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Social and economic vulnerability of coastal communities to sea-level rise and extreme flooding

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Abstract This paper assesses the socioeconomic consequences of extreme coastal flooding events. Wealth and income impacts associated with different social groups in coastal communities in Israel are estimated. A range of coastal flood hazard zones based on different scenarios are identified. These are superimposed on a composite social vulnerability index to highlight the spatial variation in the socioeconomic structure of those areas exposed to flooding. Economic vulnerability is captured by the exposure of wealth and income. For the former, we correlate the distribution of housing stock at risk with the socioeconomic characteristics of threatened populations. We also estimate the value of residential assets exposed under the different scenarios. For the latter, we calculate the observed change in income distribution of the population under threat of inundation. We interpret the change in income distribution as an indicator of recovery potential.

Keywords Social vulnerability · Asset vulnerability · Income distribution · Flood hazard zones · Sea-level rise

1 Introduction

The recent ravages of Superstorm Sandy and prior to that Hurricane Katrina have highlighted the social and income distribution outcomes of extreme flooding events. Traditionally, both the public discourse and the professional literature on extreme flooding (EF) and sea-level rise (SLR) have dealt with forecasting trends, costs of defense and protection and ecological impacts (for example Koch 2010). Most of the vulnerability literature has emphasized the physical and ecological vulnerability of coastal areas (Chakraborty et al. 2005). With a few notable exceptions (for example, Shaughnessy et al. 2010), the literature on the social welfare and income distribution effects of SLR and EF is sparse. Until

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recently, the natural hazard literature has tended to emphasize hazard assessment and has placed less effort on estimating economic or behavioral responses. Flooding events affect communities and social groups differentially. This results from their distribution across space and also from their differential ability to cope with the event. Certain population groups possess higher adaptive capacities. They have the attributes and resources that can be used to accommodate negative impacts or exploit the beneficial opportunities arising from a hazardous event. As such, they are inherently more resilient. This is expressed in their ability to anticipate, absorb and recover from the effects of a hazardous event. Thus, social welfare impacts lie at the heart of the vulnerability issue. Following the IPCC SREX definition, we conceive of vulnerability as 'the propensity or predisposition to be adversely affected' and the 'capacity to anticipate, cope with, resist, and recover from the adverse effects of physical events' (Lavell et al. 2012, p. 32).

We treat vulnerability as a relative concept. The same level of natural hazards may have very different consequences for different individuals or communities. In the context of flooding, even if the magnitude of damage from extreme inundation is borne by the richer in absolute terms (income, assets and property of greater value), the poor might still suffer greater relative damage due to their inability to cope with natural disasters (Wu et al. 2002). Additionally these effects may be cumulative, having inter-generational consequences persisting over time and inducing a downward spiral of vulnerability as the poor lack the resources that enable recovery (Masozera et al. 2007). Thus, the key socioeconomic issues to do with SLR/EF relate to their differential impacts. Faced with flooding, who is likely to be most affected: the rich or the poor, the able or disabled, the young or the old?

The aim of this paper is to assess the socioeconomic consequences of extreme coastal flooding and SLR. This is undertaken in three ways. First, the population groups and physical assets exposed to flooding under different flooding scenarios are identified. Second, the social vulnerability (SV) and asset vulnerability (AV) of population groups and communities are estimated. Our approach to understanding community vulnerability differs from common index construction. We start by calculating a vulnerability index that is based on the socioeconomic attributes of the individuals comprising the community. Then we incorporate the exposure component of each flooding scenario by aggregating the different vulnerability distributions prevalent in the community. In this sense, our assessment presents a distribution of vulnerabilities and their corresponding spatial patterns in the exposed area, rather than assigning one aggregate score to the community. Finally, we assess the ex post effect of extreme events on community income distribution. This assumes a differential behavioral response across subpopulations located in and around the hazard zone.

Understanding the relative vulnerability of population subgroups and their spatial distribution can aid the management of rescue operations in the event of EF. It can also lead to improved management and planning of coastal defenses and other adaptation strategies in the case of a slow evolving hazard such as SLR. Effective disaster risk reduction can therefore be achieved through the ex ante identification and assessment of vulnerability (Birkmann 2007). Additionally, understanding vulnerability can empower the public and inform practice. The identification of population at risk and the potential physical damage to assets and property is valuable knowledge. To assist in communicating this information, we have constructed a dedicated online interactive web-map (http://ccg.huji.ac.il/dynamicmap/index.html) that dynamically visualizes the outcome of different flooding situations. The user can simply simulate different flooding levels and observe their socioeconomic consequences at different spatial scales. In this way, valuable information is transmitted to both professional and civic communities and the provision of this know-how is made increasingly symmetric to different stakeholders. This in itself contributes to augment the resilience of both individuals and the community.

We distinguish between flooding effects on wealth (capitalized in housing) and income. While loss of the former encapsulates the level of immediate exposure to a flooding for both the household and community, the distribution of the latter (pre- and post-event) is a potent indicator of the ability to rejuvenate. With respect to the level of wealth exposure, we correlate housing stock at risk (buildings and their values) with social indicators in order to ascertain the socioeconomic impacts of flooding on wealth. Additionally, we estimate an asset (wealth) vulnerability index that incorporates normative policy choices. In the case of income effects, we look at the change in earning distribution pre- and post-flooding by different topographical heights and under different flooding scenarios. The ex post change in earnings distribution is interpreted as a major factor in community recovery. Our findings relate to flooding effects in two main areas in Israel: the city of Tel Aviv and a collection of different-sized coastal communities along the Northern coastal plain north of the city of Haifa.

2 Literature review

Natural disasters[1] capture public attention because of their destructive consequences and the relative helplessness of human response when faced with the raw power of these unleashed forces. However, from a socioeconomic perspective, it is not so much the magnitude of the event that is important, but the ability to cope with its results. A natural disaster of a given magnitude can have differential impacts just depending on where it occurs or which population groups are affected. Where exposure and vulnerability are high, even non-extreme events can lead to serious consequences (IPCC 2012). Thus, the relative burden of coping is more important from a socioeconomic perspective than the absolute size of the event. Obviously, personal wealth and income are major factors in coping with the worst excesses of natural hazards. The former is a potent factor as long as it is tied to risk insurance coverage. Population subgroups with a tradition or culture of underinsurance will be relatively more susceptible than others. Evidence on the extent to which risk is embodied in asset value is mixed. Work in the USA has shown flood risk disclosure to be inversely related to asset prices, reducing property values by over 7 % (Bin et al. 2008). Slightly lower levels of impact have been estimated in developing countries (Lall and Deichmann 2009). This linkage is often determined by institutional characteristics such as housing tenure and physical attributes such as site characteristics and location. It is necessary to decouple the disamenities of proximity to a natural hazard (e.g., a fault line) with the potential risk of it becoming active. Lall and Deichmann (2009) using propensity scoring find that households and businesses trade off the advantages and accessibility afforded by a favorable location with the risk of hazard occurrence. This trade-off is more likely in the case of seismic activity than flood or cyclone hazards.

Despite some literature that seems to imply that low-level shocks can cause communities to bounce back with renewed invigoration (Wright et al. 1979), it seems logical to suggest that lower-income communities are likely to be highly vulnerable to the disruptions resulting from natural hazards. First, their narrow business base is likely to contract even further when faced

[1] Due to the role of human agency, this question of just how 'natural' these disasters really are is a contentious issue (see Wisner et al. 2004; Bosher and Dainty 2011).

with an unanticipated shock, and their credit rating is unlikely to be high enough to compensate for temporary shocks. Second, the value of local capital stock (houses, industrial plant, etc.) is likely to be low in the first place. Given these two factors, even small shocks can push households and communities into financial crisis. Vulnerable communities can therefore be disproportionately affected by hazardous events, and these are more likely to push them into crisis relative to the general population. Over time, this can lead to a cut back in consumption levels and further inequality. Much of this can only be detected at the micro-level such as the household or small statistical area (Cutter et al. 2008). It is often masked in studies dealing with aggregate community impacts and focusing on longer-term effects such as employment, retail sales and government spending.

A further inequality and income distribution issue relates to whether the weakest social groups are forced into the most hazardous or marginal areas due to the pricing system. Income itself is correlated with social characteristics such as age, education, health status and institutional characteristics such as housing tenure and risk insurance. Thus, vulnerability is not equitably distributed across space because it is systematically tied to household social and demographic attributes. Ostensibly, hazardous areas are shunned by the rich and mobile. However, when there is a trade-off between risk and other amenities (agglomeration, natural resources, etc.), the literature is often ambiguous with respect to the outcomes. On the one hand, we can posit that the poor 'sort themselves' into low-cost, hazardous locations (Lall and Deichmann 2009). On the other hand, in terms of response to natural hazard risk, we can surmise that both the poor and middle-income groups actively respond to threat. The poor move to other low-cost areas outside the immediate hazard range, while middle-income groups can afford to relocate to areas with a lower hazard potential. Ironically, the wealthy who can afford insurance, self-protection and the cost of dislocation may be the least likely to move (Whitehead et al. 2000). Literature on the social welfare and income distribution effects of natural hazards especially the local impacts of coastal storms and hurricanes in the USA such as Katrina, Andrew and Floyd (West and Lenze 1994; Bin and Polasky 2004; Elliot and Pais 2006; Logan 2006; Kerry Smith et al. 2006) shows in one way or another that the economic capacity of households explains most of the difference in their response to natural hazards. More aggregate studies that look at the macro-effects of natural disasters on employment, gross regional product (GRP) and economic output also reach very similar conclusions with respect to ability to recover from such shocks. These results are notwithstanding the very different methodologies used that run the gamut of regional economic analysis, ranging from cost accounting (Gaddis et al. 2007) through difference in difference analysis (Lall and Deichmann 2009) to general regional (CGE) equilibrium analysis (West and Lenze 1994).

In contrast to the micro (household level) and the macro (economy-wide) approaches, our interest lies in the place-based impacts on specific locales or communities. This leads to an emphasis on identifying populations in the hazard zones, estimating their assets at risk and calculating the income distribution effects of flooding. Meeting this objective involves highlighting the asset (wealth) vulnerability of different communities under varying flooding scenarios and emphasizing the Rawlsian-type effects of making policy choices that favor certain population groups over others. For populations at risk, the main questions that inform any distributional analysis are as follows: What is the likely level of exposure to a natural event, who is at risk and how much is at risk (wealth and income) in the advent of a natural hazard.

To address issues of social equity and differential coping capacities, social vulnerability indicators are invariably used. These vary as a function of the scale of analysis, the specificities of the hazard under investigation and the particular conception of vulnerability adopted by the study. Conceptions of vulnerability are largely scale and discipline dependent (Miller et al. 2010; Fuchs et al. 2011; Hufschmidt 2011). At the global scale, specific indicators such as relative mortality rate and relative GDP losses have been used (Birkmann 2007). At the regional scale, a combination of indices encompassing aspects of exposure, socioeconomic status and resilience have been suggested using numerous indicators (Balica et al. 2009). At the local scale, methodologies for assessing social vulnerability vary greatly with the context of the analysis and availability of the data. In the context of coastal flooding, Balica et al. (2012) have constructed a vulnerability index and applied it to a variety of coastal cities around the world. The index is composed of indicators of the natural system (exposure), the socioeconomic system (susceptibility) and the institutional system (resilience). A composite index is calculated to represent the vulnerability of the entire city.

At the local or community scale, vulnerability indices are typically composed of age, disabilities, income, occupation, race, family status, housing and infrastructure and lifelines (Clark et al. 1998; Chakraborty et al. 2005). Many studies attempt to synthesize these indicators and use factor analysis to cluster variables that measure the same theme (Cutter et al. 2003; Fekete 2009). After choosing the relevant indicators, the index is composed either by simply adding or averaging all components, or by assigning weights to each component, which requires subjective expert judgment. Rygel et al. (2006) use a Pareto ranking method in order to avoid subjective weighting. They rank each case in the data set by a composite indicator score that relates to all other cases. A thorough assessment of vulnerability analyses and indices, their data quality, scale compatibility and application have been presented elsewhere (Fekete 2012). Hinkel (2011) concurs that indicator-based social vulnerability assessment is useful for identifying vulnerable populations and communities but cautions against its use in the allocation of resources or policy. Cutter et al. (2003) make the case for social vulnerability indices to include place inequalities such as differential community growth rates and economic opportunities. As we conceive of 'community' as a socio-spatial entity, this implies that community vulnerability is composed of more than the sum of the individual vulnerabilities of its households. The value added of being part of a community can, in some instances, augment and in other instances, reduce individual vulnerability.

3 Study area

Our approach is applied to a variety of different-sized communities located along the Israeli Mediterranean coastal plain. We define communities as municipal jurisdictions, as much decision making and planning is implemented at this level. The empirical findings reported relate to flooding effects in two main areas: the city of Tel Aviv and a collection of different-sized coastal communities along the Northern coastal plain north of the city of Haifa (Fig. 1). These areas represent the most densely populated part of the country with the two metropolitan areas of Haifa and Tel Aviv covering the majority of the national coastline. The city of Tel Aviv is the second largest municipality in Israel with a population of 403,300 and a further 2,829,000 inhabitants in a metropolitan region that encompasses over 40 jurisdictions and local authorities. Note that a recent study analyzing potential flooding losses in major coastal cities by 2050 ranked Tel Aviv in 15th place in terms of the likely increase in average annual losses relative to 2005 (Hallegatte et al. 2013). Haifa is Israel's fifth largest city with a population of 264,700 and an additional 762,400 inhabitants in the metropolitan area, which includes suburbs and satellite towns in the low-lying Zevulun Valley to the north.

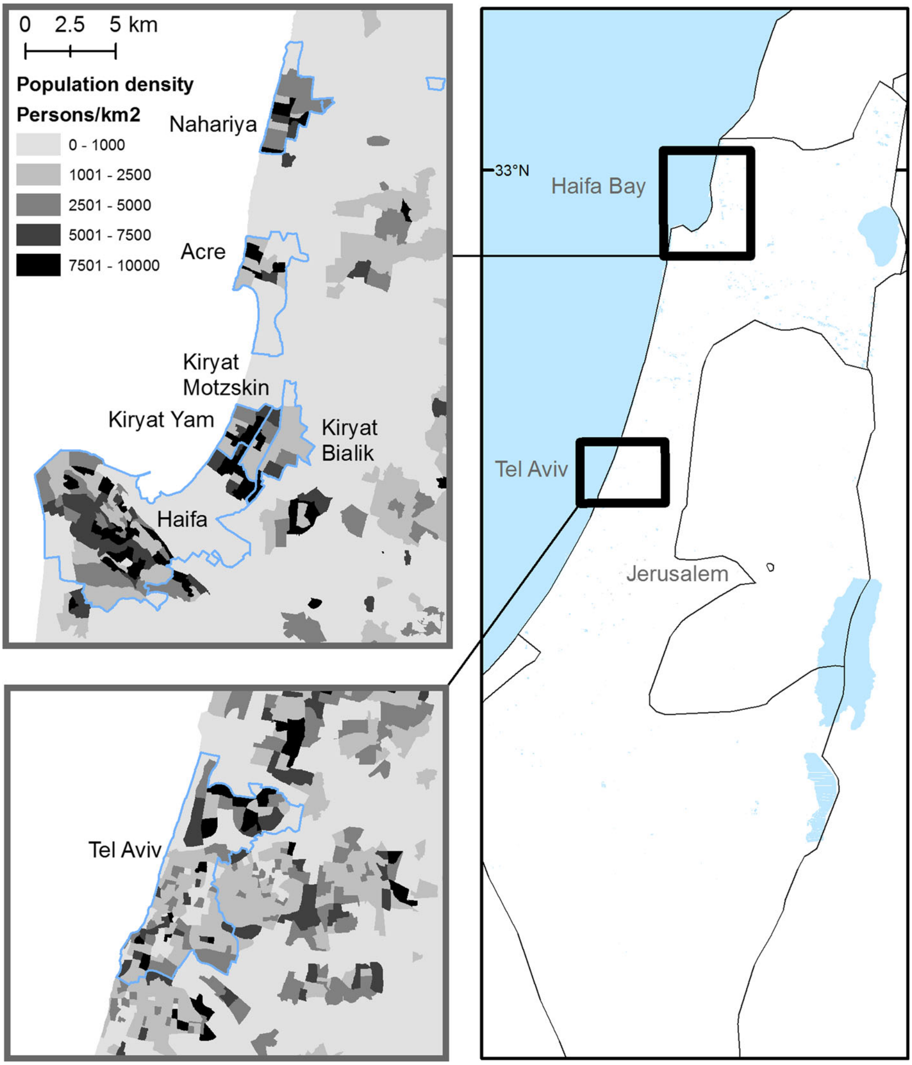

Fig. 1 The study area—municipal boundaries of selected cities presented in this study

The coastal plain, with the exception of the Haifa Bay, has a straight shoreline with relatively narrow beaches 20–100 m wide and up to 300 m in width in the vicinity of river mouths. The shoreline, which extends for 195 km, is characterized by 70-km-long aeolianite ridges backing the beaches. Tel Aviv, located in the central section of the coastal plain, has a relatively flat topography with the highest point of the city reaching an elevation of 62 m. The city is traversed by two rivers, the Yarkon and Ayalon which coalesce and drain to the Mediterranean. Haifa is characterized by diverse topography, as parts of the city are located on the Carmel Mountain range (max elevation of 546 m), which protrudes from the coastline forming Cape Carmel. North of Cape Carmel lie Haifa Bay and the Zevulun Valley. The main river flowing through the metropolitan area is the Kishon River which drains to the Mediterranean in the Zevulun Valley north of the city of

Haifa. This area houses a series of contiguous coastal suburbs collectively labeled the 'Krayot' but consisting of four separate municipalities of very different social complexions (total population 160,000). Ten km north of the Krayot lies the ancient port city of Acre which consists of 46,000 inhabitants and the town of Nahariya further north with a further 52,000 inhabitants. In addition to these, the Mateh Asher jurisdiction covers the rural area that fills in the coastal areas between the aforementioned towns (22,000 inhabitants).

The study areas are all parts of the low-elevation coastal zone (LECZ), i.e., the entire area below 10-m elevation that is hydrologically connected to the sea (McGranahan 2007). Comparing the LECZ with the national averages in terms of incomes and house prices (per sq m), the former is found to be higher on both counts: \$1,702 versus \$1,468 with respect to monthly earnings (per person) and \$2,228 versus \$1,946 per square meter in relation to average house prices. With respect to socio-demographic indicators, the averages are more ambiguous. The LECZ has a smaller share of <18 years population (21.8 vs. 33.4 % nationally) while at the other end of the demographic scale, the LECZ has a larger share of >65 residents (13.8 vs. 8.7 % nationally). In terms of physical disabilities, the LECZ share of visually impaired population is lower than the national share (0.46 vs. 0.52 %) but in terms of mobility impaired residents, the share in the LECZ (5.4 %) is higher than the national share (4.2 %).

4 Method

The roadmap of our method is presented in Fig. 2. At the outset, we assess the social and economic vulnerability of populations residing in flood hazard areas. Social vulnerability is

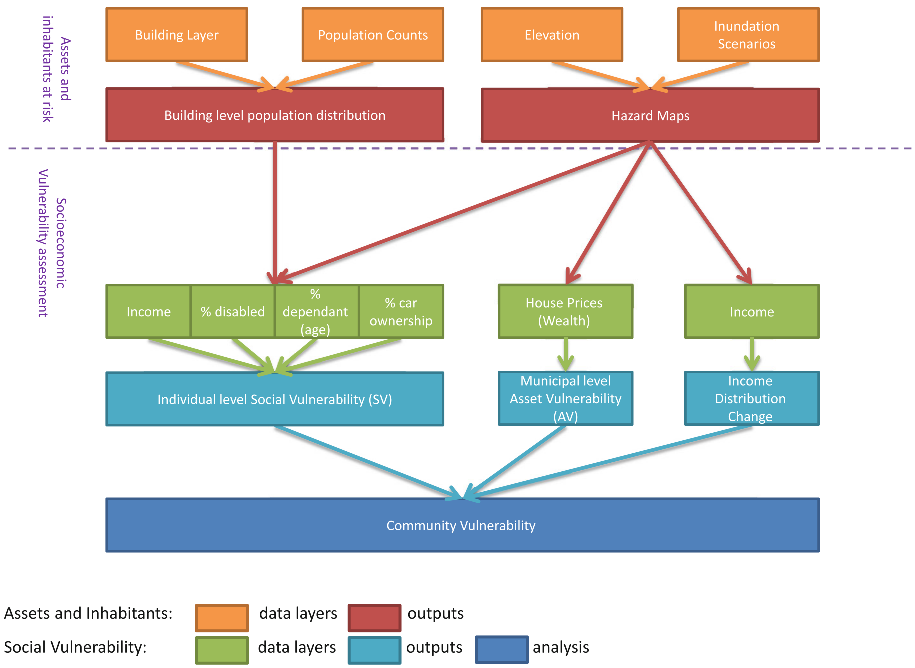

Fig. 2 Outline of method

assessed by a composite index that encompasses the leading variables likely to affect individual socioeconomic status and thereby ability to recover. It is captured at the micro-household level and aggregated to the community level. Economic vulnerability is assessed in two dimensions: wealth and income. These are captured at the community and national levels. The former is capitalized in value of residential stock. The latter is expressed in the change in income distribution in the community in the advent of inundation. Our approach differs to common social vulnerability index construction. Initially, we calculate an index that is grounded solely in socioeconomic indicators for individuals. These vulnerabilities are then spatially distributed within the spatial unit of analysis for different levels of flooding exposure as dictated by the flood hazard scenarios. In this way, the distribution of social vulnerability scores is more accurately represented rather than the alternative of presenting one aggregate score per spatial unit, which does not usually correspond with the exposed area.

The distinction between wealth and income effects is important as the relative weights and importance of these two components will vary by socioeconomic status. Lower-income groups are relatively more vulnerable to income losses as less of their wealth is capitalized in housing assets. The opposite is likely to be true for higher income groups. It should be noted that this approach is not hazard specific and that social vulnerability analysis of this kind can be used in any kind of hazard management context. The stages comprising the method are represented in Fig. 2.

4.1 Identifying relevant hazard zones

Sea-level rise projections for the twenty-first century vary in the range of 0.2–2 m (Rahmstorf 2007; Pfeffer et al. 2008; Grinsted et al. 2010; IPCC 2013), but fail to provide an accurate rate (Willis and Church 2012). We complement SLR projections with local scenarios of periodic flooding driven by extreme events of high tides (1 m represents a return period of 1:50 years (Golik and Rosen, 1999)) and tsunamis in the area (Salamon et al. 2007) in order to delimit flood hazard zones. The result is a range of flooding magnitudes in which SLR (permanent inundation) of different magnitudes is supplemented by flooding from periodic sources such as high tides or tsunami waves. We present results for the following combination of scenarios: 1 and 2 m SLR; a 1:50 year 1-m high tide superimposed over 1 and 2 m SLR and a 4-m tsunami superimposed over 1 and 2 m SLR. In addition, we delineate the LECZ as the area, which even if not directly flooded, might suffer residual effects due to its proximity. Note that our flood areas represent simple 'passive' inundation increments based on topography and connectivity to the sea and do not reflect actual flood areas. This is especially the case with respect to tsunamis where flooding processes are likely to be much more complicated and differentiated in outcomes along the coastline. The full methodology for identifying the flood hazard zones is described in Lichter and Felsenstein (2012). Dynamic visual representations of the flood hazard zones can be accessed online at http://ccg.huji.ac.il/dynamicmap/index.html.

4.2 Spatial representation of population and assets at risk

The basic spatial aggregate unit of the socioeconomic data used in this study is the statistical area (SA).[2] However, given the fact that flood scenarios do not necessarily

[2] A statistical area (SA) is a uniform administrative spatial unit defined by the Israeli Central Bureau of Statistics (CBS) corresponding to a census tract. It has a relatively homogenous population of roughly 3,000 persons. Municipalities of over 10,000 inhabitants are subdivided into several SA's.

correspond with SA boundaries and in order to count only those exposed populations and not all SA inhabitants, we use a GIS polygonal building layer provided by the Survey of Israel updated to 2009, to spatially re-distribute populations. This facilitates a more realistic spatial representation of the exposed population. The building layer provides land elevation, roof height and aerial footprint per building. On this basis, we calculate total floor space per building.[3] We proportionately allocate people and their socioeconomic characteristics to buildings on a per sq m basis, and then reaggregate to the necessary spatial configuration. This yields a spatially disaggregated picture of the social vulnerabilities of inhabitants by their socioeconomic attributes (disabilities, dependency, income level). The result allows us to generate data on community level vulnerability for each inundation scenario with a more accurate spatial distribution of inhabitants than hitherto available. Additionally, it allows us to accommodate spatial variation within a given SA and to isolate populations at risk when a flood hazard zone does not wholly cover an individual SA. This approach is also used for data relating to residential assets (number of units, floor space and value of capital stock).

4.3 Creating the social vulnerability (SV) index

We use four-key social variables to define social vulnerability at the statistical area level. These are average income, disabilities, age groups and number of vehicles per household. We divide the national distribution of each indicator into quintiles (1-least vulnerable, 5-most vulnerable) and assign each SA to its respective class. Following Cutter et al. (2003), we derive a weighted composite index as follows:

$$SV = I_i \times 0.5 + I_d \times 0.2 + I_a \times 0.2 + I_v \times 0.1$$

where: SV $=$ the composite vulnerability index, $I_i =$ income quintile, $I_d =$ disability quintile, $I_a =$ age quintile, $I_v =$ vehicle quintile. After ascribing a vulnerability score (SV) to each SA in the country, we divide national population into quintiles in order to ensure the same number of persons in each vulnerability category. This way, social vulnerability is assessed in relative terms, and each vulnerability category is equal to the other in terms of the number of persons it contains.

The source of all variables for the SV index is the 2008 National Census (CBS). Household income represents the most direct measure of social welfare. It is also correlated with other measures of socioeconomic status such as occupation, education, ethnicity, age and marital status (Masozera et al. 2007). Of the additional variables used, disabilities (I_d) describe the share of disabled persons in a statistical area. This combines the share of persons who are unable or have difficulty walking, hearing, seeing, have memory problems or unable to dress and shower independently. Age (I_d) depicts the size of the dependent population in the SA and combines the percentage of persons over 65 and under 18 in the SA. Vehicles (I_v) relate to the percent of households in a SA with one car or more. While this can be construed as a measure of wealth, it is also a measure of evacuation capacity in the case of an extreme event. We regard this indicator with caution. In large cities, for

[3] Following Lichter and Felsenstein (2012), building height (H_B) is calculated as follows: $H_B = H_R - H_L$, where: $H_R =$ building roof height, $H_L =$ building land height. The number of floors in residential buildings (F_R) is calculated by dividing building height by average floor height of 5 m: $F_R = \frac{H_B}{5}$

Floor space for each building (S_B) is calculated by multiplying the number of floors per building by its polygon area representing roof space: $S_B = S_R \times F$

where: $S_R =$ building roof space, $F =$ building number of floors.

example, it is not always an efficient indicator of wealth and some hazards (SLR for example) do not require sudden evacuation. Therefore, this indicator is assigned a weight of 0.1 in the overall index.

4.4 Asset vulnerability (AV) assessment

In properly functioning markets, the hazard effect associated with a location is capitalized in house value. While a hedonic pricing model would ostensibly catch this effect at an aggregate scale, for our scale of analysis, we opt for two approaches. First, we correlate house values with both vulnerability indicators and flood plain characteristics (elevation, gradient) in order to capture the spatial differentiation in vulnerability within the flood area. We look for statistical verification of the correlation between asset values and physical and social characteristics. We then proceed to estimate wealth vulnerability in the wake of a flood hazard. Following Kurban and Kato (2009), we estimate asset vulnerability (AV) as the adjusted marginal wealth loss of SA i in area j with initial wealth W_0, under flooding scenario (X) as:

$$\mathrm{AV}_{ij\left(X,W_{0ij}\right)} = \frac{\partial W_{1ij(X,W_{0)})} \Big/ \partial X}{\left[W_{1ij(X,W_0)} \big/ \underline{W}\right]^{1+\sigma}}$$

AV is a continuous measure of vulnerability. As wealth and flooding scenario vary, this will induce a unit change in AV. The numerator $(\partial W_{1ij}/\partial X)$ represents marginal loss due to hazard intensity represented by the different flooding scenarios. The denominator $\left(1/W_{1ij}/\underline{W}^{1+\sigma}\right)$ describes the relation between post-flooding asset value and a minimal asset poverty level, and σ denotes a normative policy measure. If $W_{1ij}/\underline{W} < 1$ then post-flooding wealth is below a socially acceptable level. If $W_{1ij}/\underline{W} > 1$ then post-flooding asset value is above a social minimum and the statistical area is not considered vulnerable. As the socially acceptable level of the policy measure is a normative choice, the value chosen for the policy weight (σ) is naturally critical. The larger the value of σ, the more policy attention is directed to those who fall below the critical value of $\underline{W}$ giving the measure a Rawlsian emphasis.

The question of whether the wealthy suffer greater absolute asset loss under the different flooding scenarios is ultimately an empirical issue. However, the relative impact is likely to be greater for those with lower value assets (Masozera et al. 2007). Additionally, a larger share of their net worth is tied up in their property, thereby increasing their vulnerability to flooding.

House price data relate to average sq m price per SA, 1997–2008. This is derived from a house price series made available by the Israel Tax Authority. This registers all housing transactions in nominal prices. Given the fact that not all SA's register transactions in certain years, we aggregate all transactions across each SA, divide by the average housing unit size in the SA and standardize all prices in terms of real 2008 values. In SAs with less than three annual transactions, coarser resolution regional-level data are used.

4.5 Income distribution effects

To investigate income distribution effects, we compute the Gini coefficients of the pre-flood income distribution for different topographical height increments of 0.5 m in the

LECZ.[4] We then impose the relevant flood zones pertaining to the different scenarios and recalculate the resultant Ginis. This involves generating transition conditions in order to create a post-flood distribution. Based on empirical evacuation behavior, individuals are redistributed according to the following decision rules:

Low-income residents: They move to the closest area outside the flood zone and are added to the income distribution of that area. This is because low-income residents tend to evacuate to a safe area as close to place of employment as possible (Lall and Deichmann 2009) and are less likely to return to their former place of residence post-flooding (Landry et al. 2007). Their housing assets are likely to be of low quality and non- or underinsured (Stein et al. 2010). Furthermore, for the poor, the most important factor in the evacuation decision is the monetary costs of dislocation and travel which this income group tries to minimize by moving short distances (Whitehead et al. 2000; Whitehead 2003).

High-income residents: They are disinclined to move due to their ability to afford flooding protection and mitigation measures. They are also likely to be home owners with full insurance coverage. Therefore, they are assumed to stay put to 'weather the storm' (Masozera et al. 2007). However, once a level of flooding reaches more than 2 m above current elevation, we assume they evacuate to the nearest height increment beyond the flood zone.

Middle-income residents: Given the evacuation behavior described above, under the flood scenarios, we distribute half of these residents to the closest area outside the hazard zone while the other half continue to reside in the zone. This condition holds as long as flooding is up to 1 m above current topographical elevation. Once flooding increases beyond this cutoff, we assume they move to the closest height beyond the flood hazard zone.

Income data by topographical elevation are made available by the CBS from tax authority data. Since this is micro-data for households, it cannot be made available on a municipal level but rather only as national totals due to privacy issues. The data were prepared in the following manner: our flood scenario maps were superimposed on a vector buildings layer. Incomes relating to each household were subsequently allocated to each geocoded building. Average income was then aggregated nationally by topographical elevation in 0.5 m increments. For each elevation class, the income distribution was calculated.

5 Results

5.1 Mapping social vulnerability

We calculate the shares of population in each vulnerability score category under the different SLR and EF scenarios. These results are presented for the two largest coastal cities in Israel (Haifa and Tel Aviv) in Table 1 and for a collection of smaller cities along the northern coastal plain in Table 2. As can be seen, the numbers of people affected are much lower in Haifa than in Tel Aviv for all levels of inundation with Haifa having 50 % of the Tel Aviv total inhabitants at lower flooding levels and 20–25 % at the higher levels. However, the population in Haifa seems to be highly concentrated at the high end of the

[4] We use the unweighted Gini index:
$Gini = \frac{1}{2n^2\bar{y}} \sum_{i=1}^{n} \sum_{j=1}^{n} \left| y_i - y_j \right|$
where y_i and y_j = income of group i and group j; $\bar{y}$ is the area average; n = overall income groups;.

Table 1 Total inhabitants and their percentage share in each vulnerability score category affected by different SLR and EF scenarios in the two largest coastal cities in Israel (Haifa and Tel Aviv) and national sums

	SLR permanent inundation	Municipality	Total inhabitants	% Inhabitants per social vulnerability index				
				1	2	3	4	5
SLR permanent inundation	1 m	Haifa	398	12	0	0	88	0
		Tel Aviv—Yafo	748	0	11	89	0	0
		National	4,330	8	3	25	43	21
	2 m	Haifa	1,308	7	0	0	86	7
		Tel Aviv—Yafo	2,512	8	29	62	0	0
		National	13,470	6	13	19	48	14
1:50 year 1-m high tide	1 m	Haifa	1,308	7	0	0	86	7
		Tel Aviv—Yafo	2,512	8	29	62	0	0
		National	13,470	6	13	19	48	14
	2 m	Haifa	1,997	6	0	0	88	6
		Tel Aviv—Yafo	5,636	9	29	62	0	0
		National	23,849	7	13	20	45	15
4-m tsunami	1 m	Haifa	5,584	3	0	1	82	15
		Tel Aviv—Yafo	26,754	32	32	34	0	3
		National	74,272	17	18	22	28	16
	2 m	Haifa	9,359	2	0	1	57	41
		Tel Aviv—Yafo	37,334	24	44	26	1	5
		National	11,3,512	16	24	21	23	16
LECZ		Haifa	31,746	19	18	1	35	27
		Tel Aviv—Yafo	111,187	20	43	26	7	3
		National	377,453	15	28	29	16	12

Table 2 Total inhabitants and their percentage share in each vulnerability score category affected by different SLR and EF scenarios along the northern coast of Israel

	SLR permanent inundation	Municipality	Total inhabitants	% Inhabitants per social vulnerability index				
				1	2	3	4	5
SLR permanent inundation	1 m	Acre	2,420		2		61	37
		Matte Asher	401	62		38		
		Nahariya	34	14	65		21	
		Qiryat Bialik						
		Qiryat Motzkin						
		Qiryat Yam						
	2 m	Acre	7,791		10	1	65	24
		Matte Asher	666	30		23	48	
		Nahariya	232	24	54		22	
		Qiryat Bialik						
		Qiryat Motzkin						
		Qiryat Yam	5				79	21
1:50 year 1-m high tide	1 m	Acre	7,791		10	1	65	24
		Matte Asher	666	30		23	48	
		Nahariya	232	24	54		22	
		Qiryat Bialik						
		Qiryat Motzkin						
		Qiryat Yam	5				79	21
	2 m	Acre	11,976		10	1	62	27
		Matte Asher	1,680	26		21	52	
		Nahariya	706	39	46		15	
		Qiryat Bialik						
		Qiryat Motzkin						
		Qiryat Yam	349				30	70

Table 2 continued

	SLR permanent inundation	Municipality	Total inhabitants	% Inhabitants per social vulnerability index				
				1	2	3	4	5
4-m Tsunami	1 m	Acre	21,833		7	15	46	32
		Matte Asher	2,947	22		21	57	
		Nahariya	4,947	35	43	6	16	
		Qiryat Bialik	863			96		4
		Qiryat Motzkin						
		Qiryat Yam	5,707		15	6	29	50
	2 m	Acre	24,493		6	21	45	28
		Matte Asher	3,228	21		25	54	
		Nahariya	11,201	20	50	16	14	
		Qiryat Bialik	4,588	28	13	30		29
		Qiryat Motzkin	866	80	20			
		Qiryat Yam	10,345	1	10	15	35	39
LECZ (10 m)		Acre	38,678		4	37	39	19
		Matte Asher	3,796	21		29	49	
		Nahariya	32,550	15	60	17	9	
		Qiryat Bialik	34,495	6	29	49		16
		Qiryat Motzkin	36,676	9	14	51		26
		Qiryat Yam	35,877	6	12	32	25	25

vulnerability scale especially at lower levels of flooding magnitude, than in the case of Tel Aviv. The population in Tel Aviv is proportionately less concentrated in high vulnerability classes. In contrast to Haifa, social vulnerability in Tel Aviv is much more heavily represented in classes 1–3 whereas in Haifa, 60–80 % of inhabitants in exposed areas are found in class 4. In this respect, Haifa is closer to the national picture, than is Tel Aviv (Table 1).

In the smaller cities, many inhabitants of Acre exposed in the different scenarios are in vulnerability categories 4 and 5 (>60 %) (Table 2). This is irrespective of the inundation scenario. In contrast, the similar-sized city of Nahariya has fewer inhabitants classified as socially vulnerable with the majority of them concentrated in SV classes 1–3. For the Krayot area, social vulnerability is not an issue for lower-level flooding scenarios, as exposure is minimal. Kiryat Yam is the most vulnerable of the Krayot cities and under the most extreme tsunami-level inundation has 5,000–10,000 inhabitants exposed (>75 % in vulnerability categories 4–5). This is the same magnitude of effect as in the case of Nahariya but with a very different level of social severity. For the other cities comprising the Krayot area, flooding only becomes a social issue at tsunami-type magnitudes with many more inhabitants at risk in Kiryat Bialik than in Kiryat Motzkin.

Mapping the social vulnerability scores yields further insights. The north–south wealth division in Tel Aviv emerges clearly with respect to the spatial patterns of incomes and vehicle ownership and also in the composite index (Figs. 3, 5a). For the Krayot area, an east–west division is discernible. Clearly, social vulnerability is highest in those communities astride the coast with Kiryat Yam a case in point. The vehicle, income and composite index maps all show this divide clearly, while physical disabilities do not reflect any clear spatial pattern (Figs. 4, 5b). As spatial variation within small statistical areas is often unknown to local decision makers and planners, the ability to accurately pinpoint pockets of disability or vulnerability provides valuable information.

5.2 Asset vulnerability under different scenarios

In order to estimate asset vulnerability, we initially identify residential assets, floor space and their value for the case study communities. Table 3 shows that whatever the scenario, Tel Aviv represents a large share of residential capital stock at risk. Consistently, Tel Aviv residential stock is above 50 % of total value, while accounting for roughly one-third of households and one-fifth of the number of buildings. Comparing Tel Aviv with Haifa, we find that at lower levels of flooding, residential floor space exposed in Haifa is similar to that in Tel Aviv but its value is much lower. At more extreme flooding levels, the number of buildings at risk and their value is much greater in Tel Aviv than in Haifa. Acre and Nahariya are similar-sized towns, less than 15 km apart but very different in terms of exposure levels with respect to number and value of residential buildings and households which are all greater in the former. At more extreme scenario levels, the total value of residences at risk in Nahariya is two-thirds that of Acre but representing only 20 % of households. For the Krayot area, at low levels of flooding, only Kiryat Yam is exposed. At higher levels, Kiryat Bialik residential exposure reaches 38 % of the value of Kiryat Yam but the former has only 16 % of households exposed and 42 % of buildings, in comparison with Kiryat Yam.

Mapping the spatial distribution of house prices for both Tel Aviv and the Krayot area (Fig. 5a, b) gives a much clearer picture in the former than the latter. For Tel Aviv, the north–south income divide is reiterated in the pattern of house prices with the wealthier assets of the northern part of the city, clearly differentiated from the southern sections (Fig. 5a). For the Krayot, the picture is less equivocal. Residential values are all generally

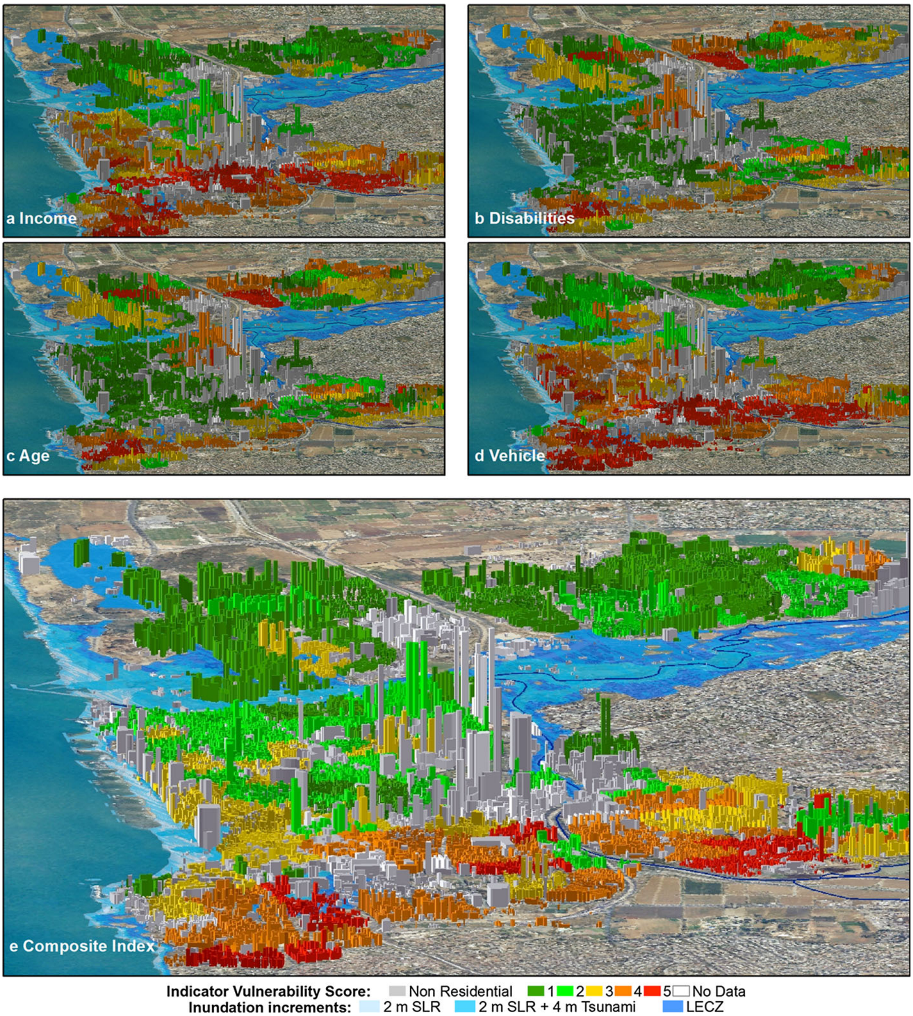

Fig. 3 The four vulnerability indicators comprising the composite vulnerability index (**a**–**d**) and composite index (**e**) in Tel Aviv

low (in comparison with Tel Aviv), but the east–west demarcation identified for some of the social variables is not represented in house prices (Fig. 5b).

Having identified residential assets, we then correlate them with the physical and social attributes of the area in which they are located. We choose average statistical area topographical (land) elevation and gradient (derived from the appropriate DEM model) to capture the physical attributes and average levels of disabilities in the SA population (mobility, visual impairment, etc.). These correlations are calculated for both the cases where relationships are not spatially explicit and for cases where they are spatially articulated, for example the impact of neighbors. In addition to correlations between asset value (wealth) and physical and social attributes, we also observe correlations between income and the same attributes. Table 4 shows that nationally, wealth and income are inversely correlated with topographical elevation and gradient and with average level of social

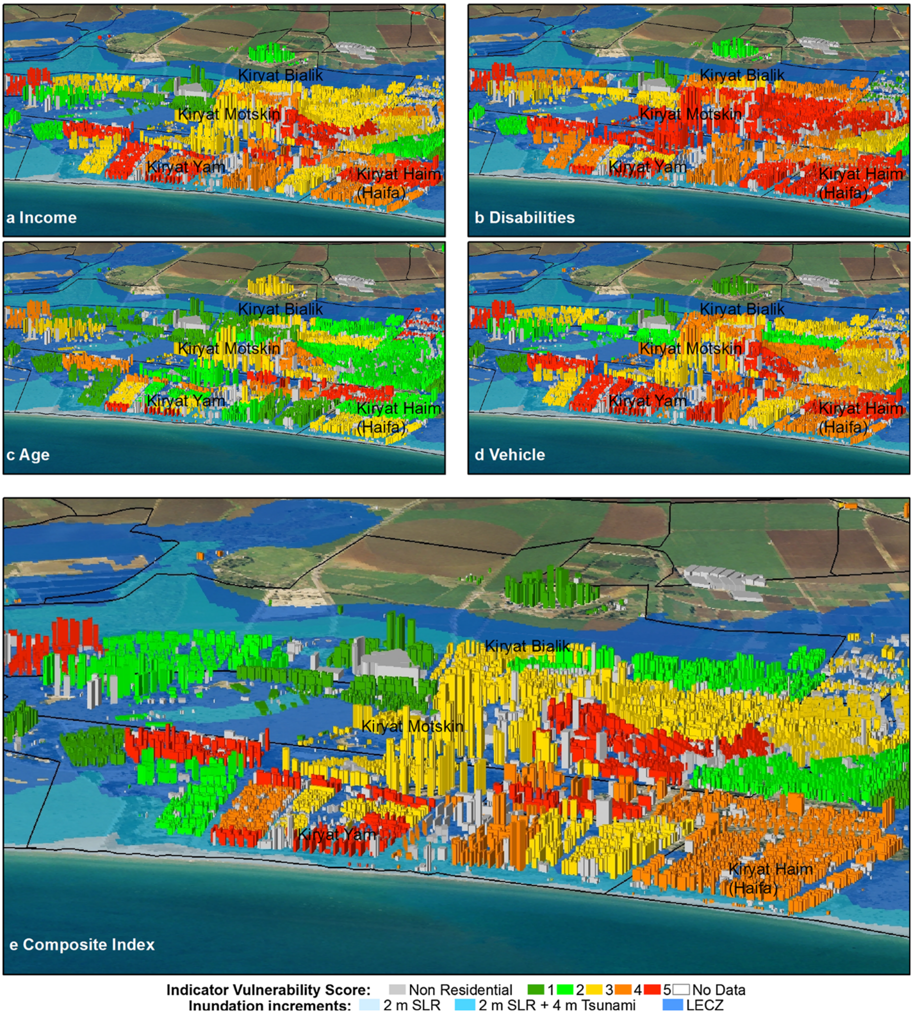

Fig. 4 The four vulnerability indicators comprising the composite vulnerability index (**a**–**d**) and composite index (**e**) in selected municipalities along the northern coast of Israel

disability. Thus, wealthier and less disabled populations tend to live in flatter lower elevation areas. This seems to match the popular conception of Israel's social geography whereby minority lower-income groups live in the internal hilly areas of the country (Galilee, Jerusalem, Zefat) and the more affluent colonize the coastal plains. However, at the coastal community level, things are more textured. In general, wealth and income are positively correlated with topographical elevation and gradient in Haifa and Krayot and inversely related to disabilities in all locations. In the case of Acre, the correlations between income and wealth and physical attributes are not significant while in the case of Tel Aviv, correlations of wealth are inconsistent.

We also investigate the spatial correlation using both univariate correlations (for example, the correlation of house prices with neighboring house prices) and bivariate correlations (the correlation between house prices and topographical heights in neighboring

Table 3 Residential Assets, value and floor space by municipality and scenario

	SLR permanent inundation	Municipality	Total residential building value (thousand US$)	No of households	No or residential buildings	Total residential building floor space (m^2)
SLR permanent inundation	1 m	Haifa	122,386	166	90	64,237
		Qiryat Bialik				
		Qiryat Yam				
		Qiryat Motzkin				
		Acre	55,934	770	65	62,043
		Nahariya	2,089	9	17	1,044
		Tel Aviv—Yafo	305,425	450	124	60,754
		National	485,834	1,395	296	188,077
1:50 year 1-m high tide	1 m	Haifa	200,824	515	201	108,228
		Qiryat Bialik				
		Qiryat Yam	74	2	2	75
		Qiryat Motzkin				
		Acre	184,592	2,735	310	184,062
		Nahariya	14,778	79	35	7,466
		Tel Aviv—Yafo	904,154	1,506	267	174,150
		National	1,304,423	4,837	815	473,982
4-m tsunami	1 m	Haifa	461,277	2,439	512	270,591
		Qiryat Bialik	40,217	367	76	24,512
		Qiryat Yam	108,065	2,322	183	101,862
		Qiryat Motzkin				
		Acre	455,388	7,595	758	460,091
		Nahariya	314,321	1,595	612	163,581
		Tel Aviv—Yafo	6,691,732	15,484	1,575	1,271,974
		National	8,070,999	29,802	3,716	2,292,611

Table 3 continued

	SLR permanent inundation	Municipality	Total residential building value (thousand US$)	No of households	No or residential buildings	Total residential building floor space (m^2)
LECZ		Haifa	1,803,823	12,485	2,648	1,128,367
		Qiryat Bialik	1,500,137	12,930	2,237	977,259
		Qiryat Yam	994,817	13,053	1,804	802,023
		Qiryat Motzkin	1,528,939	14,220	1,584	1,003,684
		Acre	908,317	12,514	1,753	867,875
		Nahariya	1,941,744	10,874	2,860	1,060,929
		Tel Aviv—Yafo	25,246,960	61,195	5,638	4,898,274
		National	33,924,737	137,271	18,524	10,738,411

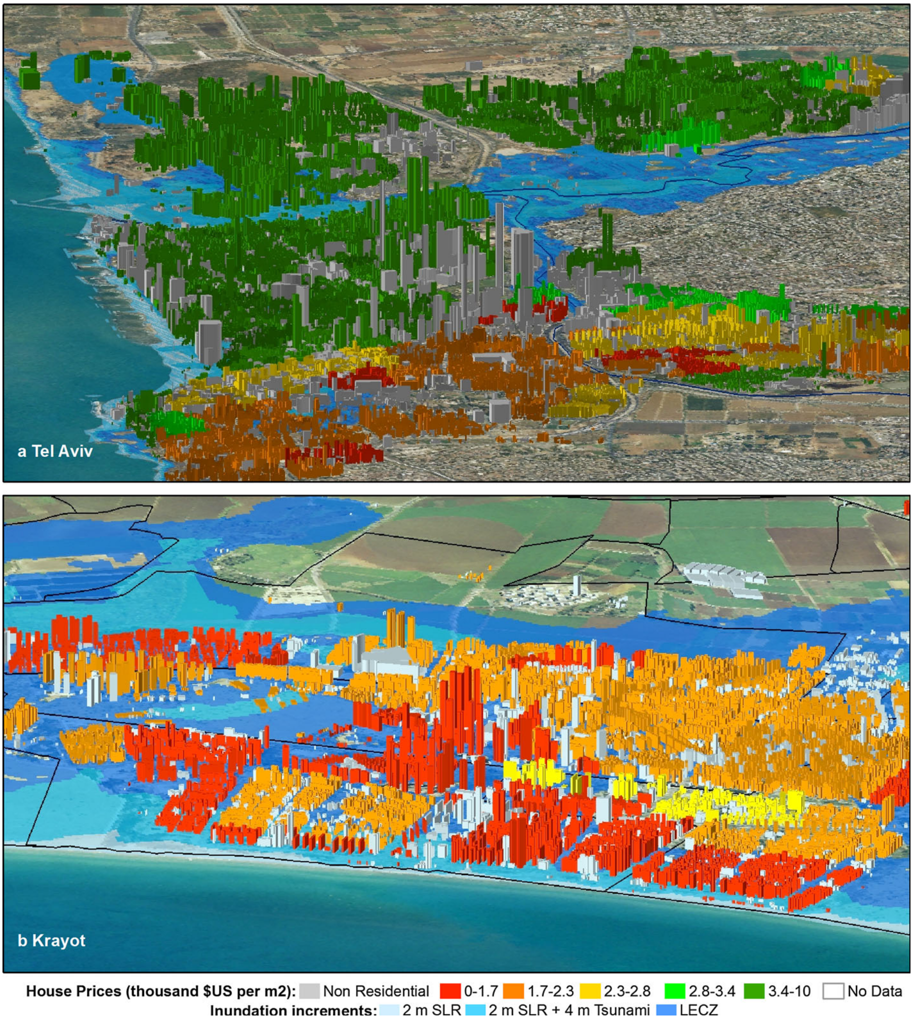

Fig. 5 Spatial distribution of house prices **a** Tel Aviv and **b** Krayot

observations) (Table 5). For the univariate spatial correlations, the Moran's I statistics (spatial correlation coefficients) are all positive as expected, but decrease in size as the study areas get smaller and contain less observations. The bivariate spatial correlations imply that asset wealth is negatively related to neighboring physical attributes in Tel Aviv but positively related to neighboring elevations in the case of Nahariya and Acre and inversely related to neighboring gradients. Asset wealth is also generally inversely related to neighboring levels of disability, a pattern that is consistent across all types of correlation. These correlations therefore underscore the fact that in contrast to the national pattern of asset wealth and income being inversely related to topographical elevation and gradient, in coastal communities the opposite seems to be the case. Populations with lower wealth and income are found closer to the coast line, with wealthier communities found along the coastal ridges, presumably in areas less exposed to flooding.

Table 4 Correlations: income and wealth with physical and social indicators

	Elevation	Gradient	Disabilities[b]
National[a]			
House price	−0.2854	−0.3042	−0.3241
Earnings	−0.1443	−0.1877	−0.2167
Tel Aviv[c]			
House price	−0.3411	0.1440*	0.4489
Earnings	0.3330	0.2810	−0.3619
Haifa			
House price	0.7835	0.2782	−0.4750
Earnings	0.6216	0.2408	−0.6143
Krayot			
House price	0.7515	−0.0359*	−0.4202
Earnings	0.5206	−0.2369*	−0.7429
Acre			
House price	0.0317*	0.3377*	−0.6334
Earnings	0.4549*	0.0622*	−0.5548

All non-spatial correlations significant ($p < 0.0001$), unless noted (*)

[a] Based on 197 local authorities

[b] Percentage population with disabilities (hearing, visual mobility, etc.)

[c] Tel Aviv, Krayot and Acre based on 146, 31 and 15 SA's, respectively

Table 5 Spatial correlations (univariate and bivariate)[a]: Income and wealth with physical and social indicators

	Moran's I[b]	Elevation	Gradient	Disabilities
LECZ				
House price	0.8807	0.0944	0.2277	−0.4598
Earnings	0.7101	0.3135	0.2301	−0.2495
Tel Aviv[c]				
House price	0.8067	−0.3427	−0.1522	−0.4494
Earnings	0.7741	0.2889	0.2205	−0.2486
Krayot				
House price	0.3482	0.3789	−0.2376	−0.1086
Earnings	0.2986	0.1958	0.2040	−0.1991
Acre				
House price	−0.0450	0.0946	−0.0824	0.0374
Earnings	−0.0552	0.2413	0.0513	0.0270

[a] Univariate: correlation between Y prices and neighboring Y (Moran's I);bivariate: correlation between Y and (spatially lagged) neighboring X (e.g., house prices and average height of neighboring unit)

[b]Moran's I is defined as: $MI = N/S_0 \sum_i \sum_j w_{ij} * (x_i - \mu) * (x_j - \mu) / \sum_i (x_i - \mu)^2$ where $S_0 = \sum_i \sum_j w_{ij}$(constant weight), N number of observations, w_{ij} Spatial weights based on aerial distances between centroid of the SA's, x_i, x_j observations i, j with average value μ

[c] Tel Aviv, Krayot and Acre based on 146, 31 and 15 SA's, respectively

Table 6 Asset recovery capabilities (post-event wealth versus asset poverty level $W_1/\underline{W}$) for flood zone areas in case study cities—no social preferences

Measure of $\underline{W}$	City	$\underline{W}_{(\$US)}$	$W_1/\underline{W}$		
			1 m SLR	1 m SLR + 1-m high tide	1 m SLR + 4-m tsunami
Average W_0 in city-1SD.	Acre	31,384,312	1.583681	1.578047	1.721541
	Krayot	62,712,420	2.048503	1.991568	1.673185
	Tel Aviv	171,178,168	2.631653	2.564393	2.421809
Overall Average W_0-1SD.	Acre	76,526,765	0.649482	0.647171	0.706019
	Krayot	76,526,765	1.678714	1.632057	1.371147
	Tel Aviv	76,526,765	5.886588	5.736137	5.4172

Table 7 Asset Vulnerability (AV) measures by scenario, minimum asset levels ($\underline{W}$) and range of social preference (σ)

Measure of $\underline{W}$	σ Scenario	0.1 1	0.1 2	0.1 3	0.2 1	0.2 2	0.2 3	0.3 1	0.3 2	0.3 3
Average W_0 in city-1SD.	Acre	0.77916268	0.66598	0.176052	0.744152	0.636281	0.166744	0.710714	0.607907	0.157927
	Krayot	0	0.20013	0.400213	0	0.186807	0.380134	0	0.174371	0.361062
	Tel Aviv	0.05657081	0.077725	0.082773	0.051353	0.07074	0.075766	0.046617	0.064382	0.069353
Average W_0 in city-1.2SD.	Acre	0.542814748	0.463964	0.122649	0.501666	0.428945	0.112409	0.463636	0.396569	0.103024
	Krayot	0	0.154484	0.308931	0	0.140846	0.286607	0	0.128411	0.265896
	Tel Aviv	0.035287527	0.048483	0.051632	0.030688	0.042272	0.045276	0.026688	0.036857	0.039703
Minimum W_0 in city.	Acre	0.453445922	0.387577	0.102456	0.412274	0.352512	0.092379	0.37484	0.320618	0.083293
	Krayot	0	0.087418	0.174815	0	0.07568	0.154001	0	0.065518	0.135665
	Tel Aviv	0.016804507	0.023088	0.024588	0.013661	0.018818	0.020155	0.011105	0.015337	0.016521
Overall AverageW_0-1SD	Acre	2.077011792	1.7753	0.469301	2.168614	1.854257	0.485926	2.264256	1.936725	0.503139
	Krayot	0	0.249126	0.498192	0	0.237217	0.482712	0	0.225877	0.467713
	Tel Aviv	0.023334252	0.03206	0.034142	0.019544	0.026922	0.028835	0.016369	0.022607	0.024352

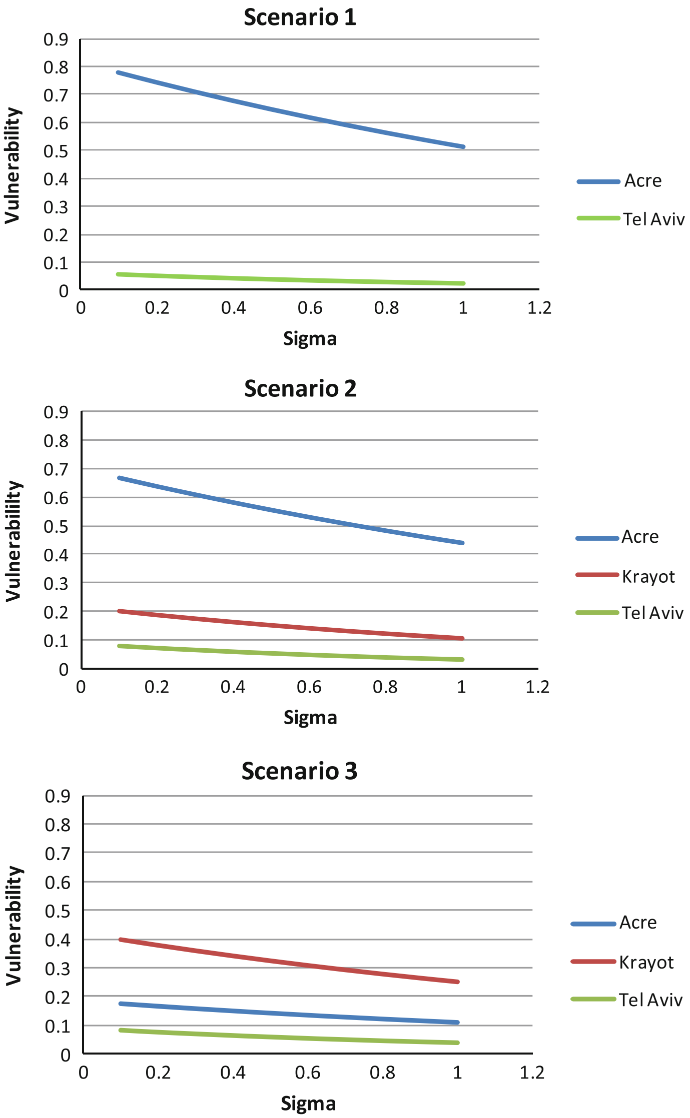

Fig. 6 AV measures for different levels of social preference

Given estimates of residential asset values for each statistical area (or share thereof) that fall in a flood zone (W_1), the pre-flood asset value (W_0) and a minimal asset poverty level ($\underline{W}$) that is subject to a normative policy weight (σ), we can estimate the asset vulnerability (AV) measure for each flooding scenario (X). The AV measures for two different poverty levels under three different flooding scenarios are given in Table 6 for the case study communities. Initially we present results for two different asset poverty levels but with no specific policy preference. The first is a place-specific asset poverty level where the minimum asset level is defined as one standard deviation (SD) below the city average residential capital stock level. AV scores are lowest for Acre and highest for Tel Aviv

Table 8 Income Distribution Effects of Flooding: Gini indices by Elevation Increments

Scenario	0.5 m	1.0 m	1.5 m	2.0 m	2.5 m	3.0 m	3.5 m	4.0 m	4.5 m	5.0 m	5.5 m
No flooding	0.3896	0.4386	0.4386	0.4581	0.4647	0.4659	0.4659	0.4696	0.4623	0.4705	0.4687
1 m SLR		0.2108	0.4338	0.4581							
1 m SLR + 1-m high tide			0.2025	0.2215	0.4387						
1 m SLR +2-m tsunami					0.1920	0.2216	0.4252				
1 m SLR +3-m tsunami							0.1750	0.2220	0.4649		
1 m SLR +4-m tsunami									0.2068	0.2202	0.4474

indicating higher vulnerability in the former. For all communities, these measures show a tendency to decline indicating the hardships of recovery as flooding becomes more extreme. When a general minimum asset poverty level is used (1 SD below the overall average for all observations), the results are much more volatile. For Acre, $W_1/\underline{W} < 1$, indicating the difficulties in recovery in that community, whereas for Tel Aviv, the high AV measures indicate the opposite.

Combining different levels of $\underline{W}$ with a range of σ for the different scenarios yields the AV measures reported in Table 7. We report these for $\sigma = 0.1$–0.3, and the full range is depicted in Fig. 6. AV measures naturally drop as σ increases but the most interesting insights refer to this rate of decrease and the magnitude of the measures. Figure 6 shows that even at low-level inundation, social preference can make a major difference in weak communities as can be seen for Acre in the 1 m SLR scenario. In contrast, for Tel Aviv, there is only minimal decline in AV despite greater social preference. In the case of the mid-level scenario, a similar picture emerges for Acre but the magnitude of the AV measures and the rate of their decline are more modest while the opposite is true for Tel Aviv. This seems to imply that higher levels of flooding lead to some convergence in AV across communities. At the most extreme level, vulnerability becomes even more homogenous across places and Acre becomes less vulnerable than the Krayot, for all levels of social preference.

5.3 Changing income distributions pre and post-flooding

In contrast to the foregoing, this analysis uses micro (household data) relating to over 46,000 households identified in the LECZ and allocated to buildings in order to accurately represent their spatial distribution. For the pre-flooding stage, we calculate the Gini indices of income distribution at each topographical height, in 0.5-m increments. From Table 8, we can see that income distribution worsens with elevation up to a height of approximately 5 m. Average annual income rises from less than \$16,901 at 1 m to over \$31,831 at 4.5 m leveling off to \$25–26,000 for topographical elevations in the 5–10 m range. We posit five flooding scenarios ranging from inundation levels of 1–5 m. These represent the post-flooding situation for which the Gini is recalculated.

Given the behavioral mobility rules for different income classes outlined above (Sect. 4.5) we proceed to ‘flood’ increasing areas and re-estimate the effect on income distributions. As the lower-income classes have a greater propensity to move in the wake of flooding, we expect a more unequal income distribution to develop through the cumulative effects of increased low-income mobility. The income effects of a flood are felt at the next height increment and thus for example, the income effects of a 3 m inundation will be felt at height increment of 3.5 m. The most radical effects relates to the growth in Gini for the flooded elevation and the increment directly above it. In all cases, floods more than double income inequality in the nearest flood-free high ground. This, however, increases at a slightly slower rate beyond an elevation of 4–5 m.

6 Conclusions

We make the case for distinguishing between social vulnerability and asset vulnerability. While the two are inherently linked in that socially vulnerable populations are also likely to suffer the greatest relative asset loss, we show that this is true at the community scale and not just for individuals. Community vulnerability is more than just the sum of the vulnerability of its individuals. Once individuals and their assets are displaced, social and economic traditions and conventions embodied in those individuals and institutions are also uprooted. Even if places recover in terms of population numbers, infrastructure and capital stock, the rejuvenation of these 'softer' factors is by no means assured.

Recovery means something qualitatively different to the mirror image of vulnerability. In this respect, a full understanding of vulnerability is one step toward recovery. Our findings show that while social vulnerability is correlated with physical attributes of place, asset vulnerability beyond a certain level of flooding affects all communities in a homogenous manner irrespective of their socioeconomic levels. Finally, we show income distribution effects are related to physical (elevation) attributes but are nonlinear beyond a certain critical level.

The implications of these findings for policy point to the limited impacts of engineering and regulatory 'fixes' in dealing with flooding situations. While speed of response, availability of shelter and public services are all important reactions, their range of effectiveness is limited either because physical attributes of a community render them ineffectual beyond a certain magnitude of shock or because their impacts have marginal decreasing effectiveness. It may be that improved social policy is the key to deal with natural shocks such as flooding. Ensuring a more equitable initial distribution of resources may be the most effective strategy for reducing vulnerability and exposure and increasing ability to cope.

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