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Multi-temporal assessment of vulnerability to climate change: insights from the agricultural sector in Mexico

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Abstract Vulnerability to climate change was evaluated for three different time periods: 1990, 2000, and 2010. Our objective was to discuss the scope of a multi-temporal assessment of vulnerability. The method used 55 indicators—with emphasis on the agricultural sector in Mexico—of which 27 were updated for the year 2010 and 33 were retrospectively estimated for the year 1990. The results show that in the 20-year study period, the exposure of the municipalities (and inhabitants) has increased, and sensitivity and adaptive capacity have decreased. The number of municipalities vulnerable to climate change declined over the 20-year period. We found that calculating vulnerability by adding exposure and sensitivity and subtracting adaptive capacity ($E + S - AC$) can lead to unintentional underestimation of total vulnerability. When rating vulnerability, care must be taken in what is reported: the results differ for the number of inhabitants versus the number of municipalities. Our previous published vulnerability evaluation was for the year 2000, so we wanted to evaluate the sensitivity of some variables and the vulnerability formula itself we used in that moment. It is possible to evaluate the vulnerability multi-temporally, which allows to evaluate the sensibility and calibration of the variables and indicators used and the reconsideration of their application.

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1 Introduction

Estimating vulnerability to climate change is necessary to promote adaptation. Detailed information is required to define thresholds at different scales (Aall and Norland 2005), and discussions are ongoing regarding the use of different methods and indicators that best reflect vulnerability (Monnereau et al. 2017). In addition, the need for clear information for decision-making remains under discussion (IPCC 2007; Mandal et al. 2017). Vulnerability to climate change has been understood to be dynamic over time (Downing et al. 2001) and this is the main motivation for this article.

Most retrospective studies that use the term vulnerability refer to land use change dynamics (Singh Boori and Eustáquio Amaro 2011) or to the analysis of some natural phenomenon (Keiler et al. 2006), such as floods or landslides. Modern technologies such as remote sensing and satellite images are commonly used in the study of some phenomena. However, the vulnerability to climate change in the past, as a useful tool to assess achievements and scope in the present, has yet to be estimated. Retrospective analysis may be useful as calibration or validation of a known method and has primarily been used in health and medicine. Donatti et al. (2017) found that if the specific needs of a place had been known, such as the impacts of climate change or areas susceptible to flooding, drought, or landslides, measures to address vulnerability could have been implemented. Therefore, vulnerability assessment should provide information useful to decision-making regarding, e.g., the present adaptation needs or whether current actions are based on past information.

Monnereau et al. (2017) summarized clearly that macroscale national vulnerability assessments suffer from four methodological shortcomings: (1) an inconsistent representation of countries belonging to a group (among least developed countries and small island developing states); (2) use of socioeconomic indicators that are not scaled to population size; (3) use of a small number of indicators; and (4) lack of accounting for potential redundancy among indicators. At a smaller scale, for example within a country, the sector (e.g., agriculture) and the administrative boundaries (e.g., a municipality) should be considered the basis for a study.

Heterogeneity in the degree of vulnerability within countries requires the definition of specific adaptation projects to address the impacts of climate change (Mandal et al. 2017). In addition, the characterization and ranking of variables, such as those of exposure, sensitivity, or adaptive capacity, are complementary methods that allow the prioritization and identification of strategies to encourage adaptation (Bouroncle et al. 2017). Even recently, the implications for the selection of aggregation methods for vulnerability studies are being studied (Machado and Ratick 2017). For this reason, vulnerability to climate change should be evaluated at the national scale to identify regional areas of opportunity for effort. Thus, the objective of the present study was to estimate the vulnerability over two different time periods by applying a known method to monitor progress and estimate changes in vulnerability for a country. We start with the first vulnerability assessment carried out for the year 2000 by Monterroso-Rivas et al. (2014), and from there, we calculated the other 2 years under the same method and variables. It was considered feasible to estimate the earlier value of a current estimate of vulnerability to calibrate or validate the variables and indicators used in previous studies. Twenty years and three different population censuses should allow for clearer information to assess the current vulnerability within the country.

2 Methods

The methods used followed those proposed by Monterroso-Rivas et al. (2014) to assess the vulnerability of Mexico's agricultural sector to climate change using information primarily from 2000, 2005, and 2007 (INEGI 2006, 2009). Because the sources of information were not necessarily from a given year, in this study, we will refer to this study as *centered* on the year 2000. Similarly, the retrospective exercise is *centered* on 1990, and the most recent work is *centered* on 2010, for which the information was also not from a single year. In the article, we use the terms retrospective, original, and updated to refer that years (1990, 2000, and 2010, respectively), although they can be used for some other analysis in climate change. Therefore, we used different sources of information and different censuses and surveys that we then generalized to the years 1990, 2000, and 2010. In the first vulnerability assessment which was published in 2014, 55 variables were chosen at the municipal level to estimate the current and future vulnerability of the agricultural sector to climate change. In the present study, the same indicators were chosen, and the 1990 (INEGI 1995) and 2010 (INEGI 2011) population censuses were explored to prepare two vulnerability proposals, retrospective and updated. Although the method was applied for current (3) and future (6) scenarios when considering climate change, in this study, we will only refer to the three current vulnerability scenarios. The future vulnerability scenarios will be addressed in future work. We obtained the vulnerability data for the agricultural sector for 1990, 2005, and 2010. Table 1 shows the variables and sources of information used.

For the year 1990, the database available in Desinventar (2015), which was highest in richness and the most accurate for the exposure indicators for that year, was explored. Soil and vegetation mapping from INEGI (1996) was used to define the unvegetated area of the municipality. Because of a lack of information regarding the S1 and S7 sensitivity variables, their values were estimated as follows: the annual rate of change was calculated for the period 2000–2010, and then that rate was applied back to the year 1990 using regression analysis. All agricultural sector variables (S10 to S21) were unmodified from the original, under the premise that the suitability of the land should not have changed since 1990. For nine adaptive capacity variables, the original study value was reduced to 70% of the original value in the census of 2007 since no information exists from the production units for that year (sensibility analysis). We assumed that agricultural production in the past was not the same as that presented in the agricultural, livestock, and forestry census of 2007 (INEGI 2009). The reduction to 70% was according to the gross domestic product (GDP) of Mexico. The World Bank (https://datos.bancomundial.org/pais/mexico?view=chart) reports that the growth of GDP per capita between 1990 and 2012 was 1.21% annual, so we assume a total accumulated value of 24.2% for the 20-year period studied. In addition, since our focus is mainly for rural communities and agricultural sector, we add up 5.8%.

For the year 2010 update, CENAPRED (2016) was used as an updated source of four exposition variables information through 2015 (Table 1). The spatial resolution of the climate and climate change information was improved, as indicated in the sources consulted (Fernández Eguiarte et al. 2015). The 2010 population census by INEGI (2011) was one of the main sources of information, as were CONAPO (2012) and INAFED (2005).

For both 1990 and 2010, official and available information (INEGI, CONAPO, and CONEVAL) was consulted, following the criteria suggested by Monterroso-Rivas et al. (2014) that the indicators come from publically available information.

Once the variables were updated, they were standardized, and three indices were obtained: a climate and climate change exposure index, composed of three subindices, extreme events, environmental problems, and climate and climate change; a sensitivity index constructed with

Table 1 Indicator list and source for past and present vulnerability assessment: from original vulnerability estimated by 2000 and retrospective (1990) and update (2010), where no data or source presented were used as the original indicator (SO = same as original)

	1990 retrospective	Original indicators by ± 2000 (Monterroso–Rivas et al. 2014)	2010 update
Exposition			
a) Extreme events			
E1	Total floods, 1980–1990 (Desinventar 2015)	Total floods, 1985–2000 (CENAPRED 2010)	Total floods, 2000–2015 (CENAPRED 2016)
E2	Total frost and hail, 1980–1990 (Desinventar 2015)	Total frost and hail, 1985–2000 (CENAPRED 2010)	Total frost and hail, 2000–2015 (CENAPRED 2016)
E3	Total heavy rains, 1980–1990 (Desinventar 2015)	Total heavy rains, 1985–2000 (CENAPRED 2010)	Total heavy rains, 2000–2015 (CENAPRED 2016)
E4	Total landslides, 1980–1990 (Desinventar 2015)	Total landslides, 1985–2000 (CENAPRED 2010)	Total landslides, 2000–2015 (CENAPRED 2016)
b) Environmental problems			
E5	Total of five problems 1980–1990 (illegal logging, fires, pests, biodiversity loss, and water pollution) (Desinventar 2015)	Total of five problems (illegal logging, fires, pests, biodiversity loss, and water pollution) by 2005 (SEDESOL 2010)	S.O.
E6	Surface without vegetation (%) by 1990 (INEGI 1996)	Surface without vegetation (%) by 2006 (INEGI 2009b)	S.O.
E7	S.O.	Production units (PU)* with losses due to a climatic factor by 2007 (INEGI 2009a)	S.O.
E8	S.O.	PU with losses due to lack of soil fertility (%) by 2007 (INEGI 2009a)	S.O.
c) Climate and climate change			
E9	S.O.	Mean summer temperature (°C, May–August), 1950–2000 from UNIATMOS (Fernandez et al. 2009)	Mean summer temperature (°C, May–August), 1950–2000 from Worldclim
E10	S.O.	Mean summer precipitation (mm, May–August), 1950–2000 from UNIATMOS (Fernandez et al. 2009)	Mean summer precipitation (mm, May–August), 1950–2000 from Worldclim
E11	Future temperature (°C), model HADGEM1, A2, by 2050 from UNIATMOS (Fernandez et al. 2009)	Future temperature (°C, May–August), HadGEM1, A2 by 2030 from UNIATMOS (Fernandez et al. 2009)	Future temperature (°C, May–August), HADGEM2, RCP 8.5, 2015–2039 (Fernández Eguiarte et al. 2015)
E12	Future precipitation (mm), model HADGEM1, A2, by 2050 from UNIATMOS (Fernandez et al. 2009)	Future precipitation (mm, May–August), HadGEM1, A2 by 2030 from UNIATMOS (Fernandez et al. 2009)	Future precipitation (mm, May–August), HADGEM2, RCP 8.5, 2015–2039 (Fernández Eguiarte et al. 2015)
E13	Future temperature (°C), model MPI ECHAM5, A2, by 2050 from UNIATMOS (Fernandez et al. 2009)	Future temperature (°C, May–August), MPI ECHAM5, A2 by 2030 from UNIATMOS (Fernandez et al. 2009)	Future temperature (°C, May–August), MPI ESM, RCP 8.5, 2015–2039 (Fernández Eguiarte et al. 2015)
E14	Future precipitation (mm), model MPI ECHAM5, A2, by 2050 from UNIATMOS (Fernandez et al. 2009)	Future precipitation (mm, May–August), MPI ECHAM5, A2 by 2030 from UNIATMOS (Fernandez et al. 2009)	Future precipitation (mm, May–August), MPI ESM, RCP 8.5, 2015–2039 (Fernández Eguiarte et al. 2015)
Sensitivity			
a) Population			
S1	Female-headed households (%) (INEGI 2006)	Female-headed households (%) (INEGI 2006)	Female-headed households (%) (INEGI 2011b)

Table 1 (continued)

	1990 retrospective	Original indicators by ±2000 (Monterroso-Rivas et al. 2014)	2010 update
	Retrospectively 10 years' rates (2000–2010) were applied to 1990		
S2	Indigenous households in the municipality (%) by 1990 (INEGI 1995)	Indigenous households in the municipality (%) (INEGI 2006)	Indigenous households in the municipality (%) (INEGI 2011b)
S3	Population in food poverty (%) by 1990 (CONEVAL 2010)	Population in food poverty (%) by 2000 (CONEVAL 2008)	Population in food poverty (%) by 2010 (CONEVAL 2010)
S4	Population in primary activities (%) by 1990 (INEGI 1995)	Population in primary activities (%) by 2005 (INEGI 2006)	Population in primary activities (%) by 2010 (INEGI 2011b)
b) Health			
S5	S.O.	Children under 5 years old who were small at birth (%) (CONAPO 2005)	S.O.
S6	S.O.	Children under 5 years old who were underweight at birth (%) (CONAPO 2005)	S.O.
S7	Retrospectively 10 years' rates (2000–2010) were applied to 1990	Population without access to health services (%) by 2005 (INEGI 2006)	Population without access to health services (%) by 2010 (INEGI 2011b)
c) Agriculture, livestock, and forestry			
S8	Land area devoted to primary activities (%), (INE-SEMARNAP 2000)	Land area devoted to primary activities (%) (INEGI 2009a)	S.O.
S9	Rainfed land in municipality (%) by 1990 (INEGI 1996)	PU without irrigation systems (%) (INEGI 2009a)	S.O.
S10	S.O.	Average yield of rainfed maize in 2005 (tn/ha) (INEGI 2008)	S.O.
S11	S.O.	Likelihood of low yields in beans (Cruz 2011)	S.O.
S12	S.O.	Likelihood of low yields in maize (Cruz 2011)	S.O.
S13	S.O.	Agricultural suitability for maize, 1950–2000 (Monterroso-Rivas et al. 2011)	S.O.
S14	S.O.	Livestock potential, 1950–2000 (Monterroso-Rivas et al. 2011)	S.O.
S15	S.O.	Forestry potential, 1950–2000 (Gómez-Díaz et al. 2011)	S.O.
S16	S.O.	Future agricultural aptitude Model MPI ECHAM5 to 2030 (Monterroso-Rivas, Conde-Álvarez et al. 2011)	S.O.
S17	S.O.	Future livestock potential Model MPI ECHAM5 to 2030 (Monterroso-Rivas et al. 2011)	S.O.
S18	S.O.	Future forestry potential Model MPI ECHAM5 to 2030 (Gómez-Díaz et al. 2011)	S.O.
S19	S.O.	Future agricultural aptitude Model HadGEM1 to 2030 (Monterroso-Rivas et al. 2011)	S.O.
S20	S.O.		S.O.

Table 1 (continued)

	1990 retrospective	Original indicators by ±2000 (Monterroso-Rivas et al. 2014)	2010 update
S21	S.O.	Future livestock potential Model HadGEM1 to 2030 (Monterroso-Rivas et al. 2011) Future forestry potential Model HadGEM1 to 2030 (Gómez-Díaz et al. 2011)	S.O.
Adaptive capacity			
a) Human capital			
C1	Population aged 15 years and older who can read (%) by 1990 (INEGI 1995)	Population aged 15 years and older who can read (%) by 2000 (CONAPO 2005)	Population aged 12 years and older who can read and write (%) by 2010 (CONAPO 2012)
C2	School attendance by people from six to 14 years of age (%) by 1990 (INEGI 1995)	School attendance by people from 6 to 24 years of age (%) by 2005 (INEGI 2006)	School attendance by people from 5 or older years of age (%) by 2010 (INEGI 2011b)
C3	Literacy rate at municipality (%) by 1990 (INEGI 1995)	Literacy rate at municipality (%) by 2005 (INEGI 2006)	Literacy rate at municipality (%) 15 to 24 years old by 2010 (INEGI 2011b)
C4	Change in the municipality's population from 1990 to 2030 (%) (CONAPO 2006; INEGI 1995)	Change in the municipality's population from 2005 to 2030 (%) (CONAPO, 2006; INEGI 2006)	Change in the municipality's population from 2010 to 2030 (%) (CONAPO 2012; INEGI 2011a)
b) Social capital			
C5	PU organization to access some support (%), valued 70% from original data in census 2007 (INEGI 2009a)	PU organization to access some support (%) by 2007 (INEGI 2009a)	S.O.
C6	No litigation or disputes over land in PU (%) valued 70% from original data in census 2007 (INEGI 2009a)	No litigation or disputes over land in PU (%) by 2007 (INEGI 2009a)	S.O.
C7	PU with technical training (%) valued 70% from original data in census 2007 (INEGI 2009a)	PU with technical training (%) by 2007 (INEGI 2009a)	S.O.
C8	Possession or land tenure (%) valued 70% from original data in census 2007 (INEGI 2009a)	Possession or land tenure (%) by 2007 (INEGI 2009a)	S.O.
C9		Civil protection unit (SEDESOL 2010)	S.O.
C10		Map of natural hazards (SEDESOL 2010)	S.O.
c) Financial capital			
C11	PU without difficulty accessing credit (%) valued 70% from original data in census 2007 (INEGI 2009a)	PU without difficulty accessing credit (%) by 2007 (INEGI 2009a)	S.O.
C12	PU that receive remittances from abroad (%) valued 70% from original data in census 2007 (INEGI 2009a)	PU that receive remittances from abroad (%) by 2007 (INEGI 2009a)	S.O.
C13	PU reporting some type of savings (%) valued 70% from original data in census 2007 (INEGI 2009a)	PU reporting some type of savings (%) by 2007 (INEGI 2009a)	S.O.
C14			S.O.

Table 1 (continued)

	1990 retrospective	Original indicators by ±2000 (Monterroso-Rivas et al. 2014)	2010 update
	PU with credit and insurance coverage (%) valued 70% from original data in census 2007 (INEGI 2009a)	PU with credit and insurance coverage (%) by 2007 (INEGI 2009a)	
C15	S.O.	Gross domestic product in 2000 ($)	Gross domestic product in 2005 ($) (INAFED 2005)
C16	Population in patrimony poverty (%) in 1990 (CONEVAL 2010)	Population with income greater than two times the minimum wage (%) by 2005 (INEGI 2006)	Population with income greater than two times the minimum wage (%) by 2010 (INEGI 2011b)
C17	Estimated change (%) between gross domestic product ($) from 1990 and 2030 UNIATMOS (Fernandez et al. 2009)	Estimated 2030 gross domestic product ($) from UNIATMOS (Fernandez et al. 2009)	S.O.
d) Natural capital			
C18	Surface with forests and/or rainforests (ha) (INEGI 1996)	Surface with forests and/or rainforests (ha) (INEGI 2005)	S.O.
C19	Reforested surface in the municipality (ha) valued 50% from original census (INEGI 2009b)	Reforested surface in the municipality (ha) (INEGI 2009b)	S.O.
C20	S.O.	Rate of water extraction from aquifers (CONAGUA 2009)	S.O.

*The production units (PU) are defined in Mexico as "areas with or without agricultural or forest activity, belonging to the same municipality and have been managed under one family or commercial administration by March–September census of 2007." The National Institute of Statistics and Geography (INEGI) found 5,548,845 production units in 2455 municipalities

subindices of population, health, and primary activity (agriculture, livestock, and forests); and an adaptive capacity index, which included human, social, financial, and natural capital. Then, the vulnerability was estimated by adding exposure plus sensitivity and subtracting adaptive capacity as follows: $V = (E + S) - AC$. For the three evaluated time periods, the vulnerability classes were grouped into quintiles, with the same grading ranks used for the three time periods, allowing them to be comparable [five classes with normalized values were used: very low (0–0.2), low (0.21–0.40), medium (0.41–0.60), high (0.61–0.80), and very high (0.81–1)]. Finally, maps were developed to illustrate the spatial distribution of the vulnerability of the agricultural sector. More details on these methods can be found in Monterroso-Rivas et al. (2014).

3 Results and discussion

Vulnerability to climate change was evaluated based on indicators that reflect exposure to climate and climate change in municipalities: the sensitivity of the agricultural, livestock, and forestry sectors to climate change and the adaptive capacity of the people who inhabited and currently inhabit the municipalities of Mexico. Therefore, our vulnerability assessments correspond to the agricultural sector of the country. Next, the results are described for each of the dimensions and then for the three vulnerabilities studied.

3.1 Dimensions of vulnerability

The methods applied in Monterroso-Rivas et al. (2014) are sensitive and respond well to the observed data and to the evaluation of the three dimensions of vulnerability. For example, a greater frequency of climate events was expected to result in greater exposure of municipalities, or vice versa, and thus, *climate exposure* in Mexico has increased in recent years as a result of more frequent climate events. For example, considering floods at the national level, in 1990, 708 affected municipalities were reported; in 2000, 3268 floods occurred, and in the most recent year (2010), 7195 were reported (Fig. 1). The exposure variables showed a tendency to increase over the three time periods, with a lower frequency in 1990 and a higher frequency in 2010.

For the exposure assessment, in 1990, 11 municipalities were in the high- and very high-exposure classes, representing slightly more than 7% of the population (5.8 million). In 2000, 51 municipalities were in the same classes (10.3 million people), and in 2010, 70 municipalities were in the same classes (12 million people). Therefore, for the 1990–2000 period, the population facing high and very high exposure increased by 70%, and for 2000–2010, the increase was 20%. From 1990 to 2010, the number of people exposed to climate events almost doubled (Table 2).

Exposure remains a factor in the vulnerability of the country. The exposure events evaluated were the same for the three time periods studied; however, the number of cases reported increased in quantity and likely also in magnitude. The method used could detect this change and reflect it in the evaluation of the exposure index. Over time, extreme weather events have become more frequent. In addition, human activities that promote greater exposure, such as changes in land use, modification of vegetation cover, or land clearing resulting in unprotected sites, should be added to the analysis. Natural phenomena, in particular climatic phenomena, continue to affect the population. CENAPRED (2014) has reported increased frequency and damage from flooding. The fifth IPCC assessment report (2013) confirms similar data and indicates continuation and increases over the next 100 years.
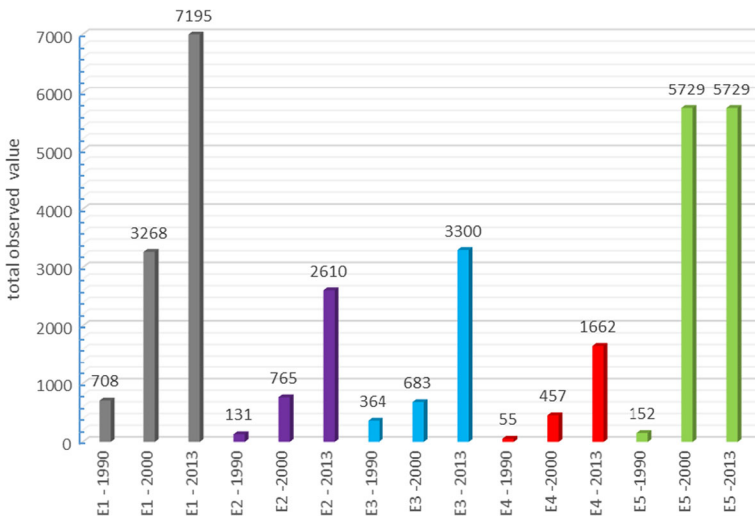
Fig. 1 Total exposition events in exposition over time: 1990, 2000, and 2010 (E1 = floods, E2 = frost and hail, E3 = heavy rains, E4 = landslides, E5 = total of five problems)

It should be noted that we do not include three important extreme events in climate exposure: droughts, high temperatures, and winds. The first one because is related to crop suitability and is better represented in sensibility; the second one is because there is no clear information of their impact. Both of them have impacted the region strongly in the last years and are expected to be recurrent, so we hope data collected in census can reflect them in near future. In recent years, the impact of strong winds on agricultural and forestry activity in the country has been recorded. Studies have recognized the importance of incorporating the effect of wind on agricultural production (Asensio et al. 2015; Lozano et al. 2013). The ministry of agriculture (SAGARPA) and the national center for disaster prevention (CENAPRED) have begun to record the impact of wind in some regions of the country, particularly, the effect of strong winds. We consider that this variable should be included later in the current vulnerability studies. If future wind information is available, it can be considered in the vulnerability to climate change analysis.

Over the years, municipalities with high and very high *sensitivity of the agricultural sector* have declined, but the population that inhabits them has not. Thus, in 1990, 716 municipalities (8.1 million inhabitants) were in these two sensitivity classes; in 2000, 633 municipalities (11 million) fit these two categories; and by 2010, the total had decreased to 282 municipalities, but with 12 million inhabitants (Table 2). The number of inhabitants in sensitive areas for the period 1990–2000 increased by 35%, and for 2000–2010, it increased by 48% compared with the year 1990, while the number of municipalities decreased by 12 and 60% for the first and second periods, respectively, because of the spatial distribution of the population within areas of high sensitivity. The maps indicate high agricultural sensitivity in the states of Guerrero, Hidalgo, Oaxaca, Puebla, and Veracruz, which traditionally have high percentages of areas with temporary agricultural activity. In addition, the population dedicated to primary activities in the municipalities has decreased in the national figures of INEGI (2016). However, municipalities whose population is devoted almost exclusively to primary activities remain in parts of the country. This polarization translates into a population with exclusively primary activities dependent on agricultural productivity and that is consequently very sensitive to climate change. According to the Intercensal Survey (INEGI 2015), 29% of all households are run by a woman. In 2010, that number was 24%, and in 1990, it included

Table 2 Total municipalities and population (millions in parenthesis) by exposition, sensitivity, adaptive capacity, and vulnerability class in Mexico

	Exposition			Sensitivity			Adaptive capacity			Vulnerability		
	1990	2000	2010	1990	2000	2010	1990	2000	2010	1990	2000	2010
Very low	1187 (28.8)	762 (20.0)	562 (16.0)	51 (9.5)	4 (0)	136 (9.3)	*3 (0)*	*7 (0.1)*	*21 (0.1)*	35 (3.5)	8 (0.1)	384 (30.7)
Low	1151 (36.0)	1276 (49.6)	1308 (53.8)	586 (40.5)	317 (19.6)	1145 (73.8)	*147 (1.8)*	*293 (3.8)*	*683 (12.0)*	918 (37.6)	764 (39.4)	1194 (54.6)
Medium	107 (10.4)	367 (21.9)	516 (31.3)	1103 (22.9)	1502 (71.2)	893 (25.6)	*2044 (70.1)*	*1863 (60.0)*	*1690 (76.1)*	1001 (29.7)	1240 (49.8)	655 (21.9)
High	*8 (4.0)*	*44 (6.7)*	*59 (6.3)*	*606 (7.4)*	*602 (10.7)*	*256 (3.2)*	257 (8.6)	282 (35.5)	56 (22.3)	433 (9.2)	405 (11.9)	203 (4.6)
Very high	*3 (1.8)*	*7 (3.6)*	*11 (4.8)*	*110 (0.7)*	*31 (0.2)*	*26 (0.1)*	5 (0.6)	11 (2.3)	6 (1.7)	69 (1.2)	39 (0.8)	20 (0.5)

Italicized entries indicate population and municipalities with the lowest scores in each class. The total population is 81,249,645 (1990), 101,991,998 (2000), and 112,336,538 (2010).

even fewer homes. Female heads of household increased by 4 percentage points between 2010 and 2015. CDI-INEGI (CDI-INEGI 2006) reported in 2005 that the indigenous population accounted for 9.8% of the country's total population, lower by 0.7% than in 2000; i.e., the 2005 population count (INEGI 2006) recorded 150 thousand fewer indigenous people than in 2000. Thus, this decrease in the number of indigenous people and all the above changes cited influences the global indicator of sensitive municipalities.

The evaluation model is sensitive and captured the degree of sensitivity. The greater the area, people, and agricultural activity present in a municipality, the greater is the sensitivity of its population. According to Beddington et al. (2012), food security in the world is defined by three elements: the amount of food that can be produced, the amount of food needed, and the effect of food production on the climate. Therefore, the change in climatic variables determines agricultural production globally, particularly in those places where the activity is performed without irrigation or with high inputs. We do not include soils and land degradation in our sensitivity analysis. The current state of the land is a variable that should be included in future vulnerability studies particularly because it largely defines food production and food security.

In our evaluation of *adaptive capacity*, we examined those municipalities in the low and very low classes. In 1990, 150 municipalities and 1.9 million inhabitants were included. For the year 2000, 300 municipalities were in the two classes (4 million people). In the most recent year, in 2010, 704 municipalities (12 million people) were in the low and very low adaptive classes (Table 2). For the first period, 1990–2000, the population with low and very low adaptive capacity increased by 110%, and for the period 2000–2010, the population with low adaptive capacity increased by 500%. Similarly, the number of municipalities with little adaptive capacity for the same periods increased 100 and 370%, respectively. Therefore, adaptive capacity has declined in recent years in Mexico, both in the population and in municipalities.

Of the variables used to estimate the adaptive capacity of the municipalities, those referring to social capital (organization, disputes, consultation, and civil protection) were not updated for the most recent year. The last agricultural, livestock, and forestry census was in 2007 (INEGI 2009), and it is expected to be updated by the institution in 2017. Evaluation of the natural capital variables (land use, reforestation, and aquifers) was also not possible because more recent information was not available. In contrast, some financial capital (two variables) and human capital (four variables) were updated, and thus, the decline in the adaptive capacity of municipalities in the period 2000–2010 is explained by these factors.

Human capital is determined by the literacy and school attendance in a municipality, as well as the projected population change by the year 2030. These values were slightly higher in the most recent year compared with previous years. More education and school attendance drive adaptive capacity, whereas a higher population in some municipalities implies a greater challenge. Per capita income is closely related to poverty and is perhaps the variable that, together with the gross domestic product, best defines the observed changes in adaptive capacity. Gross domestic product data only was updated by 2010 (1990 remains as original of 2000) and has improved as the economy of the country has been growing. Income greater than minimum wage was the variable with greater changes between years studied. In fact, the number of people living in poverty has increased in recent years. CONEVAL (2014) indicates that by 1992, 18.6 million poor people lived in the country; in 2005, the number reached 19.0 million; and by 2010, it reached 21.5 million. Nevertheless, if we look these values as a percentage of total population, the data shows 22.9, 18.6, and 19.1%, respectively, showing that poverty has decreased relative to the total population of the country, but it can hide the

reality of poverty in the country (3 million more poor). Thus, the low adaptive capacity is due to lower income, greater increases in population size, and the change in the gross domestic product of the municipalities.

Thus, of the six variables modified, five variables improved and one decreased the overall adaptive capacity in the years studied. According to our method, it is the latter that helps explain the change in adaptive capacity. However, we recognize that it is likely that the applied method does not allow these changes to be highlighted, since the method is a central tendency process and does not adequately respond to the analysis of extremes. This is a topic that other authors have begun to study (Machado and Ratick 2017).

3.2 Multi-temporal vulnerability to climate change

The 10.4 million inhabitants who were vulnerable in 1990 represented 12% of the total population and lived in 223 municipalities. The 5.1 million inhabitants in 2010 in vulnerable municipalities represented 4.5% of the population living in 502 municipalities (Fig. 2): showing a clear change. Based on the method applied, the population vulnerable to climate change was halved in 20 years, but the number of vulnerable municipalities expanded almost twofold, an interesting pattern. The analysis is based on the components of vulnerability studied, but we recognize that the dynamics of growth and migration of populations in communities have not been included. Vulnerable people are not so mobile as other people with unlimited resources, so we attribute the changes in vulnerability to the behavior of the exposure, sensitivity, or adaptive capacity.

The proportions of those exposed, sensitive, or with low adaptive capacity have changed, and the method used was able to detect these changes (Fig. 2). The climatic events have increased the total number of municipalities exposed, from 11 (1990) to 70 (2010). The number of sensitive municipalities has decreased, from 716 (1990) to 282 in 2010. There
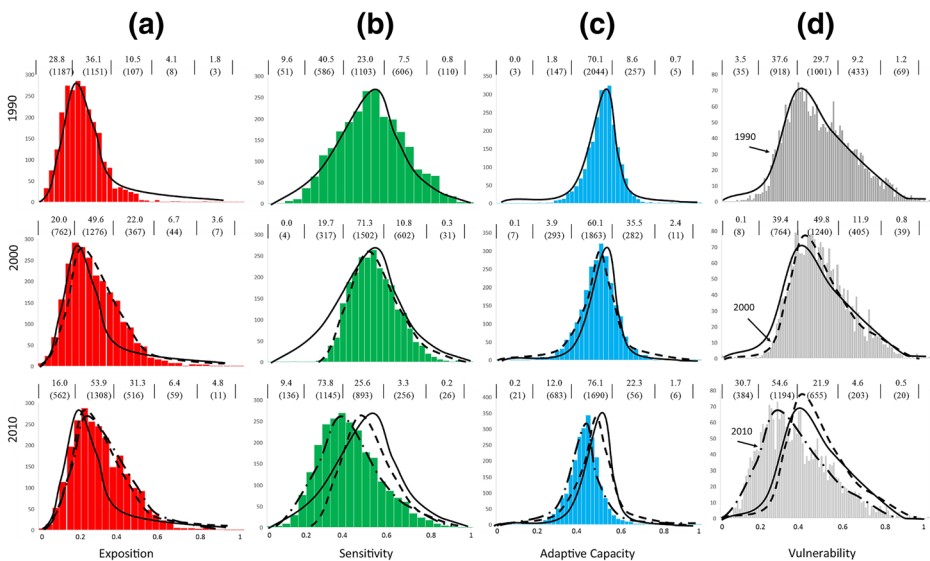

Fig. 2 Frequency histogram of the total number of municipalities for each dimension and vulnerability to climate change. Continuous or dotted lines show overall trends. The total number of people (in millions) and the total number of municipalities (in brackets) by class are also shown

were 262 municipalities with low adaptive capacity in 1990 and 62 in 2010. The final formula defines the number of municipalities that fit some category of vulnerability. In this case, following the formula indicated in the methodology section ($V = E + S - \mathrm{AC}$), the number of vulnerable municipalities has decreased overall.

In the most recent year, the number of vulnerable municipalities has clearly declined considerably compared with the earliest year. However, as noted above, municipalities with greater exposure have been found. Thus, the above must be considered with caution in advancing conclusions regarding the overall vulnerability rating. Instead, more attention must be paid to each of the three dimensions rather than to the final sum. The advantages of analyzing and addressing each individual dimension (E, S, and AC) should be explored, and vulnerability should be considered as only an indicator of progress.

The change in the spatial distribution of vulnerable municipalities is presented in Fig. 3, which also includes those municipalities in Mexico considered to be the most vulnerable to climate change by federal government (SEMARNAT 2014). Vulnerability increased slightly (from 1990 to 2000) and then decreased in 2010 substantially; this decrease seems to be linked mainly to a decrease in sensitivity. The adaptive capacity also decreases but not as much, so the overall effect is a decrease in vulnerability. The central and western states have remained less exposed to those coastal and in both peninsulas (see supplemental figures), suggesting that in recent years, there have been more climatic events that affect agricultural production in these regions, and promoting vulnerability. Sensitivity depends on where the agricultural activity is concentrated, in this case, rained agriculture. Maps show that most sensitive regions are towards the south center of the country, and thus, they have remained in years studied. In summary, Fig. 3 shows that in the first period, 1990–2000, 1249 municipalities increased in vulnerability, and 1131 experienced a decrease, with 76 remaining unchanged. For the second period, 2000–2010, 44 increased in vulnerability, 2402 experienced a decrease, and only 10 municipalities remained unchanged. Thus, over the last two decades and in absolute terms, the municipalities and total population in the country vulnerable to climate change have declined.

However, of note are those areas on the maps that continue to show vulnerability over the years: Chihuahua and Sonora in the north and Guerrero, Oaxaca, Chiapas, Puebla, Veracruz, and Tabasco in the south central region of the country. The entities with the highest vulnerabilities in the three periods studied were examined further.

Despite efforts to reduce economic and social regression, vulnerability persists over time. For example, GDP increased from just over seven billion to just over 12 billion from 1990 to 2010; public spending on education in 1990 was 2.3% of GDP, increasing to 5.1% in 2010, and public health expenditure was 2.3% of GDP in 2000, increasing to 3.1% in 2010 (Banco Mundial 2017). All of the above indicators are included in this analysis, and improving them should reduce vulnerability. Although this change has occurred globally, isolated regions remain where the indicators suggest that further efforts must be made. Therefore, each of the three dimensions of vulnerability must be closely observed, rather than just vulnerability alone since important and valuable information could be omitted.

Measuring vulnerability by adding $E + S$ and subtracting CA can reduce the signal of municipalities vulnerable to climate change. In a quick exercise (and not entirely valid), the populations in the two largest categories for each dimension in the most recent year are easily counted: exposure (11.2 million people), sensitivity (3.5 million), and adaptive capacity (12.2 million). Following the formula, 14.7 million people could be impacted by climate change ($E + S$), but 12.2 experience some adaptive capacity, and thus, 2.5 million are vulnerable. Where are the 11.2 million people currently exposed? Here, two points must be highlighted:
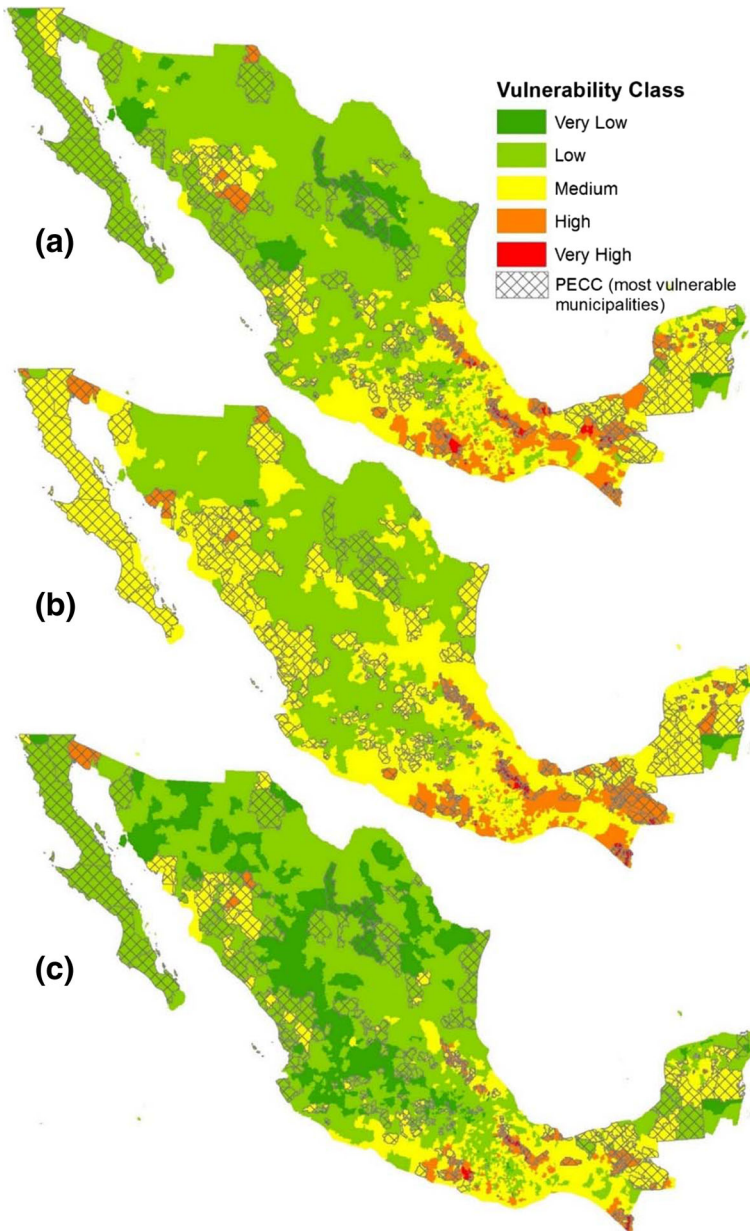
Fig. 3 Vulnerability classes by municipality in **a** 1990, **b** 2000, and **c** 2010. Shaded are the most vulnerable municipalities in Mexico, according to PECC (SEMARNAT 2014)

the first one is the undervaluation resulting from algebraically adding the impact $(E + S)$ and the second one is the error when considering that the exposed people are different than the sensitive people.

Another similar point is the way in which we add multi-temporal information to the vulnerability index: in exposure, we consider climatic events that may seem overlapping

(E1), or in adaptive capacity change in population (C4) that may seem double calculation. We wanted the results to be cumulative, instead of independent. We looked for the magnitude of the sub-index to reflect the magnitude of the events that have impacted (exposure) or the population growth (adaptive capacity).

Returning to the results, vulnerability maps have been and will continue to be useful in designing adaptation actions. Donatti et al. (2017) note that having scientific information for decision-making is fundamental; however, they found that some decision-makers do not consider this information in the adaptation process. Therefore, having information on the location of those most vulnerable to climate change aids in the design and management of targeted adaptation actions. Places exist for which the expected temperature and precipitation are unknown, and even less is known regarding the expected impact on crop yield or animal productivity.

Finally, 4 years after the establishment of the special climate change program in Mexico (PECC) is a convenient time to analyze how and where progress in reducing vulnerability can be observed. Figure 3 shows those municipalities identified as the most vulnerable in the country (SEMARNAT 2014). In the most recent period analyzed, 2010, those municipalities have reduced the degree and intensity of their vulnerability compared with 2000. Although the methods followed in the PECC are very similar to those used here, they have different approaches. Hence, the list of vulnerable municipalities is not exactly the same, but quite similar, indicating that vulnerability monitoring is possible. However, as vulnerability is dynamic over both time and space, a review of the indicators used will be necessary to explore the feasibility of improving some or eliminating others.

4 Conclusions

The methods applied in Monterroso-Rivas et al. (2014) are sensitive and respond well to the observed data and to the evaluation of the three dimensions of vulnerability. The present work improves our understanding of vulnerability to climate change, particularly in Mexico. Through the historical study of some variables, past trends in vulnerability were mapped, and the methods used were calibrated for the country.

The results of the three evaluations show that climate exposure in Mexico has increased in recent years as a result of the greater frequency of climatic events (exposure to floods, frost, hail, heavy rains, landslides, and climate change, since they were the variables studied). The number of municipalities with high and very high sensitivity has decreased, but the size of the affected population has not decreased. In contrast, adaptive capacity in Mexico has diminished in recent years. However, both the number of vulnerable municipalities and the population of vulnerable people have declined over the 20 years studied.

We estimated vulnerability for the three different time periods by applying a known method to test whether it is possible to monitor progress and estimate changes in the vulnerability of the country. It was found to be feasible to provide a past value for a present vulnerability, which allows the calibration of the variables and indicators used. Some variables, however, were left unchanged in one or two of the years. This was done because no new information exists or because the variables are assumed to remain constant. Perhaps this is a limitation of the model as we are forcing them to remain fairly constant and to vary only depending on the few variables that were modified. As regards the variables, some may resemble and therefore they appear to be overrepresented. In adaptive capacity, literacy variables (e.g., C1 and C3)

sound similar so they should be evaluated if its application is viable in other countries. Nevertheless, we believe vulnerability monitoring is possible. The economic and social advancement of societies requires that some of the variables determining vulnerability be changed over time.

In the present case, when speaking of vulnerability, care must be taken in what is reported, e.g., the number of inhabitants versus the number of municipalities. For example, fewer sensitive municipalities were reported over time, but the number of people in those municipalities who remain sensitive to climate change has increased. Therefore, the quantification of vulnerability in a comprehensive way, by integrating exposure, sensitivity, and adaptive capacity ($E + S - CA$), can lead to an involuntary underestimation of global vulnerability. Maybe someone really wants to know the global vulnerability but, as we have shown, it is possible that the results may be biased about how much population is exposed, is sensitive, or has little adaptive capacity. It is better to maintain the independence of the three dimensions when analyzing and addressing them and to observe the exposure, sensitivity, and adaptive capacity of individual geographical areas so that they can be studied regionally and better addressed. We believe that the final vulnerability score or value should be estimated only as an indicator of progress or success, as a signal that aids in the directing of resources and policies. But we recognize that it is likely that the applied method does not allow to highlight all changes occurred or made. The approaches to reduce vulnerability, people, or municipalities have to be different so decision-makers need both pieces of information: how many people are vulnerable and where they are located.

Finally, the applied variables must be subjected to ongoing analysis, and the incorporation of new variables (e.g., droughts, high temperatures, winds and soils) must be explored since vulnerability is dynamic.

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