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MULTIDISCIPLINARY APPROACHES TO COASTAL ADAPTATION

A dissertation submitted in partial
satisfaction of the requirements for
the degree of

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in

OCEAN SCIENCES

by

Juliano Calil

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The dissertation of Juliano Calil
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Professor Zdravka Tzankova

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Vice Provost and Dean of Graduate Studies

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Abstract

MULTIDISCIPLINARY APPROACHES TO COASTAL ADAPTATION

by

Juliano Calil

This dissertation contributes to the pressing need to improve the connections between quantitative scientific studies and policy in the context of human vulnerability to costal hazards, at multiple spatial and temporal scales. This dissertation integrates diverse tools and methods (including GIS, Machine Learning Clustering Techniques, and spatial indices), to assess risks and vulnerabilities of coastal communities to select natural hazards, at multiple geographies and scales (i.e. California, Florida, and Latin America and Caribbean). Statistically sound methods were applied to integrate data from multiple disciplines, including: natural hazards, geographical distribution of natural habitats, population, and assets, as well as socioeconomic vulnerability, providing insights to adaptation alternatives.

The first chapter of this dissertation demonstrates that flood losses in California could be mitigated through action that meets both flood risk reduction and conservation objectives. The study demonstrates that government funded buyouts, followed by restoration of targeted lands, can support social, environmental, and economic objectives: reduction of flood exposure, restoration of natural resources, and efficient use of limited governmental funds.

In the second chapter of this dissertation, a revised and improved version of the model developed in chapter 1 is applied to the state of Florida. In addition to flood exposure and natural habitats, social vulnerability was also included in the prioritization scheme. Further, inland habitats were also included, expanding the focus of the analysis beyond just the coast. Results identified lands in Florida that are eligible to receive federal funds to attain multiple benefits: (i) reduce flood risk to home owners; (ii) reduce FEMA's financial burden (from future flood claim payments); (iii) restore/protect natural habitats; (iv) remediate social vulnerability, and (v), identify potential sources of funding for projects. There were at least 10,000 km^2 of land in Florida where such objectives may be achieved simultaneously. In a targeted case-study our model identified 92 RLPs in Miami-Dade located in areas of high social vulnerability, high flood exposure, and where natural habitats coexist. Collectively, these 92 RLPs filed 207 claims against NFIP from 1978 to 2011.

In the third chapter, I employed a combination of machine learning clustering techniques (Self Organizing Maps and K-Means algorithms) and a spatial index (GIS), to assess coastal risks in Latin America and the Caribbean (LAC) on a comparative scale. The third study meets multiple objectives, including the identification of hotspots and key drivers of coastal risk, and the ability to process large-volume multidimensional and multivariate datasets - effectively reducing sixteen variables related to coastal hazards, geographic exposure, and socioeconomic vulnerability, into a single index.

Dedication

I dedicate this dissertation to my mom (who keeps sending me butterflies from heaven).

And to my wife Juliana, my sister Janaína, my brother Julio, and little Hanan.

Acknowledgements

I would like to express my deepest and most sincere gratitude to a few very special people, who were instrumental in the completion of this dissertation. I would not have finished this work without your combined support.

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INTRODUCTION

Backing away from estimates from less than a decade ago, the United Nations now predicts that the world population is unlikely to stabilize by the end of the century. The global population, currently at 7.46 billion, is increasing by nearly 230,000 people every day, at a growth rate of 1.18% per year [1]. In the next 15 years, the global population is expected to grow by an additional 1 billion, reaching 11.2 billion people by 2100 [1]. Concurrently, the number of people living in low elevation coastal areas, exposed to natural hazards, continues to increase [2]. There is a clear trend of coastal populations growing globally, with an estimated 230% increase (from 2000 to 2030) in the size of urban areas within the Low Elevation Coastal Zone (LECZ) - defined as "the contiguous area along the coast that is less than 10 meters above sea level", and which accounts for only 2% of the planet's total land area [3,4]. Moreover, critical infrastructure and valuable assets continue to be placed in areas exposed to coastal hazards [5].

In 2013, almost 22 million people were displaced by extreme weather events across the globe, with 37 events displacing at least 100,000 people each [5]. All but one of the top 15 largest events were either typhoons or floods, with at least three million people displaced from coastal areas [6]. In 2012, more than 30 million people were dislocated worldwide by climate or weather-related disasters [6]. From 1995 to 2015, worldwide losses resulting from minor but recurrent natural hazards, including flash floods, landslides, and storms, reached $94 billion [7].

A significant percentage of the expected global population will be exposed and vulnerable to coastal hazards by 2100. Therefore, it is becoming more and more important to devise accurate and effective ways to quantify and communicate coastal risks in a relevant manner, one that accounts for local, regional and international policies. Moreover, risks related to natural hazards are determined by a complex interaction between physical hazards, the vulnerability of a society or social-ecological system and its exposure to such hazards; these risks are amplified by challenging socioeconomic dynamics, including ill-advised urban development, income inequality, and poverty. There is a pressing need for studies that go beyond quantitative analyzes, studies that also consider governance realities and incorporate links to existing policies and societal realities.

This dissertation contributes to a pressing need to improve the connections between quantitative scientific studies and policy in the context of human vulnerability to coastal hazards at multiple spatial and temporal scales. Diverse tools and methods (including GIS, Machine Learning Clustering Techniques, and spatial indices) are utilized to assess risks and vulnerabilities of coastal communities to selected natural hazards at multiple scales (i.e. California, Florida, and Latin America and the Caribbean). Furthermore, statistically sound methods are applied to integrate data from multiple disciplines, including present physical hazards, population and assets exposure to such hazards, socioeconomic vulnerability and insights to adaptation alternatives.

"Aligning Natural Resource Conservation and Flood Hazard Mitigation in California" (Chapter 1) demonstrates that flood losses in California could be mitigated through action that meets both flood risk reduction and habitat conservation objectives. There are at least 11,243 km^2 of land in coastal California, which is both flood-prone and has natural resource conservation value, and where a property/structure buyout and habitat restoration project could meet multiple goals. In Sonoma County, for example, 564 km^2 of land meets these criteria. Further, we explore flood mitigation grant programs that can be a significant source of funds to such projects. Government funded buyouts followed by restoration of targeted lands can support social, environmental, and economic objectives, including reduction of flood exposure, restoration of natural resources, and efficient use of limited governmental funds.

In chapter 2, "Aligning Natural Resource Conservation, Flood Hazard Mitigation, and Social Vulnerability Remediation in Florida", a revised and improved version of the model developed in chapter 1 is applied to the state of Florida. In addition to flood exposure and conservation priorities, this chapter also prioritizes areas with high social vulnerability and includes inland habitats, expanding the analysis beyond the coast. Our results identified lands in Florida that are eligible to receive federal funds to attain multiple benefits: (i) reduce flood risk to home owners; (ii) reduce FEMA's financial burden (from future flood claim payments); (iii) restore/protect natural habitats; (iv) remediate social vulnerability, and (v), identify potential sources of funding for projects. We found at least 10,000 km^2 of land in Florida

where such objectives may be achieved simultaneously. In a targeted case-study our model identified 92 RLPs in Miami-Dade located in areas of high social vulnerability, high flood exposure, and where natural habitats coexist. Collectively, these 92 RLPs filed 207 claims against NFIP from 1978 to 2011.

Finally, in chapter 3, A combination of machine learning clustering techniques (Self Organizing Maps and K-Means algorithms) and a spatial index (GIS), are utilized to assess coastal hazard risks in Latin America and the Caribbean (LAC) on a comparative scale. The methods proposed in chapter 3 meet multiple objectives, including the identification of hotspots and key drivers of coastal risk, and the ability to process large-volume multidimensional and multivariate datasets, which effectively reduces sixteen variables related to coastal hazards, geographic exposure, and socioeconomic vulnerability, into a single index. This study demonstrates that in LAC, more than 500,000 people live in areas where coastal hazards, exposure (of people, assets and ecosystems) and poverty converge, creating the ideal conditions for a perfect storm. Hotspot locations of coastal risk, identified by the proposed Comparative Coastal Risk Index (CCRI), contain more than 300,000 people and include: El Oro, Ecuador; Sinaloa, Mexico; Usulutan, El Salvador; and Chiapas, Mexico. The results provide important insights into potential adaptation alternatives that could reduce the impacts of future hazards. Effective adaptation options must not only focus on developing coastal defenses, but also on improving practices and policies related to urban development, agricultural land use, and conservation, as well as ameliorate socioeconomic conditions.

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CHAPTER 1. ALIGNING NATURAL RESOURCE CONSERVATION AND FLOOD HAZARD MITIGATION IN CALIFORNIA.

Juliano Calil, Michael W. Beck, Mary Gleason, Matthew Merrifield, Kirk Klausmeyer, and Sarah Newkirk.

Abstract

Flooding is the most common and damaging of all natural disasters in the United States, and was a factor in almost all declared disasters in U.S. history. Direct flood losses in the U.S. in 2011 totaled $8.41 billion and flood damage has also been on the rise globally over the past century. The National Flood Insurance Program paid out more than $38 billion in claims since its inception in 1968, more than a third of which has gone to the one percent of policies that experienced multiple losses and are classified as "repetitive loss." During the same period, the loss of coastal wetlands and other natural habitat has continued, and funds for conservation and restoration of these habitats are very limited. This study demonstrates that flood losses could be mitigated through action that meets both flood risk reduction and conservation objectives. We found that there are at least 11,243km^2 of land in coastal California, which is both flood-prone and has natural resource conservation value, and where a property/structure buyout and habitat restoration project could meet multiple objectives. For example, our results show that in Sonoma County, the extent of land that meets these criteria is 564km^2. Further, we explore flood mitigation grant

programs that can be a significant source of funds to such projects. We demonstrate that government funded buyouts followed by restoration of targeted lands can support social, environmental, and economic objectives: reduction of flood exposure, restoration of natural resources, and efficient use of limited governmental funds.

Introduction

Flooding is the most common and damaging of all natural disasters in the United States [1]. Historically, floods have caused more economic loss to the nation than any other natural hazard and flooding has been a factor in almost all declared disasters in the U.S. [2]. Recently, several perilous and costly flood events including super storm Sandy and Hurricanes Irene, Ike and Katrina, have once again raised public awareness of the threats posed by coastal and riverine floods nationally. The average annual value of insured losses related to storms from 2007 to 2011 is $12.1 billion [3]. Direct flood losses in the U.S. in 2011 totaled $8.41 billion [4]. It is likely that with climate change the frequency of heavy precipitation will increase in some areas over the 21st century, and that the return interval of floods will be shorter thus increasing the frequency of such events [5].

In 1968, the National Flood Insurance Program (NFIP) was created in response to wide spread demand for private insurance resulting from a series of catastrophic flood losses early in the twentieth century [6]. From its inception in 1968 until December of 2011, NFIP insured a total of 5.58 million policies and paid more than $38 billion in claims [7]. In addition to covering flood losses, one of the objectives

of the NFIP was to encourage communities to adopt risk-minimizing measures by promoting floodplain management regulations to ultimately lower their flood risks [8], but for the most part, this has not occurred [9]. Partially because the NFIP has no strong provisions to guide development away from floodplains, many flood-prone areas of the United States are still subject to development [10] .

As a consequence of existing and ongoing risky development, 1% of all NFIP policies are classified as Repetitive Loss Properties (RLPs) [7] – a detailed definition of RLPs and recent NFIP regulatory updates can be found in S1 Appendix [11]. According to the Federal Emergency Management Agency (FEMA), from 1978 to 2011, 166,368 Repetitive Loss Properties across the U.S. filed 496,178 claims resulting in more than $12.1 billion in payments, an average of $24,386 per claim [7]. One out of every ten Repetitive Loss Properties has received more money in reimbursements than the estimated market value of their property [1]. This startling fact suggests that purchasing RLPs for restoration to open space would save FEMA, and U.S. taxpayers, money.

Currently, FEMA administers three Hazard Mitigation Assistance (HMA) grant programs: (i) the Hazard Mitigation Grant Program (HMGP), focused on post-disaster reconstruction efforts including mitigation measures to reduce future risk; (ii) the Pre-Disaster Mitigation (PDM) grant program, supporting activities that reduce overall risk of future natural hazard events; and (iii), the Flood Assistance Mitigation (FMA) grant program, focused on reducing the number of NFIP claims

[12]. In 2013, FEMA announced national grant opportunities for PDM and FMA of $23.7 million and $120 million respectively [13][14]. These funds may be used to acquire and remove or relocate structures away from risky areas [12], but to date that has not yet been a widespread activity [15]. Property acquisition and structure removal or relocation are the most permanent forms of mitigation, and are eligible activities under all three programs [12]. Nevertheless, from 1989 through 2011, only 28 acquisition projects were funded in California [15].

Protecting communities and private property from flooding has traditionally been accomplished through the use of fortifying structures (e.g., seawalls, dikes, and levees). However, natural habitats and ecosystems offer significant, and often overlooked and undervalued, protection, mitigating or buffering flood hazards [16–20]. Restored areas within the floodplain usually regain their natural function of attenuating floods and reduce cyclical flood damages [21]. The value of wetlands in protecting coastal communities against floods globally has been estimated at $6,923 per hectare per year [22].

While FEMA aims to protect people and properties from future floods and other disasters, the conservation community attempts to protect valuable threatened floodplain habitats and species. From the 1780's to 1980's California has seen the highest percent loss of coastal wetlands in the U.S., 91% [23]. This represents more than 4.5 million acres of wetlands lost [23]. Floodplain habitats and species are continuously under tremendous pressure from human impacts including: urban

development, agricultural expansion, water quality issues, and habitat fragmentation from dams and other physical barriers [24].

Until very recently, hazard mitigation plans and conservation project plans did not explicitly recognize the flood protective value of natural habitats, even though this value has been well documented [19,20,25]. Increasingly, conservationists and risk managers are looking for approaches to accomplish multiple objectives with a single project [21,26,27]. In addition, conservation groups, in particular the National Wildlife Federation and The Nature Conservancy (TNC), have engaged in FEMA policy under the premise that flood risk response has direct impacts on natural resources [28,29]. However, to date, the development of tools for flexible, multi-objective flood exposure reduction and conservation prioritization permitting the identification of projects with the greatest likelihood of success, has been limited.

Recent studies have presented spatially explicit models of flood risk with diverse focuses. Some studies produced maps of flood prone areas based on terrain and hydraulic models [30,31], while others evaluated the costs and benefits associated with the use of land conservation as a flood mitigation strategy (including the impacts of flooding on housing values) [26,32,33]. However, to our knowledge, the study presented herein is the first detailed spatial analysis in the context of existing policy instruments which may be applied to achieve multiple benefits.

Here, we examine the potential to identify projects with multiple objectives in which flood exposure is reduced and conservation benefits are achieved. We test an

approach for identifying developed and federally-insured lands that are prone to flooding and therefore not ideal for development, and where valuable natural resources, such as salmon habitat or estuaries, are also present. We examine whether, by defining appropriate flood exposure and conservation proxies, decision makers could identify and prioritize parcels and neighborhoods where flood exposure reduction and conservation objectives could be achieved simultaneously. Further, we describe federal funding programs that could be applied to achieve both flood mitigation and conservation objectives.

This study used coastal California as a model to evaluate the alignment between coastal flood mitigation and natural resource conservation because of the high number of RLPs and flood claims [7], and the many highly threatened floodplain habitats (e.g. saltmarsh) [23], including areas that support multiple salmonid species listed as either threatened or endangered [34]. By the end of 2011, more than 3,200 RLP owners in the state of California filed more than 9,000 claims against NFIP totaling $155.3 million [1]. The average claim payment was $21,200. At the same time, California hosts floodplain natural resources that provide important functions including water filtration, erosion control, pollution prevention and control, fish production, and recreation amongst many others [35]. Finally, California's Multi-Hazard Mitigation Plan (SHMP) contains several explicit objectives to integrate hazard mitigation and environmental protection, calling for solutions that enhance natural processes with minimal negative impacts on natural ecosystems [36].

Additionally, we present a case study focused on the Sonoma County, where flooding has been a historical problem dating back to 1862 [37]. During the last twenty years, Federal and state disaster declarations were made following 8 significant flood events affecting the county [37]. Sonoma County, which occupies roughly 1% of the total area of California, accounts for 27.5% of all RLPs and 32% of all NFIP claims in the state. Sonoma County also represents an area of significant critical habitat for biodiversity conservation [38], thus representing a high priority area in coastal California for multi-benefit restoration and hazard mitigation projects.

Materials and Methods

We used a weighted overlay spatial model developed in a desktop geographic information system (ESRI ArcGIS version 10.2) and applied it to the 21 coastal counties in California (total study area covers 94,500km^2). Based on multiple flood exposure and conservation components (details below), we developed two indices: The Flood Exposure Index (FEI) and the Conservation Priority Index (CPI). The model calculates the spatial extent of overlap (km^2) between selected indicators of conservation priorities and flood exposure. Each indicator of Conservation Priority and Flood Exposure received a score of 1 or 0, based on the occurrence or absence of the indicator as described in detail below. The FEI and the CPI have equal weight and vary from 0 to 10. These indices are intended to be qualitative and relative, rather than quantitative measures of any specific feature.

Using data from the FEMA's Repetitive Flood Claims program and Digital Flood

Insurance Rate Maps (DFIRM) [39], sea level rise projections from the California

Climate Change Center [40], and spatial data on natural habitats and other indicators

of conservation value in California, we examine the potential for projects with

multiple management benefits in which flood exposure is reduced and conservation

benefits are achieved.

1. Flood Exposure Index (FEI)

The FEI scores each grid cell in the study area according to multiple indicators of

exposure to flooding events (grid cells are 50m by 50m or $0.0025km^2$).

The FEI was calculated based on the following components (table 1):

Whether or not the area is in either the 100-year or 500-year floodplain, based on

FEMA's digital Flood Insurance Rate Maps (DFIRM) [39]. DFIRMs are developed

by FEMA based on detailed Flood Insurance Studies that include hydraulic,

hydrologic and wave height analyses to determine the water surface elevations for

the 100-year and 500-year floodplains [41,42].

Whether or not the area is in California's Coastal Zone, based on data from the

National Oceanic and Atmospheric Administration (NOAA) [43].

Sea Level Rise (SLR) projections at the year 2100, based on the "California Climate

Change Scenarios Assessment" of 2009 [40,44,45]. The SLR components include

areas projected to be below the mean high high water mark (MHHWM), and areas

projected to be inside the 100-year floodplain at the year 2100 (based on a projected

SLR of 1.4m). SLR projections are based on simulations of six global climate

models which were forced by the greenhouse gases emissions scenario A2 (high

emissions scenario) developed by the Intergovernmental Panel on Climate Change

(IPCC) [46], and have a considerable level of uncertainty attached to them (future

sea levels are very sensitive to changes in global temperatures resulting from

uncertain greenhouse gases emissions scenarios [40]).

RLPs and surrounding areas, based on data from FEMA's Repetitive Loss Program.

Areas surrounding RLPs (within 1,000m) were included in this index for three main

reasons; first, RLPs are point occurrences, which have no area associated with them.

By adding a buffer, we can ensure that the area of the flooded parcel is include in the

criterion; second, the accuracy of geographic coordinates of the RLPs data provided

by FEMA is roughly 100m by 100m (for latitude and longitude); third, the exposure

of areas adjacent to RLPs is also high and not all properties in the surrounding area

may be insured, or have filed multiple claims against the NFIP, and therefore would

be absent from the RLP dataset.

An overall FEI was calculated by summing up the values of individual flood

exposure indicators within each grid cell according to the following equation

$$FEI = F100 + F500 + RLP + CZ + SLR1 + SLR2$$

(1)

where F100 represents the 100-year floodplain score, F500 represents the 500-year floodplain score, WL is the wetland score, RLP is the proximity to RLPs score, CZ is the coastal zone score, SLR1 is the area inside the MHHWM at the year 2100 score, and SLR2 is the areas projected to be inside the 100-year floodplain at the year 2100 score. FEI score values range from 0 to 6 (Table 1) and were scaled to range between 0 and 10 to balance its weight with that of the CPI, which also ranges from 0 to 10 (details below). The FEI score values were scaled according to the following feature normalization equation:

$$Flood\ Exposure\ Index = \frac{(X - Min)}{(Max - Min)} * 10$$

(2)

where X is the value of the FEI for each grid cell before the normalization, Min is the minimum value of the index before normalization (i.e. 0), and Max is the maximum value of the index before normalization (i.e. 6).

Table 1. Flood Exposure Index (FEI).

FEI Components – data sources in parenthesis	Score
Area located within the 100-year Floodplain (FEMA)	1
Area located within the 500-year floodplain (FEMA)	1
RLPs and surrounding areas (1,000m buffer) (FEMA)	1
Area located in the California Coastal Zone (NOAA)	1

Area inside the projected MHHWM at the year 2100 (California Climate Change Center)	1
Area located inside the projected 100-year floodplain at the year 2100 (California Climate Change Center)	1
Maximum possible FEI score	**6 Points**

2. Conservation Priority Index (CPI)

There are many conservation prioritization schemes, developed by diverse institutions for multiple purposes [47–51]. Recognizing this variety, we demonstrate the flexibility of our approach by evaluating conservation priority in two ways. First, we used generally available raw spatial data representing natural resources and land cover to develop a unique CPI (Table 2). Second, we used TNC's Priority Areas [47,52] as an alternative, pre-existing prioritization scheme[47].

The CPI was calculated based on the following components (table 2):

 Areas located inside estuaries (excluding water bodies), based on spatial data from the National Wetlands Inventory (NWI) produced by the U.S Fish and Wildlife Service [53].

Areas Located inside wetlands (excluding deep water marine and lake interior), based on data from the Coastal Change Analysis Program (CCAP) produced by NOAA [54].

Presence of salmonids, based on current and historical observations and expert opinion data from the Wild Salmon Center (WSC) [55]. There are three species of

salmonids included in the study (Coho, Steelhead, and Chinook), which may be observed at different locations at different seasons of the year.

Area covered by sand dunes, based on TNC's northern California Current Ecoregion Assessment [56].

Urbanization level, based on data from the Coastal Change Analysis Program (CCAP) produced by NOAA [54]. Areas with urbanization levels lower than 50% received a score of 1.

Every grid cell received a unique value for each Conservation Priority component. An overall CPI score was calculated by summing up conservation components scores according to the following equation:

$$CPI = ES + WL + SM1 + SM2 + SM3 + SM4 + SM5 + SM6 + S + U$$

(3)

where ES represents the Estuaries score, WL is the Wetlands scores, SM1 through SM6 are the individual Salmonid scores, S is the Sand Dunes score and U is the Urbanization score. CPI score values can range from 0 to 10 (Table 2).

Table 2. Conservation Priority Index (CPI)

CPI Components – data sources in parenthesis	Score
Area Located Inside Estuaries (U.S Fish and Wildlife Service)	1
Area Located Inside Wetlands (NOAA)	1
Salmon – Presence of Coho (WSC)	1

Salmon – Presence of Steelhead in the winter (WSC)	1
Salmon – Presence of Steelhead in the summer (WSC)	1
Salmon – Presence of Chinook in the fall (WSC)	1
Salmon – Presence of Chinook in the spring/summer (WSC)	1
Salmon – Presence of Chinook in the winter (WSC)	1
Area covered by Sand Dunes (TNC)	1
Areas with Urbanization Levels lower than 50% (NOAA)	1
Maximum Possible CPI Score	**10 Points**

We have assigned uniform weights to each conservation criterion of the study. However, scores and weights can be adjusted to reflect conservation values of specific communities or conservation programs. A large proportion of CPI weight (60%) is based on the presence of three salmon species listed as either Endangered or Threatened. This specific prioritization scheme reflects the high restoration value of salmonid habitats and their special status under the Endangered Species Act (ESA). ESA mandates the identification and protection of all lands water and air necessary to recover endangered species [57]. Other applications of the method introduced here may consider other relevant criteria to calculate indices that reflect specific stakeholder's interests.

In addition, to further illustrate the flexibility of our approach, we included an example of an existing conservation prioritization scheme in the study. We used TNC's Priority Areas, [47] which were developed through comprehensive eco-

regional assessments of species and habitat types [58]. Grid cells within a TNC Priority Area were given a score of 10. Because we use this index only to evaluate the spatial overlap between TNC Priority Areas and the FEI, our use of a Boolean data type is justified.

3. Spatial Model Description

All the spatial data layers described above were converted into raster format (grid cells), throughout the study area, each raster cell was attributed with three final scores representing Flood Exposure Index (Table 1), Conservation Priority Index (Table 2), and TNC's Priority Areas.

The spatial extent of overlap between the FEI and the CPI was calculated by multiplying the CPI raster by the FEI raster, and can potentially vary from 0 to 100. Grid cells with scores equal to zero (indicating total absence of Conservation Priority, Flood Exposure, or both), resulted in a zero value, indicating no overlap between the two scores. The spatial extent of overlap between TNC's Priority Areas and the FEI was calculated in a similar way, by multiplying TNC's Priority Area raster values (0 or 10) by the FEI (0 to 10) in each grid cell. The final step in the calculation was the multiplication of the number of grid cells in the resulting raster by the area of each grid cell.

Additionally, we analyzed the distribution of Repetitive Loss Properties throughout our study areas and how their distribution relates to our three categories (Conservation Priority, Flood Exposure and TNC's Priority Areas). Finally, we

chose Sonoma County, the county with the highest number of repetitive loss claims in California, to conduct a focused case study. The same methodology used in the broader study area was applied in the case study.

Results

We found that there are at least 11,243 km^2 in coastal California which represent both flood exposure reduction and conservation value, and where property/structure buyouts and habitat restoration projects would meet multiple objectives. This area covers almost 12% of the total study area of 94,500 km^2, with the extent of land decreasing as each score increases.

We scored areas in the 21 coastal counties of California based on flood exposure and conservation priority, and applied the spatial model described above to calculate the areal extent of overlap between them in order to prioritize potential areas for multiple-benefit projects, which accomplish both flood mitigation and conservation or restoration of natural habitats.

Areas that scored at least 1 point for both Flood Exposure and Conservation Priority intersect extensively in the 21 coastal counties of California. For example, the area of overlap between the Flood Exposure Index greater than 1 and the Conservation Priority Index equal to or greater than 5, is 954 km^2. The highest priority areas for both indices (FEI ≥5 and CPI ≥ 5) covers 340 km^2 (total area calculated from Fig. 1).

Fig. 1. Area of overlap between CPI and FEI scores greater than or equal to 5.
CPI scores equal to 7 and FEI scores equal to 6 and 9 did not occur in the study area, therefore are not shown in Fig. 1.
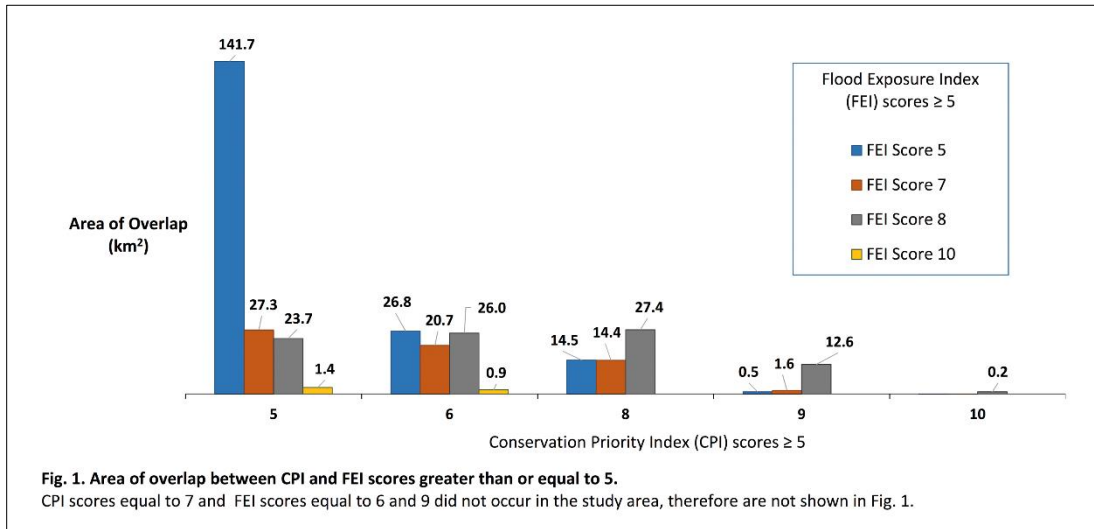
Figure 1. Area of overlap between CPI and FEI scores greater than or equal to 5. CPI scores equal to 7 and FEI scores equal to 6 and 9 did not occur in the study area, therefore are not shown.

Additionally, we substituted a score based upon a pre-existing conservation prioritization scheme (TNC's Priority Areas) for the CPI briefly described above (see Materials and Methods). In coastal California, the overlap between TNC's Priority Areas and areas where the FEI scores greater than 0 covers an area of 3,665km^2 (total area calculated from Fig. 2). This extent is much smaller than the total coverage of TNC's Priority Areas (more than 40,000 km^2), across the entire study region. If we focus only on areas where TNC's Priority Areas overlap with high FEI scores (overlap scores > 50), the resulting area is roughly 218 km^2, spread across 15 coastal counties. Moreover, if we focus on areas where TNC's Priority Areas overlap with very high Flood Exposure score (overlap score equal 100) the resulting area is only about 10 km^2, spread across 8 coastal counties.

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Fig. 2. Area of overlap between TNC's Priority Areas and FEI greater than or equal to 1.
FEI scores equal to 1, 4, 6 or 9 did not occur in the study area, therefore are not shown in Fig.2.
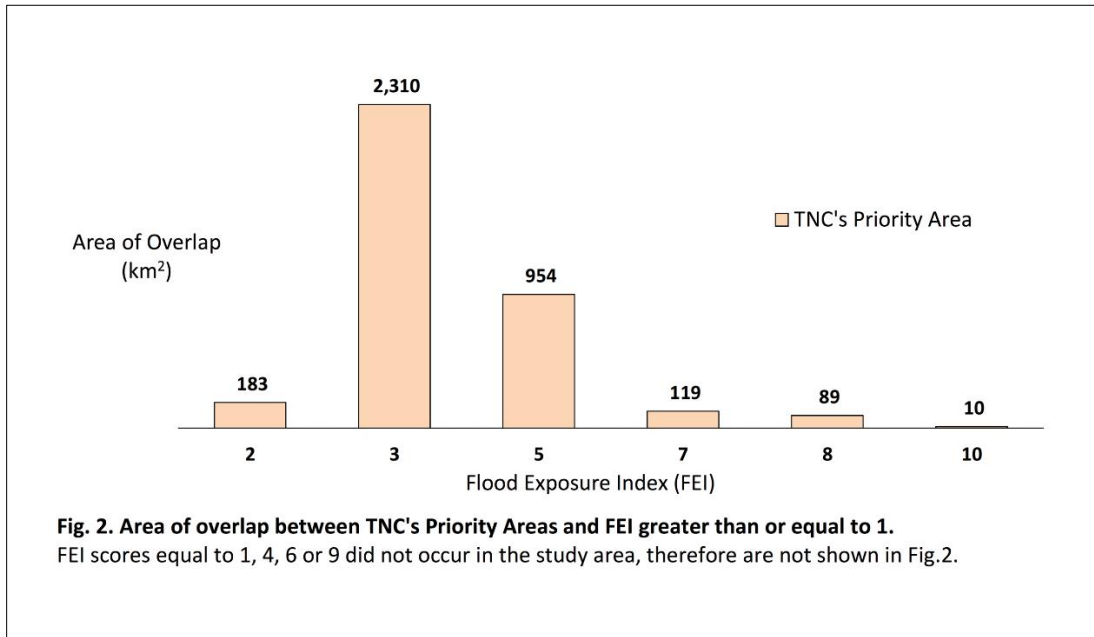
Figure 2. Area of overlap between TNC's Priority Areas and FEI greater than or equal to 1. FEI scores equal to 1, 4, 6 or 9 did not occur in the study area, therefore are not shown.

The area of intersection between CPI and FEI ($11,243km^2$) is larger than the area of intersection between TNC's Priority Areas and the FEI ($3,664km^2$). Broadly, however, this indicates that the model can be applied to reflect distinct conservation priorities of the user.

There are over 3,200 Repetitive Loss Properties located throughout California (Fig. 3). In the 21 coastal counties included in the study area, 2,395 Repetitive Loss Property owners filed 6,794 claims against the NFIP from 1978 to April 2010. This represents 77% of the total number of Repetitive Loss Properties and 79% of the total number of claims in the state for the same period.

Figure 3. Repetitive Loss Properties throughout California (fuchsia circles). The diameter of each circle increases with number of losses (ranging from 2 to 9 losses) [59].

Sixty-six percent of the Repetitive Loss Properties (1,589 properties) located in our study area, are situated in areas with a CPI score greater than 0. Roughly 18% of all Repetitive Loss Properties (440 properties) are located in areas with a CPI score of at least 5. Approximately 44% of all Repetitive Loss Properties in the state (1,051 properties) co-occur with TNC's Priority Areas.

Sonoma County Case Study

Here we highlight results from Sonoma County, which is a hotspot of repetitive loss in California (Table 3). Flood Exposure and Conservation Priority intersect to a very significant degree in Sonoma County. The area of intersection between FEI scores greater than 1 and CPI scores greater than 1, is 564 km^2 – roughly 12.6% of the county area (Fig. 4, left panel). The intersection of areas having a FEI score greater than 0 and TNC's priority areas in Sonoma covers an area of 128 km^2, roughly 3% of the county area (Fig. 4, right panel). The overlap between TNC's Priority Areas and FEI score greater than or equal to 5 is about 42km^2.

Fig. 4. RLPs in Sonoma County and a) overlap between the FEI and CPI; b) overlap between the FEI and TNC's Priority Areas. Darker green indicates areas where higher indices values overlap. Fuchsia circles represent the locations of RLPs (as of April 2010). The size of the circles represents the total number of flood claims filed (from 2 to 9) by each RLP.
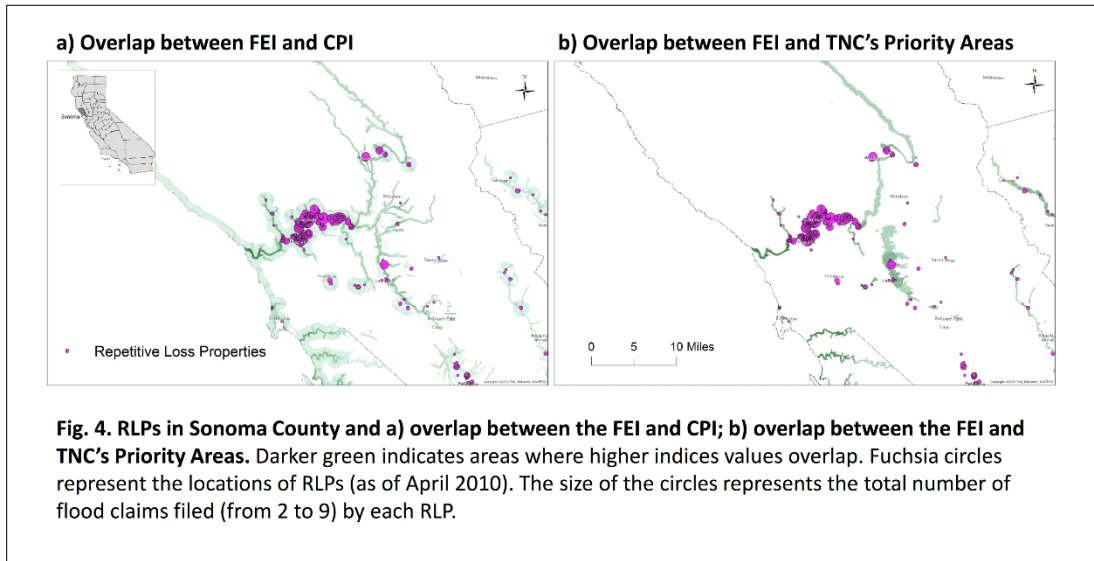
Figure 4. RLPs in Sonoma County and a) overlap between the FEI and CPI; b) overlap between the FEI and TNC's Priority Areas. Darker green indicates areas where higher indices values overlap. Fuchsia circles represent the locations of RLPs (as of April 20).

Table 3. Distribution of Repetitive Loss properties and Claims in California by County

County	Number of RLPs	% of RLPs	Number of Claims	% of Claims
Sonoma	**853**	**36%**	**2734**	**40%**
Los Angeles	434	18%	1147	17%
Marin	192	8%	532	8%
Napa	114	5%	346	5%
Monterey	112	5%	248	4%
San Diego	106	4%	282	4%
Orange	101	4%	251	4%
Santa Cruz	89	4%	254	4%
Ventura	77	3%	201	3%
Santa Barbara	74	3%	165	2%
Contra Costa	66	3%	169	2%
Solano	48	2%	125	2%
San Mateo	32	1%	83	1%
San Luis Obispo	32	1%	87	1%

Santa Clara	29	1%	84	1%
Alameda	15	1%	32	0%
Other	36	2%	86	1%
Total	**2,395**	**100%**	**6,794**	**100%**

Table 3 only contains data for the 21 coastal counties in California, from January 1978 to April of 2010 (Source: FEMA).

Nearly all of the Repetitive Loss Properties in Sonoma (95.3% or 813 properties) are located in areas where Flood Exposure and Conservation Priority indices overlap. The total number of properties where there is an overlap between FEI and TNC's Priority Areas is slightly lower but still large (83.1% or 709 properties). The highest priority areas in Sonoma County may be located where the highest FEI (10) overlap with CPI greater than or equal to 5. In Sonoma County, 32 Repetitive Loss Properties are in such areas and have filed at least 95 combined claims.

Discussion

Our results demonstrate that there can be significant synergies between the objectives of flood exposure reduction and those of habitat conservation and restoration projects. We have identified and prioritized high-leverage sites for such multi-objective projects in California, and our approach can be applied to any geography where floods have repeatedly resulted in financial and human losses, and where critical natural resources are present. For the purposes of this discussion, a

multi-objective project should be understood as one in which structures associated with a RLP are removed from the floodplain to permit habitat restoration.

Buyouts of property and structures have been a part of the FEMA's overall risk reduction strategy since the 1980s [60], but a number of factors – including an understandable hesitation to abandon homes and neighborhoods – have limited its application [61]. Removal of structures from floodplains has ecological benefits in addition to hazard mitigation benefits, including increases in wetland acreage, restoration of wildlife habitat and reconnection of fragmented habitat [62]. An important added benefit of wetlands restoration is that, in some cases, restored floodplains may also function as natural flood mitigation infrastructure [21,63].

Communities are increasingly considering the application of buyouts as a strategy to reduce their long term risks and therefore need to prioritize parcels for the application of limited funds [64]. Following super storm Sandy in October 2012, New York State conducted a needs assessment to prioritize the allocation of federal disaster recovery funds, and 34% of responders (totaling 2,582 people) indicated interest in a buyout of their home [64]. The present study demonstrates a prioritization scheme that would support the elimination of flood exposure for the target parcel (and possibly to neighboring parcels as well), restoration of natural resources, and efficient use of limited governmental funds.

Our analysis of Sonoma County, California's epicenter of repetitive losses with 36% of all Repetitive Loss Properties (853) and 40% of all individual claims (2,734) filed

in the study area (as of April 2010), is particularly illustrative of this principle. As of June of 2010, Sonoma County had received more than $53 million in payments from grants intended to mitigate flooding on Repetitive Loss Properties; this value represents more than 30% of the total amount of RLP grants received by California for the same period ($171.7 million) [36]. Meanwhile, Sonoma County has critical biodiversity conservation objectives, including restoration of steelhead trout, Chinook and Coho salmon, all of which are listed as threatened or endangered under the federal Endangered Species Act [38] . Our results suggest that Sonoma County's efforts to restore salmonid habitat and its efforts to reduce Flood Exposure are very well aligned.

There is a significant need for conservation and restoration of coastal habitats, but limited resources available for accomplishing these goals. Specifically, the National Oceanic and Atmospheric Administration's Restoration Center has a planned budget of $42 million for 2015, [23]. By contrast, FEMA's obligated funds for the Hazard Mitigation Grant Programs in 2013, exceeded $700 million [24]. Nonprofit organizations, federal, state, and local agencies, and other decision makers should use analyses like the one presented here to strengthen the case for the application of hazard mitigation funds to acquire properties or engage in restoration in areas with both high flood exposure and high conservation value.

The multiple benefits to this approach include: elimination of risk for the target parcel, reduction of the financial impact to NFIP of repeated flood claims, and restoration of land to a more natural condition.

The qualitative approach proposed here could be further enhanced by additional case studies that should focus on Los Angeles, Marin, Napa and Monterey Counties, which combined account for 36% of RLPs and 33% of the total number of claims in the study area. Additionally, including a third index scoring socioeconomic vulnerability would provide valuable insight to the potential benefits or consequences of buyout projects to disadvantaged demographics. Finally, our proposed approach should be applied to other coastal states of the country, utilizing substitute relevant local conservation criteria (e.g. sea grass and mangroves instead of salmonids could be used in Florida).

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CHAPTER 2. ALIGNING FLOOD EXPOSURE MITIGATION, NATURAL RESOURCE CONSERVATION, AND SOCIAL VULNERABILITY REMEDIATION IN FLORIDA.

Juliano Calil & Sarah Newkirk

Abstract

Flooding continues to be the most common and damaging of all natural disasters in the United States. In 2016, twelve individual weather and climate events caused more than $1billion in damages each. During 2016, the U.S. was hit by six once-in-1,000 years precipitation events, and severe floods resulted in more than $17 billion in damages. Currently, more than 5.5 million flood insurance policies are active under the National Flood Insurance Program (NFIP). Combined, these policies underwrite more than $1.6 trillion in assets. Since 1978, NFIP has paid out more than $38 billion in claims, with more than 30% paid to the one percent of policies that experienced multiple losses and are classified as "repetitive loss properties" (RLPs).

Flood impacts are determined by a complex interaction between physical hazards, the vulnerability of a society or social-ecological system, and its exposure to such hazards. The extent and severity of flood impacts are amplified by challenging socioeconomic dynamics, including ill-advised urban development, lack of access to resources and information, social vulnerability, and poverty.

Addressing this complex interaction between hazards, exposure and social vulnerability, this study identifies and prioritizes land in Florida, where multiple

management benefits can be achieved: flood exposure is reduced, conservation benefits are achieved, and social vulnerability is remediated. We found at least 10,000 km^2 of land in Florida where such objectives may be achieved simultaneously. In a targeted case-study our model identified 92 RLPs in Miami-Dade located in areas of high social vulnerability, high flood exposure, and where natural habitats coexist. Collectively, these 92 RLPs filed at least 207 claims against NFIP between 1978 and 2011.

The multiple benefits of the presented approach include: reduction of flood exposure, reduction of NFIP's financial impact, restoration of the floodplain to a more natural condition; and the identification of efficient application of federal funds, usually destined to single-objective projects - e.g. grants from Federal Emergency Management Agency (FEMA), and the U.S. Department of Housing and Urban Development (HUD).

We argue that government funded buyouts, followed by structure demolition and/or relocation, and the restoration of floodplain habitats, can support social, environmental, and economic objectives, as long as such projects are executed in a thoughtful and fair manner.

Introduction

Flooding continues to be the most common and damaging of all natural disasters in the United States. According to the Federal Emergency Management Agency (FEMA), 44 out of the 46 major disaster declarations in 2016 were related to storms, with flooding being a significant factor in almost 70% of them (30 events) [1]. In 2016, severe floods in the U.S resulted in more than $17 billion in damages (six times higher than in 2015). Twelve individual weather and climate events caused more than $1 billion in damages each, and six severe 1,000-yr precipitation events occurred in the U.S. in 2016 [2].

The National Flood Insurance Program (NFIP), created by FEMA in 1968 following a series of severe floods, aimed at providing flood loss coverage for home owners, as well as promoting risk-reduction measures for properties located in floodplains across the country. Until 1986, NFIP finances were self-sustainable, with premiums collected roughly balancing the total claim payments [3]. However, due to disastrous recent flood seasons, and insurance rates that do not reflect real flood risks, NFIP has accrued a total debt of more than $23 billion during the last decade [4]. Roughly $16.4 billion was paid to claims related to Hurricane Katrina (2005), and $8.3 billion paid to claims related to superstorm Sandy (2012) ($24.7 billion total) [5]. One critical component of NFIP losses are repetitive loss properties, which account for roughly 1% of all policies, but received roughly 30% of all NFIP claims payments until 2011 [6].

In an effort to bring stability and fiscal soundness to the national flood insurance program, in July of 2012 Congress approved the Biggert Waters Flood Insurance Reform Act (BW-12). Among other provisions, BW-12 reauthorized NFIP for an additional 5 years (from 2013 to 2017), and defined a gradual adjustment of insurance rates to reflect true risk [7]. However, in response to strong public reaction and concerns that the new flood insurance rates triggered by BW-12 would affect the housing market, as well as drive home owners from their properties, in March of 2014 Congress enacted the Homeowner Flood Insurance Affordability Act of 2014. This modified and repealed several provisions of BW-12 by implementing measures including: limiting the increase of annual flood insurance premiums to 18%, repealing any rate increases triggered by property sales or the acquisition of new and voluntary flood insurance policies, refunding select policy holders for recent rate increases, and authorizing additional funds for the National Academy of Sciences to complete a series of affordability studies [7]. According to the first report from the series, entitled "Affordability of National Flood Insurance Program Premiums/ Report 1", published in 2015, 60% of all NFIP policies (5.5 million in total), are located in Florida, Texas, and Louisiana [8].

As of November, 2016, property owners in Florida held the highest number of NFIP polices in the nation (almost 1.8 million policies, roughly 35% of all NFIP claims at the time), with insured property values reaching $429 billion (almost 35% of the entire NFIP coverage of $1.25 trillion) [9]. However, until 2012, home owners in Florida paid roughly four times more in premiums than they received in flood claim

payments from NFIP ($16.1 billion vs. $4.5 billion) [10]. As of September 2011, there were more than 15,000 repetitive loss properties in FL. From 1978 to 2011, these RLPs received payments for almost 40,000 claims (an average of 2.7 claims per property). A stunning 808 RLPs filed at least 5 claims against NFIP during that same period, with 70 RLPs having filed at least 9 claims. Nationwide, the number of RLPs has outpaced FEMA mitigation efforts by a factor of 10 [6].

FEMA continues to offer significant funds in Flood Mitigation Assistance (FMA) grants destined to reduce or eliminate the risk of repetitive flood damage to NFIP customers. In 2016, FEMA allocated almost $200 million in FMA funds, eligible to be used in pre-disaster planning and mitigation activities including: property acquisition and structure demolition or relocation, and structure elevation and building retrofitting [11].

The U.S. Department of Housing and Urban Development (HUD) is another potential source of significant funds for projects within the scope of this study. On the aftermath of superstorm Sandy, HUD offered $930 million through the Rebuild by Design competition [12] to seven proposals that developed innovative regionally-scalable, locally-contextual approaches to increase coastal resilience in the region affected by Sandy. In 2015, through the National Disaster Resilience Competition, HUD offered an almost $1 billion in additional funding, destined for disaster recovery and long-term community resilience [13]. More recently, in October of

2016, HUD proposed new property elevation standards for all HUD support properties of at least 2 feet [14].

Losses related to coastal hazards are not uniformly distributed, and depend greatly on socioeconomic conditions of the population exposed to environmental hazards [15]. Social vulnerability relates to the characteristics of a person or group and their capacity to anticipate, cope with, resist, or recover from the impacts hazards [16]. Some of the major factors that increase social vulnerability include: lack of access to resources, limited access to political representation, beliefs and customs, building stock and age, and frail and physically limited individuals. Additionally, socioeconomic status, gender, race and ethnicity, and special needs, are also relevant drivers of vulnerability [15]. Social vulnerability becomes much more apparent after the onset of a disaster, when impacts can be observed in specific groups of the population [15]. Flood events cause disproportionate impacts on more vulnerable groups (e.g. the poor, minorities, the elderly, and the disabled), which usually live in high-risk areas, lack basic resources to prepare for floods and other natural hazards, and are not aware of available resources that may reduce their sustainability [17].

Social Vulnerability is a complex subject and difficult to evaluate at large scales. However, multiple social vulnerability analysis tools are available in the United States, including: The Social Vulnerability Index (SoVI©) (University of South Carolina, Hazards and Vulnerability Research Institute), Social Vulnerability Mapping Tools (Texas Coastal Planning Atlas), the Roadmap for Adapting to

Coastal Risk (NOAA, Coastal Services Center), and the USA – Social Vulnerability Thematic Maps (ESRI). Most of the tools above are either based on SoVI©, or mention it as a more comprehensive tool [17], therefore SoVI© was chosen as the social vulnerability index for this analysis. SoVI© has some known limitations, including the complexity of the statistical methods applied, including principal component analysis, but it is generally recognized as the standard for social vulnerability studies.

The Social Vulnerability Index (SoVI©) measures community vulnerability, defined as a reduction in the community's ability to prepare for, respond to, and recover from hazards [18]. In the 2006 to 2010, nearly 30 variables we reduced to seven independent components, which describe social vulnerability: (i) race (Black) and class (poverty); (ii) wealth; (iii) elderly residents; (iv) Hispanic ethnicity; (v) special needs individuals (nursing home residents); (vi) Native American ethnicity; and (vii), service industry employment [19]. SoVI© is a dynamic index and future iterations are expected to include additional variables including: homeless population, physical mobility constraints, and social capital [20].

Conservation objectives can also align with those of flood exposure reduction, and social vulnerability remediation. Ecosystems provide numerous services to humans, beyond just coastal and flood protection, including: fisheries improvement, water filtration, transportation, and recreation. While the benefits provided by nature are widely accepted, there is still a great need to account for natural habitat in

multidisciplinary community decision making processes. To address this need, in this study we include various ecosystems in Florida in the Conservation Priority Index (CPI). Further, we give CPI the same weights as Flood Exposure, and Social Vulnerability in our final calculations and land prioritization. Recognizing the value of various habitats, CPI includes marine, terrestrial, and freshwater ecosystems.

The goal of this study is to identify and prioritize lands in Florida that are potential targets for projects that can result in multiple benefits: flood exposure is reduced, conservation benefits are achieved, and social vulnerability is remediated.

Using spatial data related to flood exposure, natural habitats, and SoVI©, we build on the methods proposed by Calil et al. (2015), who demonstrated that flood losses could be mitigated through action that meets both flood risk reduction and conservation objectives [21]. Calil et al. (2015) identified developed and federally-insured lands in California that are prone to flooding and therefore not ideal for development, and where valuable natural resources, such as salmon habitat or estuaries, are also present. Further, that study described federal funding programs that could be applied to achieve both flood mitigation and conservation objectives.

We propose that flood losses can also be mitigated through action that remediates social vulnerability. The present study greatly improves on Calil et al. (2015). In addition to flood exposure and natural habitats, we include social vulnerability in the prioritization scheme. Furthermore, we include inland habitats, expanding the focus of the analysis beyond just the coast. Our results identified lands in Florida that are

eligible to receive federal funds to attain multiple benefits: (i) reduce flood risk to home owners; (ii) reduce FEMA's financial burden (from future flood claim payments); (iii) restore/protect natural habitats; (iv) remediate social vulnerability, and (v), identify potential sources of funding for projects. To our knowledge, this is the first study to present a detailed spatially explicit analysis of the overlap between flood exposure, natural habitats, and social vulnerability in Florida.

Materials and Methods

Our model identifies and prioritizes land in Florida where valuable habitats and socially vulnerable population are exposed to flooding. Flood exposure was evaluated based on data from the FEMA's Repetitive Flood Claims program and Digital Flood Insurance Rate Maps (DFIRM), as well as sea-level rise projections from NOAA. Conservation priority lands were identified in two ways. First, we used The Nature Conservancy's (TNC's) Priority Areas, a conservation prioritization scheme developed through comprehensive eco-regional assessments of species and habitats. Second, we developed a Conservation Priority Index (CPI) based on habitats data from the Cooperative Land Cover dataset, published by Florida's Fish and Wildlife Conservation Commission 2016. Areas of high social vulnerability were identified using the social vulnerability index (SoVI©).

We used an equal-weight overlay spatial model, developed in a geographic information system (ESRI ArcGIS 10.2), and applied it to all census tracts in Florida (total study area of roughly 125,000 km²). Four indices were considered in the study

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(at a resolution of 50m by 50m, or 0.0025 km^2): (i) Flood Exposure Index (FEI); (ii) TNC's Priority Areas; (iii) Conservation Priority Index (CPI); and (iv), SoVI©. Note that these indices are intended to be qualitative and relative, rather than quantitative measures of specific features.

First, we developed a Flood Exposure Index, by combining four attributes: the 100 yr. and 500 yr. floodplains as defined by FEMA; proximity to repetitive loss properties; (also based on FEMA's data); and the projected area located below the mean high water levels in year 2100 from the National Oceanic and Atmospheric Administration (NOAA).

Second, we evaluate conservation priority utilizing The Nature Conservancy's (TNC) priority areas, and develop a custom conservation priority index (CPI). CPI is based on selected natural habitats in Florida, as identified by the Cooperative Land Cover dataset, recently published by Florida's Fish and Wildlife Conservation Commission (see detailed habitat list below). It is useful to have a comparison of prioritization schemes to demonstrate that this approach can be adjusted to reflect specific users interests and available data.

Finally, we use the pre-existing Social Vulnerability Index (SoVI©) in the study to identify areas of high social vulnerability in Florida. To support calculations SoVI© original values (low, medium, and high) were replaced by numerical scores (25, 50, and 100, respectively).

The final step of the model, was the calculation of overlapping scores across the indices, as explained below. Results are presented in overlapping scores and areal extent (in km^2).

1. Flood Exposure Index (FEI)

An overall FEI was calculated by summing up the values of individual flood exposure indicators within each grid cell (Table 1, Fig 1), according to equation 1:

$$FEI = F100 + F500 + RLP + SLR$$

(1)

where F100 represents the 100-year floodplain score, F500 represents the 500-year floodplain score, RLP is the proximity to RLPs score, and SLR is the area inside the MHHWM at the year 2100 score. FEI score values range from 0 to 400 (Table 1). FEI scores were then normalized from 0 and 100 according to (equation 2):

$$Flood\ Exposure\ Index = \frac{(X - Min)}{(Max - Min)} * 100$$

(2)

where X is the value of the FEI for each grid cell before the normalization, Min is the minimum value of the index before normalization (i.e. 0), and Max is the maximum value of the index before normalization (i.e. 400).

Table 1. Flood Exposure Index (FEI).

FEI Components – data sources in parenthesis	Score
Area located within the 100-year Floodplain (FEMA)	100
Area located within the 500-year floodplain (FEMA)	100
RLPs and surrounding areas (1,000m buffer) (FEMA)	100
Area inside the projected MHHWM at the year 2100 (NOAA)	100
Maximum possible FEI score	**400 Points**
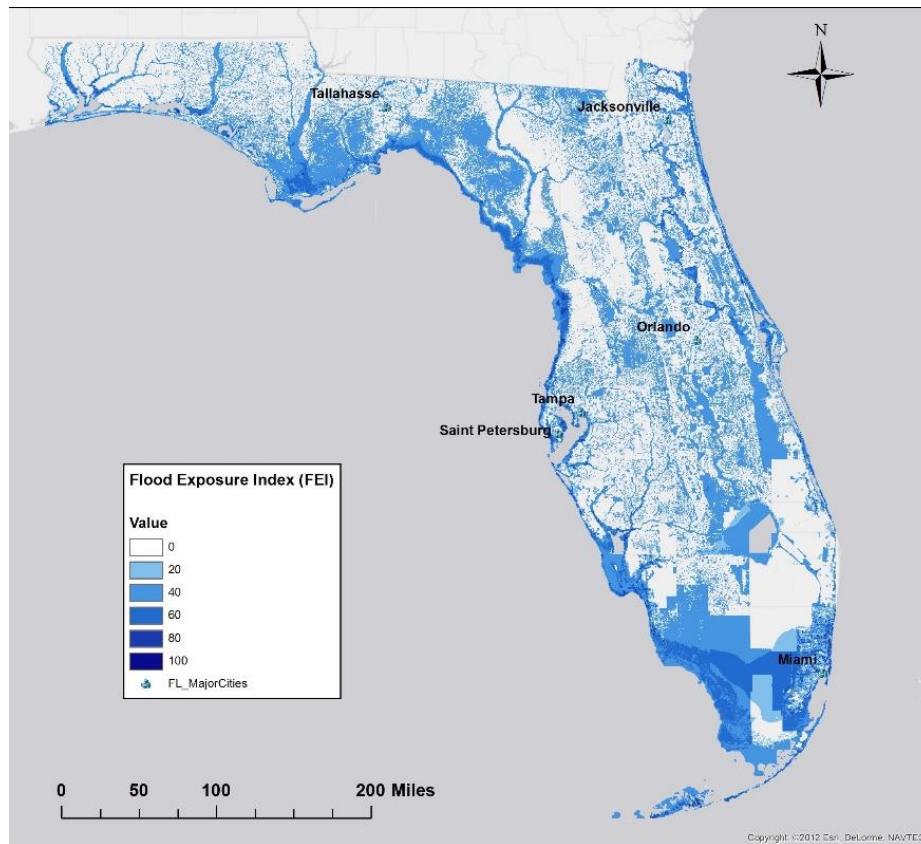
Figure 1. Flood Exposure Index (FEI).

2. TNC Priority Areas and the Conservation Priority Index (CPI)

Following the model outlined by Calil et al. (2015) [21], we include an example of an existing conservation prioritization scheme in the study. We use TNC's Priority Areas, developed through comprehensive eco-regional assessments of species and habitat types [22] (Figure 2). TNC's priority areas cover approximately 17.2% of Florida (24,000km^2), across four ecoregions (areas of similar climate, topography that support a range of habitats): Tropical Florida, Florida Peninsula, and part of the East Gulf and South Atlantic Coastal Plains located within state boundaries [22–24].
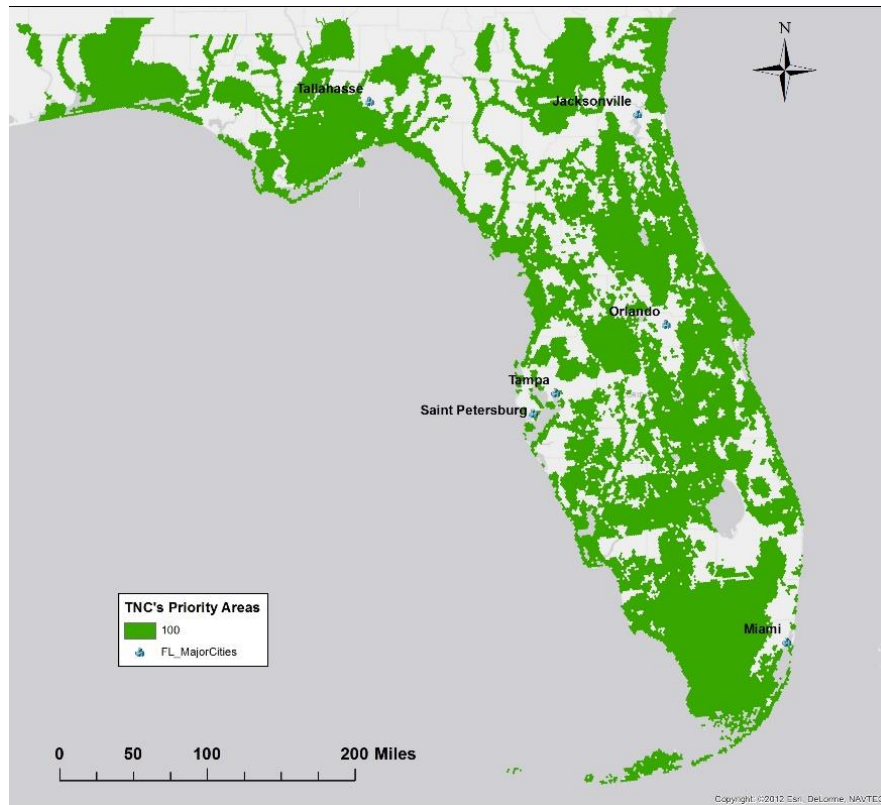
Figure 2.TNC's priority Areas.

Additionally, following the approach from Calil et al. (2015) - and to illustrate that the proposed approach is flexible, and can be adjusted to represent specific conservation interests - we have substituted a custom conservation priority index (CPI) for TNC's priority areas.

The CPI is based on habitat data derived from the Cooperative Land Cover dataset, published by Florida's Fish and Wildlife Conservation Commission in October of 2016 [25]. The original dataset was developed based on ecologically-based statewide land cover from existing sources and expert review of aerial photography, and is used inform various conservation and management activities in Florida [25]. The following habitats (extracted from the Cooperative Land Cover dataset) were included in the CPI: Upland Hardwood Forest; Mesic Hammock; Rockland Hammock; Slope Forest; Xeric Hammock; High Pine and Scrub; Sand Pine Scrub; Coastal Scrub; Upland Pine; Sandhill; Pine Flatwoods and Dry Prairie; Dry Flatwoods; Mesic Flatwoods; Scrubby Flatwoods; Dry Prairie; Palmetto Prairie; Mixed Hardwood-Coniferous; Coastal Strand; Maritime Hammock; Sand Beach (Dry); Upland Glade; Freshwater Non-Forested Wetlands; Prairies and Bogs; Marshes; Isolated Freshwater Marsh; Floodplain Marsh; Freshwater Forested Wetlands; Cypress/Tupelo(including Cy/Tu mixed); Cypress; Isolated Freshwater Swamp; Strand Swamp; Floodplain Swamp; Other Coniferous Wetlands; Wet Flatwoods; Other Hardwood Wetlands; Baygall; Hydric Hammock; Non-vegetated Wetland; Lacustrine; Riverine; Natural Rivers and Streams; Estuarine; Tidal Flat; Salt Marsh; Mangrove Swamp; Scrub Mangrove; Dome Swamp; Basin Swamp.

In addition to the data above, seagrass coverage, based on data from Florida's Fish

and Wildlife Conservation Commission [26] was also included in the CPI, and the

resulting raster received a value of 100 (figure 3).
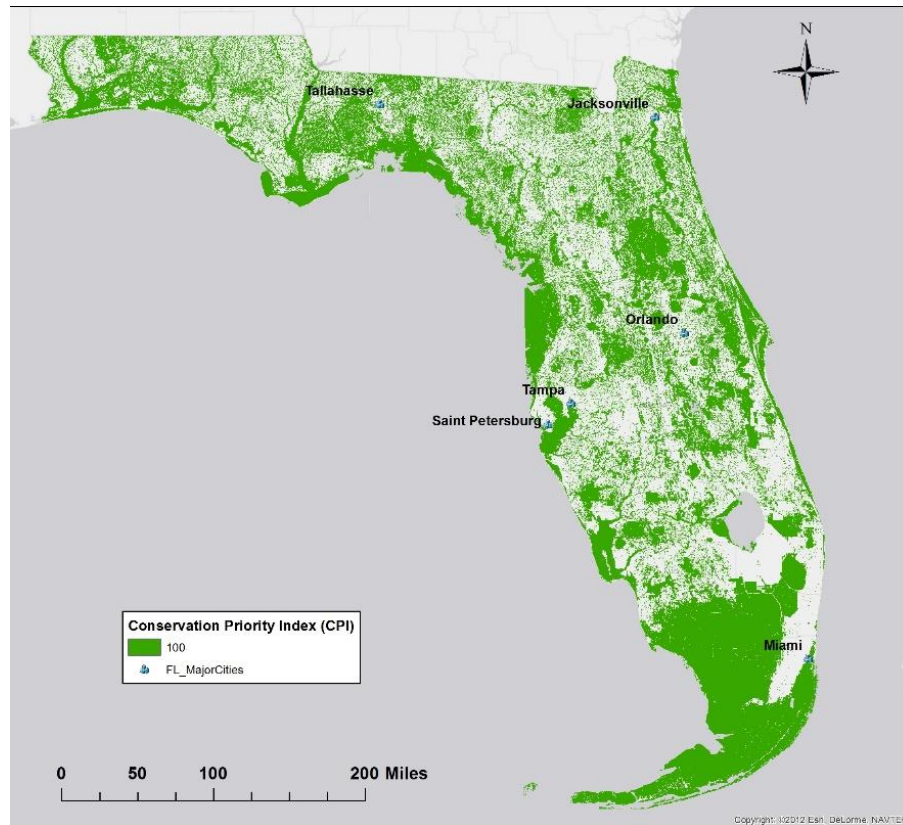
Figure 3. Conservation Priority Index (CPI).

3. Social Vulnerability Index (SoVI©)

Cutter et al. (2003), developed the Social Vulnerability Index (SoVI©), which

measures community vulnerability, defined as a reduction in the community's ability

to prepare for, respond to, and recover from hazards [18]. The 2006-2010 version of

SoVI© for Florida, was calculated at the census tract level, by the use of principal

component analysis. Principal component analysis reduces a number of correlated

variables into a smaller number of uncorrelated variables called principal components. The first component explains as much of the variability in the data as possible, with succeeding components accounting for as much of the remaining variability in the data as feasible [27]. In Florida, the 2006-2010 SoVI© reduces 29 independent socioeconomic variables into seven components that explain 72% of the variance in the data [18].

Positive and negative values are then assigned to each of the seven components, based on their impact on social vulnerability. Values are tallied up at the census tract level, determining a numerical social vulnerability score. The seven independent components that describe social vulnerability in Florida are: race (Black) and class (poverty) combined; wealth; elderly residents; Hispanic ethnicity; special needs individuals (nursing home residents); Native American ethnicity; and service industry employment [19]. The 2006-2010 SoVI® data sources include primarily the United States Census Bureau (from 2005 to 2009). SoVI® is a dynamic index and future iterations are expected to include additional variables including: homeless population, physical mobility constraints, and social capital [20].

One of the main focal points of social vulnerability in Florida is in urban areas in the southeast of the state, north from Miami-Dade, through Broward, and into Palm Beach County, where 76%, 31%, and 29% of the respective populations live in areas with high vulnerability [28]. Miami-Dade contains the most vulnerable census tract

in the state [28]. For the purposes of this study, SoVI© values were transformed

from medium, high, and low, to 25, 50, and 100, respectively.
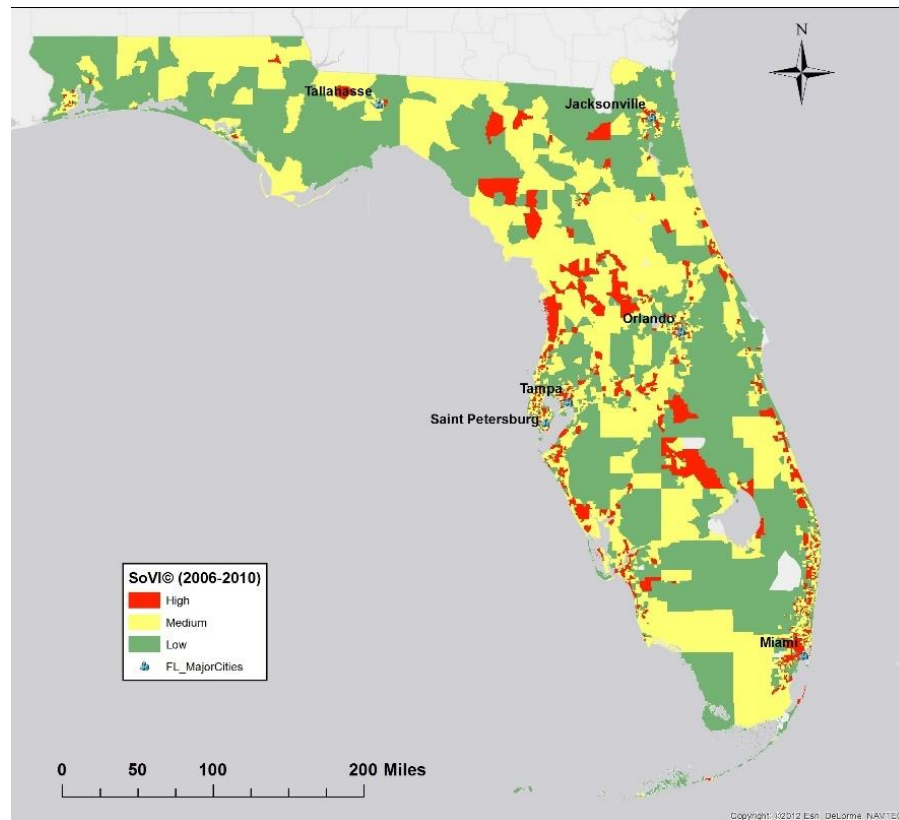
Figure 4. SoVI© 2006 - 2010.

4. Spatial Model Description

The four spatial layers above (FEI, TNC's Priority Areas, SoVI©, and CPI) were

converted into raster format at the same resolution (0.0025 km^2). Next, the geometric

average between the raster values (i.e. individual indices) was calculated, resulting in

overlapping scores (equations 3, 4, and 5). Areas where either layer was not present

(i.e. index value equal 0) were excluded from the results. An equal weights approach

was applied but the model is flexible enough that different weights may be used in

the future, to represent specific values of model users. As an example, a future application of the model may give a heavier weight to high social vulnerability.

The total extent of overlapping land was calculated in three ways:

(i) extent of overlap between FEI and SoVI©:

$$\text{Overlap between FEI and SoVI©} = \sqrt{(FEI * SoVI©)}$$

(3)

(ii) extend of overlap between FEI, SOVI©, and CPI:

$$\text{Overlap between FEI, SoVI©, and CPI} = \sqrt[3]{(FEI * SoVI© * CPI)}$$

(4)

(iii) the extent of overlap between FEI, SOVI©, and TNC's Priority Areas:

$$\text{Overlap between FEI, SoVI©, and TNC Priority Areas} = \sqrt[3]{(FEI * SoVI© * TNC\ Areas)}$$

(5)

Additionally, the distribution of Repetitive Loss Properties in Florida, and their overlap with the three land prioritizations above was evaluated, and a case study was conducted for Miami-Dade, the county with the highest number of repetitive loss claims in Florida.

Results

1. Extend of overlap between SOVI© and FEI

The first step in the analysis was to evaluate the extent of overlap between flood exposure and social vulnerability in Florida. Results are presented as scores, calculated by equation 3, with overlapping scores ranging from 0 to 100.

The state of Florida contains a total area over land of 138,887 km^2. Our results indicate the extent of overlap between FEI (values> 0), and medium SoVI© (values >=50), cover nearly 22% of the state (30,205km^2). As expected, the areal extent of overlap diminishes as the scores increases: There are roughly 870 km^2 in the state where SoVI© is high (i.e. score is 100), and FEI values >= 60 overlap (red categories in Figure 5). Finally, there are 162 km^2 in Florida where high social vulnerability (SoVI© = 100) and high flood exposure (FEI >=80) overlap (figures 5 and 6).
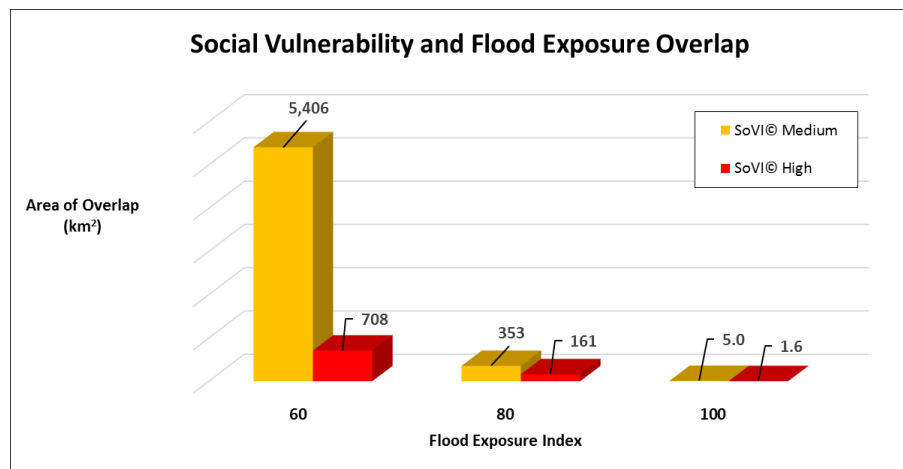
Figure 5. Area of overlap between FEI scores greater than or equal to 60, and SoVI© values medium and higher. FEI scores equal to 30, 50, 70 and 90 did not occur in the study area, therefore are not shown in figure 5.
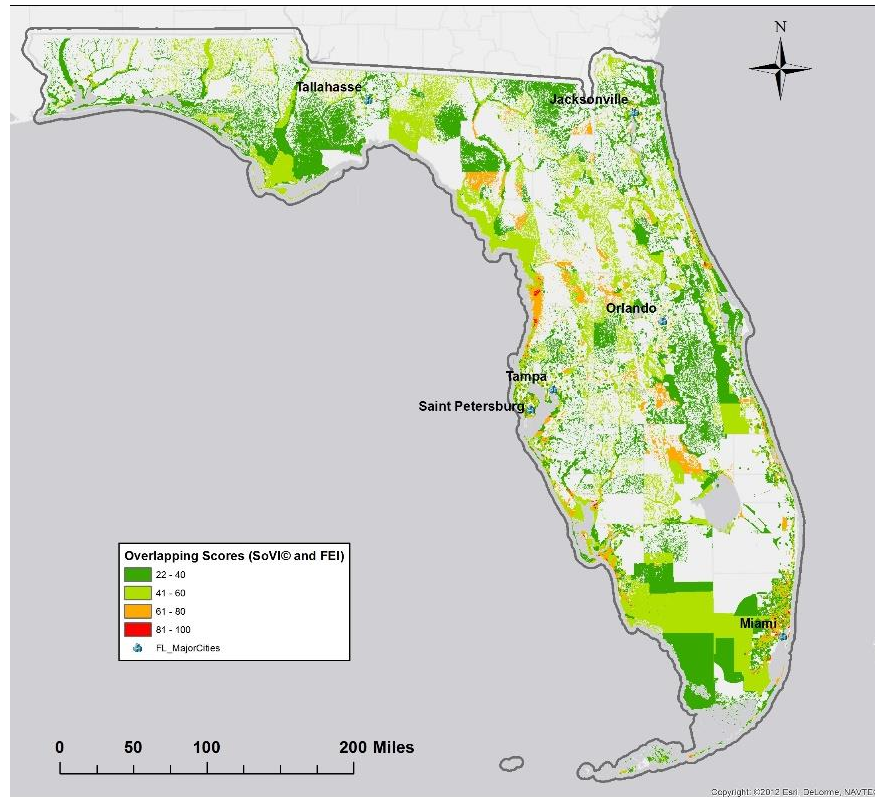
Figure 6. SoVI© and FEI Overlap

2. Extent of overlap between FEI, SoVI© and TNC's Priority Areas

TNC's priority areas cover approximately 24,000 km^2 in Florida (17.2% of the state).

Roughly 42% of that total (nearly 10,000 km^2) overlaps with areas where both

SoVI© and FEI also coexist in Florida. Overlapping scores range from 0 to 100.

There are 75 km^2 of land in Florida, where TNC's priority areas overlap with FEI >=

80, and SoVI© >= 50. Finally, there are 20 km^2 of land in Florida, where TNC's

priority areas overlap with high FEI >= 80 and SoVI©=100 (figures 7 and 8).
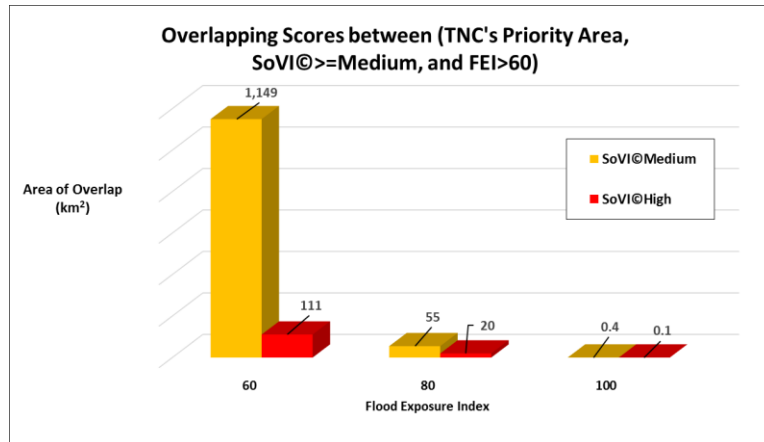
Figure 7. TNC, SoVI©, and FEI Overlapping Scores (excludes areas where TNC areas are not present).
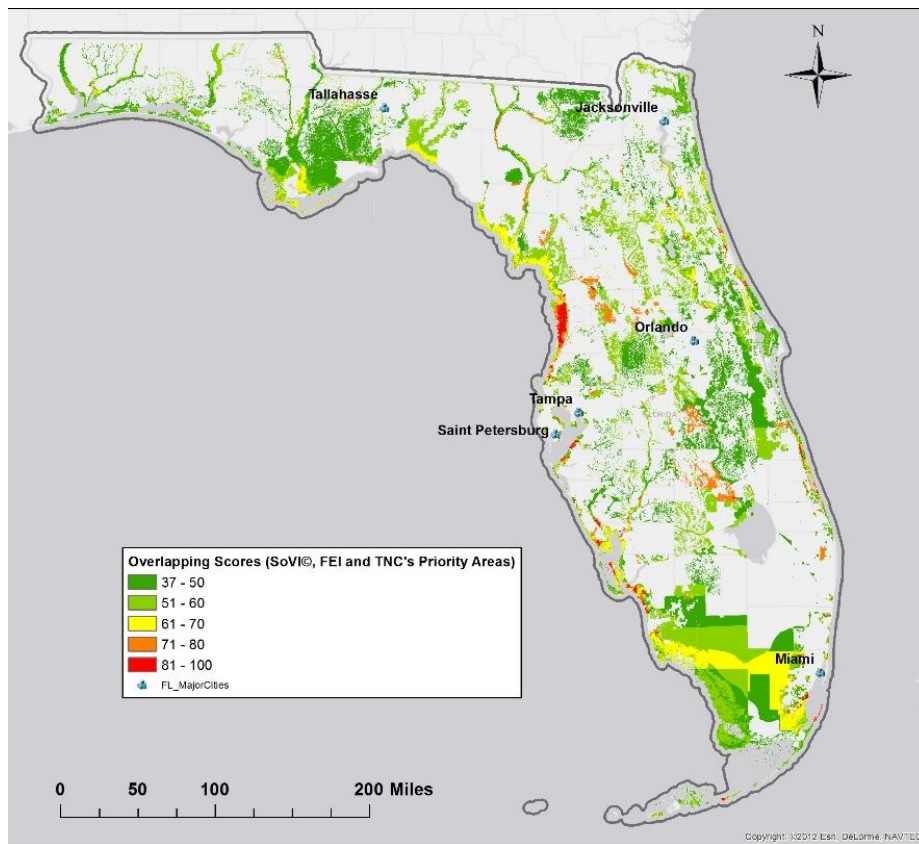
Figure 8. TNC, SoVI©, and FEI Overlapping Scores

3. Extent of overlap between SoVI©, FEI, and CPI

The extent of overlap between FEI >0, CPI >0, and SoVI© >=50 covers more than 30% of Florida, 45,350 km^2 (Figure 6). Overlapping scores range from 0 to 100 (equation 4). Generally, the amount of land where the three indices overlap diminishes as the indices values increase. Nearly 19% of the state (26,171 km^2) is in areas with an overlapping score greater than 50 (Table 2). The areal extent where overlapping scores are 80 or higher is 553 km^2.

As expected, the total areal extent with maximum overlapping scores (i.e. 100), is very limited, roughly 0.2 km^2. As previously mentioned, the fact that the areal extent of overlap between the indices generally diminishes as the values of each index increase, provides a valuable land prioritization tool.
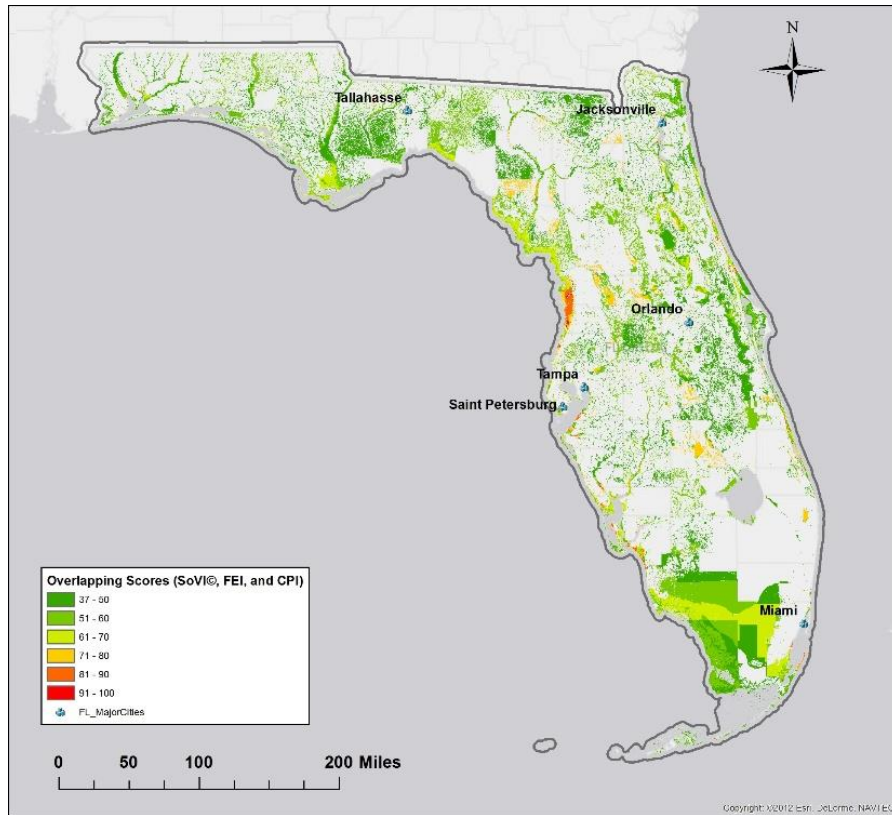
Figure 9. SoVI©, FEI and CPI Overlap.

4. Repetitive Loss Properties in Florida

According to FEMA, as of December 31, 2011, there were 16,546 RLPs located throughout Florida (table 3, Figure 10). Collectively, these RLPs filed 42,092 claims against NFIP, with total claim payments reaching more than $1.3 billion (average claim value of almost $33,000) [6]. Five counties are responsible for 52% of claims and 52% of all repetitive loss properties in Florida: Miami-Dade, Pinellas, Escambia, Santa Rosa, and Broward (Table 3). Not all RLPs had their locations included in the database used in this study (provided by FEMA), therefore the number of RLPs analyzed here is slightly lower (15,274).

Table 2. Distribution of Repetitive Loss properties and Claims in Florida – top 12 Counties.

County	Number of Claims	% of Claims	Number of RLPs	% of RLPs
Miami-Dade	7,886	20%	3,415	22%
Pinellas	4,226	11%	1,418	9%
Escambia	3,956	10%	1,373	9%
Santa Rosa	2,380	6%	953	6%
Broward	1,834	5%	724	5%
Monroe	1,702	4%	747	5%
Okaloosa	1,699	4%	715	5%
Pasco	1,610	4%	650	4%
Lee	1,575	4%	641	4%
Hillsborough	1,238	3%	424	3%
Manatee	1,051	3%	333	2%
Sarasota	1,010	3%	326	2%
Other	8,961	23%	376	23%
Total	**39,128**	**100%**	**15,274**	**100%**
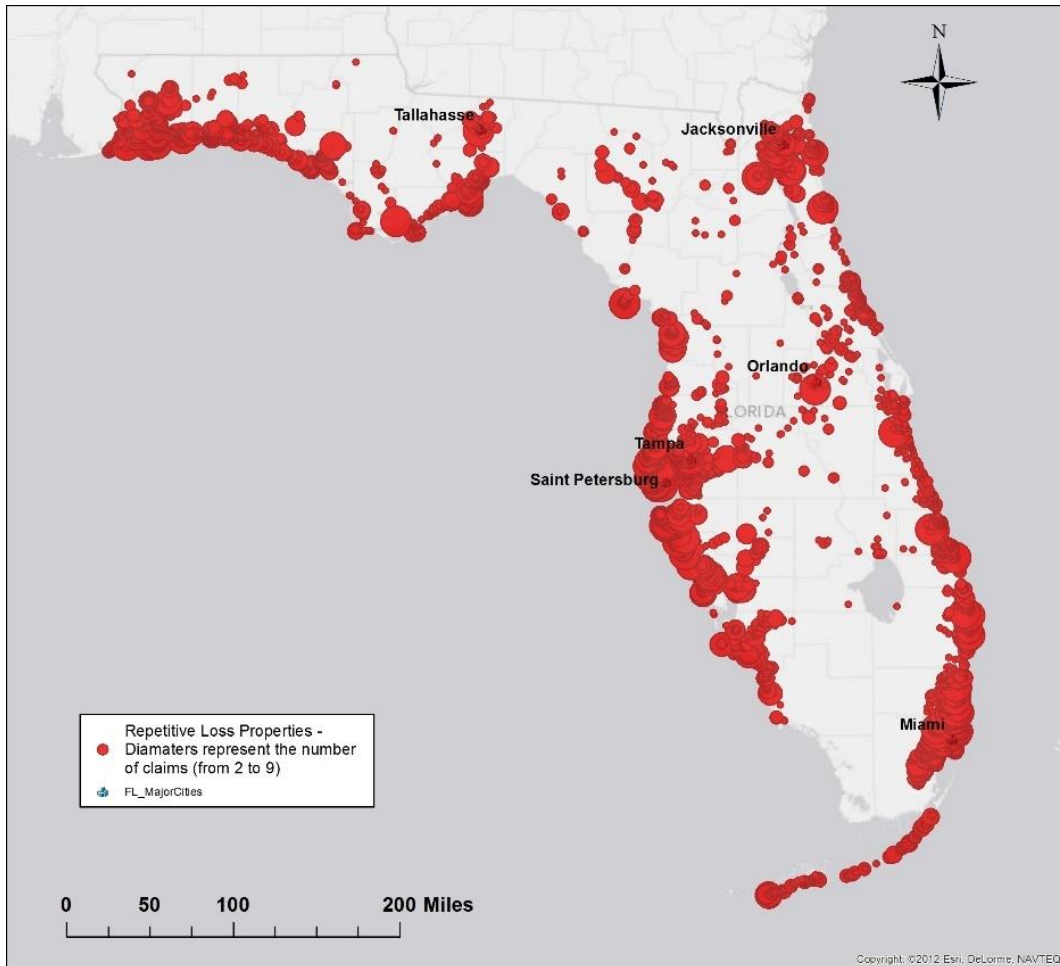
Figure 10. Repetitive Loss Properties throughout Florida (red circles). The diameter of each circle increases with number of losses (ranging from 2 to 9 losses).

There are at least 824 RLPs in Florida, located in areas where SoVI©, FEI, and CPI overlap. Collectively, these properties filed more than 2100 claims against NFIP between 1978 and 2011. At least 185 RLPs (that filed more than 500 claim during the same period), are in areas where the overlapping scores between these three indices are 70 or higher.

Miami-Dade County Case Study

Miami-Dade County is an ideal geography for a targeted case study of our methods, as it contains extensive areas with high exposure to floods, high social vulnerability, and valuable habitats.

Miami-Dade contains the largest number of RLPs in Florida; more than 3,400 RLPs have filed more than 7,800 claims against NFIP in the County, between 1978 to 2011. There are more than 500 km^2 of land in the County where FEI is 60 or higher.

The total area of Miami-Dade County is approximately 6,296 km^2. Nearly 90% of the county's area (5,600 km^2) is classified as TNC's Priority areas, with extensive coverage of marshes (2,264 km^2), estuaries (650 km^2) and other natural habitats [25]. Nearly 67% of the county (4,254 km^2) is in areas where FEI, SoVI©, and TNC areas overlap. The extent of land in the county where FEI, SoVI© and PCI areas overlap is slightly smaller, roughly 50% of the county (3,148 km^2).

Finally, Miami-Dade is a hotspot of social vulnerability in Florida, holding the most vulnerable census tract in the state, with almost 2 million people living in areas with high social vulnerability [28] (roughly 76% of the total 2.6 million population in the county [29]). More than 20% of the Miami-Dade's population (nearly 540,000 people) are living in poverty, and more than 680,000 people did not have health insurance in the county as of July of 2016 [29].

We found 92 RLPs in Miami-Dade located in 61 km^2 where the overlapping score between FEI, SoVI, and TNC areas is high (overlapping scores >= 84). Collectively, these 92 RLPs filed at least 207 claims against NFIP between 1978 and 2011. Such properties are eligible for HMA grants, which support flood-risk mitigation activities that can improve the livelihoods of socially vulnerable neighborhoods, and promote the conservation of critical habitats.
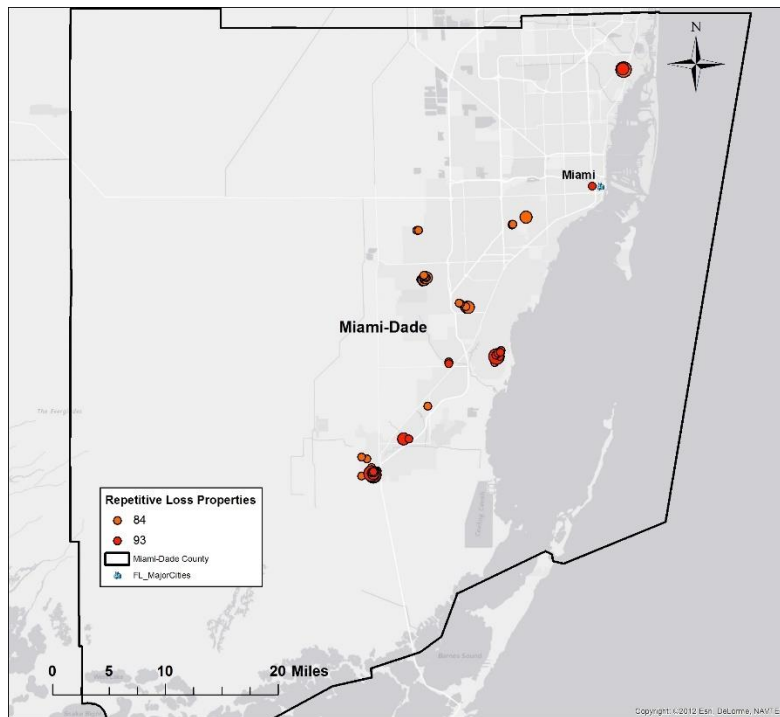
Figure 11.RLPs in Miami-Dade County. Color represents Overlapping Scores (SoVI© FEI, and TNC areas).
Diameters represent the number of claims filed (from 2 to 9).

Discussion

Our methods identified and prioritized multiple location in Florida, where multi-objective projects can be implemented to simultaneously reduce flood exposure, restore natural habitats and improve social vulnerability. As an example, in a targeted case-study, we identified 92 RLPs in Miami-Dade County located in areas where these objectives are very well aligned.

It is important to note that, due to privacy concerns, FEMA restricts the accuracy of RLPs locations to a city block level, not individual parcels. However, such accuracy is sufficient for the objectives of the present study, and the identification of potential locations for acquisition projects. Another limitation of the study is that in addition to the 15,274 RLPs records used in the model, there are roughly 1,200 RLPs records that did not have adequate geolocation information and therefore were excluded from the study. Other limitations are related to SoVI©: since the social vulnerability index is calculated at a census tract level, some uninhabited areas (e.g. Biscayne National Park) receive high overlap scores between the indices used, but are not necessarily relevant. Additionally, social vulnerability is a very complex subject, and SoVI© is based on broad assumptions of drivers of vulnerability. It is important to ground proof the index, validate its assumptions, and incorporate local knowledge before any project implementation.

Future research and applications of our model should focus on specific locations of higher resolution (e.g. Miami-Dade County), through partnerships with local

communities, government agencies and officials, NGO's, and the private sector (which should also be considered as a relevant partner in such projects). Our model can also be improved by the addition of population data in the social vulnerability category. Finally, it would be interesting to include information about property values in the study, which could be done by cross referencing RLP locations and claims dates with property value records. Despite these limitations and opportunities for future improvement, our results provide a valuable first step in the identification of candidate neighborhoods for the implementation of multi-objective projects.

The presented approach identifies a valuable opportunity for the coordinated use of funds previously destined to single objective projects. Since the 1993 floods in the Midwest, FEMA has spent hundreds of millions of dollars to remove repetitive loss structures from the floodplains across the country [6]. Additionally, in recent years, the U.S. Department of Housing and Urban Development (HUD) offered almost $2 billion in funding, destined for disaster recovery and long-term community resilience [12–14].

There is a growing realization that integrated approaches to flood mitigation yield better benefits than single objective approaches. As an example, building a seawall on a sandy beach, which in theory may protect a community from flooding, does very little to improve social vulnerability, or to sustain the natural environment. In fact, as a consequence of coastal dynamics, seawalls may result in beach loss, diminishing the social, economic, and ecosystems benefits the lost beach provided,

further impacting social vulnerability. Conversely, relocation, or managed retreat, the relocation of properties to safer areas, followed by the restoration of the floodplain to a more natural state, is an example of an integrated approach. Understandably, this is a controversial topic, and not always viable on the short-term, especially in denser urban areas where other structural measures (i.e. engineered coastal defenses including building seawalls and elevating properties) will continue to be important for some time in the future. The comparison between seawalls and managed retreat is illustrative of two contrasting approaches, and by no means all inclusive. Nonetheless, the emphasis is slowly transitioning from large engineered solutions to more creative approaches that are better aligned with natural processes, less costly in the long-term [30,31], and reduce future impacts on socially vulnerable communities and beyond.

We argue that government funded buyouts, followed by structure demolition or relocation, and the restoration of floodplain habitats can support social, environmental, and economic objectives. It is important to note that buyouts must be done from willing and volunteer sellers, and relocation projects must be executed in a thoughtful and fair manner. Kick et al. (2011) found through interviews with flood victims from repetitive loss sites and FEMA officials, that a community-system is the most efficient approach to such projects. Kick et al. (2011) show that financial variables are not the only critical factor, with perceptions of future risk, attachments to home and community, and the relationships with flood management officials, are also critical decision factors that homeowners must consider [32]. Additionally, the timing of relocation is critical. While it is harder to make the case for

relocation before the onset of a disasters, the occurrence of disasters reduces income and consumption levels, further aggravating poverty [33]. Moreover, availability of affordable housing in economically thriving areas where relocated families can find work and become productive members of the community, should be a key component of the relocation process. As it was previously mentioned, input from vulnerable communities must be taken into consideration during all phases of potential projects, from the early planning stages, to actual implementation.

The availability of current technology, supported by well-developed climate science, well-known floodplain processes, and a multitude of high-resolution data, provide decision makers with all the tools required to reduce flood exposure across the country, improving livelihoods, and restoring natural habitat at the same time.

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CHAPTER 3. COMPARATIVE COASTAL RISK INDEX (CCRI): A MULTIDISCIPLINARY RISK INDEX FOR LATIN AMERICA AND THE CARIBBEAN.

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Abstract

As the world's population grows to a projected 11.2 billion by 2100, the number of people living in low-lying areas exposed to coastal hazards is projected to increase. Critical infrastructure and valuable assets continue to be placed in vulnerable areas, and in recent years, millions of people have been displaced by natural hazards. Impacts from coastal hazards depend on the number of people, value of assets, and presence of critical resources in harm's way. Risks related to natural hazards are determined by a complex interaction between physical hazards, the vulnerability of a society or social-ecological system and its exposure to such hazards. Moreover, these risks are amplified by challenging socioeconomic dynamics, including poorly planned urban development, income inequality, and poverty. This study employs a combination of machine learning clustering techniques (Self Organizing Maps and K-Means) and a spatial index, to assess coastal risks in Latin America and the Caribbean (LAC) on a comparative scale. The proposed method meets multiple objectives, including the identification of hotspots and key drivers of coastal risk,

and the ability to process large-volume multidimensional and multivariate datasets, effectively combining sixteen variables related to coastal hazards, geographic exposure, and socioeconomic vulnerability, into a single index. Our results demonstrate that in LAC, more than 500,000 people live in areas where coastal hazards, exposure (of people, assets and ecosystems) and poverty converge, creating the ideal conditions for a perfect storm. Hotspot locations of coastal risk, identified by the proposed Comparative Coastal Risk Index (CCRI), contain more than 300,00 people and include: El Oro, Ecuador; Sinaloa, Mexico; Usulutan, El Salvador; and Chiapas, Mexico. Our results provide important insights into potential adaptation alternatives that could reduce the impacts of future hazards. Effective adaptation options must not only focus on developing coastal defenses, but also on improving practices and policies related to urban development, agricultural land use, and conservation, as well as ameliorate socioeconomic conditions.

Introduction

Backing away from estimates from less than a decade ago, the United Nations now predicts that the world population is unlikely to stabilize by the end of the century. The global population, currently at 7.46 billion, is increasing by nearly 230,000 people every day, at a growth rate of 1.18% per year [1]. In the next 15 years, the global population is expected to grow by an additional 1 billion, reaching 11.2 billion people by 2100 [1]. Concurrently, the number of people living in low elevation coastal areas, exposed to natural hazards, continues to increase [2]. There is a clear

trend of coastal populations growing globally, with an estimated 230% increase

(from 2000 to 2030) in the size of urban areas within the Low Elevation Coastal

Zone (LECZ) - defined as "the contiguous area along the coast that is less than 10

meters above sea level", and which accounts for only 2% of the planet's total land

area [3,4]. Moreover, critical infrastructure and valuable assets continue to be placed

in areas exposed to coastal hazards [5].

In 2013, almost 22 million people were displaced by extreme weather events across

the globe, with 37 events displacing at least 100,000 people each [5]. All but one of

the top 15 largest displacements were related to typhoons or floods, with at least

three million people displaced from coastal areas [6]. In 2012, more than 30 million

people were displaced worldwide by disasters related to climate and weather events

[6]. From 1995 to 2015, worldwide losses resulting from minor but recurrent natural

hazards, including flash floods, landslides, and storms, reached $94 billion [7].

Natural events are not the only reason why disasters occur. Disaster risk is defined

by a complex interaction between physical hazards and the vulnerability of a society

or social-ecological system, and its exposure to such hazards [8]. The disaster risk-

poverty nexus has been well documented [8–12]; Poor communities suffer a

disproportionate share of losses resulting from disasters, are usually less resilient to

losses, and have very limited or no access to insurance and social protection [9].

Furthermore, the occurrence of disasters reduces income and consumption levels,

further aggravating poverty [9].

Social, political and economic conditions are often ignored determining factors for the consequences of the onset of disasters [13–16]. Coastal risks are amplified by challenging socioeconomic dynamics, including ill-advised urban development, income inequality, and poverty. Lack of access to critical resources including food, fresh water, shelter, medicine and evacuation routes, can greatly intensify the damaging effects of coastal hazards [16]. Finally, income inequality is frequently associated with larger damage [17]. Inequality increases poverty and creates processes of social and political exclusion, possibly resulting in social instability, reduced accountability and enabling corruption [17].

There is a well-documented need for studies that explicitly integrate exposure and vulnerability to coastal hazards, disaster risk management, and adaptation [18,19]. Further, multidisciplinary approaches are an effective way to evaluate and solve complex environmental and social problems [19–23].

Previous research addressed the exposure of critical resources to coastal hazards in Latin America and the Caribbean (LAC). In 2011, the Economic Commission for Latin America and the Caribbean (ECLAC) published an assessment of the risks and impacts of climate change in coastal areas of LAC [24]. The 2011 study produced a comprehensive high-resolution database containing more than 15,000 coastal segments of 5-km length each. Individual coastal segments contain multiple attributes related to natural hazards (e.g. significant wave height, storm surge, and wind) and geographic exposure (e.g. urban and cropland area, beaches, and

ecosystems, critical infrastructure, and Gross Domestic Product (GDP)). Coastal risks and hotspots were evaluated for flooding and coastal erosion, resulting from both sea-level rise and extreme weather events. Losada et al. (2013) [25] studied historical sea-level rise and extreme sea levels in LAC, while Reguero et al. (2013) [26], and Izaguirre et al. (2012) [27] described changes in wave conditions in the region. More recently, Reguero et al. (2015b) [28] assessed the exposure of people, land, and built capital to coastal flooding in LAC under current and future conditions of sea level rise (SLR), El Niño induced sea level rise, and storms.

While the studies above address important knowledge needs, they do not incorporate important drivers of risk, such as poverty and inequality. Building on the works from ECLAC (2011) [24], Losada et al. (2013) [25], Reguero et al. (2015a, 2015b) [28,29], and based on the methods developed by Camus et al. (2011) [30], and Ramos et al. (2012) [31], we present a method that identifies critical drivers of coastal risks and isolates hotspots of coastal vulnerability. Combining multiple variables related to the three dimensions of risk (coastal hazards, geographic exposure, and socioeconomic vulnerability) a Comparative Coastal Risk Index (CCRI) is proposed. Areas with higher scores of coastal hazards, exposure, and vulnerability, receive a higher CCRI value (see methods).

Study Region – Latin America and The Caribbean

Despite recent advances in promoting economic and social development, efforts in LAC have failed to significantly reduce poverty [32]. There are a large number of

people in the region with no access to basic services including water and sanitation [32], a situation that greatly increases the vulnerability of coastal populations to natural hazards.

The total population in the LAC region in 2014 was approximately 623 million people (with an annual growth rate of 1.1% between 2010 and 2015) [33]. The GDP in LAC in 2014 was approximately $5.7 trillion. Brazil, Mexico and Argentina had the highest GDPs in 2014 ($2.4 trillion, $1.2 trillion and $0.5 trillion, respectively) [34]. In Colombia, Venezuela, Costa Rica, El Salvador, and Panama, more than 30% of the total population is located in the LECZ [35]. In 2000, roughly 32.2 million people lived in the LECZ in LAC [36,37].

From 1972 to 2010, 88 natural disasters caused nearly 310,000 deaths and 236 billion dollars in damages (2015 $) in LAC [38]. During the same period, 63 meteorological events caused roughly $118 billion [38]. Storms and hurricanes were responsible for 40 disasters, resulting in 50.2% of all deaths, and almost 40% of total damages [38]; in 1998, a single event, Hurricane Mitch, caused more than 23,000 deaths in Central America [38]. From 1972 to 2010, El Niño and La Niña events caused 17 disasters in the region, resulting in approximately 50% of all damages and 4.1% of all deaths [38].

This study focuses on coastal areas (i.e. under 10m in elevation and within 5km of the coast) of LAC, and includes more than 13,000 unique coastal segments covering more than 59,000km of coastline. The study area includes a total population of

almost 23 million people in 26 countries, and is bounded by Mexico (north and west), Chile (south), and Brazil (east).

Methods and Materials

a) Methodology

This study employs a combination of machine learning clustering techniques (Self Organizing Maps and K-Means) and a spatial index, to classify and rank coastal areas according to coastal risk. Hazards, exposure, and vulnerability data were combined to calculate a comparative coastal risk index (CCRI).

The benefits of the proposed approach include: (i) the identification of hotspots and key drivers of coastal risk; (ii) the ability to process large-volume multidimensional and multivariate datasets, effectively reducing sixteen variables related to coastal hazards, geographic exposure, and socioeconomic vulnerability, into a single index; and (iii), clustering of coastal areas according to similar attributes, where consistent risk reduction strategies may be applied to minimize future risk.

Methodology steps (see Fig 1):

First, variables within each risk dimension (hazards, exposure, and vulnerability) were clustered. Second, individual scores for each risk dimension were calculated. Finally, a Comparative Risk Index (CCRI) was calculated.

The flow chart contains two levels.

Level 1 (left column labels):
- Data Collection and Preparation (Validation, Transformation, and Normalization)
- Cluster Step 1: 100 Self-Organizing Maps
- Cluster Step 2: 9 k-means clusters
- Individual Scores (1:5) (See Figs 2, 3 and 4)
- Comparative Coastal Risk Index (CCRI) (1:5) (See Fig 5)
- Hotspots (See Fig 6)

Level 2 (right column):
- Coastal Hazards
- Geographic Exposure
- Socioeconomic Vulnerability

(1:5)   (1:5)   (1:5)

$$CCRI = \sqrt[3]{(H * E * V)} \; ; \; (1:5)$$

CCRI = 5

Figure 1. Methods Flow Chart

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Within the context of this study, risk is defined as the geometric mean between the individual scores describing various degrees of hazards, exposure, and vulnerability. Areas with higher individual scores receive a higher comparative risk index value. For this first implementation of CCRI, an equal weights approach was chosen. However, future applications may consider different weighting scenarios.

b) Data:

The methodology leverages several datasets, including the ones published by Reguero et al. (2013 and 2015a, 2015b) [28,26], Losada et al. (2013) [25], Izaguirre et al. (2013) [39], and ECLAC (2011) [40]. Several new attributes were appended to the original datasets, including: cumulated cyclone winds (used as a proxy for hurricanes), GDP, Gini coefficient of inequality, and Infant Mortality Rates (IMR). A description of the individual variables used in each score follows:

Coastal Hazards

Coastal hazards may be related to extreme weather events (e.g. storm surge and winds from tropical storms), or to low intensity events (e.g. sea level rise due to El Niño events) [16,41,42]. Table 1 contains a description of the coastal hazards variables included in the study.

Table 1. Coastal Hazards Variables

Coastal Hazards Score Components	Data Source	Resolution (degrees of Latitude or km)	Period of Data	Unit
Wave Energy	Reguero et al. (2015a) [29]	0.25º (Caribbean) 0.50 º remaining areas	1948 - 2008	W/m^2
Storm Surge 99% (m)	Losada et al. (2013) [25]	0.25º (Caribbean) 0.50 º remaining areas	1948 - 2010	m
El Nino 1997-1998 (m)	Losada et al. (2013) [25]	0.50º	1997 - 1998	m
Significant Wave Height Ratio (HS 12 / HS mean)	Reguero et al. (2013 and 2015b) [28,26]	0.25º (Caribbean) 0.50 º remaining areas	1948 - 2008	ratio
Cumulated Tropical Cyclone Winds	Global Risk Data Platform, United Nations Environment Programme (UNEP), [43]	2 km	1975 - 2007	km (km/h*h)

Geographic Exposure

Geographic exposure is defined as the presence (of people, ecosystems, infrastructure, and assets) in places that could be adversely affected by physical hazards [19]. The variables included in this study representing exposure are: coastal population, GDP, urban area, cropland and various ecosystems.

An ecosystems category was included to reflect the valuable (and often overlooked) services that ecosystems provide. As an example, wetlands and mangroves provide valuable services to neighboring communities in the form of coastal protection, enhancement of fisheries, water filtration, sediment trapping, and many others [44].

As ecosystems are impacted by the onset of coastal hazards, however, their value to coastal communities is diminished, hence their inclusion in the exposure category.

The following ecosystems were included in this study: beaches, mangroves, estuaries, marshes, grasslands, deciduous, mixed and conifer forests, and deserts [25]. Ecosystems data were summarized into three components: (i) beach area; (ii) wetlands (sum of saltmarshes and estuaries); and (iii), coastal forests (sum of mangroves, grasslands, deciduous, and mixed forests). First, linear densities were calculated for each component by normalizing their areas by the length of coastal segments. Second, the linear densities of beaches, coastal forests and wetlands were added into a broader ecosystems category, calculated for each coastal segment (equation 1):

$$Ecosystems\ Component = \ Beach\ (Linear\ Density) +$$
$$Coastal\ Forests\ (Linear\ Density) + Wetlands\ (Linear\ Density)\ (1)$$

Table 2 contains a description of the geographic exposure variables included in the study.

Table 2. Geographic Exposure Variables

Exposure Score Components	Data Source	Resolution	Date	Unit / Year
Coastal Population	Reguero et al. (2015b) [28]	1 km^2	2000	Number of People
% Urban Coverage	ECLAC (2011) [45]	5km	2000?	Ratio
% Crop Coverage	ECLAC (2011) [45]	5km	2011	Ratio
Beach Linear Density	ECLAC (2011) [45]	5km	2011	Km (km^2/km)
Coastal Forests Linear Density	ECLAC (2011) [45]	5km	2011	Km (km^2/km)
Wetlands Linear Density	ECLAC (2011) [45]	5km	2011	Km (km^2/km)
Per Capita GDP (average)	Global Risk Data Platform, (UNEP) [43] (see S2 Appendix for additional sources)	30 arc second resolution, roughly 1 km^2	2000	USD (year 2000, extrapolated to 2010)

Socioeconomic Vulnerability

Within the context of this study, socioeconomic vulnerability is described in terms of the ability of a coastal community to cope with and adapt to a coastal hazard that may impact livelihoods and well-being [46]. Poverty and welfare are common indicators of socioeconomic vulnerability, and can be evaluated by proxy variables [47,48]. Vulnerability variables used in this study, namely: Infant Mortality Rate (IMR), Child Malnutrition, GDP, and Income Inequality, are commonly accepted

indicators of socioeconomic vulnerability and poverty [47–49]. Table 3 contains a list of the socioeconomic vulnerability variables included in the study.

Table 3. Socioeconomic Vulnerability Variables

Vulnerability Variable	Data Sources	Resolution	Period	Unit
Gini coefficient	Socioeconomic Data and Applications Center (SEDAC) [50,51] (see S2 Appendix for other sources)	National	1995-2012	N/A
Child Malnutrition Rate (%)	SEDAC [50] (see S2 Appendix for other sources)	Subnational	1990 - 2000	%
Infant Mortality Rate (%)	SEDAC [50] (see S2 Appendix for other sources)	Subnational	2000	number of deaths
Per Capita GDP (average)	Global Risk Data Platform, (UNEP) [43] (see S2 Appendix for other sources)	Subnational	2010	USD

c) Clustering Analysis

Clustering techniques were used to investigate how coastal areas in the LAC region may be grouped according to similar characteristics of hazards, exposure, and vulnerability. We follow the techniques and recommendations from Camus et al. (2011, and 2016) [30,52], and Ramos et al. (2012) [31]. Clustering, in this context, means partitioning of each dataset into smaller groups of similar characteristics. Two clustering algorithms were applied in two subsequent steps. First, the Self-Organizing Maps (SOM) algorithm was applied to distribute 13,426 study units into 100 maps. Second, the K-Means algorithm was applied to further group the 100 resulting SOM maps into 9 clusters (S1 Appendix). The application of two

abstraction levels proved more consistent than applying either one independently, confirming the findings from Vesanto and Alhoniemi (2000) [53]. Recent studies applied similar methods of data classification in various research fields [30,54–57].

One of the limitations of the used algorithms is that they do not propose an optimal number of clusters. Therefore, it was necessary to test multiple values for each abstraction level (SOM and K-Means), until it was possible to validate that the resulting clusters indeed consisted of locations with similar features. Several attempts were made to adjust the best number of final clusters (from 2 to 25), with 9 clusters best representing the data. As an index is introduced in the analysis, the issue of the number of clusters is greatly minimized, as similar clusters receive similar values for the final index.

The benefits of clustering the data before applying an index are multiple. The categorization of multivariate datasets according to similar attributes simplifies the analysis; SOM provide intuitive visualization of results, greatly facilitating the analysis of multivariate sets in a 2D plane. Further, the clustering analysis produces risk profiles across the region allowing areas of similar risk profiles to be easily identified; the most relevant variables of hazards, exposure, and vulnerability can be traced back from the final risk index, to individual clusters. Finally, clustering techniques allow the analysis of large datasets at a low computational cost.

Data Transformation and Normalization

The exposure dataset contains a significant number of coastal segments with no

population or GDP (values equal 0), resulting in a highly-skewed distribution. To

improve the distribution, the Box-Cox transformation (equation 2) was applied to the

relevant variables.

$$x'_\lambda = \frac{(x^\lambda - 1)}{\lambda} \qquad\qquad (2)$$

Subsequently, all variables were then transformed to range from 0 to 1. This step

ensures that all variables have equal weight in the clustering analysis.

Maximum Dissimilarity Initialization

The Maximum Dissimilarity algorithm was used to pre-select the most distinct

values within the dataset as the initial centers for each cluster, ensuring that the

resulting clusters are as diverse as possible [30,58].

First Clustering Step – Self-Organizing Maps (SOM)

The SOM algorithm [59] facilitates the visualization of high-dimensional data by

converting nonlinear statistical relationships between multiple dimensions into

simple geometric shapes, usually a simple grid of nodes. SOM compresses

information but retains the most important relationships of the original data

elements. Formally, SOM is the nonlinear mapping of high-dimensional input data

into a linear array. Each map unit produced represents a vector, comprised of as

many columns as the original dataset (i.e. each hazards, exposure, and vulnerability

attributes). The most commonly used SOM output is a topological representation of the data, where each cell represents a cluster and contains a number of data entries, or samples, associated with it. All samples within a cell are similar, and also similar to samples in adjacent cells, while samples assigned to distant cells are less similar. A probability matrix is also produced, which represents the number of records belonging to each cluster. SOM reduced the dimensionality of each data set into a single value for each cluster.

Hazards, exposure, and vulnerability data were clustered independently. Several attempts were made to perform a single cluster analysis utilizing a single database containing all variables. However, clustering results, based on 16 variables, proved to be too complex and cumbersome to be analyzed.

Second Clustering Step – K-Means Algorithm

As a second clustering step, the K-Means algorithm was applied to further reduce the 100 SOM groups (resulting from the first clustering step) into 9 clusters. This step was repeated for each category (hazards, exposure, and vulnerability), independently. Using K-means to assign each one of the 100 SOM groups into 9 clusters provides additional benefits beyond the initial clustering provided by SOM. It provides a smaller number of clusters, and the ability to compare similar values that were placed further apart in the SOM maps. K-means cluster centers (mean values) represent prototypes for the records belonging to it. Individual SOM groups were assigned to the prototypes with the closest mean value in a two-step iterative way.

On each step, the algorithm calculates a mean value for each cluster, based on the values of the points belonging to it. In a second step, individual points are reassigned to the cluster with the closest value [60]. Values within clusters are more similar, and closer in value to the cluster's mean value, than other clusters. This process is repeated until points no longer jump between clusters. In this study, the process was repeated 100 times. Several numbers of K-Means clusters were evaluated (from 3 to 25) with the best results achieved with 9 clusters.

Hazards, Exposure, and Vulnerability Scores

The next step in the analysis was to assign individual scores to the 9 clusters (for each category), and rank them by intensity. Scores were calculated according the equations described below, and variables within each score were equally weighted.

The rationale behind developing these scores is that areas where more than one variable is present receive a higher score than areas where only one, or no variables are present (e.g. areas impacted by both high wave energy and tropical storm winds would be ranked higher than areas only affected by one of these hazards).

Once scores were calculated, each one of the 9 clusters within each category (hazards, exposure, and vulnerability), was ranked from 1 to 5 (with 1 representing the lowest severity, and 5 representing the highest severity).

One limitation of this approach is the assumption that that the impacts from individual hazards are equal in severity. As an example, we assume that elevated sea levels during an El Niño event have the same impact as areas of high accumulated

winds. This assumption is adequate for the objectives and spatial scale of the current analysis, and illustrates a basic implementation of the proposed approach. However, it may not be adequate for other applications of this method, or the selection of local risk reduction strategies. Moreover, the proposed index is not meant to represent a definite result, but rather a starting point, showcasing the benefits of the method presented here. However, the model is flexible, and different weights can be easily assigned to specific variables within the model, making it suitable to be used by diverse stakeholders. Future applications of this model should ensure that each variable receives the appropriate weight that represents the study's objectives.

Coastal Hazards Score

An overall coastal hazards score was calculated by summing up the values of individual hazard variables at each coastal segment (equation 3). Variables included in the hazards score are: waves (average between significant weight height ratio, and wave energy), storm surge, wind, and El Niño. Hazards scores for the 9 clusters were ranked from 1 to 5 (low to high), according to severity.

$$Coastal\ Hazards\ Score\ (HS) = Waves + Storm\ Surge + Wind + El\ Niño \ (3)$$

Geographic Exposure Score

An overall Exposure Score was calculated by summing up the values of individual exposure variables for each coastal segment. Variables included in the exposure score are: coastal population, GDP, cropland ratio, urban ratio, and coastal

ecosystems (equation 4). Exposure scores for the 9 clusters were ranked from 1 to 5 (low to high) according to severity.

$$Geographic\ Exposure\ Score\ (ES) = Coastal\ Population + GDP +$$
$$Cropland\ Ratio + Urban\ Ratio + Ecosystems\ (4)$$

The presence of ecosystems in low elevation areas is an important component of coastal exposure. Coastal ecosystems provide valuable services to neighboring communities in the form of coastal protection, enhancement of fisheries, water filtration, sediment trapping and many others [44].

Ecosystems data were summarized into three components: (i) beach area; (ii) wetlands (sum of saltmarshes and estuaries); and (iii), coastal forests (sum of mangroves, grasslands, deciduous, and mixed forests). First, linear densities were calculated for each component by normalizing their areas by the length of coastal segments. Second, the linear densities of beaches, coastal forests and wetlands were averaged into a broader ecosystems category, calculated for each coastal segment (equation 5).

$$Ecosystems = (Beach\ Linear\ Density + Coastal\ Forests\ Linear\ Density +$$
$$Wetlands\ Linear\ Density)/3\ (5)$$

Socioeconomic Vulnerability Score

An overall vulnerability score was calculated by summing up the values of individual vulnerability variables for each coastal segment. The following variables

were included in the vulnerability score: a social welfare function (SWF), IMR, and malnutrition (equation 7). Vulnerability score scores for the 9 clusters were ranked from 1 to 5 (low to high) according to severity.

A social welfare function (SWF), which combines GDP and the Gini coefficient was used in the vulnerability score, as it better describes aggregated income and its distribution [61,62] (equation 6). Areas with higher value of SWF are wealthier, therefore less vulnerable than areas with low values of SWF. Given the inverse relationship between SWF and socioeconomic vulnerability, SWF is negative.

$$\text{SWF} = -\big(GDP * (1 - Gini\ index)\big) \text{ (6)}$$

$$Socioeconomic\ Vulnerability\ Score\ (VS) = IMR + Malnutrition + SWF \text{ (7)}$$

d) Comparative Coastal Risk Index (CCRI)

Finally, CCRI was calculated as the geometric mean of the hazards, exposure, and vulnerability scores, for each coastal segment. CCRI values range from 1 to 5 (equation 8).

$$Comparative\ Coastal\ Risk\ Index\ (CCRI) = \sqrt[3]{(HS * ES * VS)} \text{ (8)}$$

Results

The results from this first implementation of CCRI in LAC, which are based on an equal weights approach, are meant to illustrate different kinds of analysis that this method can support. Values described as "high", "large", or "low" and "small" are

relative to values from other areas in the study region. They may still be considered higher or lower when compared with other regions of the planet not included in the study.

The following section describes the resulting clusters for each category of CCRI. The 13,426 original coastal segments were reduced to 9 hazards clusters (H1 to H9), 9 exposure clusters (E1 to E9), and 9 vulnerability clusters (V1 to V9).

Coastal Hazards – Clusters and Scores

First, coastal hazards data were clustered according to characteristics of: waves, storm surge, wind, and El Niño induced sea level changes. Second, hazards scores were calculated (equation 4), and range from 1 to 5, with 5 being the most severe. The resulting scores were scaled from 0 to 1. Clusters H1 and H8 received the maximum hazards score, and are characterized by El Niño induced sea levels, and strong cumulated winds, respectively (Table 4).

As previously discussed, one of the benefits of applying clustering techniques, prior to the index calculation, is that drivers of coastal risks can be traced back to individual clusters for each category (hazards, exposure, and vulnerability).

Table 4. Coastal Hazards Clusters (sorted by Hazards Score)

Cluster	% of Coastal Segments	Coastal Length (km)	Coastal Population	Most Relevant Attribute	Top 3 Affected Countries (by population)	Hazards Score
H1	16%	10,312	2.2 million	Strong El Niño	Mexico, Ecuador, Peru	5
H8	7%	4,673	1.0 million	Strong winds	Puerto Rico, Mexico, and Caribbean	5
H3	7%	3,628	3.3 million	High Waves	Argentina, Uruguay, Brazil	4
H4	8%	4,985	0.6 million	Moderate El Niño	Peru, Puerto Rico and the Dominican Republic	3
H6	11%	5,184	27,000	Moderate Waves	Chile and Mexico	3
H5	9%	4,147	3.4 million	Weak Storm Surge	Brazil, Argentina, and Chile	2
H7	10%	6,213	2.1 million	Moderate winds and weak El Niño	Cuba, Dominican Republic, and Haiti	2
H9	8%	5,043	2.0 million	Small waves and Weak El Niño	Mexico, Cuba and Haiti	2
H2	24%	15,119	8.3 million	Weak El Niño	Brazil, Venezuela, Colombia	1

The spatial distribution of the hazards clusters (Fig.2) is consistent with recent

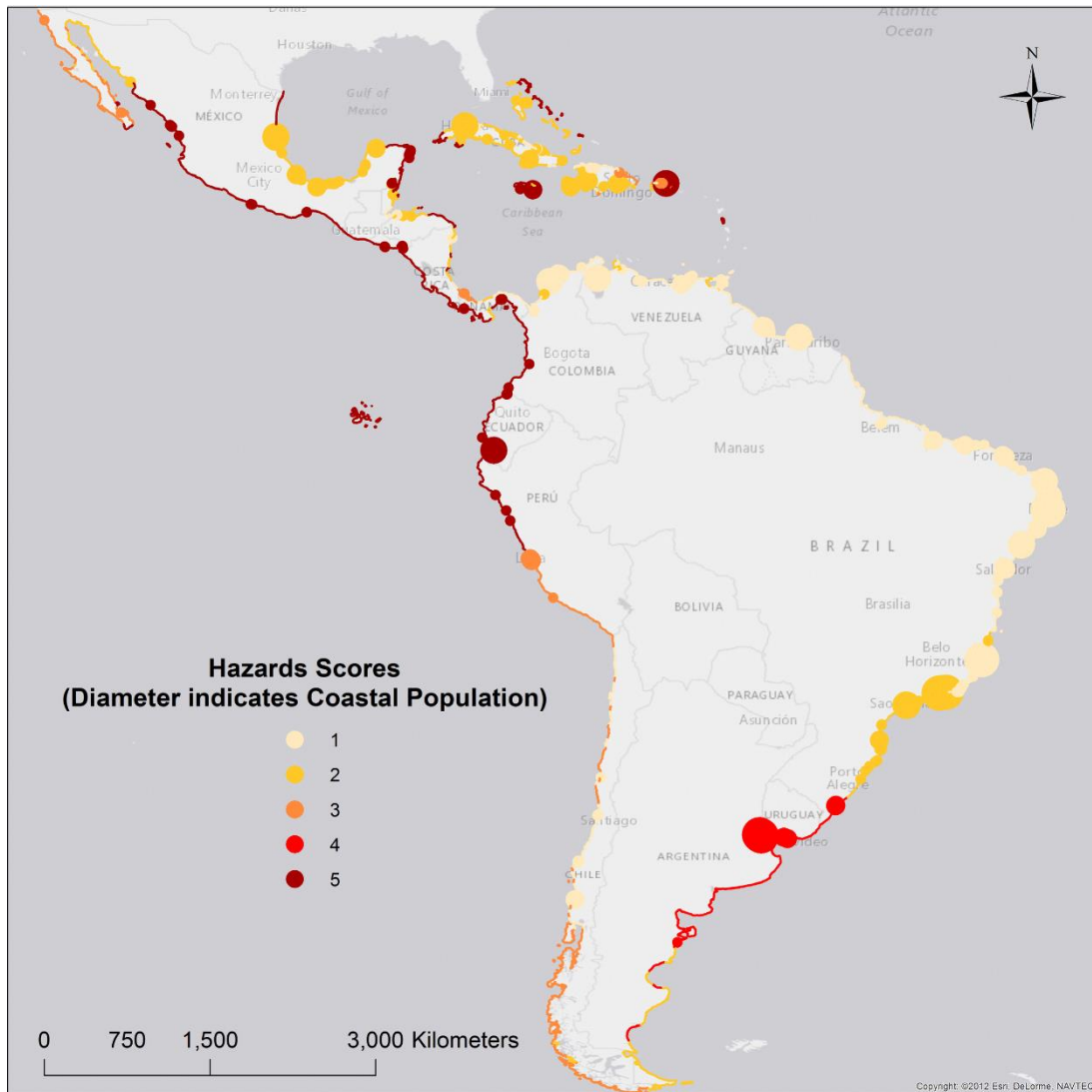studies of coastal hazards in the LAC region [25,26,40].

Figure 2. Coastal Hazards Scores

First, geographic exposure data were clustered according to characteristics of: coastal

population, GDP, urbanization, cropland, and ecosystems. Second, exposure scores

were calculated (equation 5), and range from 1 to 5, with 5 indicating the highest

geographic exposure levels. Geographic exposure clusters are not as geographically concentrated as the coastal hazards discussed above. Clusters E1, E8, and E6 received the maximum exposure score. These three clusters include coastal segments with large population. However, E1 includes large urban areas while E8 and E6 are characterized by a more significant presence of ecosystems and croplands, respectively (Table 5, and Fig 3).

Table 5. Geographic Exposure Clusters (sorted by Exposure Score)

Cluster	% of Coastal Segments	Coastal Length (km)	Coastal Population	Most Relevant Attribute	Top 3 Affected Countries (by population)	Exposure Score
E1	2%	1,410 km	8.0 million	Largest population, GDP, and urban areas	Brazil, Argentina, Mexico	5
E8	4%	2,706 km	2.9 million	Large population, ecosystems and croplands	Brazil, Colombia, and Ecuador	5
E6	7%	4,818 km	2.3 million	Large population and ecosystems	Mexico, Brazil, and Guyana	5
E4	16%	9,821 km	6.1 million	Large population and croplands	Brazil, Mexico, Cuba	4
E7	13%	8,247 km	1.6 million	Croplands and moderate GDP	Haiti, Dominican Republic, and Brazil	3
E9	25%	15,220 km	1.5 million	Moderate GPD	Brazil, Mexico, and Chile	2
E5	7%	4,477 km	0.5 million	Moderate GDP; ecosystems	Peru, Venezuela, and Colombia	2
E3	5%	2,685 km	0	Moderate croplands and GDP	Trinidad Tobago,	2

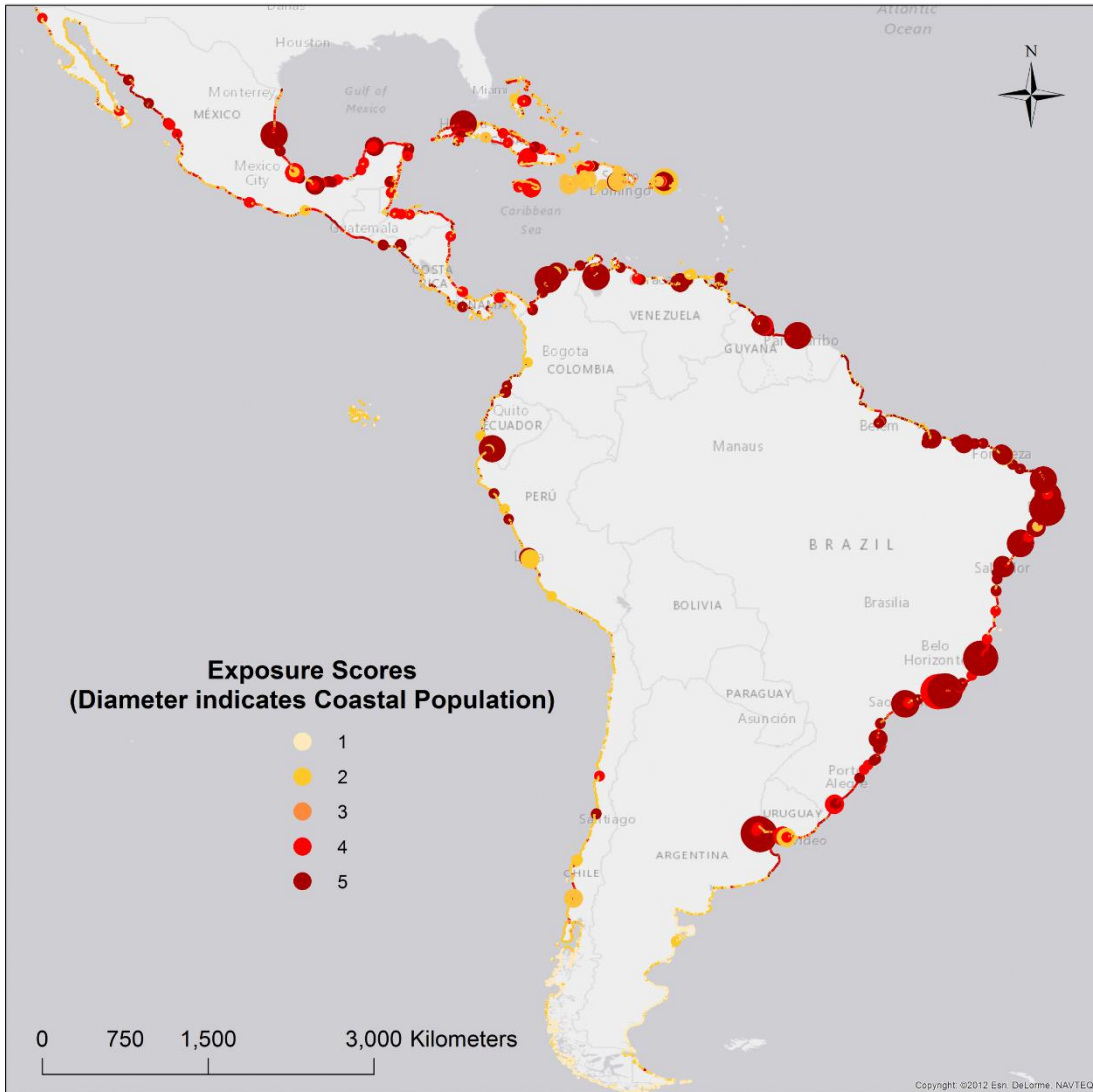|					Mexico, and Haiti	
E2	20%	9,921 km	1,780	Low presence of all variables	Cuba, Mexico and Belize	1

Figure 3. Exposure Scores

Socioeconomic Vulnerability – Clusters and Scores

First, socioeconomic vulnerability data were clustered according to characteristics of: GDP, Inequality, IMR, and malnutrition. Second, vulnerability scores were calculated as the sum of SWF, IMR, and malnutrition (equation 6), and range from 1 to 5, with 5 indicating the highest socioeconomic vulnerability. Clusters V1, V9 received the maximum vulnerability score, with high IRM, malnutrition, and low social welfare (Table 6, and Fig 4).

Table 6. Socioeconomic Vulnerability Clusters (sorted by Vulnerability Score)

Cluster	% of Coastal Segments	Coastal Length (km)	Coastal Population	Most Relevant Attributes	Top Countries Affected (by population)	Vulnerability Score
V1	10%	6,491	5 million	Highest IMR and malnutrition; low SWF	Haiti, Brazil, and Honduras	5
V9	13%	8,324	1.6 million	High IMR and malnutrition; low SWF	Mexico, Guyana, and Ecuador	5
V3	14%	8,784	7.7 million	High IMR and malnutrition; low SWF	Brazil, Mexico, and Colombia	4
V7	15%	8,567	521,000	High malnutrition; medium IMR; low SWF	Mexico, Argentina and Peru	4
V8	2%	1,285	84,000	Medium malnutrition and IMR; low SWF	Brazil, Colombia, and Panama	4
V4	13%	7,561	4.7 million	Medium malnutrition; low IMR; high SWF	Argentina, Mexico, and Uruguay	3
V5	6%	3,123	1 million	Low malnutrition and IMR; low SWF	Peru, Chile and Brazil	2
V2	14%	6,690	14,741	Low malnutrition	Chile, Peru and Brazil	1

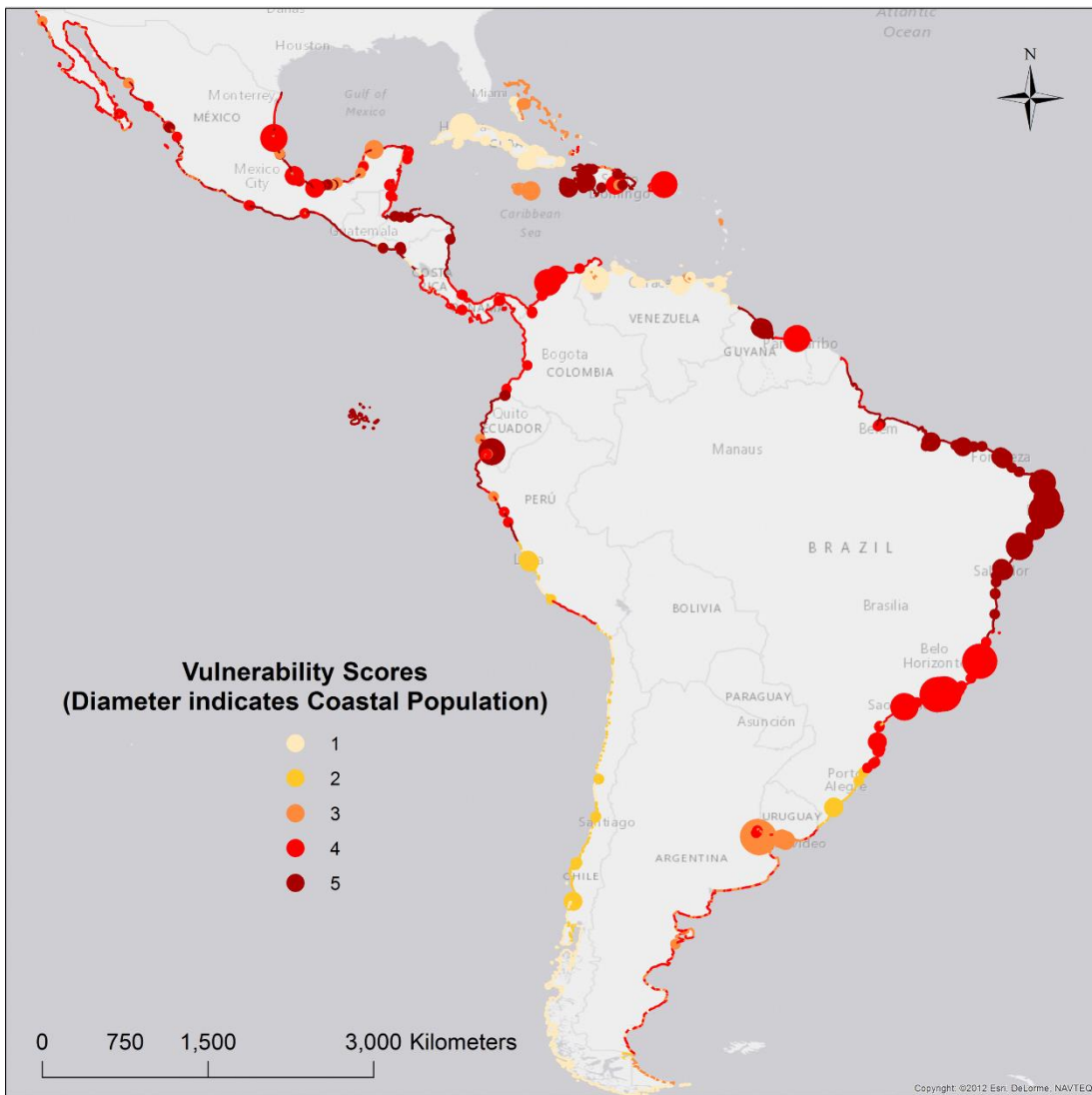|				and IMR; low SWF		
V6	14%	8,479	2.2 million	Medium malnutrition; low IMR; highest SWF	Cuba, and Venezuela	1

Figure 4. Socioeconomic Vulnerability Scores

Comparative Coastal Risk Index (CCRI) – equal weights scenario

Our results show that nearly 1.79 million people live in areas of high or very high CCRI (4.6 or 5, respectively) in LAC. This number represents almost 8% of the 23 million people population in the study area. Roughly 560,000 people live in areas of maximum CCRI value equal 5. These are areas where the maximum scores for hazards, exposure, and vulnerability (all equal 5) coexist. Areas with the second highest CCRI value (i.e. 4.6), include a coastal population of 1.2 million people.

Brazil, the largest country in the study region, also contains the largest coastal population, more than 8.6 million people. Mexico and Argentina have the second and third largest coastal populations (2.9, and 2.7 million people, respectively). However, the largest populations in areas of maximum CCRI (equal to 5) are in Ecuador (222,404 people), Mexico (130,810 people), and El Salvador (91,965 people).

The total coastal population in the LAC in areas of maximum CCRI, (more than 566,000 people) are spread in 223 coastal segments, across 29 provinces in seven countries: Ecuador, Mexico, El Salvador, Honduras, Nicaragua, Guatemala, and Peru. Ecuador, Mexico, El Salvador and Honduras hold 87% of the total population (494,330 people) and 80% of the number of coastal segments (179 segments) in areas of maximum CCRI. The above provinces are in countries in Northern, Central, and South America, facing the Pacific Ocean.

The roughly 560,000 people in areas of maximum CCRI values are distributed as follows: The majority (98.8%, or almost 560,000 people) belong to cluster H1,

characterized by El Niño induced sea levels. Roughly 66% (372,000 people), belong to exposure cluster E6, characterized by large population and ecosystems. Roughly 32% belong to areas in cluster E8, characterized by large population, ecosystems and croplands; and 2.3% live in areas assigned to cluster E1, characterized by large population, GDP, and urban areas. Finally, 68.1% of the coastal population belong to cluster V9 (386,000 people), and almost 32% in cluster V1 (181.000 people). Both V1, and V9 clusters are characterized by high IMR, malnutrition, and low SWF. Cluster V1, however, has the highest IMR in the study (62 deaths per 1,000 births on average).

See Fig 5, and Table 7, for a geographic distribution of CCRI in LAC.
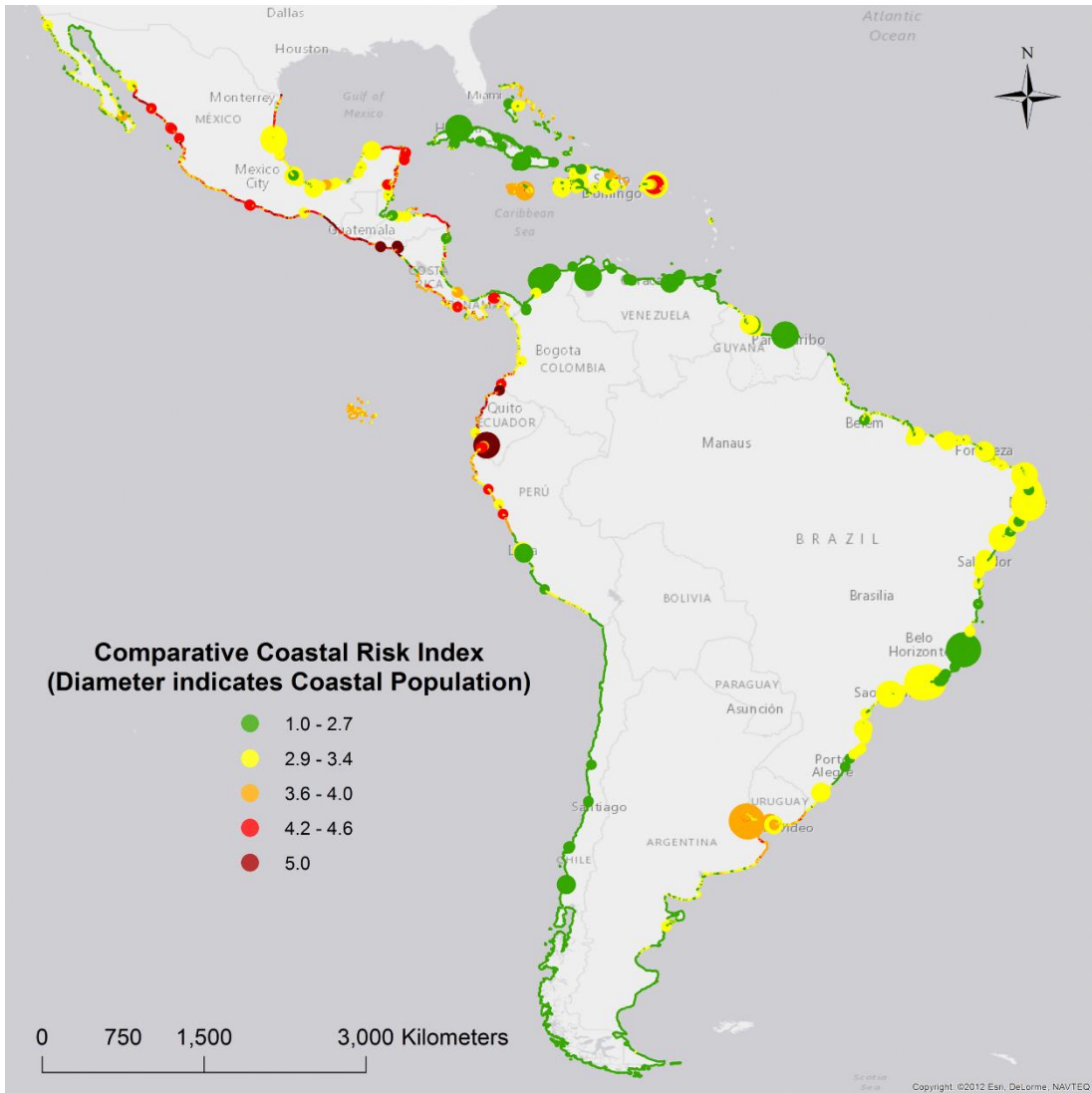
Figure 5. Comparative Coastal Risk Index (CCRI)

Table 7. Coastal Population living in areas of maximum CCRI (value of 5)

Country	Locality	Coastal Population
Ecuador	El Oro	164,623
	Esmeraldas	38,170
	Manabi	17,442
	Guayas	2,169
Total Ecuador		**222,404**
Mexico	Sinaloa	51,936
	Chiapas	44,709
	Nayarit	17,262
	Oaxaca	10,564

	Guerrero	6,339
	Tamaulipas	1,464
Total Mexico		**132,274**
El Salvador	Usulutan	51,404
	La Paz	17,641
	La Union	11,092
	Ahuachapan	8,569
	Sonsonate	2,259
Total El Salvador		**90,965**
Honduras	Choluteca	22,905
	Valle	20,683
	Gracias a Dios	4,858
	Colon	241
Total Honduras		**48,687**
Nicaragua	Chinandega	35,988
	Carazo	714
	Zelaya	184
Total Nicaragua		**36,886**
Guatemala	Santa Rosa	13,377
	Escuintla	10,172
	Jutiapa	3,935
	Retalhuleu	1,856
Total Guatemala		**29,340**
Peru	Piura	3,794
	Ancash	2,059
	La Libertad	319
Total Peru		**6,172**
Grand Total		**566,728**

Hotspots (areas of maximum CCRI = 5)

Our results show that 55% of the coastal population (more than 310,000 people)

living in areas of maximum CCRI, are concentrated in four provinces: El Oro,

Ecuador; Sinaloa and Chiapas, Mexico, and Usulutan, El Salvador (Fig 6). Ranked

by coastal population, the analysis below focuses on these four areas. In these

locations, the three dimensions of coastal risk (hazards, exposure, and vulnerability)

have maximum scores (equal to 5).

During the 1982/1983 El Niño, infant mortality rates in flood affected areas in El

Oro, increased 16% (from 52 to 65 per thousand live births) [63]. In Chiapas,

Mexico, 76.2% of the population live below the poverty line, with 44.4% of the

population living in extreme poverty. Infant mortality rates in Chiapas, are three

times higher than the Mexican average [64]. In Sinaloa, Mexico, 36% of the

population currently live below the poverty line [65]. In Usulutan, El Salvador,

37.4% of the population live below the poverty line, with more than 11% living in
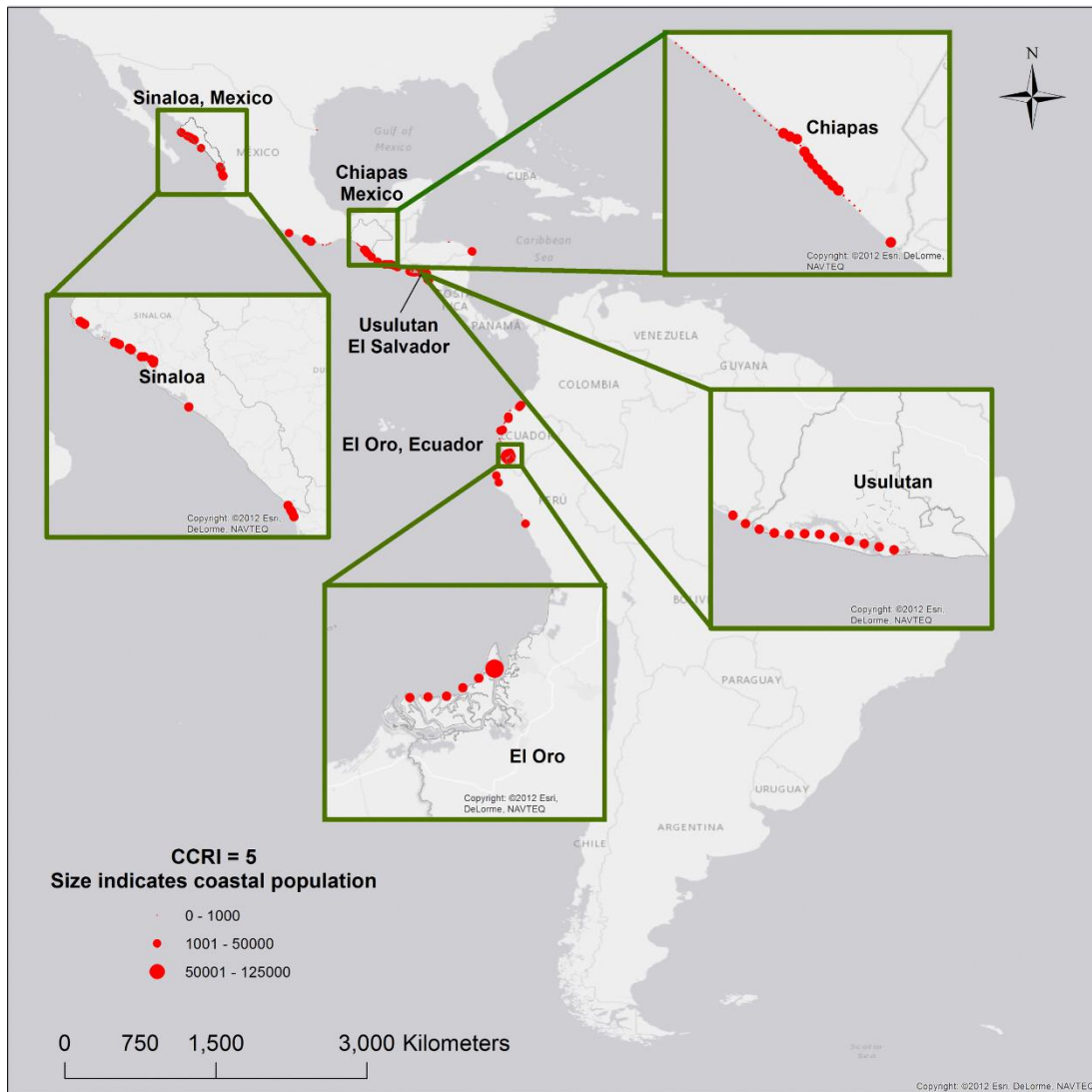
extreme poverty [66].

Figure 6. Hotspots of Coastal Risk

1) El Oro, Ecuador

Ecuador contains the largest coastal population in the study area with CCRI index

value equal 5 (222,404 people). El Oro, the southernmost coastal Province of

Ecuador, contains almost 30% of that population (164,623 people), concentrated in

six coastal segments. The most relevant drivers of coastal risk in El Oro are:

- **Hazards**: all six coastal segments in El Oro belong to cluster H1, with El Niño as the main driver of coastal hazards;

- **Exposure**: five coastal segments belong to cluster E8, characterized by large population, ecosystems and croplands; one coastal segment belongs to cluster E6, characterized by large population and ecosystems.

- **Vulnerability**: five coastal segments belong to cluster V9, and one coastal segment belongs to cluster V1. Both V1 and V9 clusters are characterized by high IMR (35 deaths per thousand births), high malnutrition rates (14.8%), and low SWF. However, cluster V1 has much lower SWF values than V9.

2) Sinaloa, Mexico

Mexico contains the second largest coastal population in the study area with maximum CCRI value of 5 (132,274 people). The state of Sinaloa, on the Gulf of California, contains roughly 39% of that total (51,936 people) concentrated in 24 coastal segments. The most relevant drivers of coastal risk in Sinaloa are:

- **Hazards**: All 24 coastal segments in Sinaloa belong to cluster H1, with El Niño as the main driver of coastal hazards.

- **Exposure**: 21 coastal segments belong to cluster E6, characterized by large population and ecosystems; the 3 remaining coastal segments belong to cluster E1, characterized by large population, GDP, and urban areas.

- **Vulnerability**: All 24 coastal segments in Sinaloa belong to cluster V9, characterized by high IMR (24.3 deaths per thousand births), high malnutrition rate (7.5%), and low SWF values.

3) Usulutan, El Salvador

El Salvador contains the third largest coastal population in the study area with maximum CCRI value of 5 (90,965 people). The province of Usulutan, in the southeast region of El Salvador (facing the Pacific Ocean), contains 57% of that population (51,404 people), concentrated in 12 coastal segments. The most relevant drivers of coastal risk in Usulutan are:

- **Hazards**: All 12 coastal segments in Usulutan belong to cluster H1, characterized by El Niño as the main driver of coastal hazards.

- **Exposure**: All the 12 coastal segments in Usulutan belong to cluster E6, characterized by large population and ecosystems.

- **Vulnerability**: All 12 coastal segments in Usulutan belong to cluster V9, characterized by high infant mortality rate (31.2 per thousand births), high malnutrition rate (11.3%), and low SWF values.

4) Chiapas, Mexico

The state of Chiapas, on the shoreline of the Gulf of California, contains 35 coastal segments with 44,709 people living in areas of maximum CCRI. This represents roughly 33.8% of the total population in maximum CCRI areas in Mexico. The most relevant drivers of coastal risk in Chiapas are:

- **Hazards**: All 35 coastal segments in Chiapas belong to cluster H1, characterized by El Niño as the main driver of coastal hazards;

- **Exposure**: All 35 coastal segments belong to cluster E6, characterized by large population and ecosystems;

- **Vulnerability**: All 35 coastal segments in Chiapas belong to cluster V9, characterized by high infant mortality rate (31.9 deaths per thousand births), high malnutrition rate (7.5%), and low SWF values.

Discussion

As coastal populations increase around the globe, the combination of coastal hazards, geographic exposure and socioeconomic vulnerability can greatly intensify coastal risks. In a vicious cycle, the occurrence of disasters leads to a reduction of income and consumption levels, aggravating poverty, and limiting the population's ability to minimize and cope with future impacts.

Our results show that in LAC, more than 500,000 people live in areas of maximum CCRI, with more than 310,000 people concentrated in four hotspot locations: El Oro, Ecuador; Sinaloa and Chiapas, Mexico, and Usulutan, El Salvador (Fig 6). These are communities where scarce critical resources are consistently placed in hazards prone areas further exacerbating risks and impacts from coastal hazards.

Notably, some areas considered hotspots of coastal exposure in previous studies, including a number of Caribbean islands, and Rio de La Plata [16,28], do not peak within CCRI. Several areas of the Caribbean received maximum hazards scores (e.g. The Bahamas) and maximum vulnerability scores (i.e. Haiti). However, except for very few coastal areas (e.g. Havana, Cuba), exposure scores in The Caribbean ranged

from 2 to 3, driving lower CCRI values. Similarly, coastal segments in the Rio de la Plata region received maximum coastal hazards scores, but did not receive highest vulnerability and hazards scores, resulting in CCRI values from 2.9 to 4.3. Nevertheless, coastal risk affects areas beyond those where CCRI equals 5. Particularly, areas where CCRI is >=4 and <5 include an additional 1.6 million people, and should also be prioritized. Such areas did not peak in the CCRI index due to the variables selected, and due to the equal weight scheme utilized in the calculations. If variables are substituted, or if individual scores are weighted differently, the results are likely to change.

While the impacts from climate change are not in the scope of the present study, it is important to acknowledge that they pose additional threats to coastal areas [19]. Climate change impacts, including more frequent high-intensity storms, higher sea-levels, and more severe floods will pose additional challenges to coastal communities [4,25,67]. Global sea-level rise projections for the year 2100 range from 81cm to 179cm, which will lead to more frequent and widespread coastal flooding [68–71]. Nuisance floods – minor, recurrent flooding that takes place at high tide – already cause frequent road closures, overwhelm storm water drainage, having a non-linear impact on critical infrastructure [72,73] .

Despite recent efforts to assess coastal risks in a multidisciplinary way, further research is still needed. The methods proposed here can be enhanced by the introduction of temporal variability via the addition of future projections (e.g.

population growth, land use, and hazards projections). Additionally, a panel of experts could be convened to review the input variables and weighting of CCRI. Finally, higher resolution, small scale studies, focused on coastal risk reduction are needed.

The techniques employed here provide a robust toolset to identify patterns through multivariate and complex datasets. The benefits of the proposed approach are multiple and include: reduction of multiple independent variables into a single coastal risk index; the identification of major drivers of coastal risk and related hotspots; the ability to identify coastal areas seemly unrelated, but facing very similar challenges and may benefit from future collaborations to reduce coastal risk.

The current study can inform coastal policies. Coastal risks reduction and adaptation efforts must not only focus on developing coastal defenses, but also on improving practices and policies related to urban development and zoning, agriculture, and conservation, as well as on ameliorating socioeconomic conditions. Policies including restoration and preservation of natural habitat, and agricultural practices, should also be considered. As an example, the conservation and restoration of coastal habitats, which may act as coastal defenses to natural hazards, can also improve fisheries, positively impacting the livelihoods of local fishing communities reducing their vulnerability.

The implementation of a sisters-city like approach (where cities, or provinces, form partnerships to promote cultural and commercial ties) should be considered. Coastal

communities of similar coastal risk profiles, can greatly benefit by an exchange of

experiences and lessons learned from past disasters, coastal adaptation projects, and

coping mechanisms.

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