Applied Geography 74 (2016) 56–64

Contents lists available at ScienceDirect

Applied Geography

journal homepage: www.elsevier.com/locate/apgeog

Integrating resident digital sketch maps with expert knowledge to assess spatial knowledge of flood risk: A case study of participatory mapping in Newport Beach, California

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A R T I C L E I N F O

Article history:
Received 26 August 2015
Received in revised form
7 July 2016
Accepted 9 July 2016
Available online 15 July 2016

Keywords:
Flooding
Flood perception
Public participation
GIS
PPGIS
Sketch mapping

A B S T R A C T

Public participation geographic information systems (PPGIS) have been increasingly used to assess resident spatial knowledge of environmental hazards and to validate and supplement expert estimates of hazardous areas with local knowledge, but few studies have demonstrated methods for directly comparing local and expert knowledge of the spatial distribution of hazards. This study collected PPGIS digital sketch maps of flood-prone areas from 166 residents living adjacent to the Newport Bay Estuary in Southern California to examine variations in spatial knowledge of flood risk. First, we assessed agreement among participants and found that residents of areas with a higher percentage of homeowner, older, and higher income residents had greater agreement regarding areas at risk of flooding. Second, we introduced composite indices to assess the agreement between participant sketches of flood-prone areas with modeled estimates of the distribution of flood hazards, and found that the level of agreement between local and expert knowledge varied by the scale of analysis and by personal and contextual factors. Respondents with higher educational attainment, household income, and homeownership were associated with greater agreement between resident sketch maps and expert estimates of hazardous areas. Results inform spatial aspects of flood risk planning and communication by demonstrating how digital sketch maps can be used to identify potential shortcomings of expert hazard models, as well as hazardous areas where resident risk perception may be weak.

1. Introduction

Sketch maps have been increasingly used in conjunction with digital mapping tools in environmental hazard research to characterize spatial awareness of environmental risk and to validate and supplement expert estimates of hazardous areas with local knowledge (O'Neill, Brennan, Brereton, & Shahumyan, 2015). This approach builds on the cognitive mapping research by geographers, urban designers, and environmental psychologists which used sketches or maps to provide important insights regarding how individuals perceive and orient themselves to their environment, and how such spatial perceptions are influenced by age, gender, economic class, familiarity, and physical and social aspects of the environment assessed (Appleyard, 1981; Golledge, 2008; Kitchin, 1994; Lynch, 1960). Sketch maps have also been used to help delineate neighborhood boundaries and perceptions of place (Coulton, Korbin, Chan, & Su, 2001; Haney & Knowles, 1978), assess spatial aspects of crime perception and fear (Curtis et al., 2014), and understand variations in spatial knowledge by travel mode (Mondschein, Blumenberg, & Taylor, 2010).

Although early studies required participants to sketch maps of their perceptions in a free-form fashion using a blank sheet of paper or on a hardcopy base map, in recent years sketch maps have been integrated with and analyzed using Geographic Information Systems (GIS). Researchers often digitize participant hardcopy sketch

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http://dx.doi.org/10.1016/j.apgeog.2016.07.006
0143-6228/

maps into GIS or have participants draw sketches and/or record spatial data directly into GIS using web-based tools which enable interactive and dynamic mapping (Brown & Kyttä, 2014; Cadag & Gaillard, 2012; Curtis, 2012). This shift has given rise to the field of public participation GIS (PPGIS), which engages non-experts using mapping technologies to identify spatial aspects of social and ecological problems (Brown & Kyttä, 2014; Elwood, 2006). PPGIS has been used as a decision support tool in the fields of agricultural systems (Debolini, Marraccini, Rizzo, Galli, & Bonari, 2013), coastal ecosystem management (Levine & Feinholz, 2014), and urban forest and greenspace management (Hawthorne et al., 2015).

A few environmental hazard studies have used participatory data collection integrating paper sketch maps and/or PPGIS to characterize spatial awareness of environmental risk, and to integrate local and non-expert knowledge into decision-making processes. Assessing resident spatial awareness and knowledge of hazards and hazardous areas is particularly important because it could improve our understanding of individual actions and decisions prior to and during a disaster event, inform public debate about flood risk management, help identify areas where public perceptions or science-based assessments might be weak, and contribute to research on how risk perception might affect variables such as mental heath or policy support (Blum, Silver, & Poulin, 2014). Moreover, given the prohibitive cost associated with hiring professional engineers to develop products such as fine resolution flood models, alternative tools such as PPGIS can be used to create cost effective preliminary flood hazard assessments that can be widely disseminated. Sketch maps and/or PPGIS have been used to collect information on spatial awareness of natural hazards including riverine flooding (Brilly & Polic, 2005; Hung & Chen, 2013) and volcanic hazards (Gaillard, 2008; Leone & Lesales, 2009). These studies compared spatial knowledge and risk perception across different respondents to support planning and decision-making, but they did not quantify the level of spatial agreement between sketch maps and official warnings systems or scientific forecasts.

A handful of studies has compared non-expert spatial environmental knowledge collected through sketch maps and/or PPGIS with knowledge from official hazard designations or historic impact zones to support decision-making. In the area of conservation planning, Brown (2012) found an error rate of only about 6% when comparing participant PPGIS locations of native vegetation to official land cover data (Brown, 2012), and Brown, Weber, and De Bie (2015) found that over 70% of PPGIS points identified as having biological/conservation value were aligned with modeled areas of high conservation importance (Brown et al., 2015). In the area of spatial awareness of flood risk, Ruin, Gaillard, and Lutoff (2007) asked 200 participants in Southern France to draw sketch maps of roads prone to flooding, and subsequently compared respondents' drawings with official sources. They found that motorists who traveled on short daily itineraries in close proximity to their residences had high flood risk perception (Ruin et al., 2007). Pagneux, Gísladóttir, and Jónsdóttir (2011) compared sketch maps of areas perceived to be at risk of flooding from 90 residents in Iceland with areas impacted by historic flood events, and found that spatial knowledge of the boundaries of previous inundations was very poor (Pagneux et al., 2011). O'Neill et al. (2015) collected sketch maps of areas vulnerable to inundation during a severe flood event from 305 participants in Ireland, and found significant deviations between the participant risk perceptions and the extent of a historic major flood (O'Neill et al., 2015).

Our research investigates the application of digital sketch maps of flood-prone areas collected from 166 residents living adjacent to the Newport Bay Estuary in Southern California as a potential decision support tool given increasing flood hazard in coastal areas due to climate extremes, extensive urban development, and sea level rise (Burby, 2002). This study has two objectives: (1) to assess the level of agreement among participants with regards to their perceptions of areas vulnerable to flooding, and (2) to assess the level of agreement between participant sketches of flood-prone areas with modeled estimates of the distribution of flood hazards. It contributes to the geography and environmental hazard literatures, as well as advances disaster response planning. First, given the limitations of flood hazard models (Gallien, Sanders, & Flick, 2014; Thompson & Frazier, 2014), it demonstrates how local knowledge of hazards could help validate and inform expert models by identifying potential model shortcomings and hazardous areas that may have been overlooked by the models. Second, it demonstrates how digital sketch maps can be used to identify hazardous areas where resident risk perception may be weak, and to inform spatial aspects of flood risk planning and communication.

2. Methods

2.1. Study area

This study focused on the highly urbanized low-lying coastal lowlands of the Newport Bay Estuary within the City of Newport Beach, California (Fig. 1) and is part of the Flood Resilient Infrastructure and Sustainable Environments (FloodRISE) research project to promote resilience to coastal flooding in Southern California. The city encompasses Newport Harbor, which includes the constructed islands of Lido Isle and Balboa Island, and the urban coastal lowlands of Balboa Peninsula. Large portions of the city are below extreme high tide levels, and one study estimates that four decades of sea level rise could transform the present 100 year flood event along this coast into an annual occurrence (Gallien et al., 2014; Tebaldi, Strauss, & Zervas, 2012).

2.2. Modeled estimates of the distribution of flood hazards

Our analysis incorporates two modeled estimates of the distribution of flood hazard in the study area: (1) 2009 areas predicted by FEMA (Federal Emergency Management Agency) to flood from an event with a 1% annual chance (100 year flood), and (2) 2014 areas predicted by our street-level FloodRISE model to flood from an event with a 1% annual chance (100 year flood). The FEMA flood hazard mapping approach for the Newport Beach site involved one-dimensional hydrologic analysis of ocean water levels considering storm surge, waves, and wave runup followed by mapping still water flood elevations along the coastline and urbanized embayment by applying an equilibrium mapping approach (Gallien, Schubert, & Sanders, 2011; National Research Council, 2009). FEMA flood hazard maps are used by lenders during real estate transactions, federal and state agencies, and the National Flood Insurance Program to determine whether a property is inside a Special Flood Hazard Area.

The FloodRISE model is a two-dimensional hydraulic model that was developed at the University of California, Irvine, and has been used in this project for flood hazard mapping in Newport Beach, California. The model relies on an unstructured grid of triangles, which can be locally refined for accurate topographic representation of the site's terrain and infrastructure geometries, such as streets and flood defenses. The model is also able to account for a wide range of flow regimes resulting from abrupt changes in topography like those caused by flood walls. The model has been previously validated for the modeling of storm tides and wave overtopping in Newport Beach (Gallien et al., 2014, 2011).

Results of our quantitative comparison of resident digital sketch

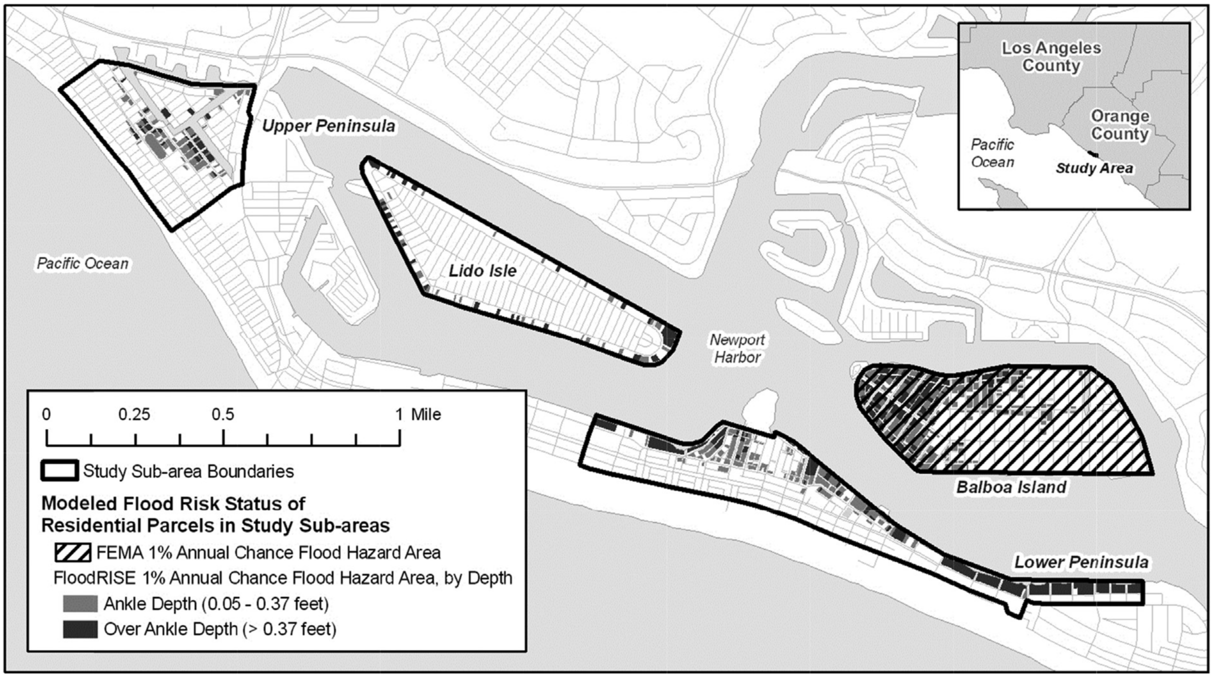

Fig. 1. Study sampling areas and modeled flood hazard estimates.

maps with each of the two modeled hazard estimates (i.e. FEMA, FloodRISE) could differ substantially since the predicted distributions of impacts are substantially different between the models. For example, although the FEMA model indicates all of Balboa Island is at risk, the FloodRISE model provides a more spatially refined street level estimate of at-risk areas and indicates that only some areas on the western portion of Balboa Island, the bayside of the Lower Peninsula sub-area, and portions of the Upper Peninsula sub-area are at risk (Fig. 1). Given that the FloodRISE model is more spatially refined, incorporates finer resolution topographic datasets, and accounts for coastal flood defenses, it could more accurately reflect local conditions and correspond with local knowledge. Residents may be more familiar, however, with the flood hazard designations by FEMA given these data are used by federal and state agencies, and are revealed as part of real estate transactions.

2.3. Survey design

Based on the distribution of residential parcels as well as the FEMA and FloodRISE estimates of areas at risk of flooding, the study area in Newport Beach was divided into four study sub-areas: Upper Peninsula, Lido Isle, Lower Peninsula, and Balboa Island (Fig. 1). These sub-areas were delineated to contain a comparable amount of residential addresses and parcels within and outside of the areas designated to be at risk by the models. About 25–40% of each sub-area's parcels are residential parcels that FEMA and/or FloodRISE models suggest could experience future flooding. Two island and two peninsula sub-areas were chosen based on the hypothesis that these areas could potentially have different experiences with flooding. The sub-areas each include about 33–50% multi-family residential parcels (remaining residential parcels are single-family residential).

We stratified our sample of parcels in an effort to gather an equal number of responses from island sub-areas and peninsula sub-areas. Within each of these sub-areas we stratified the sample further to obtain comparable responses from each of the following categories of parcels based on modeled flood hazard classifications: (1) those outside of both the FEMA and FloodRISE impacted areas, (2) those within the FEMA impacted area but outside the FloodRISE impacted area, (3) those outside the FEMA impacted area but within the FloodRISE impacted area, and (4) those inside both the FEMA and FloodRISE impacted areas. Although we initially sought to obtain a random sample of residents, we ultimately implemented quota sampling in order to obtain enough respondents in each of these four categories. To this end, in island sub-areas we oversampled parcels in category #3 and #4, whereas in peninsula sub-areas we oversampled parcels in categories #2. For island sub-areas we had a response rate of 7.5% resulting in 90 overall respondents. For peninsula sub-areas we had a response rate of 8.4% resulting in 102 respondents. Due to low response rates, we used limited snowball sampling in order to enhance our sample. We added 7 residents from the island areas and 15 residents from the peninsula areas to the sample based on snowball sampling, resulting in a total sample of 214 respondents. Although our final sample was not truly random, our survey provides valuable insights for understanding factors associated with spatial knowledge of flood hazards. Our final analysis sample for the current sketch map analysis included 166 survey participants (75 island residents and 91 peninsula residents) who provided complete responses for key questions regarding personal and household characteristics and the sketch mapping exercise. Specifically, the sample was reduced from 214 responses to 166 responses due to missing values caused by technical challenges (e.g. overheating of tablet units, program crashes, dead batteries) and/or data entry errors (e.g. entry of invalid respondent ID).

We sent a pre-notice letter to sampled households which described the purpose of the study and survey procedures, indicated the general time period when the survey team planned to visit the household's neighborhood to conduct surveys. During April, May and June in 2014, survey teams visited sampled households and knocked on participant doors or rang doorbells and invited a head of household who was 18 years or older to participate. Potential respondents could choose to complete the survey at that time, schedule a subsequent time the team could visit to complete the survey, or refuse to participate. Surveys lasted approximately 40–60 min.

During the mapping exercise each participant was asked to sketch areas that he/she considered to be at risk of flooding on a tablet computer. Rather than requesting participants to cognitively map out their neighborhoods or its hazards on a blank piece of paper without predetermined geographic reference points as was done by Lynch (1960) or Brilly and Polic (2005), we followed Bell (2002)'s recommendation to provide all participants with familiar pre-determined mapping control points and geographic boundaries within which they can sketch their perceptions and knowledge. Specifically, we provided respondents with an interactive map showing the study area boundary, major roads, and landmarks, and then asked them to sketch areas that were prone to flooding (Fig. 2). Unlike previous studies in which participants entered responses using a map at a static scale, our use of tablet devices enabled participants to interactively adjust the level of details (e.g. zoom in/out, pan) in the map as they sketched flood-hazard areas (Bell, 2002). Participant sketch maps were stored digitally in the ArcGIS Online cloud, and downloaded, processed, and analyzed using the ArcGIS Desktop software. Portions of participant sketch maps that were outside of the pre-defined study area were excluded for the purpose of analysis.

We also collected supplemental survey data about residents' risk, informational, personal, and contextual factors, which have been examined by previous studies on flood risk perception (Grothmann & Reusswig, 2006). Given the influence of personal and contextual factors on an individual's risk perception is not consistent across the literature (Wachinger, Renn, Begg, & Kuhlicke, 2013), we collected information on personal factors including age, gender, flood knowledge, and experience, and information on contextual factors including home ownership, residential location, and closeness to waterfront.

2.4. Agreement among participant sketch maps of flood hazards

In order to quantify the extent of agreement between our respondents' sketches, digital sketch mapping responses were combined, and vulnerable areas commonly sketched by different respondents were identified. We assessed agreement both for the study areas as a whole and for sub-areas since previous research cautions that results of spatial analysis could vary depending on the level of aggregation used (Brilly & Polic, 2005; Hipp, 2007; Houston, 2014). To the authors' knowledge, there is no universal approach for categorizing space based on sketch maps responses. Thus, we categorized the study area based on level of agreement quartiles, where areas included in 76%–100% of the sketches of flood-prone areas were considered areas of high agreement. Areas that were included in only 0%–25% of respondent sketches were considered areas of low agreement. Given previous research indicates that contextual factors such as place of residence may influence one's perception of flood risk (Wachinger et al., 2013) and one's knowledge of flood hazards in his/her immediate neighborhood (Brilly & Polic, 2005), we hypothesized that respondents from a particular sub-area will have high level of agreement with each other over the distribution of flood hazards within the sub-area in which they reside.

2.5. Agreement between participant sketch maps and modeled distributions

We developed three spatial alignment indices to assess and quantify the agreement between participant sketches of flood-vulnerable areas and modeled estimates of the distribution of flood hazards. In contrast to previous studies, our comparisons did not privilege one set of data as the gold standard against which local PPGIS knowledge should be compared. Instead, we assume that both modeled distributions of flood hazards and resident sketch maps provide important insights into the location of potential hazards. By understanding the causes of agreement (or lack of agreement) between expert models and resident sketch maps, we can provide the basis for future deliberation among residents, public officials, and emergency responders that supports greater integration of local and expert knowledge in our understanding, preparation for, and response to flood hazards.

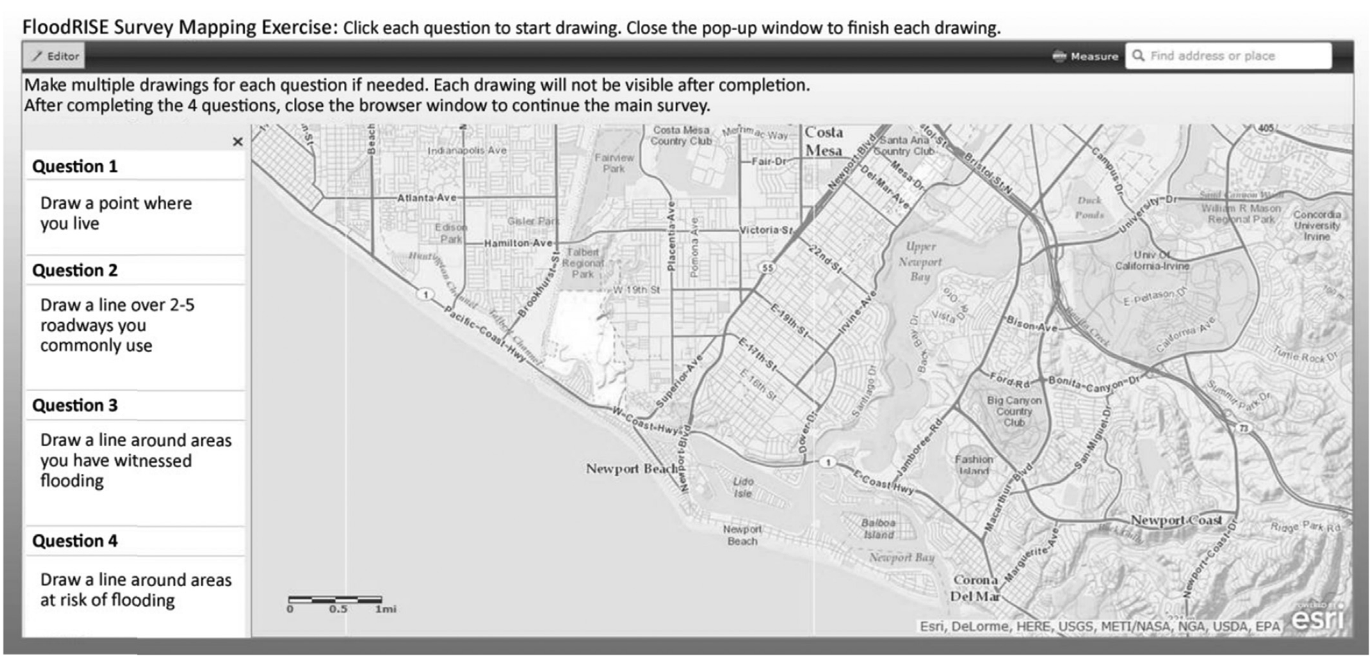

Fig. 2. Survey tablet computer mapping interface.

Our spatial alignment indices were developed for each participant based on whether the respondent's sketch of hazardous areas overlapped with modeled estimates of hazardous areas (Table 1). They were developed by designating three types of areas: (1) Alignment (A) areas, which are areas estimated to be hazardous by both participant sketches *and* the models, (2) Sketch Miss (SM) areas, which are areas estimated to be hazardous by the models but not by participant sketches, and (3) Model Miss (MM) areas, which are areas estimated to be hazardous by participant sketches but not by the models. The Sketch Alignment with Model (SAM) index is the proportion of all areas estimated to be hazardous by the models (A + SM) that were also identified as hazardous by a participant (A), and can be represented by this equation: $SAM = A/(A + SM)$. The Model Alignment with Sketches (MAS) index is the proportion of all areas estimated to be hazardous by participant sketches (A + MM) that were also identified as hazardous by the models (A), and can be represented by this equation: $MAS = A/(A + MM)$. The Composite Alignment Index (CAI) provides a more integrative perspective on spatial alignment, represents the proportion of the total areas estimated to be hazardous by participant sketches *or* the models (A + SM + MM) that was estimated to be hazardous by both participant sketches *and* the models (A), and can be represented by this equation: $CAI = A/(A + SM + MM)$. The value for these indices ranges from 0 to 1, where 0 indicates there was no spatial alignment in the hazardous areas estimated by the participant sketch and the models, and 1 indicates there was complete alignment in the hazardous areas estimated by the participant sketch and the models. Each index was calculated separately for the FEMA and FloodRISE model estimates.

Our use of composite indices improves on the methods of previous studies which conducted basic spatial comparisons of agreement between flood sketches and models (O'Neill et al., 2015; Pagneux et al., 2011; Ruin et al., 2007) or the analysis of self-reported (non-spatial) rating of risk perception (Burningham, Fielding, & Thrush, 2008; Grothmann & Reusswig, 2006). Our approach builds on confusion matrix or contingency table measures commonly used in fields such as atmospheric science, GIS, and remote sensing (Aghakouchak & Mehran, 2013). It enables us to take into account multiple sources of discrepancies, and provides additional insights into respondent's flood risk perception.

After the SAM, MAS, and CAI indices were calculated by comparing respondents' sketches with the FEMA and FloodRISE model distributions, average index values were calculated by taking the mean of the index values for respondents who were grouped by the study area, individual sub-areas, FEMA designated 100 year floodplain, FloodRISE modeled high and low impact zones, and various social and demographic groups. The Student's t-test was conducted to compare the various groups' average index values with the overall study area average in order to see if each group's average index value differed significantly from the study area's overall average.

3. Results

3.1. Participant characteristics by study sub-area

We analyzed responses from 166 survey participants who provided complete responses for the mapping exercise and key questions regarding personal and household characteristics and self-rated awareness of nearby areas at risk of flooding. The participants in our sample were similar to the overall study area population profile in the sense that they were older (median age of 58), had higher income (median income of $125,000), and were more educated (36% of respondents with graduate degrees or above) than the county's population (US Census, 2015). Results from *t*-test show differences across sub-areas. Namely, residents in the Upper Peninsula study sub-area were significantly younger, had lower income and a lower rate of homeownership, as well as lower self rated awareness of flood risk compared to the study area average. The Balboa Island sub-area had a significantly higher percentage of respondents who were homeowners, older, higher income, and had a higher self rated awareness of flood risk.

3.2. Agreement among participant sketch maps of flood hazards

We overlaid all participant sketches of areas they perceived to be at risk of flooding, and classified portions of the study area based on the percentage of participants who indicated a given area was at risk of flooding (Fig. 3). Visual analysis revealed that more than half of all participant sketches were in agreement that the southern portion of the Balboa Island sub-area was at risk, but less than one quarter of participant sketches were in agreement that the northern portion of the Upper Peninsula sub-area was at risk of flooding. Participant sketches revealed moderate agreement that the remainder of the study area was at risk.

Since previous studies support our hypothesis that contextual neighborhood factors such as one's residential location could influence one's perception of flood hazards, we examined the level of participant sketch map agreement separately for each of the study's sub-areas (Fig. 3). Results indicate over 50% of sketches from Balboa Island sub-area residents agreed that Balboa Island was at risk, and over 50% of sketches of Lower Peninsula sub-area residents agreed that most of the Lower Peninsula was at risk. Over 50% of sketches from Lido Isle sub-area residents agreed that the northern shore of Lido Isle was at risk, and interestingly, they agreed that the western portion of Balboa Island and most of the Lower Peninsula was at risk. Between 26 and 50% of sketches by participants from the Upper Peninsula sub-area indicated the entire study area was at risk of flooding, and unlike the other sub-areas, there was no majority consensus among Upper Peninsula residents (i.e. >50%) that the sub-area was at risk of flooding. This could reflect a low level of concern about flooding among Upper Peninsula residents, or this pattern could reflect that flood hazards identified by Upper Peninsula residents vary substantially.

The aggregated sketch maps for all study participants (Fig. 3) did not consistently overlap with estimates of locations at risk of flooding identified by FEMA and FloodRISE models (Fig. 1). The sketch maps for Balboa Island participants and FEMA estimates indicated that all of Balboa Island was at risk of flooding. Compared to the FloodRISE model, which indicated only the western half of Balboa Island was at risk, however, Balboa Island participant sketches could have overestimated hazardous areas. Although the sketch maps for Lower Peninsula residents were in agreement with FloodRISE estimates that the northern bay-side of the peninsula

Table 1
Components used to derive spatial indices to compare sketches and models.

		Respondent sketched/perceived area at risk of flooding	
		Yes	No
Models indicated area at risk of flooding	Yes	Alignment (A)	Sketch Miss (SM)
	No	Model Miss (MM)	True Null

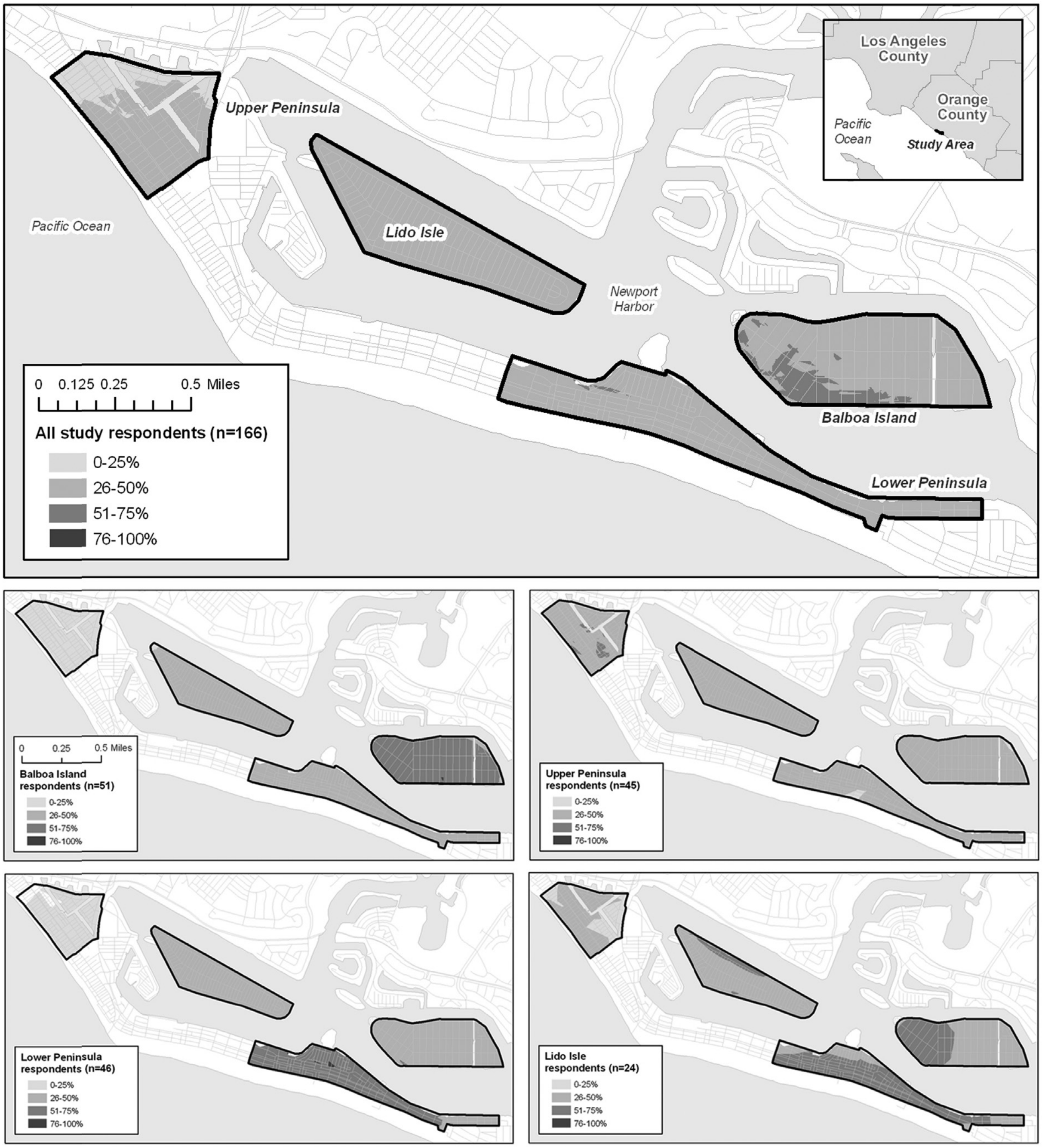

Fig. 3. Percentage of residents who agreed particular areas were at risk of flooding.

was at risk of flooding, sub-area sketch maps could have overestimated hazardous areas by indicating that the ocean-side of the peninsula (which models indicated were not at risk) was at risk of flooding.

3.3. Agreement between participant sketch maps and modeled distributions

3.3.1. Agreement by study sub-area

Given that aggregate participant sketch maps of hazardous areas diverge somewhat from estimates of hazardous areas identified by FEMA and FloodRISE models, we aggregated our respondent-level spatial alignment indices to examine differences between the average index value of survey participants from each subarea and the average index value for all survey participants. All results discussed in this section were statistically significant. Indices comparing FEMA and sketch estimates of hazardous areas indicate that there was consistently higher alignment among Balboa Island participants compared to the entire study population (Table 2). Their significantly higher SAM index (0.54 versus 0.42) indicates their sketches had higher alignment with FEMA model estimates compared to all study participants, and their higher MAS index (0.69 versus 0.39) indicates FEMA model results had higher alignment with their sketches. Balboa Island participants also had a significantly higher CAI index (0.34 versus 0.24), which provides a more integrative perspective of spatial alignment by comparing

Table 2
Agreement of flood prone areas by study sub-area: Participant sketch maps versus modeled distributions.

	Comparison with FEMA Model					Comparison FloodRISE Model				
	Entire study area	Balboa Island	Lido Isle	Upper Peninsula	Lower Peninsula	Entire study area	Balboa Island	Lido Isle	Upper Peninsula	Lower Peninsula
Total participants	**166**	**51**	**24**	**45**	**46**	**166**	**51**	**24**	**45**	**46**
Sketch Alignment with Model: SAM = A/(A + SM)	0.42	0.54*	0.44	0.29*	0.39	0.40	0.43	0.46	0.33	0.41
Model Alignment with Sketch: MAS = A/(A + MM)	0.39	0.69**	0.30	0.23**	0.28**	0.31	0.37**	0.27	0.30	0.27*
Composite Alignment Index: CAI = A/(A + SM + MM)	0.24	0.34**	0.23	0.15**	0.20	0.17	0.18	0.18	0.13*	0.17

Significance indicates that the sub-area index average is significantly different from the overall study area's average value. Significance level based on a two-tail *t*-test: $^{**}p < 0.01$, $^{*}p < 0.05$.

sketch areas to all areas designated as at risk by participants and the FEMA model. All three spatial alignment indices for Upper Peninsula participants were lower than those for all study participants combined, and the MAS index for Lower Peninsula participants was lower than that for all study participants combined.

The spatial alignment patterns when comparing FloodRISE and sketch map estimates by study sub-area were less distinct. Balboa Island participants had the highest MAS index (0.37) indicating that FloodRISE model results had higher alignment with their sketches; Lower Peninsula participants had the lowest MAS index (0.27) indicating that FloodRISE model results had lower alignment with their sketches. Upper Peninsula participants also had a lower CAI index than all study participants (0.13 versus 0.17).

3.3.2. Agreement by residence flood hazard designation

All three indices comparing FEMA and sketch estimates of hazardous areas indicate that there was consistently higher alignment among participants residing in an area designated by FEMA as a floodplain compared to all study participants (Table 3). Although there was no statistically significant difference in these three mean index values between residents who resided in a lower impact FloodRISE-designated floodplain (risk of ankle depth flooding, 0.05–0.37 feet) and all participants, residents who resided in a higher impact FloodRISE-designated floodplain (risk of knee depth flooding, 0.37–1.48 feet) had significantly higher SAM index and MAS index. This respectively suggests that the sketch miss and model miss among participants in the high impact areas are smaller than all study participants. The only significant difference in the spatial alignment patterns when comparing FloodRISE and sketch estimates was that participants in a FEMA-designated floodplain had a statistically higher MAS index, which indicates that a higher percentage of hazardous areas identified by sketches of participants in these areas were also classified as hazardous by the FloodRISE model.

3.3.3. Agreement by personal and household characteristics

We found no significant differences in the CAI index comparing FEMA and sketch estimates of hazardous areas and the CAI index comparing FloodRISE and sketch estimates of hazardous areas by gender, age, previous flood experience, self-rated flood awareness, length of home tenure, elevation of residence, and distance to the nearest water body (Table 4). Participants with higher educational attainment (a Bachelor's degree or higher), higher annual income (greater than $100,000), and participants who were homeowners had a statistically higher CAI average index comparing FEMA and sketch estimates, but the CAI index averages comparing FloodRISE and sketch estimates is only significantly different for participants with higher educational attainment.

4. Discussion

Our case study demonstrates how PPGIS digital sketch maps can provide valuable insights into the spatial knowledge of flood-prone communities. We found spatial knowledge of flood hazards varied substantially by the scale of analysis and by personal and contextual factors among residents living adjacent to a major coastal estuary in Southern California. Consistent with previous research indicating greater risk perception in areas of moderate or substantial flood hazard (Siegrist & Gutscher, 2008), we also found evidence that the sketch maps of residents living in areas at risk of higher-depth flooding had greater agreement with modeled hazard estimates.

We found that the CAI method was particularly informative because it takes into account alignment, sketch misses, and model misses in a single composite measure. This is important since we observed that the level of precision respondents used in creating

Table 3
Agreement of flood prone areas by modeled hazard designation: Participant sketch maps versus modeled distributions.

	Comparison with FEMA Model				Comparison FloodRISE Model			
	Entire study area	Within FEMA floodplain	Within FloodRISE low impact zone	Within FloodRISE high impact zone	Entire study area	Within FEMA floodplain	Within FloodRISE low impact zone	Within FloodRISE high impact zone
Total participants	**166**	**53**	**30**	**20**	**166**	**53**	**30**	**20**
Sketch Alignment with Model: SAM = A/(A + SM)	0.42	0.54*	0.44	0.61*	0.40	0.43	0.43	0.51
Model Alignment with Sketch: MAS = A/(A + MM)	0.39	0.68**	0.43	0.55*	0.31	0.37**	0.33	0.30
Composite Alignment Index: CAI = A/(A + SM + MM)	0.24	0.34**	0.23	0.33	0.17	0.18	0.17	0.19

Significance indicates that the hazard zone's index average is significantly different from the overall study area's average value. Significance level based on a two-tail *t*-test: $^{**}p < 0.01$, $^{*}p < 0.05$.

Table 4
Analysis of Composite Alignment Index (CAI) by socio-demographics.

Variable	Variable categories	Average FEMA CAI	Statistical results FEMA	Average FloodRISE CAI	Statistical results FloodRISE	Conclusion
Gender	1 = Female	0.27	t = −1.26,	0.17	t = −0.28, p = 0.78	No relationship
	0 = Male	0.22	p = 0.21	0.16		
Age	1 = ≥65 years	0.25	t = −0.38,	0.16	t = 0.93, p = 0.35	No relationship
	0 = <65 years	0.23	p = 0.70	0.17		
Educational attainment	1 = Bachelor's degree or above	0.26	t = −2.88,	0.18	t = −2.83,	Residents with higher educational attainment had higher CAI
	0 = Less than bachelor's degree	0.14	p = 0.0054	0.13	p = 0.0063	
Annual income	1 = Greater than $100,000	0.27	t = −2.07, p = 0.04	0.18	t = −1.71, p = 0.09	Higher income participants had higher FEMA CAI
	0 = Not greater than $100,000	0.19		0.15		No relationships with FloodRISE CAI
Flood experience	1 = Has experience	0.20	t = 1.68,	0.16	t = 1.01, p = 0.31	No relationship
	0 = No experience	0.26	p = 0.10	0.17		
Self-rated flood awareness	1 = Above slightly aware	0.24	t = −0.20,	0.17	t = −0.82, p = 0.42	No relationship
	0 = Slightly aware or below	0.24	p = 0.84	0.15		
Home ownership	1 = Home owner	0.27	t = −2.19, p = 0.03	0.18	t = −1.77, p = 0.08	Homeowners had higher FEMA CAI
	0 = Not home owner	0.19		0.15		No relationships with FloodRISE CAI
Length of home tenure	1 = ≥10 years	0.23	t = 0.23,	0.16	t = 0.10, p = 0.92	No relationship
	0 = <10 years	0.24	p = 0.82	0.17		
Elevation of residence	1 = Elevation above 10 ft.	0.20	t = 1.24,	0.17	t = 0.0038, p = 1.00	No relationship
	0 = Elevation below 10 ft.	0.25	p = 0.22	0.17		
Distance, residence to water body	1 = Within 100 m	0.24	t = −0.05,	0.17	t = −0.41, p = 0.68	No relationship
	0 = >100 m	0.24	p = 0.96	0.16		

Significance level based on a two-tail *t*-test.

their sketch maps varied. It is conceivable that a respondent who drew a small area as prone to flooding could receive a high MAS alignment score if the small area identified by the respondent's sketch was also identified as hazardous by the models. However, this participant would receive a low SAM alignment score since the sketch identified only a small portion of the overall area identified to be at risk by the models. For this reason, it is important to simultaneously account for alignment, sketch misses, and model misses using the CAI alignment score.

While this research produced important findings in the application of PPGIS and quantitative geography, there are some limitations to our study. Since study respondents were drawn from a nonrandom sample, and the studied community was comprised of relatively affluent and older residents who may be at relatively higher risk of flood hazards due to climate extremes, extensive urban development, and sea level rise, the findings from this study may not be generalizable to other communities that may have different socio-demographic composition or suffer from other forms of flooding (e.g. riverine flooding). Less affluent communities may have fewer resources to cope with flooding, and could be more likely to deny flood hazards in order to minimize the cognitive dissonance created by the intractable hazard. The high population density and high degree of urbanization of the Newport Beach coastal community, however, is typical of many coastal settlements. Thus, our findings and methodology might be transferable to coastal settlements with similar characteristics. Moreover, our study methods which value and integrate both expert and nonexpert spatial knowledge could be useful in future assessments of flood hazards in disadvantaged and diverse communities.

In summary, we believe that our approach of valuing and integrating both expert and nonexpert spatial knowledge in the assessment of flood hazards could foster greater collaboration between residents, public officials, and emergency responders, and could encourage a larger two-way communication process of flood hazards planning and communication between experts and nonexperts. Integrating resident spatial knowledge using tools such as digital sketch maps could be particularly important because it could shape individual actions and decisions during a disaster event. The identification and understanding of discrepancies between expert and nonexpert knowledge could not only inform the development of outreach strategies to build trust between experts and citizens, but could also reduce flood vulnerability by motivating individuals and communities to adopt self-protective measures against flood hazard.

Acknowledgements

The data used for this work were collected with support from the National Science Foundation under Grant No 1331611. Any opinions, findings, and conclusions, or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the National Science Foundation. The authors will also like to thank survey participants, our undergraduate hazard scholars, and Abigail Reyes and Kimberly Serrano for their invaluable support and advice throughout the data collection and analysis process.

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