Natural Hazards
https://doi.org/10.1007/s11069-020-04247-7

ORIGINAL PAPER

Development of a drought vulnerability index using MCDM and GIS: study case in São Paulo and Ceará, Brazil

Gabriela de Azevedo Reis[1] · **Francisco Assis de Souza Filho**[1] · **Donald Robert Nelson**[2] · **Renan Vieira Rocha**[1] · **Samiria Maria Oliveira da Silva**[1]

Received: 31 January 2020 / Accepted: 21 August 2020

Abstract

Although climate change vulnerability research in general has increased over the last decade, Latin American countries have more directed more limited efforts toward vulnerability and its social aspects. To respond to this gap, the authors developed a method to quantify drought vulnerability, which is key climate risk in Brazil. The *iSECA* model uses MCDM techniques to calculate vulnerability indexes by applying weighting schemes to indicators that represent climatological, social, economic, and water management factors. GIS software was used to classify and to map vulnerability. The model output is a drought vulnerability index, displayed through maps and graphs, including a vulnerability triangle and frequency curves. The results provide a clear understanding for water managers and non-specialists and can serve as an indispensable tool for water management in drought-prone regions. A sensitivity analysis confirms the model's robustness. *iSECA* was applied to Ceará and São Paulo, two states with distinct climatological and socio-economic contexts. The application demonstrated how the model works well across different spatial scales within these different contexts. The study found that in São Paulo more than 30 million people are living with very high vulnerability to drought primarily due to water management characteristics. However, in Fortaleza, Ceará, the climatic factors are the most critical. Even the state's robust interbasin water infrastructure system does not significantly reduce the drought risk. The ability to identify vulnerability hotspots and the underlying characteristics that influence the rankings provides the necessary input of policy decisions.

Keywords Vulnerability · Drought · MCDM · GIS

✉ Gabriela de Azevedo Reis
gabrielareisazevedo@gmail.com

[1] Department of Hydraulic and Environmental Engineering, Federal University of Ceará, Fortaleza, Ceará, Brazil

[2] Department of Anthropology, University of Georgia, Athens, GA, USA

Published online: 31 August 2020

1 Introduction

Water demand tends to increase with population growth, and in conjunction with changing climate risks, a constant water supply can become increasingly uncertain. Over the last decades, the growth of water consumption has more than doubled population growth (Cosgrove and Loucks 2015). This increase in water demand combined with water scarcity will likely aggravate already existing water stress scenarios in various areas of the planet (Suárez-Amiñana et al. 2017). For their part, industrialized countries contend with conflicts related to water allocation, non-point source pollution, and extreme events, including droughts (Pryshlak et al. 2014). Less privileged countries also face water uncertainty and scarcity due to similar factors, but which are often exacerbated by the lack of sufficient infrastructure. As a result, the negative impacts of climate change events are a major obstacle for sustainable development in these regions, though the magnitude of the challenge is unevenly distributed between and within countries. As a result, vulnerability assessment and prioritization are fundamental needs for scientific studies on climate change adaptation (Vargas and Paneque 2017).

Drought events, depending on their frequency, intensity, and duration, amongst other physical aspects, cause a range of impacts on the environment and to human society. These impacts generate additional, secondary complexities for water resource management (Montanari et al. 2013). The subsequent uncertainty related to dependable water provision requires increased efficiency in planning and management (Pienaar and Hughes 2017). Responding to drought through post hoc crisis management strategies is inefficient (Wilhite et al. 2014), and it is up to the water resource managers to develop and apply proactive strategies that mitigate the impacts of water scarcity. To do so effectively requires guidelines for the development of drought management plans, with proactive and risk-based management strategies (Wilhite et al. 2014), based on social, technical, and scientific findings. The vulnerability analysis of a water system is an essential contribution to the elaboration of such strategies.

Vulnerability is usually presented as an aggregate measure of human welfare, which assesses environmental, social, and economic susceptibility to potentially harmful disturbances. It is not a static measure, but rather, vulnerability varies through time and space according to political and social actions (Bohle et al. 1994; Hewitt 2013; Thomas et al. 2016). Analyses therefore require a robust methodology to identify and categorize vulnerability, and a strong connection between researchers and decision-makers (Turner et al. 2003). Since 2006, climate change vulnerability studies have increasingly focused on water resource management. Most of the publications stem from research in European and North American countries (Nazemi et al. 2013; Acosta and Martínez 2014; Asefa et al. 2014; Chanda et al. 2014; Goharian et al. 2016; Mateus and Tullos 2017; Vargas and Paneque 2017; Zhang et al. 2017; Anandhi and Kannan 2018), and there is a gap in South American research. Within Brazil, there is also a demand for increased research on water resources vulnerability, including the social components (Wang et al. 2014) since contemporary climate research focuses primarily on renewable energy systems, rather than water, and tends not to engage with the social aspects of vulnerability.

This paper proposes an improved method to quantify and classify drought vulnerability through a multi-criteria decision making (MCDM), GIS-based analysis of exposure and sensitivity, and the adaptive capacity of a population to cope with drought. The iSECA model and its innovations offer technical and conceptual contributions to and serve as a tool for the elaboration of drought management plans. The method is based on the IPCC definition of vulnerability, which includes the concepts of sensitivity, exposure, and adaptive capacity (IPCC 2001) and can be applied to both regional and local scales by using existing secondary data. Prioritizing areas not covered by the majority of climate change vulnerability research, the authors applied iSECA to two distinctive areas in Brazil: the states of Ceará and São Paulo. These states represent regions with different social and economic activities and dynamics, as well as different biophysical and climatic characteristics.

The method does not demand extensive fieldwork or substantial financial costs. The data can be obtained through local officials, publications, and online databases. The indicators used in this model quantify meteorological, hydrological, and socioeconomic aspects of drought (Eslamian and Eslamian 2017). The differing characteristics of the two study areas demonstrate the value and relevance of iSECA for drought studies in other contexts. iSECA considers the complexity of diverse agents and aspects that interfere with the resilience of a water system by following straightforward, logical steps. The results are easy to understand and to visualize, making it accessible to decision-makers and the broader communities facing drought risks. The results of iSECA can contribute to drought management plans, on national, state, or basin scales. In sum, iSECA is an easy-to-build model, with a wide range of scalar applications and clear results, which makes it possible to analyze the outcomes of drought-related public policies.

2 Background considerations

The notion that populations are differently vulnerable to natural hazards has been a focus of disaster research for many years. Hashimotto et al. (1982) brought the definition of vulnerability and resilience to the study of water systems, and Susmam et al. (1983) demonstrate that different groups within a society are at different levels of risk since they present varied capacities to absorb impacts and to recover. Several works present vulnerability as a dynamic between external (biophysical) and internal (socioeconomic) factors (Bogard 1988; Dow 1992), adding that the degree of impact suffered from a harmful event is related to the regional risk and the social and economic conditions of the population affected (Bohle et al. 1994; Cutter 1996).

Given the evolution of the concept of vulnerability and its different interpretations by the various disciplines, there is not a technical consensus around a definition. Here, we define vulnerability to drought as a function of the level of exposure to physical climatic factors, sensitivity to drought impacts, and a population's ability to cope with these impacts (IPCC 2001; Abraham 2006; Fontaine 2007). Exposure represents the magnitude, in time and space, of extreme climate events. Sensitivity is the degree of preparedness of a system and the capacity to absorb impacts without long-term harm or without presenting any significant change in its state. Lastly, adaptive capacity is the degree to which the adjustments and adaptations, in the form of actions, processes, or structures, can mitigate and minimize the potential impacts of climate change occurrences (IPCC 2001; Abraham 2006).

Using an alternative methodology, Nazemi et al. (2013) measured the vulnerability of a Canadian water system based on potential variations in flow rate that represent a response to climate change. Goharian et al. (2016) combined the severity of the failures of a reservoir system in Salt Lake City, USA, with a sensitivity analysis to climate change. Some works applied a reliability-resilience-vulnerability (RRV) analysis to assess climate change and climate events (such as droughts) impacts on water systems (Asefa et al. 2014; Chanda et al. 2014; Mateus and Tullos 2017; Zhang et al. 2017).

Anandhi and Kannan (2018) and Acosta and Martínez (2014) merged the IPCC structure of vulnerability with the Pressure-State-Impact-Response framework and with GIS techniques, respectively, to quantify water resources vulnerability to climate change. Vargas and Paneque (2017) developed an index to quantify vulnerability to drought at the river basin level. The studies mentioned here were developed through Europe and North America.

3 Study area

The iSECA method was applied in the states of São Paulo and Ceará, located in the southeast and northeast of Brazil, respectively (Fig. 1). The areas were purposively chosen to test the applicability of the iSECA across different social and biophysical contexts. Both states, although located within the same western country, present divergent dynamics that guarantee the functionality of the method for different regions. São Paulo is the most populous and wealthiest state in Brazil, representing 32% of the national GDP (CRH/CORHI 2017). The state is located between 20° and 25° of latitude in the southern hemisphere and presents a primarily humid subtropical climate. The state of Ceará is located between 3° and 7° south latitude. It is a primarily semi-arid region, and its history is marked by recurrent severe and prolonged drought events.

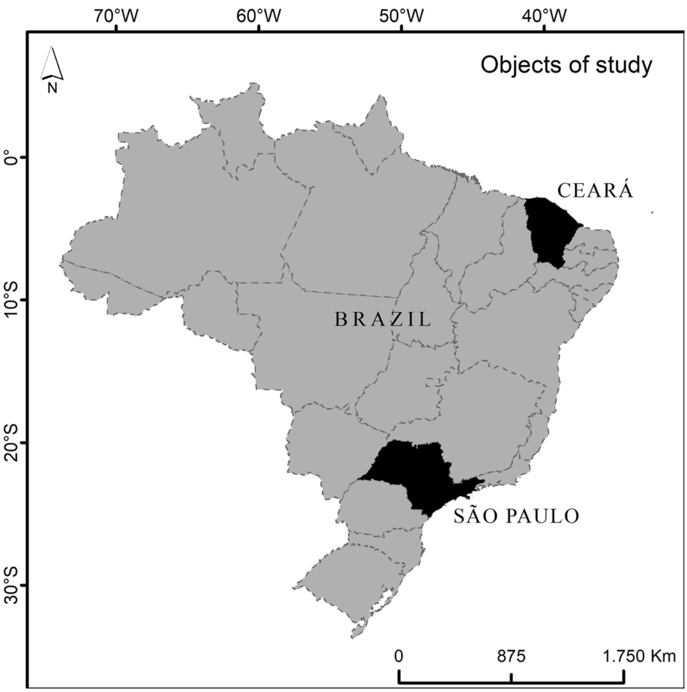

Fig. 1 Objects of study: Ceará and São Paulo, Brazil

3.1 Ceará

Ceará comprises a total area of 148,920 km^2 and approximately 9 million people. The annual average precipitation is less than 800 mm, which primarily falls between February and April. The latter part of the year is characterized by little to no precipitation. The annual average temperature in Ceará is about 26 °C, with little seasonal variation. Ceará has an average surface water supply of 128 m^3/s and an estimated water demand of 50 m^3/s (INESP 2008). A few essential biophysical characteristics of Ceará are its semi-arid climate, caatinga vegetation, the predominance of a crystalline basement, the occurrence of shallow soils—reducing its potential to store underground water, and the presence of intermittent rivers, combined with intense solar radiation and high evapotranspiration rates (INESP 2008). The state encompasses 184 municipalities, and its water bodies are divided into 12 hydrographic regions. Each region has a watershed committee that is responsible for its participative and integrated management of water resources (Araújo 2012). The most crucial water system of the state is the Jaguaribe-Metropolitano. It unites 5 out of the 12 hydrographic regions of the state through water transfer channels and reservoirs that have a water volume capacity of more than 10,000 hm^3 (Silva et al. 2017).

3.2 São Paulo

With an area of approximately 248,209 km^2 and a population of 43.35 million people, São Paulo is the most populous state in Brazil, representing 22% of the country’s total population. The percentage of urban population in the state of São Paulo is of 96%. (CRH/CORHI 2017; Martirani and Peres 2016). Sixteen percent of the population is classified as highly or very highly vulnerable, according to Index of Social Vulnerability of São Paulo (IPVS) (SEDAE 2010). The annual average precipitation is about 1377 mm, with July being the driest and coldest month (15 °C, 35 mm average) and January being the wettest and warmest month (22 °C, 218 mm average) (CRH/CORHI 2017). São Paulo has an average surface water supply of 3121 m^3/s and an estimated water demand of 443 m^3/s. It is divided into 22 hydrographic regions, with a management system similar to Ceará. Between 2013 and 2015, São Paulo faced a historic water crisis and the São Paulo Macrometropolis, with 30 million people, was the region most affected. 2014 recorded the lowest rainfall levels since the beginning of the monitoring of the historical series (CRH/CORHI 2017). However, the water crisis should not be attributed only to climatic factors without considering the role of water managers (Jacobi et al. 2015), as well as the socio-economic context of the state.

4 Methods

4.1 MCDM for indicator analyses

Management decisions within the water resources domain must account for a diversity of participants and perspectives, creating complexity and space for a variety of possibilities and scenarios. Multi-criteria decision making (MCDM) is an evaluation approach designed to deal with this type of complexity, in which alternative choices are analyzed by considering a set of multiple (and frequently conflicting) criteria (Ishizaka and Siraj 2018). MCDM integrates hierarchical division by weighting the aspects considered in the analysis (indicators) and expert empowerment (Lin et al. 2019). These techniques can also be applied to quantify analyses that are commonly assessed qualitatively, such as vulnerability assessments. However, it is important to note that MCDM entails uncertainty, notably when the weighting process occurs subjectively based on the analyst experience, and models should be subject to sensitivity analysis (see Sect. 4.5).

MCDM techniques are used for other types of water resources research. For example, Kim and Chung (2013) assessed the vulnerability to climate change and variability in South Korea using a suite of MCDM methods. Lin et al. (2019) presented a flood susceptibility analysis framework for a Chinese city based on an MCDM method that quantifies the potential flood scale and extent, all in a GIS platform. In Iran, Mostafazadeh et al. (2017) built eight structural management scenarios that were analyzed using spatial distribution and an MCDM technique to choose the best scenario. Overall, these techniques are easily adaptable to different contexts and scenarios, and they can also be found in a variety of other types of research applications (Kumlu and Tüdes 2019; Mela et al. 2012; Hülle et al. 2011; Triantaphyllou 2000; Ozernoy 1987).

For this study, the authors apply an MCDM approach in order to analyze indicators and build them into a unified index, making it possible to quantify vulnerability. Based on the concepts introduced by IPCC (2001), the method considers the vulnerability (*V*) of a given system as a combination of the sensitivity (*S*) and the exposure (*E*) to drought discounted by the adaptive capacity (CA) of the built infrastructure.

The index represents the relative vulnerability of the population within the system and its intrinsic conditions to cope with drought events. To represent *S*, the authors considered social and economic indicators, as well as sanitation conditions and water supply/demand of the system. *E* represents the external climate conditions of the systems and was built based on historical rainfall patterns. Lastly, in order to quantify CA and to represent the structure of the system to deal with drought events, we considered management indicators as well as water infrastructure (such as canals and reservoirs).

The method follows a logical sequence of steps: selecting indicators, normalizing indicators, clustering indicators between sectors, weighting indicators and sectors, calculating indexes, classifying indexes, and spatializing indexes. The sequence is described in the following sections. The sectors, indicators, and index calculations are summarized in Fig. 2.

iSECA was developed for application at different spatial scales and was applied the model on both river basin and local (municipality) levels. To analyze the relative importance of adaptive capacities, the authors evaluated the model with and without the influence of adaptive capacity. Considering the more favorable hydrological situation in São Paulo, with a higher annual rainfall average and the presence of various perennial rivers, the authors ran the model at the river basin level and without considering adaptive capacity. In Ceará, the model considered adaptive capacity and was applied at the local level. The authors also compared both sets of results with and without the adaptive capacity to quantify the importance of water resources infrastructure and management in scenarios of high (São Paulo) and low (Ceará) water availability.

4.2 Index elaboration

Within each vulnerability component (Exposure, Sensitivity, Adaptive Capacity), indicators are categorized into sectors. Sensitivity is divided into four sectors: social aspects, economic aspects, sanitation, and water conditions. Sanitation considers the level of untreated sewage, which ends up being dumped into water bodies. With the

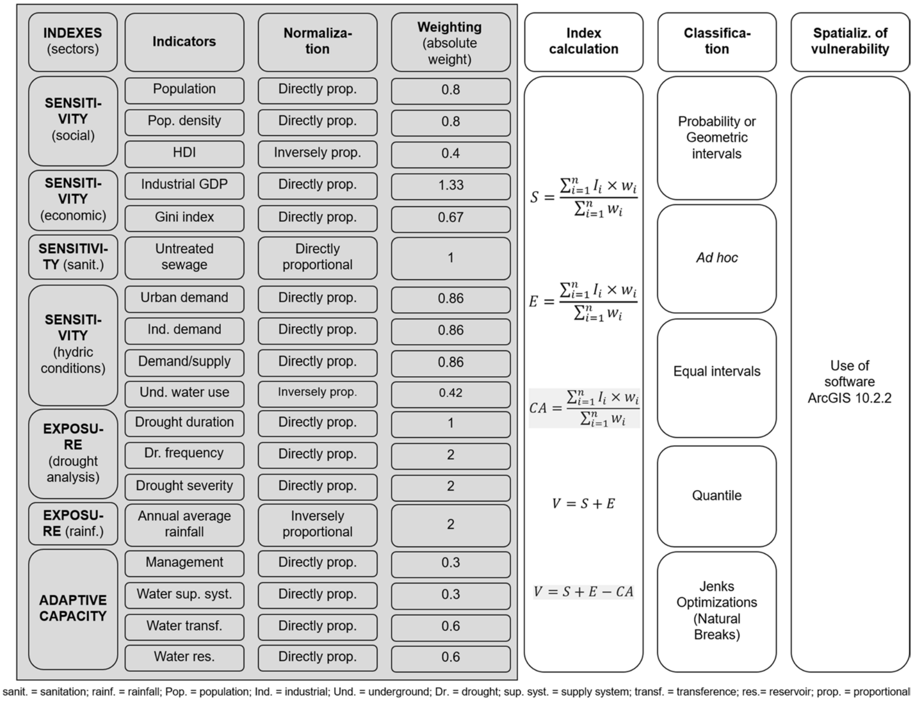

Fig. 2 Sectors of the indexes and steps towards its calculation

increase of the organic load, the water bodies become unfit for human consumption and, consequently, in periods of drought, the number of alternative water sources is reduced. Drought has diverse impacts on the economic and social development of affected communities since water is a natural resource used in the means of production and the daily habits of the population. The precarious development of some communities represents poor preparation to deal with crises and emergencies (Veyret 2007). In this context, the social and economic aspects appear with weight 2 in the calculation of sensitivity. The authors considered population, quality of life, income distribution, and economic activity as indicators of both aspects. Finally, the supply and demand scenarios of the population located in the study areas were combined to represent the water conditions, which received triple the importance in the sensitivity analysis considering that the study is focused on the susceptibility to a scenario of water scarcity. Sanitation and water supply and demand data were obtained through the National Water Agency (ANA). Socioeconomic data are from the national census and the Brazilian Institute of Geography and Statistics (IBGE).

To compute the exposure index, we used three indicators representing drought analysis, rainfall, and another alternative water source. This last indicator considers the exploitable groundwater potential of the aquifers of São Paulo, taking into account that the surface water sources are more vulnerable to droughts. The analysis of droughts represents the variability of the rainfall regime in the chosen area. The monthly precipitation average of each group was obtained, composing a time series of 36 years (1979–2014) in São Paulo and 106 years (1911–2017) in Ceará. In addition, the authors calculated the Standardized Precipitation Index (Mckee et al. 1993) for the timescale of 12 months (SPI-12) for each group in order to identify the frequency and duration of droughts over the time series and to classify them according to their intensity. Rainfall data were collected from the ANA website.

Finally, the adaptive capacity index considered aspects of water management, water transfer, water reservoir capacity, and the situation of water supply systems. We considered that adaptive capacity can reduce vulnerability to drought, but it is not capable of canceling out sensitivity or exposure. Therefore, for the calculation of the vulnerability index in Eq. (6), we considered a scale of 30% of the total adaptive capacity index. Hydrographic and water infrastructure data were obtained from the Water Resources Management Company of Ceará (COGERH) as a georeferenced database, making it possible to measure the length of the water channels and the maximum capacity of the reservoirs.

The calculation of the indexes proceeded as a multivariate analysis, including normalization and weighting of the indicators. The normalization process computed each indicator, with its different numeric scales and units, as a value varying mainly between 0 and 1, where 0 means low sensitivity, exposure or adaptive capacity, and values greater than 1 represent extreme conditions. This process occurred through Eqs. (1) and (2), where (1) was applied to indicators directly proportional to the index and (2) to indicators inversely proportional to the index. I_i represents the indicator, and X_i represents the variable. Min and Max are the minimum and maximum values that were fixed for each indicator.

$$I_i = \frac{X_i - \mathrm{Min}}{\mathrm{Max} - \mathrm{Min}} \tag{1}$$

$$I_i = \frac{X_i - \mathrm{Max}}{\mathrm{Min} - \mathrm{Max}} \tag{2}$$

Each index (sensitivity *S*, exposure *E*, and adaptive capacity CA) was divided into different sectors, composed by the indicators, with different weights, as described later in this paper and illustrated in Fig. 2. Each indicator was also attributed to a weight that represented said variable within its sector. The absolute weight (w_i) is then computed through Eq. (3), where SW is the weight of the sector, and IW_i is the weight of each indicator within the sector.

$$w_i = \frac{\mathrm{SW}}{\sum_{i=1}^{n} \mathrm{IW}_i} \times \mathrm{IW}_i \tag{3}$$

The indexes (*S*, *E*, CA) are calculated by applying Eq. (4). Finally, the Vulnerability Index is calculated using Eq. (5) for the first analysis and Eq. (6) for the second analysis.

$$\mathrm{INDEX}(S, E, \text{or CA}) = \frac{\sum_{i=1}^{n} I_i \times w_i}{\sum_{i=1}^{n} w_i} \tag{4}$$

$$V = S + E \tag{5}$$

$$V = S + E - \mathrm{CA} \tag{6}$$

The weights were first applied to each sector within the indexes (*S*, *E*, CA) and then distributed amongst the indicators of their sectors. The weighting step proceeded with sessions of *brainstorming* with specialists on water resources management. The sensitivity analysis tested the robustness of the model, including the effects of the indicators and the given weights, and is described later in this paper in Sect. 4.5.

4.3 Classifying and mapping vulnerability

In order to assess the fit of classification methods, a chi-square test was used to test the adherence of the indexes to the normal distribution model. To avoid methodological bias, the classification scheme was based on five different methods. The Probability Method or The Geometric Intervals method was applied. The former was applied to the normally distributed data, where the intervals are established according to the mean and standard deviation of the distribution. The latter method was applied to data with asymmetric distributions, which create geometric intervals by minimizing the sum of the squares of the number of elements in each class, so that the classes have approximately the same amount of elements and that the difference between the classes is consistent. The second was the Ad Hoc Method, in which the authors used their empirical knowledge to define the classes. Third, for the Equal Intervals Method, intervals were defined with equal values (such as 0 to 0.25, 0.25 to 0.50, and so on). Fourth, in the Quantile Method, each class was assigned the same number of elements, and there are no empty classes or disparities in the number of elements in the different classes. Finally, the Jenks Optimization Method optimized the difference of values between classes and maximized the similarity of values in the same classes, based on the Best Variance Adjustment index (Ramos et al. 2016). Geometric Intervals, Equal Intervals, Quantile, and Jenks Optimization were calculated through ArcMap® 10.2.2, and their specific methods are detailed by Ramos et al. (2016). The Probability method is the same as that utilized by the Institute of Research and Strategic Economics of Ceará (IPECE 2016).

Classification methods divided the values into five classes for each index (sensitivity, exposure, adaptive capacity, and vulnerability): low, moderate, high, very high, or extreme. In order to synthesize the five methods, the final classification was made from the assignment of grades to each group according to their acquired classifications.

The final score (FS) was obtained from Eq. (7), where GL_i, GM_i, GH_i, GVH_i, and GE_i represent the number of times each group was classified as low, moderate, high, very high and extreme and LS, MS, HS, VHS, and ES represent, respectively, the score of each class.

$$FS = GL_i \times LS + GM_i \times MS + GH_i \times HS + GVH_i \times SVH + GE_i \times ES \tag{7}$$

The classification is georeferenced and spatialized using the ArcGIS software. This permits a visual and spatial representation of the final classification of drought vulnerability and identification of where and who is more vulnerable to the impacts of water scarcity.

4.4 Vulnerability triangle

The vulnerability triangle (Vargas and Paneque 2017; Liu et al. 2013) graphically represents the three components of vulnerability (sensitivity, exposure, and adaptive capacity) by using the relative weight calculated with Eq. (8). OI stands for the original index, and it can be replaced by the exposure (E), sensitivity (S), or adaptive capacity (CA) indexes. RI is the relative index, where REI represents the Relative Exposure Index, RSI is the Relative Sensitivity Index, and RCAI represents the Relative Adaptive Capacity Index.

$$\mathrm{RI} = \frac{\mathrm{OI}}{E + S + |-\mathrm{CA}|} \times 100 \tag{8}$$

The authors used the tool to visualize and analyze the natural shape of drought vulnerability in both states. The vulnerability triangle represents the municipalities as points, and in Ceará, zone in which each point is located tells us if the municipality's vulnerability is more influenced by the sensitivity, exposure, or adaptive capacity index. The same approach was not used to analyze São Paulo's results because that states the vulnerability index considered two components (sensitivity and exposure) instead of three.

4.5 Sensitivity analysis

Since the model was built with multiple indicators and different weights to calculate the indexes, it is fair to assume that there is a level of uncertainty attached to the results. Therefore, in order to assess the robustness of the model and the reliability of the results computed from the indicators, the authors ran a sensitivity analysis.

The test analyzed three scenarios where the data suffered a variation of 5%, 10%, and 20% from its original values. To do so, we used the original and normalized data to generate three datasets of synthetic values through triangular distribution with $\alpha-\beta$ and $\alpha+\beta$ as minimum and maximum values, respectively, and α as the mode value. α represents the original value for each indicator in each object (city or river basin), and β is the limit value of variation (5%, 10%, 20%). For each variation scenario, the test generated 1000 synthetic values for each α represented. Then, the authors ran the model in order to obtain 1000 values of the vulnerability index. The sensitivity test permitted visualization of whether the model was sensitive or not to the computation of data from different entry datasets, i.e., if iSECA can be used for different study objects with distinct behaviors, characteristics and numeric values.

5 Results

This section presents the results for each study area and their interpretation. The authors highlight the results obtained from sensitivity, exposure, and adaptive capacity indexes and present the description of the aggregate vulnerability index with a georeferenced map for both states (Figs. 3, 4). Even though the analysis of Ceará uses the municipality scale, the map of the vulnerability of Ceará (Fig. 4) also highlights the boundaries of the 12 main river basins of the state.

5.1 São Paulo

The values obtained for the exposure index fit within a range of 0.26–0.68, presenting a low amplitude. The results suggest that the state of São Paulo does not present tendencies of water scarcity. There were no occurrences of long periods or high frequency of drought events during the period analyzed. The exposure values do not demonstrate much variation, in part, because the study area is not large and does not contain multiple climatic regions.

On the other hand, sensitivity values vary from 0.21 to 1.29. The maximum value, in the Alto Tietê region, is considerably higher than values for other basins, which only vary from 0.21 to 0.62. Alto Tietê encompasses the municipality of São Paulo and part

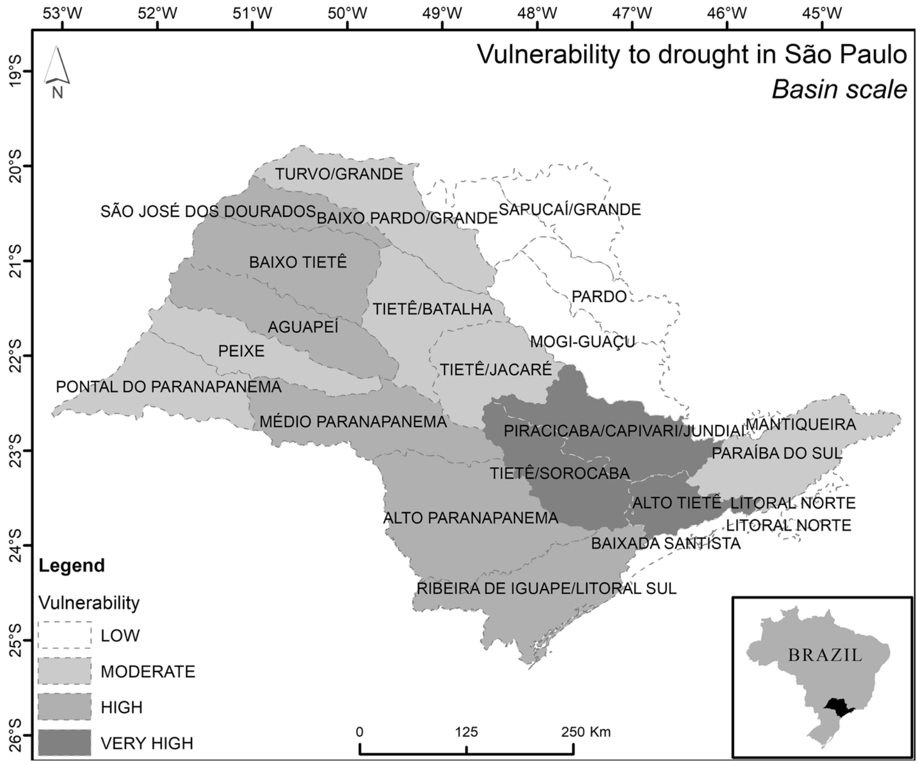

Fig. 3 Drough vulnerability in São Paulo: river basin level

of the Metropolitan Region of São Paulo (MRSP), which presents social and economic aspects distinct from the other regions. It was observed that, among the indicators utilized in the sensitivity calculation, the values of industrial production, population, and population density for the Alto Tietê unit exceeded the limit value of 1. The industrial activity should not be significantly impacted in periods of water scarcity since there is a lower relative water demand for this sector. It can be inferred, therefore, that the higher sensitivity of the MRSP, faced with a scenario of water scarcity, would be its large number of inhabitants and the spatial density of these inhabitants. However, due to a medium level of exposure, the vulnerability to drought of Alto Tietê is not as extreme as its sensitivity. Given these results, in assessing the water crisis that affected São Paulo in 2014, it is likely that water management efficiency was a key factor.

Based on the results presented in Fig. 3, it is estimated that 64% of the state's population is living in a situation of very high vulnerability to drought. This corresponds to more than 30 million inhabitants. It is also estimated that the areas with very high vulnerability account for about 70% of the state's GDP and approximately 20% of the national GDP. Including adaptive capacity in São Paulo reduced vulnerability in most of the regions with an average of 29%. However, in Alto Tietê, the inclusion of water resources infrastructure and management only reduced the vulnerability index value by 4%. This is explained in part by the fact that only 6% of the water supply system within

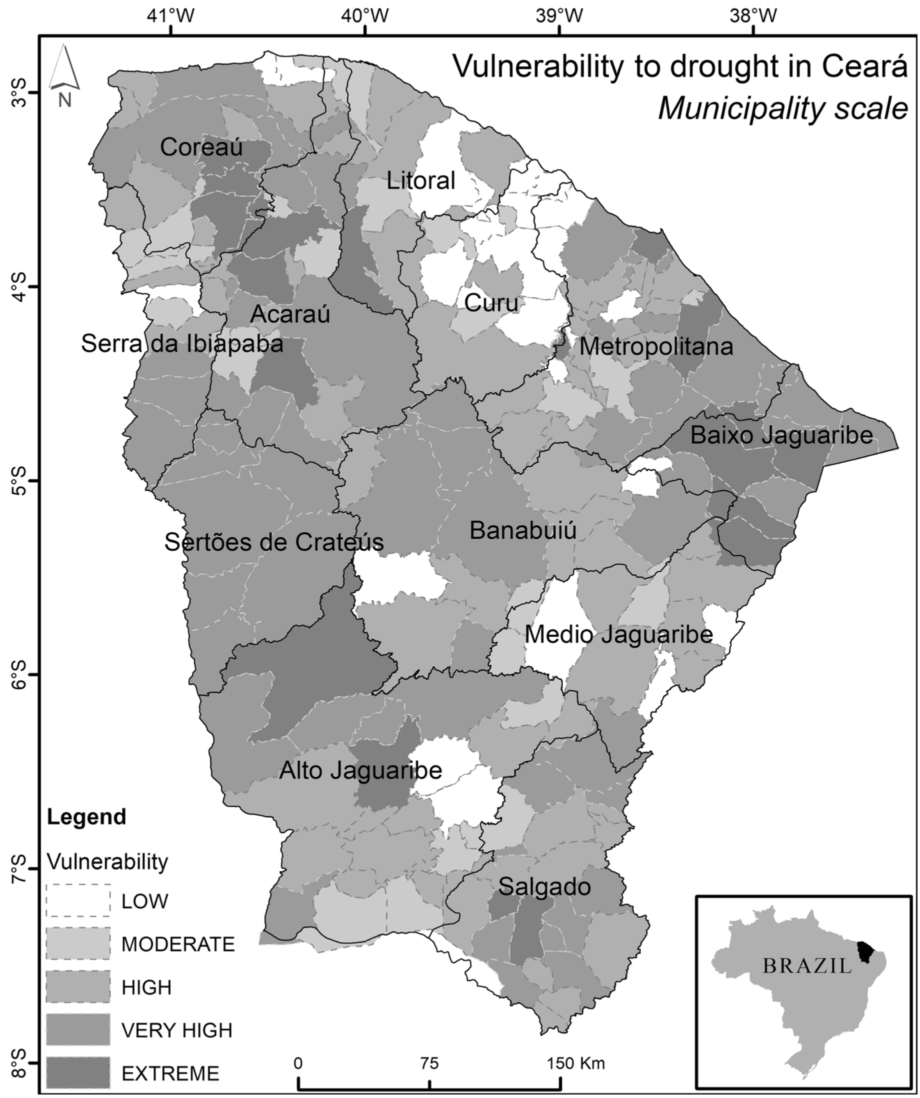

Fig. 4 Drough vulnerability in Ceará: municipality level

the Alto Tietê region is considered satisfactory, i.e., capable of supplying water to the population with satisfactory quantity and quality.

5.2 Ceará

The sensitivity of the municipalities that encompass the major metropolitan area of Ceará was classified as extremely vulnerable, similar to São Paulo. This indicates the need for more attention to the social, economic, and sanitation characteristics of more populated areas in periods of drought, in addition to water supply and demand.

The authors can also infer that densely populated locations tend to be more sensitive to drought. Additionally, the municipalities within the Baixo Jaguaribe basin present a higher sensitivity index. Even though it does not fall within the extremely vulnerable category, Baixo Jaguaribe presents the highest ratio between total demand and water supply. This basin has large irrigated regions and areas with intense shrimp farming activity. These activities have high water demand and may be responsible for the high ratio for most of the municipalities located within this basin.

The exposure index points to extreme situations of municipalities located at the western area of Ceará, highlighting the basins of Alto Jaguaribe, Sertões do Crateús, and Coreaú. The areas categorized with lower exposure include the municipalities located in the central coastal region of the state, in the basins of Metropolitana, Curu, and Litoral.

The adaptive capacity results highlight the significant influence of the integrated systems of interbasin water transfer in the state. The Jaguaribe-Metropolitano System is responsible for supplying the Metropolitan Region of Fortaleza (MRF), which includes the capital of Ceará, Fortaleza. The capital has a population of approximately 2.6 million people and is surrounded by intense industrial activity, including the Pecém Industrial and Port Complex. The system has a robust water channel network that integrates important and strategic reservoirs, such as Orós, Castanhão, and Banabuiú, through extensive water channels. Some regions within Coreaú and Acaraú basins also demonstrate higher adaptive capacity due to the concentration of water channels.

Drought vulnerability, as measured by the sensitivity, exposure, and adaptive capacity indexes, is shown in Fig. 4. Most of the municipalities classified as low vulnerability are surrounded either by water channels or essential reservoirs. The municipalities located on the western side of Ceará are primarily classified as very high or extreme vulnerability. The central region of the state, known as "Sertão Central", is also classified as being very high vulnerability.

In the Metropolitana basin, which is part of the MRF, there are occurrences of very high vulnerability. Some of these occurrences coincide with the critical situation of the municipal supply system. Fortaleza, however, presented a score of 60% of the total value possible for the adaptive capacity index. Nevertheless, the capital of Ceará was still classified as extremely vulnerable. Although Fortaleza has considerable water infrastructure to mitigate drought impacts, the capital of Ceará is still highly exposed to the effects of water scarcity. Including adaptive capacity only reduced 6% of Fortaleza's vulnerability, while the average reduction of the other municipalities was 19%. Additionally, 5 out of 12 cities of the Baixo Jaguaribe basin were classified as extremely vulnerable. This reflects the intense agricultural and shrimp farming activities that happen in this region.

Figure 5 presents the modified vulnerability triangles obtained through Eq. (8) for the state of Ceará. We improved the vulnerability triangle used by Vargas and Paneque (2017) and Liu et al. (2013) by adding frequency curves, based on confidence levels (50%, 90%, 95%, and 99%), which informs the zones that concentrate a given percentage of the municipalities. The curves were calculated according to Hamilton and Ferry (2018). Observing Fig. 5, it is clear that exposure has the most influence on the vulnerability to drought in Ceará. These results are in line with the state's semi-arid climate and the historical occurrences of prolonged drought events, precipitated by lack of rainfall. Additionally, the low frequency of municipalities located in the adaptive capacity zone demonstrates that, even though the state of Ceará invests in the construction and management of water systems, its physical and institutional structures are not yet sufficient to significantly reduce drought vulnerability.

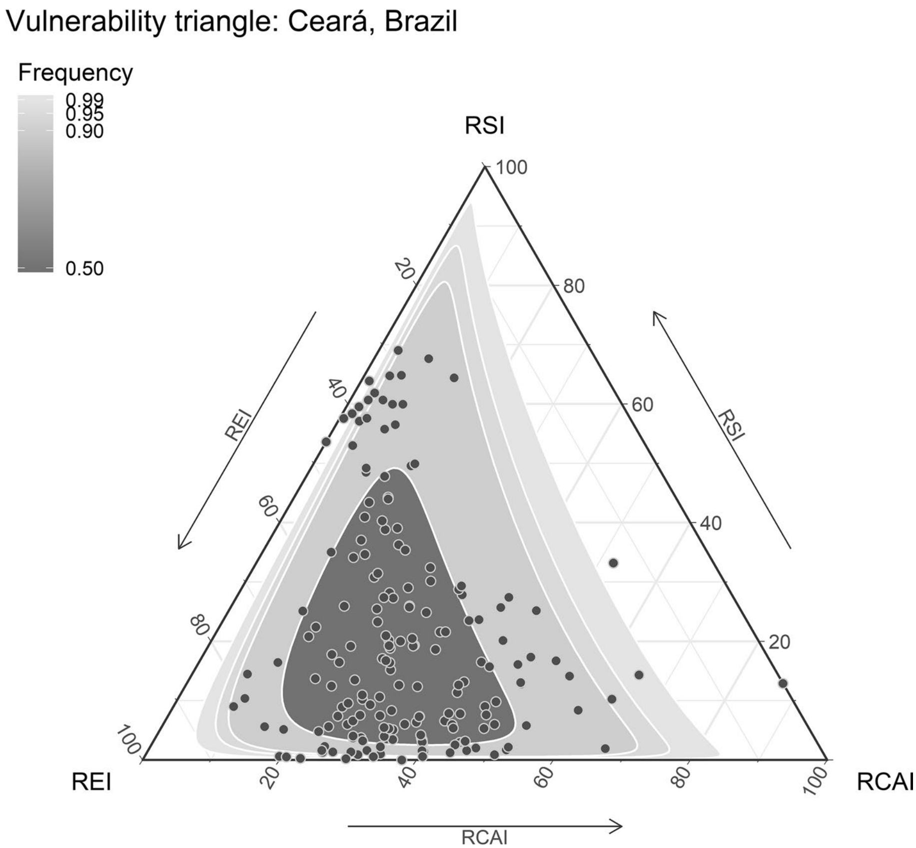

Fig. 5 Modified vulnerability triangle for Ceará

6 Discussion

The model uses components that represent vulnerability to drought following the definition provided by IPCC (2001). iSECA makes it possible to quantify a complex concept using simplified MCDM techniques with a logical and easy to follow a sequence of steps. Additionally, it provides spatial visualization of the vulnerability diagnosis. Its comprehensive aspects facilitate the replication of the model and the comprehension of its outcomes, making it useful for water managers and non-specialists. It can be updated and run on a regular basis as a way to explore how changes in social characteristics and water infrastructure are influencing vulnerability.

Research regarding drought vulnerability in Brazil mainly comprises qualitative, social analyses (Nelson and Finan 2009; Lemos et al. 2016; Sena et al. 2018), and it focused primarily in the Northeastern region where Ceará is located. Applying iSECA to São Paulo and Ceará fills part of the academic and technical gap of research on drought vulnerability in South America, identified by Wang et al. (2014). The different contexts in which the model was applied demonstrate the flexibility of the model to accommodate variable configurations and yet provide satisfactory results. iSECA also quantifies and highlights the importance of increasing adaptive capacities through water resources infrastructure and management for the reduction of drought vulnerability.

The sensitivity analysis validates the choice of indicators and their corresponding weights. Figure 6 presents the amplitude of the synthetic data generated for the worst-case scenario of variation (20%) of each object of study (municipalities in Ceará and river basins in São Paulo). Both graphs present satisfactory amplitude of variation, demonstrating the robustness of iSECA and its reliability to reapplication in different areas of study, with distinct datasets. The outlier objects in both graphs represent the city of Fortaleza, capital and most populous city of the state of Ceará, and the Alto Tietê river basin, where the Metropolitan Region of São Paulo is located with the largest population in Brazil.

Overall, the dataset required to apply iSECA is easy to acquire and to organize. Rainfall data are available through weather stations or public datasets such as the Climate Research Unit (CRU). Social and economic data are generally easy to obtain through a national census. Information regarding water systems, river basins, and water structures can be acquired with water management bodies and even with satellite images and processed with simple georeferencing and remote sensing techniques.

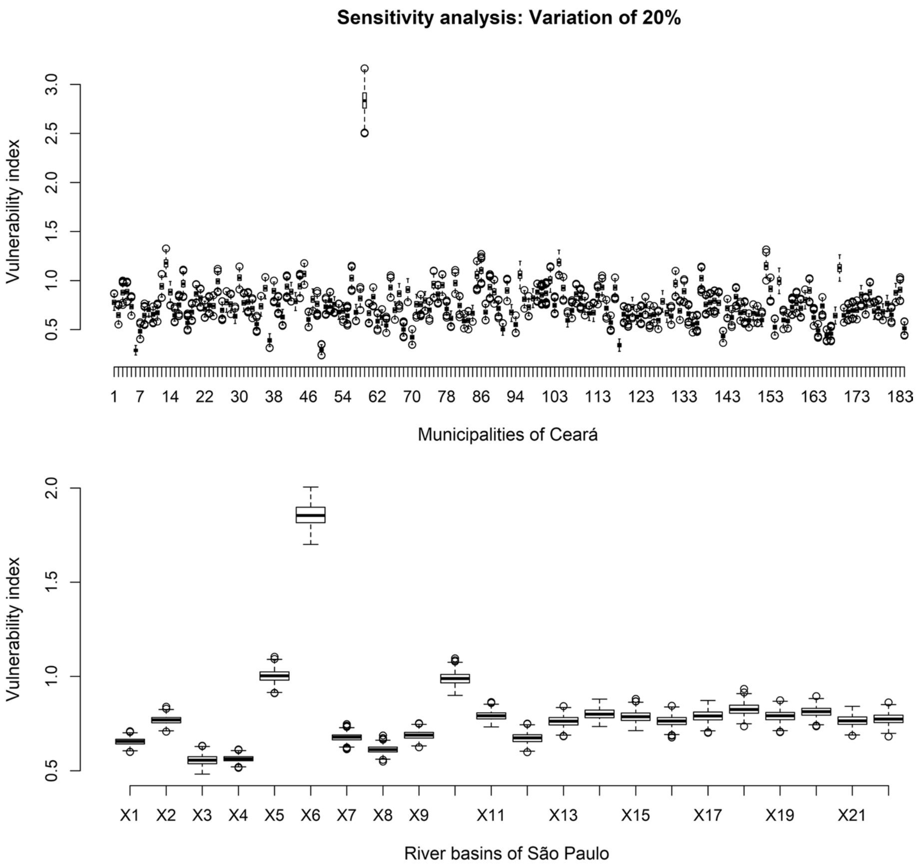

Fig. 6 **Sensitivity analysis: amplitude for a data variation of 20%**

iSECA provided satisfactory and reliable results. Compared with similar works published by Vargas and Paneque (2017) and Liu et al. (2013), our model presents equally necessary and indispensable outcomes. However, iSECA demonstrated its adaptability to different spatial scales and its efficiency and accessibility by using fewer and simpler indicators and yet providing robust and comprehensive results.

7 Conclusion

The number of research projects addressing vulnerability to climate change has increased considerably increased during the last decade. In part, this is in response to the effects of extreme weather events, including droughts, facing populations around the globe. However, Latin American countries, e.g., Brazil, have not yet undertaken a significant level of research on vulnerability to climate change and its social aspects (Wang et al. 2014).

Using the IPCC (2001) definition of vulnerability to climate change, iSECA provided a logical and parsimonious model capable of quantifying vulnerability to drought. Using a solid and straightforward MCDM GIS-based structure, the model considers not only climate aspects but also social, economic, and water management features. In order to fill the science gap, iSECA was applied to Ceará and São Paulo, Brazilian states with very different climatic and social conditions. The application showed how the model can fit different spatial scales and regions with different social, economic, and climate aspects.

iSECA identified vulnerable locations, also pointing to the areas with water infrastructure that improves local and regional adaptive capacity. Historically, São Paulo has not suffered long periods of water scarcity nor high frequency of drought events. However, the Metropolitan Region of São Paulo (MRSP) corresponds to about 64% of the state's population and 20% of the national GDP and it was classified as very highly vulnerable mainly due to the complexity of its social and economic activities. Given the abundant water availability in the state, the 2013–2015 water crisis in São Paulo was significantly influenced by water management.

While water transportation in São Paulo is not as fundamental to vulnerability due to the higher number and spatial distribution of perennial rivers, the principal challenge for Ceará is to maintain the water supply to the Metropolitan Region of Fortaleza (MRF), a context with highly complex interactions of social, industrial, and economic intense activities. In this state, characterized by low water availability and limited spatial distribution of water sources, adaptive capacity through the development of infrastructure is key for maintaining the water supply. Despite the strong water resources infrastructure built to guarantee water transportation to the (MRF), the authors concluded that the water supply system is not yet sufficient to reduce the high vulnerability scenario of the state's capital Fortaleza.

The model results are clear and easy to understand, and so can serve as an indispensable tool for water management and drought planning. The model outcomes are accessible for water managers and non-specialists. The vulnerability maps can identify the most and least vulnerable areas, facilitating the planning of priority actions to develop water management strategies. The vulnerability triangle combined with frequency curves is also useful as a graphical diagnosis to help visualize the most influential components of vulnerability. Additionally, the sensitivity analysis attested to the robustness of the model across applications.

iSECA does not demand fieldwork or extensive financial costs. The dataset for an application can easily be built with local official data, rainfall datasets, and information provided by a national census. The methodology is a simple solution for a complex matter. The model facilitates the indispensable use of vulnerability analysis for applied policies and the development of plans such as drought and water security management for different scales (national, state, or basin plans).

Acknowledgements This study was financed in part by the Conselho Nacional de Desenvolvimento Científico e Tecnológico—Brasil (CNPq) and the Coordenação de Aperfeiçoamento de Pessoal de Nível Superior—Brasil (CAPES) (Grant No. 446222/2015-1).

References

Abraham JS (2006) Assessing drought vulnerability. Dissertation, University of Arizona

Acosta IR, Martínez MJM (2014) Assessment of surface runoff vulnerability to climate change in the Lerma-Chapala basin, Mexico. J Water Resour Plan Manag 140(12):04014042

Anandhi A, Kannan N (2018) Vulnerability assessment of water resources—translating a theoretical concept to an operational framework using systems thinking approach in a changing climate: case study in Ogallala Aquifer. J Hydrol 557:460–474

Araújo BAM (2012) Water allocation in Ceará: diagnosis and challenges. Dissertation, Federal University of Ceará

Asefa T, Clayton J, Adams A, Anderson D (2014) Performance evaluation of a water resources system under varying climatic conditions: reliability, resilience, vulnerability and beyond. J Hydrol 508:53–65

Bogard WC (1988) Bringing social theory to hazards research: conditions and consequences of the mitigation of environmental hazards. Sociol Per 31(2):147–168

Bohle HG, Downing TE, Watts MJ (1994) Climate change and social vulnerability. Glob Environ Change 4(1):37–48

Chanda K, Maity R, Sharma A, Mehrotra R (2014) Spatiotemporal variation of long-term drought propensity through reliability-resilience-vulnerability based Drought Management Index. Water Reour Res 50:7662–7676

Cosgrove WJ, Loucks DP (2015) Water management: current and future challenges and research directions. Water Resour Res 51:4823–4839

CRH—Water Resources State Council/CORHI—Water Resources State Plan Committee (2017) São Paulo Water Resources State Plan 2016–2019, São Paulo

Cutter SL (1996) Vulnerability to environmental hazards. Prog Hum Geogr 20(4):529–539

Dow K (1992) Exploring differences in our common future(s): the meaning of vulnerability to global environmental change. Geoforum 23(3):417–436

Eslamian S, Eslamian FA (2017) Handbook of drought and water scarcity: principles of drought and water scarcity. Taylor & Francis Group, London

Fontaine MM (2007) Assessing vulnerability to natural hazards: an impact-based method and application to drought in Washington State. Dissertation, University of Washington, p 165

Goharian E, Burian SJ, Bardsley T, Strong C (2016) Incorporating potential severity into vulnerability assessment of water supply systems under climate change conditions. J Water Resour Plan Manag 142(2):04015051

Hamilton NE, Ferry M (2018) ggtern: ternary diagrams using ggplot2. J Stat Softw 87(3):1–17

Hashimoto T, Stedinger JR, Loucks DP (1982) Realiability, resiliency and vulnerability criteria for water resource system performance evaluation. Water Resour Res 18(1):14–20

Hewitt K (2013) Environmental disasters in social context: toward a preventive and precautionary approach. Nat Hazards 66(1):3–14

Hülle J, Kaspar R, Möller K (2011) Multiple criteria decision-making in management accounting and control—state of the art and research perspectives based on a bibliometric study. J Multi-Criteria Decis Anal 8:253–265

INESP—Institute of Studies and Research for the Development of the State of Ceará (2008) Water Pact: Current Scenario of Water Resources in Ceará, Fortaleza, Brazil

IPCC (Intergovernmental Panel on Climate Change) (2001) Climate change 2001: impacts, adaptation, and vulnerability. Contribution of working group II to the third assessment report of the intergovernmental panel on climate change. Cambridge University Press, Cambridge

IPECE—Instute of Economic Research and Strategy of Ceará (2016) Municipal Alert Index: IMA, Fortaleza, Brazil

Ishizaka A, Siraj S (2018) Are multi-criteria decision-making tools useful? An experimental comparative study of three methods. Eur J Oper Res 264:462–471

Jacobi PR, Cabim J, Leão RS (2015) Water crisis at Paulista macrometropolis and civil society answers. Estud Av 29(84):27–42

Kim Y, Chung ES (2013) Assessing climate change vulnerability with group multi-criteria decision making approaches. Clim Change 121:301–315

Kumlu KBY, Tudes S (2019) Determination of earthquake-risky areas in Yalova City Center (Marmara region, Turkey) using GIS-based multicriteria decision-making techniques (analytical hierarchy process and technique for order preference by similarity to ideal solution). Nat Hazards 96:999–1018

Lemos MC, Lo YJ, Nelson DR, Eakin H, Bedran-Martins AM (2016) Linking development to climate adaptation: leveraging generic and specific capacities to reduce vulnerability to drought in NE Brazil. Glob Environ Change 39:170

Lin L, Wu Z, Liang Q (2019) Urban flood susceptibility analysis using a GIS-based multi-criteria analysis framework. Nat Hazards 97:455–475

Liu X, Wang Y, Peng J, Braimoh A, Yin H (2013) Assessing vulnerability to drought based on exposure, sensitivity and adaptive capacity: a case study in middle Inner Mongolia of China. Chin Geogr Sci 3(1):13–25

Martirani LA, Peres IK (2016) Water crisis in São Paulo: news coverage, public reception and the right to information. Ambiente Soc 19(1):1–20

Mateus MC, Tullos D (2017) Reliability, sensitivity, and vulnerability of reservoir operations under climate change. J Water Resour Plan Manag 143(4):04016085

McKee TB, Doesken NJ, Kleist J (1993) The relationship of drought frequency and duration of time scales. In: Eighth conference on applied climatology, American Meteorological Society, Jan 17–23, 1993, Anaheim CA, pp.179–186

Mela K, Tiainen T, Heinisuo M (2012) Comparative study of multiple criteria decision-making methods for building design. Adv Eng Inform 26:716–726

Montanari A, Young G, Savenije HHG, Hughes D, Wagener T, Ren LL, Koutsoyiannis D, Cudennec C, Toth E, Grimaldi S, Blöschl G, Sivapalan M, Beven K, Gupta H, Hipsey M, Schaefli B, Arheimer B, Boegh E, Schymanski SJ, De Baldassarre G, Yu B, Hubert P, Huang Y, Schumann A, Post DA, Srinivasan V, Harman C, Thompson S, Rogger M, Viglione A, McMillan H, Characklis G, Pang Z, Belyaev V (2013) Panta Rhei—everything flows: change in hydrology and society—the IAHS scientific decade 2013–2022. Hydrol Sci J 58(6):1256–1275

Mostafazadeh R, Sadoddin A, Bahremand A, Sheikh VB, Garizi AZ (2017) Scenario analysis of flood control structures using a multi-criteria decision-making technique in Northeast Iran. Nat Hazards 87:1827–1846

Nazemi A, Wheater HS, Chun KP, Elshorbagy A (2013) A stochastic reconstruction framework for analysis of water resource system vulnerability to climate-induced changes in river flow regime. Water Resour Res 49:291–305

Nelson DR, Finan TJ (2009) Praying for drought: persistent vulnerability and the politics of patronage in Ceará. Northeast Braz Am Anthropol 111(3):302

Ozernoy V (1987) A framework for choosing the most appropriate discrete alternative multiple criteria decision-making method in decision support systems and expert systems. Lecture Notes in Economics and Mathematical Systems, pp 56–64.

Pienaar GW, Hughes DA (2017) Linking hydrological uncertainty with equitable allocation for water resources decision-making. Water Resour Manag 31:269–282

Pryshlak TT, Sawyer AH, Stonedahl SH, Soltanian MR, Al RET (2014) Water demand management in times of drought: what matters for water conservation. Water Resour Res 51:125–139

Ramos PA, Marcato Junior J, Decanini MMS, Pugliesi EA, Oliveira RF, Paranhos Filho A (2016) Quantitative and qualitative evaluation of data classification methods for choropleth mapping. Rev Bras Cartogr 68(3):609–629

SEDAE—State System of Data Analysis Fundation (2010) Paulista Social Vulnerability Index 2010 edition, São Paulo

Sena A, Freitas C, Souza PF, Alpino T, Pedroso M, Corvalan C, Barcellos C, Carneiro F (2018) Drought in the semiarid region of Brazil: exposure, vulnerabilities and health impacts from the perspectives of local actors. PLoS Curr 10

Silva SMO, Sousa Filho FA, Aquino SHS (2017) Risk assessment of water allocation on water scarcity period: the case of Jaguaribe-Metropolitan system. Eng Sanit Ambient 22(4):749–760

Suárez-Almiñana S, Pedro-Monzonís M, Paredes-Arquiola J, Andreu J, Solera A (2017) Linking Pan-European data to the local scale for decision making for global change and water scarcity within water resources planning and management. Sci Total Environ 603–604:126–213

Susman P, O'Keefe P, Wisner B (1983) Global disasters, a radical interpretation. In: Hewitt K (ed) Interpretations of calamity for the viewpoint of human ecology. Allen & Unwin, Boston, pp 263–283

Thomas T, Jaiswal RK, Galkate R, Nayak PC, Ghosh NC (2016) Drought indicators-based integrated assessment of drought vulnerability: a case study of Bundelkhand droughts in central India. Nat Hazards 81(3):1627–1652

Triantaphyllou E (2000) Multi-criteria decision making methods: a comparative study. Springer, New York

Turner BL, Kasperson RE, Matson PA, McCarthy JJ, Corell RW, Christensen L, Eckley N, Kasperson JX, Luers A, Martello ML, Polsky C, Pulsipher A, Schiller A (2003) A framework for vulnerability analysis in sustainability science. PNAS 100(14):8074–8079

Vargas J, Paneque P (2017) Methodology for the analysis of causes of drought vulnerability on the River Basin scale. Nat Hazards 89:609–621

Veyret Y (2007) Risks: the man as the agressor and victim. Contexto, São Paulo

Wang B, Pan SY, Ke RY, Wang K, Wei YM (2014) An overview of climate change vulnerability: a bibliometric analysis based on Web of Science database. Nat Hazards 74:1649–1666

Wilhite DA, Sivakumae MVK, Pulwarty R (2014) Managing drought risk in a changing climate: the role of national drought policy. Weather Climate Extremes 3:4–13

Zhang C, Xu B, Li Y, Fu G (2017) Exploring the relationships among reliability, resilience, and vulnerability of water supply using many-objective analysis. J Water Resour Plan Manag 143(8):04017044