



Climate change vulnerability hotspots in Costa Rica: constructing a sub-national index

Raphael J. Nawrotzki¹ · Marina Tebeck¹ · Sven Harten¹ · Venya Blankenagel¹

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Abstract

For policies and programs aiming at reducing climate risk, it is important to obtain vulnerability information at the sub-national level to identify hotspots. For the case of Costa Rica, no sub-national climate vulnerability index exists to date. To fill this gap, we constructed a climate vulnerability index at the canton level. We ground our work in the conceptual framework that vulnerability is a function of exposure, sensitivity, and adaptive capacity. Making extensive use of geographic information systems and publicly available data, we constructed 13 spatial layers to reflect the multi-dimensionality of vulnerability. Layers reflect for example, changes in climatic extremes, flood risk, vegetation cover, access to infrastructure (road density) and health services (distance to hospitals), as well as various socioeconomic (wealth level, employment rates, remittances, literacy rate) and demographic (infant mortality) characteristics. Following normalization, we constructed an inverse variance weighted index of canton-level climate vulnerability. We confirmed the validity of our climate vulnerability index through correlation with disaster damage data. We find the strongest climate vulnerability not only in the rural, agricultural producing border cantons (*Los Chiles, Matina, Talamanca, Buenos Aires*), but also for a few central urban cantons (*Tibas, San Jose*). Projects and interventions in these hot spot cantons may reduce sensitivity through strengthening hydrological infrastructure and economic development, while adaptive capacity may be improved through addressing barriers of remittance transfer, and via public health programs.

Keywords Climate Vulnerability · Vulnerability Mapping · Sub-national · Climate Change Index · Climate Risk · Costa Rica

Abbreviations

CCVA	climate change vulnerability analysis
CIA	Centro de Investigaciones Agronomicas
CRI	Global Climate Risk Index
CRU-TS	Climate Research Unite-Time Series
DEM	Digital Elevation Model
EVI	Environmental Vulnerability Index
GDP	gross domestic product
GIS	Geographic Information System
IMN	National Meteorological Institute of Costa Rica
INEC	Instituto Nacional de Estadística y Economía
LCLU	Land Cover Land Use

MIDEPLAN	Costa Rica planning ministry (Ministerio de Planificación Nacional y Política Económica)
ND	University of Notre Dame
SD	standard deviation
SRTM	Shuttle Radar Topographic Mission
USDA	United States Department of Agriculture
USGS	United States Geological Survey

Introduction

Background

Climate change is an issue of global magnitude (IPCC 2014a, 2022a). Particularly countries highly dependent on natural resources will suffer through adverse effects on sectors such as agriculture (Nawrotzki and Bakhtsiyarava 2017), forestry, or tourism (Hoogendoorn and Fitchett 2018). These countries frequently lack the resources and

✉ Raphael J. Nawrotzki
r.nawrotzki@gmail.com

¹ Competence Center for Evaluation Methodology, German Institute for Development Evaluation, Fritz-Schäffer-Straße 26, 53113 Bonn, Germany

infrastructure to adjust to climatic changes (Thomas and Twyman 2005; Gutmann and Field 2010). Climate change is defined as a change in the global and regional climatic system over long periods of time (IPCC 2014a), resulting not only in an increase in the intensity and frequency of extreme weather events (e.g., storms and floods) but also in more gradual slow-onset changes (e.g., desertification, sea-level rise) (James et al. 2014). The degree to which populations suffer from the adverse effects of climate change depends on their level of vulnerability (Tanner et al. 2015).

Conceptual framework

Scholars have proposed many different conceptualizations of vulnerability over the past decades. These concepts vary by academic discipline with a focus on physical causes of vulnerability by engineers and natural scientists, an understanding that human behavior and perceptions are important determinants of vulnerability found in human ecology, or the political economy focus on structure and institutions as main causes of vulnerability (Füssel 2007). In this article, we follow the International Panel of Climate Change's definition of vulnerability as "a function of the character, magnitude, and rate of climate change and variation to which a system is *exposed*, its *sensitivity*, and its *adaptive capacity*" (Parry et al. 2007, p. 6). The "system" here is a social-ecological system composed of a natural system (biological and biophysical processes) and a social system (rules, institutions, knowledge, and ethics that mediate human use of resources) that are deeply intertwined (Berkes and Folke 1998; Tanner et al. 2015).

Climate change constitutes an external shock or stress to which the system needs to respond. Some systems can absorb large disturbances and have the capacity to self-organize and adapt to the new circumstances (Carpenter et al. 2001; Berkes et al. 2003; Folke 2006). Such systems are resilient and have a low level of vulnerability. In contrast, systems that are susceptible to disturbances and quickly change to a radically different state are considered highly vulnerable (Adger 2006; Parry et al. 2007). Figure 1 provides a visual representation of our conceptual framework, which has been widely used in research on climate change vulnerability (o'Brien et al. 2004; Eakin and Bojórquez-Tapia 2008; Sietz et al. 2012; Shukla et al. 2021).

The three dimensions of vulnerability (exposure, sensitivity, and adaptive capacity) are not always clearly distinguishable. For example, some characteristics of a system may be classified as both adaptive capacity and sensitivity (overlap in circles). Nevertheless, following empirical and theoretical considerations (Feyissa et al. 2018), we conceptually separate the three dimensions as described in the next paragraphs. We select components, conceptually following

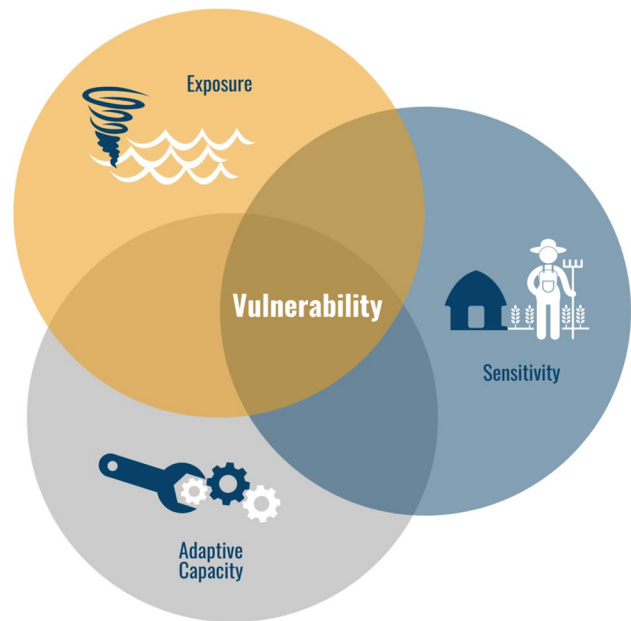


Fig. 1 Visual depiction of the conceptual framework of vulnerability. Source: own figure

the climate change vulnerability model introduced by Sullivan and Meigh (2005).

Exposure

A recent evidence gap map on climate change adaptation demonstrated that only limited research has focused on measures to reduce exposure to climate events (Doswald et al. 2019). For this research, we understand exposure as the degree to which a system experiences climatic stress. Stress can be characterized in terms of magnitude, frequency, duration, and areal extent (Burton et al. 1993). Climate change-related stresses include heat waves (Nawrotzki et al. 2017), droughts (Leng et al. 2015), or an increase in the risk of flooding due to sea-level rise or storms (Arnell and Gosling 2016).

Sensitivity

Sensitivity is the degree to which a system is affected by a stressor (Adger 2006). Sensitive systems are affected deeply even if the perturbation is minor, while less sensitive systems can more easily absorb effects without major changes. Various characteristics determine the sensitivity of a system. For example, poor and marginalized populations are often highly sensitive to climate change impacts (Adger 2006). The agricultural sector is highly vulnerable to the effects of climate variability (Bouroncle et al. 2017), and therefore, working in this sector makes individuals highly sensitive to climate impacts due to the direct link between climate

and crop production (Nawrotzki and Bakhtsiyarava 2017). In contrast, access to natural resources may serve as a safety net (Nawrotzki et al. 2014). For example, if crop fails due to a drought, households may collect fruits and edible roots in the forest (Walter 2001). However, generally, resources are limited and population pressure can put strain on scarce resources, making population dense regions more sensitive to the impacts of climate change (Yusuf and Francisco 2009).

Adaptive capacity

Adaptive capacity is the ability of a system to evolve in order to accommodate climatic changes and to expand the range of variability with which it can cope (Adger 2006). Population characteristics and access to important infrastructure determine a system's adaptive capacity. For example, the level of employment and the literacy rate may serve as a proxy indicator for human capital (Nawrotzki et al. 2013). Similarly, infant mortality can be used as an indicator of a population's health and ability to deal with stressors with the assumption that higher infant mortality rates imply lower levels of adaptive capacity (Thornton et al. 2008).¹ The money obtained via remittances from a family member living abroad may be used to adapt to changes in the climatic system (Nawrotzki et al. 2015). For example, farmers may use funds remitted by a family member living abroad to purchase improved irrigation systems if droughts increase (Schuck et al. 2005). Finally, infrastructure may assist in adapting to climate change (o'Brien et al. 2004). For example, roads will permit accessing alternative labor markets and to diversify income sources (Thornton et al. 2008). In addition, access to hospitals will allow coping with the adverse effects of extreme weather events (Keim 2008).

While our conceptual framework considers various influential factors, we are unable to cover all aspects. For example, vulnerability is also a function of various macro-level factors such as the political economy and governance quality of a region or country (o'Brien et al. 2004; Adger 2006). Similar, vulnerability may be subjectively perceived by various groups of people dependent on culture, norms, and geographic location (Adger 2006; Sietz et al. 2012).

Literature review

Many climate change vulnerability indices exist. These include, for example, the University of Notre Dame (ND) GAIN index (Chen et al. 2015), the Global Climate Risk Index (CRI) (Eckstein et al. 2018), and the Environmental

Vulnerability Index (EVI) (Barnett et al. 2008), which have been used extensively in published research (Barrett 2014; Betzold 2015; Betzold and Weiler 2017). While using a large number of variables and sophisticated modelling techniques, these indicators generally operate at the country level. Although macro-level indicators are of strategic importance for allocation decisions (Betzold and Weiler 2017), they hide local variability. There is considerable regional variation in climate impacts, households' access to resources, and livelihood strategies to cope with climate extremes. This heterogeneity is only captured properly at the sub-national level.

To date, sub-national climate vulnerability indices exist for only a selection of countries. Cutter et al. (2003) constructed an index at the county-level for the USA based on 11 dimensions to capture social vulnerability towards environmental hazards including climate extremes. A country that recently received substantial scholarly attention is Ethiopia (Feyissa et al. 2018; Shukla et al. 2021). Feyissa et al. (2018) constructed a climate vulnerability index based on 15 different indicators with a distinctly urban focus for sub-regions of Ethiopia's capital (Addis Ababa). Shukla et al. (2021) built a semi-dynamic climate vulnerability index for zones across Ethiopia comparing changes in vulnerability across four periods (past, present, near future, distant future) considering different future scenarios. Considering the effects of economic globalization as a source of vulnerability, O'Brien et al. (2004) constructed a climate vulnerability index at the district-level for India. Focusing on the agricultural sector by combining crop and ecological models, Parker et al. (2019) generated sub-national climate vulnerability indices for Vietnam, Uganda, and Nicaragua. Using variables of exposure and vulnerability, Rod et al. (2015) computed a climate vulnerability index at the municipality level for Norway. A number of other studies have constructed climate vulnerability indices for a small selection of geographic units, such as districts in Mozambique (Hahn et al. 2009), and villages in South Africa (Vincent 2007).²

Important for this study, the National Meteorological Institute (IMN) of Costa Rica has constructed a socio-economic vulnerability index for the hydrological sector based on 14 variables (IMN 2012). They investigated variations in the socio-economic portfolio for regions of observed climate risks but neglected to combine the socio-economic and climate components in one unified index.

Substantively related, a separate body of research has tried to map climate vulnerability hotspots and to perform

¹ Infant mortality can also be seen as a measure of sensitivity (Barrett 2014).

² Other studies have computed vulnerability indices that are related to specific climate impacts. For example, Fekete (2009) constructed a social vulnerability index in the context of river-floods for a selection of counties located in certain river basins in Germany. Similarly, Quesada-Román (2022) recently computed a flood risk index at the canton-level for Costa Rica.

climate change vulnerability analysis (CCVA). These studies often quantify climate-related vulnerability at the sub-national level for individual countries (Bouroncle et al. 2017), regions (Thornton et al. 2008), and globally (Sietz et al. 2011). These studies usually focus on selected sectors (Thornton et al. 2008; Bouroncle et al. 2017) or specific types of ecosystems (Sietz et al. 2011). Generally, this line of research finds highest vulnerability among economically disadvantaged populations, residing in remote locations, that are highly dependent on agricultural production (Sietz et al. 2011; Bouroncle et al. 2017).

Nevertheless, we still lack more general sub-national climate vulnerability information for most countries of the world, including Costa Rica. Sub-national climate vulnerability indices are particularly important as planning tool for the allocation of resources for development interventions based on an objective measure to identify vulnerability hot spots (o'Brien et al. 2004; Malone and Engle 2011; Shukla et al. 2021).³

The case

We constructed a climate change vulnerability index for Costa Rica. The Costa Rica government is aware of the societal dangers associated with the various adverse impacts of global climate change and seeks to expand its support for climate change adaptation measures at the national and local level (MIDEPLAN 2018). For the strategic allocation of resources as well as for evaluation purposes, it is of high importance for planners and policymakers to have a sub-national climate vulnerability metric at hand.

The climate in Costa Rica

A volcanic mountain range divides Costa Rica into a Pacific and a Caribbean region with distinct climatic zones (Quezada-Román 2022). The Pacific climate regime shows a clear division between the dry season (December–March) and the rainy season (May–October). In contrast, the Caribbean climate regime is more homogenous and generally hot and humid throughout the year (with somewhat less precipitation in February–March as well as in September–October) (MINAE and IMN 2015). Inter-annual variations in climate are influenced by the Southern Oscillation with El Niño and La Niña producing extreme weather events such as storms, floods, and droughts (MINAE and IMN 2015). Droughts are generally restricted to the Pacific climatic regime (mainly

the northwest and the center of the country), whereas extreme precipitation events are a problem for the entire country (IMN 2012). Extreme weather events have steadily increased over the last decades (Magrin et al. 2014).

Future projections of climate change

Central America is considered to be the tropical region that will experience the strongest changes in the climatic system (Giorgi 2006), attributable to changes in the larger climate regime (Yeh et al. 2009; Cai et al. 2018; Power and Delage 2018). Projections anticipate that Central America will generally become hotter and dryer with a concomitant increase in climate extremes (Imbach et al. 2012). These continental tendencies apply similarly to Costa Rica. Specifically, projections suggest that the north/northwest as well as the central regions of the country will experience highest increases in maximum temperatures and a decline in precipitation. In contrast, regional climate models suggest for the Caribbean regions and the southern Pacific coastline a general increase in the risk of storms and floods (MINAET and IMN 2009).

Socio-economic context

The specific socio-economic context contributes to Costa Rica's climate vulnerability. While Costa Rica belongs to the more developed countries of Central America (Bouroncle et al. 2017), about 80% of the country's GDP is generated in areas highly exposed to extreme weather events (Dilley et al. 2005). Specifically, the three main agricultural export products, bananas, pineapples, and coffee, are highly sensitive to climate change and future projections anticipate heavy production losses (GFA Consulting Group 2010; CEPAL and CAC/SICA 2014; Varma and Bebbler 2019). Also, the production of staple food such as beans and rice is in danger of decline due to climate change (CEPAL and CAC/SICA 2013). Particularly for smallholder farmers, climate change may undermine their livelihoods resulting in food insecurity and poverty (Warner et al. 2015).

Aims and scope

Given the lack of a sub-national climate vulnerability index, and the political importance and demand, we constructed a canton-level climate vulnerability index for Costa Rica. In the following sections, we describe the employed methodology. We do not consider the vulnerability for a specific sector but assess climate vulnerability in a general sense to permit a wide application of the index (Rød et al. 2015). The resulting index reveals several climate vulnerability hotspots in rural, agricultural producing border cantons (Los Chiles, Matina, Talamanca, Buenos Aires), but also for few central urban cantons (Tibas, San Jose).

³ While research has shown that more climate vulnerable countries receive more international adaptation aid (Betzold and Weiler 2017, 2018), such evidence is rare at the sub-national level (Barrett 2014; Bouroncle et al. 2017).

Table 1 Sources of various data used for the computation of the climate vulnerability index

Dimension	Component	Year	Source
Exposure	Heat months	1961–2013	CRU-TS
	Drought months	1961–2013	CRU-TS
	Flood risk — vicinity to rivers	2014	ArcGIS Online
	Flood risk — coastal flooding	2000	SRTM DEM
	Flood risk — land cover class	2015	East View Geospatial
	Flood risk — flat slope	2000	SRTM DEM
	Flood risk — impermeability of soil	2015	CIA
Sensitivity	Asset index	2011	IPUMS International
	Work in climate sensitive industry	2011	IPUMS International
	Population density	2015	INEC
	Tree cover	2015	East View Geospatial
Adaptive capacity	Employment	2011	INEC
	Literacy	2011	INEC
	Remittances received	2011	INEC
	Infant mortality	2011	INEC
	Road density	2016	ArcGIS Online
	Distance from health centers	2004	Ministerio de Salud

Notes: *CRU-TS*, Climate Research Unite-Time Series (CRU-TS) data (v3.22) (Harris et al. 2014) accessed via the IPUMS-Terra extract system (Nawrotzki et al. 2016; Ruggles et al. 2018); The rivers poly-line shapefile (Ríos de Costa Rica) as well as the roads poly-line shapefile (Carreteras de Costa Rica) was obtained from ArcGIS Online (ESRI 2019); A Digital Elevation Model (DEM) derived from the Shuttle Radar Topographic Mission (SRTM), at 1 arc second (~30 m) resolution (NASA JPL 2013) was used for computations of elevation and slope; Land Cover Land Use (LCLU) classification (15 m resolution) and Tree cover (30 m resolution) raster data sets were generated as commercial product by East View Geospatial (<https://geospatial.com/>) using Landsat 8 data; Microdata (10 % Extract) from the 2011 full population census of Costa Rica, collected by Dirección General de Estadística y Censos, was obtained via the IPUMS International (MPC 2018) extract system; A polygon shapefile of soil classifications was obtained from Centro de Investigaciones Agronómicas (CIA) (CIA 2016); Various sociodemographic variables were obtained from Instituto Nacional de Estadística y Economía (INEC) (<http://www.inec.go.cr/>)

Methodology

For the selection of components to be included in the climate vulnerability index, we employed a deductive theory-driven approach (Vincent 2007; Fekete 2009). Within the constraints of availability of spatially explicit subnational data, we selected variables based on theoretical considerations and empirical evidence gathered through a thorough review of the climate-vulnerability literature and closely following the selection proposed by similar studies (Sullivan and Meigh 2005; Feyissa et al. 2018). The development of a vulnerability index constitutes a multi-stage sequential process including the selection of components, construction of variables, aggregation, normalization, and weighting. During each stage, the researcher is faced with a choice between multiple legitimate options. There is not necessary a right, wrong, or even best choice of method (Tate 2012). For the sake of transparency, we justify our methodological choice with reference to the pertinent literature in the following paragraphs.

Data sources

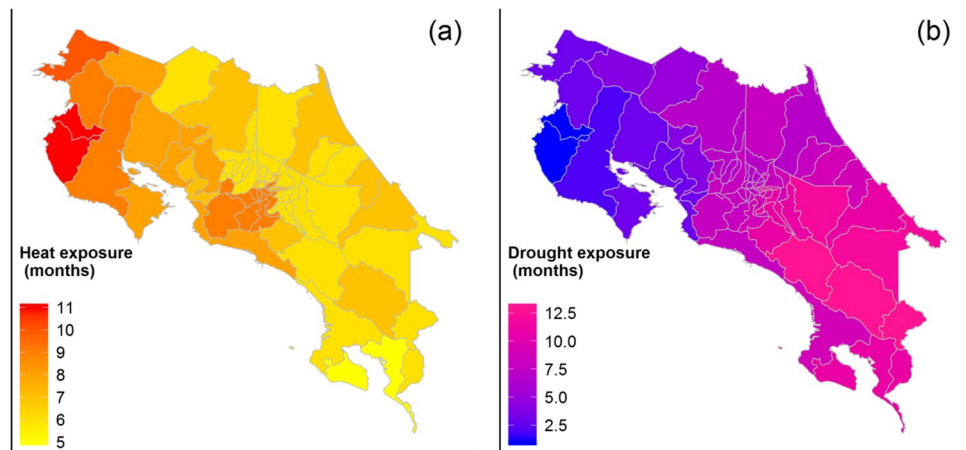
Table 1 provides relevant information on the various data sources and the respective years for which we obtained the data.

To validate our climate vulnerability index, we make use of the DesInventar Sendai data collection, which provides georeferenced information on disaster occurrence and associated losses for Costa Rica (UNDRR 2019). DesInventar Sendai is sponsored by the United Nations Office for Disaster Risk Reduction (UNDRR) and the United Nations Development Programme (UNDP) and has been widely used for research on natural hazards (Marulanda et al. 2010; Runfola et al. 2016; Panwar and Sen 2020; Quesada-Román et al. 2021).

Variable construction

We constructed the climate vulnerability index at the canton-level. Cantons ($N = 82$) are defined by the Costa Rica government and constitute the second level of administrative

Fig. 2 Heat and drought exposure months by canton for the period 2011–2013. Notes: Heat and drought exposure months were computed for a 36-month observation period (2011–2013) in reference to a 30-year long-term climate normal period (1961–1990)



division.⁴ This is the smallest administrative unit for which most socio-economic data was available, improving on prior work on climate vulnerability conducted predominantly at the first level (provinces) (e.g., Bouroncle et al. 2017). While the following paragraphs explain important steps in the variable construction, more details can be found in the Appendix. In line with a common trend in climate vulnerability assessment (Rød et al. 2015; Woodruff et al. 2018; Shukla et al. 2021), we heavily employ Geographical Information Systems (GIS) and geoanalytical scripting tools in the variable construction (see Appendix 1).

Exposure

In this study, we incorporate three exposure components (layers) that measure changes in temperature, precipitation, and the risk of flooding.

In Costa Rica seasonal occurrences of heat and drought events influence various industries including agriculture (Warner et al. 2018) and tourism (Little and Blau 2020). To capture these effects, we extracted a time series of monthly temperature and precipitation information from the University of East Anglia Climate Research Unit (Harris et al. 2014) via the IPUMS-Terra data extract system (Nawrotzki et al. 2016; Ruggles et al. 2018). This information is available as high resolution (0.5 degree) gridded data and summarized by IPUMS-Terra at the canton level. Following an established method (Nawrotzki and Bakhtsiyarava 2017; Nawrotzki et al. 2017), we generated measures of drought and heat months during the 2011–2013 observation period. More specifically, we

computed the number of months during the observation period in which the maximum temperature was more than 1 standard deviation (SD) above and precipitation was more than 1 SD below the 30-year (1961–1990) climate normal period.⁵ Figure 2 shows canton aggregates of heat and drought months for Costa Rica.

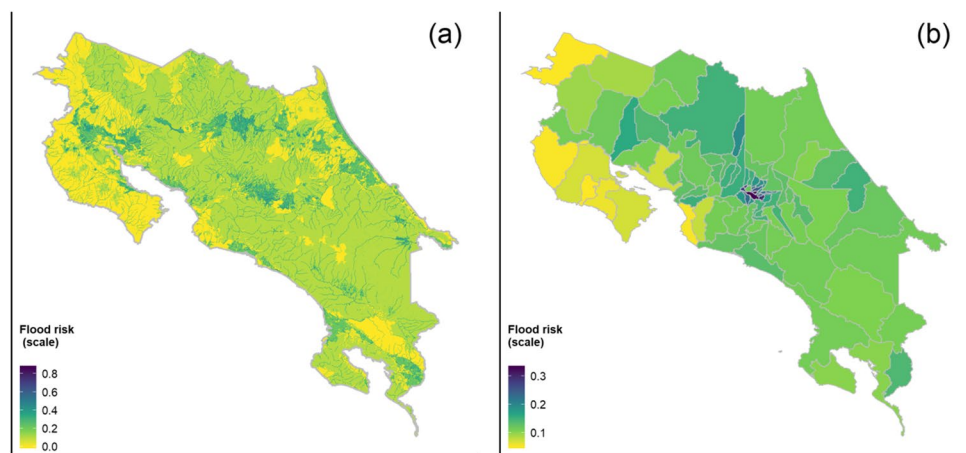
An increase in heat months occurred largely on the western Pacific coast. In contrast, the largest increase in drought months was obvious for cantons in the east, bordering Panama.

For Costa Rica floods constitute the climate risk associated with the largest economic damages (Quesada-Román 2022). The risk of flooding is a function of various geospatial conditions (Feyissa et al. 2018). First, we assume that the risk of flooding is highest in areas up to 100 m around a river. As such we obtained a polyline layer of all rivers in Costa Rica from the ArcGIS Online data collection (ESRI 2019), constructed a 100 m buffer around the lines, and ultimately rasterized the layer. Appendix 2 (Flood risk layers) provides images of the various layers. Second, we accounted for the risk of coastal flooding. Using a high-resolution (30 m) Digital Elevation Model (DEM) (NASA JPL 2013), we identified pixels that were below 5 m in elevation and up to 1 km from the coastline following an established procedure (Leppert et al. 2018). Pixels at risk for coastal flooding were coded 1 and otherwise coded 0. Third, the particular land use will determine the risk of flooding. As such, we purchased a high resolution (15 m)

⁴ Costa Rica has now 84 cantons. Two new cantons (*Monteverde* and *Puerto Jiménez*) were created in 2021/2022 and are located in the province of *Puntarenas*.

⁵ The period 1961–1990 is the standard climate normal period recommended for the computation of climate change indicators by the World Meteorological Organization (Arguez and Vose 2011). Our measures capture climate change above and beyond the usually prevailing climatic conditions. For example, a given month is only counted as a “drought month” if the monthly precipitation is considerably lower during the observation period as compared to the long-term baseline climate normal conditions.

Fig. 3 Flood risk layer for Costa Rica. Notes: (a) representation of the raster layer (30-m resolution) and (b) flood risk aggregated to the canton level



raster layer, generated using Landsat 8 data, and classified by EastView Geospatial according to an updated version of the land cover and land use (LCLU) classes developed by the United States Geological Survey (USGS) (Anderson et al. 1976). We reclassified the various LCLU classes as high flood risk (coded 1) and low flood risk (coded 0) (see Appendix 2 for details on the reclassification). Fourth, we used the DEM to detect pixels with a slope of less than 2% (Feyissa et al. 2018). Based on the assumption that those regions with a flat slope are particularly at risk for flooding if surrounded by a steep hillside, we assigned pixels a value of 1 if they were flat (2%) and within 500 m of a steep slope (slope of 30%). Fifth, the soil type will determine the drainage capacity of an area. To this end, we obtained a polygon layer classified according to the United States Department of Agriculture (USDA) soil taxonomy (USDA and NRCS 2014) by the University of Costa Rica Centro de Investigaciones Agronomicas (CIA) (CIA 2016). Informed by a thorough literature review, we first reclassified soil types based on their drainage capacity as having a high (coded 1) or low (coded 0) risk of flooding. Mixed soil types composed of high and low flood risk are considered having a medium flood risk (coded 0.5). Following the recoding, we rasterized the layer. After weighting, we combined the five layers to an additive scale, conceptually following Feyissa et al. (2018). We employed the following weighting schema reflecting importance in descending order: vicinity to rivers ($w = 0.25$), vicinity to coast ($w = 0.25$), LCLU class ($w = 0.20$), flat slope ($w = 0.20$), soil type ($w = 0.10$). We then used zonal statistics to compute the average flood risk score for each canton (see Appendix 2 for details). Figure 3 depicts the final flood risk layer.

Figure 3 (b) shows highest flood risk for the small central cantons as well as several cantons in the north. This pattern has been confirmed by other studies of flood risks in Costa Rica (Quesada-Román 2022).

Sensitivity

We make use of four components (layers) to capture sensitivity including an asset index, employment in climate sensitive industry, population density, and tree cover (for details see Appendix 3: Sensitivity layers). First, we constructed an asset index using seven variables derived from census microdata (10% extract) via IPUMS-International for the year 2011 (MPC 2018).⁶ These variables measure household possessions (computer, cars), building materials (floor, walls), and services (cooking fuels, trash collection, internet) and were combined to an additive asset index (Cronbach's $\alpha = 0.75$). Access to services, possessions, and high-quality housing considerably reduces the sensitivity of a household to climate impacts (c.f., Vincent 2007). For example, a home built of solid material such as bricks will reduce structural sensitivity to floods, storms, and heat waves (Bouroncle et al. 2017; Feyissa et al. 2018).

In addition, we computed the percentage of household heads working in climate sensitive industries (agriculture, forestry, fishery) also based on IPUMS-International microdata records. Although climate change will influence various industries, the agricultural sector is particularly sensitive to adverse climate impacts (IPCC 2022a).

Directly from the Costa Rica Instituto Nacional de Estadística y Economía (INEC), we derived canton-level information on population density (INEC 2019). We conceptually assume that an increase in population density leads to

⁶ The IPUMS International data extract system specifies a random sample of 10% of data points as the default extract size. This ensures full national representativeness but at the same time reduces the amount of data for processing. As such, 10% constitutes a common extract size in the field of population-environment research using census data (Nawrotzki and DeWaard 2018; Nawrotzki et al. 2022).

higher sensitivity as more people will be affected by climate impacts and because of an increased pressure on vital resources such as food, water, and services (Klein Goldewijk et al. 2010; Sietz et al. 2017).

Finally, we purchased a high-resolution (30 m) raster layer of the percentage of tree cover, generated by East-View Geospatial based on Landsat 8 data for the year 2015. Using zonal statistics, we computed the average (mean) tree cover value for each canton. Vegetation and tree coverage have many benefits, such as absorbing excess rainwater and preventing floods and landslides (Quesada-Román 2022), protection against temperature extremes through shading (Akbari et al. 2001), and as source of food, resources, and income (Walter 2001). In sum, these beneficial effects reduce the sensitivity to adverse climatic changes.

Adaptive capacity

We use six components (layers) to account for adaptive capacity (for details see Appendix 4: Adaptive capacity layers). The employment rate, literacy rate, the remittances received, and the infant mortality rate were obtained directly from INEC as canton-level aggregates (INEC 2019). Relative to the unemployed, people that are formally employed usually have higher socioeconomic status and better access to resources, enabling the adaptation to climate impacts and changes (Bouroncle et al. 2017; Feyissa et al. 2018). Literacy is an indicator for employability but also facilitates access to information and knowledge important to cope and adapt (Shukla et al. 2021). Remittances provide an additional source of income when climate impacts lead to harvest failure and can be used to finance climate adaptation technologies (Nawrotzki et al. 2015). Infant mortality is a general indicator of development status, well-being, and health of a population and frequently used as measure of adaptive capacity (Mortreux and Barnett 2017). Higher infant mortality indicates lower adaptive capacity.

For the computation of road density, we obtained a polyline shapefile of all major roads of Costa Rica from ArcGIS Online (ESRI 2019). We then performed an intersection operation to obtain separate line-segments for each canton, computed the total road length per canton, and expressed the total road length relative to the area of each canton (unit: km/km²). Road density is a proxy indicator for infrastructure access and development, frequently used to approximate adaptive capacity (Feyissa et al. 2018; Parker et al. 2019). Good access to roads may permit redirecting shipment routes or to access alternative markets and job opportunities, thus, increasing adaptive capacity (Cinner et al. 2018).

Finally, we computed the distance to hospitals and clinics in Costa Rica. We employed a polypoint layer of health centers, georeferenced based on information from the Costa Rica Ministry of Health. We first rasterized the points, and

then computed a distance grid, indicating for each pixel the distance to the nearest health center. We then computed the average distance (in km) for each canton. Climate change is directly and indirectly associated with various adverse health impacts that can be best treated at health centers (Watts et al. 2015; Bakhtsiyarava et al. 2018). As such, we assume that better access to health infrastructure permits people to better cope with adverse climate impacts (Rød et al. 2015).

Normalization

To combine different components into one composite index, we need to transform the variables to a common scale. To this end, we employed an established normalization procedure known as minimum-maximum transformation (UNDP 2006; Fekete 2009; Rød et al. 2015; Bouroncle et al. 2017; Sietz et al. 2017). We used Equation (1), if the component had a positive functional relationship with the dimension (e.g., increase in sensitivity), and Equation (2), if the component had a negative functional relationship (e.g., decline in sensitivity) (Iyengar and Sudarshan 1982; Feyissa et al. 2018).

$$Y_{ij} = \frac{X_{ij} - \min(X_{ij})}{\max(X_{ij}) - \min(X_{ij})} \quad (1)$$

$$Y_{ij} = \frac{\max(X_{ij}) - X_{ij}}{\max(X_{ij}) - \min(X_{ij})} \quad (2)$$

In Equations (1) and (2), X_{ij} represents the i -th component ($i = 1, 2, \dots, m$) of a given dimension (i.e., exposure, sensitivity, adaptive capacity) measured for the j -th canton ($j = 1, 2, \dots, n$). $\max(X_{ij})$ and $\min(X_{ij})$ are the maximum and minimum values of the distribution ($X_{i1}, X_{i2}, \dots, X_{in}$). The normalized values Y_{ij} then vary from 0 to 1 ($0 \leq Y_{ij} \leq 1$).

Computation of weights

There are many ways in which relative importance can be assigned to the components of an index. Methods include equally weighting all components (Cutter et al. 2003; o'Brien et al. 2004; Shukla et al. 2021), assigning weights based on theoretical considerations and qualitative information (Alcamo et al. 2008; Bouroncle et al. 2017), quantitatively optimizing weights based on an external standard (Rød et al. 2015), and assigning weights based on data variability (Feyissa et al. 2018).⁷ We opted for a weighting

⁷ Some authors have suggested the use of “fuzzy” methods (e.g., fuzzy logic), which explicitly consider uncertainty in the construction of weights, but at the cost of precision (Eakin and Bojórquez-Tapia 2008; Cheng and Tao 2010).

schema that account for differences in variability of the components following an established methodology (Iyengar and Sudarshan 1982; Feyissa et al. 2018). Highly variable components receive a lower weight than more stable ones. This method helps to prevent highly volatile components from dominating the pattern of the resulting composite index (Feyissa et al. 2018). “It is well-known that, in statistical comparisons it is more efficient to compare two or more means after equalizing their variances” (Iyengar and Sudarshan 1982, p. 2049). As such, we computed weights according to Equations (3) and (4) (Iyengar and Sudarshan 1982; Feyissa et al. 2018).

$$w_i = \frac{k}{\sqrt{\text{var}(Y_i)}} \quad (3)$$

$$k = \left[\sum_{i=1}^m \frac{1}{\sqrt{\text{var}(Y_i)}} \right]^{-1} \quad (4)$$

Let w_i represent the component-specific weight for a given dimension, with $\text{var}(Y_i)$ the variance of normalized component Y_i and k representing a constant. All weights have values that fall between 0 and 1 ($0 < w_i < 1$) and sum up to 1 ($w_1 + w_2 + \dots + w_m = 1$). We computed weights separately for each dimension ($d = \text{exposure, sensitivity, adaptive capacity}$) and generated dimension specific indices (I_d) (Equation (5)).

$$I_d = w_1 Y_1 + w_2 Y_2 + \dots + w_m Y_m \quad (5)$$

Computation of index

We computed the final climate vulnerability index (CVI) according to Equation (6). We first normalized the dimension specific sub-indicators. Conceptually, we assume that exposure and sensitivity increase vulnerability, while adaptive capacity decreases vulnerability. As our theoretical framework is agnostic regarding the relative importance of each dimension for the overarching concept of climate vulnerability, we assigned equal weights (e.g., $w_d = 0.33$) to all three dimensions. As with the individual components, values of the normalized canton-specific climate vulnerability index range from 0 to 1 with higher values indicating higher vulnerability.

$$CVI = (0.33 * I_{\text{Exposure}} + 0.33 * I_{\text{Sensitivity}}) - 0.33 * I_{\text{Adaptive Capacity}} \quad (6)$$

To facilitate interpretation and use, we categorized the CVI and its components into five equal classes: very

low (0–0.2), low (0.201–0.4), moderate (0.401–0.6), high (0.601–0.8), and very high (0.801–1).

Validation measure

From the DesInventar Sendai data repository (UNDRR 2019), we extracted information on disaster occurrence and damage for the period of 1994 to 2021. We focus on disasters caused by climatic events (e.g., droughts, floods, storms), computing the cumulative damage (in US dollars) for each canton. Floods are the most frequent climate event (49.4%) in Costa Rica attributable to losses of 1.37 billion USD across the 28-year time period. We log-transformed the disaster damage variable to approximate normality. We then computed Spearman’s rank correlations (Zar 2005) for the damage variable and our climate vulnerability index following Shukla et al. (2021).

Outliers

We investigated variables for the presence of outliers using an upper and lower threshold of three times the median absolute deviation (MAD) (Leys et al. 2013). While their detection is a routine operation, it remains a contested topic in the methods literature what to do with outliers (see Osborne and Overbay 2004; Aguinis et al. 2013). The treatment depends on the causes of the outlier, which can be grouped into two major categories: (a) errors in the data (e.g., measurement-, computing-, reporting-, recording-error) or (b) inherent variability of the data. Outliers should be removed if they are the result of an error (Osborne and Overbay 2004; Cousineau and Chartier 2010). Yet, if outliers are the result of true variability, they accurately reflect reality and should be retained (Orr et al. 1991; Aguinis et al. 2013). We checked outliers and confirmed the plausibility of more extreme values (e.g., large values on population density of urban cantons in the greater metropolitan area). It is important to stress that we employ validated and quality-checked publicly available data sources that have been extensively screened for data errors (see individual codebooks and documentation).

Software

We performed all geospatial analysis using various spatial packages including *sp* (Bivand et al. 2013), *rgdal* (Bivand et al. 2019), *raster* (Hijmans 2019), *rgeos* (Bivand and Rundel 2018), *sf* (Pebesma 2018) within the R Statistical Environment (R Core Team 2022). Maps were generated using *ggplot2* (Wickham 2016) and *ggmap* (Kahle and Wickham 2013).

Table 2 Functional relationship, variances, and weights for components (layers) contributing to the dimensions of the climate vulnerability index

Dimension	Component	Relationship	Variance	Weight
<i>Exposure</i>	Heat months	+	0.054	0.324
	Drought months	+	0.066	0.294
	Flood risk	+	0.039	0.382
<i>Sensitivity</i>	Asset index	–	0.061	0.223
	Work in climate sensitive industry	+	0.061	0.223
	Population density	+	0.029	0.324
	Tree cover	–	0.058	0.230
	Employment	+	0.056	0.154
<i>Adaptive capacity</i>	Literacy	+	0.038	0.187
	Remittances received	+	0.047	0.167
	Infant mortality	–	0.046	0.169
	Road density	+	0.045	0.171
	Distance from health center	–	0.057	0.152

Notes: Relationship = Functional relationship of a particular component with its dimension; Weights were computed based on Equation (3)

Results and discussion

Climate vulnerability in Costa Rica

We computed the dimension-specific sub-indices using the weights displayed in Table 2.

Employing the above weighting scheme, we were able to construct sub-indicators of the three dimensions: exposure, sensitivity, and adaptive capacity.

The visual depiction reveals distinct patterns for each dimension.

Exposure

As Fig. 4(a) shows, the highest exposure can be observed in the small central and south-central cantons of the greater metropolitan area⁸. Our flood exposure layer suggests strong flood risks for urban cantons in line with evidence from recent hydro-meteorological studies (Quesada-Román et al. 2021; Quesada-Román 2022). The increased risk of flooding in these cantons has been attributed to a combination of geographic location, inefficient sewer systems, and dam failures (Durán and Quesada-Román 2017). Yet, during El Niño years droughts are also common phenomena in this region (Quesada-Román et al. 2021) with adverse impacts on water supplies, hydroelectric power generation, and peri-urban agriculture. Finally, the central cantons in the greater metropolitan area have experienced an increase in the number of

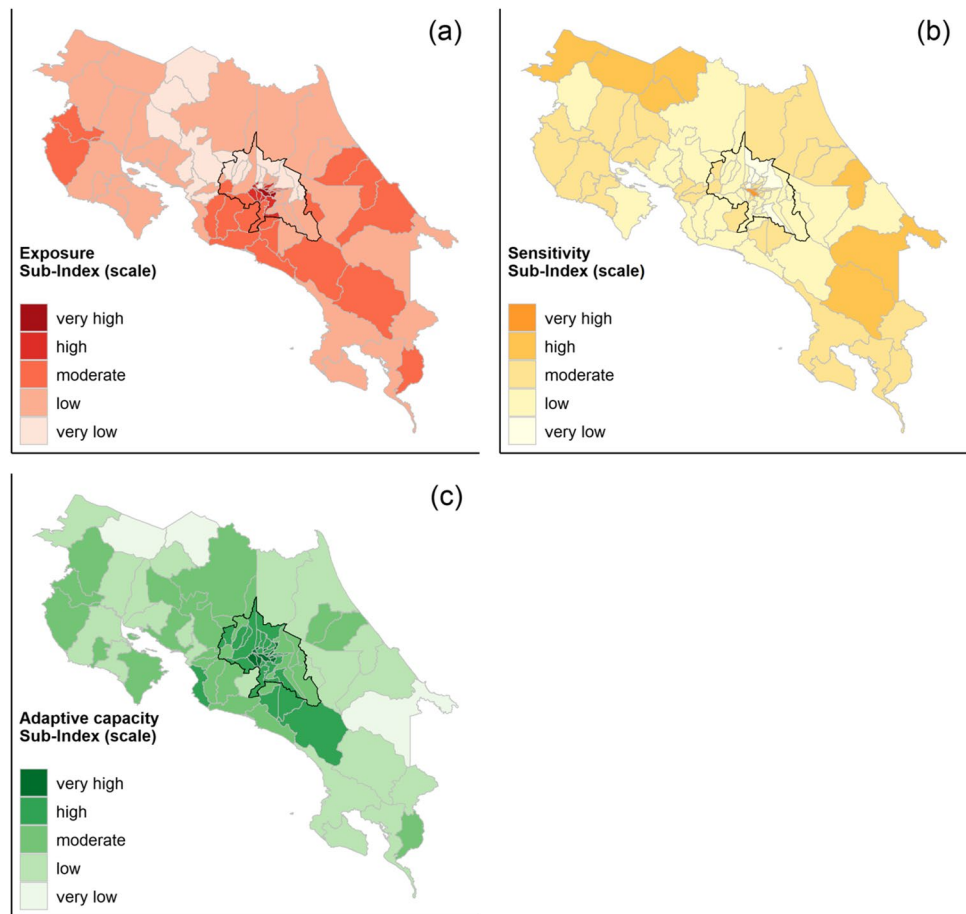
heat months relative to a long-term historical baseline period (Fig. 2a). This may be in parts attributable to the urban heat island effect observed for various Latin American metro areas (Palme and Carrasco 2022). The combination of high flood risks, drought- and heat-months results in high and very high exposure ratings for several of the central cantons of the greater metropolitan area.

Sensitivity

For the sensitivity sub-indicator, we find a somehow different spatial pattern (Fig. 4b), resembling socioeconomic sensitivity observed by IMN (IMN 2012). Highest levels of sensitivity are visible in the border cantons, particularly in the north (border to Nicaragua) and the southeast (border to Panama). The resulting pattern can be explained with reference to the underlying components including the asset index, work in climate sensitive industry, population density, and tree cover (see Appendix 3 for maps of all components). For example, employment in the agricultural sector results in considerable sensitivity to climate impacts. Explaining the observed patterns in Fig. 4b, studies found highest levels of agricultural dependency along the Atlantic coast and the Nicaragua and Panama border (Bouroncle et al. 2015). In this region, most of Costa Rica's bananas and pineapples are grown, as Costa Rica's most important export products (BASIC 2016; FAO 2018). Particularly the pineapple production is sensitive to adverse weather events such as floods and tropical storms (FAO 2017). As such, existing sensitivity may likely increase in the future as climate change leads to an increase in severe weather events (IPCC 2014a). The border cantons also experience lowest values on the asset index (see Appendix Figure 12a). Poverty in the border regions is known to be high due to a lack of economic

⁸ The greater metropolitan area comprises 35 cantons, covering an area of 1779 km². It contains four large cities (*San José, Heredia, Alajuela, and Cartago*) and their peripheries, home to approximately 65% of Costa Rica's population (Quesada-Román et al. 2021).

Fig. 4 Exposure, sensitivity, and adaptive-capacity sub-indicators for Costa Rica. Note: The sub-indices were categorized into five equal classes: very low (0–0.2), low (0.201–0.4), moderate (0.401–0.6), high (0.601–0.8), and very high (0.801–1); black line around the smaller central cantons delineates the greater metropolitan area



opportunities and limited access to markets (Andam et al. 2010). This results in high sensitivity as economically poor rural dwellers lack the resources to cope with adverse climate impacts (Tanner et al. 2015). For some of these rural households, access to natural resources that can be extracted from surrounding forests may serve as a safety net in times of distress (Shackleton and Shackleton 2004).

We also find high sensitivity in some of the small urban cantons in the greater metropolitan area. The population density in these cantons is on the rise and people are forced to settle in floodplains and on mountain slopes at risk of floods and landslides (Quesada-Román et al. 2021), resulting in elevated levels of sensitivity.

Adaptive capacity

Overall, high levels of adaptive capacity (Fig. 4c) can be found particularly in the small central cantons of the greater metropolitan area, while lower adaptive capacity is concentrated along the border to Nicaragua, Panama, and the Atlantic Coast. Contributing to this pattern is the influence of employment, literacy, remittances, infant mortality, road

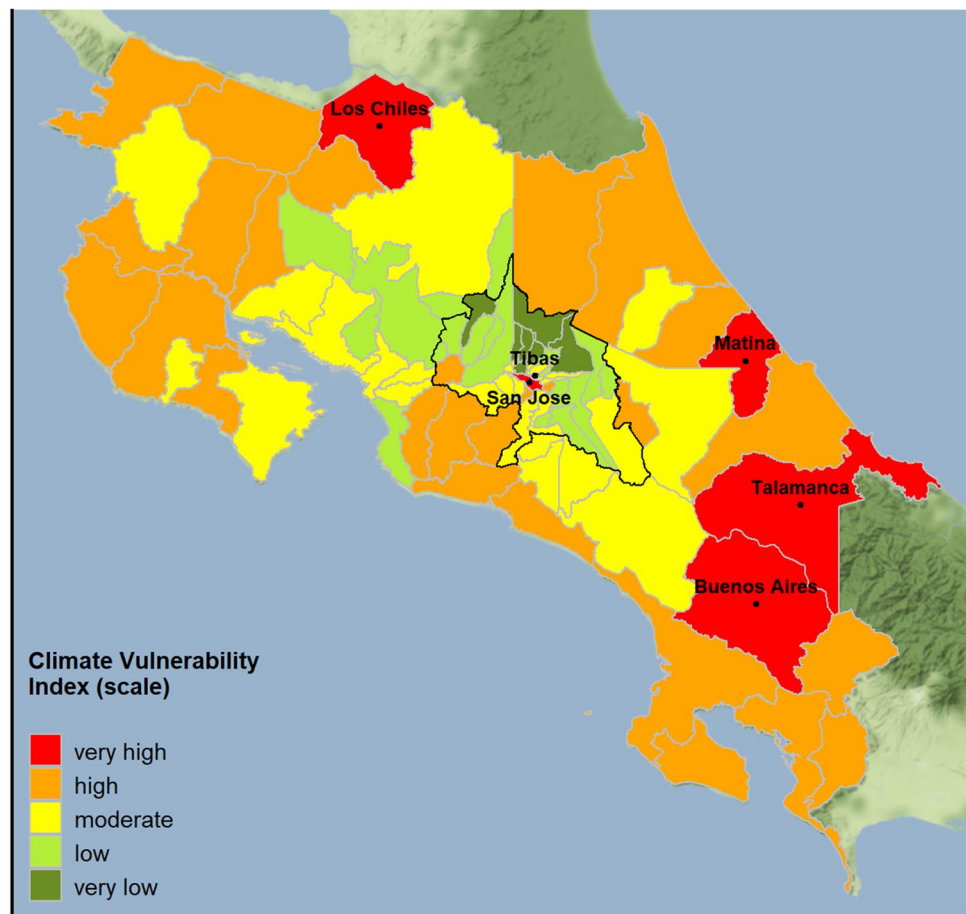
density, and distance to health centers (see Appendix 4 for maps of these components).

The high levels of adaptive capacity in several south-central cantons, results from their disproportionately large receipt of remittances (see Appendix Figure 15a). Compared to the national average, twice as many households in these cantons have migrant relatives (Gatica López 2017). In these regions, remittances have strong positive economic effects leading to substantially reduced poverty rates (Céspedes Torres 2009), and thereby increasing the populations adaptive capacity.

The two infrastructure layers (Appendix 4, Figure 16 and 17) also show distinct patterns that in sum produce the observed levels of high adaptive capacity in the south-central cantons. In these cantons, a dense road network connects places and the distance to the next hospital is usually less than 5 km (Rosero-Bixby 2004).

Lowest levels of adaptive capacity are observed in the border cantons in the north (border to Nicaragua) and in the south-east (border to Panama). The underlying causes are low literacy rates (Appendix 4, Figure 14), and high infant mortality rates (Appendix 4, Figure 15). While at the national level, infant mortality has dropped substantially in

Fig. 5 Climate vulnerability index (CVI) for Costa Rica. *Note:* The climate vulnerability index (CVI) was categorized into five equal classes: very low (0–0.2), low (0.201–0.4), moderate (0.401–0.6), high (0.601–0.8), and very high (0.801–1); Cantons with very high climate vulnerability are labeled; black line around the smaller central canons delineates the greater metropolitan area



Costa Rica over the past decades (Dow and Schmeer 2003), the situation remains challenging in the remote border regions, where people are frequently economically poor, uneducated, and lack access to important health infrastructure (Rosero-Bixby 2004; Quesada-Román 2022). The overall socioeconomic status of populations in the border cantons is shaped by a large migrant population from Nicaragua, Panama, and recently the African continent (Bouroncle et al. 2015; Winters and Mora Izaguirre 2019).

Climate vulnerability index

Ultimately, we combined the three dimension sub-indicators to generate the final climate vulnerability index (Fig. 5). We have labeled cantons with very high vulnerability in Fig. 5. We found strongest climate vulnerability in the rural agricultural production cantons on the Atlantic coast (*Matina*) and on the border to Nicaragua (*Los Chiles*) and Panama (*Talamanca*, *Buenos Aires*). As an example, *Buenos Aires* is characterized by moderate exposure, high sensitivity, and low adaptive capacity, resulting in an overall very high climate vulnerability. Pineapple production is the primary economic activity in *Buenos Aires* offering employment for

many residents of the canton (González et al. 2022). The agricultural sector in general (Thornton et al. 2014) and pineapple production in particular is highly vulnerable to climate impacts such as floods and tropical storms (FAO 2017), explaining the high ranking of *Buenos Aires* on the climate vulnerability index.

We also find high levels of climate vulnerability for the two central urban cantons of *Tibas* and *San Jose*. *San Jose*, for instance, shows very high exposure, very high sensitivity, but also very high adaptive capacity, resulting in an overall classification of very high climate vulnerability. While through different pathways, non-agricultural production will also be impacted by climate change (Hsiang 2010). Urban areas face unique climate threats (IPCC 2014b, 2022a) associated with an increased risk of flooding due to sealed surfaces and insufficient drainage infrastructure (Durán and Román 2017), as well as the heat island effect (Kleerekoper et al. 2012). *San Jose* is one of the cantons most effected by floods in Costa Rica (Quesada-Román 2022), explaining the classification of “very high” climate vulnerability.

We find the lowest climate vulnerable for peri-urban cantons on the outskirts of the greater metropolitan area north of *Tibas*, a pattern confirmed for other countries of Central America (Bouroncle et al. 2017).

Methodological considerations

Different approaches to measure vulnerability exist including cluster analysis and composite indices. For example, Sietz et al. used a cluster analysis to determine the composition of factors contributing to climate-vulnerability among farmers in the Peruvian highlands (Sietz et al. 2012), and to identify archetypes of vulnerability across African drylands (Sietz et al. 2017). Each method comes with a unique set of assumptions, limitations, advantages, and disadvantages. We selected the composite indicator approach, given several desired properties: (a) reduction in complexity and a final map that permits identification of vulnerability hotspots; (b) transparency regarding the inclusion of components and their relative importance (e.g., weights).

Other factors to consider are the spatial scale of the analysis (Vincent 2007). We constructed a vulnerability index at the canton level for Costa Rica. While the canton level can be considered “high resolution”, we aggregated area-based as well as population-based information. Aggregation may mask local variations in vulnerability and patterns may differ at each level of aggregation (Vincent 2007; Eakin and Bojórquez-Tapia 2008). Yet, for the purpose of the present analysis, the canton level seems an appropriate scale as policies and programs in Costa Rica frequently operate at this level.

Validation

Validating a climate change vulnerability index is challenging because vulnerability is a multidimensional theoretical construct and not directly observable (Tate 2012). Some studies employ qualitative case studies in an attempt of ground-truthing results (o’Brien et al. 2004; Sietz et al. 2012). Another approach has become known as “outcome-based” validation (Sietz et al. 2012; Shukla et al. 2021). In this approach, an independent data source is used to triangulate results (Fekete 2009). Frequently direct (Shukla et al. 2021) and indirect (Sietz et al. 2012) measures of climate-related damages have been employed. A positive correlation between climate-related damage and the climate vulnerability index is then considered proof of validity (Shukla et al. 2021). We follow this approach and make use of the DesInventar Sendai database (UNDRR 2019). Specifically, we computed correlations between our final climate vulnerability index and the damage in US dollars caused by climate events. We find a positive correlation ($r = 0.54$), indicating that cantons ranked as highly vulnerable on the CVI have indeed experienced high climate-related disaster damages over the past 28 years. The strength of the positive correlation in our validation exercise is similar to those observed in other studies (Shukla et al. 2021), leading us to conclude that our vulnerability index is able to explain observed vulnerability-related outcomes sufficiently well.

Sensitivity analyses

We estimated the relative importance of the various components in our final vulnerability index using the approach known as “local sensitivity analysis” (Tate 2012). Specifically, we estimated changes in rank order when one of the components is omitted from the construction of the final composite measure (Shukla et al. 2021). Figure 6 shows boxplots of the changes in CVI when omitting any of the 13 underlying components. The magnitude of change indicates the relative importance of a component in determining the vulnerability score. The results show that the omission of any exposure or sensitivity component has a stronger effect on the resulting vulnerability index than omitting any adaptive capacity component. Omitting the asset or the flood risk component leads to the highest mean shift of about 7% in vulnerability rank scores. The magnitude of the observed sensitivity is comparable to other studies (Shukla et al. 2021), indicating an overall high degree of robustness of the final index.

Conclusions

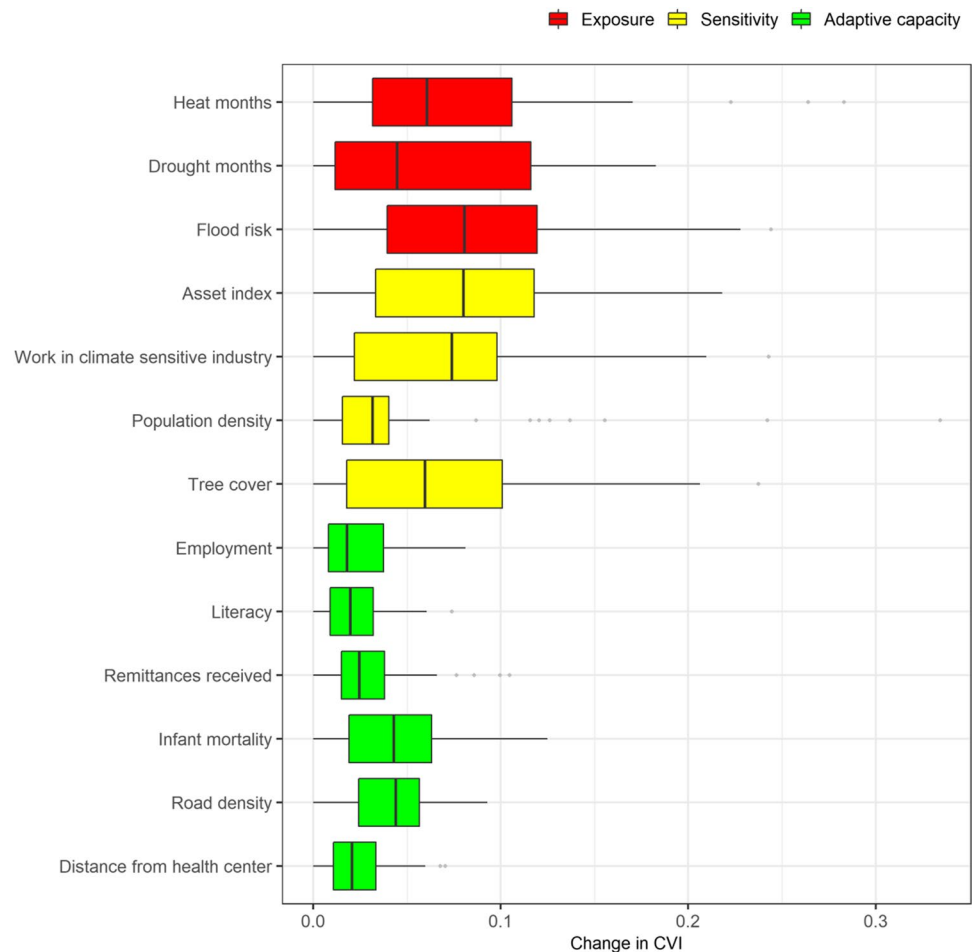
Summary

The primary purpose of this study was to develop a sub-national climate vulnerability index that can be used by policy makers and program managers to identify vulnerability hot spots in Costa Rica. We combined 13 geographic layers into a variance-weighted index, capturing exposure, vulnerability, and adaptive capacity. We find highest climate change vulnerability for the cantons of *Tibas*, *San Jose*, *Los Chiles*, *Matina*, *Talamanca*, and *Buenos Aires*. The strength of our climate vulnerability index is its independence from direct climate-hazard information (Fekete 2009). Our index captures vulnerability to climate change that would not be identified by a pure climate hazard assessments (c.f., Runfola et al. 2016). Yet it is important to note that vulnerability is context and scale specific (Vincent 2007) and researchers should consider these dimensions when constructing similar indices for other countries.

Limitations

While our climate change vulnerability index was carefully constructed, this work shares the general and well-documented limitations of indicator-based approaches, resulting from the process of selecting components, transformation, aggregation, and weighting (Tate 2012; Shukla et al. 2021). We tried to limit the sources of uncertainty through

Fig. 6 Estimate of relative importance of components for the climate vulnerability index (CVI). *Note:* CVI scale ranges from 0 to 1; absolute change in CVI (rank order) is displayed on the x-axis



transparent explanations of index composition and construction, as well as validation and robustness tests. Yet a few specific limitations deserve mention:

First, we did not incorporate future predictions of climate change in the exposure layer (Thornton et al. 2008; IMN 2012; Shukla et al. 2021). There is still a large degree of uncertainty involved in climate change scenarios (o'Brien et al. 2004; Shukla et al. 2021) and we decided to employ a more conservative approach of identifying climate change hotspots based on historically observed patterns (see Vincent 2007).

Second, we included exclusively quantitative information in our climate vulnerability index. Yet, qualitative evidence may add a more nuanced understanding for certain aspects of vulnerability (Kelman et al. 2017). As such, future work may amend the vulnerability index by qualitative evidence and local scale case studies (Sietz et al. 2011), or by involving local actors in the validation of vulnerability classifications (Rød et al. 2015).

Third, while we incorporated a large number of variables based on the pertinent literature and prior work (Feyissa et al. 2018), we were limited by data availability. For example, we were not able to consider the quality

of drainage systems in our flood risk layer (Durán and Román 2017). Moreover, it would be beneficial to update the climate vulnerability index periodically as new data (e.g., new census) become available.

Outlook

The sub-national vulnerability index presented in this article may be used employing a forward- and backward-looking perspective.

Employing a backward-looking perspective, the index may be used to evaluate the international development portfolio of Costa Rica. It will allow answering the question to what extent the most vulnerable regions have received climate change adaptation projects in the past or if other factors dominated allocation decisions (Thornton et al. 2008).

In addition, the index may serve as a strategic tool for future decisions (forward-looking perspective) to implement climate change adaptation interventions in the most climate vulnerable regions of Costa Rica (Sullivan and Meigh 2005;

Thornton et al. 2008). Particularly for the most climate-vulnerable cantons, programs and policies should aim at reducing vulnerability by focusing on the underlying dimensions of exposure, sensitivity, and adaptive capacity. Reduction of exposure requires a collective global approach to reduce greenhouse gas emission as the anthropogenic cause of climate change (IPCC 2022b). Research predicts an increase in hydro-meteorological events for Costa Rica (Imbach et al. 2018). While only a measure of last resort, resettlement might be an option to remove populations from highly exposed regions (de Sherbinin et al. 2011). In this context, development programs might support and incentivize voluntary migration to safer areas (Stojanov et al. 2021). Given that a reduction in exposure will be difficult to accomplish, policies and development programs need to focus on reducing sensitivity and increasing adaptive capacity.

Sensitivity in urban cantons is related to weaknesses in hydrological infrastructure and settlement in at-risk areas (Quesada-Román et al. 2021). Development projects may address these issues through infrastructure improvement projects and regulation of settlement patterns. In rural border cantons, the greatest source of sensitivity is the overall poverty status and lack of resources to cope with adverse climate impacts. For the rural poor, economic development projects may lead to a reduction in overall sensitivity and increase resilience (Tanner et al. 2015). This may include providing vocational trainings to improve the possibility for livelihood diversification and employment in less climate-dependent industries. In addition, climate insurance schemes may help vulnerable populations to recover after severe climate events have destroyed their livelihoods (Surminski et al. 2016).

In Costa Rica, adaptive capacity may be strengthened through projects in the following thematic areas: *First*, remittances may provide the necessary economic resources for households to invest in climate change adaptation technologies (e.g., installing a functional drainage system on farms) (Bendandi and Pauw 2016). Our data shows that receipt of remittances is concentrated in few southwestern cantons (Gatica López 2017). Projects may address obstacles to sending remittances including high fees for wiring

money and at the same time increasing knowledge about efficient climate change adaptation strategies (Maduekwe and Adesina 2022). *Second*, the quality and access to infrastructure is unequally distributed across Costa Rica with a spatial concentration in the small central cantons of the greater metropolitan area. Communities with inadequate access to health care and road infrastructure could be targeted with infrastructure development programs (Rosero-Bixby 2004). *Third*, particularly the border regions in the north (Nicaragua) and southeast (Panama) are characterized by low adaptive capacity given high infant mortality coupled with low literacy rates. Public health programs that address the sources of infant mortality such as infectious diseases and hygiene (Jiménez and Romero 2007) with a particular focus on migrant populations may be particularly well placed in the border regions.

In sum, our study adds to a small but growing repository of sub-national climate change vulnerability indicators. Specifically, we offer a detailed vulnerability map identifying vulnerability hotspots in Costa Rica. Policy makers and program managers may use this information to reduce vulnerability and build resilience to prepare the Costa Rican society for a future of increasingly severe climate impacts.

Appendix 1. Methodology

We make frequent use of the geoanalytical tool “zonal statistics”, available in all major GIS software and scripting tools. Zonal statistics select all raster cells within a given polygon (e.g., canton), compute the average (mean) value across the selected raster cells, and ultimately assign the mean value to the polygon. Zonal statistics are commonly used to compute land use changes in related research (Sierra-Soler et al. 2015; Youneszadeh et al. 2015; Rahman 2016).

Prior to performing any geospatial operation, all layers were reprojected using the coordinate reference system UTM Zone 16 with the WGS84 datum and ellipsoid (unit = meters).

Appendix 2. Flood Risk layers

Fig. 7 Rivers of Costa Rica. *Note:* Inset shows the area surrounding San Jose enlarged

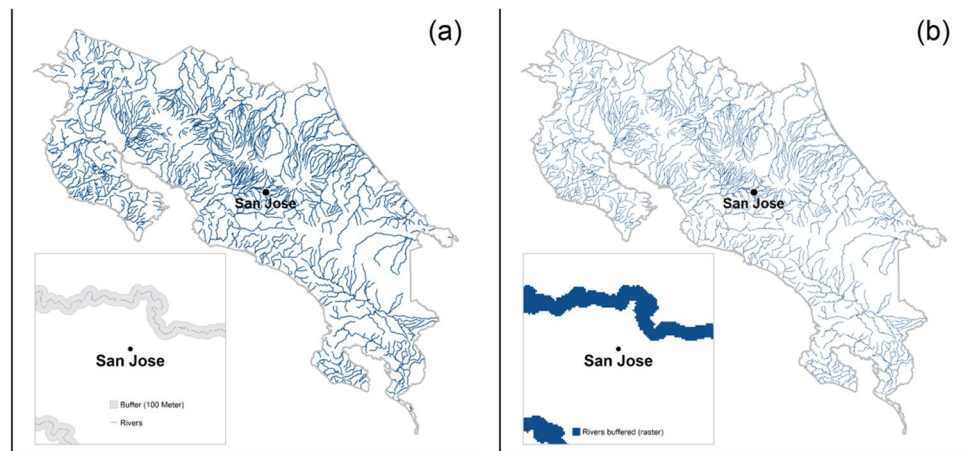


Figure 7 (a) shows the 100-Meter buffer radius surrounding each river. In this area, we expect a high chance of river flooding. Figure 7 (b) shows the rasterized version of the buffered rivers.

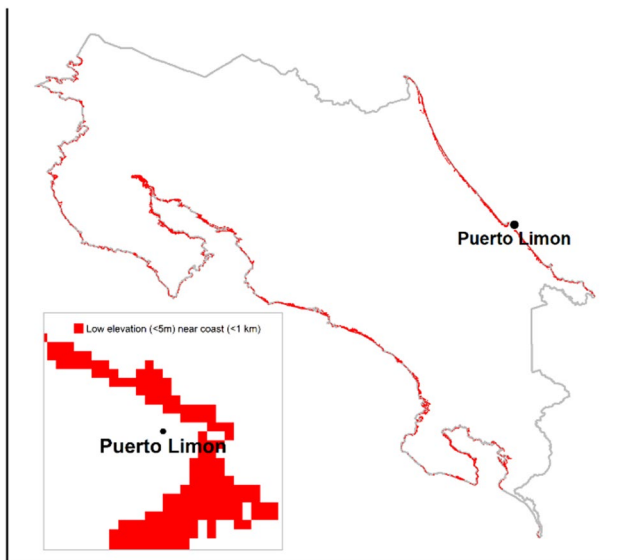


Fig. 8 Coastline of Costa Rica. *Note:* Inset shows the port city of Puerto Limon

Figure 8 shows pixels in regions of Costa Rica that have a high risk for coastal flooding. These pixels are close to the coastline (< 1 km) and show a low elevation (< 5 m)

Fig. 9 Land cover and land use classification of Costa Rica in 2015

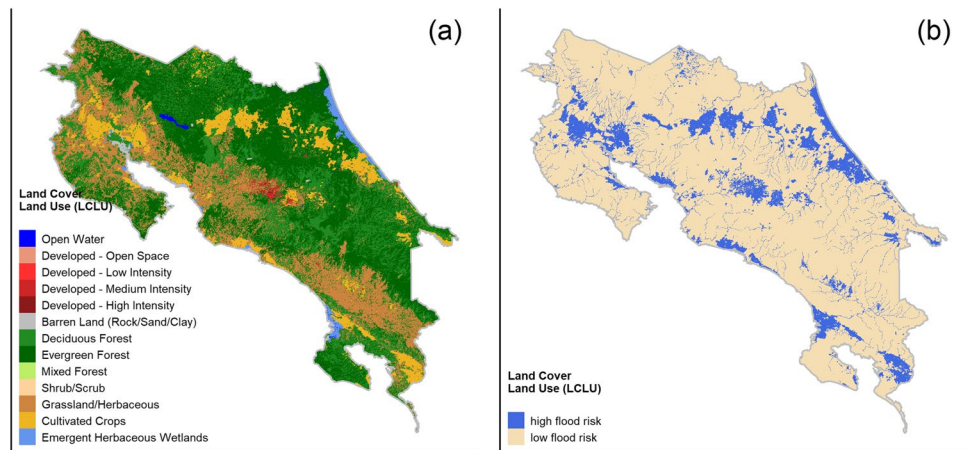


Figure 9(a) shows the original land cover land use (LCLU) classifications (15 m resolution), while Figure 9(b) illustrates the reclassification in high and low flood risk pixels. *High flood risk*: Open water, Developed – Medium Intensity, Developed – High Intensity, Barren Land (Rock/Sand/Clay), Cultivated Crops, Emergent Herbaceous Wetlands. *Low flood risk*: Developed – Open Space, Developed – Low Intensity, Deciduous Forest, Evergreen Forest, Mixed Forest, Shrub/Scrub, Grassland/Herbaceous.

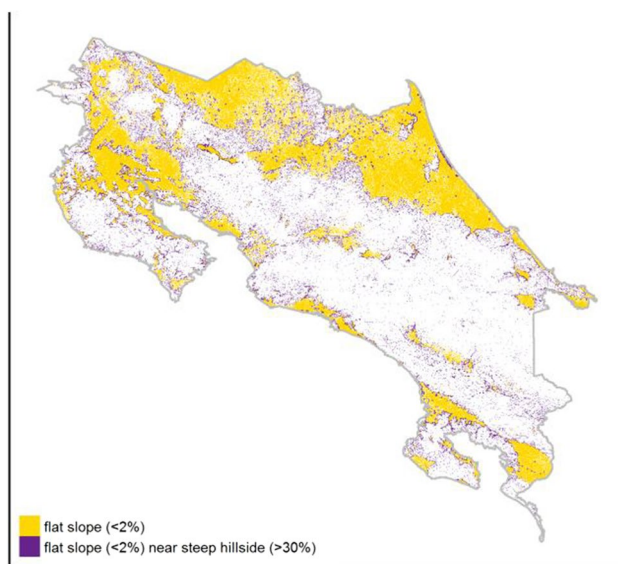


Fig. 10 Regions of low slope in Costa Rica

Pixels (30 m resolution) were classified as moderate risk of flooding when the slope was below 2% and as high risk of flooding when the flat slope was within 500 m of a steep slope (>30%) (Fig. 10). With this coding, we account for the added risk of flooding in valleys surrounded by steep hillsides that may function as a funnel and lead to higher levels of rainwater run-off.

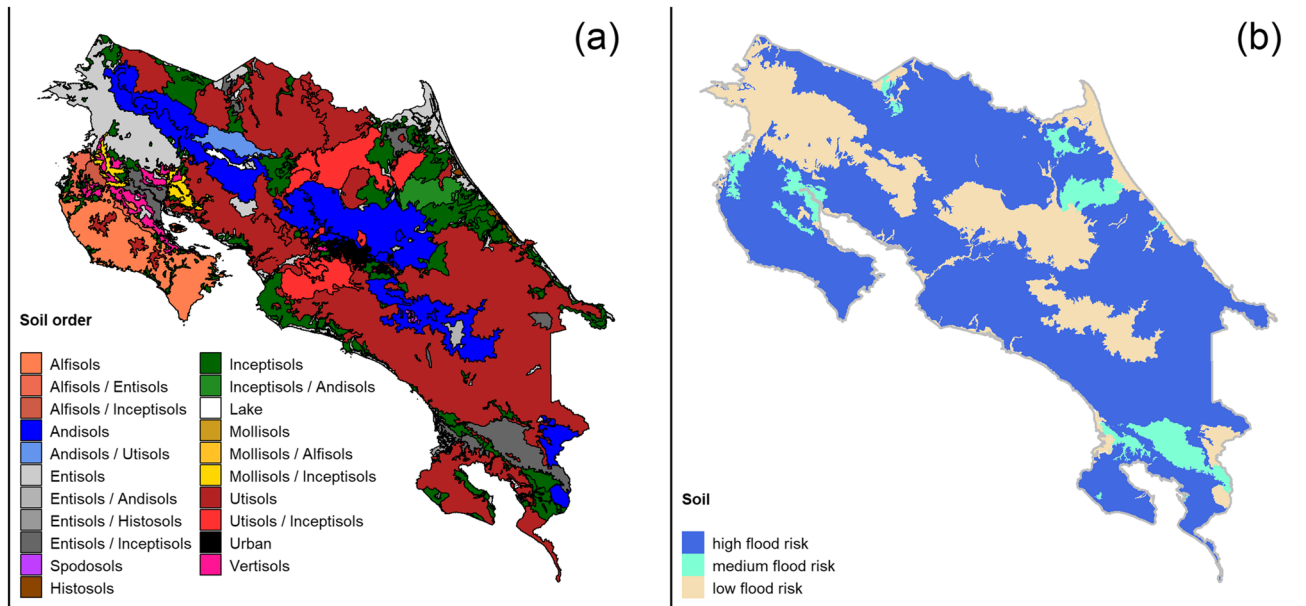


Fig. 11 Soil types in Costa Rica

Figure 11(a) shows the original soil types using the USDA soil taxonomy. Figure 11(b) presents a reclassified layer in which soil types were categorized as high, medium, and low flood risk. We classified soils based on their texture and composition following an established approach (Feyissa et al. 2018). Fine textured soils with a high clay content have a low drainage capacity while coarse textured soils with a high sand content have a high drainage capacity (Brown 2003). Soils with low drainage capacity and high risk of flooding include Vertisols (Sawe 2017), Alfisols, Inceptisols, Utisols and Mollisols (Aydinalp 2013; FAO and ITPS 2015). Soils with high drainage capacity and associated low risk of flooding include Andisols, Spodosols, Entisols, and Histosols (Yenter 1984; Nanzyo et al. 1993; Hong et al. 2013; Balasubramanian 2017).

Appendix 3. Sensitivity layers

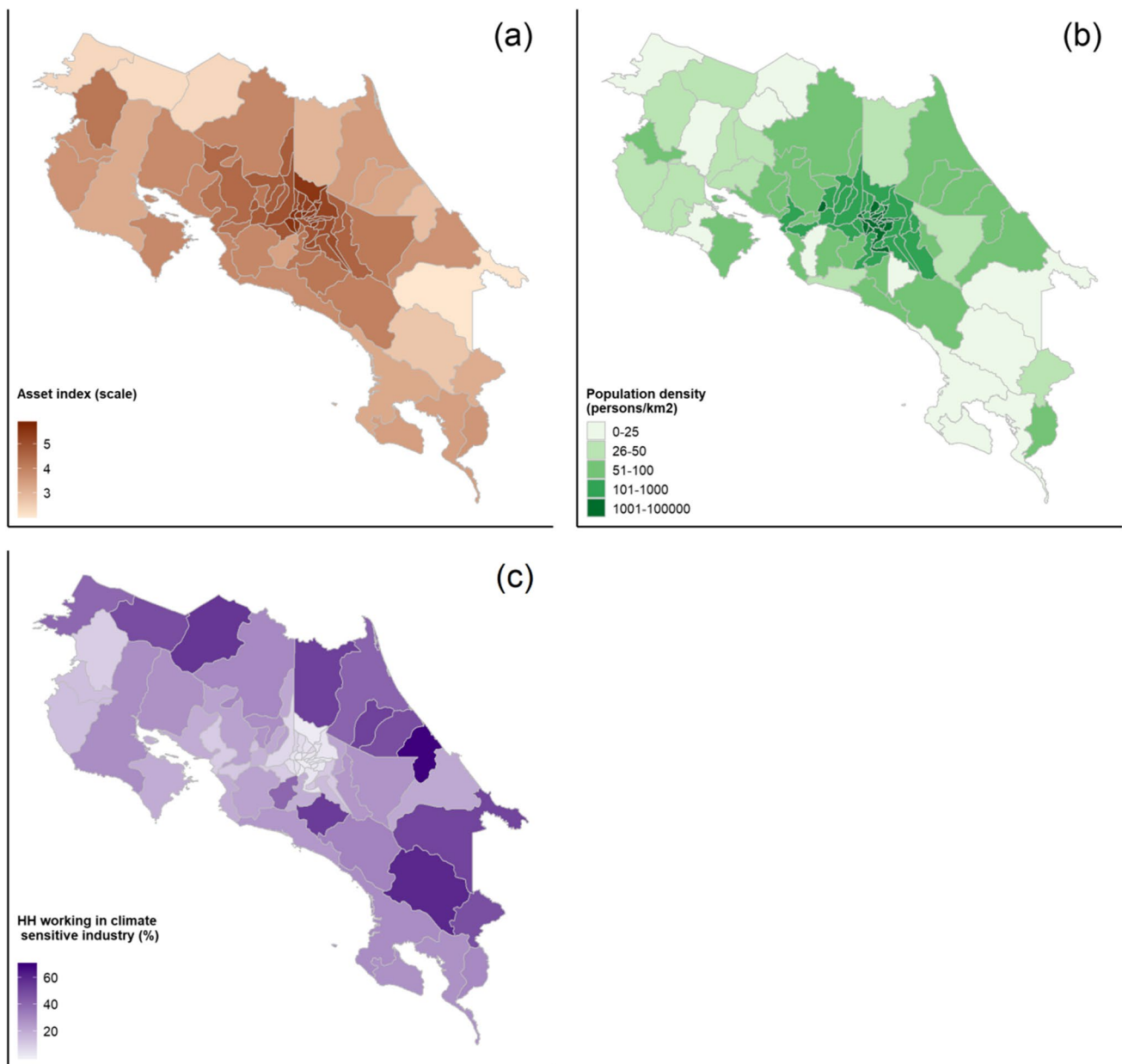


Fig. 12 Asset index, population density, and household heads working in climate sensitive industry. *Note:* HH = household head

The asset index and the percentage of household heads working in climate sensitive industries were constructed using microdata from IPUMS-International (MPC 2018). We initially considered 13 variables for the asset index. Performing a factor analysis (based on principle components and *varimax* rotation) we identified seven variables with high factor loadings (computer, cars, floor, walls, cooking fuels, trash collection, internet) indicative of the presence of a latent construct (i.e., “wealth”). Factor analysis is frequently employed as a method for variable reduction when generating vulnerability indices with the goal to measure a latent or underlying construct (Fekete 2009). We then combined these variables to form an additive asset index (Cronbach’s alpha = 0.75) (Fig. 12).

Population density was available as canton aggregate from the Costa Rica statistical office (INEC 2019). For all INEC data, we adjusted values for the recently formed canton *Río Cuarto* and its original source canton *Grecia* to better reflect the demographic properties of the new administrative divisions. Until May 19, 2017, *Río Cuarto* was part of the canton *Grecia* but was geographically removed and showed a very different sociodemographic profile. As such, the Costa Rican statistical office (INEC, personal communications) recommended adjusting the values for *Grecia* and *Río Cuarto*. When underlying district data was available (population density, employment rate), we used this information to directly compute values for *Río Cuarto* and *Grecia*. When no district-level but only canton-level data was available (variables: infant mortality, literacy, remittances), we computed the value for *Río Cuarto* as the average (mean) of its surrounding neighbor cantons. For *Grecia*, we adjusted the value by removing the influence of *Río Cuarto* using population and household weights.

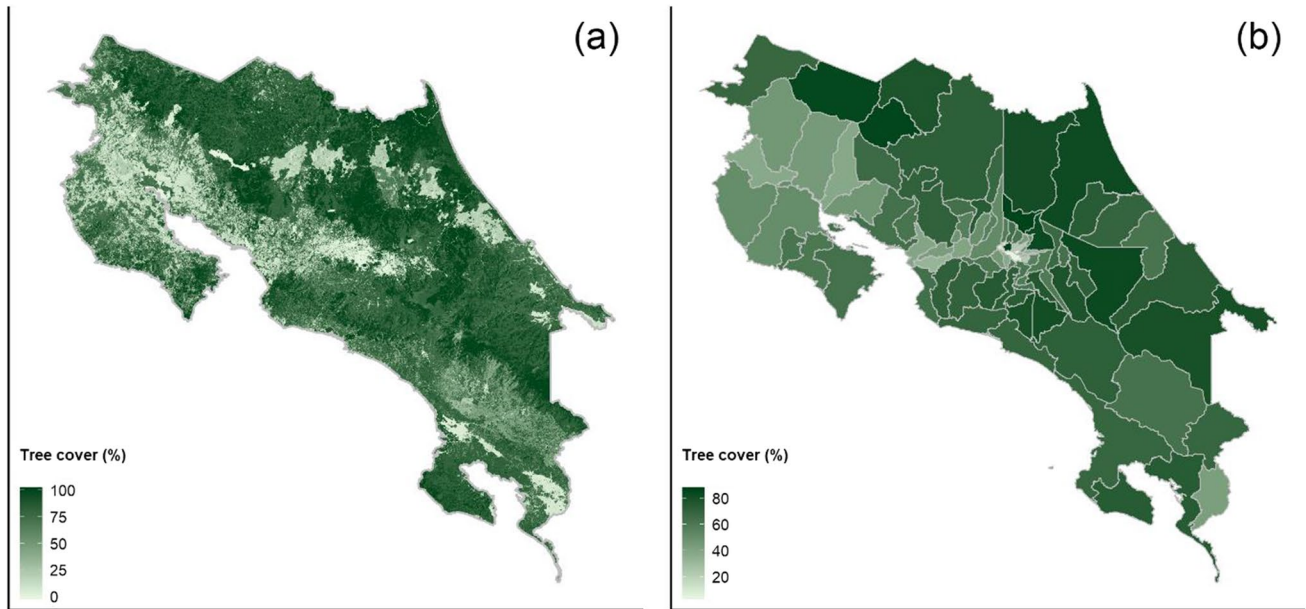


Fig. 13 Tree cover for Costa Rica year 2015

Figure 13(a) shows the original raster layer (30 meter resolution) of percentage tree cover while Figure 13(b) shows the aggregated values (mean) for each canton.

Appendix 4. Adaptive capacity layers

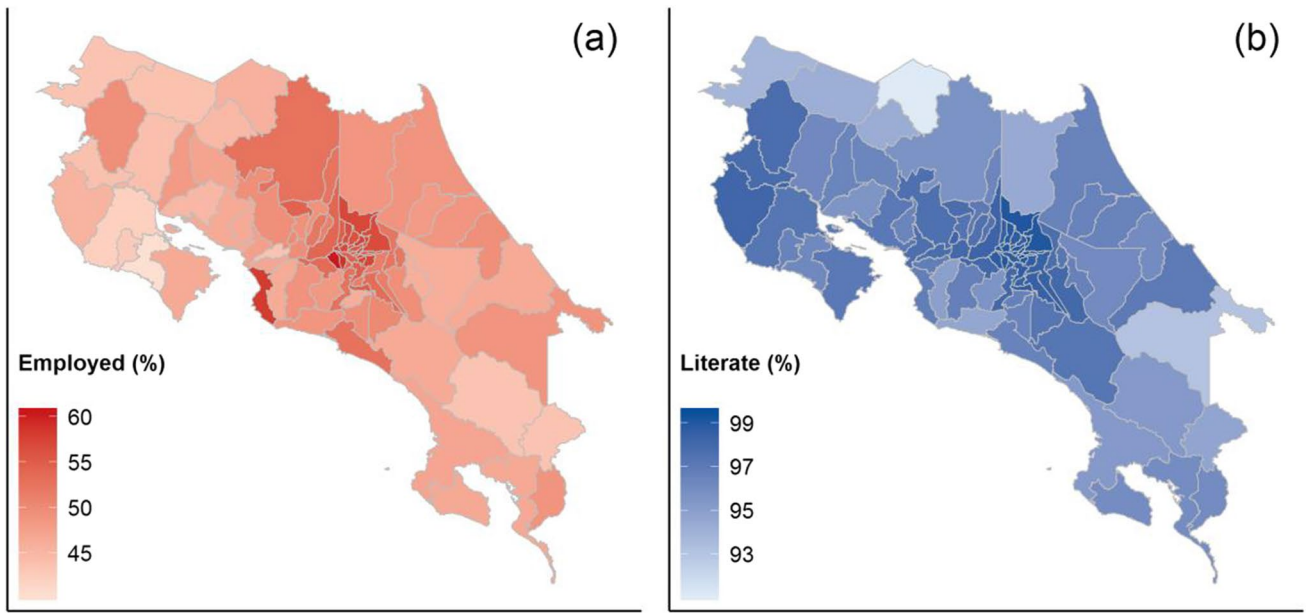


Fig. 14 Employment and literacy in Costa Rica, 2011. *Note:* Data were obtained as canton-level aggregates from the Costa Rica statistical office (INEC 2019)

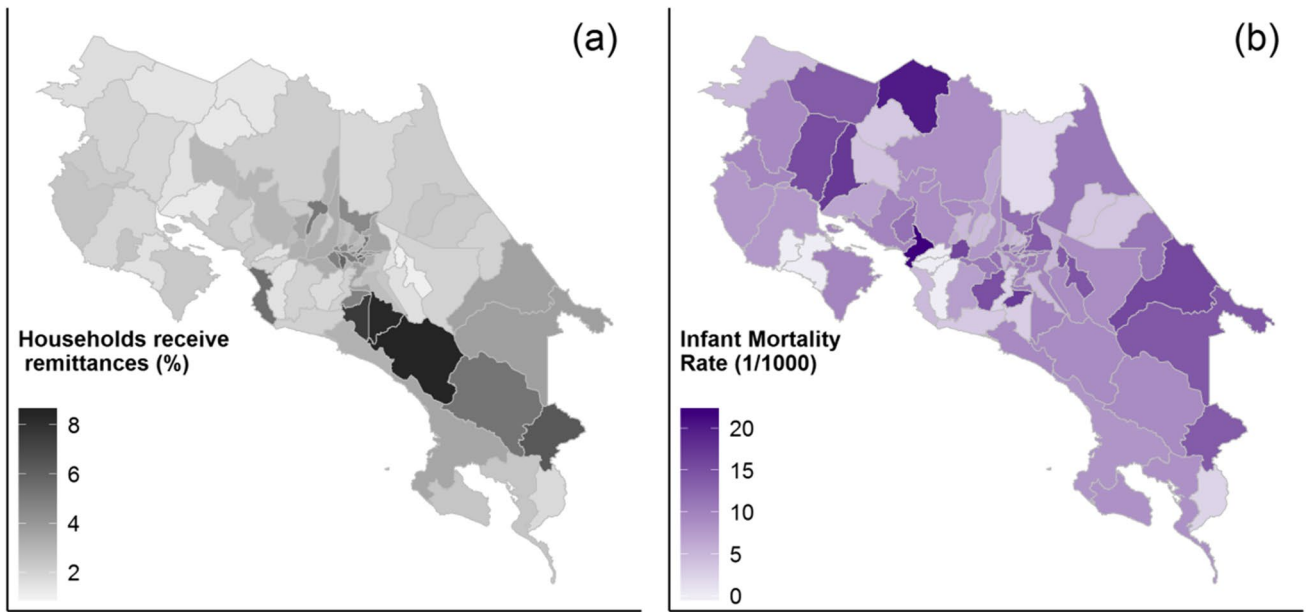


Fig. 15 Remittances and infant mortality in Costa Rica, 2011. *Note:* Data were obtained as canton-level aggregates from the Costa Rica statistical office (INEC 2019)

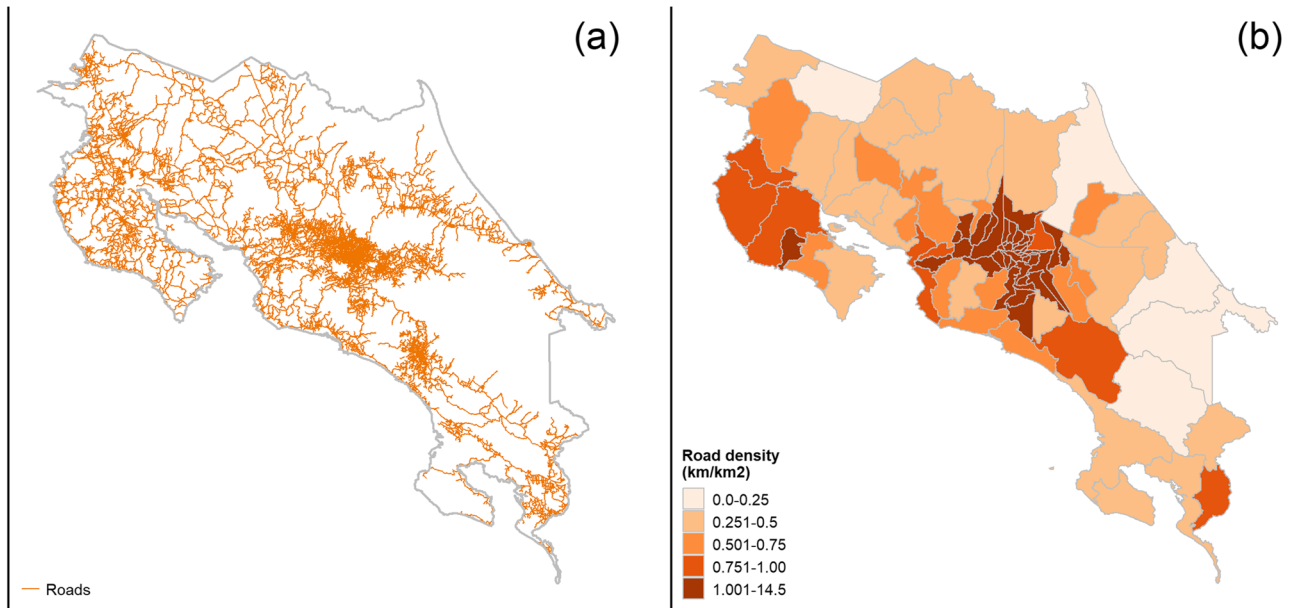


Fig. 16 Road density in Costa Rica

Figs. 14 and 15 show spatial patterns of employment, literacy, remittances, and infant mortality as important components of adaptive capacity.

Figure 16 (a) shows the original polyline layer of roads in Costa Rica. We performed an intersection operation with the canton shapefile which assigned each road segment a specific canton ID. Using a by-group operation, we were able to compute the sum of all road segments for each canton. We then related the combined road length to the area of each canton to obtain a measure of road density as graphically depicted in Figure 16(b).

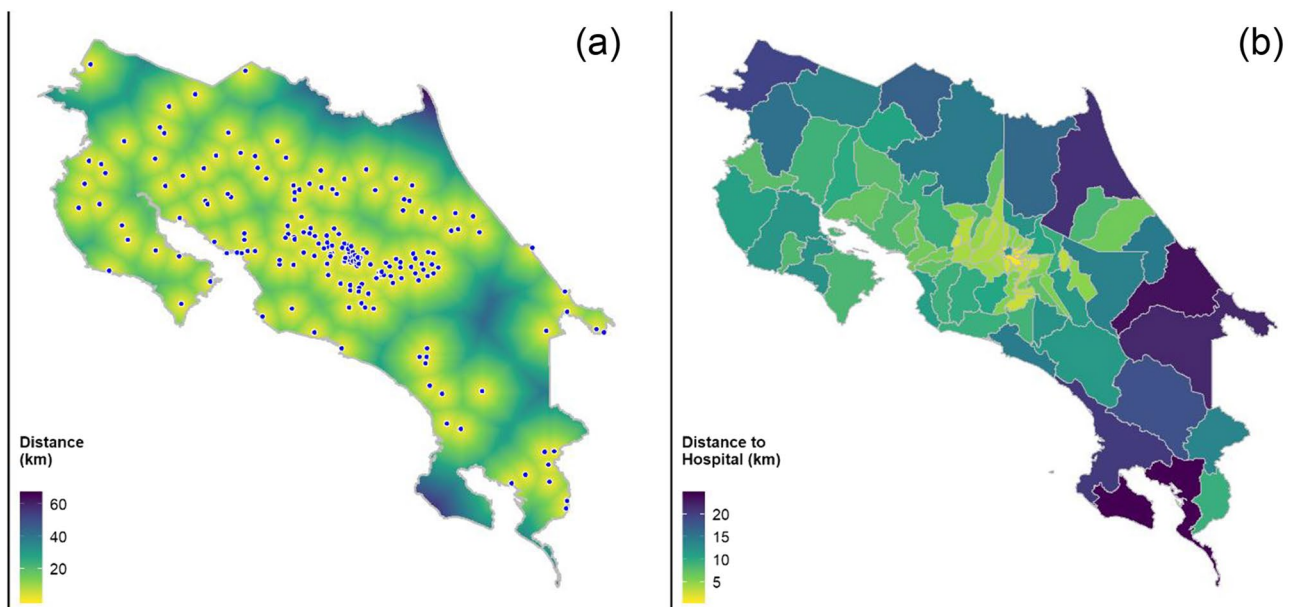


Fig. 17 Distance to health centers

Figure 17(a) visually shows the location of all health centers (Hospitals: $N = 36$; Clinics: $N = 291$) and the distance for each grid cell (30 m resolution) from the nearest health center. Figure 17(b) depicts the aggregate (mean) distance for each canton.

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discussed in this article are based on the authors' interpretation of findings in the light of the pertinent literature and do not constitute an official recommendation by DEval.

Author contributions RN and SH designed the study. RN and MT performed the geospatial analysis and constructed the climate change vulnerability index. RN, SH, MT, and VB were major contributors in writing the manuscript. All authors read and approved the manuscript.

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Data availability The datasets employed for the construction of the sub-national climate vulnerability index for Costa Rica are largely publicly available with few exceptions as outlined in Table 1. The sub-national climate vulnerability index dataset is available as .csv or .shp file from the corresponding author on reasonable request.

Code availability The R code used for the data computation and analysis is available from the corresponding author on request.

Declarations

Competing interests The authors declare no competing interests.

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