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Analytic hierarchy process and sensitivity analysis implementation for social vulnerability assessment: A case study from Brazil

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Abstract

One major challenge of social impact assessment concerns the implementation of multicriteria decision analysis (MCDA) to ascertain the vulnerability of households to environmental change. While MCDA has been widely used to combine vulnerability indicators into an aggregated vulnerability score, the sensitivity of vulnerability indices to uncertain appraisals and judgements of the magnitudes and weights of indicators has been largely ignored so far. In this work, based on vulnerability indicators previously selected and ranked using the analytic hierarchy process (AHP) technique, for household Brazil surveys carried out in 1998 and 2012, a sensitivity analysis (SA) was implemented to account for the variation of vulnerability indicators over time and space. In particular, two techniques were applied: the indicator removal and the threshold value tests. The indicator removal test involved setting to zero a particular indicator weight and rescaling the remaining indicator weights linearly. The threshold value test aimed to identify which indicators had the most relative influence on both indices. Finally, the critical threshold value showed the most important vulnerability indicators and allowed to summarise and contrast the standardized scores differences of the indicators between the two surveys. The results showed which indicators were the most important in increasing or decreasing the vulnerability and improved the understanding of how the overall vulnerability of rainfed farming households changed through time as a function of changes in sensitivity and adaptive capacity.

KEYWORDS
analytic hierarchy process, household vulnerability, sensitivity analysis

1 | INTRODUCTION

Social vulnerability assessment is a tool to understand the differential propensity for impacts of environmental change on units of analysis such as places, populations, or households (Eakin & Bojórquez-Tapia, 2008). Its results are critical for designing strategies and interventions to address the impact of climate change on human systems such as households, places, or populations (Dwyer et al., 2004; Heitzmann & Siegel, 2002; Hoddinott & Quisumbing, 2010). Yet, vulnerability is a multidimensional concept difficult to measure and describe. Typically, its assessment involves defining indicators and proxy variables and then developing a social vulnerability index (SVI) of the differential impacts of socio-environmental drivers of change on units of analysis (Adger et al., 2004).

In conventional SVI (Eakin & Bojórquez-Tapia, 2008; Moss et al., 2001), the human systems are classified using three dimensions of vulnerability: exposure (the contact between systems and climate-related stimuli), sensitivity (the degree to which systems are affected by climate-related stimuli) and adaptive capacity (the assets and/or resources that can be deployed to plan, cope, recover and adjust to undesirable disturbances). The three dimensions are shaped not just by the magnitude and frequency of climate events, but also by multiple stressors and deficits that affect human systems, such as economic crisis, social instability, or poor access to social services. These stressors and deficits are represented analytically by diverse and often incommensurate indicators and the respective proxy variables (Eakin & Luers, 2006). Hence, multicriteria decision analysis (MCDA) has been applied for developing a SVI (Eakin & Bojórquez-Tapia, 2008; Kubal et al., 2009; Kuhlicke et al., 2011).

Once the appropriate vulnerability indicators have been identified for the specific place or unit of analysis, applying MCDA entails weighing the indicators, normalising the incommensurable proxy variables into a commensurate scale, and aggregating the transformed proxy variables and the weighted indicators, typically using a weighted linear combination (WLC; see Malczewski & Rinner, 2015). In particular, Saaty's (1980) analytic hierarchy process (AHP) is an MCDA technique that has been successfully applied to generate SVI (Eakin & Bojórquez-Tapia, 2008; Fatemi et al., 2017).

However, one vexing problem of the SVI concerns the variation of vulnerability indicators over time and space. This variation is related to the uncertainty arising from the implicit or explicit assumption regarding both the characteristics and the aggregation of the vulnerability indicators (Adger et al., 2004; Tate, 2012; Wigtil et al., 2016). These assumptions imply internal and external sources of uncertainty. The first source relates to the inherent subjectivity involved in assigning weights to the indicators, the assumptions involved in transforming the incommensurable variables, and the modelling structure, whereas the second source relates to the variability of the proxy variables over time and space. Therefore, sensitivity analysis (SA) is a crucial step to deal with both the internal and the external uncertainties in SVI (May et al., 2013; Schmidtlein et al., 2008).

In this paper, we present an implementation of SA to account for the variation of vulnerability indicators over time and space in SVI. We illustrate the approach through a case study of drought vulnerability in NE Brazil. The goal of this case study was to understand the role of anti-poverty programs in building adaptive capacity and shaping vulnerability profiles of impoverished agricultural households in the region. It entailed a longitudinal analysis of households using surveys carried out in 1998 and 2012 (Lemos et al., 2016; Nelson et al., 2016). Accordingly, we applied the AHP to account for the differential importance of the many variables shaping sensitivity and adaptive capacity of households in the study region and then performed extensive SA to determine the probability of changes in the rank ordering of households given the internal and external sources of uncertainty (Bojórquez-Tapia et al., 2005; Eakin & Bojórquez-Tapia, 2008; Triantaphyllou & Sánchez, 1997). The results of SA showed what indicators were the most important in increasing or decreasing the vulnerability and improved the understanding of how the overall vulnerability of rainfed farming households changed through time as a function of changes in sensitivity and adaptive capacity.

2 | CASE STUDY

We implemented our SA approach using the output of longitudinal research carried out in six municipalities of the state of Ceará, Brazil, to examine the role of anti-poverty governmental programs in building adaptive capacity and shaping vulnerability profiles of impoverished agricultural households (Lemos et al., 2016; Nelson et al., 2016). A randomised sample of the rural population in each municipality was identified and surveyed in 1998 ($n = 484$) and 2012 ($n = 477$) to assess how sensitivity and adaptive capacity had changed over time. The surveys integrated qualitative and quantitative data, which was analysed using mixed methods to attain valid and reliable results while providing balance and cogency to the causal mechanisms.

2.1 | Vulnerability indices

Following Eakin and Bojórquez-Tapia (2008), vulnerability indices for sensitivity and adaptive capacity were developed using the AHP for the two household surveys (exposure to drought was controlled by selecting our household samples across Ceará's agro-climatic zones). Accordingly, the indicators describing vulnerability in terms of both sensitivity and adaptive capacity indices were first organised into hierarchies. For each hierarchy, top-level corresponded to the overall goal (to rank households in terms of their vulnerability related to either adaptive capacity or sensitivity), intermediate levels corresponded to the set of criteria to specify the overall goal, and the lowest level to the alternatives (households). For each level, a pairwise comparison matrix was generated to elicit the relative weights for each indicator. Given a hierarchy, the elements at each level were weighted according to their importance on the level above.

Because the results of the household surveys included incommensurate data (e.g., in different scales and units), value functions were used to transform the natural scale of each proxy variable into a standardized score using a [0,1] scale with ratio properties, 0 representing the most undesirable state and 1 the most desirable state (Beinat, 1997). The value functions reflected the assumption that vulnerability was higher as sensitivity increases and as adaptive capacity decreases; they accounted for the possibility of nonlinear or nonmonotonic relationships between natural and value scales.

We aggregated the indicator weights and standardized scores of the proxy variables into either sensitivity or adaptive capacity index using a WSM; formally:

$$V_i^h = \sum_j^J w_j x_{ij}^h \quad (1)$$

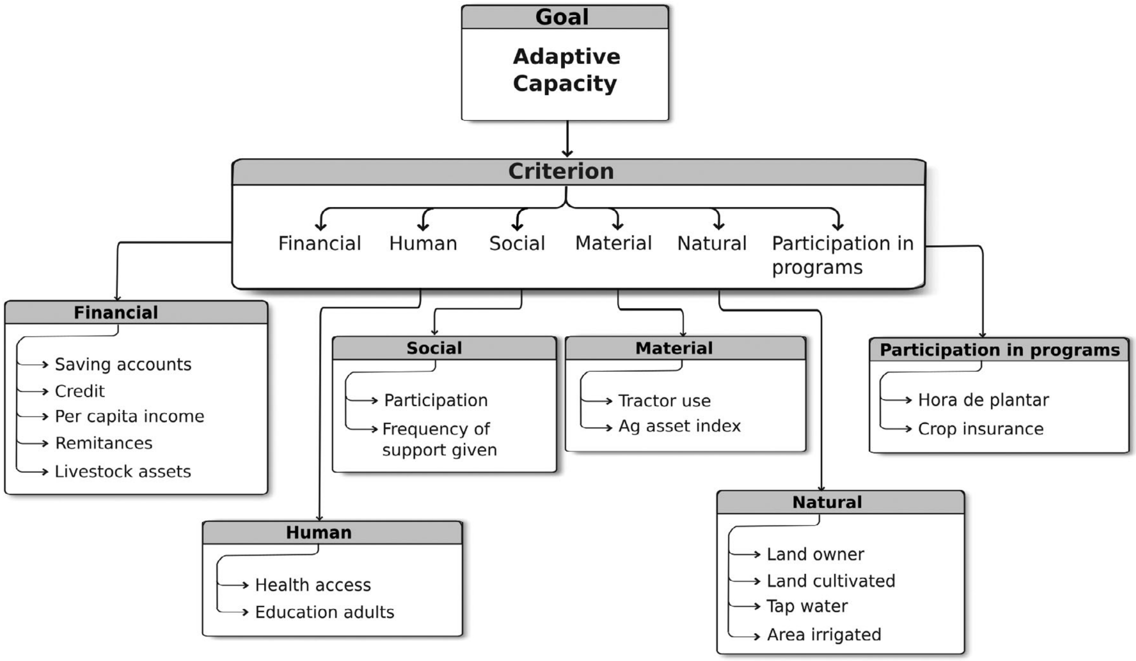

FIGURE 1 AHP model for adaptive capacity of households

where V is the index value, w is the weight of an indicator obtained from the AHP, x is the standardized score obtained from the proper value function, and h, i, and j indicate household, index, and indicator, respectively.

Equation (1) must satisfy the following conditions:

$$0 \le x_{ij}^h \le 1, 0 \le w_{ij} \le 1, \text{and} \sum_j w_j = 1.$$

2.2 | Sensitivity analysis 1: Indicator removal test

The indicator removal test involved setting to zero the weight for indicator r $(w_{ir} = 0)$ and rescaling the remaining indicator weights linearly $\left(w'_{ij} = w_{ij} \div \sum_{j \ne r}^{J} w_{ij}\right)$. Then, Equation (1) was applied to generate the respective household vulnerability index $\left(V_{ij \ne r}^h = \sum_{j \ne r}^{J} w'_{ij} x_{ij}^h\right)$. The change (in percentage) of the median vulnerability by the removal of the r-th indicator was obtained as follows (Bojórquez-Tapia et al., 2009):

$$V_{ir}^{\Delta Q_2} = \left| \frac{V_{ij \ne r}^{Q_2} - V_i^{Q_2}}{V_i^{Q_2}} \right| \times 100, \qquad (2)$$

where $V_{ij \ne r}^{Q_2}$ is the median vulnerability by the removal of the r-th indicator and $V_i^{Q_2}$ is the median vulnerability of all the indicators.

2.3 | Sensitivity analysis 2: Threshold value test

The threshold value test measures the expectation that a change in x would result in a new vulnerability score, V_i^h, that crosses some

TABLE 1 Importance weights, w, of elements of the adaptive capacity index for 1998 and 2012 surveys

	Importance weight (w)		
		Global	
Criterion/indicator	Local	1998	2012
Financial	0.47		
Saving accounts	0.06	–	0.027
Credit	0.33	0.178	0.157
Per capita income	0.48	0.259	0.228
Remittances	0.05	0.027	0.024
Livestock assets	0.08	0.042	0.037
Human	0.20		
Health access	0.20	–	0.040
Education adults	0.80	0.183	0.161
Social	0.04		
Participation	0.60	–	0.025
Frequency of support given	0.40	–	0.017
Material	0.07		
Tractor use	0.40	0.034	0.030
Ag asset index	0.60	0.051	0.045
Natural	0.19		
Land owner	0.20	0.043	0.038
Land cultivated	0.07	0.015	0.014
Tap water	0.07	0.016	0.014
Area irrigated	0.66	0.143	0.126
Participation in programs	0.03		
Hora de plantar	0.30	0.009	–
Crop insurance	0.70	–	0.018

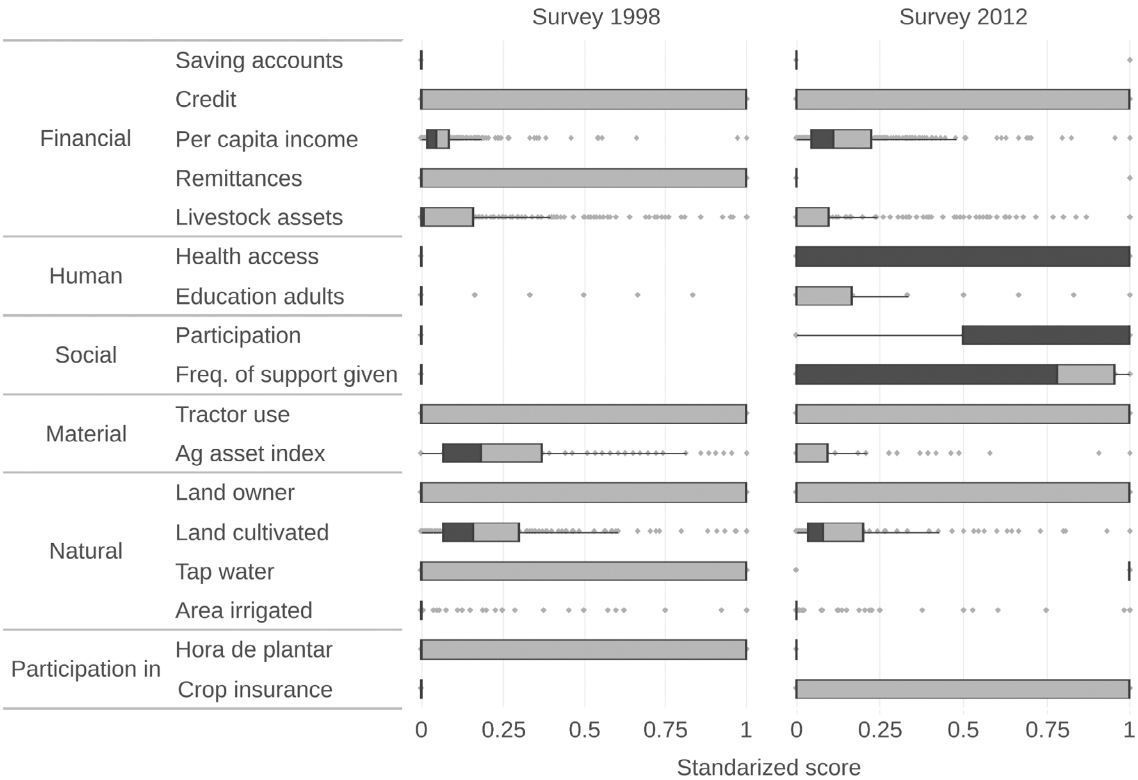

FIGURE 2 Box plots of the standardized scores of adaptive capacity indicators

reference value or threshold, V_i^ρ. The magnitude of such a change, τ_{ij}^h, is calculated in relation to the weight of the indicators as follows (Triantaphyllou & Sánchez, 1997):

$$\tau_{ij}^h = \frac{V_i^h - V_i^\rho}{w_{ij}}, \tag{3}$$

That is, for $V_i^h \neq V_i^\rho$, if τ_{ij}^h is large enough then $V_i^\rho \geq V_i^h$ swaps to $V_i^\rho < V_i^h$, or $V_i^\rho \leq V_i^h$ swaps to $V_i^\rho > V_i^h$. Because the condition $0 \leq x_{ij}^h \leq 1$ from Equation (1) must be satisfied, it follows that $0 \leq x_{ij}^h - \tau_{ij}^h \leq 1$, so the feasibility of change in x_{ij}^h that results in a vulnerability score that crosses the reference value is conditioned to,

$$x_{ij}^h - 1 \leq \tau_{ij}^h \leq x_{ij}^h. \tag{4}$$

Next, the absolute value for the magnitude of change for the households is summarised using a statistical parameter of data dispersion, such as quartiles, to obtain $\Delta_{ij} = \left|\tau_{ij}^h\right|^{Q_m}$ where Q_m is a particular quantile. Thus, the criticality degree, c_{ij}, is obtained by:

$$c_{ij} = \frac{1}{\Delta_{ij}} \tag{5}$$

The critical threshold, $\mathcal{C}_{ij}$, of indicator j is obtained in terms of the probability p_{ij} of a feasible τ_{ij}^h changes (Equation (4)) and the criticality degree (Equation (5)):

$$\mathcal{C}_{ij} = p_{ij} c_{ij}. \tag{6}$$

3 | RESULTS

3.1 | Adaptive capacity index

The AHP model for the adaptive capacity index (Figure 1) included six elements in the second level that corresponded to the livelihood capital of households (financial, human, social, material, natural, and participation) and the participation in government support programs, and 17 elements in the third level that corresponded to the respective indicators´ proxy variables. The number of indicators differed in the two surveys. Five indicators were not included in the 1998 survey (savings accounts, health access, participation, frequency of support program, and crop insurance), and one indicator was not included in the 2012 survey (hora de plantar). Accordingly, the indicators´ weights were obtained using the complete set of elements in the third level and rescaled as appropriate for each survey.

Results showed that the six elements at the second level capitals could be divided into three tiers according to their weights (Table 1). The first tier corresponded to the financial capital. The second tier grouped the human and natural capitals whose weights were 43% of that for the financial capital. And the third tier grouped the material, social, and participation capitals whose weights ranged from 8% to 15% of that for the financial capital).

Regarding the relative importance of the indicators (Table 1), results also unveiled three tiers according to their weights. The first one was the per capita income of the financial capital. The second tier grouped indicators of three capitals whose weights ranged from 55%

TABLE 2 Summary statistics of standardized scores, x_{ij}^{h}, obtained from value functions of adaptive capacity indicators in the 1998 and 2012 surveys; minimum: $x_{ij}^{-}=0$; maximum: $x_{ij}^{*}=1$; median: x_{ij}^{Q2}

Capital/indicator	x_{ij}^{-} 1998 (%)	x_{ij}^{-} 2012 (%)	x_{ij}^{*} 1998 (%)	x_{ij}^{*} 2012 (%)	x_{ij}^{Q2} 1998	x_{ij}^{Q2} 2012
Financial						
Saving accounts	–	79	–	21	–	0.00
Credit	71	58	29	42	0.00	0.00
Per capita income	4	2	0	1	0.05	0.11
Remittances	74	84	26	16	0.00	0.00
Livestock assets	49	61	4	5	0.01	0.00
Human						
Health access	–	38	–	62	–	1.00
Education adults	91	65	0	0	0.00	0.00
Social						
Participation	–	13	–	52	–	1.00
Frequency of support given	–	43	–	5	–	0.78
Material						
Tractor use	69	54	31	46	0.00	0.00
Ag asset index	19	59	0	0	0.19	0.00
Natural						
Land owner	52	58	48	42	0.00	0.00
Land cultivated	3	4	5	4	0.16	0.08
Tap water	70	19	30	81	0.00	1.00
Area irrigated	83	79	3	8	0.00	0.00
Participation in programs						
Hora de plantar	62	–	38	–	0.00	–
Crop insurance	–	61	–	39	–	0.00

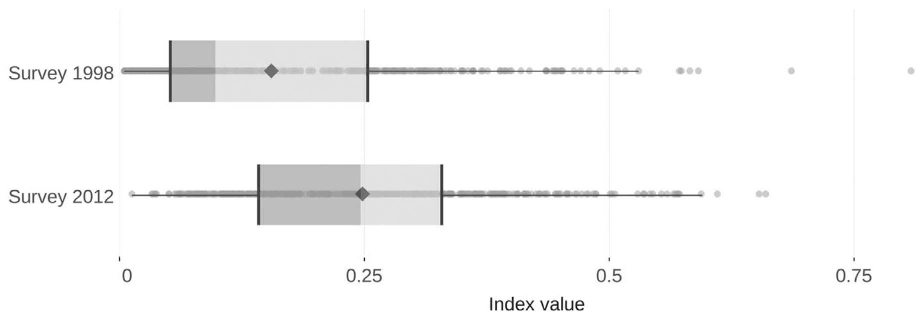

FIGURE 3 Box plot for the adaptive capacity index for the 1998 and 2012 surveys (diamonds = mean)

to 71% of that for per capital income: education adults of the human capital, credit of the financial capital, and area irrigated of the natural capital. And the third tier grouped remaining indicators with weights ranging from 3% to 20% of that for per capita income.

Overall, the effect of rescaling the 1998 survey increased on average the weights of the 11 indicators by 11%.

With regards to Equation (1), the standardized scores for, binary value functions were applied to nine indicators (saving accounts, credit, remittances, health access, tractor use, land owner, tap water, hora de plantar, and crop insurance), and continuous value functions to the remaining ones (per capita income, livestock assets, education adults, participation, frequency of support program, ag asset index, land cultivated, and area irrigated).

The summary of the statistics of the standardized scores revealed some contrasting differences between the two surveys (Figure 2 and Table 2). In the 1998 survey, the proportion of households having the minimum standardized score was higher than 49% for all indicators, except for per capita income and land cultivated, and to some extent for the ag asset index. Also, the proportion of households having the maximum standardized scores varied between 29%–48% for all indicators, except for per capita income, livestock assets, education adults, land cultivated, and area irrigated. Likewise, median

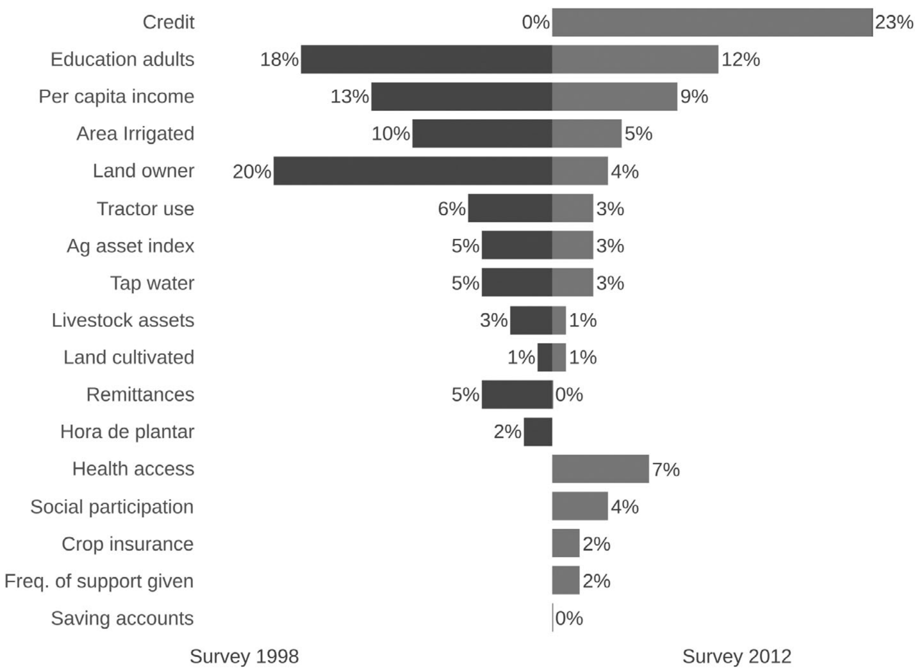

FIGURE 4 Results of the indicator removal test for adaptive capacity

TABLE 3 Criticality degree, c_{ij} and probability, p_{ij} for adaptive capacity indicators

Criterion/indicator	1998 $c_{ij}^{Q_2}$	1998 p_{ij}	2012 $c_{ij}^{Q_2}$	2012 p_{ij}
Financial				
Saving accounts	–	–	2.17	0.07
Credit	3.30	0.61	1.84	0.66
Per capita income	5.89	0.54	2.60	0.61
Remittances	1.73	0.10	1.90	0.06
Livestock assets	1.76	0.22	2.85	0.08
Human				
Health access	–	–	2.04	0.11
Education adults	3.98	0.51	1.87	0.44
Social				
Participation	–	–	2.23	0.08
Frequency of support given	–	–	1.63	0.05
Material				
Tractor use	1.72	0.18	2.06	0.08
Ag asset index	2.13	0.25	2.52	0.09
Natural				
Land owner	1.61	0.19	2.10	0.09
Land cultivated	2.15	0.06	2.55	0.03
Tap water	1.73	0.08	1.41	0.04
Area Irrigated	3.12	0.52	1.70	0.36
Participation in program				
Hora de plantar	1.41	0.03	–	–
Crop insurance	–	–	1.53	0.04

standardized scores were higher than the minimum for only four indicators: the higher values corresponded to ag asset index and land cultivated, followed by per capita income, and livestock assets.

In the 2012 survey, the proportion of households with the minimum standardized score increased for remittances, livestock assets, and ag asset index, and decreased for credit, education adults, tractor use, tap water, and area irrigated. Moreover, the proportion of households having the maximum standardized score increased for credit, per capita income, livestock assets, tractor use, and tap water and area irrigated, whereas that proportion decreased for remittances, land owner, land cultivated. Also, the median increased for per capita income and tap water and decreased for livestock assets, ag asset index, and land cultivated.

For financial capital indicators, credit and per capita income improved, while remittances and livestock assets worsened. For remittances, the households with the minimum value increased 14% and with maximum value decreased 63%. For livestock assets, the households with the minimum value increased by 24%. In contrast, for credit, the households with the minimum value decreased 18%, with the maximum value increased 31%. For per capita income, the median value increased twofold. Likewise, most households had minimum value for saving accounts in 2012.

For human capital (Figure 2 and Table 2), indicator education adults improved in the period. For education adults, the households with the minimum value decreased 29%. Likewise, for health access, two-thirds of the households obtained the maximum value in the 2012 survey.

For social capital (Figure 2 and Table 2), indicators participation and frequency of support given obtained a high median. For participation, most households obtained the maximum value. For frequency of support given, in contrast, most households obtained the minimum value.

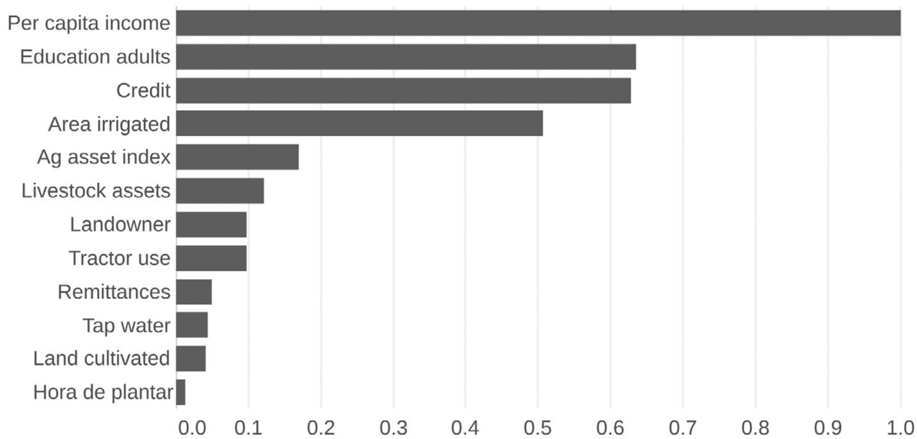

FIGURE 5 Normalized critical threshold value for adaptive capacity (1998)

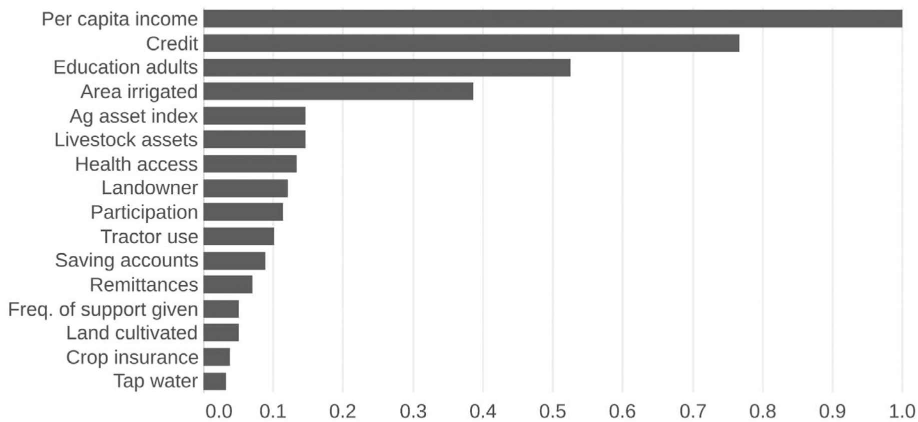

FIGURE 6 Normalized critical threshold value for adaptive capacity (2012)

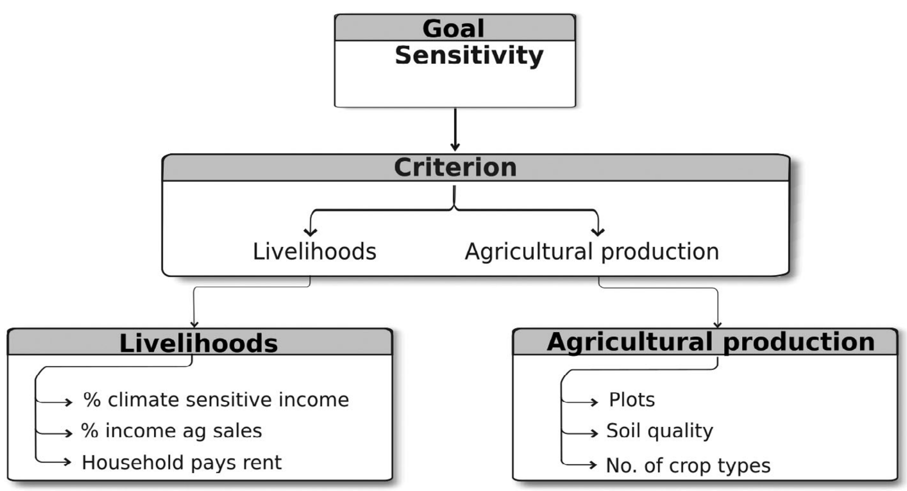

FIGURE 7 AHP model for sensitivity of households

For natural capital (Figure 2 and Table 2), indicators tap water improved, while both land owner and land cultivated worsened, and area irrigated remained unchanged. For tap water, the households with the minimum value decreased 73%, with the maximum value increased 63%, and the median increased from 0 to 1. For land owner, the households with the minimum value increased 12%, and the maximum value decreased 14%. For land cultivated, the median decreased 50%.

For participation in capital (Figure 2 and Table 2), two-thirds of the households obtained the minimum value for indicators hora de plantar and crop insurance.

Results for the adaptive capacity index (Figure 3) showed that the average and median was higher for the 2012 survey ($\overline{V_i} = V_i^{Q2} = 0.25$) than for the 1998 survey ($\overline{V_i} = 0.15; V_i^{Q2} = 0.10$). Furthermore, the value of the first quartile for the 2012 survey was equivalent to the average for the 1998 survey.

3.1.1 | Sensitivity analysis 1: Indicator removal test

The indicator removal test showed that the indicators with high weights did not necessarily produce the largest change of the adaptive capacity index. For the 1998 survey (Figure 4), the removal of indicator land owner produced the largest index change, followed by education adults, per capita income, and area irrigated. Surprisingly, the removal of land owner, an indicator with relatively low weight (Table 1) produced a change of the index value 54% larger than the removal of per capita income, the indicator with the highest weight. These results were an outcome of the large percentage of households with the minimum value, and in the case of credit, conversely, the relatively large percentage of households with the maximum value (Table 2).

For the 2012 survey (Figure 4), the removal of credit produced the largest index change, followed by education adults, and per capita income. Likewise, the removal of health access generated a higher index change than the removal of area irrigated, even though the weight of the former was one-third of that of the latter.

TABLE 4 Local and global weights, *w*, of elements of the sensitivity index for the 1998 and 2012 surveys

Indicator	Importance weight (*w*)		
	Local	Global 1998	Global 2012
Livelihoods	0.75		
% Climate sensitive income	0.70	0.636	0.525
% Income ag sales	0.24	0.218	0.180
Household pays rent	0.06	0.055	0.045
Agricultural production	0.25		
Plots	0.09	0.027	0.023
Soil quality	0.70	—	0.175
No. of crop types	0.21	0.064	0.053

3.1.2 | Sensitivity analysis 2: Threshold value test

For the 1998 survey, results of the criticality degree, c_{ij}, and probability, p_{ij}, showed that the indicators could be divided into four tiers

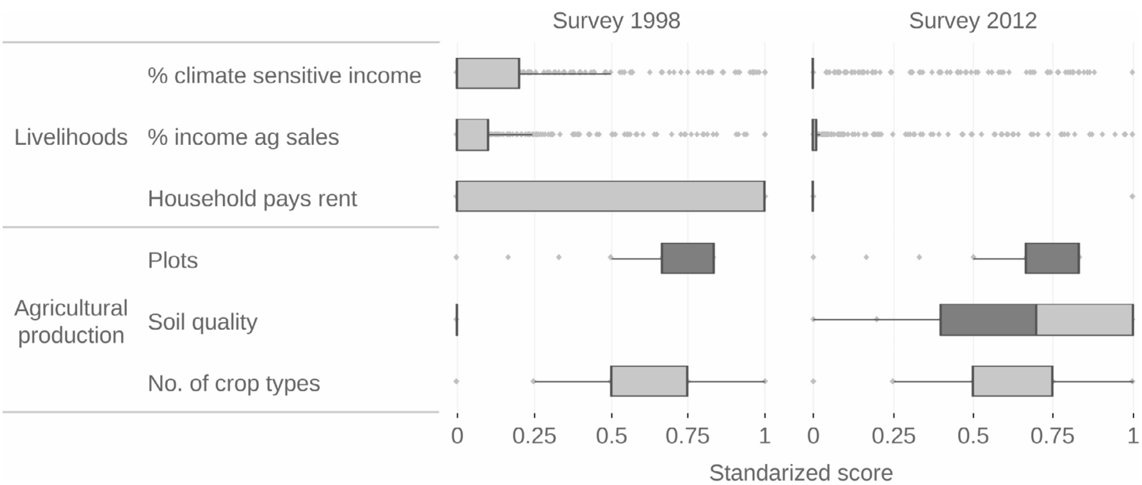

FIGURE 8 Box plots of the standardized scores of sensitivity indicators

TABLE 5 Summary of standardized scores, x_{ij}^{h}, obtained from value functions of sensitivity indicators of the 1998 and 2012 surveys; minimum: $x_{ij}^{-}=0$, maximum: $x_{ij}^{*}=1$, median: x_{ij}^{Q2}

Capital/indicator	x_{ij}^{-} 1998 (%)	x_{ij}^{-} 2012 (%)	x_{ij}^{*} 1998 (%)	x_{ij}^{*} 2012 (%)	x_{ij}^{Q2} 1998	x_{ij}^{Q2} 2012
Livelihoods						
% Climate sensitive income	67	81	9	0	0.00	0.00
% Income ag sales	58	73	5	1	0.00	0.00
Household pays rent	52	87	48	13	0.05	0.00
Agricultural production						
Plots	2	2	0	0	0.83	0.83
Soil quality	—	2	—	37	—	0.70
No. of crop types	5	2	3	6	0.50	0.50

(Table 3). The first one included per capita income, the indicator with the highest criticality degree and probability. The second tier included three indicators, education adults, credit, and area irrigated, which obtained criticality degrees values from one third to one half of that of the first tier ($3.12 \le c_{ij} \le 3.98$) and very high probabilities ($0.51 \le p_{ij} \le 0.61$). The third tier included two indicators, land cultivated and ag asset index, that obtained criticality degree values of one-third of that the first tier, but the former with a very low and the latter with a high probability of occurrence. The four-tier the included the remaining indicators that obtained criticality degree values from one fourth to one-third of that of the second tier ($1.41 \le c_{ij} \le 1.76$) and probabilities of occurrence form very low to high.

For the 2012 survey, results unveiled three tiers regarding the criticality degree (Table 3). The first tier included four indicators, livestock assets, per capita income, land cultivated, and ag asset index, with the higher criticality degree values ($2.52 \le c_{ij} \le 2.85$). The second tier grouped five indicators, participation, savings accounts, land owner, tractor use, and health access with criticality degree values within the range of $2.04 \le c_{ij} \le 2.23$. The third tier included the remaining seven indicators with the lower criticality degree values.

The critical threshold $\mathcal{C}_{ij}$ was calculated considering the second Q_2 quartile or median. A comparison between 1998 (Figure 5) and 2012 (Figure 6) surveys showed that the indicator with the highest value was Per capita income, moreover, a switch in the ranking between Education adults and Credit is observed from 1998 to 2012. Ag asset index ($\mathcal{C}_{ij} = 0.17$) and Livestock assets ($\mathcal{C}_{ij} = 0.12$) critical threshold value in 1998 were equal in 2012 ($\mathcal{C}_{ij} = 0.15$). The introduction of new indicators (saving accounts, health access, participation, frequency of support given, and crop insurance) in 2012 changed the ranking for the rest of the indicators between surveys.

3.2 | Sensitivity index

The AHP model for the sensitivity index (Figure 7) included two elements in the second level that corresponded to the susceptible household attributes (i.e., livelihood and agricultural production). In the third level, the indicators related to each one and represented the necessary assets for farmers to engage in specific adaptations. Results showed that three of the six proxy variables obtained high importance weights (Table 4). Two of these variables, % climate-sensitive income and % income ag sales, pertained to the livelihoods for the 1998 survey, whereas the other variable, soil quality, pertained to agricultural production for the 2012 survey. The remaining proxy variables obtained relatively low importance weights.

Regarding the proxy variables (Figure 8 and Table 5), the proportion of households having the minimum standardized score was considerably higher for indicators of livelihoods than for those for agricultural production in the two surveys. Likewise, the proportions of households having the maximum standardized scores tended to be rather low for all indicators, except for Household pays rent in the 1998 survey, and soil quality in the 2012 survey. The median standardized scores were considerably higher for the indicators of agricultural production than for those of the indicators of livelihood.

Results of the sensitivity index showed that the mean value did not differ between the two surveys ($\overline{V_i} = 0.23$), but that the dispersion of the household sensitivity scores was higher for the 1998 survey

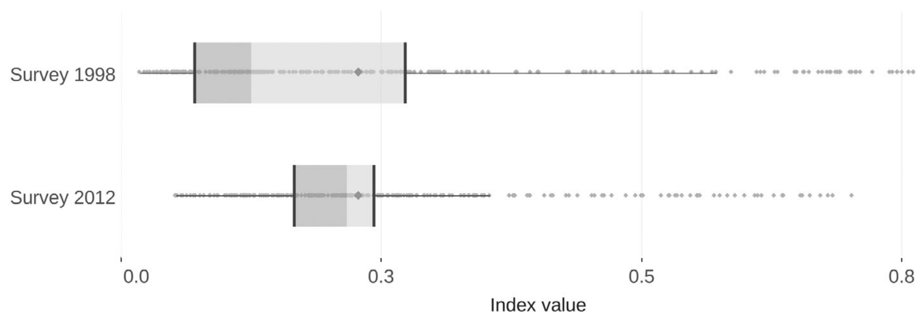

FIGURE 9 Box plot of the sensitivity index for the 1998 and 2012 surveys (diamond = mean)

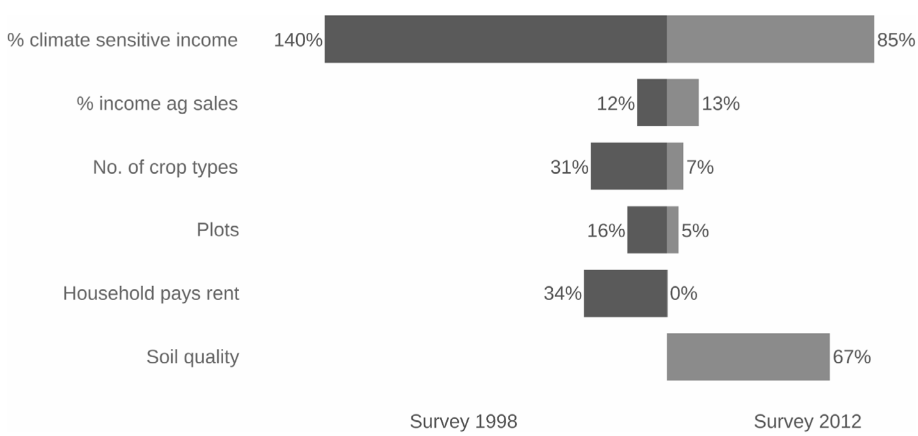

FIGURE 10 Results of the indicator removal test for the sensitivity index

(Figure 9). The median sensitivity was lower for the 1998 survey ($V_i^{Q2} = 0.13$) than for 2012 survey ($V_i^{Q2} = 0.22$).

3.2.1 | Sensitivity analysis 1: Indicator removal test

Similar to the adaptive capacity index analysis, the indicator removal test (2) was applied separately for each survey. The indicator that produced the largest changes in both surveys (Figure 10) was % climate sensitive income, moreover, the effect of the removal of such indicator was reduced in 2012 by the introduction of Soil quality. Household pays rent and No. of crop types changes in the sensitivity index were significantly reduced between 1998 and 2012.

3.2.2 | Sensitivity analysis 2: Threshold value test

In the following, the results (Table 6) for the criticality degree, Equation (5), and the probability of feasible calculations are described. For the 1998 survey, Plots had the highest criticality degree $(c_{ij} = 14.11)$, but the lowest probability $(p_{ij} = 0.17)$, and % climate sensitive income had the highest probability $(p_{ij} = 0.76)$ but the second largest criticality degree $(c_{ij} = 9.21)$. For 2012% climate sensitive income had the highest criticality degree $(c_{ij} = 14.11)$ and the second largest probability $(p_{ij} = 0.59)$, while Soil quality had the highest probability $(p_{ij} = 0.59)$ with the second largest criticality degree $(c_{ij} = 14.11)$.

TABLE 6 Criticality degree, c_{ij} and probability, p_{ij}, for sensitivity indicators

	1998		2012	
Attribute/indicator	$c_{ij}^{Q_2}$	p_{ij}	$c_{ij}^{Q_2}$	p_{ij}
Livelihoods				
% Climate sensitive income	9.91	0.71	9.21	0.59
% Income ag sales	4.00	0.62	3.66	0.57
Household pays rent	8.25	0.19	1.30	0.20
Agricultural production				
Plots	14.11	0.17	2.53	0.26
Soil quality	—	—	4.85	0.76
No. of crop types	5.35	0.32	5.32	0.33

For the 1998 survey, the critical threshold results were divided into three tiers (Figure 11). In the first one, the indicator with the highest critical threshold was % climate sensitive income. In the second tier, the indicators % income ag sales and Plots were included $(0.33 \le \mathcal{C}_{ij} \le 0.35)$. The third tier included No. of crop types and Household pays rent $(0.22 \le \mathcal{C}_{ij} \le 0.24)$.

For 2012 the critical threshold values were grouped in three tiers (Figure 12). The first tier included two indicators: % climate sensitive income and Soil quality $(0.67 \le \mathcal{C}_{ij} \le 1)$. The second tier included % income ag sales and No. of crop types $(0.32 \le \mathcal{C}_{ij} \le 0.38)$ and the third one contains the indicators Plots and Household pays rent $(0.05 \le \mathcal{C}_{ij} \le 0.12)$. The effect of the introduction of Soil quality indicator in 2012 is observed in the critical threshold value results, where Soil quality is in the first tier. For Plots and No. of crop types a switch in the ranking is observed between 1998 and 2012.

4 | DISCUSSION AND CONCLUSIONS

We have shown in this paper the use of SA to ascertain the variation of vulnerability indicators over time on SVI. While we concur with Hyde and Maier (2006) on the importance of SA for evaluating the internal and external sources of uncertainty in MCDA, our results underscore the potential of SA in studying the evolution of social vulnerability. Using the empirical data from two household surveys carried out 12 years apart (Lemos et al., 2016; Nelson et al., 2016), the two SA tests—indicator removal and threshold value—captured the differential importance of incommensurate household vulnerability indicators.

Results shed light on how the vulnerability of households had changed through time as a function of government-led interventions to increase both specific and generic adaptive capacities. The approach presented here thus adds to the typical use of SA to analyse the uncertainties and subjectivities involved in SVI regarding the indicator weights and the standardized scores of the proxy variables, (e.g., Bojórquez-Tapia et al., 2005; Eakin & Bojórquez-Tapia, 2008; Eakin et al., 2011).

Our focus was on explaining the differences observed in two SVI 12 years apart for the Ceará case study. Results suggest that the adaptive capacity index of households improved between the two surveys. The value of this index for the third quartile in the 1998 survey was equivalent to the median in the 2012 survey (Figure 3). The

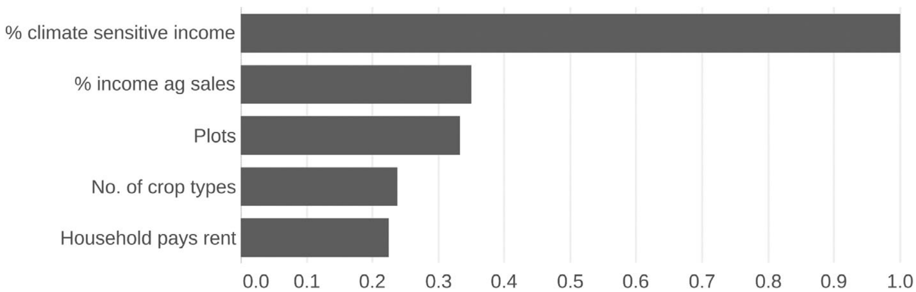

FIGURE 11 Normalized critical threshold value for the sensitivity index (1998)

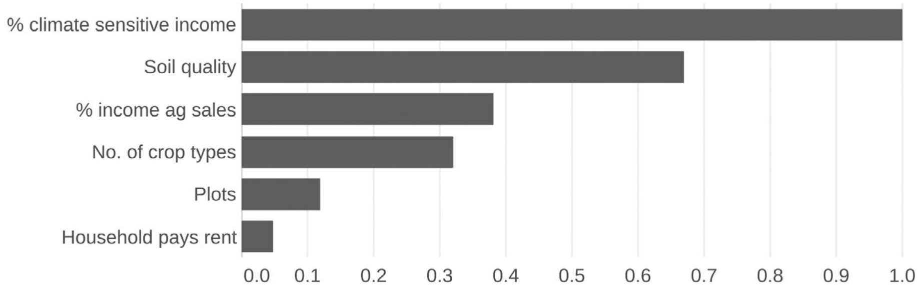

FIGURE 12 Normalized critical threshold value for the sensitivity index (2012)

two SA tests revealed to which vulnerability indicators those changes could be attributed.

The indicator removal test helped clarify the external sources of uncertainty of the two SVI examined here. Results corroborated the findings by Triantaphyllou and Sánchez (1997) and Winston (1991) that the indicator with high importance weights did not necessarily produce the largest change of the SVI (Figure 4 and Table 1). For the 1998 survey, the removal of one indicator of relatively low importance weight—land owner—produced a change of the adaptive capacity index 2%–200% larger than the one produced by the removal of the indicators of high importance weights—education adults, and per capita income, area irrigated, and credit.

For the 2012 survey, the removal of indicators of high importance weights produced larger changes of the adaptive capacity index than the removal indicator of low importance weights. Credit produced a change of the index value that ranges from 2 to 5 times the one produced by either education adults, per capita income, area irrigated, health access, and land owner.

Adger and Vincent (2005) asserted that the adaptive capacity is constrained and vulnerability increases whenever institutions fail to plan for changing environmental conditions and risk. In this regard, a close inspection of the most relevant indicators identified by the SA helped explain the improvement of the adaptive capacity index from 1998 to 2012. Threshold value test results showed a 23% increase in credit, and a 19% decrease in households lacking education adults, whereas land owner remained practically identical. Overall, these results suggest that to reduce vulnerability in the future, the public policies that these indicators imply should be strengthened. Moreover, results of the indicator removal test revealed the importance of the inclusion of soil quality in 2012: a significant reduction of the indicator removal score in all the indicators was observed with exception of % income ag sales, such importance was also corroborated by the threshold value test.

One of the principal limitations of the techniques presented in this work is the fact that, even when the uncertainty in the judgements and magnitude evaluation is considered, only indices defined as linear combinations can be analyzed. However, it is important to emphasise that this also gives a wide field of applications in problems related to land suitability (Chen et al., 2010), environmental impact assessment (Bojórquez-Tapia et al., 2005), and socio-ecological vulnerability indicators. In this sense, two interesting lines of research can be explored: one is the application of the sensitivity tools to geographic information systems to determine the reliability of geographical attributes and the other one is the exploration of sensitivity techniques for different indices definitions, including nonlinear relationships.

In conclusion, we have demonstrated an additional application of SA that goes beyond the challenges of ascertaining the uncertainty of MCDA models. Both the indicator removal and the threshold value test proved useful not only for identifying the critical indicators of household vulnerability to environmental change. These tests also allowed us to determine how household vulnerability evolves as a function of the changes induced over time by public policies in the sensitivity and adaptive capacity of households in NE Brazil. Our implementation of SA has wider applications in the temporal evaluations of plans, projects, and programs of the governments of the private sector.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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