preparation and response indicators - Disasters frequency; Internet penetration rate; Number of disaster prevention facilities; Perceived safety ; Number of medical doctors; Financial independence of the borough
6	Perera, 2019	Sri Lanka	Kegalle district	Location (Distance from surrounding landslides); Elementary Risk level based on slope; Construction material (Material of which the building is made) Mitigation measures (Retaining Wall); Land use practices (Surface water management, Plantation and home Garden); Use (building use); Human Capital (Dependency ratio; Education level; Emergency response capacity); Financial Capital (Monthly income; Savings; Income source); preparedness (Awareness of landslides; Early warning system)

2 ECONOMETRIC MODELING

1.1 Introduction

The econometric modelling aims to determine the effects of different socio-economic variables on disaster impacts. A review of the existing literature identified econometric models used either focusing on the economic impact of floods a significant piece of infrastructure damaged by a single hazard or the macro-economic impact on large economic measures such as GDP growth. Our econometric model focuses on the local economic impact on GDP at the district level, and how the socio-economic composition of the local population (businesses and people) affects the disaster's impact on the local economy. Our proposed model is designed to be a general model which can be applied to any test bed, for this deliveralw we focus on just one testbed, Essex to illustrate the proposed model. In focusing on the local geography of Essex, data on individual people and businesses of each county district were mined from the Office for National Statistics (ONS). We can identify a set of commonly measured socio-economic variables that decision-makers can use to inform six key determinants of investments to reduce the impact of multiple future hazards. In times of significant financial constraint within local authority budgets in the UK, this model guides the areas of Essex that should be the focus for local authority strategic invest, both as high risk areas and areas with populations that will struggle to regroup without significant support.

1.2 Review of theory and approaches

The literature review on the use of econometric models identifies two main approaches to measuring the economic impact of floods, (1) the macroeconomic impact on the economy or (2) the local economy's impact from the loss of a specific piece of infrastructure. In both cases the impact is measured post-disaster and although such studies provide insights in to the types of preventative action which would have been useful, with the benefit of hindsight, they lack the development of a tool to forecast at some period of time the likely effect of a new disaster and where it is wise in preparation to invest to reduce future risk.

Firstly, the macroeconomic impact on the economy evidence is summarised in Zhou and Chen (2021). They undertake a meta-analysis of 57 empirical papers applying a computable general equilibrium model (CGE). Their work suggests a focus on business resilience as the key finding from the field, and given the sensitivity to model assumptions and structure as well as data type (real-world or simulated), they suggest this modelling approach is used with caution. In our context with Canvey Island, which our partners at Essex County Council identified, this approach is unlikely to be appropriate given the nature of the local economy.

Another common measure of economic impact is the use of an input-output model. The application of this approach, which has informed the development of our own approach to the econometric modelling for this work package, is Khalid and Ali (2019), which seeks to assess the vulnerability of interdependent sectors to determine the impact of disaster. They use an inoperability input-output model (IIM) together with a preference ranking organization method for enrichment evaluations (PROMETHEE) to identify potential losses and rank them in terms of importance. Our focus on Canvey Island makes this approach impractical but it has informed our thoughts on the approach taken to the econometric modelling. In our model, we seek to use the current census data to pick out the various socio-economic factors commonly used in the literature and provide a ranking of these to identify the key variables to be used for the forecast model using historical disaster data provided by the test bed partner, Essex.

Secondly, for the local economy impact from the loss of a specific piece of infrastructure, Gajanayake et al. (2019) is an example of a systematic review of literature review in terms of post-disaster impact assessment of road infrastructure. They find a wide range of methods to measure economics impacts, the majority focused on the macroeconomic impact measures, and less on both the environmental and indirect social impacts. For socioeconomic impacts, they find the literature focus on bottom-up models to assess socioeconomics impacts through official government data. Boakye et al. (2022) attempt to build a theoretical model taking a capability approach to support the choice of key metrics from an extensive list drawn from the literature, assessing the impact of disasters and predicting the impact of extreme events. We shall build on this work by seeking to use the data to inform the section of the key variables using a Principal Components model.

Gonzalez and London (2020) complete a methodological review of natural disasters and their impact. They undertake a systematic review and find that most studies focus on the direct effect of physical damage and less frequently focus on the indirect effects of productive flows. They also find very little focus on the loss of the natural environment. Kharb et al. (2022) completed a review of the measures for valuing the human impact of natural disasters. They find the value of a life varied from 143,000-15 million dollars but also that a full financial cost of disaster, including the value of a statistical life, is rare in the literature. From these papers, we have decided to focus on the socio-economic factors related to the context at Canvey Island, including a significant focus on the impact of an ageing population on disaster impact.

In the next section, we will set out the approach to econometric modelling taken.

1.2.1 Approaches to econometric modelling

This econometric model aims to model the local GDP impact of a flood using making use of the publicly available data to identify the key metrics of the community and local economy at the last census date (2021). We have selected a modelling approach that enables the ground-up approach recommended for measuring impact from the field and exploits the data held by the Office for National Statistics (OFS), which uses individual data held on the population of Essex to develop a model which can forecast likely speed of recovery at the district level. The overarching econometric model is:

Disaster impact on GDP = f (social vulnerability, community resilience)

The purpose is to develop a baseline model which can be used to forecast the Canvey Island community ability to respond to natural disasters especially when confronted with interacting/cascading hazards. It is important for the usual metrics used to be assessed for their descriptive power of the population of interest. Although historical data will be used to assess how well these perform for forecasting the community's socio-economic ability to rebound, it is important that models are built for Canvey Island's community today and not the last substantial flood in 1953. Instead we shall make use of the evidence provided by Essex County Council on the 24 flooding events recorded in the county since 2011 and especially the flood on 20th July 2014 on Canvey Island "a 1 in 316-year flood event occurred and caused somewhere between 600 & 1000 properties to be flooded. The cause of this flooding was multiple, ranging from temporary failure of the pumping stations and blockages of gullies as well as the sheer magnitude of rainfall" (Farnham 2022, page 11)

1.3 Development of the econometric model for the Essex County

1.3.1 Overview

The final econometric model is presented as follows:

$$D_{it} = a + b\, S_{it-1} + c\, E_{it-1} + u_{it} \tag{1}$$

where
i is the district within Essex
t is time
D is disaster impact which will be measured as a pure economy impact (log local GDP per capita),
S is the key social vulnerability index
E is the key community resilience index
U is the error term

1.3.2 Methodology

The principal components analysis is the first stage estimation and follows Bergstrand et al. (2015) to identify the key measures for social vulnerability index (SoVI) and community resilience index (CRI) for hazards. We follow this approach as Bergstrand et al (2015) takes a local geography approach which fit well to the structure of the political geography of Essex County council, which has consists of 12 district, borough or city councils. Whilst Canvey Island was the test bed identified by our partners at Essex, we have developed a data set using the whole of Essex County to ensure a counterfactual analysis from a change of location and/or scale of previous events is leveraged to estimate the social impacts of past near misses.

Our estimation strategy consists of two stages. In the first stage, we follow Bergstrand et al. (2015) and use the UK Census data for 2021 from the ONS. We are able to provide SoVI and CRI at various geographic units for the whole of England & Wales: County level (Essex), District level (Castle Point), Ward level (Canvey Island Winter Gardens) and in some cases Super Output Area (SOA – 200 households). Given the data coverage, we will focus the analysis on the district level for stage 1.

For the final model, we use the ONS data on Regional gross domestic product: local authorities, to obtain local GDP data to model the impact of the 2014 flood on local economy taking into account SoVI and CRI measures developed. We then generate some values for the coefficients of the regression (a, b, and c) to use to develop a forecast model for the test bed to run various multiple hazards.

Manual data mining from a range of publicly available data sources (Census data, labour force survey data, Gross disposable household income (GDHI), labour force survey headline indicators (national and regional), the Annual Population Survey (APS), UK business; activity, size and location: 2021 and the UK House Price Index England were used to identify socio-economic vulnerabilities at the district level for two stages explained above.

1.3.3 Development of the Econometric model for the Essex Testbed

Tables 2.1 and 2.2 provide the links to the data sources used for the first stage, constructing a ward level measure of social vulnerability and community resilience. For the second stage, local GDP data can be found here [Regional gross domestic product: local authorities - Office for National Statistics (ons.gov.uk)]

Table 2:1 Data sources for Essex Test Bed SoVI

Name	Definition	Source
TS006 - Population density	Population density is the number of usual residents per square kilometre	https://www.nomisweb.co.uk/datasets/c2021ts006
TS021 - Ethnic group	The ethnic group that the person completing the census feels they belong to. This could be based on their culture, family background, identity or physical appearance.	https://www.nomisweb.co.uk/datasets/c2021ts021
TS054 - Tenure	% of household rented accommodation that it occupies.(social & private)	https://www.nomisweb.co.uk/datasets/c2021ts054
TS038 - Disability	% Disabled under the Equality Act	https://www.nomisweb.co.uk/datasets/c2021ts038
TS044 - Accommodation type	% of mobile or temporary structure	https://www.nomisweb.co.uk/datasets/c2021ts044
TS007 - Age by single year	% children under 5 years	
	Median age	
	% Aged 65 & Over	https://www.nomisweb.co.uk/datasets/c2021ts007
TS003 - Household composition	% Lone Parent Family(Female Headed Households)	https://www.nomisweb.co.uk/datasets/c2021ts003
TS067 - Highest level of qualification	% with no education qualification	https://www.nomisweb.co.uk/datasets/c2021ts067
TS029 - Proficiency in English	% with limited english ability	https://www.nomisweb.co.uk/datasets/c2021ts029
unemployment	This dataset gives the official unemployment figures for local authorities. Model-based estimates are only available for total unemployed - % unemployed @ Dec 2021	https://www.nomisweb.co.uk/query/construct/summary.asp?reset=yes&mode=construct&dataset=127&version=0&anal=1&initsel=
Per Capita Income	Regional gross disposable household income (GDHI)	https://www.nomisweb.co.uk/datasets/gdhi

Female Participation in Labour Force	% Female Participation in Labour Force	https://www.nomisweb.co.uk/datasets/nrhix
TS003 - Household composition	% of Children living in Household(dependant & non-Dependant)	https://www.nomisweb.co.uk/datasets/c2021ts003
Proportion Claimount Count	Proportion Claimount Count	https://www.nomisweb.co.uk/query/construct/components/ratecomponent.asp?menuopt=23&subcomp=
TS045 - Car or van availability	% of housing units with no car or Van	https://www.nomisweb.co.uk/datasets/c2021ts045
TS060 - Industry	% employed in extractive and Service Industry	https://www.nomisweb.co.uk/datasets/c2021ts060
TS011 - Households by deprivation dimensions	% Poverty	https://www.nomisweb.co.uk/datasets/c2021ts011
TS007 - Age by single year	Median Age	https://www.nomisweb.co.uk/datasets/c2021ts007
Median House Value (HPI)	Median House Value	https://www.gov.uk/government/statistics/uk-house-price-index-for-december-2021/uk-house-price-index-england-december-2021
Median Rent	Median Rent	https://www.ons.gov.uk/peoplepopulationandcommunity/housing/datasets/privaterentalmarketsummarystatisticsinengland

Table 2:2 Data sources for Essex Test Bed CRI

Name	Definition	Source
TS066 - Economic activity status	This dataset provides Census 2021 estimates that classify usual residents aged 16 years and over in England and Wales by economic activity status.	https://www.nomisweb.co.uk/datasets/c2021ts066
annual survey of hours and earnings - resident analysis	Median: In published reports, median earnings rather than the mean will generally be used. The median is the value below which 50% of employees fall. It is preferred over the mean for earnings data as it is influenced less by extreme values and because of the skewed distribution of earnings data.	https://www.nomisweb.co.uk/datasets/asher
TS067 - Highest level of	The sum of level 2 education and below	https://www.nomisweb.co.uk/datasets/c2021ts067

qualification		
TS060 - Industry	(2 digit sic code 94/ Pop_density) *10000	https://www.nomisweb.co.uk/query/construct/components/simpleapicomponent.aspx?menuopt=20770&subcomp=
TS060 - Industry	Number of arts/sports organizations/10,000 is a measure of social capital in resilience, according to the theory of Norris et al. (2008) 1. Social capital refers to the resources and relationships that exist within a community, such as trust, cooperation, civic engagement, and participation in social networks and groups. These resources can help a community cope with and recover from collective traumas, such as disasters or conflicts. The number of arts/sports organizations/10,000 is an indicator of the extent and diversity of social participation and interaction in a community, which can foster social cohesion and support. sum of sic code 90 and 93 divided by population density and multiplied by 10000	https://www.nomisweb.co.uk/query/construct/components/simpleapicomponent.aspx?menuopt=20770&subcomp=
TS045 - Car or van availability	The number of motor vehicles per 1000 population is used to measure urban influence	https://www.nomisweb.co.uk/datasets/c2021ts045
TS030 - Religion	Total number of religious and other groups/population density *1000	https://www.nomisweb.co.uk/datasets/c2021ts026
TS003 - Household composition	Total sum of 2 parents household with children/ sum of 2 parents household and lone parents household with children	https://www.nomisweb.co.uk/datasets/c2021ts003
TS064 - Occupation - minor groups	total sum of 113 213 243 245 247 312 341 342 354 521 544	https://www.nomisweb.co.uk/datasets/c2021ts064
Number of VAT and/or PAYE based enterprises	Table 10 - Number of VAT and/or PAYE based enterprises in districts/population density *1000	https://www.ons.gov.uk/businessindustryandtrade/business/activitysizeandlocation/bulletins/ukbusinessactivitysizeandlocation/2021

1.3.4 Stage 1 – Principal Components Analysis for Ward Level SoVI and CRI measures for the Essex Testbed

The results of the principal components analysis for social vulnerability show that together, the first four components explain more than 90% of the cumulative variance of all 26 variables. Eigenvalues correspond to the standardized variance explained by each component. With 26 variables, the total standardized variance is 26. Of this, we see that component 1 explains 11.2762, which amounts to 11.2762 /26 = 0.4337 or about 43% of the total. Component 2 explains 7.92824/26 = 0.3049, or an additional 30%. Principal components having eigenvalues below 1.0 are explaining less than the equivalent of one variable's variance, which makes them unhelpful for data reduction.

After factoring and the variance rotation, we assign each variable to a certain factor based on the highest absolute loading. We could see that for factor 1, Population density, ethnicity variables, rented apartments, mobile homes, children under 5, adults 65 and over, female headed household and those with limited English as well as median age load heavily on factor 1. This area is highly populated with people from other ethnicity living in rented apartments and limited English ability – this could be a "**demographic dimension**". Factor 2 loads heavily on households with no car, disabled, no education, unemployed, female labour, household with dependent children, claimant count, poverty, and median house value. Thus factor 2 is classified as the "**poverty dimension".** Factor 3 loads heavily on per-capital income, 65 and over in community establishment and employed in service industry. This dimension consists of those with good or high earning job "**Employed dimension".** Lastly the fourth factor loads heavily on median rent and median house value, **this could be the rented/unsecured housing (housing quality) dimension.** Here negative values are seen as reducing a district vulnerability and positive values as contributing to overall vulnerability.

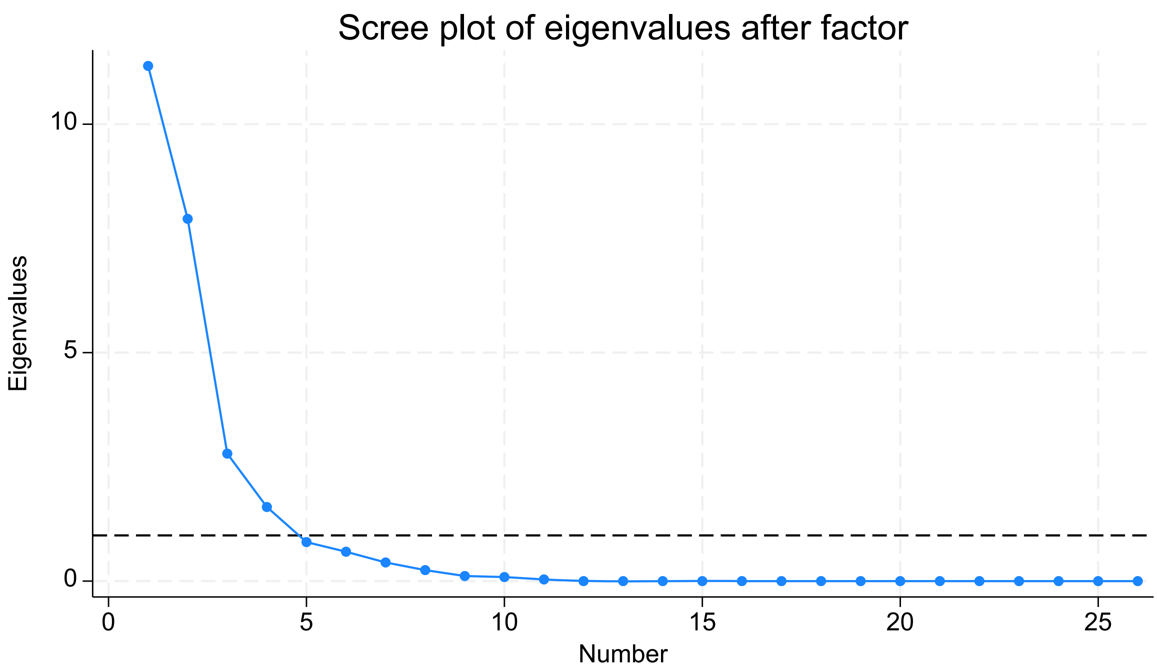


Figure 2:1a Scree plot of eigenvalues after factor

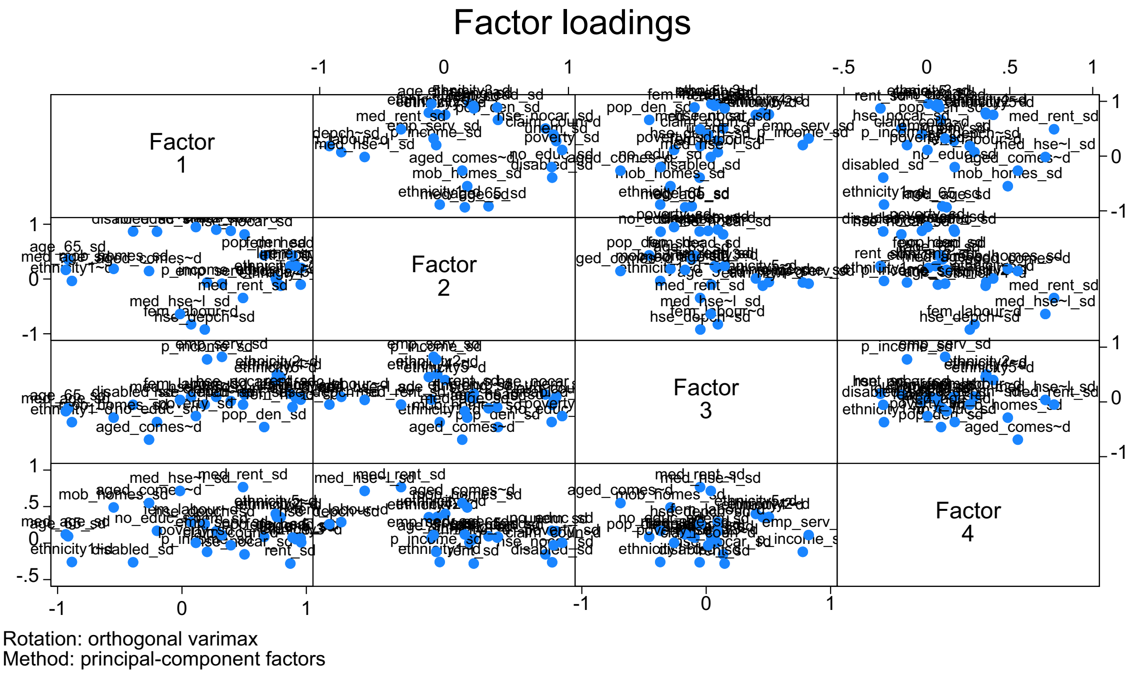


Figure 2:2a Factor loadings on the orthogonal varimax

Therefore the four key variables for social vulnerability for stage 2 are:

label variable s1 "demographic"
. label variable s2 "poverty"
. label variable s3 "employed"
. label variable s4 "housing_quality"

Thus, the factor scores are measured in units of standard deviations from their means. Basildon, for example, is about .98 standard deviations above average on demographic (s1) dimension. .47 above average on poverty dimension, .20 below average on the employed dimension and .26 below average on housing quality dimension.

Table 2:3a Factor analysis results

Factor Scores for Each District In Essex UK						
	District	s1	s2	s3	s4	
1.	Basildon	.9887693	.4706082	-.2081682	-.2641935	
2.	Braintree	-.1872489	-.5677451	-.4549989	-1.209245	
3.	Brentwood	.1091598	-.6651238	.4448029	.9377892	
4.	Castle Point	-.7446084	.5741578	-1.183099	.8913317	
5.	Chelmsford	.0439497	-.5716628	1.384853	-.5056739	
6.	Colchester	.4885251	.0456087	1.560852	-1.315957	
7.	Epping Forest	.4074665	-.1822345	1.045291	2.33406	
8.	Harlow	2.338058	.8799796	-1.218812	-.1366569	
9.	Maldon	-.990164	-.272853	-1.082779	-.3748991	
10.	Rochford	-.8202187	-.5691428	-.6962046	.2028936	
11.	Tendring	-1.346056	2.401625	.6937245	-.2494024	

12.	Uttlesford	-.2876327	-1.543217	-.2854621	-.3100466	

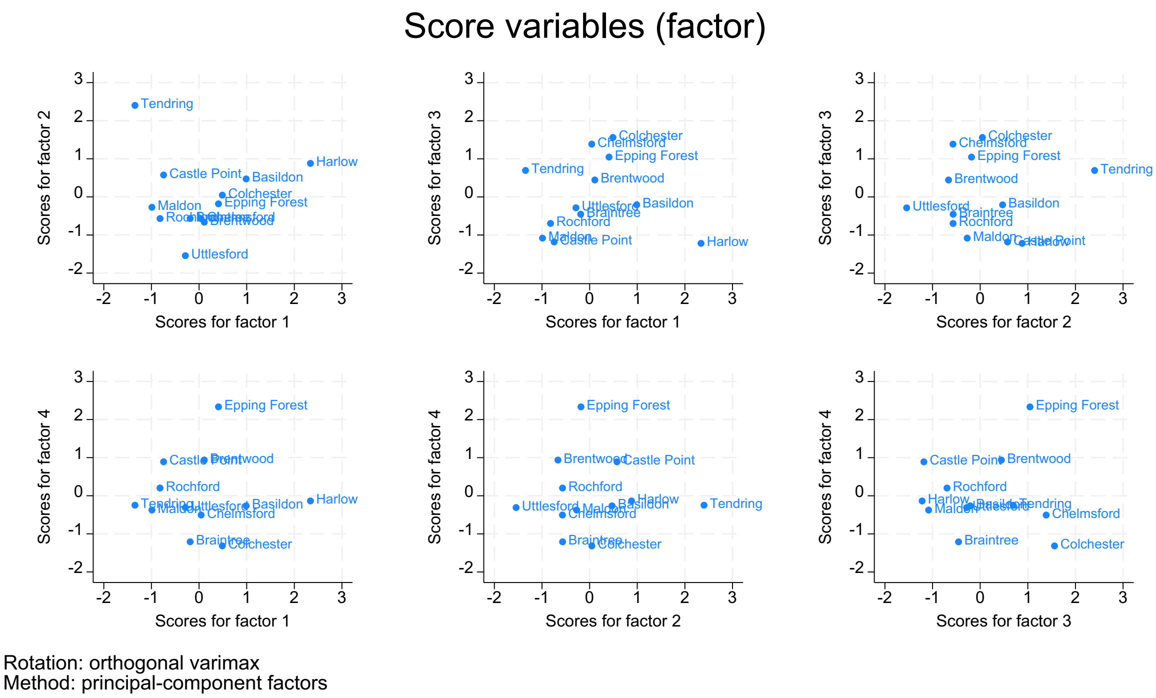


Figure 2:3a Score variables for each factor

The results of the principal components analysis for community resilience show that together, the first three components explain more than 90% of the cumulative variance of all 10 variables. Eigenvalues correspond to the standardized variance explained by each component. With 10 variables, the total standardized variance is 10. Of this, we see that component 1 explains 5.9305, which amounts to 5.9305/10 = 0.5930 or about 59% of the total. Component 2 explains 2.1191/10 = 0.2119, or an additional 21%. Principal components having eigenvalues below 1.0 are explaining less than the equivalent of one variable's variance, which makes them unhelpful for data reduction.

After factoring and the variance rotation, we assign each variable to a certain factor based on the highest absolute loading. We could see that for factor 1, number of arts orgnaisations, number of civic organisations, number of reglious organisations and number of local business load heavily on this factor. . This area is highly populated social and business resources, this could be a "**community organisations dimension**". Factor 2 loads heavily on median household income and number of creative assets. Thus factor 2 is classified as the "**household income dimension".** Factor 3 loads heavily on local employment rate, household income and higher education engagement. This dimension consists of those with higher education engagement and the subsequent human capital return "**higher education dimension".** Here negative values are seen as reducing a district vulnerability and positive values as contributing to overall resilience.

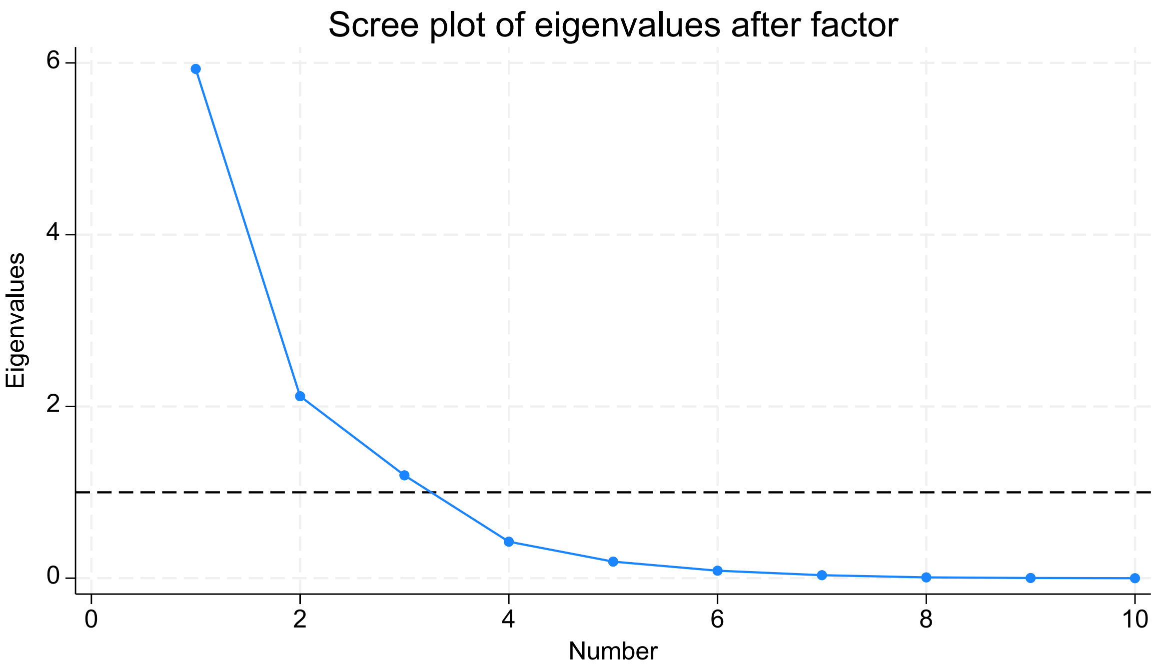


Figure 2:4b Scree plot of eigenvalues after factor

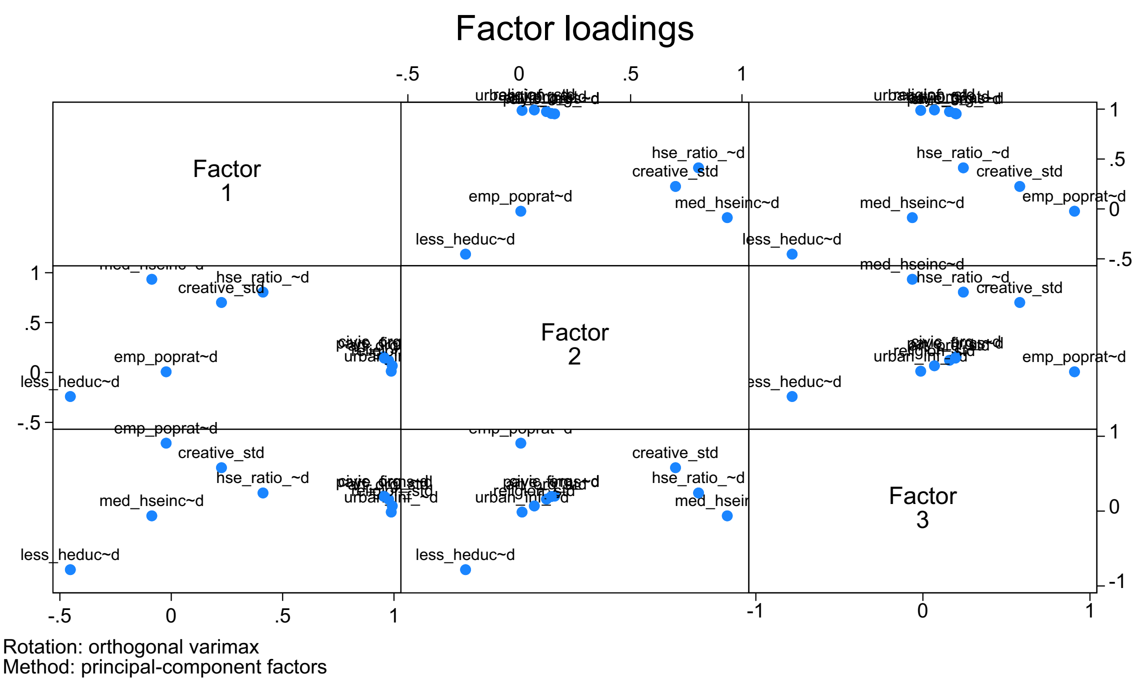


Figure 2:5b Factor loadings on the orthogonal varimax

Therefore the three key variables for community resilience for stage 2 are:

label variable f1 "community organisations"

label variable f2 "household income"
label variable s3 "higher education"

Thus, the factor scores are measured in units of standard deviations from their means. Basildon, for example, is about .98 standard deviations above average on demographic (s1) dimension. .47 above average on poverty dimension, .20 below average on the employed dimension and .26 below average on housing quality dimension.

Table 2:4b Factor analysis results

Factor Scores for Each District In Essex UK						
	District	f1	f2	f3		
1.	Basildon	-.9760131	-.3328647	.1904827		
2.	Braintree	1.382482	-.4872591	-.1934203		
3.	Brentwood	-.6831936	-.6831936	1.173712		
4.	Castle Point	-1.098549	.1423287	-.9256214		
5.	Chelmsford	.0905651	.0905651	.598561		
6.	Colchester	.1577237	-1.140281	.8460079		
7.	Epping Forest	.475946	.4965022	.3765228		
8.	Harlow	-1.282777	-1.734678	.7935718		
9.	Maldon	.4537498	.4019698	-.6657271		
10.	Rochford	-.8039425	1.864148	-.7209921		
11.	Tendring	.4014306	-1.023801	-2.285479		
12.	Uttlesford	1.882578	.1827392	.8123813		

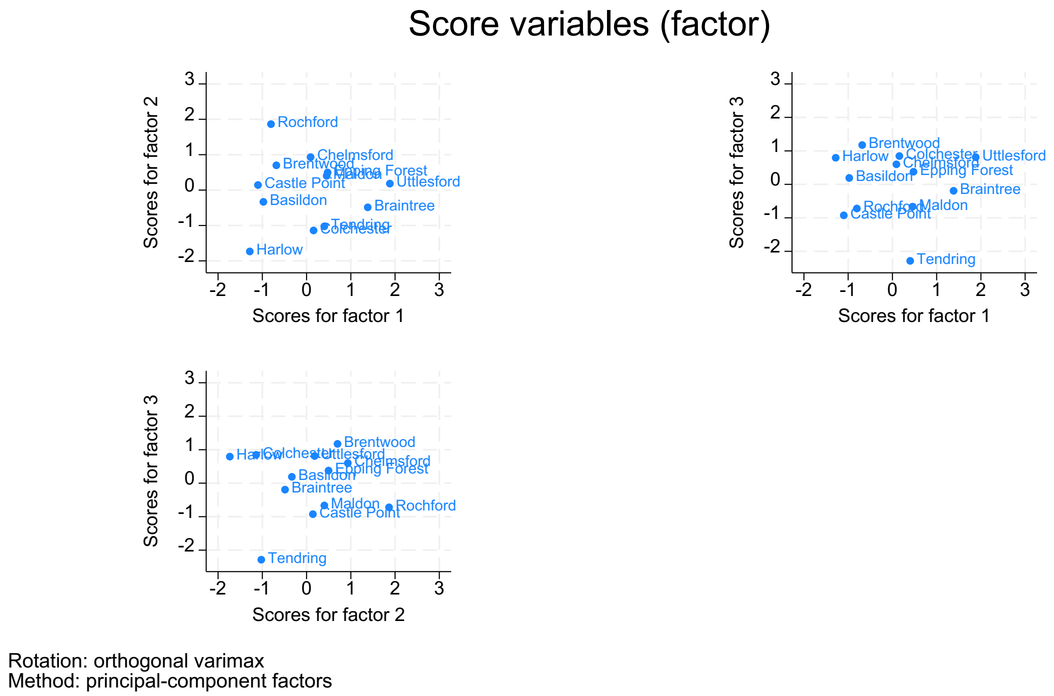


Figure 2:6b Score variables for each factor

These 4 identified factors for social vulnerability and the 3 identified factors for community resilience are combined to create the SoVI and CRI for each district of Essex. The results are presented below both as a table and mapped.

Figure 2:7 Community Resilience Index for Essex UK computed at the District level

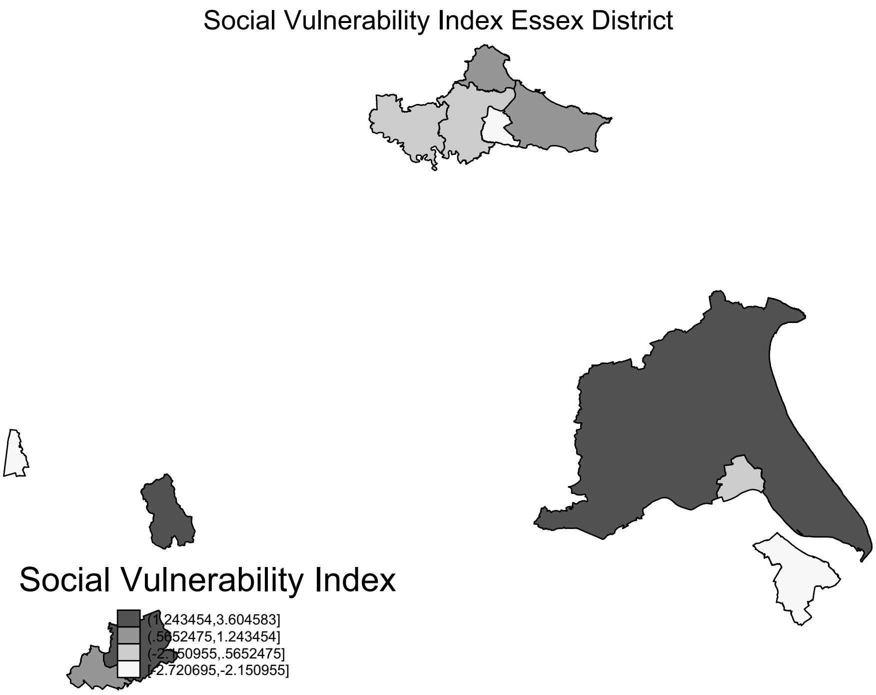


Figure 2:8 Social Vulnerability Index for Essex UK computed at the District level

Table 2:5c Factor analysis results (SoVI and CRI)

SoVI and CRI scores for Each District In Essex UK			
	District	SoVI	CRI
1.	Basildon	.9870158	-1.118395
2.	Braintree	-2.419238	.7018029
3.	Brentwood	.8266281	1.18977
4.	Castle Point	-.4622178	-1.881842
5.	Chelmsford	.3514661	1.62107
6.	Colchester	.7790291	-.1365492
7.	Epping Forest	3.604583	1.348971
8.	Harlow	1.862569	-2.223882
9.	Maldon	-2.720695	.1899925
10.	Rochford	-1.882672	.3392135
11.	Tendring	1.499891	-2.907849
12.	Uttlesford	-2.426359	2.877698

1.3.5 Stage 2 – Panel Data Regression GDP and SoVI/CRI measures at district level for the Essex Testbed

The second stage estimates equation 1, using the stage 1 constructed SoVI and CRI as independent variables and using log GDP per capita. We estimate this model using data from 2011 census for the independent variables and GDP data from 2011 to 2019. This time period is selected given the 1 in 316-year flood event on Canvey Island on 20th July 2014 on Canvey Island. We have not selected the more recent 20th October 2021 flood given COVID impact on GDP data in 2020 and 2021.

Table 2:6d Final Econometric Model

Dependent Variable Ward level log GDP per capita	Model 1	Model 2	Model 3
	Coeff/standard error	Coeff/standard error	Coeff/standard error
flood	-0.050	-0.050	-0.050
	(0.03)	(0.03)	(0.03)
SoVI		0.097 *	0.098 *
		(0.04)	(0.04)
CRI		0.143 **	0.143 *
		(0.05)	(0.05)
Flood CRI inteaction			-0.003
			(0.02)
Flood SOVI interaction			-0.007
			(0.02)

Note: ** significant at 1% * significant at 5%, estimated using random effects and include a constant term

In model 1, we estimate the raw effect of the 2014 flood on log local GDP per capita. This coefficient is significant at 15% and considered economically significant even though it is not statistically significant. This is because of the small number of observations, 108 observations and 12 districts. This shows that the effect of a 1 in 316 year flood is to reduce local GDP by 5%.

Model 2 includes our SoVI and CRI measures. Whilst this does not alter the effect on local GDP from the flood directly, areas with with less social vulnerability and more community resilience, are able to compensate for the effect of flood. Improving social vulnerability by one unit improves GDP by almost double the flood effect (-5% of flood impact on GDP compared to 9.8% in response to improved social vulnerability). More importantly improving community resilience by one unit improves GDP by almost triple the flood effect (-5% of flood impact on GDP compared to 14.3% in response to improved community resilience).

2.1.1 Counterfactual analysis

The counterfactual analysis is undertaken in model 3. Model 3 includes interaction terms between the flood and SoVI-CRI measures. These interaction terms are not statistically or economically significant and suggest that there is no additional impact from weak SoVI or CRI scores when floods occur. This suggests that a focus on the key determinants of SoVI and CRI in Canvey Island would be most effective. In terms of the components of the SoVI and CRI the counterfactual analysis suggest that the demographic characteristics of Canvey Island make it especially sensitive to demographic composition of the population. This suggests a need for Essex County Council to place strategic thought around disaster planning for areas with high proportions of elderly people in their population.

1.3.6 Discussion

The econometric model highlights the importance of flood management in Essex to focus belong the physical prevention investment to focus on wider social and economic interventions to improve community resilience and social vulnerability to migagte the wider economic impact of floods on the local economy, as measured by GDP. The scale of the impact suggest a programme of social interventions could be considered as an investment that is worthwhile both in terms of the local economy and in terms of the ability to respond to multiple environmental hazards.

For social vulnerability we have identified four key variables to consider ***"demographic", "poverty", "employed***" and ***"housing_quality".*** In terms of Canvey Island, the important target group for investment to improve in social vulnerability is the significant elderly population often living in pensioner poverty on state pensions, not in work and living in residential care. Investment in the housing stock for those in residential care to ensure the ability to respond to multiple hazards and especially flood could be a worthwhile investment in terms of improved GDP as well as ability of this vulnerable community to respond to a future flood.

For community resilience we have three key variables to consider ***"community organisations", "household income" and "higher education".*** In terms of Canvery Island, the important target group for investment to improve community resilience are community organisations focused at supporting the elderly community. In addition given supporting workforce for this community is likely to be relatively low paid care workers, supporting paid support packages that enable care workers to improve their household income and have access to higher education could also support community resilience and therefore support economic growth.

The two stage model above has suggested a set of 7 key indicators that underpin community resilience and social vulnerability. Investment in these indicators suggest a return on investment in terms of economic growth as well as building the ability for communities to ensure they are able to respond to multiple hazards and particulary floods. The econometric model therefore highlights the importance of including economic and social measures in the Mediate tool to ensure a holistic response to the potential impacts of climate change.

3 NETWORK ANALYSIS

Understanding how physical damage to transport infrastructure impacts social activities is important in disaster risk management. Road networks, in particular, if damaged or become unusable in the event of a natural hazard, could cause additional social impacts on communities. MEDiate project investigated how network analysis approaches could be used and embedded in a risk management platform to make informed decision making. Whilst we tested the concept for a selected one test bed (Canvey Island, Essex, UK) due to data and time availability the proposed methodology can be implemented to assess the social impact due to damage or closure of transport networks induced by natural hazards.
This chapter explains the background to the network analysis and an application of graph concept and network analysis for Canvey Island UK. In the detailed analysis, we analysed the vulnerability of the Canvey Island road network to flooding and the impact of road closures on the connectivity of 11 service providers (Fire station, Surgery (GP), College/university, Library, Town Office, Police and five schools) in Canvey Island and the residents who received their service.

3.1 Application of Network Analysis in Disaster Impact Assessment Research

Network analysis supported by Graph Theory has been used for various disaster management purposes. Table 3:1 below summarises selected recent applications of similar methodologies to assess the vulnerability of road networks.

Table 3:1: A review of Network analysis applications for vulnerability analysis of road networks

	Citation	City & County	Type of Disaster	Brief overview of the application
1	Appert and Laurent 2013	Montpellier, France	N/A	The authors measured urban road network vulnerability using graph theory. The authors mainly focused on congestion in junctions for any risk. The authors also developed road network vulnerability indices that planners and road agencies can use to evaluate the risk of incidents to their road network.
2	Arosio et al., 2020	Mexico City	Flooding	Using Graph Theory and Network Analysis, the authors modelled the number of services lost after the impact due to the dismissal of service providers (Hospital, Fuel station, Fire station, Education providers and Transport) and service receivers.
3	Arosio et al., 2021	Monza city (northern Italy)	Flooding	The authors presented a methodology to estimate the service accessibility risk (SAR) that considers the accessibility of roads and the connection between providers and users of services in a city.
4	Aydin et al., 2018	Kathmandu in Nepal	Natural Hazards/ Earthquake	Using Stress Testing methodology and graph theory metrices, authors developed a tool for detecting the resilience of entire transportation network topologies as well as spatial resilience under seismic hazards.
5	Bono and Gutiérrez 2011	Haiti	Earthquake	The authors proposed an alternative approach to define urban accessibility following earthquake damage by combining graph theory concepts and

				GIS-based spatial analysis to assess how urban space accessibility decreases when the road network is damaged.
6	Khademi et al., 2015	Tehran, Iran	Earthquake	Using network vulnerability analysis and graph matrices, the authors proposed an approach to evaluate post-earthquake response and recovery routes by identifying redundancy-based isolation measures to determine which zones in the city are most susceptible to transport system disruptions following destructive earthquakes. The authors also presented a comprehensive review of previous literature related to indicators of network vulnerability
7	Mossoux et al., 2018 & Mossoux et al., 2019	Ngazidja, Madagascar	volcanic hazards	Using network analysis, authors proposed a methodology to identify which road segments of a road network are the most strategic in terms of the impact of a road closure on access to crucial infrastructure for volcanic lava flow hazards.
8	Péroche et al., 2014	Martinique Island, Caribbean Coastline	Tsunami	The authors presented a model of tsunami evacuation sites accessibility for Martinique. The methodology supported measuring the access time along the shortest routes between hazard zones and refuge areas, estimating the number of evacuees using accessibility curves, and automatic selection of the evacuation sites and most relevant itineraries based on the best pair time/distance route and the number of people who converge there.
9	Porta et al., 2006	Ahmedabad, Venice, Richmond, CA, and Walnut Creek, CA,	N/A	The authors performed a network analysis of four 1-square-mile samples of urban street systems to distinguish between homogeneous and heterogeneous patterns. Authors did not perform a vulnerability analysis.
10	Gil and Steinbach, 2008	London	Flooding	The authors introduced a Space Syntax based methodology to analyse and visualise the wider impact of flooding on the urban street network, measuring its performance

3.2 Application to Canvey Island (Essex UK Test Bed)

We applied network analysis to estimate service accessibility risk by considering the accessibility of roads and the connection between providers and users of services in case of flooding hazards for Canvey Island, Essex, UK. We followed the methodology proposed and validated in the work of Arosio et al. (2021).

Convey Island is one of the two parishes in the District of Castle Point. The Figure 3:1 below shows the Castle Point boundary. The area shaded in pink is Canvey Island.

Figure 3:1 Castle point boundary and the location of Canvey Island

The following steps explain the analysis and results in detail.

3.2.1 Step 1- Distribute population from census areas to buildings

There are 25 Lower Super Output Areas (LSOAs) in Canvey Island. Based on the data from the Census 2021, UK, Table 3:2 below shows the population density of each area of Canvey Island.

Table 3:2. Summary of population information on 25 areas of Canvey Island

Area Code	Area Name	Population Density	Area (sqKM)	Population
E01021484	Castle Point 011A	5384.6	0.249	1341
E01021485	Castle Point 010A	4592.1	0.267	1226
E01021486	Castle Point 010B	6942	0.191	1326
E01021487	Castle Point 008A	5509.4	0.234	1289
E01021488	Castle Point 010C	5793.1	0.262	1518
E01021489	Castle Point 012A	5670.6	0.242	1372
E01021490	Castle Point 012B	4662.1	0.305	1422
E01021491	Castle Point 012C	2642.3	0.617	1630
E01021492	Castle Point 009A	4920.8	0.334	1644
E01021493	Castle Point 009B	5426.5	0.278	1509
E01021494	Castle Point 008B	6370.5	0.223	1421
E01021495	Castle Point 009C	1801.9	1.084	1953
E01021496	Castle Point 009D	6451	0.227	1464
E01021497	Castle Point 012D	6430.1	0.237	1524
E01021498	Castle Point 011B	3364	0.491	1652
E01021499	Castle Point 011C	4752.2	0.332	1578
E01021500	Castle Point 012E	4003.7	0.594	2378
E01021501	Castle Point 011D	701.2	1.984	1391
E01021502	Castle Point 011E	2864.6	0.714	2045

E01021503	Castle Point 010D	215.6	6.74	1453
E01021504	Castle Point 008C	1061.8	1.38	1465
E01021505	Castle Point 008D	6641.9	0.213	1415
E01021506	Castle Point 008E	5830.3	0.226	1318
E01021507	Castle Point 010E	7387.7	0.201	1485
E01021508	Castle Point 010F	8894.1	0.149	1325

We determined the population for different areas of Canvey Island by multiplying the population density by the respective area size. The total number of residents in Canvey Island are 38144.

Figure 3:2 below shows the distribution of population density of Canvey Island for each of the LSOAs.

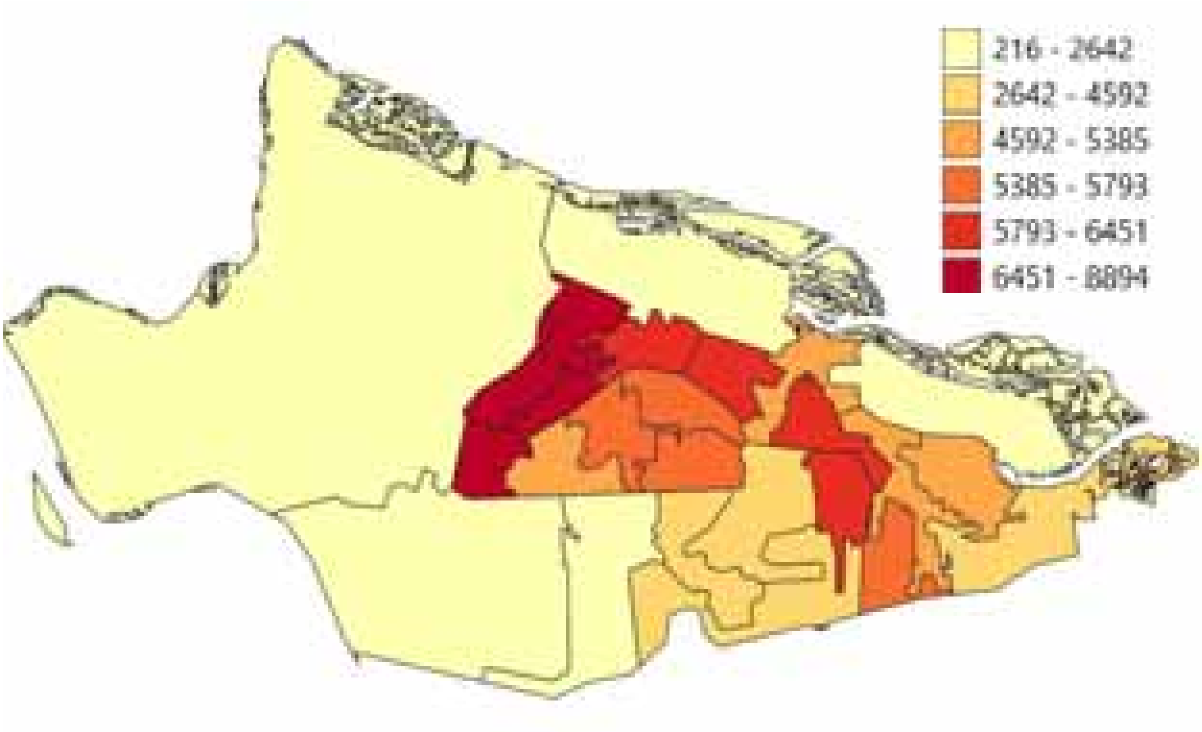


Figure 3:2 Distribution of population density in Canvey Island

3.2.2 Step 2- Graph Construction

The graph construction involved four main steps: i) defining elements to be considered, ii) establishing connections between elements, iii) extracting connections and building the graph, and iv) weighing the connections of the graph. This section explains the data and results for these four steps.

3.2.2.1 Define elements to be considered

The table below shows the type of providers and their numerosity in Canvey Island. There are 11 providers under seven categories (see Table 3:3). We did not consider *home care* and *heavy industry* as a provider for the following reasons. The number of home care receivers has already been considered as people living in the census area. Heavy industry is not known as a public provider. So, we removed them from the analysis.

Table 3:3. Service provider information in Canvey Island

ID	Type of providers	Number
1	Surgery (GP)	1
2	Fire station	1
3	College/university	1
4	Library	1
5	Town Office	1
6	Police	1
7	School	5
	Total	**11**

Overall, we consider 25 LSOA areas identified in the previous step as receivers that are supposed to receive service from providers. Therefore, our graph will have a dimension of 11* 25, representing 11 providers serving 25 LSOA areas.

3.2.2.2 Establish connections between elements

The main purpose of establishing the connections is to ensure all receivers can receive the service from providers. We have a matrix including 11 providers and 25 receivers to establish the connection between elements. Except for ***School***, all other providers have a numerosity of 1 and must be linked to every residential area. Regarding the ***School*** provider, as the number of schools is more than 1, we apply Voronoi polygons for schools to allocate each residential area to the nearest schools under the assumption that students go to the nearest school. In other words, we assumed that each receiver receives the service from only the nearest provider. Figure 3:3 shows the Voronoi polygon for ***schools*** in Canvey Island. It divides the Canvey Island area into 5 Voronoi around schools. When a residential area is split between two Voronoi polygons, we assign the area to the Voronoi region that encompasses the majority (over 50%) of the residential space. Orange dots in the map represent the locations of 5 schools.

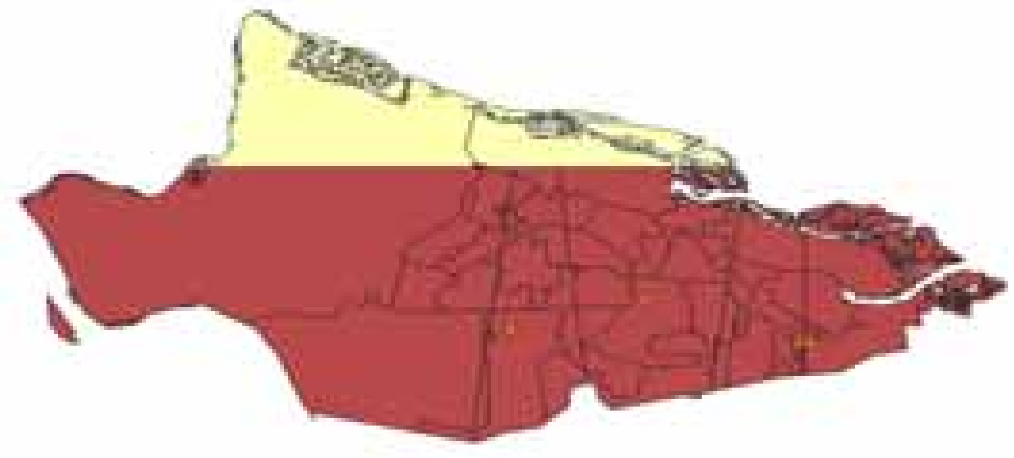


Figure 3:3 Allocation of the schools and LSOAs to Voronoi polygons

Table 3:4 below shows the allocation of the residential areas to the five schools. Areas allocated to each school are identified with a specific colour.

Table 3:4 Allocation of the schools and LSOAs to Voronoi polygons

Area Code	Area Name	School Name
E01021488	Castle Point 010C	Canvey Infant School
E01021502	Castle Point 011E	Canvey Infant School
E01021506	Castle Point 008E	Canvey Infant School
E01021485	Castle Point 010A	Canvey Junior School
E01021486	Castle Point 010B	Canvey Junior School
E01021501	Castle Point 011D	Canvey Junior School
E01021503	Castle Point 010D	Canvey Junior School
E01021505	Castle Point 008D	Canvey Junior School
E01021507	Castle Point 010E	Canvey Junior School
E01021508	Castle Point 010F	Canvey Junior School
E01021484	Castle Point 011A	The Castle View School
E01021487	Castle Point 008A	The Castle View School
E01021493	Castle Point 009B	The Castle View School
E01021494	Castle Point 008B	The Castle View School
E01021496	Castle Point 009D	The Castle View School
E01021497	Castle Point 012D	The Castle View School
E01021498	Castle Point 011B	The Castle View School
E01021499	Castle Point 011C	The Castle View School
E01021500	Castle Point 012E	The Castle View School
E01021504	Castle Point 008C	The Castle View School
E01021491	Castle Point 012C	Leigh Beck Infant School & Nursery
E01021492	Castle Point 009A	Leigh Beck Infant School & Nursery
E01021495	Castle Point 009C	Leigh Beck Infant School & Nursery
E01021489	Castle Point 012A	Leigh Back Junior School
E01021490	Castle Point 012B	Leigh Back Junior School

3.2.2.3 Extract the List of Connections and build the graph

As stated earlier, the graph will consist of a matrix of 11 (providers)*25(receivers), hence 275 (11x25) elements. Each element will have a score of 1 or 0. 1 denotes a link between the provider and the receiver, and 0 represents no link between the provider and the receiver.

We assumed that each of the seven types of providers should offer services to all residential areas. Therefore, there would be a total of 175 (7*25=175) elements with a score of 1 (see Table 3:5) to denote that every element represents a connection between a provider type and each LSOA area.

We applied Voronoi polygons for the school and identified the residential areas applicable to each school. It is worth noting that there is no link between all schools to all areas. There are only 25 links between all 5 schools and residential areas. Zero shows no link between the school and the residential area. Table 3:5 shows the final scoring matrix.

Table 3:5. Matrix providers and receivers

	E01021484	E01021485	E01021486	E01021487	E01021488	E01021489	E01021490	E01021491	E01021492	E01021493	E01021494	E01021495	E01021496	E01021497	E01021498	E01021499	E01021500	E01021501	E01021502	E01021503	E01021504	E01021505	E01021506	E01021507	E01021508
Surgery (GP)	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Fire station	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
College/university	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Library	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Town Office	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Police	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
School-4 (Canvey Infant School)	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0
School-5 (Canvey Junior School)	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	1	0	1	1
School-6 (The Castle View School)	1	0	0	1	0	0	0	0	0	1	1	0	1	1	1	1	1	0	0	0	1	0	0	0	0
School-8 (Infant School & Nursery)	0	0	0	0	0	0	0	1	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
School-9 (Leigh Back Junior School)	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

3.2.2.4 Weighing the connections of the graph

As the next step, we identified the weight of each link between providers and receivers. In a weighted graph, each edge has attached an attribute as a numerical value functioning as a weight. The attachment of the weight changes depending on the application. In this study, each provider-receiver link is weighted by the number of people that use the service. We assume all providers, except the school, serve all those living in the residential areas.

To weigh each link between areas and schools, as schools provide service to students, we use the age information from the Census 2021 (see Table 3:6) to identify the weight of links. We assume schools serve people under 16 year-old. Therefore, we identify the weight of the link between the residential area and the school by calculating 17.1% of people living in each area. Table 3:7 shows the weight of each link computed during this step.

Table 3:6. Distribution of residents' age (Source: Census UK, 2021)

	All Ages	**Aged 0 to 15**	**Aged 16 to 24**	**Aged 25 to 49**	**Aged 50 to 64**	**Aged 65+**
Number	89,731	15,303	8,007	25,057	18,493	22,871
% of Population	100.0	17.1	8.9	27.9	20.6	25.5

Table 3:7. Weight of the connections based on the population age

LSOA Code	***Surgery (GP)***	***Fire station***	***College /university***	***Library***	***Town Office***	***Police***	***School-4 (Infant School)***	***School-5 (Junior School)***	***School-6 (The Castle View School)***	***School-8 (Infant School & Nursery)***	***School-9 (Junior School)***
E01021484	1341	1341	1341	1341	1341	1341	0	0	229	0	0
E01021485	1226	1226	1226	1226	1226	1226	0	210	0	0	0
E01021486	1326	1326	1326	1326	1326	1326	0	227	0	0	0
E01021487	1289	1289	1289	1289	1289	1289	0	0	220	0	0
E01021488	1518	1518	1518	1518	1518	1518	260	0	0	0	0
E01021489	1372	1372	1372	1372	1372	1372	0	0	0	0	235
E01021490	1422	1422	1422	1422	1422	1422	0	0	0	0	243
E01021491	1630	1630	1630	1630	1630	1630	0	0	0	279	0
E01021492	1644	1644	1644	1644	1644	1644	0	0	0	281	0
E01021493	1509	1509	1509	1509	1509	1509	0	0	258	0	0
E01021494	1421	1421	1421	1421	1421	1421	0	0	243	0	0
E01021495	1953	1953	1953	1953	1953	1953	0	0	0	334	0
E01021496	1464	1464	1464	1464	1464	1464	0	0	250	0	0
E01021497	1524	1524	1524	1524	1524	1524	0	0	261	0	0
E01021498	1652	1652	1652	1652	1652	1652	0	0	282	0	0
E01021499	1578	1578	1578	1578	1578	1578	0	0	270	0	0
E01021500	2378	2378	2378	2378	2378	2378	0	0	407	0	0
E01021501	1391	1391	1391	1391	1391	1391	0	238	0	0	0

E01021502	2045	2045	2045	2045	2045	2045	350	0	0	0	0
E01021503	1453	1453	1453	1453	1453	1453	0	248	0	0	0
E01021504	1465	1465	1465	1465	1465	1465	0	0	251	0	0
E01021505	1415	1415	1415	1415	1415	1415	0	242	0	0	0
E01021506	1318	1318	1318	1318	1318	1318	225	0	0	0	0
E01021507	1485	1485	1485	1485	1485	1485	0	254	0	0	0
E01021508	1325	1325	1325	1325	1325	1325	0	227	0	0	0

3.2.2.5 Allocating providers to residential areas (receivers) in an urban graph

We consider the connection between areas based on the adjacency of the areas. To this end, we first identified the LSOA areas for each of the 11 providers (see Table 3:8). 11 providers are located in 7 different areas.

Table 3:8. Area code locations for each provider

Providers	***LSOA Area Code***
Police	*E01021488*
School-8 (Infant School & Nursery)	*E01021491*
School-9 (Leigh Back Junior School)	*E01021491*
Library	*E01021498*
Town Office	*E01021498*
School-6 (The Castle View School)	*E01021498*
Fire station	*E01021499*
Surgery (GP)	*E01021501*
School-5 (Canvey Junior School)	*E01021501*
School-4 (Canvey Infant School)	*E01021502*
College/university	*E01021503*

In this analysis, we considered the following three types of connections between providers and receivers:

1) Connection when the provider and the receiver are in the same LSOA area.
2) Connections are when the provider is in an adjacent LSOA area to receivers.
3) Connections when the provider and receiver are not in adjacent LSOA areas. This implies that one must traverse through other LSOA areas to reach the receiver.

We then applied network analysis to find the connection between each of the two areas on the real network. Table 3:9 shows the types of connections between areas, including providers and receivers. The numbers indicate the types of connections based on what they were introduced. A score of 1 refers to the equity of the area as provider and receiver. A score of 2 denotes that the area, including the provider, is adjacent to the receiver. A score of 3 denotes that the areas are not adjacent, and the number after “” denotes the number of areas between the provider and the receiver. For example, 3,2 indicates two areas between the provider and the receiver.

Table 3:9 Types of connection between providers and receivers

	Locations of 7 provider types (taken from the Table 3:8)						
Receiver locations	E01021488	E01021491	E01021498	E01021499	E01021501	E01021502	E01021503
E01021484	2	3,3	2	2	3,1	2	3,2
E01021485	2	3,3	3,2	3,1	2	2	3,1
E01021486	3,1	3,4	3,3	3,2	2	3,1	2
E01021487	2	3,2	2	3,1	3,2	3,1	3,2
E01021488	1	3,3	3,1	3,1	3,1	2	3,2
E01021489	3,2	2	3,1	3,1	3,2	3,1	3,3
E01021490	3,2	2	3,1	3,2	3,3	3,2	3,2
E01021491	3,3	1	3,2	3,2	3,3	3,2	3,3
E01021492	3,3	2	3,2	3,3	3,4	3,3	3,3
E01021493	3,1	3,1	2	3,1	3,2	3,2	3,1
E01021494	3,1	3,2	3,1	3,2	3,2	3,2	3,1
E01021495	3,2	3,1	3,1	3,2	3,3	3,3	3,2
E01021496	3,2	3,1	2	3,1	3,3	3,2	3,2
E01021497	3,2	3,1	2	3,1	3,2	3,1	3,3
E01021498	3,1	3,2	1	2	3,2	3,1	3,2
E01021499	3,1	3,2	2	1	3,1	2	3,2
E01021500	3,1	3,1	2	2	3,1	2	3,2
E01021501	3,1	3,3	3,2	3,1	1	2	2
E01021502	2	3,2	3,1	2	2	1	3,1
E01021503	3,2	3,3	3,2	3,2	2	3,1	1
E01021504	3,1	3,2	3,1	3,2	3,1	3,2	2
E01021505	3,1	3,3	3,2	3,3	3,1	3,2	2
E01021506	2	3,3	3,1	3,2	3,2	3,1	3,1
E01021507	3,1	3,4	3,3	3,3	3,1	3,2	2
E01021508	2	3,4	3,2	3,2	3,1	3,1	3,1

3.2.3 Classify Connections as Open or Closed:

As the next step, we calculated the accessibility of the connections based on coastal flood risk information for a 5-year return period (provided by MEDiate Task 2.2) and vehicle vulnerability information. 5-year return period was selected for illustrative purpose only. The methodology can be applied to other hazard intensities.

The maximum vulnerability for driving vehicles is reached when flood depth equals or exceeds the threshold $H_{cr,V}$ = 0.3 m, the depth at which a standard saloon or estate car cannot operate, and roads are considered impassable. The below equation identifies the degree of vulnerability for vehicles.

$$\text{Vulnerability} = \frac{H}{\mathrm{Hcr,V}}$$

H (flood depth) was obtained from coastal flood information produced by the MEDiate Task 2.2. A vulnerability score of more than 1 indicates the vulnerability is high, and consequently, the connection between the provider and the receiver is closed. Otherwise, the vulnerability is low, meaning the connection between the provider and the receiver is open.

For the area where the provider is located, the vulnerability of road segments of the area was calculated based on its flood information. Otherwise, the maximum H among different areas connecting the provider to the receiver is considered for calculating the vulnerability of that link. Table 3:10 shows the vulnerability of connections between providers and receivers estimated based on this formula. Numbers in red colour indicate high vulnerability (closed connections), and numbers in black indicate low vulnerability (open connections). According to the results, 128 out of 175 connections are identified as closed connections, and the 47 remaining connections are open.

Table 3:10 Vulnerability of connections between providers and receivers

	Surgery (GP)	*Fire station*	*College/university*	*Library*	*Town Office*	*Police*	*School-4*	*School-5*	*School-6*	*School-8*	*School-9*
E01021484	2.4	0.8	2.8	0	0	0.2	0	0	0	0	0
E01021485	2.4	1.4	2.8	1	1	1	0	2.4	0	0	0
E01021486	2.4	1.4	2.8	1	1	1	0	2.4	0	0	0
E01021487	2.4	1.1	2.8	1.1	1.1	1.1	0	0	1.1	0	0
E01021488	2.4	0.8	2.8	0.2	0.2	2.4	1.4	0	0	0	0
E01021489	3.3	3.3	3.3	3.3	3.3	3.3	0	0	0	0	4.4
E01021490	3.3	2.5	2.8	2.5	2.5	2.5	0	0	0	0	4.4
E01021491	4.4	4.4	4.4	4.4	4.4	4.4	0	0	0	4.4	0
E01021492	3.3	3.3	2.8	2.5	2.5	2.5	0	0	0	4.4	0
E01021493	2.8	0.8	2.8	0.8	0.8	1.1	0	0	0.8	0	0
E01021494	2.8	1.1	2.8	1.1	1.1	1.1	0	0	1.1	0	0
E01021495	4.4	4.4	4.4	4.4	4.4	4.4	0	0	0	4.4	0
E01021496	2.4	0.8	2.8	0.6	0.6	1.1	0	0	0.6	0	0
E01021497	2.4	0.8	2.8	0.5	0.5	0.5	0	0	0.5	0	0
E01021498	2.4	0.8	2.8	0	0	0.2	0	0	0	0	0
E01021499	2.4	0.8	2.8	0.8	0.8	0.8	0	0	0.8	0	0
E01021500	2.4	1	2.8	1	1	1.4	0	0	1	0	0
E01021501	2.4	2.4	2.8	2.4	2.4	2.4	0	2.4	0	0	0
E01021502	2.4	1.4	2.8	1.4	1.4	1.4	1.4	0	0	0	0
E01021503	2.8	2.8	2.8	2.8	2.8	2.8	0	2.8	0	0	0
E01021504	2.8	2.6	2.8	2.6	2.6	2.6	0	0	2.6	0	0
E01021505	2.8	2.8	2.8	2.6	2.6	1	0	2.8	0	0	0
E01021506	2.4	1.1	2.8	1.1	1.1	1	1.4	0	0	0	0
E01021507	2.4	1.6	2.8	2.8	2.8	1.6	0	2.4	0	0	0
E01021508	2.4	0.9	2.8	0.9	0.9	0.9	0	2.4	0	0	0

3.2.4 Counting the Number of not delivered / not received due to closed roads:

The final step involved estimating the number of undeliverables / not received due to closed roads. Undeliverables/not received here refers to the service provider or service recipient not being reach each other due to the road closure. Based on the weight of connections from the Table 3:9, and the output of the vulnerability from Table 3:10, we can identify and quantify the services that could not be delivered or received due to road closures in detail of providers and receivers. These results are shown in Table 10. It is apparent that 12 out of 25 receivers were not able to receive any type of service, including E01021489, E01021489, E01021490, E01021491, E01021492, E01021494, E01021495, E01021501, E01021502, E01021503, E01021504, and E01021507.

Table 3:11Missed services

	Surgery (GP)	*Fire station*	*College/university*	*Library*	*Town Office*	*Police*	*School-4*	*School-5*	*School-6*	*School-8*	*School-9*
E01021484	1341	0	1341	0	0	0	0	0	0	0	0
E01021485	1226	1226	1226	0	0	0	0	210	0	0	0
E01021486	1326	1326	1326	0	0	0	0	227	0	0	0
E01021487	1289	1289	1289	1289	1289	1289	0	0	220	0	0
E01021488	1518	0	1518	0	0	1518	260	0	0	0	0
E01021489	1372	1372	1372	1372	1372	1372	0	0	0	0	235
E01021490	1422	1422	1422	1422	1422	1422	0	0	0	0	243
E01021491	1630	1630	1630	1630	1630	1630	0	0	0	279	0
E01021492	1644	1644	1644	1644	1644	1644	0	0	0	281	0
E01021493	1509	0	1509	0	0	1509	0	0	0	0	0
E01021494	1421	1421	1421	1421	1421	1421	0	0	243	0	0
E01021495	1953	1953	1953	1953	1953	1953	0	0	0	334	0
E01021496	1464	0	1464	0	0	1464	0	0	0	0	0
E01021497	1524	0	1524	0	0	0	0	0	0	0	0
E01021498	1652	0	1652	0	0	0	0	0	0	0	0
E01021499	1578	0	1578	0	0	0	0	0	0	0	0
E01021500	2378	0	2378	0	0	2378	0	0	0	0	0
E01021501	1391	1391	1391	1391	1391	1391	0	238	0	0	0
E01021502	2045	2045	2045	2045	2045	2045	350	0	0	0	0
E01021503	1453	1453	1453	1453	1453	1453	0	248	0	0	0
E01021504	1465	1465	1465	1465	1465	1465	0	0	251	0	0
E01021505	1415	1415	1415	1415	1415	0	0	242	0	0	0
E01021506	1318	1318	1318	1318	1318	0	225	0	0	0	0
E01021507	1485	1485	1485	1485	1485	1485	0	254	0	0	0
E01021508	1325	0	1325	0	0	0	0	227	0	0	0

Table 11 provides a summary of the results obtained for missed services by the providers. The total required services for all providers except for ***schools*** is equal to the number of residents in Canvey Island (38144 people), while the figure for all schools is 6523 people (17.1%* 38144) where 17.1 denotes the percentage of residents under 16 years. The third column indicates the number of services missed by the provider. The last column means the percentage of services missed by the provider. Notably, two providers, namely *Surgery (GP)* and *College/university* and four schools, namely *Canvey Infant School, Canvey Junior School, The Castle View School, Infant School & Nursery, Leigh Back Junior School* missed 100 per cent of the services.

Table 3:12 Summary of the missed services by providers

	The total required services	Services missed by the provider	The percentage of missed services by the provider
Surgery (GP)	38144	38144	100
Fire station	38144	23855	63
College/university	38144	38144	100
Library	38144	21303	56
Town Office	38144	21303	56
Police	38144	25440	67
School-4 (Canvey Infant School)	835	835	100
School-5 (Canvey Junior School)	1645	1645	100
School-6 (The Castle View School)	2671	714	27
School-8 (Infant School & Nursery)	894	894	100
School-9 (Leigh Back Junior School)	478	478	100

Results from this type of analysis could support disaster risk management decision-making. Firstly, they could be used to decide the locations of service bases and the type of services provided in each base. For instance, the location of GP practices (and their care model) and pharmacies could be carefully planned to ensure communities get health services in the event of a road closure or damage due to a natural hazard. School catchments could be carefully planned to minimize the service closures between the school and the homes of the school pupils. Secondly, existing service provisions could be evaluated for the impact of road closures on service provisions. Risk management plans could then be developed to manage service provision continuation during road closures. For instance, online teaching provisions for selected periods within schools could be planned based on the loss of connectivity between the school, pupils and teachers. The results could also be useful in developing strategies to eliminate service backlogs following a disaster event. Finally, awareness campaigns could be used to inform communities about potential service losses during hazard events, and advice could be provided to improve disaster preparedness.

4 DISAGGREGATION OF ASSET LOSSES AS A FUNCTION OF SOCIO-ECONOMIC CHARACTERISTICS

4.1 Introduction to Part 1

This section will directly disaggregate the asset losses (investigated and reported within other tasks of Work package 3 of the MEDiate project) as a function of socio-economic characteristics to identify any disproportionate effects of an event (or series of events).

- The first part of this section will provide an overview of practice on how the direct financial losses from disasters are estimated. This section provides background knowledge to interpret later sections of this report. Further explanations on estimating asset losses can be found in MEDiate deliverables 3.1 and 3.3.
- The second part of this section explains approaches that estimate the financial impact of direct losses to various social classes.
- The third part of this section explains advanced disaster impact matrices that consider socio-economics demographics in disaster loss assessment.
- The last three sections of this report present exemplary applications of selected matrices into MEDiate testbeds.
    - For Canvey Island, Essex, UK, we developed a Social Vulnerability Index (SoVI) to identify socio-economic vulnerabilities for Output Area (OA)s. Using coastal flooding as an example, we then disaggregated the direct asst losses into SoVI levels. We also estimated the financial burden of predicted asset damages based on the socioeconomic of the Output Area (OA), taking coastal flooding as an example.
    - For the Nice, we developed a bespoke Social Vulnerability Index (SoVI), considering the key types of hazards that occur in France and data availability.
    - For the Oslo testbed, we developed a bespoke Social Vulnerability Index (SoVI) index and socioeconomic status (SES) index based on the data availability. We also performed a factor analysis for the SES to reduce the number of factors.
    - We did not develop a Social Vulnerability Index (SoVI) for Mulaping testbed as the socio-economic data resolution is low. Instead, we have reported recently completed, country-wide SoVI studies.

Using the Essex testbed as an example, we have demonstrated a full application of the process of incorporating socio-economic vulnerabilities for disaster loss assessment. This methodology can be used to disaggregate asset losses by social vulnerability classes within the MEDiate platform when the asset loss data is computed within other tasks.

4.2 Overview of direct asset loss assessment for disasters

4.2.1 Damage Cost Functions

Computation of the damage to assets is a complex engineering modelling process. The damage status or levels are computed based on characteristics of the hazard (e.g. hazard type, intensity), characteristics of the asset (e.g. foundation type, frame type, building code), and, in some cases, the characteristics of the surrounding environment (e.g. soil conditions). Deliverable D3.1 of the MEDiate research provides a comprehensive account of how the asset damage status or levels are computed for various hazards. Once the damage status is computed, economic modelling is then used to convert the physical damage status into direct economic losses. Direct economic loss refers to the monetary value required to bring the asset back to its pre-disaster status. These economic models are called Damage Cost Functions or Damage Loss Ratios. Damage cost functions represent the relationship between damage levels (such as slight damage, complete damage, etc.) and an asset's replacement cost.

4.2.1.1 Damage cost functions for earthquake damaged buildings.

Damage-cost functions for buildings damaged by earthquakes were presented in the Hazus loss assessment methodology (FEMA, 2022), Meroni et al. (2017) and used by Roca et al., 2006), Milutinovic and Trendafiloski (2003), Kappos and Dimitrakopoulos (2007), Polese et al. (2015), Vecchio et al. (2018).

- For example, the Hazus MR4 loss assessment methodology of FEMA assumes 2%, 10%, 44.7%, 100% (of the property value) as the damage-cost function to calculate the repair cost associated with 'Slight', 'Moderate', 'Extensive', and 'Complete' damage states (respectively) for single-family dwellings.
- Meroni et al. (2017) produced damage-cost functions for European buildings. They assumed 5%, 20%, 45%, and 103% damage cost functions to calculate the repair cost for the building in the status of 'Slight damage', 'Moderate damage', 'Substantial–heavy damage', and 'damage beyond repair'. Whilst there are limitations associated with these economic models, these provide a quick and simple approach to antecedent earthquake loss assessment.

A detailed review of damage cost functions for earthquake-damaged buildings can be found in Wanigarathna et al. (2022). Total direct loss is then estimated by multiplying the relevant damage cost function by the replacement cost of the building. Replacement costs of houses are often obtained from local knowledge or from published cost data. Some researchers have used market prices of the houses (easier to obtain) instead of replacement cost.

4.2.1.2 Damage cost functions for flood-damaged buildings.

Functions found in the literature are either expressed as a % of building replacement cost (market value) or as total loss thresholds for flood intensity (commonly known as depth-damage functions).

- For example, Nofal et al. (2020). established 0-0.03; 0.03-0.15; 0.15-0.5; 0.5-0.7; and 0.7-1.0 damage cost functions related to 'Insignificant', 'slight', 'moderate', 'extensive' and 'complete' damage to buildings from floods. Nofal et al.'s damage cost functions represent the relationship between damage level and an asset's replacement cost.
- McGrath et al. (2019) developed damage cost functions to represent the relationship between damage class and loss thresholds. By studying buildings in southern Ontario authors identified ≤ $10,000, $10,000 - $25,000; and ≥ $25,000[1] as loss thresholds for damage classes of 'Affected', 'Minor', and 'Major' for flood damage. Some researchers have developed loss models to represent the relationship between the flood depth and the monetary value of damage to buildings. For instance, McGrath et al. (2019) extended their analysis to develop models to represent the relationship between flood depth and minor and major flood loss thresholds.
- Lazzarin et al. (2022) have presented early examples of this model and explained the limitations of not considering other important variables, such as flood duration or flood velocity.
- Local Authorities in the UK use Depth Damage functions to calculate the benefit-cost ratios for flood risk mitigation schemes. The Multicoloured Manual (MCM) (https://www.mcm-online.co.uk/manual/) provides Depth-Damage functions for residential properties. More elaborated depth-damage functions for different housing archetypes can also be found in MCM. MCM also presents depth-damage functions for non-residential properties. This data is available by subscription only.

[1] 2018 Canadian dollars.

- The Environment Agency in the UK uses the approach of 'The Weighted Annual Average Damage (WAAD)' to estimate the direct loss from flooding. This entails a methodology to assess flood damage to a geographical area based on depth-damage functions. Appraisers first calculate the number of properties at risk for each return period. This is estimated based on local flood modelling. Depth damage functions are assigned based on the updated values taken by The Multi-Coloured Manual (MCM). Further details of the is method can be found in (Environment Agency, 2021)

While a similar approach is viable, damage cost functions for other hazards such as storms or landslides could not be found in the literature. Asset damage due to heat waves are different to the damage caused by other hazards explained earlier. Therefore, a similar approach will not be suitable for assessing direct losses induced by heat waves.

4.2.1.3 Damage loss functions for contents losses and business interruption.

Some loss assessment methodologies use similar economic modelling functions to estimate content loss and business interruption losses.

- For example, LRG loss assessment software developed by LIQUEFACT research (Morga et al., 2020) assumes that slight, moderate, extensive and complete damages status to assets from liquefaction will result in 20%, 50%, 85% and 100% losses to its contents and 0% 15%, 100%, and 100% interruptions to business functions within such buildings respectively.
- Other widely known earthquake loss assessment software such as HAZUZ (FEMA, 2022b) uses a similar methodology for their regional scale loss assessment. For example, Table 15.5 of the Hazus-MH 2.1 Technical Manual presents % of contents replacement costs for different building classes (residential, commercial, agricultural, education, etc) against slight, moderate, extensive and complete damage status of a building.
- Table 15.8 of the Hazus-MH 2.1 Technical Manual (FEMA, 2022b) presents % of Business Inventory Damage for commercial, industrial and agricultural buildings against slight, moderate, extensive and complete damage status.

4.3 Financial burden of damage restoration cost on various social classes

The financial burden of disaster damage is different for households with different socio-economic characteristics and impacts how households cope with and recover from asset losses. This section explains three types of matrices that could be used to assess the financial burden of disaster damage repair costs.

4.3.1 Relative Economic Pain (REP)

Relative Economic Pain (REP) has been used as a matrix to calculate the financial burden of direct disaster losses. REP refers to the ratio between uninsured loss and income.

$$\text{REP} = \frac{(1-I)\ \text{EAD}}{\text{Income}}$$

Equation 4-1: Calculation of Relative Economic Pain

Where I = percentage of the loss covered by insurance; EAD = Expected Annual Damages; and Income = household annual income.

REP recognises the varying coping capacity between more affluent and low-income families (ibid). A report produced by the Office of Science and Technology under the direction of the Chief Scientific Adviser to HM Government (Evans et al., 2004) first introduced the matrix REP for flood loss assessment. Sayers et al. (2018)

have recently used this matrix in the context of flood loss. Kovats and Brisley (2021) identified REP as a matrix to measure UK's socio-economic disparity for common hazards such as heat waves, flood risk and sea level rise.
In developing countries, insurance penetration is minimal. De Silva and Kawasaki (2020). proposed a similar matrix named 'Relative Flood Loss' for those contexts. Authors (ibid) have presented the following formula to estimate Relative Flood Loss at the household level.

$$\text{Relative Flood loss} = \frac{\text{FLood loss}}{\text{Annual Average Income}}\, x\ 100$$

Equation 4-2: Calculation of Relative Flood loss

4.3.2 Equity Weights Expected Annual Damage (EWEAD)

Equity weight is a concept used in welfare loss assessments. Equity weights are indicators of relative importance applied to effects and opportunity costs for specific population subgroups (O'Donnell and VanOurti, 2020). Similar to financial vulnerability odd ratios explained earlier, this concept denotes that the same unit of loss has different household-level welfare impacts, which vary with socio-economic status (Soden et al., 2023). Some applications of Equity weights were found in disaster loss assessment literature (e.g. Kind et al., 2017; Hallegatte et al., 2017; Frontuto et al., 2023). Equity weights are applied in cost-benefit analyses and cost-effectiveness analyses related to disaster risk mitigation interventions (Kind et al., 2017). Kind et al. (2017) considered annual income and annual expected flood damage for four selected regions to calculate equity weight informed expected flood damage.
Frontuto et al. (2023) multiplied the annual expected flood damage by the equity weights of the region to get a more informed assessment of flood loss. Authors (ibid) used the following steps and the formula for the calculation of equity-informed flood loss.

- EAD was calculated by multiplying the annual probability of an asset to fail and the number of properties expected to flood.
- The following formula to calculate equity weight. The equity weight (W) for a marginal increase in income for a person with income Yi can be computed as

$$\omega Yi = \left(\frac{Yi}{Yavg}\right)^{-\gamma}$$

Equation 4-3: Calculation of Equity Weight

  In this formula, γ refers to the marginal utility. Whilst the equity weight can be calculated at a regional or household level, the marginal utility (γ) is often a country-specific constant[2].
- Finally, Equity Weights Expected Annual Damage (EWEAD) was calculated by Expected Annual Damage (EAD) multiplied by Equity weight.

Frontuto et al. (2023) applied this methodology to Duràn Canton in Ecuador and assessed EWEAD for eight different Census sectors. Whilst equity weights consider some socio-economic disparities of communities, a more informed loss assessment could consider other factors such as risk aversion, which require the consideration of household-level financial information (e.g., savings, insurance, government assistance, and access to loans (Soden et al., 2023).

[2] Evan (2005) presented evidence of differences in γ values by income level for all 20 OECD countries.

4.3.3 Financial Vulnerability Odd ratios

Disaster damages present unexpected financial burdens on house owners. ONS (2023) considered UK households to be financially vulnerable 'if the household could afford to pay an unexpected, but necessary, expense of £850'. In their regular Opinions and Lifestyle Survey (OPN), they identified financially vulnerable social groups/classes. In particular, they identified the financial vulnerability of adults based on Income, Housing tenure, highest education level, Age, Marital status, Parental status, Disability, Employment status, Ethnicity and Region.

Table 4:1 Financial vulnerability Odds Ratios for social structures in the UK (Source: ONS, 2023)

Social Group/Characteristic	Odds Ratio	Social Group/Characteristic	Odds Ratio
Income		**Age**	
£50,000 or more	1.00	16 to 24	0.67
£40,000 up to £49,999.99	2.62	75 years and over	1.00
£30,000 up to £39,999.99	3.43	65 to 74	1.04
£20,000 up to £29,999.99	5.80	55 to 64	1.21
£10,000 up to £14,999.99	8.45	35 to 44	1.55
£15,000 up to £19,999.99	8.65	45 to 54	1.63
Less than £10,000	8.75	25 to 34	1.78
Housing tenure		**Disability**	
Own it outright	1.00	Non-disabled	1.00
Currently paying off a mortgage and/or loan that helped to purchase the property	2.13	Disabled	1.77
Part rent/part mortgage, also known as shared ownership	3.48	**Employment status**	
Renting	6.88	Employed	1.00
Highest education level		Economically inactive retired	0.55
Degree or equivalent	1.00	Economically inactive - other	0.83
Below degree level	2.51	Unemployed	1.59
Other qualification	2.64	**Ethnicity**	
None	4.44	White	1.00
Region		Mixed	1.11
London	1.00	Asian or Asian British	1.50
Scotland	1.48	Any other ethnic group	1.87
South West	1.20	Black/Black British	2.00
Yorkshire and The Humber	1.49	**Parental status**	
South East	1.25	Not a parent	1.00
East of England	1.45	Parent of dependent child aged 5 or above	2.55
West Midlands	1.50	Parent of dependent child aged 0-4	2.81
East Midlands	1.57	**Marital Status**	
Wales	1.59	Married / Cohabiting / civil partner	1.00
North West	1.90	Widowed	1.48

North East	2.16	Single	1.99
		Divorced / Separated	2.72

4.4 Other Disaster Impacts matrices

The literature revealed recent advancements in disaster loss assessment, extending beyond physical asset damage assessments. This section explains 4 of such approaches.

4.4.1 Damage to Social Loss Functions

Damage cost functions explained earlier have been widely used in disaster loss assessments. Similar applications have been observed recently for estimating mortality, morbidity and well-being losses. After analysing historical data from various historical case studies, Sutley et al. (2017) developed damage loss functions to represent the relationships between building damage state and critical injury rate, Fatality rate and PTSD diagnosis rate for earthquake hazards (see Table 4:2).

Table 4:2 Morbidity Rates by Damage State (Source: Sutley et al., 2017)

Damage state	Critical Injury rate	Fatality rate	PTSD diagnosis rate
1	0.0000005	0.0000005	0.000005
2	0.0000003	0.0000003	0.003
3	0.00001	0.00001	0.001
4	0.03	0.05	0.2

In a World Bank-funded research, Walsh and Hallegatte (2019) explored the loss of well-being as a function of asset damage in the Philippines. After analysing asset loss data and well-being loss data from previous hazardous events across the country, Walsh and Hallegatte (2019) concluded that, on average, every \$1 in asset loss is equivalent to a \$2.70 consumption loss, as experienced by a household earning the national average income.

4.4.2 Odd ratios

The odds ratio (OR) is a measure of association that is used to describe the relationship between two or more categorical (usually dichotomous) variables (e.g., in a contingency table) or between continuous variables and a categorical outcome variable (e.g., in logistic regression) (Brave et al, 2012). Simply, Odds ratios describe the likelihood of an outcome in one group compared to a different group. ORs are comprehensively used in medical research. ORs were developed in disaster research to identify the likelihood of disaster disparities for vulnerable people and communities compared to less vulnerable people and communities across various outcomes related to disaster preparedness, disaster impact, and disaster recovery rate.

- Sutley et al. (2017) developed Odds Ratios for critical injury rate, Fatality rate and PTSD diagnosis based on Socio-economic constructs of Age, Ethnicity/race, Family Structure, Gender, Socio-Economic status and type of location (e.g. rural, urban) for earthquake disasters. They (ibid) found that elderly people (age 65 +) have higher odds of being injured (2.755), death (2.755) and PTSD diagnosis (1.303) compared to younger adults. According to their results, Females (as opposed to Males) with low Socioeconomic status (as opposed to high and medium) and people living in old urban areas have higher Odds of being injured, death and PTSD diagnosis.

- Fatmah (2023) developed Odds Ratios to compare people's ability to follow flood management plans based on flood knowledge levels. They found that the older people with good flood knowledge were 3.63 (OR) times better at implementing flood management than the older people with low flood knowledge.
- Larson et al. (2021) investigated the impacts of recurrent home flooding and social disparity in Detroit. They reported that Rented occupied units were more likely to report flooding than owner-occupied homes (Odd ratio (OR) 1.72, and Homes located in census tracts with increased percentages of owner-occupied units (vs. Renterers) had lower odds of flooding (OR 0.92)
- Based on the data from the September 21, 1999, Taiwan earthquake, Chou et al. (2004) developed ORs for deaths by an earthquake. They (ibid) found that People with mental disorders (odds ratio (OR) = 2.0), people with moderate physical disabilities (OR = 1.7), and people who had been hospitalized just prior to the earthquake (OR = 1.4) were the most vulnerable.
- Syed and Routray 2014, Paul and Bhuiyan 2009, Mulmin 2023, and Talbot 2021 have also presented Odds Ratios to confirm socioeconomic vulnerability to disasters.

4.4.3 Outcome measures

Outcome measures are one approach used in the UK to evaluate the benefits for the Flood and Coastal Erosion Risk Management (FCRM) capital programme to ensure that public money effectively delivers the expected benefits. The approach measures three types of outcomes.

1. Outcome Measure OM2 measures the total number of houses moved into a lower-risk band.
2. Outcome Measure OM2b measures the number of households for which the probability of flooding is reduced from the very significant or significant category to the moderate or low category.
3. Outcome Measure OM2c measures households in the 20% most deprived areas that are moved from the very significant or significant risk bands to the moderate or low-risk bands.

4.4.4 The exposure vs social vulnerability matrices

Place-based social vulnerability assessments have been a widely recognised method reported in the literature. Most of these studies have constructed social vulnerability status at the community or regional level, intending to produce a social vulnerability index to demonstrate regional differences. Literature reveals different types of social vulnerability assessments developed for different purposes.

- Social vulnerability indices (e.g. Mesta et al., 2022; Sayers et al., 2017; Bjarnadottir and Stewart, 2011; Eidsvig et al., 2014) are developed by incorporating data and variables exclusively related to vulnerable groups such as the female population, low-income population etc. These indices often consider social and economic vulnerabilities related to disaster exposure, adaptive capacity and recovery trajectories. For instance, Sayers et al. (2017), in their Neighbourhood Flood Vulnerability Index (NFVI), considered social and economic vulnerabilities related to 'susceptibility', 'Ability to prepare', 'Ability to respond', 'Ability to recover', and 'Community Support'.
- Socioeconomic status indices (e.g. Chakraborty et al., 2020) intend to highlight socio-economic inequalities between regions. These indices, therefore, consider data related to generic indicators of socio-economic status such as median wage, median age, and social class in addition to vulnerable population demographics.
- Resilience Indices (e.g. Cutter, 2016; Cox and Hamlen, 2014; Marzi et al., 2019) intend to assess community resilience for one or multiple disasters based on a range of measures related to communities, including social and economic capabilities. These indices comprise variables/indicators other than social and economic aspects. For instance, Cutter et al., 2014 considered indicators related to Social (10), Housing/infrastructural (9), Community capital (7),

Economic (8), Institutional (10), and Environmental (5) in their resilience assessment model. Cox and Hamlen (2014) considered indicators related to Human capital, Social capital, Built capital, Economic capital, Natural capital, Governance and Disaster preparedness.

Whilst some indices are generic to all environmental hazards (e.g. disaster resilience indicators in the USA by Cutter, 2016), the majority of indices developed by researchers are developed and tested with specific geographic and hazard focuses. Table 1:1-1:4 provides a comprehensive review of socioeconomic vulnerability and resilience indicators.
Literature reveals discussions on the suitability of (geographic)scale and accuracy of resultant indices. Researchers who developed indices for high-level regions have therefore conducted a sensitivity analysis to check changes to the index score when changing geographic resolution. Poussard et al. (2021) have conducted a building/household level analysis of hazard risk and socio-economic vulnerability using cadastral data. Authors (ibid) constructed an Index of Social Disparity (ISD) at the household level and mapped them against the flood hazard risk. This type of analysis involves a number of assumptions in allocating social and economic status at the household level, as publicly accessible census tract data or other socio-economic data is often presented at the community level. Results could, therefore, be less accurate due to a high number of subjective assumptions.

4.5 Example application of methodologies to MEDiate Testbeds.

We developed the Social Vulnerability Index (SoVI) for Canvey Island (Essex, UK), Oslo, Norway and Nice, France. We also developed a Socio-Economic Status (SES) index for Oslo, Norway, as the data related to a number of categories other than vulnerability indicators was available. A SoVI for Múlaþing was not developed as the total population was around 2500 and could not be effectively apportioned to small administrative boundaries.

4.6 Example 1 – Application to Canvey Island UK

4.6.1 Financial Vulnerability for disaster damage repair costs - Canvey Island

We used the financial vulnerability odds ratio explained and presented in Section 4.3.3 to establish financial vulnerability odds ratios for each Output Area in Canvey Island based on their socioeconomic demographics.

As the social structure data from the Census tract and social structures for the Odds ratio presented in Table 4:1 did not match, Census 2021 data categories were re-grouped to match the structures used in the financial vulnerability odds ratio (see Table 4:1). Table 4:3 provides the details and the assumptions behind this re-grouping assignment.

Table 4:3 Allocation of Census data to financial vulnerability categories

	Social Group Categories from Table 4:1	Census 2021 Variables grouped together	Odds Ratio from Table 4:1
Income	£50,000 or more	L1, L2 and L3: Higher managerial, administrative and professional occupations	1
	£40,000 up to £49,999.99	L4, L5 and L6: Lower managerial, administrative and professional occupations	2.62
	£30,000 up to £39,999.99	L7: Intermediate occupations L8 and L9: Small employers and own account workers L10 and L11: Lower supervisory and technical occupations	3.43

	£20,000 up to £29,999.99	L12: Semi-routine occupations L13: Routine occupations	5.8
	£10,000 up to £14,999.99	L14.1 and L14.2: Never worked and long-term unemployed L15: Full-time students	8.45
	£15,000 up to £19,999.99	None allocated here	8.65
	Less than £10,000	None allocated here	8.75
Housing tenure	Own it outright	1 Owned: Owns outright 1 Lives rent free	1
	Currently paying off a mortgage and/or loan that helped to purchase the property	2 Owned: Owns with a mortgage or loan	2.13
	Part rent/part mortgage, also known as shared ownership	3 Shared ownership: Shared ownership	3.48
	Renting	4 Private rented: Private landlord or letting agency 4 Private rented: Other private rented 5 Social rented: Rents from council or Local Authority 5 Social rented: Other social rented	6.88
Highest education level	Degree or equivalent	Level 4 qualifications or above	1
	Below degree level	Apprenticeship Level 3 qualifications	2.51
	Other qualification	Level 1 and entry-level qualifications: Level 2 qualifications: Other:	2.64
	None	Does not apply No qualifications None	4.44
Ethnicity	White	White: English, Welsh, Scottish, Northern Irish or British White: Gypsy or Irish Traveller White: Irish White: Other White White: Roma	1
	Mixed	Mixed or Multiple ethnic groups: White and Asian Mixed or Multiple ethnic groups: White and Black African Mixed or Multiple ethnic groups: White and Black Caribbean Mixed or Multiple ethnic groups: Other Mixed or Multiple ethnic groups	1.11
	Asian or Asian British	Asian, Asian British or Asian Welsh: Bangladeshi Asian, Asian British or Asian Welsh: Chinese Asian, Asian British or Asian Welsh: Indian Asian, Asian British or Asian Welsh: Other Asian Asian, Asian British or Asian Welsh: Pakistani	1.5
	Any other ethnic group	Other ethnic group: Any other ethnic group Other ethnic group: Arab Does not apply	1.87
	Black/Black British	Black, Black British, Black Welsh, Caribbean or African: African Black, Black British, Black Welsh, Caribbean or African: Caribbean Black, Black British, Black Welsh, Caribbean or African: Other Black	2
Parental status	Not a parent	Single family household: Married or civil partnership couple: No children Single family household: Cohabiting couple family: No children Single family household: All aged 66 years and over One-person household: Aged 66 years and over One-person household: Other	1
		Single family household: Married or civil partnership couple: All children non-dependent	2.55

	Parent of dependent child aged 5 or above	Single family household: Cohabiting couple family: All children non-dependent Other household types: Other, including all full-time students and all aged 66 years and over Single family household: Lone parent family: With dependent children Other household types: With dependent children Other household types: Other related household: Other family composition Other	
	Parent of dependent child aged 0-4	Single family household: Lone parent family: All children non-dependent Single family household: Married or civil partnership couple: Dependent children Single family household: Cohabiting couple family: With dependent children In a registered civil partnership: Opposite sex	2.81
Marital Status	Married / Cohabiting / civil partner	Married: Opposite sex Married: Same sex In a registered civil partnership: Same sex	1
	Widowed	Widowed Surviving partner from civil partnership	1.48
	Single	Never married and never registered a civil partnership	1.99
	Divorced / Separated	Divorced Separated, but still married Formerly in a civil partnership now legally dissolved Separated, but still in a registered civil partnership	2.72

Financial Vulnerability Odds Ratios presented in the table above were then used to calculate the weighted Financial Vulnerability Odds for each geographic region based on 5 key social structures based on the following steps.

- **Step 1**: The number of people belonging to each category (column 2 in Table 4:1) was first extracted from the Census data for each geographic area (OAs).
- **Step 2**: % of people belonging to each category (each geographic area - OAs) was then computed by dividing the value by the total population per geographic area.
- **Step 3**: The weighted Odds Ratio per geographic area (OAs) was then calculated by multiplying the Odds Ratio (column 4 in Table 4:1) and the % calculated in Step 2 above.
- **Step 4**: Steps 1-3 above were repeated for each social structure (Marital status-based social structure, Income based social structure, Education level based social structure, Tenure type based social structure, Parental Status based social structure and Ethnicity based social structure.

Funded by the European Union

The following maps show the Financial Vulnerability odds for each region based on 5 selected vulnerability categories (see Figure 4:1). The % of White people dominated ethnicity based social structure hence, results could not be separated into quartiles.

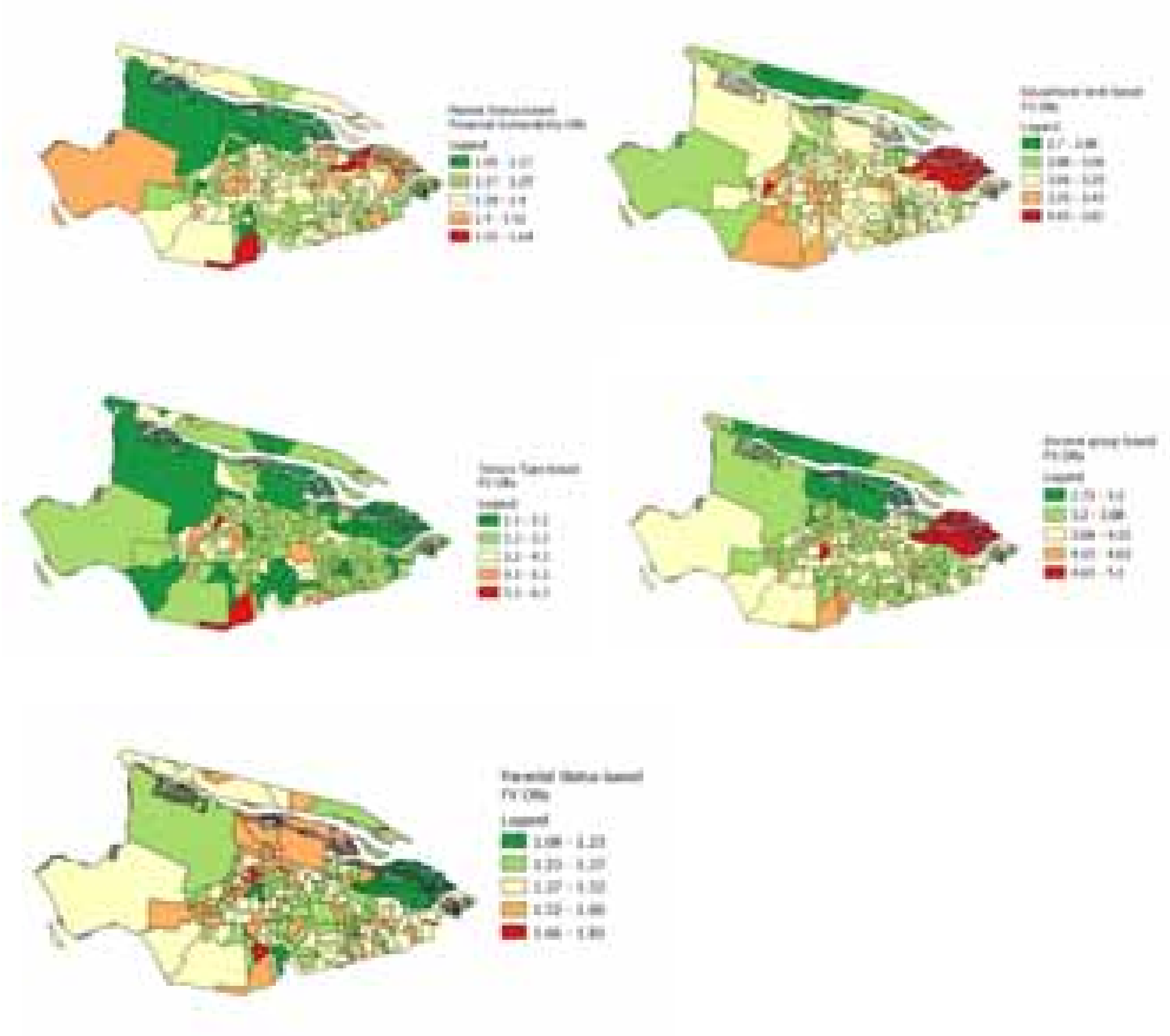


Figure 4:1: Financial Vulnerability Odds Ratios based on different social structures for Canvey Island, UK

According to the results, the financial vulnerability of geographic areas (OAs), based on five different circumstances, does not highlight any particular area as highly or very low vulnerable. Overall, areas with very high or high odds of financial difficulties are comparatively minimal as maps are dominated by green (*Very low* and *low*) or yellow (*medium*) colours.

4.6.2 Social Vulnerability Index (SoVI) for Canvey Island UK

This research developed a Social Vulnerability Index for Canvey Island, Essex, UK. The index compared socio-economic disparities at Output Area (OA) level boundaries.

4.6.2.1 Location and Geographical Scale

Canvey Island is located within the Castle Point District in Essex, UK. Canvey Island represents circa 143 Output Areas (the lowest scale boundaries used for census and administrative purposes), (see Figure 4:2below) 27 (LSOA) Lower layer Super Output Areas. We developed the Social Vulnerability Index for each of the 143 Output Areas.

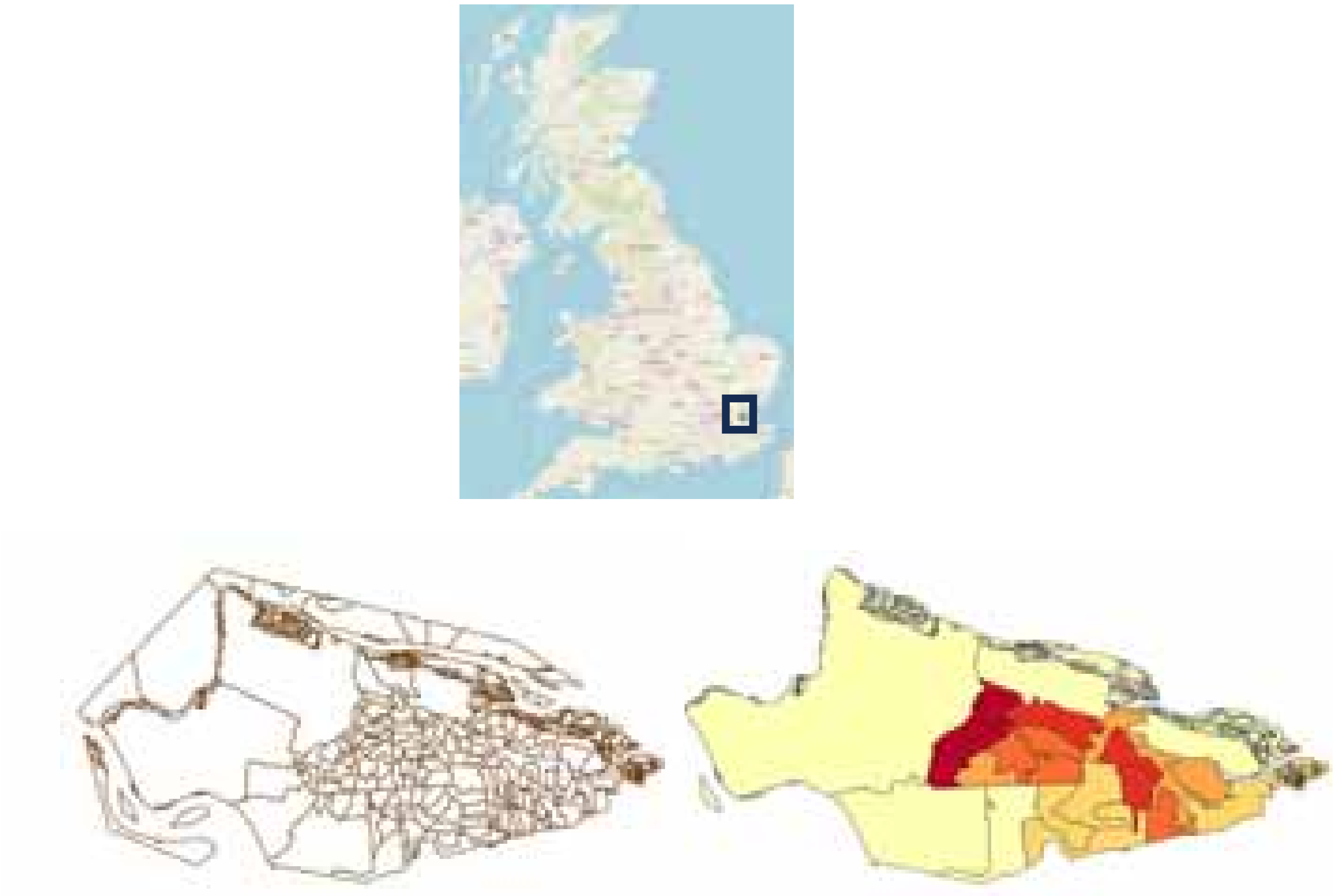


Figure 4:2: Location of Canvey Island and Output Areas boundaries (Source: Open street maps & https://geoportal.statistics.gov.uk/)

4.6.2.2 Variable selection

Variables for the Canvey Island SoVI (see Table 4:4) were selected based on the literature review and data availability. The literature revealed widely considered socio-economic vulnerability indicators irrespective of the hazard type and geographic location. These were first selected as variables. These include Gender, Age, Tenure type, Household structure, Income and Employment, Education level and Race and Ethnicity related vulnerabilities. Consideration was given to identifying any widely used Flood hazard-related vulnerability indicators, as flooding and storms are the main hazards related to the Essex testbed. However, no additional widely used vulnerability indicators for flood hazards could be identified.
Measures for each variable were selected based on the availability of publicly available data and the applicability of criteria/measures to the UK context. For example, Race and Ethnicity-related vulnerabilities were incorporated using proxy variables of migration status (% of people who lived in the UK for less than 2

years) and English Proficiency. Specific ethnic categories were not considered as vulnerable within this index for the Essex UK testbed.

Table 4:4 Variable constructs for Canvey Island SoVI

Category	**Variable**	**Measure**	**Data Source**
Gender	Female population	% of Female	Census 2021
Age	Population of young children	% of children under 5	Mid-2020 Population Estimates England and Wales
	Population of older adults	% of people over 75 of age	
Tenure type	% of private Renterers	4 Private rented: Private landlord or letting agency	Census 2021
		4 Private rented: Other private rented	Census 2021
	% of social Renterers	5 Social rented: Rents from council or Local Authority	Census 2021
		5 Social rented: Other social rented	Census 2021
Migration and English proficiency	Migrant from outside the UK	% of people lived in UK for less than 2 years	Census 2021
	English Proficiency	Main language is not English (English or Welsh in Wales): Cannot speak English well	Census 2021
		% of people with limited or no English proficiency	Census 2021
Educational status	No educational qualification	% of No qualifications people	Census 2021
	% of people with less than Level 3 qualifications	% of people with Level 1 and entry level qualifications	Census 2021
		% of people with Level 2 qualifications	Census 2021
Health based vulnerability	Health Deprivation Score	IMD 2019 Health Deprivation Score for the region	IMD 2019
Household structure based vulnerability	Single family household: Lone parent family: With dependent children	% of households Single family household: Lone parent family: With dependent children	Census 2021
Economic vulnerability	Full-time students	% of full time students	Census 2021
	Unemployed population	% of population belong to L14.1 and L14.2: Never worked and long-term unemployed category of Census 2019	Census 2021
	Low-income occupation population	% of people on L12: Semi-routine occupations	Census 2021
		% of people on L13: Routine occupations	Census 2021

	Income Deprivation index	Income Deprivation score from IMD 2019	IMD 2019
	Employment Deprivation in the area	Employment Deprivation score from IMD 2019	IMD 2019
	No cars or vans in the household	% of No cars or vans in the household	Census 2021
Migration within UK	Migrant from within the UK	% of Migrant from within the UK: Address one year ago was in the UK	Census 2021
Social support	Pensioners living alone	% of Single-family households: All aged 66 years and over	Census 2021

4.6.2.3 Methods - Data processing and Data analysis details for Social Vulnerability Index (SoVI) calculation

The SoVI analysis of Canvey Island, UK, followed the SoVI calculation steps used by Sayers et al. (2017) and Mesta et al. (2022).

Table 4:5 Details of SoVI Scores calculation for Canvey Island Output Areas

	Step	**Example**
1	Identify Data sources	The data for these variables were gathered from three sources. 1. Census data from 2021 census 2. Index of Multiple Deprivation (IMD) data from 2019) 3. Mid-2020 Population Estimates England and Wales
2	Data gathered from the three sources above were filtered to identify data related to Canvey Island.	Age statistics were downloaded from Mid-2020 Population Estimates England and Wales for all of the Castle Point District and Data related to Canvey Island were filtered and separated using Area Codes related to the Canvey Island.
3	These were then further filtered to identify data related to vulnerable categories.	Age data categories related to children under 5 and People over 75 age were combined and filtered.
4	Computing % distribution	The Number of children under 5 was divided by the total population for each geographic area and multiplied by 100 to get the % of children under 5.
5	Some data were available for Lower layer Super Output Areas only. These data were apportioned to Output Areas	Once the %s were computed, the same % was assumed for each Output Area code within a given LSOA code. This step was conducted for Age, and Deprivation scores from IMD. Overall data related to 143 Output Area codes and 21 indicators were taken for further analysis. Missing values were replaced with the mean value as we did not expect outliers in this data sets.
6	Nominalising data	Mean and standard deviations for each vulnerability indicator were computed.

		%s was converted to Z Scores using the formula (Mean -Value)/Standard Deviation Negative Z scores represent areas vulnerable than the average (high vulnerability) and positive Z scores represent areas less vulnerable than the average (less vulnerability)
7	Computing SoVI score per each geographic area	Z Scores related to each variable were summed to calculate the aggregate vulnerability score for each Output Area
8	Spatial representation	The original data processing and analysis was conducted on MS Excel. The SoVI scores were then extracted onto QGIS software to represent them on a map version for better understanding. See Map in the Figure 4:3 and Table 4:6 for the Total SoVI score for each geographic area within Canvey Island. Negative Z scores represent areas vulnerable than the average (high vulnerability), and positive Z scores represent areas less vulnerable than the average (less vulnerability)

Figure 4:3 SoVI Scores for Canvey Island Output Areas

According to these results, 31 OA areas in Canvey Island contain *very highly* vulnerable populations based on socio-economic characteristics. Further, 17 OA areas contain *highly* vulnerable populations based on socio-economic characteristics. 28 OA areas contain *highly* vulnerable populations based on their socio-economic characteristics. Population in the other 56 OA areas can be considered *medium to – very low* vulnerable comparatively. It is also apparent that vulnerable areas are scattered around the Island, not concentrated.
These results could be used to locate localised flood mitigation activities such as rain gardens so that the communities with Very High and High social vulnerabilities will benefit.

Table 4:6 SoVI Scores for Canvey Island Output Areas

Area Code LOA21	SoVI Score (Total)	Area Code LOA21	SoVI Score (Total)	Area Code LOA21	SoVI Score (Total)	Area Code LOA21	SoVI Score (Total)	Area Code LOA21	SoVI Score (Total)	Area Code LOA21	SoVI Score (Total)	Area Code LOA21	SoVI Score (Total)
E00109141	-17.35	E00109170	-5.97	E00109149	-3.76	E00109202	-2.45	E00109166	-0.33	E00109207	3.07	E00109222	10.71
E00109146	-15.40	E00109226	-5.94	E00109258	-3.70	E00109312	-2.44	E00109262	-0.19	E00109260	3.36	E00174003	10.93
E00109147	-13.49	E00109174	-5.71	E00109187	-3.70	E00109177	-2.42	E00109181	-0.15	E00109184	4.02	E00109247	11.37
E00109129	-11.89	E00109267	-5.50	E00109242	-3.67	E00109148	-1.94	E00109211	-0.07	E00109152	4.10	E00109259	11.47
E00109307	-11.66	E00109188	-5.44	E00109213	-3.66	E00109333	-1.87	E00109172	0.07	E00109178	4.37	E00109158	11.49
E00109344	-11.47	E00109203	-5.27	E00109237	-3.54	E00109208	-1.67	E00109154	0.16	E00109246	4.40	E00174006	11.54
E00109263	-10.67	E00109261	-5.06	E00109205	-3.51	E00109171	-1.55	E00109150	0.19	E00109216	5.04	E00174000	12.31
E00174007	-10.38	E00109109	-4.87	E00109185	-3.36	E00109241	-1.55	E00109210	0.21	E00109164	5.08	E00109167	12.45
E00109255	-10.20	E00109169	-4.77	E00109251	-3.18	E00109173	-1.45	E00109175	0.46	E00109160	5.34	E00180535	12.48
E00109264	-9.46	E00109266	-4.75	E00109153	-3.15	E00109197	-1.40	E00109193	0.58	E00109235	5.46	E00109257	14.31
E00109240	-8.46	E00109243	-4.65	E00109220	-2.96	E00109204	-1.37	E00109162	0.63	E00109157	5.54	E00109156	14.47
E00109108	-7.82	E00109191	-4.61	E00109212	-2.91	E00109219	-1.07	E00109163	0.73	E00109165	5.65	E00109230	14.88
E00109110	-7.73	E00109198	-4.45	E00109186	-2.89	E00109244	-0.98	E00109249	1.45	E00180479	5.87	E00109253	14.91
E00174004	-7.61	E00109182	-4.30	E00109176	-2.71	E00109195	-0.94	E00109206	1.52	E00174001	8.10	E00109151	15.34
E00109232	-7.39	E00109347	-4.01	E00109155	-2.62	E00109224	-0.88	E00109225	2.24	E00180472	8.31	E00109161	15.76
E00109183	-6.78	E00109215	-3.99	E00109223	-2.61	E00109209	-0.87	E00109201	2.25	E00109214	8.44	E00109268	18.30
E00109348	-6.72	E00109168	-3.97	E00174005	-2.60	E00109245	-0.70	E00109221	2.38	E00174002	8.57	E00109218	20.03
E00109248	-6.40	E00109234	-3.92	E00109239	-2.53	E00109199	-0.65	E00109252	2.83	E00109200	9.48		
E00109228	-6.33	E00109180	-3.92	E00109189	-2.49	E00109231	-0.50	E00109250	2.89	E00109196	9.52		
E00109236	-6.12	E00109179	-3.90	E00109217	-2.46	E00109238	-0.46	E00109265	2.96	E00173999	9.96		
E00109190	-5.98	E00109159	-3.89	E00109192	-2.46	E00109254	-0.34	E00109256	2.99	E00109229	9.96		

4.6.3 Disaggregation of Property Damage per SoVI class

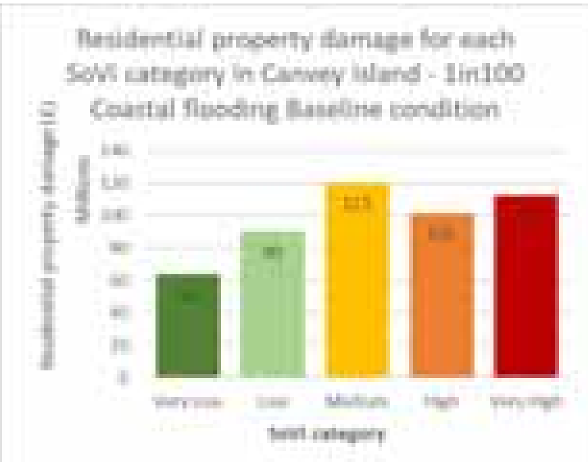
Property damage was computed using Depth damage functions presented in MCM. The following steps were followed to estimate property damage.

1. The total number of detached, semi-detached, terraced, and flat types of properties within each Output Area was identified from the UK Census data for the 2021 Census.
2. Total flood inundation depth was identified from the outputs of Task 2.2 of the MEDiate project.
3. The depth damage function for each property type and relevant flood depth were then used to calculate the total property damage per geographic area based on the following formula:

$$\begin{aligned}&\text{Total prperty damage for geographic area } E00109141\\&= Numeber\ of\ detached\ properties\ x\ Relavant\ depth\ damage\ function\ from\ MCM\\&+\ Numeber\ of\ semidetached\ properties\ x\ Relavant\ depthdamage\ function\ from\ MCM\\&+\ Numeber\ of\ terraced\ properties\ x\ Relavant\ depthdamage\ function\ from\ MCM\\&+\ Numeber\ of\ flats\ x\ Relavant\ depthdamage\ function\ from\ MCM\end{aligned}$$

4. Each Output Area was assigned its SoVI category (Very High to Very Low) based on the following quartile based on the results presented in the previous section.
   - Total SoVI score -17.4 to -4.7 was considered Very High
   - Total SoVI score -4.7 to – 2.6 was considered High
   - Total SoVI score -2.6 - -0.1 was considered Medium
   - Total SoVI score -0.1to 5.5 was considered Low
   - Total SoVI score 5.5 – 20 was considered Very Low

5. The total property damage per each SoVI category was then summed up as shown in Figure 4:4 The above steps were then repeated to estimate the 2050 property damage projections using 2050 flood inundation data.



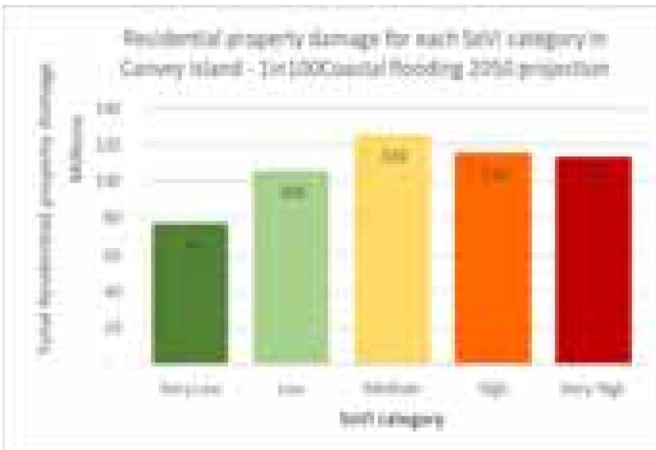


Figure 4:4 Baseline estimate (Left) and Future estimate (Right) of Residential property damage (£) for each SoVI category related to 1 in 100 Coastal flooding

These estimates show that communities with Very Low socio-economic vulnerabilities experience less damage to their properties, and communities with Very High socio-economic vulnerabilities experience comparatively higher levels of damage and economic losses to their properties. These matrices could be replicated with other hazard intensity scenarios based on the results from MEDiate Task 2.2 and 3.1. Very highly and Highly vulnerable communities will therefore need additional support to prepare for and recover from flooding hazards.

Depth damage functions for Riverine flooding from the MCM were used here as the loss values for coastal flooding damage were unavailable. According to depth damage functions, bungalows suffer higher losses compared to other archetypes, however, the number of bungalows could not be separately identified from the Census data. The resultant estimates, therefore, should be interpreted cautiously.

4.7 Example - Nice Testbed – France

4.7.1 Social Vulnerability Index (SoVI)

Nice is the capital of the Alpes-Maritimes department and consists of 53 Municipalities and 240 IRIS geographic areas. We developed the Social Vulnerability Index for each of the 240 IRIS geographic boundaries.

Figure 4:5: Location of Nice and IRIS administration boundaries

4.7.1.1 Variable Selection

Variables for the Nice France SoVI were selected based on the following criterion.

a) Literature review of social vulnerability criteria (see Table 1:4) revealed widely considered socio-economic vulnerability indicators irrespective of the hazard type and geographic location. These were first selected as variables. These include Gender, Age, Tenure type, Household structure, Income and Employment, Education level and Race and Ethnicity related vulnerabilities.
b) As the main hazards related to the Nice Testbed are heat and drought, careful consideration was given to identify any widely used heat and drought-related vulnerability indicators, Previous literature suggested some additional vulnerability indicators related to heat and drought (see Table 1:4). The SoVI for Nice, therefore, 5 additional measures related to exposure to heat due to employment-related purposes were considered. They are:
    i. Number of people aged 15 or over Farmers operating;
    ii. Number of employed workers aged 15 or over who go to work mainly on foot;
    iii. Number of employed workers aged 15 or over who mainly use a bicycle to go to work;

iv. Number of employed workers aged 15 or over who mainly use a motorized two-wheeler to go to work;
v. Number of employed workers aged 15 or over who mainly use public transport to go to work.

c) Measures for each variable were selected based on the availability of publicly available data and the applicability of criteria/measures to the Nice context. Race and Ethnicity-related vulnerabilities were incorporated using proxy variables of migration status % Pop of Immigrants, % Population of Foreigners. Specific ethnic categories were not considered as vulnerable within this study.

Table 4:7 Variable constructs for the Nice Testbed SoVI

Category	**Label**	**Construct**	**Measure**	**Data Source**
Gender	1	Female population	% of Female	Population Data Population Census 2019
Age	2	Population of young children	% of young children upto age of 5	Population Data Population Census 2019
	3	Population of older adults	% Population age 75 and over	Population Data Population Census 2019
Tenure type	4	% of renterers	% Main properties occupied Tenants in 2019 (main)	Population Data Population Census 2019
Migration status	5	Foreigners	% of Foreigners	Population Data Population Census 2019
	6	Immigrants	% Pop of Immigrants in 2019 (main)	Population Data Population Census 2019
Educational status	7	Population with No educational qualifications	Unemployed people without a diploma or CEP in 2019 (main)	Resident activity data Population Census 2019
			Active Without diploma or CEP in 2019 (main)	Resident activity data Population Census 2019
	8	Population with lower level educational qualifications	Unemployed BEPC, college certificate, DNB in 2019 (main)	Resident activity data Population Census 2019
			BEPC assets, college certificate, DNB in 2019 (main)	Resident activity data Population Census 2019
Health condition	9	Inactive population	% of Inactive 15-64 year olds other than students	Resident activity data Population Census 2019
Household structure	10	Full time student	% Elev. Study. Stag. unpaid 15-64 years Men in 2019 (main) (Number of pupils, students	Resident activity data Population Census 2019

			and unpaid interns aged 15 to 64)	
	11	Retired population	Share of pensions. retirements and annuities (%)	Indicators of distribution of household disposable income per consumption unit - Year 2020
Income and Employment	12	Unemployed population	Unemployed aged 15-64 in 2019 (main)	Resident activity data Population Census 2019
	13	Low-income occupation population	Active Without diploma or CEP in 2019 (main)	Resident activity data Population Census 2019
			In employment with BEPC assets, college certificate, DNB in 2019 (main)	Resident activity data Population Census 2019
	14	Self-employment	of which share of income from self-employed activities (%)	Indicators of distribution of household disposable income per consumption unit - Year 2020
	15	Job seekers	DEFM %	Job seekers as of December 31, 2021 (annual data)
	16	Population on unemployment benefits	of which share of unemployment benefits (%)	Indicators of distribution of household disposable income per consumption unit - Year 2020
	17	Poverty rate	Poverty rate at the threshold of 60% (%)	Indicators of distribution of household disposable income per consumption unit - Year 2020
	18	Car ownership	% No Cars or vans owned or available for use by a household	Resident activity data Population Census 2019
Expose to heat (Work-related)	19	Working outside	Number of people aged 15 or over Farmers operating	Population Data Population Census 2019

	20	Travelling to work using vulnerable transport modes	Number of employed workers aged 15 or over who go to work mainly on foot	
			Number of employed workers aged 15 or over who mainly use a bicycle to go to work	
			Number of employed workers aged 15 or over who mainly use a motorized two-wheeler to go to work	
			Number of employed workers aged 15 or over who mainly use public transport to go to work	
Social support	21	Limited local knowledge	Households moved in less than 2 years in 2019 (main)	Housing Data Population Census 2019

4.7.1.2 Methods - Data processing and Data analysis details for Social Vulnerability Index (SoVI)

Nice France SoVI scores calculation followed the steps (Table 4:8) used by Sayers et al. (2017) and Mesta et al. (2022).

Table 4:8 Nice France SoVI scores calculation details

	Step	Example
1	Identify Data sources	The data for these variables were gathered from three sources. 1. Population Data - Population Census 2019 2. Housing Data - Population Census 2019 3. Resident activity data - Population Census 2019 4. Indicators of distribution of household disposable income per consumption unit - Year 2020 5. Job seekers as of December 31, 2021 (annual data) These statistics can be accessed via: https://www.insee.fr/fr/statistiques
2	Identify data related to vulnerability constructs	Raw data were then further filtered to identify data related to vulnerable categories. Age data categories related children under 5 and People over 75 age were combined and filtered.
3	Computing % distribution	The number of children under 5 was divided by the total population for each geographic area and multiplied by 100 to get the % of children under 5. Overall data related to 240 IRIS Area codes and 21 indicators were taken for further analysis.

		Missing values were replaced with the mean value as we did not expect outliers in this data sets.
4	Nominalising data	The mean and the Standard deviation for each vulnerability indicator were computed. %s was converted to Z Scores using the formula (Mean -Value)/Standard Deviation Negative Z scores represent areas vulnerable than the average (high vulnerability), and positive Z scores represent areas less vulnerable than the average (less vulnerability)
5	Computing SoVI score per each geographic area	Z Scores related to each variable were summed to calculate the aggregate vulnerability score for each IRIS Area
6	Spatial representation	The original data processing and analysis was conducted on MS Excel. The SoVI scores were then extracted onto QGIS software to represent them on a map version for better understanding. See Maps in the Figure 4:6 for the Total SoVI score for each geographic area within Nice. Negative Z scores represent areas vulnerable than the average (high vulnerability), and positive Z scores represent areas less vulnerable than the average (less vulnerability)

According to the SoVI results, rural areas away from the Nice city centre could be considered *Very high* or *Highly* vulnerable. This could be due to the fact that there is a relatively high number of operating farmers in the rural areas compared to city centre areas.
Overall, a clear pattern is visible to confirm that communities living around the Nice City are Very low or Low vulnerable and communities living in the outer skirt of the Nice City (which can be considered as sub-urban) seem *Medium* vulnerable.

Asset loss data for the Nice testbed has not been computed at the time of submitting this report. Disaggregation of asset loss data as a function of social vulnerability classes can be performed based on the methodology explained in section 4.6.3 within the MEDiate platform when the asset loss data is generated.

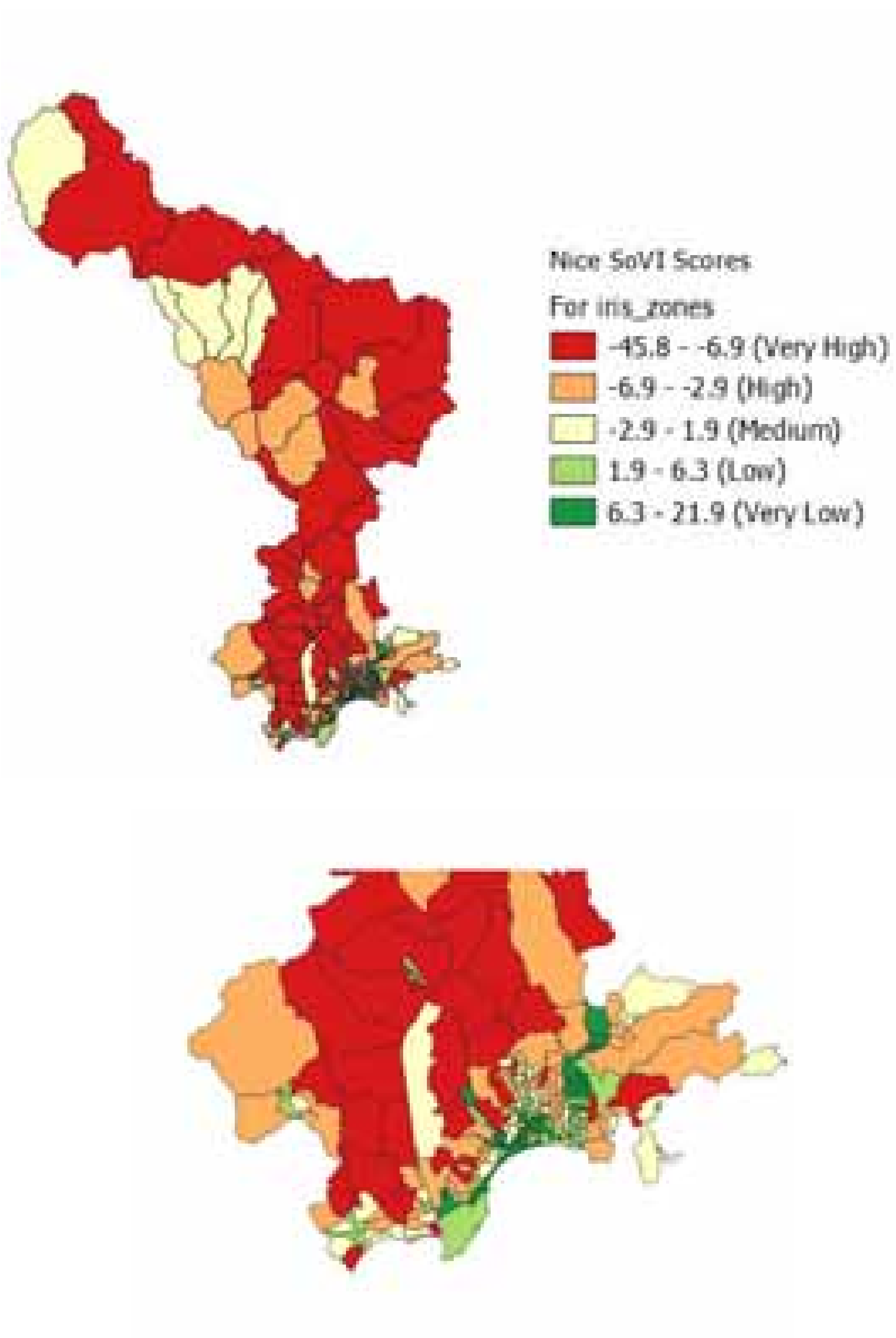


Figure 4:6 SoVI scores Map for IRIS geographic areas in Nice

Table 4:9 SoVI scores for IRIS geographic areas in Nice

IRIS Code	SoVI Score (Total)	IRIS Code	SoVI Score (Total)	IRIS Code	SoVI Score (Total)	IRIS Code	SoVI Score (Total)	IRIS Code	SoVI Score (Total)	IRIS Code	SoVI Score (Total)
060060000	-12.45	060650102	-12.72	060880702	17.09	060881602	1.46	060882702	-1.59	061220000	-8.91
060090000	-6.01	060660000	-6.93	060880801	5.16	060881603	-3.93	060882703	1.76	061230101	-32.02
060110000	-1.57	060710000	-9.4	060880901	16.97	060881604	-4.72	060882704	-6.91	061230102	-0.98
060130000	-8.33	060720000	-6.59	060880902	10.98	060881605	-1.39	060882705	-6.03	061230103	-1.57
060140000	-8.45	060730000	-7.67	060880903	8.61	060881606	-6.33	060882801	6.95	061230104	-5.19
060200000	-6.9	060740000	-7.24	060880904	15.97	060881701	3.67	060882802	-6.52	061230105	3.82
060210000	-8.28	060750000	-8.61	060880905	16.55	060881702	1.5	060882803	2.7	061230106	-4.5
060250000	-8.36	060800000	-10.23	060881001	-4.79	060881703	15.9	060882804	-6.09	061230107	1.78
060270101	4.84	060880101	3.14	060881002	-0.1	060881704	5.22	060882805	-7.46	061230108	-4.06
060270102	2.88	060880102	12.43	060881003	-7.88	060881705	3.92	060882901	15.7	061230109	-5.19
060270103	1.58	060880103	4.29	060881004	-4.98	060881801	17.16	060882902	18.92	061230110	-9.9
060270104	-6.85	060880201	-1.63	060881005	-4.98	060881802	13.18	060882903	20.16	061230111	-9.06
060270105	-1.52	060880202	3.78	060881101	-1.35	060881803	12.77	060882904	4.43	061260000	-5.67
060270106	-45.8	060880203	2.67	060881102	-4.16	060881804	5.83	060882905	-3.05	061270000	-7.45
060270107	5.31	060880204	2.99	060881103	-4.46	060881805	5.63	060882906	-5.34	061290000	-2.46
060270108	1.32	060880205	2.78	060881104	-1.24	060881901	9.58	060883001	3.87	061440000	-6.38
060270109	0.95	060880206	2.89	060881105	-1.46	060881902	5.76	060883002	12.31	061460000	-9.31
060270110	-5.56	060880301	8.34	060881201	4.69	060881903	6.42	060883003	11.86	061470000	-6.77
060270111	-6.63	060880302	5.04	060881202	-0.6	060882001	-2.16	060883101	-9.75	061490101	-2.87
060270112	-7.9	060880303	0.75	060881203	-7.95	060882002	1.58	060883102	-3.51	061490102	-4.28
060270113	-7.31	060880304	6.18	060881204	0.7	060882101	2.12	060883201	-6	061490103	-4.64
060270114	-0.47	060880305	2.5	060881301	5.41	060882102	9.85	060883202	-7.39	061490104	-4.91
060270115	-7.57	060880401	-3.22	060881302	0.87	060882103	9.17	060883301	0.39	061510000	-6.88
060270116	1.8	060880402	3.63	060881303	-0.46	060882104	9.83	060883401	-4.57	061530000	-6.96
060270117	-0.1	060880403	-3.46	060881304	-2.23	060882201	2.77	060883402	3.24	061560000	-8.39
060320000	-0.53	060880404	-8.31	060881305	0.99	060882202	7.5	060883403	8.89	061570101	5.99

060330101	-6.94	060880501	4.38	060881306	-2.17	060882203	7.91	060883501	-9.25	061570102	3.62
060330102	4.41	060880502	7.68	060881307	-4.31	060882301	3.12	060883601	-3.83	061570103	-4.72
060330103	9.78	060880503	1.26	060881308	-3.53	060882302	5.38	060883602	-10.42	061570104	-4.55
060330104	-11.01	060880504	2.39	060881309	3.05	060882303	8.91	060883701	-7.08	061570105	-5.92
060330105	-9	060880505	3.38	060881401	4.69	060882304	7.39	060883801	-5.74	061570106	-0.8
060340000	-8.63	060880506	6.48	060881402	4.42	060882401	11.83	061020000	-0.65	061570107	-7.89
060390000	-10.07	060880507	7.1	060881403	-0.91	060882402	2.48	061030000	-3.76	061590101	-2.89
060420000	-6.46	060880508	16.61	060881404	4.07	060882501	12.16	061090000	-5.29	061590102	-1.45
060460000	-11.53	060880509	21.87	060881501	9.99	060882502	10.32	061100000	-2.11	061590103	-9.83
060540000	-2.04	060880601	3.57	060881502	4.77	060882503	9.97	061110000	1.9		
060550000	-8.38	060880602	4.71	060881503	0.77	060882504	12.83	061140000	-3.47		
060590000	-6.58	060880603	8.68	060881504	-0.02	060882601	10.09	061170000	-11.23		
060600000	-10.66	060880604	11.54	060881505	2.05	060882602	8.69	061190000	-2.53		
060640000	-7.99	060880605	14.77	060881506	0.04	060882603	7.8	061200000	-9.37		
060650101	-10.36	060880701	17.32	060881601	-3.59	060882701	12.01	061210000	-2.52		

4.8 Example application to Oslo Testbed Norway

This study collected socioeconomic data regarding population, employment, income, education, and building of Oslo from the Oslo municipality statistics bank (https://www.oslo.kommune.no/statistikk/geografiske-inndelinger/#gref). The data in the Oslo municipality statistics bank were aggregated at three administrative levels (Level 1 – district, Level 2 – subdistrict, Level 3 – basic district) spanning from 1990 till now. Considering the availability in space and time, the most recent Level 2 aggregated data were used in this study. Moreover, this study focuses on the urban area in Oslo, thus data for the forest-dominated Marka district and the unregistered group were removed from the analysis (see Figure 4:7).
For the Oslo Testbed, we conducted a Social Vulnerability Index (SoVI) and a Socio Economic Status Index (SES). SoVI Index incorporated data related to vulnerable social groups only. SES Index considered a broad range of parameters related to Socio Economic Status of the population.

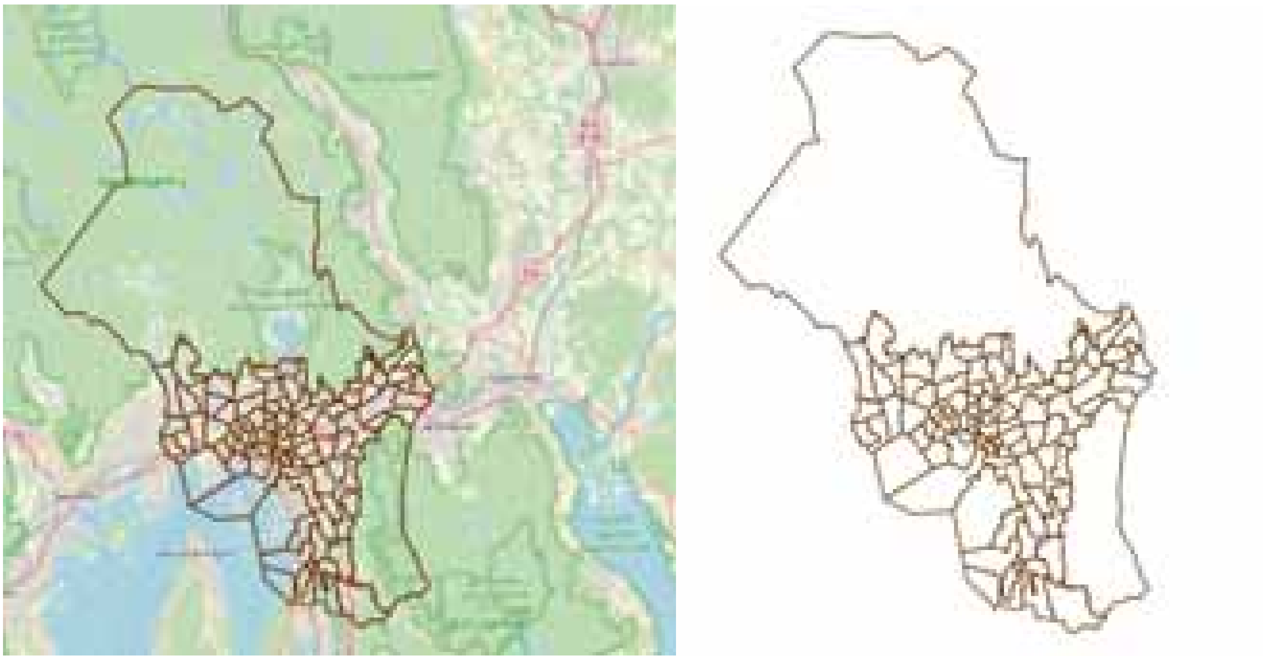


Figure 4:7 Location of the Oslo Testbed and Level 2 Administration boundaries (Source: Openstreet maps and https://www.oslo.kommune.no/statistikk/geografiske-inndelinger/#gref)

4.8.1.1 Variable slection

Originally, over 137 variables were collected to capture the socioeconomic, demographic, ethnic, and cultural characteristics of Norwegian society. After consulting with Oslo municipality and literature on socioeconomic vulnerability (Chakraborty et al., 2020; Cutter et al., 2003; Holand et al., 2011; Holand & Lujala, 2013), 47 variables within nine groups of social vulnerability indicators were considered for further analysis, as shown in the Table 4:10. It is worth noting that occupation-related variables were available at Level 1 only and it is assumed the percentage was maintained at Level 2. When no data is available, a zero value is filled. The expected variable contribution to socioeconomic vulnerability is also listed in this table.

Table 4:10 Socioeconomic vulnerability groups and description of variables considered for SoVI and SES indices.

Group	Variable	Description	Year	Increase (+)/ decrease	Used for SoVI index	Used for SES index

				(-) vulnerability		
Vulnerable population	POPDEN	Population density, in persons / km^2	2023	+		●
	MEDAGE	Median age of the population	2023	+		●
	PCTY5	Percentage of population aged 0-5yr	2023	+	●	●
	PCTY15	Percentage of population aged 0-15yr	2023	–		●
	PCTY67	Percentage of population aged 67+yr	2023	+	●	●
	PCTDIS	Percentage of population with reduced functionalities within the 16-66 age group	2019	+	●	●
	PCTFEMDIS	Percentage of female population with reduced functionalities within the 16-66 age group	2019	+		●
	PCTFEM	Percentage of female population	2023	+	●	●
Ethnicity	PCTWEU	Percentage of population from West-Europa, USA, Canada, Australia and New Zealand	2023	–		●
	PCTEEU	Percentage of population from East-European EU countries	2023	+	●	●
	PCTOTH	Percentage of population from Asia, Africa, Latin America, and East-Europa outside the EU	2023	+	●	●
	PCTIMMNOR	Percentage of Norwegian-born population with immigrant parents within the immigrant group	2023	+	●	●
Education	PCTNOEDU	Percentage of the population with unspecified or no completed education within the 16+ age group	2022	+	●	●
	PCTUNI	Percentage of the population with bachelor and above degree education within the 16+ age group	2022	–		●
Household	PCTHHICTR	Percentage of households where more than half of the income comes from transfers	2021	+	●	●
	PCTHHICTRWK	Percentage of households with kids under 18 within the households where more than half of the income comes from transfers	2021	+		●
	PCTHHICL	Percentage of households with low income	2020	+	●	●
	PCTHHWK	Percentage of households with kids under 18	2020	+	●	●
	PCTHHWKICL	Percentage of household Households with kids under 18 with low income corrected for assets	2020	+		●
	PCTHHNW	Percentage of household Households with a non-western country background	2020	+	●	●
	PCTHHNWICL	Percentage of household Households with non-western country	2020	+		●

		background with low income corrected for assets				
	PCTHHAL	Percentage of households – living alone	2022	+	●	●
	PCTHHSPWK	Percentage of households – single parent with kids	2022	+		●
	PCTHHOC	Percentage of overcrowding household	2022	+	●	●
Income	AVGICHH	Average after-tax income per consumption unit[a] in NOK	2021	–		●
	AVGICPLWK	Average after-tax income per consumption unit for couples with kids in NOK	2021	–		●
	AVGICPWK	the average after-tax income per consumption unit for single parents with kids in NOK	2021	–		●
	AVGICALO	the average after-tax income per consumption unit for Living alone in NOK	2021	–		●
	AVGIC	Average gross income in NOK	2020	–		●
	AVGICFEM	Average gross income in NOK for female	2020	–		●
	AVGICNOEDU	Average gross income in NOK for Unspecified or no completed education	2020	–		●
Employment	PCTLFNEET	Percentage of Labor force neither in employment, education, or training within the 15+ age group	2021	+	●	●
	PCTFEMICBLAVG	Percentage of Female population with gross income below average 650000 NOK	2021	–		●
	POPEMPWPDEN	Employed population density working in the subdistrict, in persons/km^2 unit	2022	–		●
	PCTEMPFEM	Percentage of female population employed within the 15-74 age group	2022	–		●
Occupation	PCTEMPWPCONMER	Percentage of employees in the construction and mechanical industry who worked in the subdistrict	2022	–		●
	PCTEMPWPTRAINF	Percentage of employees in the transportation, information, and communication industry who worked in the subdistrict	2022	–		●
	PCTEMPWPPUBINSHEA	Percentage of employees in public administration, defense and social insurance, teaching, health, and social services industry who worked in the subdistrict	2022	–		●
Dwelling	PCTRM1	Percentage of dwellings with 1 room	2023	+		●
	PCTRM23	Percentage of dwellings with 2-3 rooms	2023	–		●

	AVGM2PRI	Average price per square meter for sold residential building in NOK	2022	–		●
	AVGSLRM	Average number of sleeping rooms in sold residential buildings	2022	–		●
	PCTDH	Percentage of dwellings in detached houses or farmhouses	2023	–		●
	PCTSDH	Percentage of dwellings in semi-detached houses or other residential buildings with less than 3 floors	2023	–		●
Urban development	M2RES	The building area m^2 was completed, approved, and initiated for the residential building	2022	–		●
	M2MED	The building area m^2 was completed, approved, and initiated for the medical building	2022	–		●
	M2IND	The building area m^2 was completed, approved, and initiated for the industrial, transport, and communication buildings	2022	+		●

[a] The number of consumption units is calculated by using the "modified" OECD scale or the EU scale, where the first adult is given a value of 1, any additional adult is given a value of 0.5, and each child is given a value of 0.3, according to Statistics Norway (SSB, n.d.).

To develop the social vulnerability index, only 15 variables that are expected to increase the vulnerability are considered, as shown in Table 4:10 while all 47 variables are used to develop the socioeconomic status index. The positive and negative contributions of variables are discussed in **Error! Reference source not found.** section.

4.8.1.2 SoVI – Data Processing and Data Analysis

This analysis followed the SoVI calculation steps adapted based on the methodology used by Chakraborty et al. (2020). and Cutter et al. (2003).

Table 4:11 SoVI scores calculation details for Level 2 administration areas in Oslo

	Step	**Example**
1	Identify Data sources	The data for these variables were gathered from the Census data for Norway 2020, 2021, 2022 and (2023).
2	Identify data related to vulnerability constructs	Raw data were then further filtered to identify data related to vulnerable categories and Oslo Level 2 areas. Eg. Age data categories related population aged 0-5yr and People over 75 age were combined and filtered.
3	Computing %s	The number of population aged 0-5yr divided by the total population for each geographic area and multiplied by 100 to get the % of population aged 0-5yr. Overall data related to 99 Level 2 Area codes and 15 vulnerability indicators were taken for further analysis. Missing values were replaced with 0 as there was minimum missing values.
4	Nominalising data	The mean and the Standard deviation for each vulnerability indicator were computed. The max-Min method was then used to nominalise data.

		Standardise variables by removing the mean and scaling to unit variance. The standardised data has zero mean and one standard deviation. If the eigenvalues or variance of the components ≥ 1.0, the corresponding component explains a larger variance in the data
5	Computing SoVI score per each geographic area	Nominalised scores per each indicator were then aggregated to calculate the aggregate vulnerability score for each Level 2 geographic area.
6	Spatial representation	The original data processing and analysis was conducted on MS Excel, the SoVI scores were then extracted onto QGIS software to represent them on a map version for better understanding. See Map in the Figure 4:8 for Total SoVI categorisation for each geographic area within Oslo.

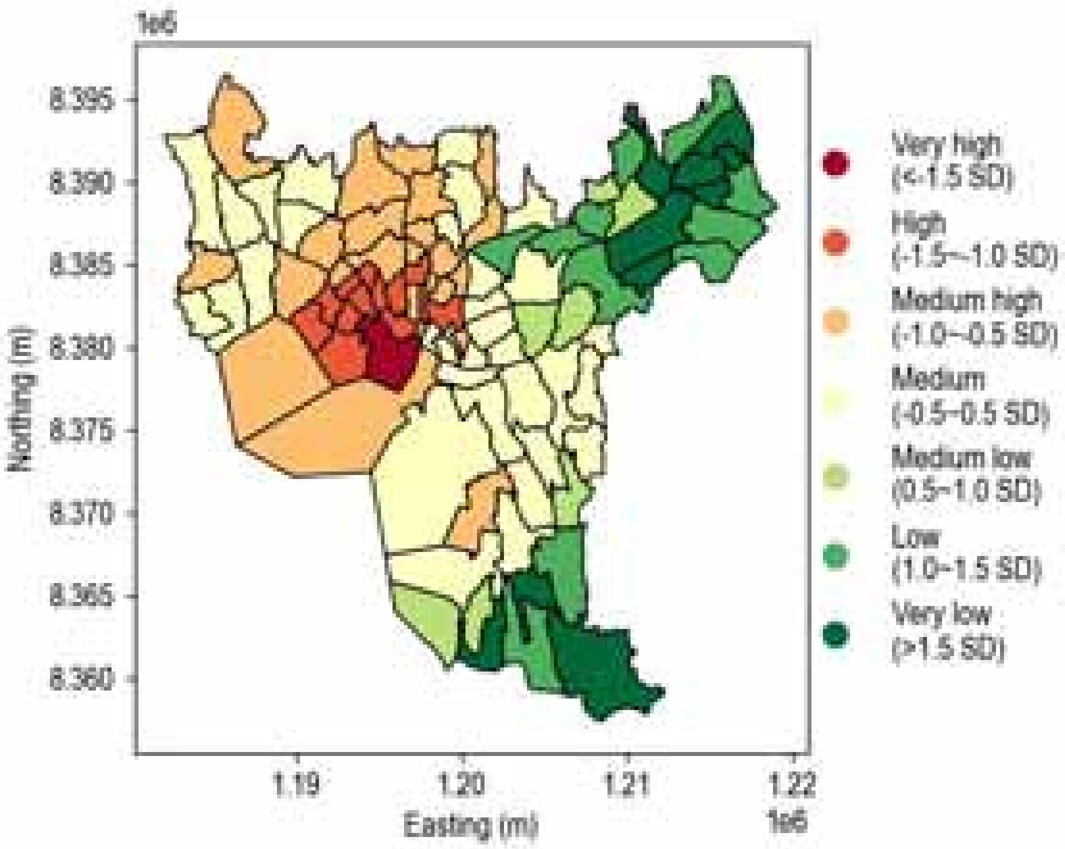


Figure 4:8 Social vulnerability classification for Level 2 administration areas in Oslo.

4.8.1.3 SES Index for Oslo – Data Processing and Data Analysis details

The index was constructed generally following the steps in Chakraborty et al. (2020).. As SES index considered a large number of SES variables, a factor analysis was performed to reduce the number of variables.

- **Step 1:** Adjust directionality to align variables with their expected contribution to socioeconomic vulnerability. For example, income-related variables are expected to negatively contribute to the vulnerability – the higher the income the less socioeconomic vulnerability, and thus, the sign of these variables was changed to negative (-).

- **Step 2:** Standardise variables by removing the mean and scaling to unit variance. The standardised data has zero mean and one standard deviation. If the eigenvalues or variance of the components ≥ 1.0, the corresponding component explains a larger variance in the data.

- **Step 3:** Preparation for Factor analysis. Perform Bartlett's test of sphericity to confirm correlation is present among the variables with a 95% confidence level. If the *p*-value is less than 5%, we can reject the null hypothesis that the variables are not correlated. The planned analysis is aimed to explain the common variance in the data (i.e. the variation due to correlation among the variables).

- **Step 4:** Perform Kaiser-Meyer-Olkin (KMO) test to confirm data has more correlation and dimensionality reduction techniques such that the factor analysis can be applied. The KMO score measures the proportion of variance that might be a common variance among the variables. The score value ranges between 0 and 1 and a value of more than 0.6 suggests the considered variables are suitable for further principal component analysis (PCA) factor analysis.

- **Step 5:** We then performed PCA with varimax rotation. The initial PCA result was used to determine the number of components with eigenvalues ≥ 1 and the final PCA given the number of selected components was used for the subsequent analysis.

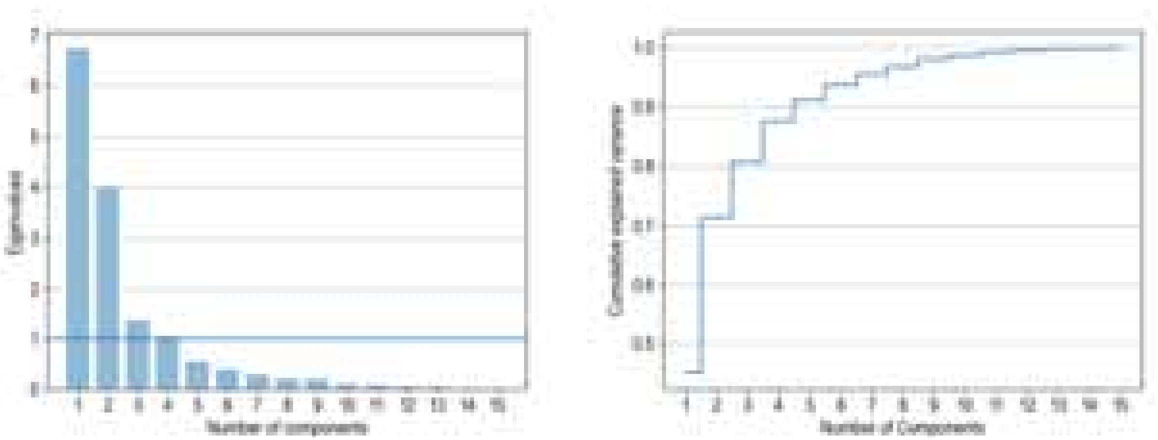


Figure 4:9 Selection of the number of components for social vulnerability index construction. Left: Scree plot of eigenvalues of components. Four components with eigenvalues ≥1.0 Right: Cumulative explained variance.

The first four components explained about 87.5% variance in the 15 variables.

Table 4:12 Component loading for socioeconomic status index. The component loadings with an absolute value ≥0.4 were highlighted. The variable contribution different from expectation was highlighted in grey.

Variables	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	Variable contribution	Communalities
POPDEN	-0.065	0.677	0.009	-0.430	-0.256	0.037	-0.054	0.097	0.015 (+)	0.727
MEDAGE	-0.093	-0.299	0.199	**0.810**	-0.096	-0.299	-0.158	0.063	0.127(+)	0.921
PCTY5	0.098	-0.585	0.385	-0.303	0.413	0.126	-0.261	-0.058	-0.184(–)	0.850
PCTY15	-0.202	0.853	-0.322	0.033	-0.177	-0.062	0.163	0.111	0.397(+)	0.947

PCTY67	-0.090	-0.449	0.266	0.696	-0.040	-0.325	-0.093	0.019	-0.017(–)	0.881
PCTDIS	0.853	-0.058	0.196	0.200	0.016	0.365	-0.078	-0.036	1.457(+)	0.950
PCTFEMDIS	0.827	-0.137	0.214	0.219	0.041	0.367	-0.140	-0.028	1.362(+)	0.952
PCTFEM	-0.179	-0.059	**0.874**	0.287	-0.041	-0.044	-0.069	0.044	0.812(+)	0.891
PCTWEU	0.413	-0.532	0.399	0.090	0.172	0.428	-0.159	-0.091	0.719(+)	0.866
PCTEEU	0.500	-0.106	-0.602	0.112	0.243	0.226	0.079	0.135	0.587(+)	0.771
PCTOTH	0.941	0.033	-0.075	-0.054	0.094	0.240	-0.003	-0.052	1.124(+)	0.965
PCTIMMNOR	0.747	-0.153	0.180	-0.028	0.150	0.475	-0.267	-0.046	1.058(+)	0.935
PCTNOEDU	0.862	0.144	-0.244	-0.123	-0.054	-0.020	0.067	-0.017	0.615(+)	0.847
PCTUNI	0.852	-0.231	-0.037	0.227	0.045	0.351	-0.065	-0.019	1.122(+)	0.962
PCTHHICTR	0.921	0.016	0.032	0.080	-0.087	0.270	0.050	0.005	1.288(+)	0.939
PCTHHICTRWK	0.825	0.358	-0.118	-0.213	-0.084	0.176	0.063	0.067	1.075(+)	0.915
PCTHHICL	0.733	0.234	-0.309	-0.310	-0.109	0.012	0.403	0.011	0.665(+)	0.957
PCTHHWK	0.136	**-0.907**	0.198	-0.004	0.172	0.081	-0.134	-0.127	-0.586(–)	0.950
PCTHHWKICL	0.929	-0.086	0.069	-0.188	0.025	0.147	0.014	0.007	0.917(+)	0.933
PCTHHNW	**0.942**	-0.024	-0.074	-0.111	0.102	0.191	0.022	-0.050	0.997(+)	0.955
PCTHHNWICL	0.903	0.045	-0.102	-0.274	-0.037	0.052	0.211	-0.011	0.787(+)	0.952
PCTHHAL	-0.113	0.906	-0.039	-0.047	-0.084	0.033	0.330	0.028	1.012(+)	0.954
PCTHHSPWK	0.578	-0.369	0.433	-0.101	0.161	0.317	-0.179	-0.048	0.791(+)	0.829
PCTHHOC	0.488	0.292	-0.078	-0.231	0.075	0.265	0.639	-0.160	1.289(+)	0.891
AVGICHH	0.443	0.262	-0.031	-0.117	0.002	**0.825**	0.095	-0.021	1.458(+)	0.969
AVGICPLWK	0.547	0.248	0.026	-0.116	0.018	0.752	-0.074	-0.003	1.398(+)	0.947
AVGICPWK	0.235	0.151	-0.079	-0.170	-0.030	0.786	0.002	0.166	1.061(+)	0.759
AVGICALO	0.449	-0.043	-0.056	-0.123	-0.008	0.765	0.256	-0.096	1.144(+)	0.883
AVGIC	0.549	0.302	-0.044	-0.123	-0.004	0.746	0.118	-0.017	1.528(+)	**0.980**
AVGICFEM	0.731	0.254	-0.089	-0.103	-0.001	0.566	0.153	-0.004	1.508(+)	0.962
AVGICNOEDU	0.251	-0.019	0.079	-0.352	0.106	0.324	0.351	-0.155	0.584(+)	0.457
PCTLFNEET	0.582	-0.456	0.177	0.429	-0.002	0.021	-0.270	-0.020	0.462(+)	0.836
PCTFEMICBLAVG	-0.832	-0.071	-0.231	-0.098	-0.057	-0.400	0.032	-0.016	-1.673(–)	0.924
POPEMPWPDEN	0.137	-0.508	0.453	0.233	0.035	-0.039	-0.045	-0.010	0.256(+)	0.541
PCTEMPFEM	0.860	-0.300	-0.273	0.157	0.000	-0.041	0.098	-0.053	0.449(+)	0.943
PCTEMPWPCONMER	-0.599	0.235	0.001	-0.396	-0.230	-0.401	0.227	0.145	-1.019(–)	0.858
PCTEMPWPTRAINF	0.003	-0.617	0.248	0.193	0.038	-0.228	0.079	0.388	0.104(+)	0.689
PCTEMPWPPUBINSHEA	0.203	0.619	-0.236	0.256	0.180	0.052	-0.340	-0.311	0.423(+)	0.793
PCTRM1	-0.138	0.428	-0.204	-0.095	-0.057	0.084	**0.792**	-0.107	0.703(+)	0.901
PCTRM23	-0.084	-0.810	-0.223	0.219	-0.102	-0.259	0.180	-0.083	-1.162(–)	0.878
AVGM2PRI	0.656	-0.542	0.111	0.168	0.005	0.359	-0.163	0.075	0.670(+)	0.926
AVGSLRM	0.040	0.868	0.076	-0.087	-0.002	0.253	0.122	-0.048	1.222(+)	0.849
PCTDH	0.202	0.814	0.195	-0.068	0.044	0.269	0.076	-0.109	1.423(+)	0.838
PCTSDH	0.139	0.872	0.060	-0.171	0.087	0.023	0.092	0.072	1.175(+)	0.835
M2RES	0.240	0.132	0.115	0.203	-0.681	0.074	0.175	0.034	0.293(+)	0.630

M2MED	-0.035	0.083	-0.050	0.026	0.077	0.058	-0.129	**0.832**	0.863(+)	0.730
M2IND	0.179	-0.030	0.019	0.109	**0.765**	0.049	0.137	0.116	1.342(+)	0.665
Total variance (86.2%)	37.7%	24.1%	6.8%	5.8%	3.6%	3.2%	2.7%	2.4%		

Step 6a: Calculate the non-standardised socioeconomic index of the *j*-th subdistrict (NSI_j),

$$NSI_j = \sum_{i=1}^{n} w_i \times PC_i \, , w_i = \frac{\text{Proportion of variance for factor } i}{\text{Total variance explained}} \quad (1)$$

where PC_i and w_i are the component score and weight of the *i*-th principle component, respectively; n is the number of selected components. The higher the score of the index, the less vulnerable of the subdistrict.

Step 6b: As the next step, we calculate the standardised socioeconomic status index of the *j*-th subdistrict (NSI_j),

$$SES_j = \frac{NSI_j - NSI_{min}}{NSI_{max} - NSI_{min}} \times 100 \quad (2)$$

where NSI_{max} and NSI_{min} are the maximum and minimum of all NSI_j. Same as Step 6, the higher the score of the index, the less vulnerable of the subdistrict.

- **Step 7:** Finally, we categorised results into seven categories of socioeconomic vulnerability as very low (>1.50 SD), low (1.00 SD to 1.50 SD), medium low (0.50 SD to 1.00 SD), medium (- 0.50 SD to 0.50 SD), medium high (- 1.00 SD to - 0.50 SD), high (- 1.50 SD to - 1.00 SD), and very high (< - 1.50 SD).

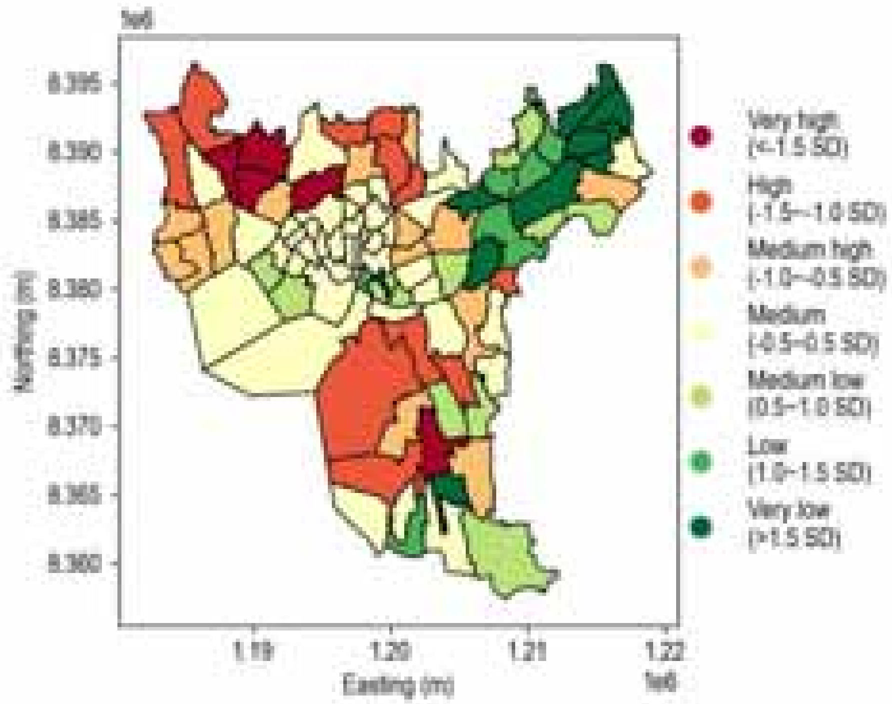


Figure 4:10 Socioeconomic status classification for Level 2 administration areas in Oslo

4.8.1.3.1 *Comparison of SoVI and SES*

Comparing Figure 4:8 and Figure 4:10, the vulnerability distribution varied between the mapping of the social vulnerability index and the socioeconomic vulnerability index. By adding socioeconomic variables to the solely social variables, the computed indexes showed the most vulnerable subdistricts shifted from city center to scattered around the urban area. Though the most vulnerable subdistricts were different between the two indexes, the least vulnerable subdistricts are similar, that is Bjørnerud subdistrict and Søndre Nordstrand subdistrict in the south and the Alna subdistrict and Stovner subdistrict.

Since different and limited variables were considered in the index construction, both indexes are seen as a partial reflection of the social aspect of the vulnerability, as summerised in Table 4:13. Both indexes are equally important in disaster management, as they together capture certain epistemic uncertainty due to the lack of data and knowledge. When communicating with disaster management authorities, it is important to point out that any index is generally a static picture to provide a first estimate of the conditions that can increase the susceptibility to the impact of hazards, which cannot capture the dynamic nature of risk and resilience. Thus, further analysis and detailed analysis, taking into account the hazard impact and physical vulnerability, are needed to reveal the changing risk and resilience landscape.

Table 4:13 The summary table of the social vulnerability index and socioeconomic status index

ID	Subdistricts	Social Vulnerability Index (SoVI)				Socio-Economic Status Index (SES)			
		NSI	SES	Rank	Class	NSI	SES	Rank	Class
102	Grønland	0.12	46.73	67	Medium	0.60	67.29	84	Low
103	Enerhaugen	0.01	42.31	62	Medium	0.46	61.43	79	Medium low
104	Nedre Tøyen	0.09	45.23	64	Medium	0.85	77.29	90	Very low
105	Kampen	-0.32	28.62	36	Medium high	0.27	54.02	69	Medium low
106	Vålerenga	-0.09	38.22	54	Medium	0.29	54.72	71	Medium low
108	Kværnerbyen	-0.28	30.32	42	Medium	-0.13	37.60	40	Medium
109	Bispevika	-0.50	21.27	18	Medium high	0.05	45.11	55	Medium
110	Ensjø	-0.07	38.90	56	Medium	-0.27	32.10	31	Medium
111	Etterstad	-0.13	36.46	51	Medium	0.16	49.41	61	Medium
201	Grünerløkka vest	-0.51	20.88	17	Medium high	0.11	47.55	58	Medium
202	Grünerløkka øst	-0.64	15.67	13	High	0.04	44.73	53	Medium
203	Dælenenga	-0.44	23.89	28	Medium high	0.31	55.35	75	Medium low
204	Rodeløkka	-0.45	23.18	25	Medium high	0.01	43.27	50	Medium
205	Sinsen	-0.33	28.31	35	Medium high	0.18	50.23	62	Medium
206	Sofienberg	-0.64	15.43	12	High	0.14	48.58	60	Medium
208	Løren	0.09	45.45	65	Medium	-0.38	27.52	23	Medium high
209	Hasle	-0.10	37.55	53	Medium	-0.41	26.17	22	Medium high
301	Iladalen	-0.71	12.59	9	High	0.01	43.43	51	Medium
302	Sagene	-0.48	21.89	20	Medium high	0.09	46.64	57	Medium
303	Bjølsen	-0.58	17.98	16	Medium high	0.26	53.57	67	Medium
304	Sandaker	-0.30	29.39	38	Medium	-0.12	37.96	42	Medium
305	Torshov	-0.47	22.58	22	Medium high	0.05	44.85	54	Medium
401	Hammersborg	-0.80	8.93	4	High	-0.25	32.82	32	Medium
402	Bislett	-0.84	7.22	2	High	-0.21	34.26	35	Medium
403	Ila	-0.79	9.27	5	High	-0.10	39.05	45	Medium

404	Fagerborg	-0.82	8.32	3	High	-0.13	37.63	41	Medium
405	Lindern	-0.45	23.48	27	Medium high	-0.02	42.28	49	Medium
501	Bygdøy	-0.45	23.38	26	Medium high	-0.10	39.02	44	Medium
502	Frogner	-0.66	14.72	11	High	0.51	63.56	80	Medium low
503	Frognerparken	-0.75	10.96	7	High	0.20	50.87	63	Medium
504	Majorstuen nord	-0.61	16.81	15	Medium high	0.23	52.08	64	Medium
505	Majorstuen syd	-0.75	10.95	6	High	0.13	48.33	59	Medium
506	Homansbyen	-0.70	13.20	10	High	0.25	52.89	66	Medium
507	Uranienborg	-0.73	11.65	8	High	0.23	52.16	65	Medium
508	Skillebekk	-0.62	16.15	14	High	0.30	54.94	73	Medium low
601	Ullernåsen	-0.40	25.21	30	Medium high	-0.34	29.24	28	Medium high
602	Lilleaker	-0.13	36.27	50	Medium	-0.50	22.67	18	Medium high
603	Ullern	-0.13	36.57	52	Medium	-0.47	24.06	20	Medium high
604	Montebello?Hoff	-0.29	29.69	39	Medium	-0.30	30.82	29	Medium high
605	Skøyen	-0.47	22.44	21	Medium high	-0.23	33.63	34	Medium
701	Røa	-0.22	32.68	46	Medium	-0.76	12.29	7	High
702	Holmenkollen	-0.32	28.82	37	Medium high	-0.63	17.46	16	High
703	Hovseter	-0.04	39.92	58	Medium	-0.12	38.08	43	Medium
704	Holmen	-0.23	32.25	45	Medium	-0.89	6.88	4	Very high
705	Slemdal	-0.24	31.74	44	Medium	-0.97	3.57	2	Very high
706	Grimelund	-0.16	35.18	49	Medium	-0.94	4.83	3	Very high
707	Vinderen	-0.46	22.82	24	Medium high	-0.36	28.23	25	Medium high
801	Disen	-0.38	26.04	31	Medium high	-0.67	15.56	14	High
802	Myrer	-0.49	21.73	19	Medium high	-0.52	22.04	17	Medium high
803	Grefsen	-0.28	30.23	41	Medium	-0.65	16.40	15	High
804	Kjelsås	-0.28	30.11	40	Medium	-0.70	14.36	12	High
805	Korsvoll	-0.47	22.64	23	Medium high	-0.77	11.83	6	High
806	Tåsen	-0.37	26.76	32	Medium high	-0.46	24.10	21	Medium high
807	Nordberg	-0.33	28.29	34	Medium high	-0.17	36.18	38	Medium
808	Ullevål hageby	-0.41	25.03	29	Medium high	-0.88	7.13	5	Very high
901	Veitvet	0.92	79.47	87	Low	0.67	69.99	86	Low
902	Linderud	0.67	69.35	79	Low	0.83	76.60	88	Very low
904	Årvoll	-0.07	38.74	55	Medium	-0.06	40.29	46	Medium
905	Refstad	0.63	67.64	77	Low	-0.06	40.57	47	Medium
906	Ulven	0.29	53.48	70	Medium	-0.34	28.94	27	Medium high
1001	Ammerud	0.73	71.82	81	Low	0.39	58.78	76	Medium low
1002	Rødtvet	0.56	64.77	76	Medium low	0.29	54.81	72	Medium low
1003	Nordtvet	0.47	60.80	74	Medium low	0.63	68.33	85	Low
1004	Grorud	0.94	80.25	88	Very low	0.60	67.06	83	Low
1005	Romsås	0.75	72.62	82	Low	0.99	83.13	95	Very low
1101	Vestli	1.21	91.49	91	Very low	0.97	82.35	94	Very low
1102	Fossum	1.41	99.30	96	Very low	1.41	100.00	97	Very low

1103	Rommen	1.40	98.98	95	Very low	1.15	89.75	96	Very low
1104	Haugenstua	1.24	92.67	92	Very low	0.84	77.08	89	Very low
1105	Stovner	0.67	69.16	78	Low	-0.18	35.55	36	Medium
1106	Høybråten	0.68	69.56	80	Low	-0.37	27.79	24	Medium high
1201	Furuset	1.33	96.27	94	Very low	0.93	80.62	92	Very low
1202	Ellingsrud	0.80	74.40	84	Low	0.27	54.00	68	Medium low
1203	Lindeberg	0.97	81.32	90	Very low	0.44	60.65	78	Medium low
1204	Trosterud	0.88	77.64	86	Low	0.76	73.68	87	Low
1205	Hellerudtoppen	0.21	50.24	68	Medium	-0.75	12.34	8	High
1206	Tveita	0.32	55.01	71	Medium low	0.96	81.71	93	Very low
1207	Teisen	0.34	55.66	73	Medium low	0.51	63.64	81	Medium low
1301	Manglerud	0.00	41.77	60	Medium	-0.17	36.07	37	Medium
1302	Godlia	-0.04	40.20	59	Medium	-0.35	28.63	26	Medium high
1303	Oppsal	0.00	41.91	61	Medium	-0.24	33.34	33	Medium
1304	Bøler	0.04	43.35	63	Medium	-0.03	41.77	48	Medium
1305	Skullerud	0.33	55.07	72	Medium low	0.40	59.34	77	Medium low
1306	Abildsø	0.28	53.36	69	Medium	-0.75	12.65	10	High
1401	Ljan	-0.17	34.60	48	Medium	-0.71	14.31	11	High
1402	Nordstrand	-0.34	27.69	33	Medium high	-0.49	22.89	19	Medium high
1403	Bekkelaget	-0.26	30.94	43	Medium	-0.75	12.53	9	High
1404	Simensbråten	0.10	45.95	66	Medium	-0.70	14.56	13	High
1405	Lambertseter	-0.19	33.77	47	Medium	0.30	55.29	74	Medium low
1406	Munkerud	-0.06	39.16	57	Medium	-1.06	0.00	1	Very high
1501	Holmlia Syd	0.94	80.34	89	Very low	0.58	66.34	82	Low
1502	Holmlia Nord	0.49	61.72	75	Medium low	0.04	44.40	52	Medium
1503	Prinsdal	0.81	74.90	85	Low	0.06	45.48	56	Medium
1504	Bjørnerud	1.31	95.52	93	Very low	0.88	78.64	91	Very low
1505	Mortensrud	0.79	74.22	83	Low	-0.30	30.83	30	Medium high
1506	Bjørndal	1.42	100	97	Very low	0.28	54.12	70	Medium low
1601	Sentrum	-1.02	0	1	Very high	-0.15	37.00	39	Medium

4.8.1.4 Disaggregation of Built Areas into Social Classes

The computed indexes were disaggregated with respect to built area in the subdistricts, as shown in Figure 4:11. The general distribution of vulnerable built areas were similar between the two indexes and most built area were medium vulnerable. The built areas with very high to high vulnerability were smaller in social vulnerability index compared to that of socio-economic status index. The built areas with medium vulnerability in the social vulnerability index were significantly higher than those of the socioeconomic status index. The built areas with very low to medium-low vulnerability were similar between the two indexes.

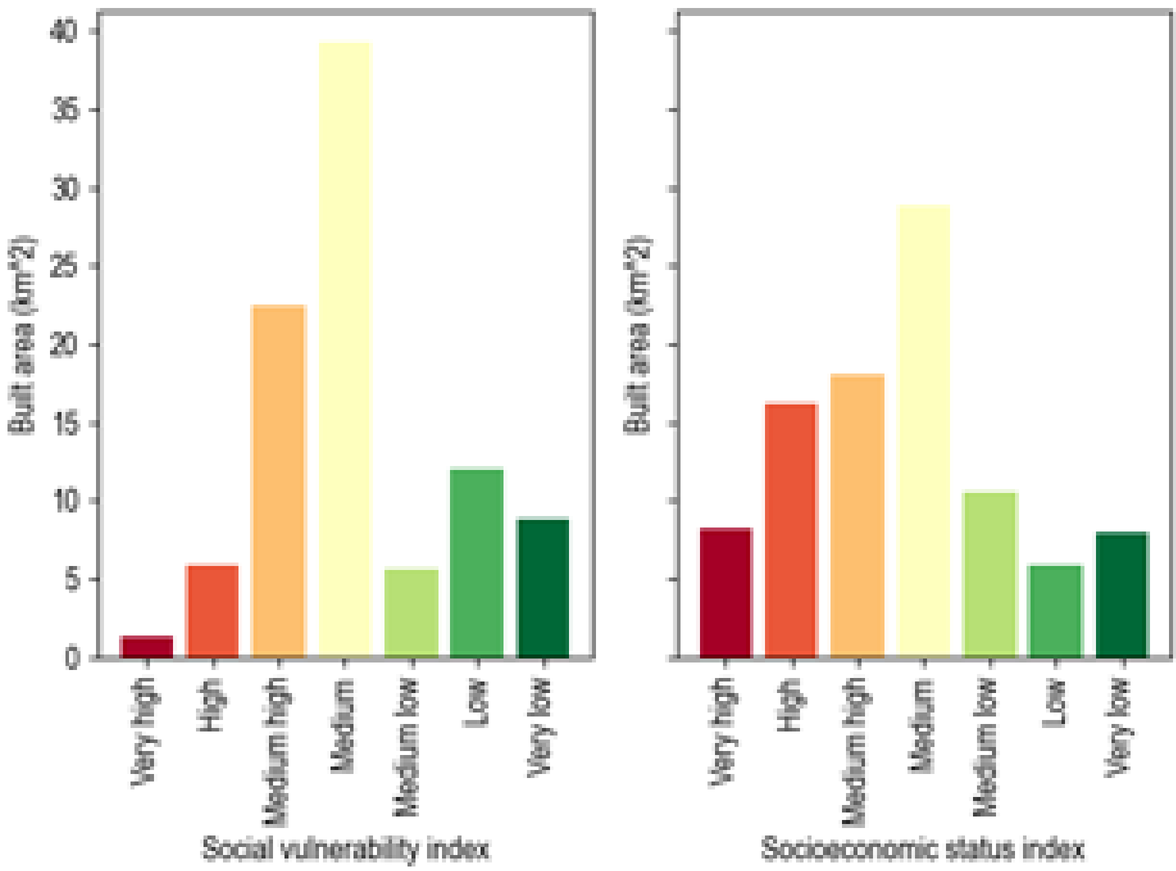


Figure 4:11 Disaggregation of the indexes with respect to built area.

Asset loss data for the Oslo testbed has not been computed at the time of submitting this report. Disaggregation of asset loss data as a function of social vulnerability classes can be performed based on the methodology explained in section 4.6.3 within the MEDiate platform when the asset loss data is generated.

4.9 Social Vulnerability Index (SoVI) for Mulaping - Iceland

Mulaping testbed in Iceland was a small geographic area with about 3500 population. Census tract data was not publicly available at the community level for Mulaping. Due to the small scale of the test bed a community level SoVI could not be calculated. However, recent studies have produced SoVI indices at the municipality level for Iceland using Census data. For instance, Ströberg (2018) has developed a municipality level SoVI by incorporating 17 socio-economic variables.

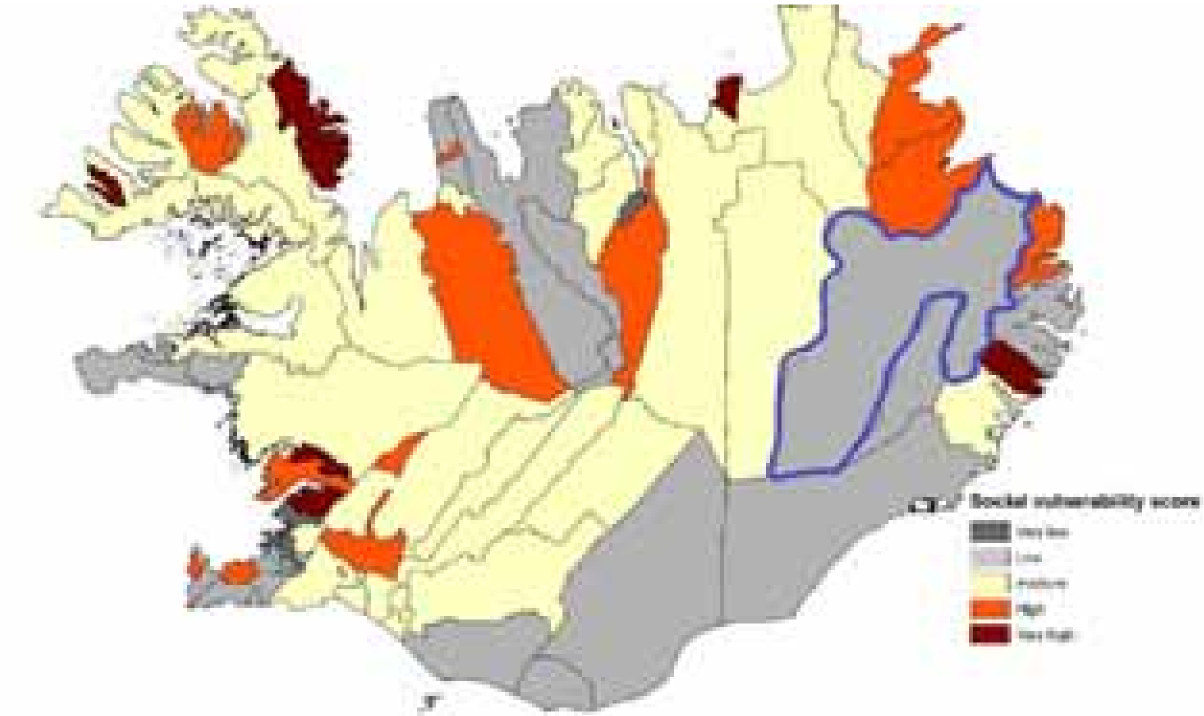


Figure 4:12: Social Vulnerability Index for Iceland (Source: Ströberg 2018, pp. 49)

The blue line marks the boundary of the Mulaping municipality. According to the Ströberg (2018)'s analysis the socio-economic vulnerability score for the Mulaping municipality is 'low'.

5 SUMMARY AND CONCLUSIONS

Climate change-induced hazards cause direct losses by damaging physical assets such as buildings and infrastructure. Loss estimates related to direct physical damage undermine the impact of such damage and the resultant financial burden associated with repair and recovery costs. In addition to the financial burden, disasters significantly impact the health and well-being of the population. Simplified approaches to disaster loss assessments also fail to consider the ability of disaster-affected households to cope with and recover from disaster asset losses based on their circumstances.

Work Package 5 of the MEDiate project extends the status quo by modelling the physical damage from multi-hazards (Task 3.1); modelling the social consequences of multi-hazards, and accounting for possible interactions with impacts on the built environment (Task 3.2), combining the results of the Tasks 3.1 and 3.3 to define a set of to risk resilience metrics that extend beyond simple asset losses considered as part of conventional risk assessment approaches. Finally, Task 3.4 will develop an integrated risk and resilience modelling framework to support the Decision Support System (DSS) developed by the MEDiate project.

This deliverable reported the work undertaken within Task 3.2 of Work Package 5.

- Chapter 2, demonstrated how the econometric modelling could be extracted and quantify the vulnerability of socio-virtual-physical networks. An application of the concept to the Essex Testbed was presented, and socioeconomic vulnerabilities and social resilience were estimated at the district level for the Essex County Council. Results confirmed that higher proportions of the elderly, higher proportions of the population receiving means-tested benefits, and higher proportions of living in social housing are linked to higher disaster impact. On the other hand, higher local employment rates, higher household incomes and more hours of volunteering are linked to smaller disaster impacts. This task developed a Social Vulnerability Index (SoVI) and CRI (Community Resilience Index) at the ward level (for Essex, UK) to provide supporting evidence for the econometric model. These should not be compared with the Social Vulnerability Index (SoVI) developed and presented in Chapter 4, as they were developed at different geographical scales and used different variables to support subsequent econometric model.
- Chapter 3, demonstrated how network analysis could be used to establish vulnerabilities brought in by damage to infrastructure which connects services and communities. We demonstrated the concept by investigating the vulnerability of the Canvey Island road network to flooding and the impact of road closures on the connectivity of 11 service providers (Fire station, Surgery (GP), College/university, Library, Town Office, Police and five schools) in Canvey Island and the residents who received their service. Results found that in case of road closures due to flooding, two service providers, namely Surgery (GP) and College/university and four schools, namely Canvey Infant School, Canvey Junior School, The Castle View School, Infant School & Nursery, Leigh Back Junior School will be completely disconnected from the service receivers and hence missed 100 per cent of the services.
- Chapter 4, demonstrated how to disaggregate the asset losses as a function of socio-economic characteristics. We developed 3 Social Vulnerability Index (SoVI)s for Canvey Island, Essex, UK; Nice, France; and Oslo, Norway, based on the relevant dominant hazard types and publicly available socioeconomic demographics. We also developed an Oslo testbed-specific socioeconomic status (SES) index. Using Canvey Island as an example, we demonstrated how to disaggregate the asset losses as a function of socioeconomic characteristics in case of flooding. Results show that communities with Very Low socio-economic vulnerabilities experience less property damage, and communities with Very High socio-economic vulnerabilities experience comparatively higher levels of damage and economic losses. Results also confirmed that Very highly and Highly vulnerable communities will need additional support to prepare for and recover from flooding hazards. These

matrices could be replicated with other hazard intensity scenarios based on the results of MEDiate Task 2.2 and 3.1.

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Matrices developed within Task 3.2 can be categorised under Type 4 approaches as per Soden et al. (2023) typology of disaster risk assessment practices. Models produced here disaggregate risk by various social groups. Differential potential socioeconomic impacts of hazards are incorporated into the model by disaggregating vulnerability.

Multi-hazard interactions were modelled within Task 2.2 of the MEDiate project, and results combined intensities were used by all tasks of Work Package 3, which considered that multi-hazard interactions are already embedded. However, the social impact of multiple hazards when they occur independently and with a gap in time (during or after the recovery from the first hazard) is a gap in practice of loss and risk assessment, which needs further investigation.

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