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Municipal Vulnerability to Climate Change and Climate-Related Events in Mexico

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Abstract

A climate change vulnerability index in agriculture is presented at the municipal level in Mexico. Because the index is built with a multidimensional approach to vulnerability (exposure, sensitivity and adaptive capacity), it represents a tool for policy makers, academics and government alike to inform decisions about climate change resilience and regional variations within the country. The index entails baseline (2005) and prediction (2045) levels based on historic climate data and future-climate modeling. The results of the analysis suggest a wide variation in municipal vulnerability across the country at baseline and prediction points. The vulnerability index shows that highly vulnerable municipalities demonstrate higher climate extremes, which increases uncertainty for harvest periods, and for agricultural yields and outputs. The index shows at baseline that coastal areas host some of the most vulnerable municipalities to climate change in Mexico. However, it also shows that the Northwest and Central regions will likely experience the largest shifts in vulnerability between 2005 and 2045. Finally, vulnerability is found to vary according to specific variables: municipalities with higher vulnerability have more adverse socio-demographic conditions. With the vast municipal data available in Mexico, further sub-index estimations can lead to answers for specific policy and research questions.

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Municipal Vulnerability to Climate Change and Climate-Related Events in Mexico†

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Introduction

Mexico is among the most exposed countries to natural hazards in the world (World Bank, 2005; de la Fuente, 2009)[1]. Only last year Mexico experienced one of its worst droughts in seven decades[2], and suffered historical losses in 2010 due to hurricane Alex in northeastern Mexico, and then serious floods in various southern states.

Moreover, recent evidence and predictions indicate that climate change is accelerating and will lead to wide-ranging shifts in climate variability (or indicators) (UNISDR, 2009; IPCC, 2012), with consequent increases in extreme weather events, and associated likely impacts on economic activities closely linked to climate.

Agriculture is one of the sectors that climate change is expected to hit hardest. Extreme weather affects agricultural productivity, and can raise the price of staple grains important to poor households. Mexican agriculture is particularly vulnerable to climate change. The participation of agriculture in the economy has shrunk over the past decades[3], but about 3 million smallholders grow maize, mainly for subsistence. Unfortunately, they do so under very precarious conditions and have restricted ability to adapt given their low income. Rain fed maize production is a critical livelihood strategy for the poor in Mexico. It therefore makes sense to start assessing the potential vulnerability of agriculture to climate change.

This paper develops a multidimensional municipal index that assesses the vulnerability (as defined by the Intergovernmental Panel on Climate Change, IPCC) of the agricultural sector in Mexico to climatic contingencies and climate change. The aim is to better understand how and why vulnerability to climate change and climate variability varies by municipality in Mexico. Akin to the marginality index[4] developed in Mexico in the mid-1990s, such an index could facilitate the (re)design of new interventions for reducing the risk to the most vulnerable populations, especially small subsistence farmers who have limited ability to adapt to adverse economic and climatic events. The index can also be used to improve the targeting of sectoral plans and the current federal system of disaster compensation and

1 "Government Expenditures in Pre and Post Disaster Risk Management" Background Note for World Bank-U.N. Assessment Natural Hazards, Unnatural Disasters: Effective Prevention through the Economic Lens. November 2009.
2 According to the Mexican Government, 21 Mexican states were affected by one of the most intense droughts in the last 70 years. The states mostly affected by this drought are Chihuahua, Coahuila, Durango, San Luis Potosi, Zacatecas and Aguascalientes, which constitute the northern-western and central agricultural areas. The percent of harvest lost in beans for 2010-2011 was around 60 percent and estimated losses amount 100 USD million. (SAGARPA, 2012;)
3 In 2010, agriculture accounted for only 3.6% of GDP, down from 7% in 1980, and 25% in 1970; Baez and Mason, 2008; INEGI, 2010.
4 The marginality index is a policy-oriented indicator, created by the National Population Council in Mexico (CONAPO) that measures the lack of basic public infrastructure, as well as education and material living conditions at the state and municipal levels. It has been based traditionally on census data, and uses the following indicators for its construction: the share of illiterate people over 15 years; the share of people over 15 years without completed primary education; the share of the employed labor force earning less than twice the minimum wage (approx. US$7 per day); the share of people living in households in localities with less than 5,000 inhabitants; the share of people without running water, electricity, sewage facilities, and solid floor materials and the share of households with some degree of overcrowding. Principal component statistical analysis is performed to construct the index which is a normalized Z-score ranging between -3 and 3 standard deviations that correspond to very low and very high marginality, respectively (CONAPO, 2006).

state agricultural subsidies to the most vulnerable groups and sectors. Finally, the proposed methodology and use of comparable municipal information could allow analysts to monitor the progress of new adaptation policies for climate change within the agricultural sector.

Despite important advances in the understanding of vulnerability, quantitative estimates of spatial and temporal vulnerability at the sub-national level are rare, and methodologies for doing this are very much in their infancy.[5] Vulnerability indices have been computed at the national level (in Europe, World Bank, 2009) and at the regional/provincial/district level (districts in India, O'Brien et al. 2004; regional in Brazil, Fontes, 2009), but never nationwide at the municipal level of resolution.

Recently climate change vulnerability indices have been constructed for Eastern European and Central Asian (ECA) countries, including Tajikistan (Fay and Patel, 2008; Heltberg and Bonch-Osmolovskiy, 2010). The Tajikistan indices combined indicators that capture each country's exposure, sensitivity and adaptive capacity to climate change. The Climate Change Vulnerability Index (CCVI) in ECA assesses current vulnerability to climate change, at the regional (Rayons; local municipal subdivision) or provincial (Oblast; Gorno-Badakshan Autonomous Provinces) levels and is useful to integrate and prioritize regional policies. However, due to the lack of data indices cannot be constructed at the more disaggregated municipal level. Much of the data and indicators necessary to compute a municipal level CCVI must be collected on a regular and consistent basis.

Mexico represents a good case to build a CCVI given its high exposure to natural hazards (and climate change) along with a vast amount of data and indicators at state and municipal levels. In addition, Mexico routinely and consistently collects quantitative historical data on climate and temperature, and socioeconomic indicators at municipal and state levels. A geographically disaggregated picture of vulnerability can help with the preparation of adaptation strategies and allocation of financial and technical assistance to municipalities. This would happen in the same manner to poverty maps, in which Mexico has a rich experience, that support the design and financing of anti-poverty policies and programs. Moreover, Mexico has established sound climate change adaptation policies that are necessary to cope with future climate-related threats. These efforts can be complemented by constructing an analytical tool that is useful for policy makers and local governments to prioritize resources and actions necessary to minimize climate change risks in the future.

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5 The literature suggests two existing approaches to assess vulnerability: As an "endpoint', in terms of the amount of damage in a system caused by a particular climate event; and as a "starting point", looking at the existing state of a system before facing a particular phenomenon (Kelly and Adger, 2000). In the "endpoint" approach, vulnerability is a residual of climate change impacts after adaptation; therefore, it is the net impact of climate change (Ribot, 1995; Clark et al, 2000; Luers, 2003). Most index vulnerability assessments have applied the "endpoint" approach looking at historic climatic variability, without making future projections of climate change. Studies based on the "starting point" approach would evaluate the different factors that can cause a society to become vulnerable. This research will assess the social and economic processes that underlie climate vulnerability from a "starting point" approach. We agree that the 'adaptation deficit'—excessive vulnerability to current climate variability—is a good proxy of future vulnerability to climate change (e.g., World Bank 2009b). This has led to our main focus on understanding vulnerability to current climate variability.

The study employs geo-physical data on climate at baseline (2005)[6] and its projections due to climate change (2045), using nine climate models (See Annex). It also relies on household surveys and censuses of municipalities and rural producers (see Annex for a full list of these data sources). A set of indicators thought to be important for assessing agricultural vulnerability were chosen in close consultation with counterparts from the Ministry of Agriculture (SAGARPA) in the Mexican government. All data were merged into a single dataset to conduct the statistical aggregation of the index, after ruling out those variables that showed high endogeneity. Once the final list of variables was selected, these indicators were combined through Principal Components Analysis to compute a vulnerability index at baseline. Then the index was recomputed based on projected climate scenarios. Alternative indicators on climate variability[7] and socio-economic factors for PCA construction were used to verify the stability of the index (see Annex).

The estimates presented here disaggregate vulnerability at the municipal level. The index allows comparisons across space and time. Our main findings suggest that the effects of climate change in Mexico will be uneven across municipalities, regardless of the model employed. Predictions point to higher vulnerability *increases* in central and northern Mexico; and states with the highest vulnerability at baseline are in coastal areas (Pacific coast, Yucatan peninsula and Gulf of Mexico). All models also showed that states with high poverty rates have consistently higher vulnerability at baseline and over the long-term.

Overall, the index shows the highest increases in vulnerability for states such as Zacatecas, Yucatan, Guanajuato, Chiapas, and Chihuahua. Other states, such as Oaxaca, Puebla and Tlaxcala, also show important increases in the index between 2005 and 2045. These states are located in Coastal and Central-Northern regions, with relatively lower levels of human development.

The states that experienced the greatest decreases in vulnerability between baseline and prediction periods are Tabasco, Sonora, Campeche, Sinaloa and Nayarit. Tabasco and Campeche are located in high vulnerability areas subject to floods and hurricanes that affect all types of farmers. However, Tabasco and Campeche have reported relatively lower agricultural losses in the presence of recent climate-related extreme events, due to their participation in Catastrophic Agricultural Insurance (ECLAC, 2008). On the other hand, Sonora, Sinaloa and Nayarit are pacific northern states with relatively high human

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[6] Climate and temperature data included in the analysis cover the period from 1960 to 2005.

[7] A main model was estimated using Growing Degree Days (GDD-Temp) and the coefficient of variation of rain (CVR) as climate variability measures for the 1960-2005 and 2005-2045 periods. An alternative model included more specific climate variability measures such as the total number of frost days (<10 Cº), the number of days with rain above 10mm, the maximum number of consecutive dry days, and the percentage of rain above the high 95 percentile. These indicators were selected because they are well accepted and defined by the literature for Mexico (Peralta et al. 2009; Biasutti et al. 2011)

development and agricultural indicators. These states also diversify their crops substantially and keep a high coverage of irrigation in the agricultural sector[8].

I. Conceptual Framework

The framework for this paper is an adaptation of the IPCC's vulnerability framework, which distinguishes between exposure, sensitivity, and adaptive capacity. The vulnerability of people can be reduced by decreasing the exposure and sensitivity of people, assets and livelihoods to climate risks, and by increasing the adaptive capacity of individuals, households, communities, and governments. Key terms are defined in the Glossary. Figure 1 offers a framework for understanding how exposure, an exogenous driver of vulnerability, interacts with endogenous drivers – sensitivity and adaptive capacity – to create vulnerability and its opposite, resilience. The level of a community's vulnerability determines the frequency and severity of climate change impacts. By contrast, a resilient community will not be significantly impacted by climate change.

Throughout this paper we use terms such as risk, vulnerability, exposure and hazard in very specific ways. There is an ongoing debate on the definitions of these terms, which are used to mean different things by different disciplines. Sorting out the differences in semantics is important for identifying causal relationships between climate change-related risks and human vulnerability, and for designing interventions to help people manage risk and vulnerability. This paper tries to present a coherent approach, focused on how risks associated with climate change may contribute to the vulnerability of individuals and households. In this framework, it is the interaction of exposure and sensitivity to risk, with adaptive actions that determine vulnerability[9]. The IPCC definition characterizes vulnerability (to climate change) as a function of a system's exposure and sensitivity to climatic stimuli and its capacity to adapt to their (adverse) effects (IPCC 2007), which corresponds to outcome (or end-point) vulnerability, but it does not provide a clear definition of these attributes or the relationship between them[10].

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[8] According to the Food and Agriculture Organization's *Aquastat*, Sonora and Sinaloa concentrate over 25 percent of the total irrigated land in Mexico, for both irrigation districts and irrigation units. See http://www.fao.org/nr/water/aquastat/countries_regions/mexico/indexesp.stm

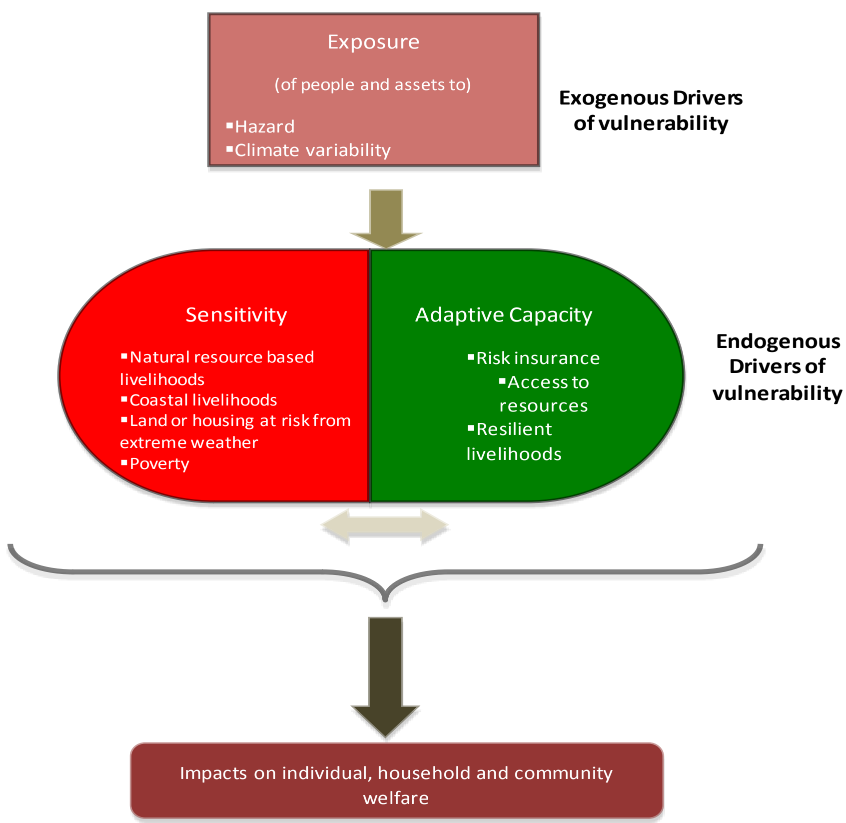
[9] Vulnerability: the extent to which a natural or social system is susceptible to sustaining damage from climate change (IPCC 2001). For practical purposes, this means that a person is vulnerable to climate change risks if he/she has a high probability of becoming poor, sick, or of food insecurity due to climate change related events.

[10] According to Fussel (2009) it is crucial to guide the development of any vulnerability index, or set of indicators. Given the diversity of decision contexts that can be informed by climate change vulnerability assessments and of normative preferences, the design of vulnerability indices is as much a political as a scientific task. Normative differences may strongly influence the combination of diverse information sources into an aggregated vulnerability index. Normative challenges include the aggregation of future and current climate risks.

As one will notice, in Figure 1 we have further adapted the IPCC vulnerability framework. In practice, it is difficult distinguish what counts as sensitivity and what is adaptive capacity, since they both deal with similar issues. For example, poverty is a good indicator of a community's sensitivity; since poor communities are often more sensitive to impacts from climate change, however, the lack of income and access to resources are important characteristics of adaptive capacity. The same can be said for other issues. For example, forest cover prevents soil erosion and run-off, thereby increasing adaptive capacity, simultaneously, the loss of forest cover makes it so erosion and soil run-off are more likely a result of climate exposure, which means that the communities become more sensitive.

So to separate issues such as poverty or forest cover into separate categories is problematic. For this reason, we have separated exogenous drivers of vulnerability (exposure) - which are not immediately impacted by human activity (excluding the role humans play in carbon emissions) – from endogenous drivers of vulnerability such as sensitivity and adaptive capacity. Sensitivity and adaptive capacity are basically two sides to the same coin in that the former refers to characteristics that increase vulnerability and the latter refers to traits that reduce it.

Figure 1 - Conceptual Framework: Drivers of vulnerability and impacts from climate change



II. Data Sources

The units of analysis for this study are 2,200 of the 2,454 municipalities in Mexico. The conceptual framework proposed requires variables that capture exposure, sensitivity and adaptive capacity to estimate vulnerability. The analysis uses four types of information: (i) historic and projected changes in precipitation and temperature, weather and climatic shock data, and use of specific variability indicators (frost and drought days, rain level variation and extremes); (ii) agricultural production, socio-economic conditions, infrastructure, and geographic data; (iii) poverty rates and other population-related variables; human, social and financial capitals; historical subsidies and transfers to municipalities; and (iv) climate scenario projections based on scientific climate models (see Annex).

Agricultural and socio-economic data come from the Agroalimentary and Fisheries Information Service (*Servicio de Información y Estadística Agroalimentaria y Pesquera*—SIAP) of the Ministry of Agriculture (SAGARPA). Weather data comes from meteorological stations and the National Weather Service (*Servicio Meteorológico Nacional*—SMN, and the *National Water Commission* (CONAGUA)); and all climate models (including the projections of temperature and rainfall) are credited to the Coupled Model Intercomparison Project Phase 3 (CMIP3) of the World Climate Research Programme (WCRP) referenced in the Intergovernmental Panel on Climate Change's (IPCC) Third and Fourth Assessment Report. Poverty rates were obtained through small area estimation techniques using data from the Income and Expenditure Household Survey (ENIGH) and the Count of Population and Housing 2005. Population data come from the National Population Council (CONAPO). Finally, important indicators were collected from the Summary Statistics of the 2007 Agricultural Census (INEGI). All data are available at the municipal (county) level. (See Annex Figure I and Table 1 for summary statistics and a detailed explanation of their construction.)

The selection of variables for each component was made in consultation with officers at the Ministry of Agriculture in Mexico, and by reviewing relevant literature. A large fraction of the population in municipalities relies also on rain fed Maize production as the main economic activity. Climate-related indicators show large variability across municipalities. For instance the standard deviation of annual rainfall (mm) is almost the same as the average annual rainfall. The maximum rain levels reported in municipalities is almost ten times the average rainfall. Socio-demographic characteristics also vary considerably. There are municipalities with practically no access to services, while others have almost universal coverage. In a similar fashion, infant mortality and poverty rates show large standard deviations with respect to their means. Finally, some agricultural variables are measured in agricultural production units[11], and not necessarily relative to households or populations.

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[11] Concept defined by the Ministry of Agriculture (SAGARPA) and by the 2007 Agricultural Census, where a production unit refers to formal production arrangement of more than one individual to exploit individual or communal land. Therefore, there can be multiple production units headed by households or one production unit (farming companies) in leased collective land.

III. Methodology - PCA Method to Build Multi-Dimensional Indices

Principal Components Analysis (PCA) was used to build a composite index for climate-related vulnerability. Because of the complexity of interactions between social, economic, climatic, disaster and agricultural dimensions, using the PCA method to aggregate variables into a single index is an efficient way to construct risk categories.

The primary problem when constructing a PCA index is the choice of *component indicators*. Most indices use only a few variables, but the principal components methodology allows the use of a *large* number of continuous variables[12]. As stated earlier, the variables were selected to capture the exposure, sensitivity and adaptive capacity of households and communities to climate-related shocks or events. Choosing appropriate component indicators minimizes errors and differences in measurement across municipalities. At the same time, the variables must fit consistently into the same general categories mentioned.

PCA creates uncorrelated indices or components, where each component is a linear weighted combination of the initial variables.

$$PC_1 = a_{11}X_1 + a_{12}X_2 + \cdots + a_{1n}X_n$$
:
:
$$PC_m = a_{m1}X_1 + a_{m2}X_2 + \cdots + a_{mn}X_n$$

where a_{mn} represents the weight for the mth principal component in the nth variable. The weights for each principal component are given in the correlation matrix, or if the original data were standardized, a covariance matrix (multi-dimension correlations). In the case where multiple variables interrelate, covariance matrices are used as weights. The components are ordered so that the first component (PC1) explains the largest possible amount of variation in the original data, subject to the constraint that the sum of the squared weights (a^2_{11+} $a^2_{12+\ldots+}$ a^2_{1n}) is equal to one.

The second component (PC2) is uncorrelated with the first component, and explains additional but less variation than the first component, subject to the same constraint. Subsequent components are uncorrelated with previous components; therefore, each component captures an additional small variation with respect to other variables within the data, while explaining smaller and smaller proportions of the variation of the original

[12] Data in categorical form are not suitable for PCA, as the categories are converted into a quantitative scale which does not have any meaning. To avoid this, qualitative categorical variables should be re-coded into binary variables. Another data issue is that of missing values. Cortinovis et al. (1993) excluded households with at least one missing value from their analysis to develop socio-economic groups. Gwatkin et al. (2000) replaced missing values with the mean value for that variable. Given that some indicators might have few observations by Municipalities in certain surveys, it is convenient to replace the mean value of each geographical unit.

variables. The higher the degree of correlation among the original variables in the data, the fewer components required.

Once the specific variables have been detailed, two interrelated issues must be addressed concerning the construction of a PCA index. The underlying variables need to be converted to compatible scales so they can be combined to produce a single index. All variables were transformed into a normal standard distribution with a mean of 0 and standard deviation equal to unity. The second issue is the choice of weights for each of variable. The issue is not just to give the appropriate weight to each of the component statistics, but also to take into account any correlation between the component statistics. Ultimately, the weights calculated at baseline (2005) for the CCVI are structurally the same weights used for the predicted scenarios in 2045.

The variance (λ) for each principal component is given by the eigenvalue of the corresponding eigenvector. As the sum of the eigenvalues equals the number of variables in the initial data set, the proportion of the total variation in the original data set accounted by each principal component is given by $\lambda i/n$. The second component (PC2) is completely uncorrelated with the first component, and explains additional but less variation than the first component, subject to the same constraint. Subsequent components are uncorrelated with previous components; therefore, each component captures an additional dimension in the data.

McKenzie (2004) highlights that a major challenge for PCA-based indices is to ensure the range of variables included have enough non-missing values to avoid problems of 'clumping' and 'truncation'. In the case of our index, we used a wide variety of variables collected as administrative records, or from CENSUS data (population and agricultural). In this sense, non-missing data in each municipality are relatively small so clumping and truncation are not affected by estimation errors. In addition, according to McKenzie (2004) the problems of clumping or truncating indices can affect the variability of the index, so the first principal component needs to be constructed for each municipality relative to its standard deviation, instead of using the standard deviation of the all municipalities.

Construction of Weights

Weights Based on Component Variance Explained at Baseline

Discriminating variables through PCA can be helpful in selecting the weights to construct the index based on the amount of variance explained for each component. The proportion of variance explained by each relevant variable is a strategy also used to weight them. The principal factors or components that explain the outcomes in the data always explain in a larger proportion the variance compared to the rest of the components. The position of each observation with the proportion of variance explained according to each component is calculated as a linear combination of the original variables. A simple regression using the principal component variables and the outcome variable would reproduce almost the exact same weights as the proportion of variance explained by each component, so:

$$Y_{kr} = a_{k1}X_{k1} + a_{k2}X_2 + \cdots + a_{kp}X_{kp}$$

In interpreting the principal components, it is often useful to know the correlations of the original variables with the principal components. The correlation of variable Xi and principal component Yj is

$$r_{ij} = \sqrt{a_{ij}^2\, Var(Y_j \big/ S_{ii}}$$

But weighting based on the percent of variance explained by each factor also involves a certain amount "rule of thumb". One common criterion is to use principal components at the point at which the next principal component offers a large increase in the total variance explained and weights can be used at baseline and prediction points. A second criteria is to include all those PCs up to a predetermined total percent variance explained (structural weights), such as 90%. A third standard is to ignore components whose variance explained is less than 1 when a correlation matrix is used or less than the average variance explained when a covariance matrix is used[13].

Estimation Procedure

We ran several specifications to estimate the CCVI. The models incorporated variables with the highest explanatory power. In addition, variables were added in the models to test the stability and sensitivity of the index. This proved to be helpful in reducing the amount of variables used to construct the index without losing conceptual rigor[14]. In addition, testing multiple variables for estimating the index helped to identify and remove endogenous variables and substitute them with variables that better fit the model.

All variables were standardized into a normal distribution, and outliers were removed to build the index. Outliers were identified based on the method by Davies and Gather (1993). The distribution of outliers was tested by constructing cutoff points for the index. The cutoff points were then used to test each variable for each municipality. When a variable failed to pass the Bonferroni's correction, which sets the alpha-value for the entire set of n comparisons equal to alpha, by taking the alpha-value for each comparison equal to alpha/n, it was not included in the model: when the value is half a percent point within an extreme cutoff point then the value was considered an outlier. Around 10 to 25 municipalities were withdrawn from the index estimation as outliers representing 0.1

[13] The distributions of each variable should be checked for normality and transforms used where necessary to correct high degrees of skewness in particular. Outliers should be removed from the data set as they can dominate the results of a principal components analysis.

[14] Annex show results for other PCA models run as robustness and index sensitivity tests.

percent of the total number of municipalities. There were three specifications used to estimate the index. The higher the consistency of index distribution and the ranking (of municipalities), based on relative risk, the better the model fit. In addition, models were built with and without outliers to verify the influence that outliers had on the index distribution.

Endogeneity tests were carried to eliminate variables. In some cases endogenous variables were substituted with proxy ones. Once endogenous variables were identified and removed, the estimation procedure was improved by incorporating other indicators collected at the municipal level that strengthened the conceptual model and proxy for relevant characteristics. For instance, Table 2 shows the endogeneity tests in four variables, all of them endogenous. In the case of total population, the variable showed considerable endogeneity because many indicators are estimated as proportions or percentages of population. Population growth substituted total population. The index was then re-estimated without endogenous variables.

Table 2 Endogeneity Tests for Some Index Variables

Variable	Observations	Sum of Residual	Durbin–Wu–Hausman Endogeneity Test (F-test)	P-value	Endogenous
Proportion of Indigenous Population	2396	1.8E-08	95.49	0.000	Yes
Cattle and non-farming activities	2447	-5.0E-10	38.82	0.000	Yes
Non-access to Health Services	1046	-2.8E-08	80.24	0.000	Yes
Total Population	2449	-2.0E-04	95.49	0.000	Yes

Source: Own estimations based on CCVI dataset

Sensitivity tests and different PCA specifications[15] were estimated to verify the changes in index distribution and rankings. Abrupt changes in rankings are indicative of an unstable index which may display an inadequate vulnerability risk distribution. Figure 2 shows the minimum and maximum values of the index at the state level using nine different prediction models with climatic scenarios. Consistent changes in risk are predicted across states for minimum and maximum index levels. That is, except for a few states, all models predict changes in the same direction.

The index ranges from -0.78 (Very Low Vulnerability) to 1.91 (Very High Vulnerability) with a S.D. of 0.652 and an Average of 0.525. The criterion for building the 5 vulnerability cohorts was based on equal counts. Out of the 2,456 municipalities in Mexico, the PCA model kept 2,257 municipalities with valid data for the main estimation specification[16].

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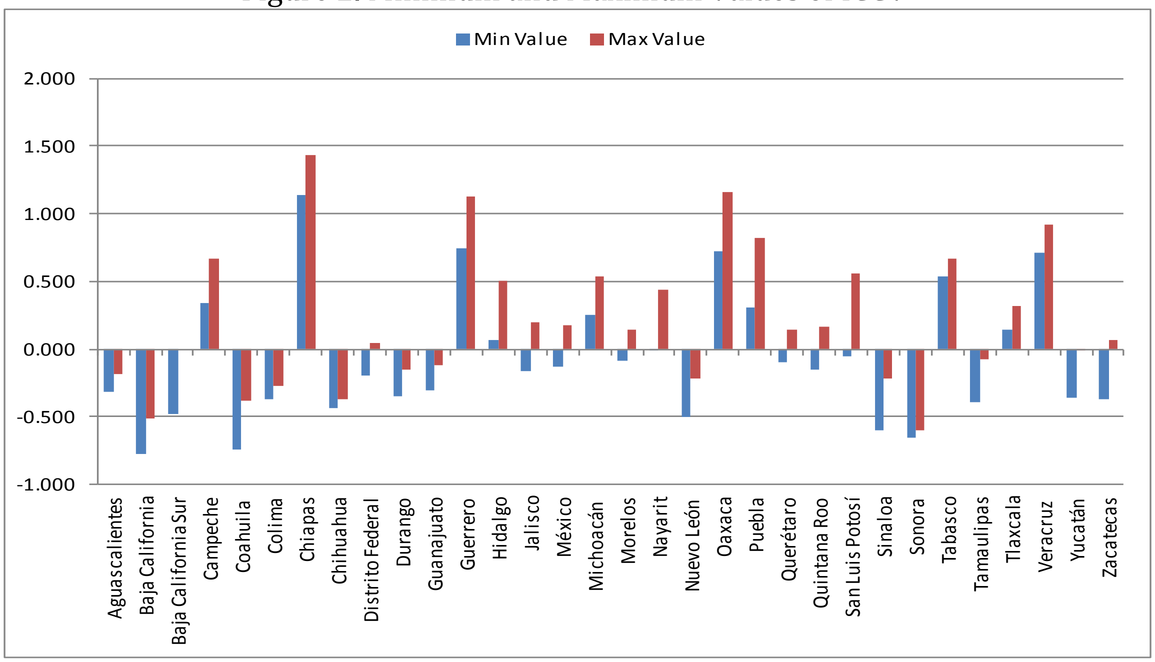
[15] The full specification model included the following core variables: drought risk; number of reported environmental risks, yield Loss due to weather; temperature and precipitation; percentage of farmers receiving remittances; percentage of farmers that belong to organizations; percentage of agricultural production units without irrigation systems; percentage of population in agricultural activities; hectares for agricultural, forestry, and cattle activity; poverty rate; Farmers lacking credit; Federal disaster assistance per capita. Upon these variables different specifications were modeled to build the index by adding and replacing variables. The more variables included, the more restrictive the model.

[16] The specifications for robustness checks and sensitivity kept 2,240 and 2,100 municipalities, respectively.

The difference between the minimum and maximum values of the index in all seven models is on average 0.299. Not a single state showed differences higher than 1. Only two states (Colima and Zacatecas) show changes in the vulnerability index from negative to positive, or vice versa. However, the differences in the index levels between baseline and prediction points are statistically significant for the states of Baja California, Campeche, Chiapas, Nayarit and Sonora[17]. It is worth considering such shifts and heterogeneity prevailing at the municipal level to better identify vulnerability risk profiles over different periods of time. The preliminary results and rankings (state level) based on risk vulnerability are shown in the next section.

Figure 2. Minimum and Maximum Values of ICCV



Source: Own estimations

IV. Index Results and Profiles

This section presents estimates of the municipalities that are the most vulnerable to climate change and climatic disasters. This study only estimates a composite index, not its parts.

[17] Based on mean differences t-test values for unequal standard deviations at 90% level.

Where Are the Most Vulnerable Municipalities?

Overall, the study results suggest a wide variation in municipal vulnerability across the country. The most vulnerable municipalities are located along the coastlines and in many Southern areas, in line with findings from similar work in Mexico (IMTA, 2009; Martinez-Austria, 2007). The Northern and Central parts of the country are comparatively less susceptible to climate change and variability, but with some pockets of high vulnerability.

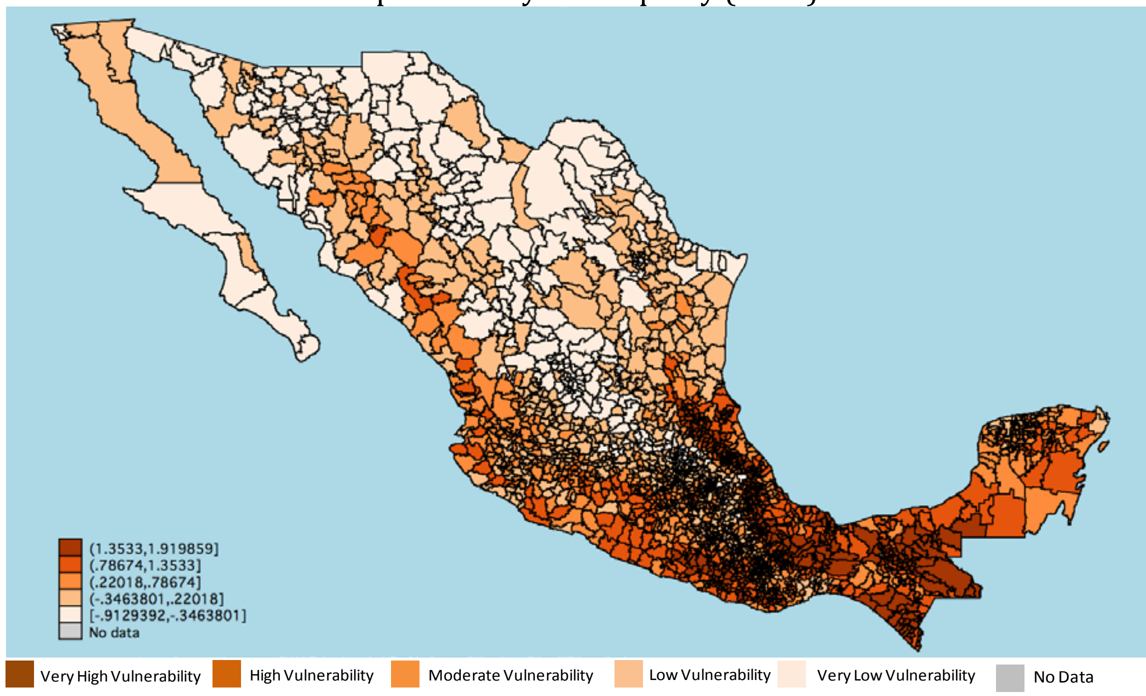
Coastal areas host some of the most vulnerable municipalities to climate change in Mexico. This is likely due to the relatively high exposure of these municipalities to hurricanes and the increased risk of flooding that comes in these areas. The drier northern and central regions of Mexico also face high exposure given recurrent droughts and a lack of protective vegetation.

The southern states of Mexico appear to be the most vulnerable to climatic events in the entire country. Many municipalities in the southern states of Guerrero, Oaxaca and Chiapas display the highest levels of vulnerability. With large and highly impoverished indigenous populations, it comes as no surprise that their relative capacity to manage climate risk is lower than other areas. By contrast, the tourist areas on the Yucatan Peninsula have a high capacity to adapt to climate change. The tourist industry has led to higher incomes, lower poverty rates, and thus less sensitivity and higher adaptive capacity. Again the north displays higher resilience than elsewhere, and this could be due to its better socio-economic development and higher access to remittances. But there are also pockets of high vulnerability in northern states. States like Chihuahua contain high vulnerability pockets due to prolonged droughts that are increasingly prevalent among the poorest Tarahumara territories. Recent droughts have affected mainly the north and central parts of the country –the states of Durango, Chihuahua, Coahuila, San Luis Potosí and Zacatecas– where the economy relies strongly on agricultural activity[18].

The estimation of the CCVI permits mapping using baseline and prediction points. Maps 1 and 2 show the spatial distribution of the CCVI in 2005 and 2045, respectively. Coastal regions show high vulnerability persistence particularly in the pacific south and Yucatan peninsula over the next 20 years. Other high-poverty incidence municipalities in the north-west show increasing vulnerability, in part due to predicted increases in temperatures.

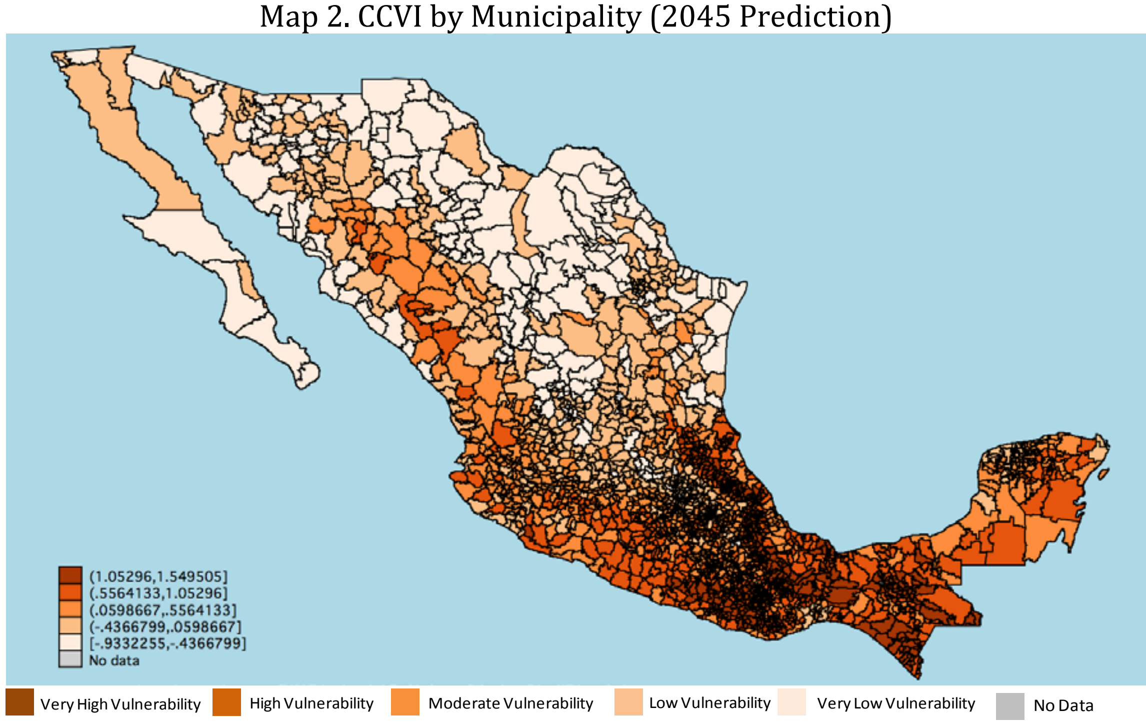
[18] The federal government through the CONAGUA (National Commission of Water) is also taking action to provide relief to Mexicans suffering from drought. As of January 2012, CONAGUA reported to have spent nearly 60 million pesos (5.4 USD million) to support the Tarahumara men and women. Part of the government's relief efforts is to provide temporary employment to the Tarahumara whose farming suffered significantly from the drought. Employment may include cleaning of the existing water bodies, channel and ditches dredging and building of dams. CONAGUA is also inspecting Mexico's water systems to ensure water provision even during times of drought. It is recognized that much of Mexico's water systems are inefficient due to leakages, and that infrastructure improvements must be made to prevent droughts from having such serious impacts on Mexico's people in the future.

Map 1. CCVI by Municipality (2005)



Note: Darker colors imply higher vulnerability
Source: Own Estimations

Map 2. CCVI by Municipality (2045 Prediction)

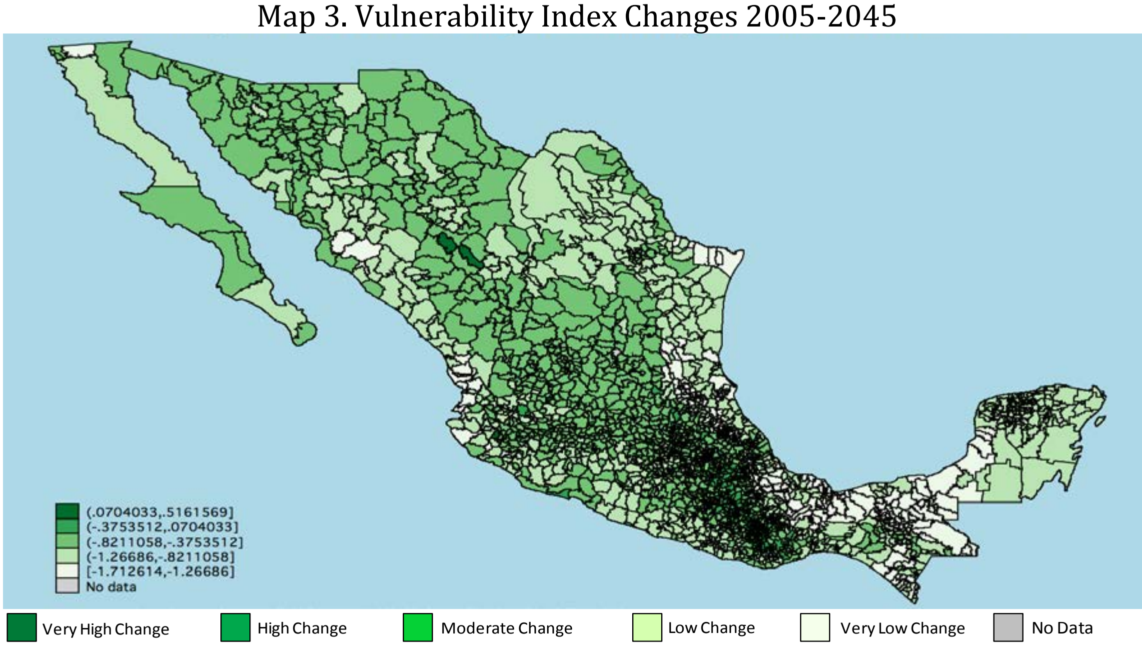


Note: Darker colors imply higher vulnerability
Source: Own Estimations

Beyond the climate change vulnerability levels in agriculture, it is relevant to identify the areas or regions where vulnerability shows the ***highest relative changes between 2005 and 2045***. Map 3 shows that most of the municipalities with the biggest changes are concentrated in Central Mexico (*Bajio*). This finding is in line with previous environmental and climate change studies conducted in Mexico (Martinez, 2010; IMTA, 2009; Martinez and Fernandez, 2004; Martinez-Austria, 2007). A number of studies predict a 10 percent reduction in water availability for agriculture between 2030 and 2050 for northwest and central Mexico (Bajio). This will especially impact states such as Sonora, Guanajuato, San Luis, that will experience critical water shortages in the predicted scenarios (Martinez, 2010). In addition, Martinez and Fernandez (2004) report that the regions with highest risk of vulnerability for the next 40 years correspond to the Bajio central region (including states such as Guanajuato and San Luis Potosi). Other states located in the Bajio region (Hidalgo and Queretaro) could experience a large shift in their vulnerability risk in the absence of investments for climate change adaptation. The reasons given to explain this shift into high vulnerability vary from water availability and temperature changes, to soil degradation and poor implementation of adaptation policies.

Martinez-Austria (2007) indicates that drought vulnerability risks will be a particular concern for national and regional policies in the northwestern region of the country due to the predicted change between 3 to 4 degrees (Cº) by 2040. The predicted shifts in territorial vulnerability associated with droughts in the *Bajio* and Northwestern regions are also confirmed in a recent study by the Mexican Institute for Water Technology (IMTA, 2009). According to this study, climate predictions for 2025 suggest risks of water shortages in northern and central regions in Mexico, where irrigated surface land will accelerate water scarcity over the years.

Map 3. Vulnerability Index Changes 2005-2045



Note: Darker colors imply higher change in index between baseline and prediction points
Source: Own Estimations

Who Are the Most Vulnerable?

The purpose of this paper is to identify which social groups in rural Mexico are the most vulnerable to climate change. First, we show how vulnerability profiles change across municipalities from baseline to prediction points. The purpose is to assess the probability and number of municipalities falling into different categories of vulnerability at baseline and prediction points[19]. Second, the municipal vulnerability profiles relate index estimates at baseline and prediction points to three different sets of variables: 1) climate indicators, 2) farmer categories, and 3) socio economic characteristics.

Changes in Vulnerability Risk Profiles

The risk profile of municipalities is shown in table 3a. Overall, almost three of every four municipalities (around 1,810 out of 2,454) do not show substantial changes between baseline and prediction points. Additionally, 344 municipalities increase their vulnerability risk, compared to 300 showing reductions in vulnerability reductions. Both sets of winners and losers are profiled below. Although shifts in vulnerability risk may not appear substantial, the fact that over a third (34.6%) of municipalities maintain high vulnerability, particularly in coastal (Pacific and Gulf) areas is relevant. The conditional probability of high vulnerability municipalities at the prediction point, having shown a high vulnerability risk at baseline, is 41%. This percentage is similar for the conditional probability of municipalities being in low vulnerability risk at baseline and prediction points (39%). Some authors stress that economic impacts in agriculture from climate fluctuations are substantial if high risks prevail over time (Deschenes and Greenstone, 2007; Lobell and Asner, 2003).

Table 3 Conditional Probabilities of Vulnerability Risks Changes Baseline and Prediction Points

Categories of Vulnerability Risk		**High Vulnerability at Baseline**	**Moderate Vulnerability at Baseline**	**Low Vulnerability at Baseline**
High Vulnerability at Prediction	Probability	*0.406*	**0.099**	**0.012**
	Number of Municipalities	850	141	23
Moderate Vulnerability at Prediction	Probability	**0.056**	*0.238*	**0.127**
	Number of Municipalities	89	218	180
Low Vulnerability at Prediction	Probability	**0.068**	**0.051**	*0.391*
	Number of Municipalities	140	71	742

Note: Numbers in Italics indicates no Change in Index Category between Baseline and Prediction

Source: Own estimations

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[19] Categories are: Very High Vulnerability, High Vulnerability, Moderate Vulnerability, Low Vulnerability, Very Low Vulnerability.

States such as Zacatecas, Yucatan, Chiapas, Guanajuato, Chihuahua, Oaxaca and Puebla exhibit the highest increases in vulnerability over time. Other states such as Campeche, Tabasco, Sonora, Sinaloa and Nayarit showed reductions in their vulnerability risk profiles between baseline and prediction points. In general, the index predictions show that high vulnerability will prevail in southern coastal areas (gulf and pacific) with a tendency to increase vulnerability in the central-norhtern basin (*Bajio*) states.

States shown in Table 3a have the highest increases and decreases in vulnerability index changes between baseline and prediction points. However, there are municipalities that rank highest in terms of index increases and decreases that may or may not belong to the states presented in Table 3a. For instance, Oaxaca has 124 municipalities with an increase higher than 0.25 in the index between baseline and prediction points (such increases are higher than the mean increase of 0.069 in the index), but the rest of the 570 municipalities in Oaxaca have relatively lower increases than the average.

Table 3a Highest Increases and Decreases in Vulnerability (2005-2045) by State

Highest Increase

	Index				
State	**Change**	**BL**	**Prediction**	**Vulnerability at Baseline**	**Vulnerability at Prediction**
Zacatecas	0.3749	-0.3273	0.0476	Very Low	Low
Yucatan	0.2667	0.5469	0.8136	Moderate	High
Guanajuato	0.1897	-0.2409	-0.0513	Very Low	Low
Chiapas	0.1725	1.3906	1.5631	Very High	Very High
Chihuahua	0.1544	0.1014	0.2558	Low	Moderate

Highest Decrease

	Index				
State	**Change**	**BL**	**Prediction**	**Vulnerability at Baseline**	**Vulnerability at Prediction**
Tabasco	-0.4630	1.1752	0.7122	Very High	High
Sonora	-0.4075	-0.0196	-0.4272	Low	Very Low
Campeche	-0.4038	0.7842	0.3804	High	Moderate
Sinaloa	-0.3407	-0.0064	-0.3471	Low	Very Low
Nayarit	-0.3246	0.6354	0.3108	High	Moderate

Source: Own estimations

Tables 4a and 4b present municipal vulnerability profiles in relation to key climate, social, and agricultural indicators. Risk categories of the index are divided in five cohorts (Very Low, Low, Moderate, High and Very High) of vulnerability. With municipalities arranged by categories of vulnerability at baseline, it is possible to construct socio-demographic and agriculture municipal level profiles. Such profiles bring additional information about the patterns of risk in the advent of climate change In terms of climate variables, municipalities with elevated vulnerability levels show higher climate extremes as measured by frost days and consecutive dry days, in both baseline and prediction points. In addition, municipalities under most vulnerable categories show an increase in the Coefficient of Variation of Rain and the Growing Degree Days (GDD) between baseline and prediction points. The shifts in this last indicator are important for assessing the suitability of a region for producing a particular crop, and to better estimate harvest dates.

Municipalities with high levels of vulnerability also have the highest ratio of increase of rain's coefficient of variation. The larger is the rain variability, the higher is the uncertainty for harvest periods for agricultural yields and outputs. In Mexico irrigated agriculture contributes about 50% of the total value of agricultural production and accounts for about 70% of agriculture exports (CONAGUA, 2008). However, the rest of agriculture depends to a larger extent on temporal or seasonal harvesting. The risks confronted by municipalities in terms of rain and temperature changes could shape the changes in cropping patterns (planting multiple crops with different vulnerabilities to weather events), irrigation systems (to decrease the farmers dependence on precipitation), farm incomes, and financial instruments available to famers to strengthen resilience.

Table 4c presents the distribution of vulnerability risk by type of agricultural producer. This table shows that larger producers are more resilient and less likely to be present in highly vulnerable municipalities. On the other hand, small and subsistence producers are more likely to live in highly vulnerable municipalities, and municipalities that will experience a high increase in vulnerability during 2005 - 2045. Low-capital intensity producers with large land sizes face the largest shifts in vulnerability between baseline and prediction points. These types of larger land-size producers often have higher rates of participation in subsidized agricultural programs. On the other hand, small land-size producers with intensive or non-intensive capital requirements, located at a higher proportion within highly rural municipalities, are more likely to be in highly vulnerable municipalities.

Table 4a also shows consistently that higher vulnerability risk is associated with less favorable socio-economic conditions. Municipalities situated within the "low vulnerability" categories show substantially lower average proportions of a) indigenous populations, b) households with elderly members, and c) households with dirt floors; compared to municipalities situated within "high vulnerability" categories. The dispersion of these socio-economic indicators also increases as vulnerability risks become higher.

The profiles are also shown for agricultural and income support variables (Table 4b). In this regard, the percentage of agricultural workers having liquid savings reduces considerably from 12.4 (for municipalities under the "very low vulnerability" category) to 1.8 percent (for municipalities under the "very high vulnerability" category). Moreover, the number of agricultural workers having outstanding credit debt for their economic activity increases as vulnerability risk increases. The average support of agricultural programs devoted to farmers does not vary substantially, but municipalities with lower vulnerability profiles tend to receive marginally higher transfers from these programs. The profiles for these variables indicate how farmers use financial instruments and other financial mechanisms to cope with vulnerability, which brings up front information useful to improving the targeting and redistributing options of current support programs and financial products.

Finally, the risk profiles are presented according to pairwise correlations between the index (at baseline and prediction points) and the socio-demographic variables in Table 4c. The results show, first, that municipalities with higher vulnerability risks have higher indigenous populations at baseline and prediction points—as shown by a positive and significant correlation. Although the correlations are not as high, there is a positive association between higher vulnerability and adverse housing conditions. Such correlations become higher as vulnerability becomes higher. The highest correlations within socio-demographic characteristics are found when households have a higher rate of elder dwellers. These living arrangements may enhance household risks to climate change through exposure, sensitivity and adaptive capacity factors. Mexico reflects high levels of family care-giving for the elderly and a high degree of continuity of parent-child co-residence over the life-course (Kanaiaupuni, 2000) fed by economic conditions and demographic patterns. Mexico will face a substantial increase in elderly populations over the next 20 years, so there may be higher vulnerability risks under these care-giving arrangements[20].

And limited access to support programs or savings (for smallholder populations), is associated with higher the levels of vulnerability. Remittances show a negative correlation with the vulnerability index at both baseline and prediction points. High vulnerability is associated with lower levels of remittances influx by municipality. Access to different forms of capital "insures" families from several forms of uncertainty. The complex migration patterns found in municipalities across Mexico are usually undertaken to insure families via remittances, which is often a result of stress-induced movements (conflict) or through resource constraints (climate change) (Schreider and Knerr, 2000; Fiki and Lee, 2004).

With the advent of climate variability and uncertainty, many small landholders will face risks of being forced to abandon agriculture, due to financial losses and the burden of debt. Improved financial instruments used to ease debt arising from agricultural credits, and financial support to improve farming activities, could in turn improve the adaptive capacity of exposed and climate sensitive farmers.

[20] Another interpretation is that a large elderly population contributes to low adaptive capacity/high sensitivity because they are not economically active, and thus more likely to be in poverty.

Table 4a Profiles of Vulnerability Risk
(Baseline Socio-economic/Climate Variables)

Risk Category **/ Statistics	CCVI Index	Index Prediction (2045)	Percent of Indigenous Population	Percent of Households with Dirt Floors	Percent of Elderly (65+) Population	Rain Coefficient of Variation	GDD
All							
Mean	0.349	0.557	24.463	10.263	7.896	0.281	9.385
Range	2.483	2.708	100.000	95.314	30.041	0.797	451.937
Standard Deviation	0.582	0.652	35.627	18.640	3.834	0.072	26.405
Percentile 5	-0.538	-0.448	0.204	0.000	3.632	0.190	1.884
Percentile 95	1.361	1.687	98.815	56.978	15.624	0.408	13.997
N	2433	2356	2455	2454	2454	2451	2451
Very Low Vulnerability							
Mean	-0.315	-0.282	4.103	0.879	7.378	0.266	6.456
Range	0.717	1.406	90.772	41.043	28.882	0.461	433.954
Standard Deviation	0.168	0.254	11.528	3.048	3.338	0.067	20.380
Percentile 5	-0.610	-0.746	0.151	0.000	3.679	0.234	1.722
Percentile 95	-0.093	0.105	19.883	5.420	13.449	0.442	11.039
N	450	451	451	451	451	451	451
Low Vulnerability							
Mean	0.108	0.171	11.299	2.841	9.399	0.275	9.580
Range	0.348	1.225	99.448	56.501	29.251	0.480	451.724
Standard Deviation	0.104	0.203	21.790	7.465	4.852	0.068	34.682
Percentile 5	-0.055	-0.183	0.163	0.000	3.807	0.217	1.139
Percentile 95	0.260	0.501	70.433	17.177	19.069	0.422	13.758
N	474	474	474	474	474	474	474
Moderate Vulnerability							
Mean	0.420	0.492	25.169	8.603	8.801	0.293	11.08
Range	0.350	1.146	100.000	95.314	28.472	0.363	443.75
Standard Deviation	0.101	0.217	34.580	16.530	3.883	0.048	36.18
Percentile 5	0.296	0.094	0.217	0.000	4.094	0.201	1.00
Percentile 95	0.610	0.819	97.478	52.536	16.702	0.350	14.19
N	430	429	430	430	430	430	430
High Vulnerability							
Mean	0.745	0.887	35.049	14.384	7.706	0.305	10.20
Range	1.098	0.541	100.000	84.475	24.051	0.266	435.50
Standard Deviation	0.211	0.157	39.813	20.431	3.190	0.044	20.49
Percentile 5	0.384	0.648	0.293	0.025	4.142	0.194	2.51
Percentile 95	1.085	1.130	99.500	61.246	14.038	0.337	14.40
N	448	450	450	450	450	450	450
Very High Vulnerability							
Mean	0.788	1.521	40.396	20.449	6.690	0.369	19.59
Range	2.483	0.746	100.000	91.217	26.562	0.785	443.82
Standard Deviation	0.745	0.193	41.562	24.060	3.137	0.092	17.47
Percentile 5	-0.707	1.204	0.284	0.000	3.014	0.174	3.48
Percentile 95	1.455	1.809	99.666	67.686	12.500	0.446	14.03
N	631	552	650	649	649	646	646

*** Vulnerability cutoff points based on baseline index*

Source: Own estimations

Table 4b Profiles of Vulnerability Risk

(*Baseline Agricultural and income support variables*)

Risk Category **/ Statistics	% of Agriculture workers with Savings	% of Agriculture workers with credit	Average Agriculture support in Pesos 2009 *	% of Agriculture workers receiving remmitances
All				
Mean	5.08	34.12	381.64	3.09
Range	40.79	100.00	999.80	37.58
Standard Deviation	2.78	28.39	311.50	4.49
Percentile 5	0	0	0.5219	0
Percentile 95	6.95	87.79	932.24	12.18
N	2447	2447	1212	2447
Very Low Vulnerability				
Mean	12.37	30.41	454.43	3.89
Range	40.79	98.82	999.80	25.18
Standard Deviation	3.02	22.61	303.86	4.53
Percentile 5	0.00	0.00	2.78	0.00
Percentile 95	6.73	79.57	951.92	13.04
N	451	451	229	451
Low Vulnerability				
Mean	8.40	31.54	440.53	3.43
Range	26.14	100.00	999.20	24.27
Standard Deviation	2.98	28.59	296.09	4.36
Percentile 5	0.00	0.00	15.17	0.00
Percentile 95	8.43	85.10	918.82	11.97
N	474	474	216	474
Moderate Vulnerability				
Mean	6.20	37.45	377.80	3.85
Range	33.01	100.00	997.13	37.13
Standard Deviation	3.28	28.87	287.97	5.38
Percentile 5	0.00	0.00	16.01	0.00
Percentile 95	7.62	88.15	941.41	14.55
N	430	430	184	430
High Vulnerability				
Mean	2.72	41.86	341.82	3.03
Range	12.48	98.99	991.09	37.58
Standard Deviation	1.96	29.56	318.44	4.55
Percentile 5	0.00	0.00	4.07	0.00
Percentile 95	5.84	89.09	922.48	12.36
N	450	450	181	450
Very High Vulnerability				
Mean	1.81	45.75	340.55	1.80
Range	22.39	100.00	997.49	34.43
Standard Deviation	2.50	30.40	322.52	3.45
Percentile 5	0.00	0.00	0.00	0.00
Percentile 95	6.35	89.14	927.52	7.26
N	642	642	402	642

* Averages computed for those municipalities that received support; some municipalities don't receive support in that year, but they are still beneficiaries.

** Vulnerability cutoff points based on baseline index

Source: Own estimations

Conclusion

Mexico is in constant threat of experiencing natural disasters, and is among the most exposed to climatic hazards in the world. Recent evidence and predictions indicate that climate changes are accelerating and will lead to wide-ranging shifts in climate variables. Agriculture is one of the sectors where climate change is expected to hit hardest. Little quantitative evidence has been produced to aggregate multidimensional aspects of livelihoods, socio-demographic and economic characteristics, and climate change historic and predicted scenarios. With rich data available for most (2,200 of 2,450) municipalities in Mexico, a statistical technique (Principal Components Analysis) was applied to estimate a Vulnerability Risk Index in Agriculture for baseline (2005) and prediction points (2045). The aim of this analytical tool is to better understand how and why vulnerability to climate change and climate variability varies by municipality in Mexico. The index can be used to better target federal and state level adaptation programs to local conditions, and to inform the design of municipality adaptation strategies. The conceptual framework used for the vulnerability analysis and the index construction is based on an adaptation of the IPCC's vulnerability framework, which distinguishes between exposure, sensitivity, and adaptive capacity.

The results of the analysis suggest a wide variation in municipal vulnerability across the country at baseline and prediction points. Currently, Coastal areas host some of the municipalities most vulnerable to climate change in Mexico. This is likely due to the relatively high exposure of these municipalities to hurricanes and the ensuing flood risk. However, Northwest and Central regions will likely experience the largest shifts in vulnerability between 2005 and 2045, in the advent of temperature increases and water scarcity for agricultural activities. Recent environmental and climate change studies conducted in Mexico [Martinez, 2010; IMTA, 2009; Martinez and Fernandez, 2004; Martinez-Austria, 2007] support these claims and trends.

The analysis presented here provides municipal estimates of agriculture vulnerability associated with temperature and rainfall changes, but it is also necessary to assess the distributional impact of climate change across urban and rural areas and population groups. The profiles of municipalities show that the shifts in vulnerability across municipalities, between 2005 and 2045, are quite heterogeneous because of differences in socio-economic, climate and agricultural variables. Highly vulnerable municipalities demonstrate higher climate extremes, which increase the uncertainty for harvest periods, and for agricultural yields and outputs. Also, municipalities with higher vulnerability have more adverse socio-demographic conditions. The profile also shows a positive correspondence between the percentage of people lacking support programs or savings and vulnerability. Finally, smallholders display higher vulnerability to climate change at baseline (2005) and prediction (2045) points.

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Figure I Core Variables Used in MAIN Model (Sources and Definitions) for the Climate Change Vulnerability Index in Agriculture

Core Variables	UNIT	DEFINITION	SOURCE
		EXPOSURE	
Total Agricultural Surface Area	ha	Total agricultural area within municipality (all crops included, subsistence and non-subsistence agriculture.	Agroalimentary and Fisheries Information Service (Servicio de Información y Estadística Agroalimentaria y Pesquera—SIAP) of the Ministry of Agriculture (SAGARPA). (www.siap.gob.mx)
Average temperatura (past 1960-2005; and predicted 2005-2065	°C	Average temperature between May-August for the period 1950-2000.	Digital Climatic Atlas for Mexico produced by the Informatics Unit for Atmospheric and Environmental Sciences (UNIATMOS in Spanish), at the Center for Atmospheric Science at UNAM. (www.uniatmos.atmosfera.unam.mx)
Average precipitation (past 1960-2005; and predicted 2005-2065)	mm	Average precipitation between May-August for the period 1950-2000.	Digital Climatic Atlas for Mexico produced by the Informatics Unit for Atmospheric and Environmental Sciences (UNIATMOS in Spanish), at the Center for Atmospheric Science at UNAM. (www.uniatmos.atmosfera.unam.mx)
Past and Future temperature variability indicators	°C	Includes variables with average, min and max temperature for the period (1961-2005) and variables with predictions averages using temperature models (Echam, Hadgem (2030) and 9 models) [projected temperature (°C) between May-August under scenario A2 for 2030 and 2045-2065 for 9 models, respectively]. Includes indicators that measure variability for historic and predicted periods (GDD, Frost days, Consecutive Drought days)	Digital Climatic Atlas for Mexico produced by the Informatics Unit for Atmospheric and Environmental Sciences (UNIATMOS in Spanish), at the Center for Atmospheric Science at UNAM. (www.uniatmos.atmosfera.unam.mx). Measurements from National Water Commission(CNA) and the Institute for Water Technology (1961-2005) (IMTA). Estimations based on World Bank's Environment Unit Predictions.
Past and Future precipitation variability indicators	mm	Includes variables with average, min and max precipitation for the period (1961-2005) and variables with predictions averages using precipitation models (Echam, Hadgem (2030) and 9 models) [projected precipitation (mm) between May-August under scenario for 2030 and 2045-2065 for 9 models, respectively]. Includes indicators that measure variability for historic and predicted periods (Variation Coefficient Rain, Number of days with precipitation>10mm, percentage of days with rain above 95 percentile of rain)	Interpolated through models Hadgem1 y MPIEcham5, A2 for 2030. Digital Climatic Atlas for Mexico produced by the Informatics Unit for Atmospheric and Environmental Sciences (UNIATMOS in Spanish), at the Center for Atmospheric Science at UNAM. (www.uniatmos.atmosfera.unam.mx). Measurements from National Water Commission(CNA) and the Institute for Water Technology (1961-2005) (IMTA). 9 models Estimations based on World Bank's Environment Unit Predictions.
		SENSITIVITY	
Food poverty	%	Households in municipality where its member's income falls below the lowest income necessary to afford a minimum basket of food.	National Council for Evaluation of Social Development Policy in Mexico (CONEVAL, 2008)
Percentage of Maize production under irrigated areas	%	Production units that are under irrigated systems and do not depend on seasonal precipitation for crop production	Agroalimentary and Fisheries Information Service (Servicio de Información y Estadística Agroalimentaria y Pesquera—SIAP) of the Ministry of Agriculture (SAGARPA). (www.siap.gob.mx)
% of Population in Agricultural Activities	%		National Agricultural and Farmin Census (2007) INEGI.
		ADAPTIVE CAPACITY	
Farmers that belong to organizations	%	Production units that belong to any producers association, especially to access credit.	National Agricultural Census, 2007 INEGI.
Farmers receiving remittances	%	Production units that self-reported receiving remittances.	Censo Agrícola, Ganadero y Forestal 2007 de INEGI.
Distance from Municipality Center to Road	km	Distance from Municipal Government location (or in its case geographical centroid for highly rural municipalities) to the main road (dirt or paved)	Agroalimentary and Fisheries Information Service (Servicio de Información y Estadística Agroalimentaria y Pesquera—SIAP) of the Ministry of Agriculture (SAGARPA). (www.siap.gob.mx)
Federal disaster assistance per capita	$	Sum of monetary transfers per cápita (population in the primary sector in municipality) from various federal programs (PROCAMPO, PET y PACC) between 2002 y 2009.	Temporary Employmet Program (Programa de Empleo Temporal – PET) Weather-Indexed Insurance (Programa de Atención a Contingencias Climatológicas –PACC).

Figure II Variables Used for Robustness Checks(Sources and Definitions) for the Climate Change Vulnerability Index in Agriculture

Complementary Variables	UNIT	DEFINITION	SOURCE
		EXPOSURE	
Total number of reported environmental risks	#	Sum of environmental problems (illegal logging, fires, pests, loss of biodiversity, water pollution), self-reported by municipality.	Encuesta Nacional de Gobiernos Municipales (SEDESOL, 2004-2005)
Reforestation Rate	%	Contains the rate of all reforested area from fires, drought and decertification per municipality	Agricultural Census (INEGI) data (2007) and National Institute of Ecology (2008)
		SENSITIVITY	
Migration Rate	%	Average net migration flow per municipality	Census (1960-2005) INEGI
Average corn yield	tons/ ha	Average rain fed maize yields during the spring-summer cycle, 2005.	Agroalimentary and Fisheries Information Service (Servicio de Información y Estadística Agroalimentaria y Pesquera—SIAP) of the Ministry of Agriculture (SAGARPA). (www.siap.gob.mx)
		ADAPTIVE CAPACITY	
Total population growth by municipality	%	Municipal population growth rate between 1960 and 2005.	Count of Population and Housing 2005 (INEGI) and National Population Council (CONAPO)
Population Density	Inhab /km2	Degree of aglommeration/urbanization of municipality	Census data 2005 (INEGI)
Farmers reporting climate-related losses	%	Refers to the proportion of agricultural production units that declare losses due to weather contingencies within each municipality	Censo Agrícola, Ganadero y Forestal 2007 de INEGI.
Population lacking access to health care	%	Percentage of population per municipality that has access to health care services (public or private).	Census data 2005 (INEGI)
Population 65 and older living within household	%	The percentage of households with at least one elderly dweller. Average aggregated by municipality	Census data 2005 (INEGI)
Indigenous Population per Municipality	%	Percentage of indigenous population relative to all population within Municipality. Definition of Indigenous is self-reported and corroborated with language spoken at home	Census data 2005 (INEGI)

Statistical Annex: Table 1 CCVI Dataset Summary Statistics

Topic	Indicator	Mean	Std. dev.	Min	Max
Climate-Related Variables					
	Mean accumulated rain (Tons)	1,042.51	633.79	61.57	4,552.01
	Average Yearly Rain (mm)	2.88	2.09	0	37.13
	Average Maximum Rain Yearly (mm)	27.66	3.98	4	43.50
	Maximum Consecutive days of Dryness (agricultural year)	71.12	48.50	0	365.00
	Heat Wave Duration Index (DAYS)	13.84	27.38	0	365.00
	Total number of Frost days in Agr. Year	0.73	5.87	0	180.00
	Average number of days per year with rain greater than 10 mm (international standard)	33.16	29.98	0	365.00
	Average aquifer extension	3,084.90	3,288.55	60.41	12,616.61
	Proportion of Overexploited aquifers	0.20	0.40	0	1.00
	Average extraction aquifer (lt/seg)	63.52	149.87	0	930.92
Sociodemographic					
	Percent non-literate population (15 and older)	16.31	11.03	0.81	70.96
	Percent population without sewage	9.95	12.29	0	82.87
	Percent population without electricity	5.28	7.87	0	70.30
	Percent households with overcrowding	50.26	13.97	10.67	90.67
	Percent Population that live with dirt floors	24.24	22.25	0.12	95.60
	Marginalization Index (CONEVAL)	-0.05	1.02	-2.37	3.36
	Infant mortality rate (per 1000)	22.65	8.22	3.02	78.83
	Poverty Rate	32.06	19.07	0.11	84.01
Other Variables					
	Proportion of Rural Households	0.49	0.50	0	1
	Average size of households	4.08	2.10	1	25
	Average Number of children per household	1.77	3.51	0	10
	Average Number of elderly per household	0.38	0.66	0	5
	Average years of education (all HH)	7.95	4.56	1	21
	Proportion of agricultural dependent HH	0.20	0.40	0	1
Agricultural					
	Average agr. prod. Units per mun.	1,714	2,058	3	17,949
	Average surface with agricultural prod. Per mun (ha)	13,407	23,085	0	258,679
	Average surface non-arable Per mun (ha)	33,575	119,026	0	2,132,465
	Average surface pastures Per mun (ha)	13,985	65,293	0	1,188,921
	Average surface forest Per mun (ha)	1,690	6,522	0	106,353
	Average surface non-vegetation Per mun (ha)	1,081	8,383	0	197,879
	Average number of males economically dependent from agriculture per mun	1,963	2,704	0	33,579
	Average number of women economically dependent from agriculture per mun	2,900	3,816	0	43,335
	Average prod units per mun with piped water	1,283	1,538	0	14,729
	Average prod units per mun with sewage	498	715	0	6,829
	Average prod units per mun with energy	1,544	1,874	3	17,321
	Average prod units per mun with gas	998	1,318	0	16,075
	Average prod units per mun with irrigation system	333	630	3	9,770

Source: CCVI dataset

Variable	Mean	St.dev.	Min	Max
Drought Risk	0.190	0.297	0	1
Total number of reported environmental risks	2.332	1.529	0	5
Yield Loss due to weather (kg/ha)				
Percentage of population receiving remittances	3.089	4.485	0	37.57
Percentage of Farmers that belong to organizations	97.273	4.694	41.4384	100
Percentage of Agricultural Production Units without irrigation systems	88.735	15.254	14.557	100
Percentage of population in agricultural activities	12.773	7.839	0	55.32
Percentage of Population with access to credit for agr. Activities	34.121	28.388	0	100
Average temp (Hadgem, 2030)	23.662	4.481	12.025	32.325
Average precip. (Hadgem, 2030)	150.380	80.648	2	609
Average temp Echam 2030)	2.232	0.522	-0.5	3.2
Average precip. Echam 2030)	-32.230	14.404	-120	30
Proportion of pop that migrated between 2000 and 2005	0.134	0.032	0.024911	0.519
Average surface of reforested area	108.211	394.238	0	8646
Average population growth	-0.041	0.433	-0.6928298	4.403
Average pop density (hab./sq km)	258.302	1122.609	0.1248199	17893.44
Average Total Indigenous population	4015.608	10154.610	0	200002
Maize Risk				
High	29.720	2.392	0	1
Low	36.380	1.542	0	1
Medium	33.900	3.544	0	1
Hurricane Risk				
High	25.270	5.347	0	1
Low	52.740	1.375	0	1
Medium	21.990	7.137	0	1
Flooding Risk				
High	30.100	10.463	0	1
Low	43.37	4.462	0	1
Medium	26.54	6.111	0	1
Type agriculture (%)				
Very Intensive Agriculture (High Production)	0.16			
Intensive Agriculture (High Production)	5.01			
Medium Intensity Agriculture (High Production)	1.1			
Low intensity Agriculture (High Production)	4.89			
Transitional extensive Agriculture	28.59			
Subsistence agriculture intensive	29.2			
Subsistance agriculture non-intensive	23.67			
Other type	7.38			

Source: CCVI dataset

Steps for Index Construction

The algorithm used to construct indices of vulnerability in this paper follows similar applications as in Cutter, Boruff, and Shirley (2003), and Schmidtlein et al (2007). First it relies on the inclusion of data standardization for the input variables and the final index scores. The computations were carried out using the following steps:

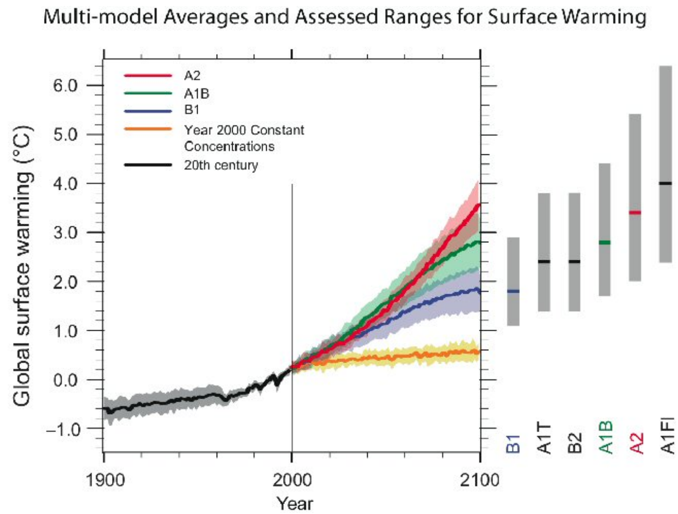
1. Standardize all input variables to mean 0 and standard deviation 1
2. Perform the PCA with the standardized input variables with the following main/core variables (all variables aggregated at the municipal level):
Total Agricultural Surface Area (ha), Average temperatura (past 1960-2005; and predicted 2005-2045, Average precipitation (past 1960-2005; and predicted 2005-2045) , Past and Future temperature variability scenarios (9 climate models, see Annex Background Paper), Past and Future precipitation variability indicators (9 climate models, see Annex Background Paper), Food poverty, Percentage of Maize production under irrigated areas, % of Population in Agricultural Activities, % Farmers that belong to organizations, % Farmers receiving remittances, Distance from Municipality Center to Road (km), Federal disaster assistance per capita ($).
3. Rotate (varimax) the initial solution and build weights matrix. [Weights are kept at baseline to allow structural relationship for predictions].
4. Order and select in matrix main components resulting from how they may influence vulnerability in three dimensions and assign eigen values to the components accordingly. [An output of the loadings of each variable on each factor was used to determine if high levels of a given factor tend to increase or decrease vulnerability.
5. Because PCA is sensitive to the values of the input variables, the data standardization step is necessary so that all variables have the same magnitude. With the standardized data set the PCA can be performed in the second step. It returns a set of orthogonal components which are all linear combinations of the original variables. By construction the first component is the linear combination that explains the greatest variation among the original variables, the second component the greatest remaining variation, and so on.
6. Based on the results of the performed PCA, select a parsimonious subset of components that explain the underlying data set as closely as possible. [the index was not bounded with upper and lower limits to allow full vulnerability assessment]
7. Perform sensitivity using Varimax rotation and the interpreted components were summed with equal weights to verify that index does not fluctuate substantially.
8. Perform same steps for predictions using Climate Change unit prediction data (with structural weights from baseline)
9. Sensitivity of this approach to creating vulnerability indices was carried out in two main phases.
    a. Change variables included in PCA with other proxy variables that can provide similar results in terms of levels and distribution of index.
    b. The correlation between the county level indices was calculated to determine how closely the index constructed with the subset of variables matched the index with the full set of social variables.

Scenarios and Climate Models Used

GCMs (Global Climate Models) are widely applied for weather forecasting, understanding the climate, and projecting climate change. Models are designed for decade to century time scale climate predictions, containing a number of prognostic equations that are stepped forward in time (typically winds, temperature, moisture, and surface pressure) together with a number of diagnostic equations that are evaluated from the simultaneous values of the variables. Predictions are also based on resolutions from globe sections. In the case of Mexico, where INEGI builds higher resolution grids, compared to other countries, HadGEM1 and ECHAM models use an grids with higher resolution in the tropics to help resolve processes transformation between spectral and grid-point space (higher local accuracy). The most widely accepted models in Mexico for climatic prediction are ECHAM and HADGEM (2030) (UNAM, 2010), which were used to estimate the CCVI, and subsequently compare results to the 9 climatic model predictions for robustness and calibration purposes. The Index reported in this document contains the 9 prediction models (2045-2065) because calibration and robustness checks showed only slight differences in the distribution of the index across municipalities. Yet, the 9 prediction models offered more detailed climatic prediction scenarios. For that reason, we report only the index built under the 9 prediction models.

For the emissions scenarios change in 2045 used the A2 scenario because is at the higher end of the SRES, and it better captures changes in adaptation and climate change. The tradeoff of using other type of scenario lies on the ability to capture a smaller climate change shifts of the lower end scenarios which is computationally intensive and provides little value added to the Index. A low emissions scenario potentially gives less information from an impacts and adaptation point of view. In addition, the current actual trajectory of emissions (1990 to present) corresponds to a relatively high emissions scenario[21].

[21] This scenario considers the following emission levels that alter climate (temperature and precipitation). Cumulative CO_2 emissions by the middle and end of the 21st century are projected to be about 600 and 1850 GtC respectively, and expected CO_2 concentrations (in parts per million, ppm) for the middle and end of the 21st century in this scenario are about 575 and 870 ppm, respectively. The current concentration of CO_2 is about 380 ppm. Methane and nitrous oxide increases grow rapidly in the 21st century. Sulfur dioxide increases to a maximum value just before 2050 (105 MtS/yr) and then decreases in the second half of the century (60 MtS/yr by 2100).



Source: http://www.narccap.ucar.edu/about/emissions.html

For the climatic predictions, there were several models used[22]:

Nine Models used for Index construction

<u>CGCM3.1</u> (2045-2065): CGCM3.1 is run at two different resolutions, with two levels of accuracy of predictions. The T47 version (used in our estimates) has a surface grid whose spatial resolution is roughly 3.75 degrees lat/lon and 31 levels in the vertical. This has a good fit into Mexico's littoral areas, but limited accuracy in central regions. The ocean grid shares the same land mask as the atmosphere, but has four ocean grid cells underlying every atmospheric grid cell. The ocean resolution in this case is roughly 1.85 degrees, with 29 levels in the vertical. The T63 version has a surface grid whose spatial resolution is roughly 2.8 degrees lat/lon and 31 levels in the vertical. As before the ocean grid shares the same land mask as the atmosphere, but in this case there are 6 ocean grids underlying every atmospheric grid cell. The ocean resolution is therefore approximately 1.4 degrees in longitude and 0.94 degrees in latitude. This provides slightly better resolution of zonal currents in the southern Tropics, more nearly isotropic resolution at mid latitudes, and somewhat reduced problems with converging meridians in the Arctic.

<u>CNRM-CM3</u> (2045-2065): This model provides similar resolutions from the above mentioned models but presents bias to the cold side in most of the tropics. This model has proven to overestimate the stream flows in summer, with the opposite occurring during the winter in the Americas (Saurral and Barros, 2009). Although for the American continent the model shows some deficiencies in the representation of the water cycle across the region, validations of temperature and precipitation fields are relatively accurate for the northern hemisphere of the Americas.

[22] Scenarios used with these models: 20c3m SRESa2 SRESb1 (IPSL does not have data for the far future under SRESB1 experiment).

CSIRO-Mk3.5 (2045-2065): Created by the Centre for Australian Weather and Climate Research, this model uses a dynamical framework of the atmospheric model is based upon the spectral model with the equations cast in the flux form that conserves predicted variables. The application of this model is vastly used over long-term climate change simulations. The most significant improvements result from the use of a more physically realistic set of parameters to represent the transport of heat and freshwater by oceanic eddies. It also features considerably more realistic circulation and stratification in the Southern Ocean, affecting precision in temperature and precipitation estimates over the fall and winter.

GFDL-CM2.0 & GFDL-CM2.1 (2 models) (2045-2065): This is a coupled atmosphere-ocean general circulation model (AOGCM) developed at the NOAA Geophysical Fluid Dynamics Laboratory in the United States. It is one of the leading climate models used in the Fourth Assessment Report of the IPCC. The atmospheric component of the CM2.X models is a 24-level atmosphere run at a resolution of 2 degrees in the east-west and 2.5 degrees in the north-south direction. This resolution is sufficient to resolve the large mid-latitude cyclones responsible for weather variability. It is too coarse, however, to resolve processes such as hurricanes or intense thunderstorm outbreaks. The inclusion of this model as part of the 9 model-prediction estimations is useful to incorporate intense outbreaks.

IPSL-CM4 (2045-2065): One of the goals of the IPSL modeling is to study how these different couplings can modulate climate and climate variability, and to determine how feedbacks in the Earth system control the response of climate to a perturbation such as the anthropogenic emissions of greenhouse gases. This is a relatively simple modeling that comprises four atmospheric prognostic variables: a) northward and eastward wind components, b) temperature, c) water availability, d) surface pressure. The data used in this model requires the time period between 1961 and 1990, for precipitation and temperature, which is data that is contained in our dataset for each municipality in Mexico on a weekly basis.

ECHO-G: Is a hybrid coupled model, using ECHAM4 atmosphere and HOPE ocean models. The model contains a control simulation, allowing 1000-year simulation with constant external forcing. The model is capable of simulating unconventional climatology, which is consistent with other similar models with flux-adjusted modulation on climate and gradients, although the flux adjustment does not guarantee a more accurate simulation (Latif et al., 2001; AchutaRao and Sperber, 2002; Davey et al., 2002).

ECHAM5/MPI-OM: This is the latest version of the ECHAM model. ECHAM5 may host submodels going beyond the meteorological processes of a GCM. The model can be used in special modes. This model perform best globally, with some biases in certain artic regions, which makes it one of the strongest models to be used in tropical and sub-tropical areas (Connolley, W. and Bracegirdle, T., 2007)

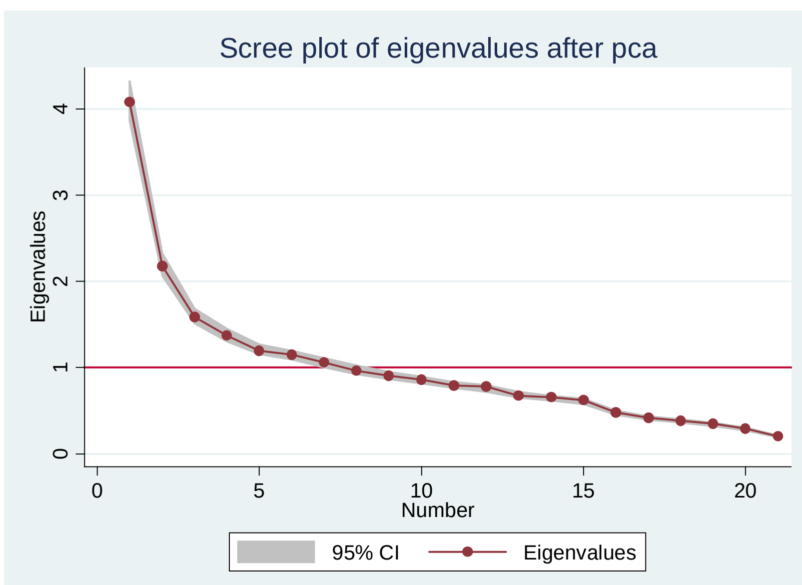
MRI-CGCM2.3.2: Meteorological Research Institute (MRI) Coupled Global Climate Model (CGCM; version 2.3.2a), produce realistic rainfall patterns at low latitudes. This model can be applied globally and regionally with the feature of permitting the partitioning of the total variance of precipitation among intra-seasonal, seasonal, and longer time scales. This is reproduced by the model, except over the western Pacific where the models fail to capture the large intra-seasonal variations.

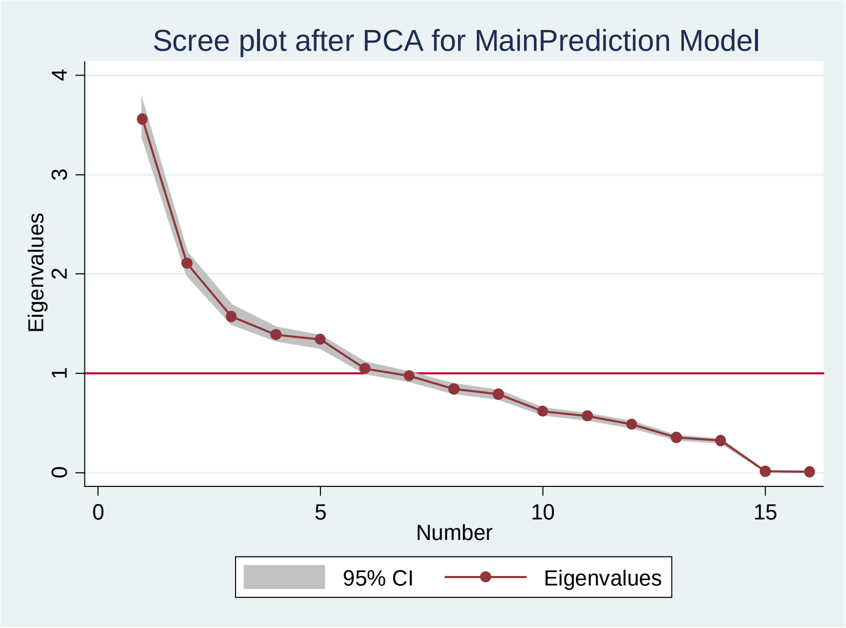
Models used for Robustness Checks

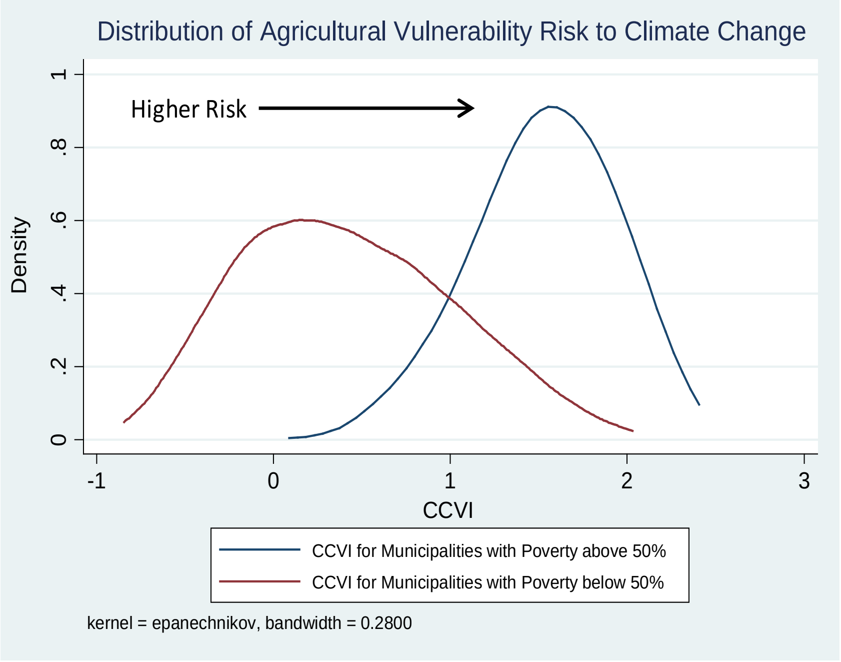
ECHAM4 (2030): This was created by modifying global forecast models default configuration of the model resolves the atmosphere (primarily used to study the lower atmosphere), targeting arid, semi-arid, sub-tropical and tropical areas. Given this climate distribution, Mexico's climates fit this model. This model has been used extensively to study the climate of the troposphere in Mexico, allowing to include also the middle atmosphere.

HADGEM (2030): Is the most recent atmospheric model (precipitation and temperature) atmospheric component has 38 levels extending to ~40km height, with a horizontal resolution of 1.25 degrees of latitude by 1.875 degrees of longitude, which produces a global grid of 192 x 145 grid cells. These grid cells are similar in size to those reported by the geographical unit of INEGI and the Autonomous National University in Mexico (UNAM). One of the main differences between this climate configuration and previous versions is the use of the New Dynamics core which is a non-hydrostatic (assumption of precipitation changes), fully compressible (ability to be disaggregated spatially), with a semi-implicit semi-Lagrangian time integration scheme (longer prediction periods).

CCVI Eigen Values for Baseline and Prediction (2005/2045)




Scree plot after PCA for MainPrediction Model
Eigenvalues
0
1
2
3
4
0
5
10
15
Number
95% CI
Eigenvalues


Distribution of Agricultural Vulnerability Risk to Climate Change
Higher Risk
Density
0
.2
.4
.6
.8
1
-1
0
1
2
3
CCVI
CCVI for Municipalities with Poverty above 50%
CCVI for Municipalities with Poverty below 50%
kernel = epanechnikov, bandwidth = 0.2800

State Level CCVI (2005-2045)

Main Model Baseline (2005)				Main Model Prediction (2045)			Change	
State	Index	S.d.	Mun	Index	S.d.	Mun	Index	Vulnerability
Aguascalientes	-0.5009	0.1243	11	-0.4061	0.1395	11	0.0948	(+)
Baja California	-0.2540	0.1428	3	-0.3823	0.1353	5	-0.1282	(-)
Baja California Sur	-0.8512	0.1929	3	-0.7969	0.1958	5	0.0543	(+)
Campeche	0.7842	0.2973	11	0.3804	0.3055	11	-0.4038	(-)
Chiapas	1.3906	0.3856	112	1.5631	0.2786	117	0.1725	(+)
Chihuahua	0.1014	0.4552	37	0.2558	0.4139	67	0.1544	(+)
Coahuila	-0.3650	0.1360	25	-0.6504	0.1700	38	-0.2854	(-)
Colima	0.1803	0.3522	9	-0.0288	0.2696	10	-0.2091	(-)
Distrito Federal	0.4160	0.2679	7	0.2436	0.1443	10	-0.1724	(-)
Durango	-0.1372	0.4382	37	-0.1825	0.4744	39	-0.0453	(-)
Guanajuato	-0.2409	0.2064	46	-0.0513	0.2085	46	0.1897	(+)
Guerrero	0.9046	0.3753	76	0.8003	0.3178	76	-0.1043	(-)
Hidalgo	0.1700	0.7793	84	0.2691	0.5747	84	0.0991	(+)
Jalisco	0.2546	0.3200	121	0.2048	0.2689	124	-0.0497	(-)
Michoacán	0.4081	0.3588	112	0.4033	0.3149	113	-0.0048	(=)
Morelos	0.4146	0.2216	31	0.3182	0.2237	33	-0.0964	(-)
México	0.2441	0.4412	121	0.2501	0.3701	122	0.0060	(=)
Nayarit	0.6354	0.2261	20	0.3108	0.2511	20	-0.3246	(-)
Nuevo León	-0.1046	0.1926	32	-0.3072	0.2121	49	-0.2026	(-)
Oaxaca	0.7378	0.5899	557	0.8766	0.4383	570	0.1388	(+)
Puebla	0.4391	0.6530	214	0.5706	0.4504	217	0.1315	(+)
Querétaro	-0.2415	0.3416	18	-0.1551	0.3522	18	0.0864	(+)
Quintana Roo	0.5705	0.3686	8	0.6398	0.3477	8	0.0694	(+)
San Luis Potosí	0.2549	0.7717	57	0.0932	0.5224	57	-0.1617	(-)
Sinaloa	-0.0064	0.3300	15	-0.3471	0.3459	18	-0.3407	(-)
Sonora	-0.0196	0.2967	10	-0.4272	0.2403	72	-0.4075	(-)
Tabasco	1.1752	0.3408	17	0.7122	0.2461	17	-0.4630	(-)
Tamaulipas	0.0156	0.3312	38	-0.2791	0.3585	43	-0.2948	(-)
Tlaxcala	0.0301	0.1664	59	0.1221	0.2110	60	0.0920	(+)
Veracruz	1.1434	0.4075	208	0.8737	0.3701	210	-0.2697	(-)
Yucatán	0.5469	0.3142	106	0.8136	0.3116	106	0.2667	(+)
Zacatecas	-0.3273	0.3087	56	0.0476	0.2742	57	0.3749	(+)

Source: Own estimations

Main Model						
State	**Index 2005**	**S.d. 2005**	**Index 2045**	**S.d. 2045**	**Mean Difference t-value**	**Significant Difference**
Aguascalientes	-0.5009	0.1243	-0.4061	0.1395	1.369	No
Baja California	-0.2540	0.1428	-0.3823	0.1353	-1.744	Yes
Baja California Sur	-0.8512	0.1929	-0.7969	0.1958	0.571	No
Campeche	0.7842	0.2973	0.3804	0.3055	-1.702	Yes
Chiapas	1.3906	0.3856	1.5631	0.2786	2.039	Yes
Chihuahua	0.1014	0.4552	0.2558	0.4139	0.407	No
Coahuila	-0.3650	0.1360	-0.6504	0.1700	-1.206	No
Colima	0.1803	0.3522	-0.0288	0.2696	-0.774	No
Distrito Federal	0.4160	0.2679	0.2436	0.1443	0.169	No
Durango	-0.1372	0.4382	-0.1825	0.4744	-0.075	No
Guanajuato	-0.2409	0.2064	-0.0513	0.2085	0.963	No
Guerrero	0.9046	0.3753	0.8003	0.3178	0.111	No
Hidalgo	0.1700	0.7793	0.2691	0.5747	0.256	No
Jalisco	0.2546	0.3200	0.2048	0.2689	-0.034	No
Michoacán	0.4081	0.3588	0.4033	0.3149	0.146	No
Morelos	0.4146	0.2216	0.3182	0.2237	-0.477	No
México	0.2441	0.4412	0.2501	0.3701	0.124	No
Nayarit	0.6354	0.2261	0.3108	0.2511	-1.747	Yes
Nuevo León	-0.1046	0.1926	-0.3072	0.2121	-0.944	No
Oaxaca	0.7378	0.5899	0.8766	0.4383	0.752	No
Puebla	0.4391	0.6530	0.5706	0.4504	0.600	No
Querétaro	-0.2415	0.3416	-0.1551	0.3522	0.300	No
Quintana Roo	0.5705	0.3686	0.6398	0.3477	0.390	No
San Luis Potosí	0.2549	0.7717	0.0932	0.5224	-0.157	No
Sinaloa	-0.0064	0.3300	-0.3471	0.3459	-1.107	No
Sonora	-0.0196	0.2967	-0.4272	0.2403	-1.761	Yes
Tabasco	1.1752	0.3408	0.7122	0.2461	-0.628	No
Tamaulipas	0.0156	0.3312	-0.2791	0.3585	-0.866	No
Tlaxcala	0.0301	0.1664	0.1221	0.2110	0.412	No
Veracruz	1.1434	0.4075	0.8737	0.3701	-0.449	No
Yucatán	0.5469	0.3142	0.8136	0.3116	0.887	No
Zacatecas	-0.3273	0.3087	0.0476	0.2742	1.278	No

Source: Own estimations

Table 3b Characteristics of States with Highest Vulnerability Shifts

Highest Vulnerability Decrease

Indicator	CCVI Index	Index Prediction (2045)	Percent of Indigenous Population	Percent of Households with Dirt Floors	Percent of Elderly (65+) Population	Rain Coefficient of Variation	GDD	% of Agriculture workers with Savings	% of Agriculture workers with credit	Average Agriculture support in Pesos 2009 *	% of Agriculture workers receiving remmitances
mean	0.562	-0.105	7.02	1.94	7.96	0.35	10.63	3.97	37.34	230.85	1.86
range	2.331	2.032	88.62	52.39	14.95	0.71	12.94	22.39	88.57	987.53	16.90
sd	0.544	0.507	15.48	5.57	3.37	0.10	2.71	4.36	19.40	290.23	3.06
p5	-0.452	-0.799	0.00	0.00	3.81	0.22	6.24	0.00	12.40	0.00	0.00
p95	1.482	0.831	40.30	11.40	14.92	0.54	14.30	14.10	75.90	839.86	8.77
N	138	138	138	138	138	138	138	138	138	97	138

Highest Vulnerability Increase

Indicator	CCVI Index	Index Prediction (2045)	Percent of Indigenous Population	Percent of Households with Dirt Floors	Percent of Elderly (65+) Population	Rain Coefficient of Variation	GDD	% of Agriculture workers with Savings	% of Agriculture workers with credit	Average Agriculture support in Pesos 2009 *	% of Agriculture workers receiving remmitances
mean	0.277	0.488	16.41	7.91	6.78	0.27	10.46	1.82	27.75	439.16	3.65
range	2.367	2.657	99.82	69.73	20.97	0.33	444.91	10.19	100.00	999.80	25.18
sd	0.724	0.887	29.47	15.26	3.47	0.06	36.13	1.56	22.83	330.08	4.40
p5	-0.701	-0.615	0.18	0.00	2.60	0.17	2.68	0.00	0.00	0.00	0.00
p95	1.327	1.756	94.01	45.46	13.45	0.36	14.58	4.82	69.80	948.68	11.96
N	289	251	289	289	289	289	289	289	289	102	289

States with highest vulnerability Decrease: Tabasco, Sonora, Campeche, Sinaloa, Nayarit.
States with highest vulnerability Increase: Zacatecas, Yucatan, Guanajuato, Chiapas, Chihuahua

Source: Own estimations

Table 4c Correlations Selected Variables and Vulnerability Risk Category

Risk Category *	Frost Days (<10 C)		Consecutive Dry Days		Growing Degree Days		Coefficient of Variation Rain	
	Baseline	*Prediction*	*Baseline*	*Prediction*	*Baseline*	*Prediction*	*Baseline*	*Prediction*
Very High Vulnerability Risk	1.83	3.06	88.37	88.26	9.59	15.72	0.32	0.46
High Vulnerability Risk	0.92	1.25	83.03	82.49	10.20	14.06	0.29	0.37
Moderate Vulnerability Risk	0.45	0.53	81.09	85.21	11.08	13.68	0.26	0.36
Low Vulnerability Risk	0.13	0.15	68.21	72.84	9.58	12.41	0.27	0.34
Very Low Vulnerability Risk	0.38	0.01	53.89	40.29	6.46	4.33	0.27	0.29

Risk Category **	Low Capital intensity Agriculture		Transitional extensive Agriculture		Subsistence agriculture Capital intensive		Subsistance agriculture non-intensive		Other (Small Farms)	
	Baseline	*Prediction*	*Baseline*	*Prediction*	*Baseline*	*Prediction*	*Baseline*	*Prediction*	*Baseline*	*Prediction*
Very High Vulnerability Risk	0.39	4.77	14.15	17.85	38.15	45.97	33.4	41.54	5.23	5.11
High Vulnerability Risk	2.22	1.85	17.08	24.44	36.89	39.51	31.78	35.19	4.00	5.97
Moderate Vulnerability Risk	2.09	4.11	30.7	32.24	27.44	27.52	31.63	26.69	6.51	7.80
Low Vulnerability Risk	5.06	5.13	32.7	39.63	20.94	23.63	16.43	23.63	12.03	13.96
Very Low Vulnerability Risk	10.2	13.17	41.91	40.53	12.86	8.23	11.09	6.17	13.08	7.20

Risk Category ***	% of Indigenous pop. by Mun.		% of HH by Mun w/ Dirt floors		% of HH in Mun. w/ dwellers above 65 yo		% of Agriculture workers with Savings		% of Agriculture workers with credit		% of Agriculture workers with support programs		% of Agriculture workers receiving remmitances	
	Baseline	*Prediction*	*Baseline*	*Prediction*	*Baseline*	*Prediction*	*Baseline*	*Prediction*	*Baseline*	*Prediction*	*Baseline*	*Prediction*	*Baseline*	*Prediction*
Very High Vulnerability Risk	**0.141**	**0.155**	**0.153**	**0.098**	**0.182**	**0.246**	**-0.177**	**-0.153**	**0.090**	**0.139**	**-0.103**	**-0.171**	**-0.153**	**-0.270**
High Vulnerability Risk	0.058	0.053	**0.069**	**0.074**	**0.048**	**0.083**	-0.117	-0.106	**0.099**	**0.103**	-0.080	-0.269	-0.140	-0.183
Moderate Vulnerability Risk	**0.089**	-0.034	**0.089**	**0.067**	**-0.026**	**-0.072**	-0.044	0.034	0.009	0.039	0.041	0.105	-0.022	-0.131
Low Vulnerability Risk	0.055	-0.026	0.056	-0.014	-0.049	-0.022	-0.048	0.079	-0.046	-0.044	0.059	0.112	0.011	-0.017
Very Low Vulnerability Risk	0.044	-0.068	0.057	-0.054	-0.094	-0.031	-0.011	-0.010	**-0.124**	**-0.054**	**0.050**	**0.135**	**0.065**	**0.065**

* Consecutive dry days based the number of days below 2 standard deviations from Monthly average or no rain at all reported. GDD are calculated by taking the average of the daily maximum and minimum temperatures compared to a base temperature. The coefficient of variation (CV) is defined as the ratio of the standard deviation to the mean.

** Percent of Municipalities under risk categories, figures don't add up to 100 horizontally because 3 categories of Capital Intensive Agriculture production units not included.

*** Pairwise Correlations between Index and Variable in question. Bold indicate significant at 10% level.

Source: Own estimations

Annex II

Literature Review on Applications of PCA to build Multidimensional (small area) Indices

For many years the statistical literature lacked a uniform approach to combine indicators that result in a composite index from multidimensional data. A number of indices were devised over the years, including Duncan's index that combined labor and income data of individuals, or the Townsend's index designed to explain variation in health in terms of material deprivation (Morris & Castairs, 1991). However, a major problem facing researchers when constructing indexes is determining an appropriate aggregation strategy to combine multidimensional variables into a composite index.

For years, researchers built aggregated indices from multidimensional variables using simple Summation of Standardized Variables (SSV). This approach initially developed by Shevky & Bell (1955) and applied by Markides & McFarland (1982), used statistical standardization of variables to add them up and test variability of the index according to different development outcomes applied to infant mortality. However, many statistical experts found that such methods rely on applying weights to the constituent variables that make up individual as well as composite indices, which rely on subjective factors, thus raising questions about internal coherence and robustness of such methods (Gjolberg, 2009).

Despite that the PCA technique is not new its application to develop composite weighted indices is relatively recent. The PCA technique developed by Pearson (1901), though it is often attributed to Hotelling (1933), is useful for transforming a large number of variables in a data set into a smaller and more coherent set of uncorrelated (orthogonal) factors, the principal components. The principal components account for much of the variance among the set of original variables. Each component is a linear weighted combination of the initial variables[23].

The components are ordered so that the first component accounts for the largest possible amount of variation in the original variables. The second component is completely uncorrelated with the first component, and accounts for the maximum variation that is not accounted for the first. The third accounts for the maximum that the first and the second not accounted for and so on.

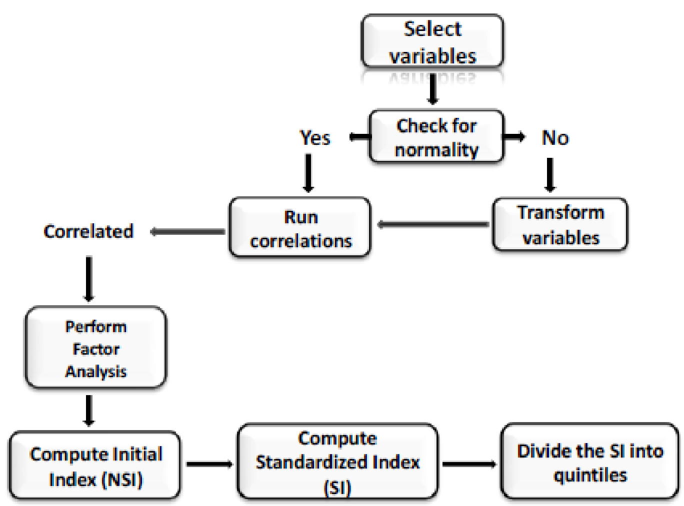
PCA was first used to combine socioeconomic indicators into a single index (Boelhouwer & Stoop, 1999). Acknowledging the inappropriateness of simple aggregation procedures, Lai (2003) modified the UNDP Human Development Index by using PCA to create a linear combination of indicators of development. Several

[23] The weights for each principal component are given by the eigenvectors of the correlation matrix or the covariance matrix, if the data were standardized. The variance for each principal component is represented by the eigenvalue of the corresponding eigenvector.

researchers have used PCA, especially since late 1990s, to compute area socioeconomic indices (Antony & Rao, 2007; Fukuda, Nakamura, & Takano, 2007; Fotso & Kuate-defo, 2005; Havard, Deguen, Bodin, Louis, & Laurent, 2008; Messer, Vinikoor, Laraia, Kaufman, Eyster, Holzman, Culhane, Elo, Burke, & O'Campo, 2008; Rygel, O'Sullivan, & Yarnal, 2006; Tata & Schultz, 1988; Sekhar, Indrayan, & Gupta, 1991; Vyas & Kumaranayake, 2006; Zagorski, 1985).

Finally, the PCA is computationally easy and also avoids many of the problems associated with the traditional methods, such as aggregation, standardization, and nonlinear relationships of variables affecting socioeconomic inequalities (refer Vyas & Kumaranayake, 2006, for an assessment of advantages and disadvantages of PCA and Saltelli, Nardo, Saisana, & Tarantola, 2004, for the pros and cons of composite indicators, in general). Graphically the steps to conduct a PCA computation are based on the following diagram:

PCA Algorithm Procedure



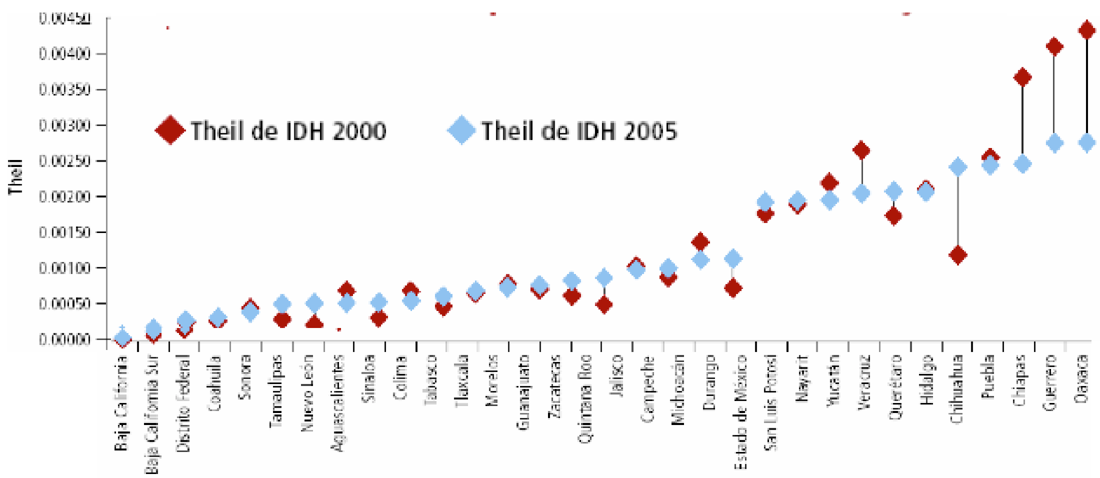
Source: Based on Krishnan, 2010

Annex III

Examples of Multidimensional Indices built for Mexico using Principal Components Analysis

Mexico has a history in building important municipal indices that capture multidimensional aspects of social and economic variables. In 2005 the United Nations Development Program (UNDP) supported the government of Mexico to build a Human Development Index at the municipal index. This indicator was build using Principal Components Analysis (PCA) combining life expectancy, literacy rates, school enrollment rates, GDP per capita, inequality and ethnic composition. The index was used to rank municipalities in order to prioritize public spending to those municipalities and regions with lowest levels of human development (IDH 2005, UNDP). Also, the index constructed at baseline (2000) and at a follow up (2005) periods, assessed changes in human development at the state and municipal levels (Graph 1a).

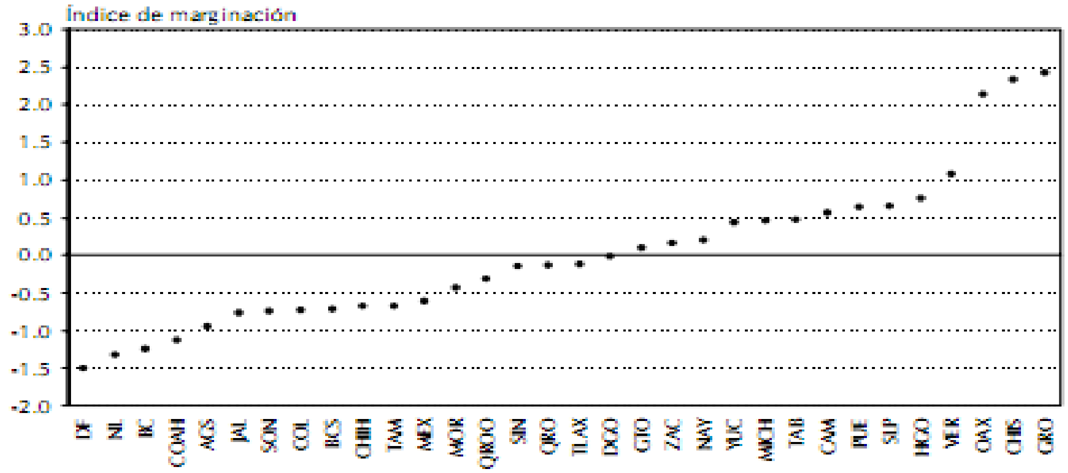
Graph 1a Mexico's Inequality in Human Development Index by State, 2000-2005



Source: IDH, UNDP 2005.

With a precedent in building a human development index for municipalities in Mexico, the National Population Council (CONAPO) in Mexico, embarked in the task of building a more refined index that incorporated other dimensions of social well-being beyond human development. In 2000 and 2005 CONAPO used PCA analysis to build a socioeconomic index that measured the level of marginalization by municipality based on three dimensions. The first dimension measured education-related indicators (years of schooling, level and type of education, literacy rates), mostly captured in CENSUS data. The second dimension of the index measured household conditions and access to public services (household physical characteristics, access to water and sanitation, and energy) collected from two sources: CENSUS data and two large sample surveys (ENOE and ENIGH). The last dimension to measure marginality incorporated variables related to municipal characteristics in terms of population size, labor occupancy rates, and urbanization collected from CENSUS and large sample data as well. This index was build based on the above-mentioned indicators including only those with highest explanatory power over the covariance of all indicators. PCA was used then to aggregate all three dimensions to build the index that categorized municipalities in five levels of marginality: very low, low, average, high and very high. The index helped to rank states in order to prospectively plan the allocation of resources from the programmatic plans elaborated by the Ministry of Finance, where high priority of funding was given to states and municipalities with high and very high marginalization (Graph 2a).

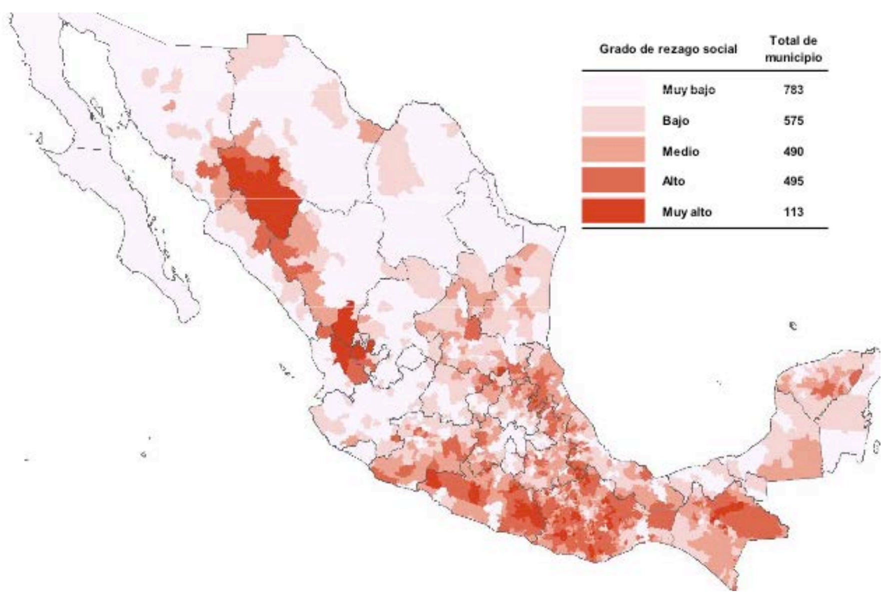
Graph 2a Marginality Index by State (Mexico 2005)



Fuente: Estimaciones del CONAPO con base en el *II Conteo de Población y Vivienda 2005*, y *Encuesta Nacional de Ocupación y Empleo 2005* (IV Trimestre).

These examples illustrate previous efforts to build indices used for important policy decisions. Other indices have been built to assess multiple dimensions of well-being. In 2010, the National Evaluation Council (CONEVAL) built a composite index using PCA analysis that measured the Social Gaps prevailing across municipalities (Graph 3a).

Graph 3a. Social Gap Index by Municipality Mexico 2010.



Source: CONEVAL, 2011

The main purpose of the social gap index is to prioritize specific policies and programs that target multiple social development interventions. This index ranks municipalities based on human development, access to social services and household conditions. The index is helping to reshape social policies and priorities at the municipal level and it is used to assess social inequality as well. With this tool state and national governments have evidence to allocate federalize funds into municipalities that show highest social gaps.

Recently, other indices have been built to assess specific inequalities in the distribution of risk against climate change. The Mexican Institute of Water Technology (IMTA) built a Municipal Index for Water Scarcity Risk from Climate Change. This index is completely submerged in the climate change agenda and has the advantage of incorporating multiple dimensions to assess Water Scarcity risks. These dimensions include health, education, household conditions, employment, population and family structure, gender, adaptive capacity and risk perception. Although this index is still under review, it conceptually measures an important challenge that municipalities will face in the future: the risk of water resources reduction and their allocation. These examples illustrate the importance of using rich data and statistical tools to assess various aspects of economic, social and sustainability issues at the local level.