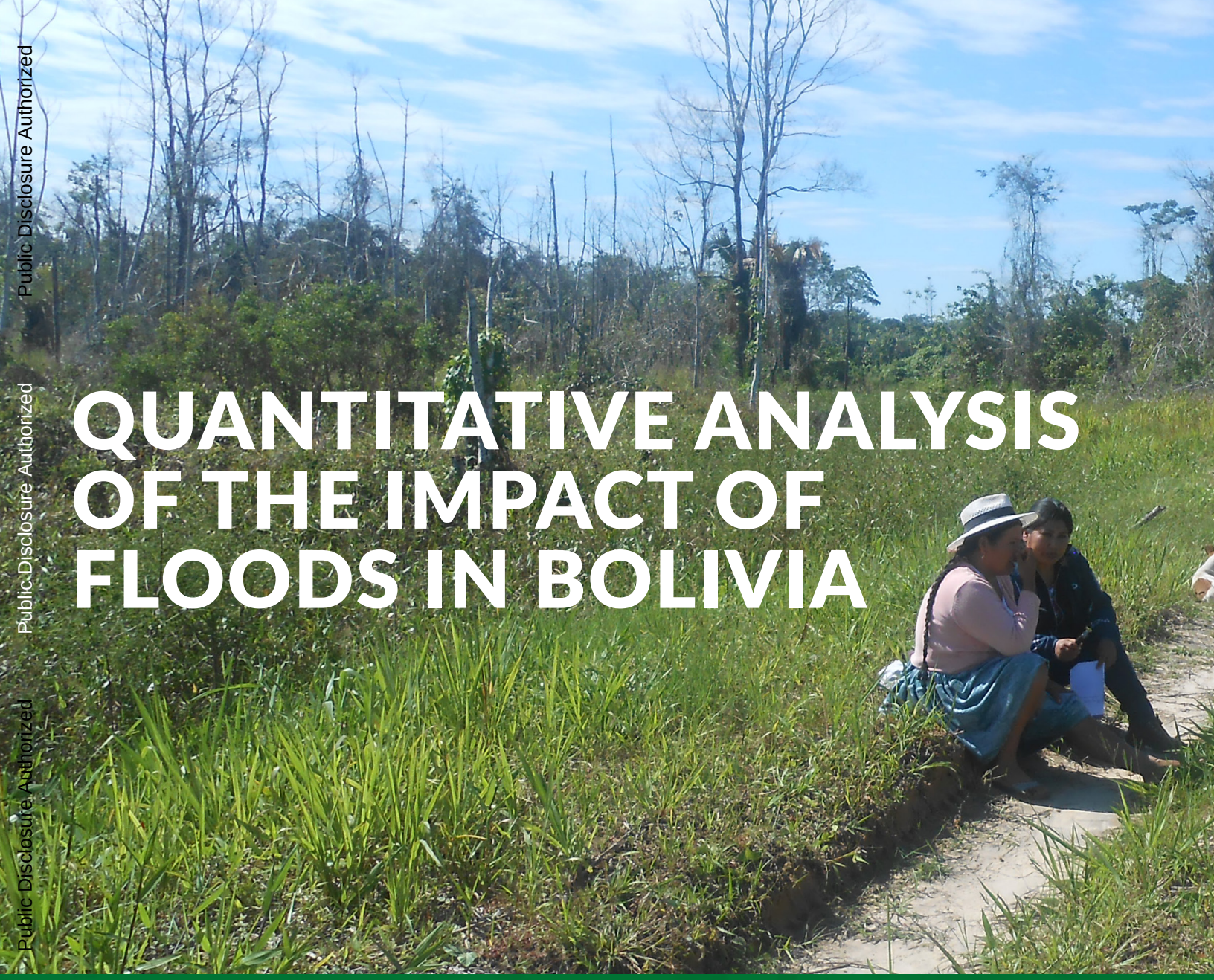

QUANTITATIVE ANALYSIS OF THE IMPACT OF FLOODS IN BOLIVIA

World Bank

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December 2017

Financed by

WORLD BANK GROUP

GFDRR
Global Facility for Disaster Reduction and Recovery

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Washington DC 20433
Telephone: 202-473-1000
Internet: www.worldbank.org

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Cover Photo Caption: *The municipality Villa Tunari is part of the Chapare Province, a region well known for the cultivation of coca leaf. The Palometas community flash flooding in 2011 and the repercussions are still latent. The overflow of waters reached more than two meters. Villagers had to escape the flooding from the roof of their houses so as not to be dragged by the water. The water swept everything in its path, razing trees and logs that in turn made the flood more dangerous and generated natural dikes that no longer allowed the water to pass, causing the water level to continue to rise.*

Back Cover Photo Caption*: Paria Soracachi is a municipality in the Altiplano (high plateau), very close to the city of Oruro. It is an area currently affected by drought, however some communities in the municipality were affected by floods in 2014 and 2015.*

Photo Credit: World Bank

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1. Introduction

In its region, the Plurinational State of Bolivia[1] is considered one of the most vulnerable countries to disasters from adverse natural events.[2] Bolivia's primary natural hazards—such as droughts, frost, severe rains, and hailstorms—are largely hydrometeorological in nature, and include phenomena derived from these, such as floods and landslides. According to the Municipal Risk Index (MRI)[3] developed by the Social and Economic Policy Analysis Unit (UDAPE) at the Ministry of Development Planning, in 2012, 43% of the population lived in areas prone to flooding, with floods (whether caused by rainfall or other factors) being the most frequent natural disaster event in Bolivia, followed by drought and hailstorms.[4] Given their frequency and the proportion of the population exposed to them, floods cause significant economic losses primarily affecting infrastructure, agricultural, and livestock production. For example, in 2015, the Government of Bolivia estimated that losses caused by flooding amounted to USD 450 million[5] (BOB 3,132 million), affecting more than 300,000 people.

Given this context, disaster risk management has been a priority in the agenda of the Government of Bolivia, which has achieved significant progress in establishing a regulatory and institutional framework for this purpose. For example, in 2012, Law No. 300, "Marco de la Madre Tierra y Desarrollo Integral para Vivir Bien" (Mother Earth Framework and Comprehensive Development for Living Well), set the prevention and reduction of the conditions of risk and vulnerability of the population of Bolivia (article 12) as objectives. In 2014, Law No. 602, "Ley de Gestión de Riesgos" (Law for Risk Management) was enacted, which provides a framework for disaster risk management and adaptation to climate change in development planning at sectoral and territorial levels.

1 In the remainder of this document, the Plurinational State of Bolivia will be referred to simply as "Bolivia".
2 According to Kreft et al. (2016), in a report published for Germanwatch Bolivia was ranked seventh among the countries most affected by extreme weather events in 2014. Also, Dilley et al. (2005) place Bolivia in the group of countries most exposed to natural hazards.
3 The Municipal Risk Index (MRI) is a benchmark measure of municipalities' exposure to natural hazards and their challenges in coping with disasters when they occur. The index ranges from 0% (minimum risk level) to 100% (maximum risk level). In practice, the MRI is a database and visualization tool which allows government officials to quickly comprehend risk levels and identify the most highly-exposed strategic structures (hospitals, schools, roads, etc.) in risk scenarios.
4 According to statistics produced by the National Disaster Observatory (NDO) at the Vice-Ministry of Civil Defense (VIDECI, Viceministerio de Defensa Civil), of the most significant natural events recorded in Bolivia between 2002 and 2012, 34.9% were floods, followed by drought and hailstorms (28.3% and 15%, respectively).
5 For the purpose of this document, all figures in United States dollars (USD) have been calculated at the average exchange rate for 2016, which equals 6.96 bolivianos (BOB) per US dollar, and have been rounded up to the closest integer value. (Source: https://www.bcb.gob.bo/tiposDeCambioHistorico/, checked on December 21st, 2016).

Disasters, especially associated with floods, have a negative and statistically observable impact in the short term.[6] However, from a statistical and causal point of view, empirical evidence about these impacts in Bolivia is very limited. For the events that took place in 2013 and 2014, UDAPE (2015) recorded direct and indirect losses associated with weather events using the ECLAC[7] methodology to assess the socioeconomic and environmental impacts of the disasters. As already mentioned, these events caused losses of approximately USD 450 million (BOB 3,132) and affected more than 300,000 people. Arenas (2014) complemented the previous methodology by evaluating the magnitude and intensity of disasters until 2100 under different climate change scenarios. The study finds that future damage to public infrastructure due to the effects of climate change (through intense precipitation and floods) would cost USD 93 billion (BOB 647,280 million), which would represent an average annual expenditure of USD 3,113 million (BOB 21,666 million). In addition, the economic value of agricultural and livestock production losses is estimated to be worth USD 82 billion (BOB 570,720 million), which would represent an annual average loss of USD 2,726 million (BOB 18 973 million).

It is worth mentioning that in these studies it is difficult to attribute specifically any associated damage due solely to disasters, as there could be other concurrent factors. Furthermore, these studies do not assess the impact on welfare variables such as poverty or household income.[8] Poverty and household income clearly shows the medium to long term impacts of natural shocks. Therefore, this study aims to assess the impact of floods in Bolivia on per capita household income and on other socioeconomic welfare indicators by using statistical methods to explicitly isolate other factors that may influence the results.

Given the difficulty of accurately measuring flood imparts—in addition to limitations inherent within the data itself—this study analyzes various indexese commonly used in economic literature to represent flood impacts. The main idea behind the use of different indexes is that floods have different causes and characteristics that define how they affect the population or economy of a given country. While all the indexes used seek to model the impact of a flood, each gives different weights to its causal factors and to the features required to deal with it in the area in which it occurs. The results show that different indexes are consistent across the different characterizations, and point to a significant negative effect of excessive precipitation, intense rainfall, and river overflow, on both per capita income and household poverty.

The rest of the study is divided into four sections. The first section describes the three indexes used in the study, the information used to calibrate them, and how their values

6 Jha et al. (2012), in Chapter 2, analyze the direct effects of flooding in the phases prior to, during, and after the event, as well as its long-term impact on some social indicators and on the environment.
7 United Nations Economic Commission for Latin America and the Caribbean.
8 The analysis took into account other relevant variables, such as unemployment and school attendance, but the results were not conclusive largely due to their low temporal variability. Therefore, those results have not been included in this document.

are calculated. The second section describes the methodology used to assess floods imparts on household income and poverty. It also shows how the indexes can be adapted to incorporate socioeconomic information, and how a range of different variants is built. The third section describes the results for different variants of the indexes and includes a comparison of the predictions of each in different scenarios. The last section shows the main conclusions of the study.

2. Characterization of Floods

In economic literature, it is common to characterize floods in a specific area as the variation of precipitation in a given period with respect to the historical average. In Latin America, this indicator has been used in different studies, as in the case of Colombia (Brando and Santos, 2015), Ecuador (Rosales, 2014), and Brazil (Rocha and Soares, 2014). This measurement evaluates the effect of extreme flooding on a given area, permitting the monitoring of the adaptive capacity in areas often exposed to high precipitation levels. Henceforth, we will refer to this indicator as a "precipitation index". Another way of characterizing flooding is by incorporating rainfall intensity, measured by the number of hours of rainfall, and constantly adjusted by the level of economic activity in the area exposed to rainfall, i.e., excessive precipitation will only cause economically significant damage if it occurs in productive or inhabited areas (Strobl, Heinen and Khadan, 2015). This method will be called an "intensity index". In addition to these two indexes, flooding is also measured by river overflow using the GLOFRIS model,[9] which models situations where the flood damage was caused by an overflowing river, rather than by extraordinary levels of stormwater. Although stormwater causes increases in the river discharge that can lead to an overflow, the relationship between flooding due to overflow or to stormwater is not always direct or proportional. We will call this third method the "river overflow flooding index".

It should be noted that this section deals mainly with the construction of the gross values of each of the aforementioned indexes. Further on, when the methodology used for this evaluation is presented, the different variants of each index and the ways in which they have been adapted to take into account socioeconomic information will be detailed.

Precipitation index

This section discusses the precipitation index and the data and methodology used to calculate it. This first index is the simplest, and is based on the idea that the higher the rainfall, the greater the likelihood of flooding. Given that intense and excessive

9 Global Flood Risk with IMAGE Scenarios.

precipitation is often the main factor provoking floods, precise rainfall measurements allow for adequate approximations related to flooding.

The index basically compares the absolute value of the current or recent precipitation to the historical average of an observation unit (which, in our case, is the municipality) and establishes a relative value with respect to the historical standard deviation. In recent literature, it is customary to use 1 standard deviation as the threshold to define flooding (see, for example, Rocha and Soares [2014], Brando and Santos [2015] and Rosales [2014]).

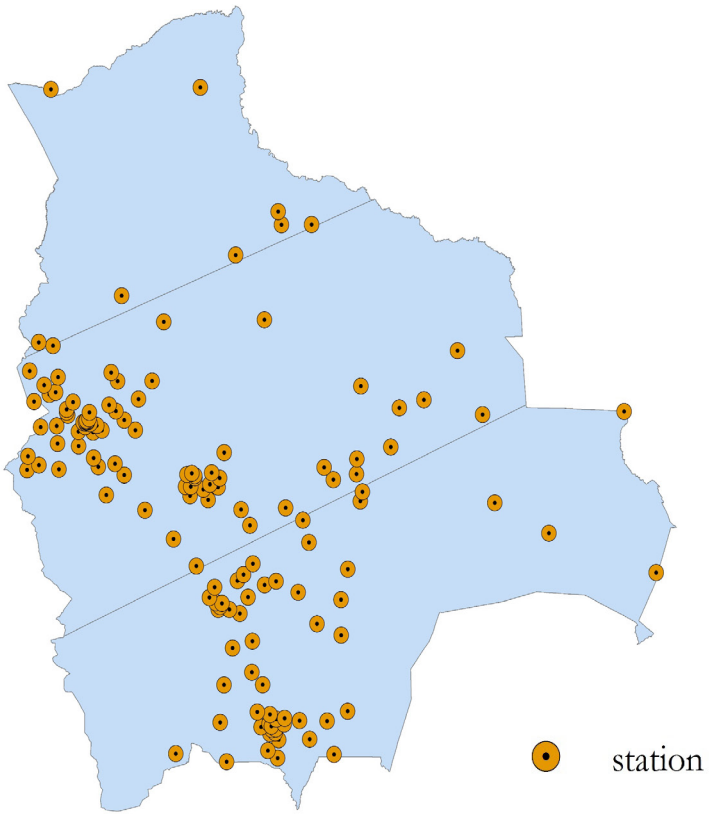
The main data used for the construction of the index are calibrated precipitation records dating back to 1940, provided by the Government of Bolivia. In addition, infrared precipitation data from the Climate Hazard Group (CHG) are used in order to include remote areas where meteorological observations are scarce. This measurement is an innovative idea which allows the merging of in situ precipitation data with infrared satellite data, optimizing both the accuracy and the geographical representation of the estimates.

Data used

Monitoring stations

This index is based on precipitation data from meteorological stations throughout the country, managed by the National Service of Meteorology and Hydrology (SENAMHI). There are a total of 235 stations with precipitation data for the period of the study (2005-2014). However, not all stations have data of consistent quality in this period. Therefore, a sorting criterion was established to select only those stations that held at least 90 months' worth of observations (out of the 96 months in the period). This reduced the total number of qualifying stations to 144 (shown in Figure 1). The mapping of the 235 stations confirmed that there was no loss of geographical representation upon ruling out the stations which did not meet the criteria for the analysis.

Figure 1. Location of monitoring stations used



Infrared precipitations from the CHG (CHIRPS)

For the construction of this index, the most recent development of precipitation data by cells or pixels, called CHIRPS[10], was used, which take satellite images, the average precipitation recorded at the weather stations, and other rainfall predictors, such as altitude, latitude, and longitude, to build monthly precipitation averages in high resolution (cells covering 0.05 degrees squared, approximately 5 km^2). The database works with information collected from 1981, which is presented as average daily precipitation inputs in groups of five or ten days, or on a monthly or yearly basis. The study used monthly datasets because the temporal unit of analysis is one month.

10 CHIRPS is a combined effort of the US Geological Survey (USGS) and the University of California, Santa Barbara (UCSB). In 2012, the USGS and the UCSB combined new satellite imagery resources, the average precipitation recorded by weather stations, and other rain predictors, such as altitude, latitude, and longitude, to build monthly precipitation averages in high resolution (cells covering 0.05 degrees squared, approximately 5 km^2) at global level to create the Climate Hazards Group's Precipitation Climatology (CHPClim) (Funk et al., 2007). These improved monthly averages were used for the 1980-2009 period to eliminate the systematic bias of the satellite-based monthly precipitation; a method used to adjust for the effects of precipitation related to the terrain (Funk et al., 2007). Lastly, a method of inverse distance interpolation was used to combine the precipitation observations of the weather stations with objective satellite precipitation estimates, in order to produce the Climate Hazards Group's InfraRed Precipitation with Station data (CHIRPS).

Calculation of the index

CHIRPS+

In Bolivia, the number of stations to which the CHG has access is limited, and this figure has fallen considerably since 2010. As shown in Figure 2, from 1980 to date, the number of stations that provided information to CHIRPS has been very inconsistent, ranging between 10 to 40. The geographical coverage of these stations is also limited, which calls into question its representativeness (Figure 3). Compared with the number of stations used by the CHG for CHIRPS, this study uses many more stations with more consistent data sources. To address the discrepancy, a supplementary procedure was used to combine the values from the VIDECI stations with those of CHIRPS.

Figure 2. Number of CHIRPS stations in Bolivia

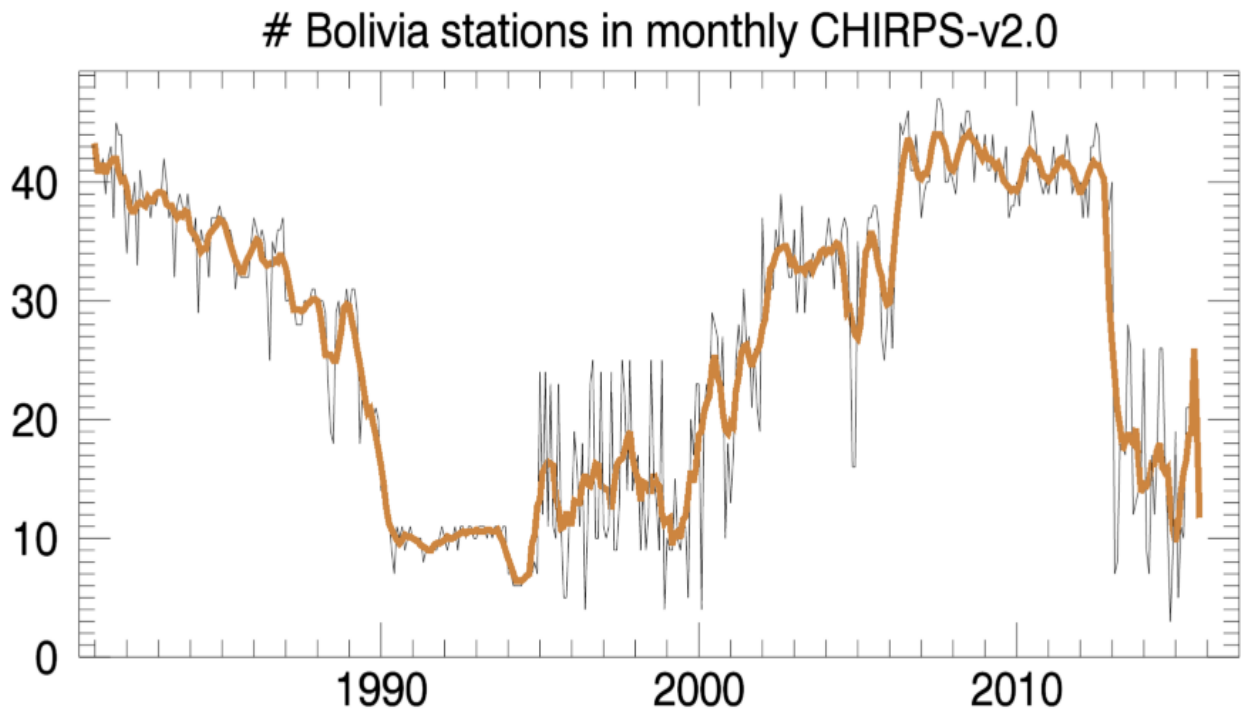
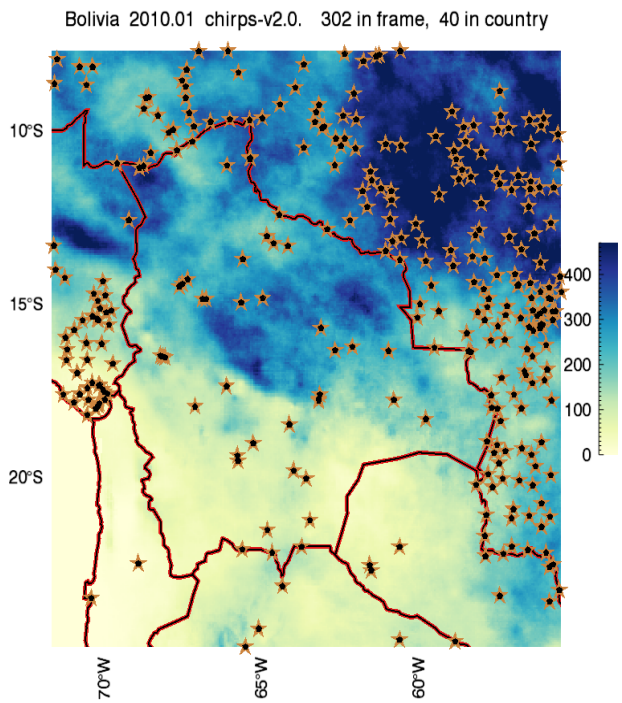


Figure 3. Distribution of CHIRPS stations in 2010



The procedure to merge the two datasets was performed with the software GeoCLIM, developed by the CHG. While the details of the methodology used are not within the remit of this study,[11] it is important to highlight its most important features.

First, the combined precipitation data are defined as follows:

$$CHIRPS+_i = \alpha_i CHIRP_i + (1 - \alpha_i) b_i CHIRP_i$$

where:

- $\mathrm{CHIRPS"+_i}$ is the combined precipitation data for cell *i*.
- $\mathrm{CHIRP_i}$ is the precipitation data for cell *i* calculated by the CHG on the basis of satellite images.
- α_i is the weight assigned to the precipitation data for cell *i* calculated by the CHG.
- $\mathrm{b_i}$ is a bias factor associated with cell *i* and estimated using precipitation data from the 144 stations and from satellite images.

11 The detailed methodology for the merging procedure can be found in Funk et al. (2015).

The incorporation of α_i, defined in the following equation, guarantees that the merging process does not only recreate the value of the station, but also takes into account the value estimated from the satellite images. Such decisions are intended to mitigate the effect of the inaccurate observations of the station on the final precipitation estimation.

$$a_i = \frac{\rho_{CHIRP}}{\rho_{CHIRP} + \rho_{ns}}$$

where:

- $\rho CHIRP$ is the expected correlation between station precipitation data and the values calculated by the CHG on the basis of satellite images. Based on the validation results, the value of $\rho CHIRP$ is fixed at 0.5, i.e., each source of information has the same impact in the final weight scheme.

- ρns is the expected correlation between the bias factor associated with cell i and the data of the nearest station to that cell.

In turn, the bias factor b_i is interpreted as the means by which both datasets are combined. Essentially, b_i is a weighted average of the ratios of the observations of the five nearest stations (in an area of influence of 500 km) and the infrared CHG precipitation data.

$$b_{ij} = \frac{s_{ij} + \epsilon}{c_{ij} + \epsilon}, \qquad \forall j = \{1, 2, 3, 4, 5\}$$

where:

- c_{ij} is the precipitation data j calculated on the basis of the CHG satellite images associated with weather station j and cell i.

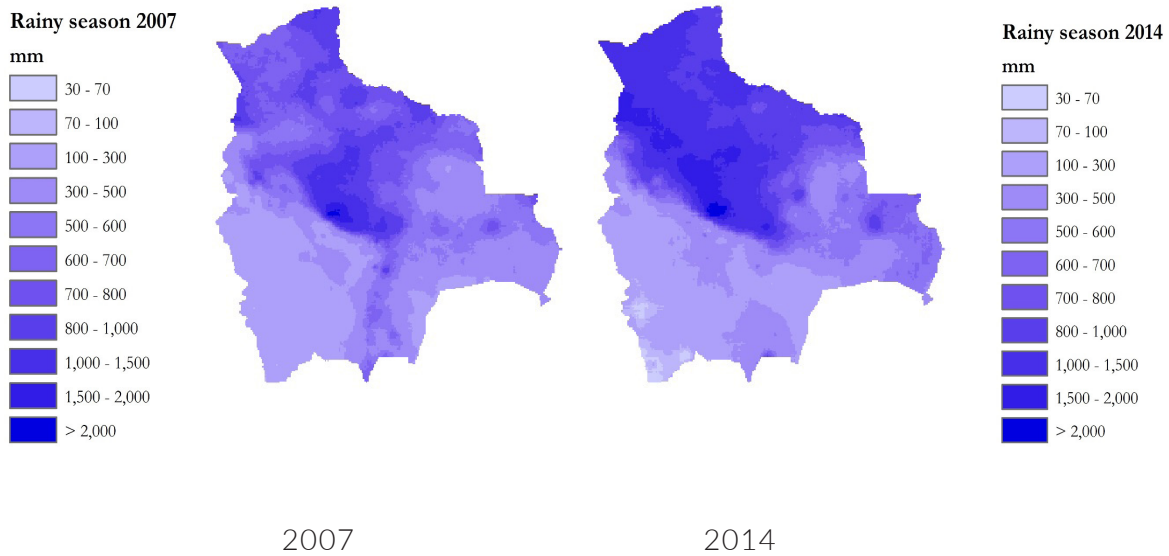
- s_{ij} is the precipitation observed by weather station j (within the area of influence).

- ϵ is a small number used to ensure that the ratio is correctly defined in case c_{ij} =0.

Then, the risk factor b_i is calculated as a weighted average of 5 ratios. The weighting used depends on the distance between the stations and the cell i, and the zero correlation curve.[12] The rationale behind this equation is simple. Each station is assigned a weight proportional to its distance from the network: the shorter the distance to the station, the greater the weight. The results of the model—which we will call CHIRPS+—for the rainy season (November through March) of 2007 and 2014, are illustrated in Figure 4. As may be seen, by combining both sources of information (VIDECI and CHIRPS), it is possible to acquire more detailed and disaggregated precipitation data for the entire country. The graph shows that in 2007 and 2014, significant rainfall was registered, mostly concentrated in the central area of Bolivia, followed by the next most concentrated rainfall in the north of the country.

12 The zero correlation curve indicates the distance at which the correlation between two points of interest is zero.

Figure 4. CHIRPS+ estimates for the 2007 and 2014 rainy season



Intensity index

The intensity index uses data from previous flooding events to define an equation that relates the rainfall duration and intensity, and sets a threshold over which the precipitation causes flooding. The ***duration*** is defined as the time (in hours) between the beginning and the end of the period of rainfall for each flood event, and the ***intensity*** is defined as the sum of milliliters of water recorded during a rainfall event in a given area, in this case, the municipality. The methodology is based on Strobl et al. (2015), and seeks to incorporate two elements in the characterization of floods: (i) variation in rainfall levels in short periods of time, which is lost when taking precipitation averages or totals, and (ii) the level of economic activity, which determines the potential damage of a flood.

This indicator was developed by Strobl et al. (2015) to measure the impact of floods on price indexes in Jamaica. This index intuitively incorporates intensity under the notion that not only is the amount of rainfall recorded important, but also the time period during which it falls continuously. For example, an annual rainfall record of 600 mm distributed between 500 mm in one month and 100 mm over the rest of the year, has not the same impact as a monthly rainfall of 50 mm. Also, this index is adjusted by the level of economic activity, which means that excessive precipitation will only cause economically significant damage if it happens in productive or inhabited areas. Due to Bolivia's environmental characteristics and rain patterns, the correlation between the precipitation index and the intensity index is high.

Data used

Historical flood data (NDO)

The historical flood data used to calculate the intensity index was obtained from the National Disaster Observatory (NDO) at the VIDECI. This database contains information about the states of emergency declared at district level in response to natural events in Bolivia from 2002-2012. The data used in this document are the date of occurrence, location (municipality), type of event, and its cause.[13] The following table shows the occurrence of major events and the number of families affected.

Table 1. Statistics of major natural events in Bolivia based on NDO data.

Event Type	Number of events	%	Families affected	%
Drought	1,472	14.02	320,517	28.25
Pluvial flooding	1,963	18.69	200,728	17.69
Fluvial flooding	2,004	19.08	195,499	17.25
Hailstorm	1,833	17.45	169,576	14.95
Frost	1,916	18.24	157,407	13.89
Others	1,315	12.52	90,318	7.97
Total	10,503	100	1,134,045	100

As may be observed, floods are the most frequent natural disaster events and affect the largest number of families in Bolivia (period 2002-2012). Only flood events caused by precipitation were used to calculate the index; floods arising from river overflow were excluded.

Precipitation data (TRMM)

Precipitation data was obtained from the Tropical Rainfall Measuring Mission (TRMM) satellite records, which are available on the website of the National Administration of Aeronautics and Space Administration (NASA) of the United States of America.[14] Each TRMM file contains information on the maximum precipitation levels, measured in millimeters per hour (mm/h) for three-hour periods,[15] which is the smallest unit of data, at a cell level of 0.25 x 0.25 degrees.

DMSP-OLS Nighttime lights (NTLs)

For a better estimate of the impact of floods, it is assumed that there will only be an economic impact in flooded areas where human activities take place, and/or which contain assets that have been affected, or more precisely, if there is a spatial overlap between

13 The NDO database also includes date of record, department, province, municipality, place, and information about the consequences (death toll and families affected).
14 URL address: http://trmm.gsfc.nasa.gov/
15 Periods: 0-3 a.m., 3-6 a.m., 6-9 a.m., 9 a.m-12 noon, 12 noon-3 p.m., 3-6 p.m., 6-9 p.m., 9 p.m.-12 midnight.

the flood and economic activity. The calculation of this index uses cloud-free nighttime lights from the US Air Force Defense Meteorological Satellite Program (DMSP) as a proxy for economic activity. Each cell or pixel is associated with a number representing the intensity of light: 0 (no light) to 63 (maximum intensity).[16] In order to avoid the problem of endogeneity in the values considered, the rainfall intensity used belongs to the year prior to the rainfall event (if the same period of that rainfall event was used, it is likely that the level of light intensity would be lower due to the precipitation itself and not necessarily because the area under analysis had a lower level of economic activity).

Calculation of the index

The first step in calculating the index is the selection of the events that will form the basis for calibrating the model. The NDO database produced information on 1,963 pluvial flooding events between 2002 and 2012. These events were grouped by date of occurrence and municipality to avoid the duplication of data on precipitation levels at any given municipality on a specific day. Given this grouping, there were a total of 709 events as the sample for the study.

For each of these events, the TRMM precipitation data for three days before and three days after the event were obtained following Strobl et al. (2015)'s methodology. To consolidate the data at municipal level, the resolution of the files was reduced from 0.25 to 0.0083 degrees (1 km^2, which is the same resolution as that used in the NTLs databases). Lastly, the maximum precipitation level (intensity) was calculated in millimeters per hour (mm/h), and the duration of the rainfall event was also obtained for each of the 340 municipalities.

According to Strobl et al. (2015), the duration (D) and the intensity (I) are related by the following equation:

$$I=\alpha*D^{\beta}$$

Where α y β are the two parameters to be estimated. Note that the relationship between intensity and duration is non-linear; it is therefore not possible to use linear estimation methods. However, if logarithms are applied on both sides of the expression (1), it is possible to transform this into a linear equation:

$$\log(I)=\log(\alpha)+\beta*\log(D)$$

The parameters were estimated using the method of ordinary least squares (OLS), taking the 709 events as the sample. The following values were thus obtained:

16 For the series of the 1999-2009 period, the nighttime lights used were recorded by four satellites: F14, F15, F16, and F18. Due to differences between sensors and lack of in-flight calibration, annual stable lights cannot be used directly for a temporal analysis. This study used an intercalibration procedure developed by Wu et al. (2013) to improve satellite comparability while reducing the problem of the urban saturation of nighttime lights.

$$\hat{\alpha} = 0{,}090$$

$$\hat{\beta} = 1{,}96$$

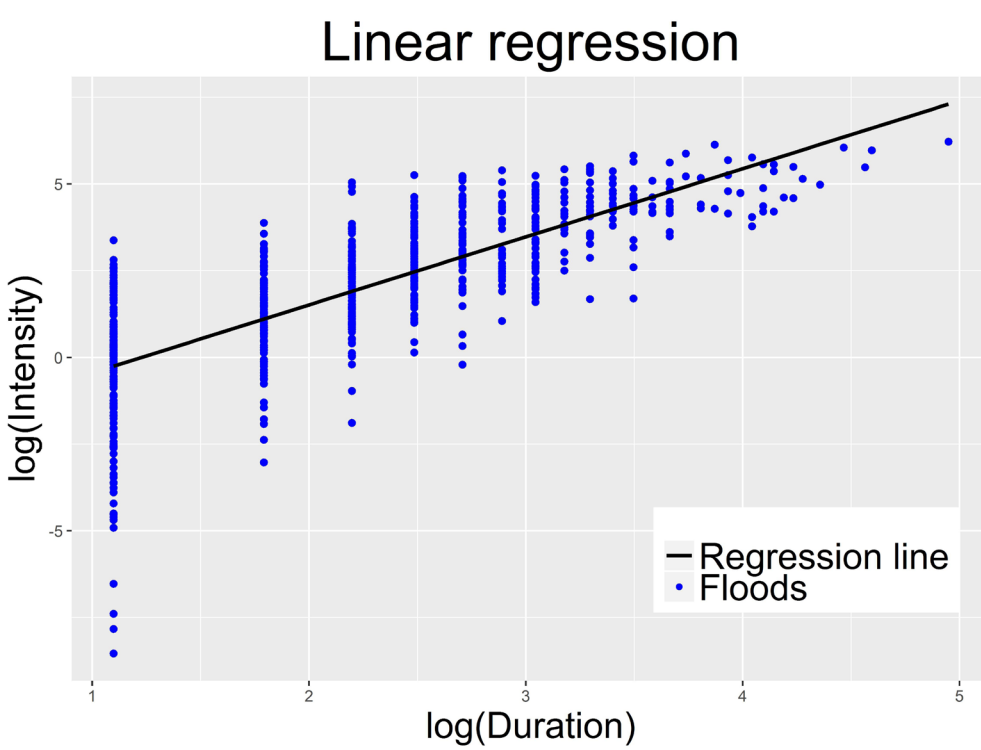
The estimated parameters are statistically significant at 1%, but the empirical evidence in other countries smaller than Bolivia reveals that the estimated parameter $\hat{\beta}$ is negative (i.e., the greater the intensity, the shorter the duration). However, in the opinion of specialists in the field, this relationship does not necessarily apply to Bolivia as there are areas of the country (such as the plains) where intensity and duration have a positive (directly proportional) relationship. When the plains are dropped from the analysis, the negative relationship does not hold anymore.

Thus, the relationship between duration (D) and intensity (I) is given by the following expression:

$$I = 0{,}090 * D^{1.96}$$

The following chart shows the points in log-values [$[\log(I) \text{ and } \log(D)$], and the linear regression line, which indicates the good fit of the model (high R^2).

Figure 5. Linear Regression (log-values)



Once the regression line has been obtained, its position is adjusted on the vertical axis to obtain the threshold. The points lying above the threshold are considered to be rainfall events with flooding, and those below, rainfall events without flooding. In other words, this threshold allows non-significant flooding events to be discarded in order to calculate the index.

Since regression provides the average value, following Strobl et al. (2015), a threshold of 10% was defined below the linear prediction line for separating events according to the presence of rain or lack thereof. This 10% threshold, which is represented by the red line, is clearly shown in Figure 6.

Figure 6. Regression line and 10% threshold

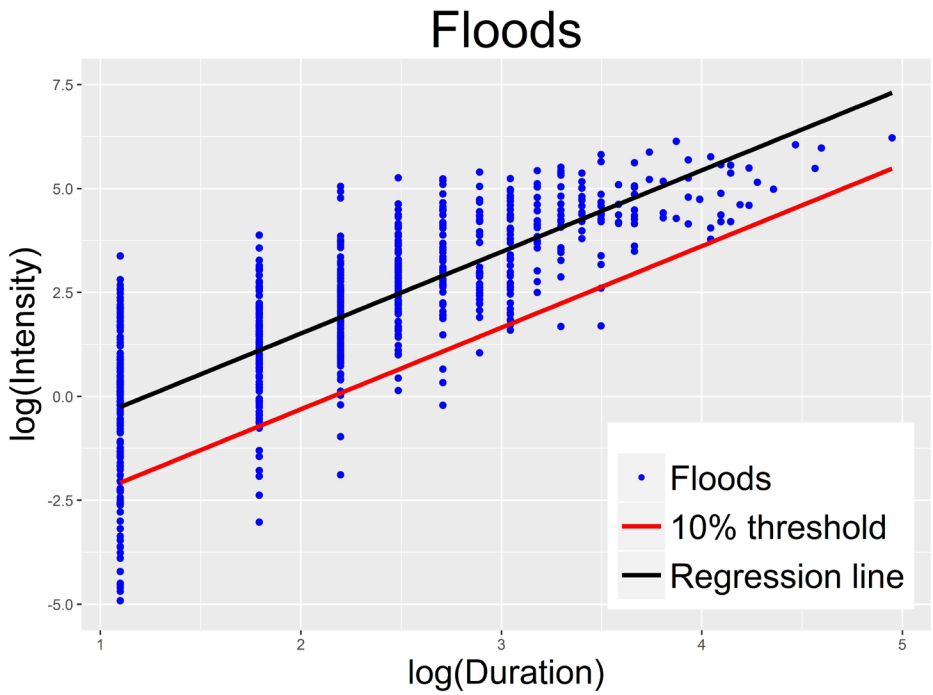


Table 2 summarizes the percentage of events below ("no flooding") and above ("flooding") for the different percentile values used (5%, 10%, 15%, and 20%). As may be seen, the variability between the thresholds of 5% and 10% is not substantial, and the difference of events considered as flooding is only 3% (as between 15% and 20%, where the difference is also about 3%). In the section under analysis, different percentile levels were evaluated.

Table 2. Results for different percentile values

Percentile	No flooding (%)	Flooding (%)
5%	5.08	94.92
10%	8.18	91.82
15%	11.28	88.72
20%	14.95	85.05

As detailed in the previous table, under percentile 10, 91.82% of the 709 flooding events used in the linear regression are above the threshold and, therefore, are considered floods. These 651 events are the basis for the construction of the index. For each of these events, the precipitation recorded in each cell of the municipality where the flooding occurred in a given year of the period of the study (2002-2012) is added.

Once the flood intensity is determined, it is adjusted by the NTLs (i.e., economic activity) in order to calculate the level of exposure. This adjustment is important to correctly estimate the potential damage of a flooding event, because regardless of its intensity, if flooding occurs in an uninhabited place, the estimated damage should be zero.

Because flooding in year ***t*** can destroy infrastructure and affect light intensity, precipitation results for the year ***t***, adjusted by the amount of light from the previous year (***t-1***), are used for each cell. NTL data are multiplied by intensity at each cell to obtain the index. This methodology is summarized in the following formula, which allows for the calculation of the index for a given year and cell:

$$I_{t,i} = NTL_{t-1,i} \times \sum_{j \in T_t} TRMM_{j,i} \times \mathbb{1}_{\{TRMM_{j,i} \in I_t\}}$$

where:

- $I_{t,i}$ is the cell index value ***i*** in the year **t**.
- $NTL_{t-1,i}$ is the cell NTL value ***i*** in the year **t-1**.
- $TRMM_{j,i}$ is the maximum precipitation level (mm/h) during a three-hour period ***j*** in the set T_t in cell ***i***.
- T_t is the set of three-hour periods in year ***t***.

  I_t is the set of three-hour periods that correspond to a flooding event in the year ***t***.

As a final step, the index for all cells belonging to each municipality is added to obtain the index at municipal level. It is important to note here that the orders of magnitude of

the two factors impact on the final index. For example, if the amount of light is negligible compared to the amount of water, the exposure will not be captured. Hence, before multiplying, the levels should be defined and the factors eventually normalized to enable comparability between the indexes.

River overflow flooding index

In the case of Bolivia, there are several types of flooding: flash floods, lake coastal floods, urban floods, fluvial floods, and pluvial floods.[17] Of all these types, fluvial flooding—caused by the overflowing of rivers—is the most common and deadly.[18] This index seeks to model flooding caused by river overflow using GLOFRIS information.

Data used

Global Flood Risk with IMAGE Scenarios (GLOFRIS)

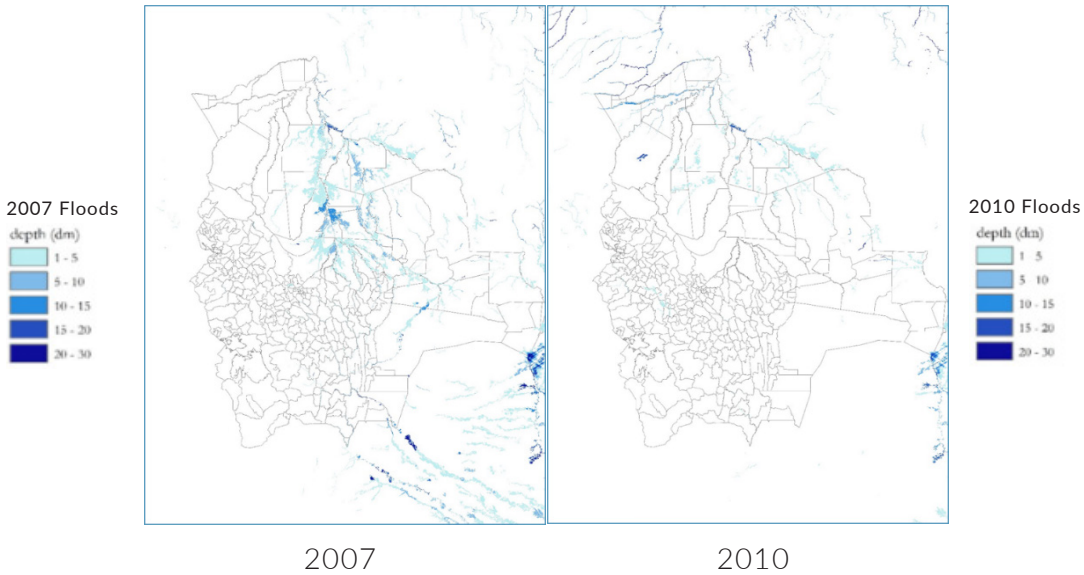
The river overflow flooding index was constructed using annual flood maps developed by the Global Flood Risk with IMAGE Scenarios (GLOFRIS) for fluvial rise. This framework proposes a cascade model of current global weather databases, a global hydrological model, a global flood routing model, and, most importantly, a downscaled flood model.[19] GLOFRIS, which has a spatial resolution of 0.00833 decimal degrees (about 1 km at the equator), represents a significant improvement over previous river overflow flooding models (with a resolution of about 0.5 decimal degrees or 60 km at the equator). Significantly, for damage assessment, the highest resolution provided by GLOFRIS can now be combined with exposure and vulnerability indicators.

To derive annual flood extremes using GLOFRIS, the hydrology and routing modules, run over a period of 30 years, are calibrated using daily global precipitation and temperature data. The result of this exercise is the maximum daily flood volume, which represents the amount of water (in decimeters) potentially residing beyond the river banks. In addition to the flood extent, the layers indicate the peak volume of the river outflow from the bank (in decimeters).

For example, Figure 7 shows that in 2007, there was significant flooding caused by river overflowing in the central-northern area of Bolivia, as compared with 2010, which was mainly dry and without any major flooding events caused by overflowing rivers.

17 VIDECI uses a different categorization for floods.
18 According to data from the VIDECI National Disaster Observatory. See Table 1 of this document.
19 The detailed methodology for GLOFRIS flooding maps can be found in Winsemius et al. (2013). There are GLOFRIS annual flooding maps available for the period 2000-2010 in a spatial resolution of 30 arc seconds (approximately 1 km^2).

Figure 7. GLOFRIS flood maps (2007 and 2010)



DMSP-OLS Nighttime lights (NTLs)

As in the case of the intensity index, the modeling of this index uses nighttime lights data of the year prior to the rainfall event to adjust the measurements of the river overflow flooding according to the degree of exposure of the economic activity and human settlements.

Calculation of the index

The flooding index is based on the assumption that the potential damage is linearly related to the extent of the flood. This is consistent with the estimated flood damage curves used by the US Federal Emergency Management Agency (FEMA) with the HAZUS flood loss estimation software. In this sense, for each location ***i*** (cell of 1 km^2), a simple multiplication is performed: the flood depth is multiplied by the exposed economic activities, represented by the nighttime lights in the year prior to the flood event (see equation below). This is based on the premise that the potential damage can only materialize if there are human settlements, infrastructure assets, and economic activities in the area under study. This method is characterized by the following equation:

$$IID_{j,t} = \sum_{i}^{j} (P_{i,t} * NTL_{i,t-1})$$

where

- $\mathrm{IID}_{j,t}$ is the municipality's river overflow flooding index in the year .
- $\mathrm{P}_{i,t}$ is the flood depth at cell in the year $\mathbf{t}$.
- $\mathrm{NTL}_{i,t-1}$ is the nighttime light intensity at cell in the year $\mathbf{t-1}$.

As with the previous index, this indicator is also normalized to allow for comparability between the indexes.

3. Empirical Strategy

Data used

The analysis of the impact of the flood events measured using the indexes described in the previous section was performed using data taken from the Household Surveys conducted by the National Statistics Institute (INE, Instituto Nacional de Estadística) for the 2005-2014 period, with the exception of the year 2010.[20] The surveys contain information on household income levels, employment, education, and the vital statistics of its members, as well as data on the conditions of their dwelling unit and the public utilities available for them. The maximum disaggregation level at which households can be identified is the municipality, which is therefore our main unit of analysis, and all precipitation indexes have been aggregated at municipal level. This level of disaggregation, although not statistically representative,[21] is important because it allows for the isolation of time-invariant unobservable heterogeneity (e.g., idiosyncratic characteristics of the municipalities accounting for differences in household income within a region that has experienced a period of high economic growth and poverty reduction), therefore permitting a more accurate estimate of the impact of flooding on per capita income and other socioeconomic indicators. Also, a higher level of disaggregation leverages the high

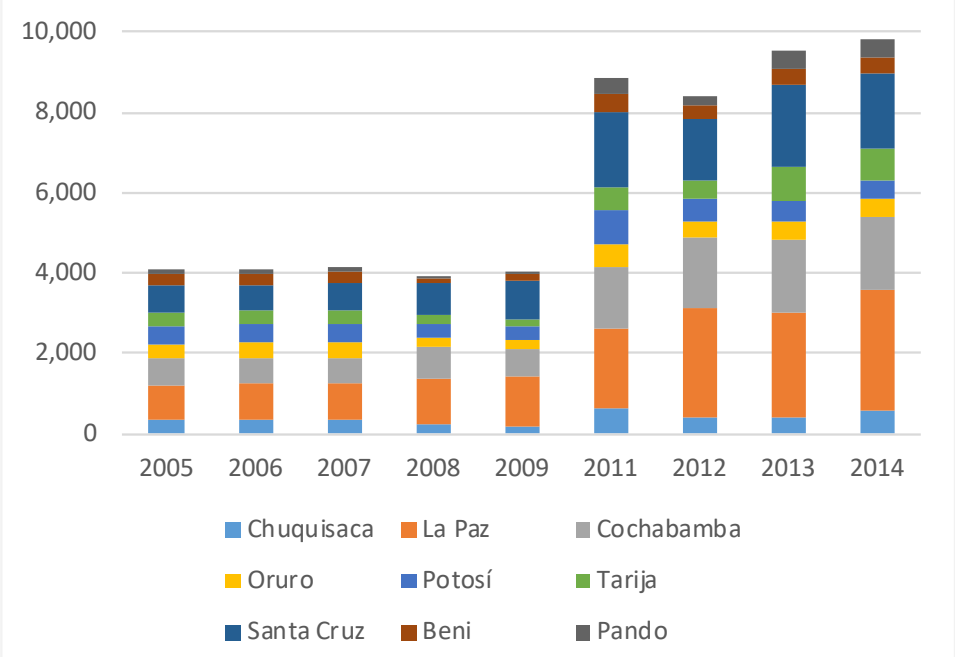
20 In general, household surveys are carried out in November and December, i.e., during the rainy season—extending from November to March. Therefore, it is worth questioning whether the impacts of the floods are being overestimated. We consider that even if there were a bias caused by the collection of data, it should not be correlated a priori with any of the three indexes used to characterize floods. As a result, the bias should not be absorbed by the coefficients associated to the indexes—which measure the impacts—but by the error term.

21 The lack of representativeness can fail to estimate an impact when there is one due to sample issues; however, we believe that the gains obtained by choosing to use the municipality as the unit of analysis outweigh the problems due to Bolivia's heterogeneity.

variability of the indexes used to characterize the floods, helping to more clearly identify the direction and magnitude of impacts.

In the ten-year period under analysis, there are 56,971 observations at household level. In this sample, 301 of the 339 municipalities (into which Bolivia is divided) are represented. The number of observations per year has increased considerably since 2011, when the survey was redesigned.[22] Figure 8 shows that there is a higher rate of observations for the departments of La Paz, Santa Cruz, and Cochabamba. This is because these are the most populated departments.

Figure 8. Number of observations per year and department



The main impact measurement was made using the monthly per capita household income at 2010 prices. Based on the values of this variable, 570 outliers or extreme observations (about 1% of all observations) were removed, whereby the number of observations in the analysis was reduced to 56,401.[23] In addition, control variables were included, such as the gender of the head of the household, highest level of education in the family, occupation of the head of the household, classification of the area of the dwelling (urban or rural), house roofing material, and type of water source. Also, data were taken from the reports by the Ministry of Economy and Finance about the budgets for the transfers

22 In order to produce representative statistics at departmental level.
23 Excluding extreme observations (outliers) is justified for two reasons. First, the objective of this study is to assess the impact of flooding on the bulk of the population, which means that excluding households with extreme income levels at either end should not be problem. Second, the exclusion of outliers is common practice in empirical studies as their inclusion could otherwise bias the estimate of the parameters of interest (for instance, the outliers could be the result of a measurement error).

sent to municipalities, which were standardized by population.[24] These controls help to isolate other potential causes for the differences in household income.

Table 3 summarizes the descriptive statistics for the dependent variable and controls. This sample does not include outliers (1% of households with higher incomes). As a reference, the nearly 600 outliers removed exhibit an average per capita income of more than BOB 11,000 (USD 1,580) in the period under analysis, which is more than 11 times the average for the rest of the sample (BOB 969 or USD 139).

The main features of Table 3 are as follows: in 25% of the households, the head of the household is a woman; 41% of the people have completed their secondary education; 31% of the sample is rural; and for 22% of the sample, agriculture is the main economic activity. Most of the households surveyed (58%) receive water through the piped water supply network.

Table 3. Descriptive statistics

Variable	Mean	Standard deviation	Min	Max
Per capita actual household income	BOB 969 (USD 139)	BOB 942 (USD 135)	0	BOB 6,197 (USD 890)
Municipal budget per capita	BOB 824.57 (USD 118)	BOB 3,065.87 (USD 440)	BOB 244.3322 (USD 35)	BOB 71,110.68 (USD 10,217)
Gender (1 = female)	0.25	0.43	0	1
Education (1 = High + Superior)	0.41	0.49	0	1
Urban/rural (1 = rural)	0.31	0.46	0	1
Roofing material (1 = tiles + concrete)	0.36	0.48	0	1
Water source (1 = piped water supply network)	0.58	0.49	0	1
Agriculture (=1)	0.22	0.42	0	1
Mining (= 1)	0.15	0.36	0	1

These statistics show significant variations by department. In the case of per capita household income, for example, while Santa Cruz, Tarija, and Pando have a mean monthly

24 (Information for the period 2005-2014): http://vmpc.economiayfinanzas.gob.bo/coparticipacion.asp?tipo=1&g=2014&flag=0, Vice-ministry of Budget and Tax Accounting, Ministry of Economy and Public Finance.

income of around BOB 1,100 (USD 158), in Potosi the average is BOB 625 (USD 90), barely 65% of the mean for the total of the sample.

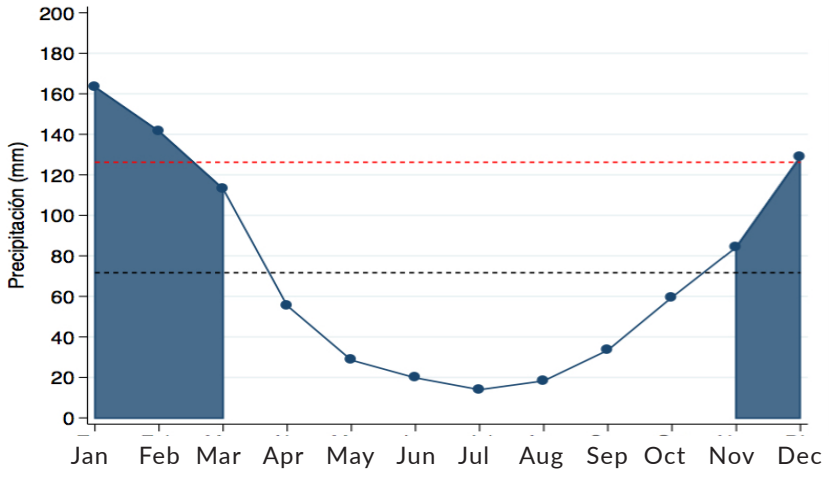
Adaptation of the indexes

For the characterization of floods, the indexes described in the previous section were aggregated at municipal level by adding the values of the cells or pixels that make up each municipality. After obtaining the value of the indexes at municipal level, dichotomous standardized variants were constructed for each one. Standardized versions allow for comparisons between the three indexes, while the dichotomous versions allow for the understanding of the impact of an additional flood. Remember that each index is expressed in different units (and sometimes difficult to interpret due to the weighting schemes), thus index comparability is easier when using the standardized versions.

Precipitation index

In the case of the precipitation index, four index variants were created: precipitation, standardization, and two dichotomous variables. For each municipality and year, the first variant (***precipitation***) adds, the values of the estimated monthly precipitation for each cell, only for the months of the rainy season (from January to March and from November to December), with a view to reducing the impact on the annual variance of the months in which there is little rainfall. It is thus better able to identify the relevant variations between municipalities. Figure 9 illustrates the historical monthly precipitation of the sample. The dotted blue line represents the average annual precipitation, taking into account every month in the year, while the red dotted line shows the average precipitation only during the rainy season. The shaded area illustrates the value of the ***precipitation*** variable.

Figure 9. 2007 Floods Precipitation (mm)



The value of the precipitation for the municipality in the rainy season was standardized using the historical distribution (1990-2004). The goal of this standardization is to incorporate the capability of municipalities to cope with a certain amount of rainfall, depending on the level of precipitation to which they are accustomed, into the analysis. That is, it is assumed that what could generate losses is not so much the level of rainfall in itself, but the amount of precipitation in excess of the historical average. This index variant (***standardization***) measures the number of standard deviations above or below the historical mean precipitation for a given year and municipality, and is calculated using the following formula:

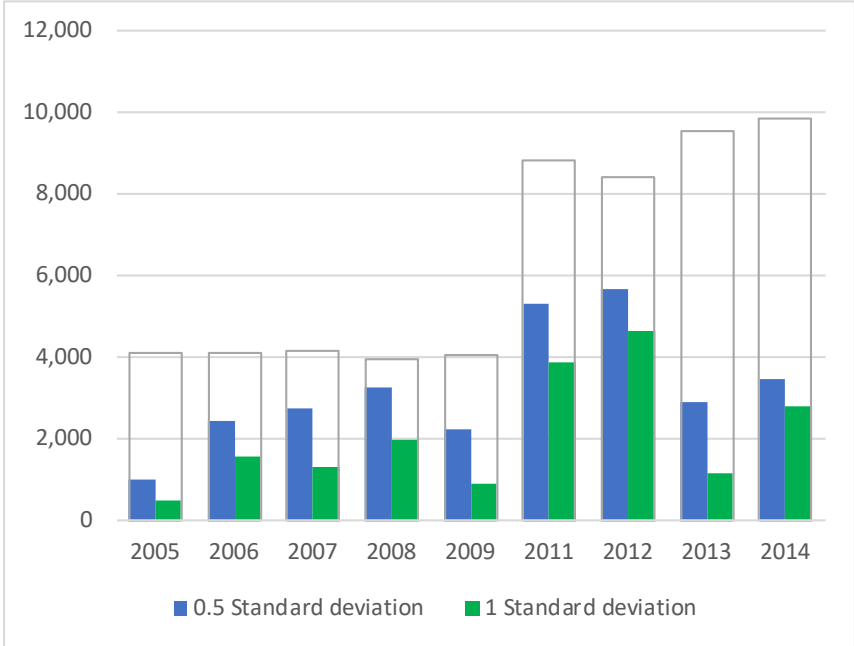
$$I_{it} = \frac{a_{it} - \hat{a}_i}{\sigma_{a_{it}}}$$

where:

- I_{it} is the number of standard deviations above or below the historical mean annual precipitation for the municipality i in year t.
- a_{it} is the annual precipitation for the municipality i in year t.
- $\hat{a}_i$ is the historical mean precipitation.
- σ_{ait} is the standard deviation.

The standardized variable is the basis for constructing dichotomous variables that take the value of 1 (households treated, or "affected") when precipitation is at a specific standard deviation above the historical mean, and 0 otherwise. The idea behind this characterization is that there is a maximum rainfall level (specific for each municipality) with which municipalities are used to dealing and which therefore has no negative impacts on them. However, if that critical level is exceeded, there are no means with which to manage the excess precipitation, and thus economic and social losses are sustained. The analysis in this study was performed based on two critical precipitation levels in line with recent literature on the subject: 0.5 and 1 standard deviations above the historical mean precipitation (Brando and Santos [2015], Rosales [2014], Rocha and Soares [2014]). Figure 10 illustrates how the number of households treated per year changes when the limit to define treatment is modified. The smaller the standard deviation, the greater the number of events considered as flooding.

Figure 10. Total households versus treated households



Intensity index

The first two variants used for this index are based on an aggregation at municipal level using thresholds of 10% and 5%, respectively. As mentioned before, the number of events considered as flooding varies by 3% between the two thresholds. In addition, a normalized variant of the index is incorporated to reduce the impact of extreme precipitation values on the calculation of the effect on income. Normalization was performed on the index calculated with a 10% threshold, based on the distribution of the whole sample for the years available (2002-2012). For this, the following formula is used:

$$\widehat{I_{t,c}} = \frac{I_{t,c} - \mu}{\sigma}$$

where:

- $\widehat{I_{t,c}}$ is the normalized intensity index (10% threshold) of the municipality c in year t.
- μ is the mean of the sample $\mu = \frac{1}{t \times c} \times \sum_{t \in T} \sum_{c \in C} I_{t,c}$.
- T are the years of the study (2002-2012 in the case of Bolivia).
- C is the sum of the codes of the municipalities.

- $I_{t,c}$ is the index value in year t for the municipality c.
- σ is the standard deviation $\sigma = \sqrt{\frac{1}{t \times c} \times \sum_{t \in T} \sum_{c \in C} (I_{t,c} - \mu)^2}$.

As with the precipitation index, a dichotomous variant is incorporated which takes a value of 1 when the intensity index is greater than zero (i.e., when there has been a flood), and 0 otherwise.

River overflow flooding index

For the river overflow flooding index, three variants were calculated. The first is the original index aggregated at municipal level. The second is the normalized index, based on the distribution of all the events for the years available, which reduces the impact of extreme events. This index is described by the following formula:

$$\widehat{ID_{t,c}} = \frac{ID_{t,c} - \mu}{\sigma}$$

where:

- $\widehat{ID_{t,c}}$ is the normalized river overflow flooding index of the municipality c in the year t.
- μ is the mean of the sample $\mu = \frac{1}{t \times c} \times \sum_{t \in T} \sum_{c \in C} ID_{t,c}$.
- T are the years of the study (2000-2010 in the case of Bolivia).
- C is the sum of the codes of the municipalities.
- $ID_{t,c}$ is the index value in year t for the municipality c.
- σ is the standard deviation $\sigma = \sqrt{\frac{1}{t \times c} \times \sum_{t \in T} \sum_{c \in C} (I_{t,c} - \mu)^2}$.

The last is a dichotomous variable which, as in the intensity index, has a value of 1 when the river overflow flooding index is greater than zero (i.e., when there has been a flood), and 0 otherwise. Table 4 shows the mean, the standard deviation and the maximum and minimum values for each of the indexes used.

Table 4. Characterization of floods

Variable	Mean	Standard deviation (SD)	Min	Max
Precipitation	665.30	325.37	122.80	2,586.73
Standardization	0.51	1.25	(2.74)	5.59
0.5 SD Treatment	0.51	0.50	0	1.00
1 SD Treatment	0.33	0.47	0	1.00
Intensity index, 10%	470,751	801,010	0	4,900,130
Intensity index, 5%	471,767	801,338	0	4,900,130
Intensity index, normalized	2.27	4.30	(0.26)	26.05
Intensity index, discrete	0.92	0.27	0	1.00
River overflow flooding	42.29	195.42	0	2,329.00
River overflow flooding, normalized	0.65	3.38	(0.08)	40.15
River overflow flooding, dichotomous	0.72	0.45	0	1.00

Econometric specification

The calculation of the impact of flooding on household income was conducted using annual data (given the period covered by the household surveys). The database of household surveys is cross sectional, and every year the selection of households interviewed changes. Only for the most important areas, mainly departmental capital cities, there is municipal information available for all years, having -in practice- a pseudo-panel at the municipality level. Since we do not have a full balanced data panel, a linear model (OLS) was calculated using fixed effects per municipality and year. This allowed for the control of each municipality or of each year on the basis of particular features defining the base income value, hence permitting the isolation of the income variation, depending on precipitation levels and intensity. The estimation strategy is characterized by the following equation[25]**:**

25 Additionally, various robustness tests were performed, including additional fixed effects based on the type of basin, both at level 2 (with a total of 14 basins) and at level 3 (with a total of 66 basins). The results are very similar to the fixed effects at municipal level, and the differences are only noticeable from the fourth or fifth decimal place. In other words, fixed effects at municipal level pick up most of the variation of the unobserved variables that may exist for each basin. See Appendix A for more details (the results in Table 12, Table 13, and Table 14, are comparable with the results in Table 7, Table 9, and Table 11, respectively).

$$y_{it} = \alpha + \beta I_{it} + \delta X_{it} + \theta t + \gamma_t + \mu_i + \varepsilon_{it}$$

where:

- y_{it} is the per capita household income in the year .
- I_{it} is the flooding index.
- X_{it} is the matrix of control variables.
- γ_t are the year fixed effects.
- μ_i are the municipality fixed effects.
- ε_{it} is the error term.

The observations were weighted with the expansion factor specified in the survey. In order to achieve a comprehensive picture of the characteristics of extreme rain or river overflow events which lead to income losses, the calculation was performed for each of the variants of the indexes specified in the previous section. In the same vein, losses were calculated using different control groups to identify the factors contributing to the exacerbation or mitigation of losses caused by flooding. Table 5 summarizes the controls used in each of the regressions. The first model only includes municipality and year fixed effects. The second model adds important features at household level. The third model, which corresponds to our preferred specification, adds the type of main economic activity for each household, under the assumption that there are certain economic activities that may be potentially more affected by flooding (such as agriculture) than other sectors (such as the services sector).

Table 5. Control groups

	1	2	3
	FE	**FE + municipal and household controls**	**2 + economic activity**
Municipality fixed effects	x	x	x
Year fixed effects	x	x	x
Municipal budget per capita		x	x
Gender (1 = female)		x	x
Education (1 = High + Superior)		x	x
Urban/rural (1 = rural)		x	x
Roofing material (1 = tiles + concrete)		x	x
Water source (1 = piped water supply network)		x	x
Agriculture (=1)			x
Mining (= 1)			x

4. Results

Precipitation index

The results for the precipitation index (Table 6) show a negative and significant effect of precipitation. Even in terms of the continuous precipitation variable, there is an estimation of an annual income loss of BOB 15 (USD 2.15) per capita for each 100 mm of precipitation recorded during the rainy season. This average value represents 1.5% of the average per capita household income, and almost 10% of household income in the lowest distribution decile.

However, this measurement is limited because it assumes that the losses caused by each 100 mm of precipitation are the same for all regions, regardless of their usual rainfall patterns. In this case, the standardized variable presents a better estimate because it incorporates the concept that 100 mm of rainfall will have a different effect on a municipality in Beni (one of the departments with the highest precipitation levels) than on one in the Potosí department (which is prone to drought). In this case, the results suggest that an increase in one standard deviation above the mean decreases the per capita annual income of an average citizen by BOB 18 (USD 2.6).

Moreover, the last two indexes (0.5 SD Treatment and 1 SD Treatment) show the effect on the income of households affected by extreme rainfall above the historical municipal average at 0.5 or 1 standard deviations. The results suggest that precipitations which are well above the usual level cause per capita annual losses of between BOB 28 and BOB 32 (USD 4 and USD 4.6), depending on the threshold used. This represents a drop in income of 4% for an average household, and of nearly 20% for the poorest households.

Table 6. Effect on income - Precipitation index

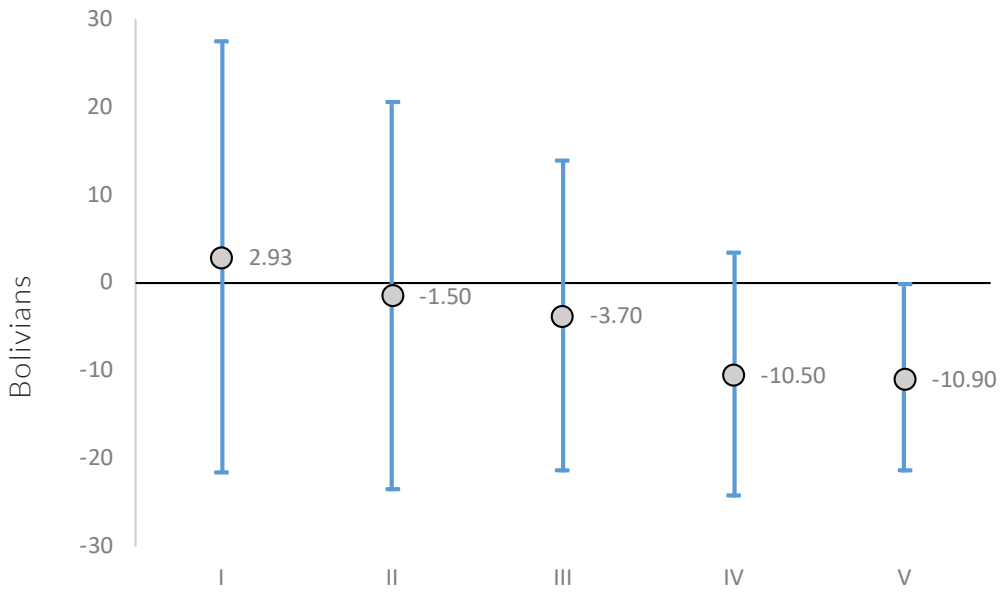
	1	2	3
	FE	FE + municipal and household controls	2 + economic activity
Precipitation (100 mm)	-16.10***	-15.10***	-15.20***
	(4.350)	(4.120)	(4.270)
Standardization	-19.46***	-18.10***	-18.32***
	(4.718)	(4.531)	(4.753)
0.5 SD Treatment	-40.84***	-34.06***	-32.54***
	(11.40)	(10.64)	(10.49)
1 SD Treatment	-40.88***	-28.77**	-28.55**
	(11.75)	(11.86)	(12.16)

*** p<0.01, ** p<0.05, * p<0.1

Standard errors in parentheses

To evaluate the existence of non-linear effects of precipitation patterns, the regression for different precipitation quintiles was calculated. Figure 11 shows the negative impact on households' annual income starting on the second precipitation quintile, and how this effect increases the higher the precipitation levels.

Figure 11. Impact by income, precipitation by quantile



In order to extend the analysis to other relevant aspects, the impact of precipitation on the likelihood that household incomes are below the poverty line, was evaluated. Table 7 shows the effect on the probability of being classified as poor after experiencing a rainy season with excessive precipitation. The results here show an increase of between 2.3 and 2.5 points in the probability of being below the poverty line for those households which suffered rainfall levels above 0.5 and 1 standard deviations, respectively. The statistical significance evidence and all indicators suggest that households close to the poverty line are deeply affected by floods.

Table 7. Effect on poverty - Precipitation index

	1	2	3
	FE	**FE + municipal and household controls**	**2 + economic activity**
Precipitation (100 mm)	0.0106***	0.0099***	0.0098***
	(0.00347)	(0.00337)	(0.00348)
Standardization	0.0129***	0.0121**	0.0121**
	(0.00474)	(0.00470)	(0.00483)
0.5 SD Treatment	0.0272**	0.0242**	0.0229**
	(0.0108)	(0.0109)	(0.0111)
1 SD Treatment	0.0311***	0.0253**	0.0248**
	(0.0110)	(0.0115)	(0.0118)

*** p<0.01, ** p<0.05, * p<0.1

Standard errors in parentheses

Intensity index

As with the precipitation index, the results obtained in this study indicate that an increase in rainfall intensity weighted by NTL (intensity index) has a negative effect on per capita income (Table 8). The interpretation of the continuous variable of the index is not direct, as changes in rainfall intensity do not translate into proportional changes in the index. Because the indicator is weighted according to light intensity (which takes a value between 0 and 63), an additional unit in the index does not necessarily represent an increase in a rain unit. However, the results obtained by using the 5% and 10% thresholds indicate a negative impact on income when precipitation levels increase.

In estimating the effects using a standardized indicator variable, it was found that an increase in 1 standard deviation decreases per capita annual income by BOB 3 (USD 0.43), whereas the dichotomous specification shows a drop of BOB 76 (USD 11). This is because the second specification is more complex, in that it requires not only extraordinary precipitation levels, but also that these be concentrated in short periods of time. This leads to a more rigorous definition of a municipality as being treated (or affected) in terms of the intensity index and, therefore, the losses are greater when those conditions are met.

Table 8. Effect on income - Intensity index

	1	2	3
	FE	**FE + municipal and household controls**	**2 + economic activity**
Intensity index, 10%	-0.0000217***	-0.0000137**	-0.0000195***
	(0.00000710)	(0.00000653)	(0.00000597)
Intensity index, 5%	-0.0000217***	-0.0000136**	-0.0000195***
	(0.00000717)	(0.00000659)	(0.00000600)
Intensity index, normalized	-4.041***	-2.546**	-3.631***
	(1.321)	(1.216)	(1.111)
Intensity index, discrete	-62.13	-68.13**	-76.04**
	(40.43)	(31.63)	(30.28)

*** p<0,01, ** p<0,05, * p<01

Standard errors in parentheses

By contrast, the impact of this index on the probability of being classified as a poor household is only significant in the discrete index. This means that different rainfall intensity levels have no clear impact on the incidence of poverty. However, crossing the flooding threshold does have an impact. Once the level of rainfall intensity deemed as flooding is crossed, the likelihood of falling into poverty is increased by 9.8%, which brings us to the conclusion that intense rainfall has a significant impact on poverty.

Table 9. Effect on poverty - Intensity index

	1	2	3
	FE	**FE + municipal and household controls**	**2 + economic activity**
Intensity index, 10%	0.0000000032	-0.0000000013	0.0000000036
	(0.00000001)	(0.00000)	(0.00000)
Intensity index, 5%	0.0000000033	-0.0000000013	0.0000000037
	(0.00000001)	(5.17e-09)	(5.40e-09)
Intensity index, normalized	0.0006000000	-0.0002440000	0.0006620000
	(0.00103)	(0.000962)	(0.00100)
Intensity index, discrete	0.0862***	0.0912***	0.0987***
	(0.0298)	(0.0240)	(0.0214)

*** p<0.01, ** p<0.05, * p<0.1

Standard errors in parentheses

River overflow flooding index

In the case of the river overflow flooding index, significant negative results are obtained in continuous indexes, but not in the dichotomous variant (Table 10). This suggests that in the case of riverine floods, the flood intensity is more relevant than the simple fact of there being a flood.

In the case of the normalized overflow index, an increase in 1 standard deviation above the mean flood level in areas with significant economic activity causes an average decrease in income of BOB 7 (USD 1). It should be noted that, as in the case of the intensity index, the NTL weighting makes it complicated to interpret the coefficients and to compare magnitudes between them. Furthermore, it is important to remember that the indexes model different types of floods and therefore estimate different magnitudes for the same event. The following section presents two examples to help acquire a better understanding of the relationship between the indexes.

Table 10. Effect on income - River overflow flooding index

	1	2	3
	FE	**FE + municipal and household controls**	**2 + economic activity**
River overflow flooding	-0.0938*	-0.121***	-0.126***
	(0.0568)	(0.0426)	(0.0431)
River overflow flooding, normalized	-5.433*	-6.998***	-7.306***
	(3.289)	(2.464)	(2.493)
River overflow flooding, dichotomous	-24.91	-14.72	-22.09
	(23.69)	(20.28)	(20.43)

*** p<0.01, ** p<0.05, * p<0.1

Standard errors in parentheses

As can be seen in Table 11, the river overflow flooding index has no significant effect on the level of poverty. This result may be due to a correlation between the type of communities living near rivers—which are therefore exposed to this type of flooding—and the probability of their being below the poverty line.

Table 11. Effect on poverty - River overflow flooding index

	1	2	3
	FE	**FE + municipal and household controls**	**2 + economic activity**
River overflow flooding	0.0000454	0.0000569	0.0000615
	(0.0000444)	(0.0000385)	(0.0000417)
River overflow flooding, normalized	0.00263	0.00329	0.00357
	(0.00257)	(0.00223)	(0.00241)
River overflow flooding, dichotomous	0.00720	0.00210	0.00844
	(0.0208)	(0.0198)	(0.0200)

*** p<0.01, ** p<0.05, * p<0.1

Standard errors in parentheses

Comparison of results

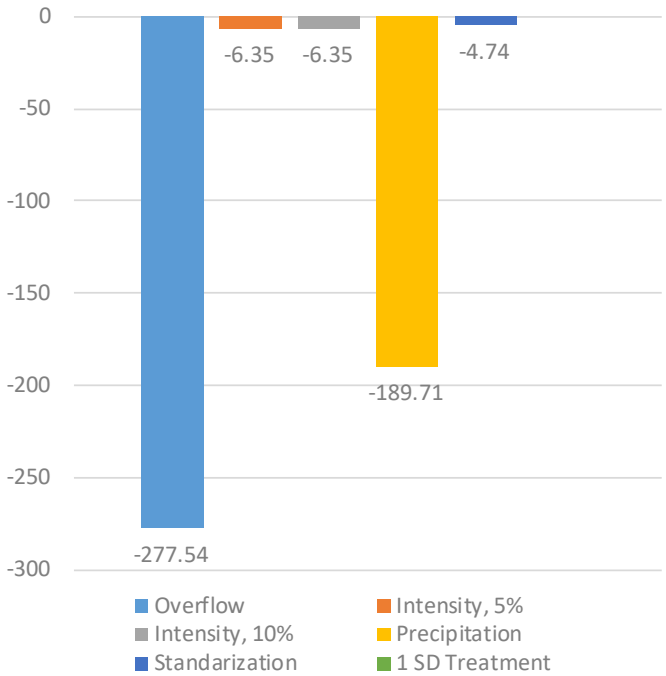
Given the difficulty of comparing the various indicators both because of the definition of what constitutes a flood and its applied expression, in this section two specific events were chosen for a clear comparison between the three indicators.

Case 1. The municipality of Trinidad is the capital of the department of Beni, one of the departments with the highest precipitation levels. According to the data used for this analysis, in 2008, the municipality suffered floods during the rainy season. Figure 12 shows the values of the various indexes used for the municipality in 2008, as well as estimated losses for each of them. Trinidad is next to a river, so it is likely that the flooding experienced was due to a river overflow. This is reflected in the high values of the losses estimated by the river overflow flooding index (blue bar). On the other hand, although the precipitation level was very high (almost twice the national mean), by the standards of the municipality, this figure is not excessive (only 0.26 standard deviations above its historical mean) and therefore, standardized or dichotomous indexes do not estimate a pluvial flooding for this observation. In this example, while the damage estimated by the river overflow and the precipitation indexes is BOB 277 and BOB 187 (USD 40 and USD 27) respectively, the dichotomous precipitation index did not detect any damage.

Figure 12. Characterization of floods, Trinidad, 2008

Trinidad Municipality, 2008

Index	Value
Overflow	2,203
Intensity, 5%	325,609
Intensity, 10%	325,582
Precipitation	1,248.08
Standarization	0.26
1 SD Treatment	0

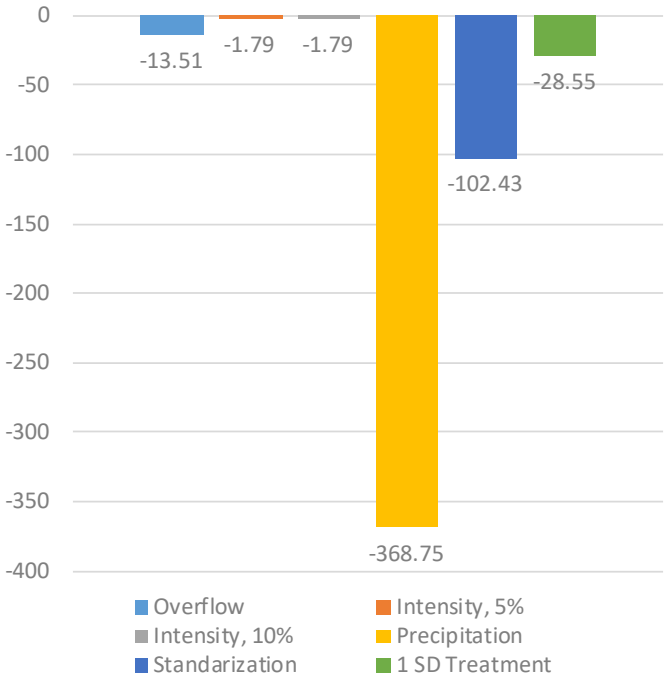


Case 2. Figure 13 shows an example which is quite the opposite of Case 1. In 2009, the municipality of Cobija recorded extraordinary levels of precipitation, characterized by a deviation from its historical mean of more than 5 times. Intensity and overflow indexes, on the other hand, show very low levels. The graph also shows that the precipitation index tends to overestimate rainfall effects, because it assumes that all precipitation is negative, regardless of the fact that moderate rainfall actually contributes to livestock and agricultural production. Thus, the estimate of the standardized index is more accurate because it considers only those precipitation levels that the municipality is not prepared to face.

Figure 13. Characterization of floods, Cobija, 2009

Cobija Municipality, 2009

Index	Value
Overflow	107.2
Intensity, 5%	91,699.2
Intensity, 10%	91,699.2
Precipitation	2,426.0
Standarization	5.6
1 SD Treatment	1



Conclusions

This study presents a quantitative evaluation of the impact of floods in socioeconomic indicators in Bolivia. The analysis covered the period from 2005-2014 (except 2010), given the availability and comparability of household surveys. The study also shows different approaches to the measurement of flood impacts, taking into account the fact that floods have different causes and characteristics that determine how they negatively affect the population.

The study develops three different definitions based on economic literature specialized in disaster and climate shocks. The first definition is based on excessive precipitation as a proxy for flooding. The second characterizes flooding by incorporating not only precipitation levels, but also rainfall intensity, measured by the number of hours of steady rainfall. The third definition employs measurements of flooding caused by river overflow using the GLOFRIS global model rather than extraordinary rainfall levels.

Based on secondary information for both socioeconomic variables (such as household surveys) and hydrometeorological variables (to define floods), it may be clearly concluded that different indicators negatively affect household income and the percentage of poor people in the country. At the upper end, it may be seen that extreme rainfall (greater than 1 standard deviation from the historical average) causes an average reduction of the monthly per capita household income of about BOB 28 (USD 4), while poverty increases by 2%. Likewise, when there is very intense rainfall, on average, the impact on households can be up to BOB 76 (USD 11) per household.

These results clearly show that it is important to promote policies to reduce and mitigate the effects of disasters associated with floods and in general, extreme hydrometeorological events. This study also demonstrates how the use of secondary information enables the drawing of interesting conclusions when combined with recent and innovative methodologies.

It is important to keep in mind that this study presents the first attempt to understand, in a comprehensive manner, the impact of floods in socioeconomic indicators in Bolivia from an economic point of view. Further analysis, i.e., the dynamic impacts over time as well as the cumulative effects overt time, warrant further research.

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Appendices

Table 12. Effect on income - Precipitation index
Basin fixed effects

	Level 2 basin			Level 3 basin		
	1	2	3	4	5	6
	FE	FE + municipal and household controls	2 + economic activity	FE	FE + municipal and household controls	2 + economic activity
Precipitation (100 mm)	-16.10***	-15.10***	-15.20***	-16.10***	-15.10***	-15.20***
	(4.350)	(4.120)	(4.270)	(4.350)	(4.120)	(4.270)
Standardization	-19.46***	-18.10***	-18.32***	-19.46***	-18.10***	-18.32***
	(4.718)	(4.531)	(4.753)	(4.718)	(4.531)	(4.754)
0.5 SD Treatment	-40.84***	-34.06***	-32.54***	-40.84***	-34.06***	-32.54***
	(11.40)	(10.64)	(10.49)	(11.40)	(10.64)	(10.49)
1 SD Treatment	-40.88***	-28.77**	-28.55**	-40.88***	-28.77**	-28.55**
	(11.75)	(11.86)	(12.16)	(11.75)	(11.86)	(12.16)

*** p<0.01, ** p<0.05, * p<0.1

Standard errors in parentheses

Note: Results comparable to Table 7.

Table 13. Effect on income - Intensity index
Basin fixed effects

	Level 2 basin			Level 3 basin		
	1	2	3	4	5	6
	FE	FE + municipal and household controls	2 + economic activity	FE	FE + municipal and household controls	2 + economic activity
Intensity index, 10%	-0.0000217***	-0.0000137**	-0.0000195***	-0.0000217***	-0.0000137**	-0.0000195***
	(0.00000710)	(0.00000653)	(0.00000597)	(0.00000710)	(0.00000653)	(0.00000597)
Intensity index, 5%	-0.0000217***	-0.0000136**	-0.0000195***	-0.0000217***	-0.0000136**	-0.0000195***
	(0.00000717)	(0.00000659)	(0.00000600)	(0.00000717)	(0.00000659)	(0.00000600)
Intensity index, normalized	-4.041***	-2.546**	-3.631***	-4.041***	-2.546**	-3.631***
	(1.321)	(1.216)	(1.111)	(1.321)	(1.216)	(1.111)
Intensity index, discrete	-62.13	-68.13**	-76.04**	-62.13	-68.13**	-76.04**
	(40.43)	(31.63)	(30.28)	(40.43)	(31.63)	(30.28)

*** p<0.01, ** p<0.05, * p<0.1

Standard errors in parentheses

Note: Results comparable to Table 9.

Table 14. Effect on income - River overflow flooding index
Basin fixed effects

	Level 2 basin			Level 3 basin		
	1	2	3	4	5	6
	FE	FE + municipal and household controls	2 + economic activity	FE	FE + municipal and household controls	2 + economic activity
River overflow flooding	-0.0938*	-0.121***	-0.126***	-0.0938*	-0.121***	-0.126***
	(0.0568)	(0.0426)	(0.0431)	(0.0568)	(0.0426)	(0.0431)
River overflow flooding, normalized	-5.433*	-6.998***	-7.306***	-5.433*	-6.998***	-7.306***
	(3.289)	(2.465)	(2.493)	(3.290)	(2.465)	(2.493)
River overflow flooding, dichotomous	-24.91	-14.72	-22.10	-24.91	-14.72	-22.10
	(23.69)	(20.28)	(20.43)	(23.69)	(20.28)	(20.44)

*** p<0.01, ** p<0.05, * p<0.1

Standard errors in parentheses

Note: Results comparable to Table 11.