Over and over again. Poverty trajectories and extreme rainfall in Mexico

Extended abstract

Landy Sánchez, Rodolfo de la Torre y Julio Postigo

Background

Several studies examine the effects of hydrometeorological disasters in Mexico. It has been found that residents of informal settlements and areas with poor infrastructure and services are more exposed to extreme events and that such exposure contributes to a deepening of historical territorial inequalities (De la Fuente 2010; Baró-Suáez et al., 2011; García 2005). These extreme-weather risks add to existing socio-economic vulnerabilities and can impact the likelihood of being in poverty and its intensity. The poor are more affected because they tend to be more exposed and because they have fewer resources to overcome them. Also, the relative losses of the poor are higher and may have longer effects Hallegatte and Rozenberg 2017). Additionally, extreme events can impact the investment and savings decisions of households, introducing greater uncertainty about the future (Hallegatte and Rozenberg, 2017).

Extreme events impact area poverty through its effects on infrastructure, housing, and income-generating activities, however, evidence of their impact on economic well-being is still limited. Studies argue that the consequences will depend on the type and magnitude of the event, as well as the geographical and social vulnerability of the different population groups. In general terms, the literature identifies the destructive effects of extreme events on economic activity, but also potential positive results in the aftermath, once the reconstruction begins. Various papers document that after hurricanes and floods of great magnitude sources of employment are lost, but these jobs are recovered once the recovery funds or insurance coverage are activated and, in general, the activities are regularized (Zissimopoulos and Karoly 2010; Moreno and Cardona 2011). Although it was also found that the degree of the affectations and their duration differ between population groups depending on their social vulnerability (Fussell et al., 2010) and the extent of the disasters (Rodríguez and Rivera 2012), while the lack of state support or community increases the vulnerability (Eakin, 2005).

Most of the population studies, however, focus on the impacts of major events, without considering extensive damage nor their repetition. However, disruptions can occur as a result of powerful events such as a hurricane (intensive damage), but also due to atypical and recurrent events, although of smaller scale (extensive damage). Although the losses of the former may be severe, growing evidence suggests that the accumulated losses of the latter are substantial and growing. It is estimated that while extensive events account for only 14% of disaster deaths, they are responsible for around 42% of material losses, as well as most of the displacements of people and associated diseases (UNISDR, 2015). These losses have multiplied in the last 15 years in middle-income countries, such as Mexico, are the most frequent in urban contexts and are expected to be accentuated by climate change (UNISDR, 2015). Also, because of their location and climatology, some regions are more prone than others to being impacted by hydrometeorological events, and these events might exacerbate vulnerable conditions in underdeveloped areas. While the geographical concentration of extreme weather is well known in the literature, few studies look at the implications of frequent events for population wellbeing. This paper seeks to contribute to the discussion by examining the impacts of recurrent extreme precipitation on poverty trajectories of municipalities in Mexico between 2000 and 2015. Intense rains are used as a proxy to account for hydrometeorological conditions that could have caused extensive damage.

Data and methods

We combine multiple data sources in our analysis. First, we used the percentage of population under poverty as estimated by CONEVAL (National Evaluation Council), the administrative body in charge of producing poverty statistics in Mexico. On the other hand, we use census data to construct social predictors of poverty (average years of schooling; female labor force as a proxy of market dynamism, percentage of manufacturing employment, infrastructure provided by the State (pipe water) and the proportion of the urban population). We estimate these variables for three points in time (2000, 2010 and 2015). Second, to identify extreme events, we concentrated on abnormally intense rainfall. Following Climdex, this study proposes an indicator for the rainy season (June-September) that counts the number of days that the daily rainfall exceeded the 95th percentile of the distribution of the reference climatology (1970-2014). As a predictor, we count extreme rainfall days for the five years preceding each census period. The index was constructed with data of daily precipitation published by the National Meteorological System that counts on 55 million daily records of rain and temperature, reported by around 5,500 climatological stations, of which 1,895 are temporarily in more than 30 years between 1970 and 2014. We employed spatial interpolation to account for inconsistency in the coverage of the stations. A threshold based on the historical average of each municipality allows accounting for differences in climatic conditions, as well as existing infrastructures set in place to deal with average weather locally. Third, we employ the official dataset of disaster and emergency declarations, once the government issues a declaration municipalities and states get access to federal relief funds. Yet, our analysis suggests that only a fraction of extreme weather events received such resources.

Using exploratory spatial data analysis, we first the spatial concentration of extreme precipitation, and to what extent we can identify places that experience them repeatedly.

We then explore cross-sectionally the association between poverty and extreme precipitation. In a second section, we employ multilevel growth curve models, where repeated measures of poverty are nested within each municipality. Using this method, we can examine a) to what extent places that experience extreme precipitation have [initial] higher levels of poverty, b) whether municipalities hit by extreme precipitation experience faster poverty growth between (2000 and 2015); c) whether receiving relief aid make a difference in the speed of poverty growth.

Preliminary results

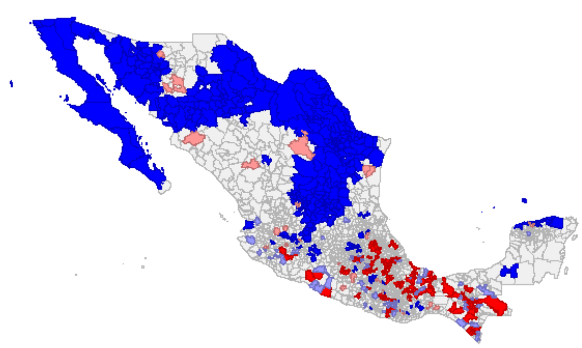
The LISA (Local Indicators of Spatial Autocorrelation) analysis suggest that places extreme precipitation tends to concentrated geographically and that such patterns largely coincides over time (Figure 1). The map also shows that Southern municipalities experience higher numbers of extreme rainfall, while the Northern region concentrated municipalities low numbers of extreme precipitation days. In addition to a clear geographical pattern, there is a strong correlation over time (0.58, on average). A subgroup of municipalities located in the South is hit by severe weather over and over again. In fact, those municipalities received had an average of 15 days of extreme precipitation, in contrast with 10 in the rest of the country.

Moreover, our analysis suggests that poverty is positively correlated with extreme precipitation, although that association is moderate (0.28, on average on the three periods). More importantly, high precipitation areas co-locate with high poverty municipalities in the South (Figure 2). While national poverty average 68% of the population in 2000, for southern municipalities that average reaches 75%. National poverty level decreased to 63% in 2015, but there is significant heterogeneity on poverty trajectories across municipalities both in the direction and the speed of the change.

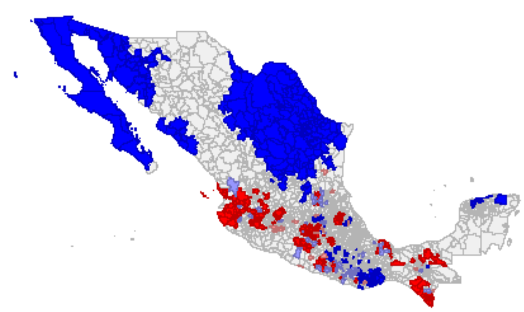
Using growth curve models (table1), we examine to what extent extreme rainfall contributes to poverty increments over time, after considering other socioeconomic characteristics. Our preliminary results suggest that near 90 % of the variance in poverty occur between municipalities, and only 10% over time (model 1). As expected, average years of schooling, labor female force participation, manufacturing employment, infrastructure and urbanization decrease poverty level at the start of the trajectory (2000) (model 2). After controlling for socioeconomic characteristics, extreme precipitation is associated with lower poverty levels in 2000, but it increases the growth rate of poverty (model 3). That is, the higher the extreme rainfall days, the faster poverty growth. In contrast, we do not find that receiving federal aid decrease poverty levels significantly, not its growth (model 4).

Figure 1. LISA. Cumulative extreme precipitation by municipalities in Mexico (2000-2015)

2000



2010



2015

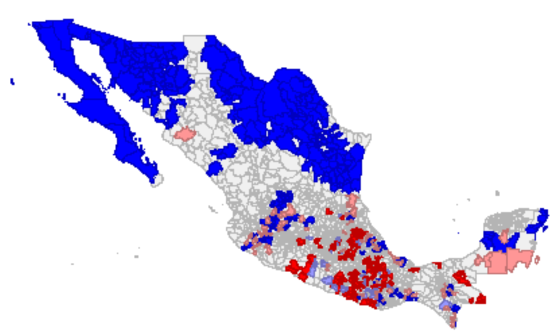


Figure 2. Number of days of extreme precipitation and poverty levels 2010

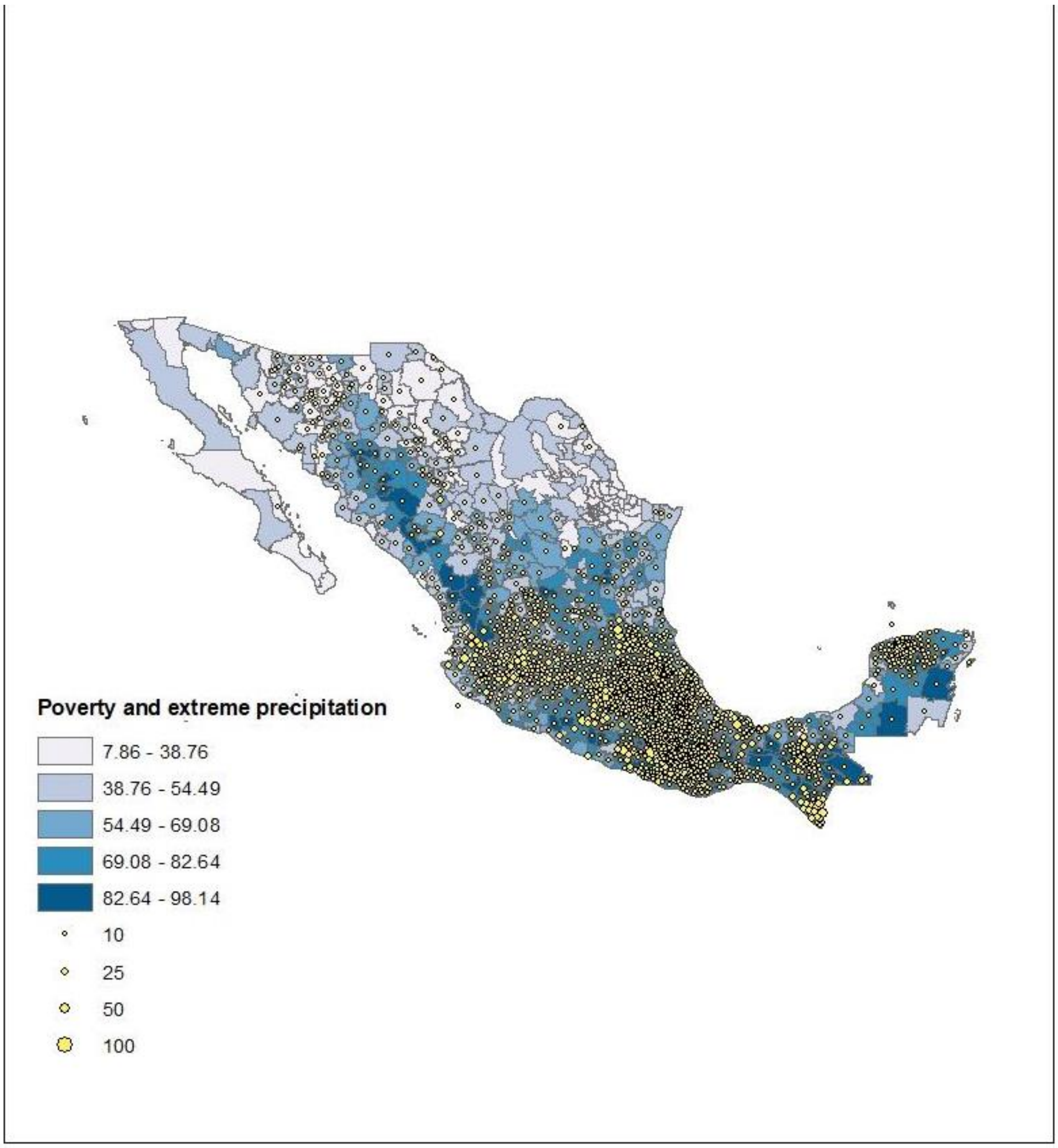


Table 1. Results

Growth curve models. Population under poverty ("welfare line")												
	Model 1			**Model 2**			**Model 3**			**Model 4**		
Fixed component	Coef.	Std.Err		Coef.	Std.Err		Coef.	Std.Err		Coef.	Std.Err	
Year (recentered 2000)	-0.303	0.012	***	0.131	0.024	***	0.045	0.034		0.057	0.035	
Extreme precipitation							-0.156	0.036	***	-0.150	0.042	***
Year*extreme precipitation							0.018	0.003	***	0.017	0.003	***
Disaster declaration										-0.099	0.215	
Year*disaster declaration										-0.004	0.017	
Avg years of education				-4.000	0.169	***	-4.149	0.169	***	-4.156	0.169	***
Female labor force participation				-0.211	0.014	***	-0.198	0.014	***	-0.200	0.014	***
manufacture				-0.125	0.020	***	-0.122	0.020	***	-0.122	0.020	***
state infraestructure				-0.020	0.008	*	-0.027	0.008	***	-0.025	0.008	**
Urban				-0.038	0.009	***	-0.033	0.009	***	-0.033	0.009	***
_cons	68.209	0.418	***	96.765	0.943	***	97.953	0.968	***	97.871	0.969	***
Variance Components												
				Estimate	Std. Err		Estimate	Std. Err		Estimate	Std. Err	
var(year2000)	Estimate	Std. Err		0.302	0.017		0.307	0.017		0.301	0.017	
var(_cons)	390.722	11.553		259.452	8.631		264.990	8.715		264.861	8.723	
cov(year2000,_cons)				-2.641	0.286		-3.353	0.303		-3.326	0.303	
var(Residual)	41.877	0.846		24.935	0.742		21.977	0.711		22.140	0.721	
Log likelihood	-28299.446			-26076.887			-24140.567			-24137.658		
observations	7354											
groups	2456											