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# ASSESSING LOCAL VULNERABILITY TO CLIMATE CHANGE IN RIO DE LA PLATA BASIN, URUGUAY

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## Resumen

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*Las evaluaciones de la vulnerabilidad al cambio climático tienen una larga historia en la investigación multidisciplinaria. El enfoque en la construcción de evaluaciones ha pasado de basarse sólo en rasgos biofísicos y climáticos hacia un enfoque más integrado, incluyendo los aspectos sociales y económicos de las comunidades humanas. Esta ampliación del alcance ha convertido las evaluaciones en herramientas útiles para la formulación de políticas y el gasto público en mitigación y adaptación al cambio climático. Sin embargo, no existe consenso sobre el modelo apropiado que se debe seguir dada la incertidumbre sobre los mecanismos de ponderación y agregación. El propósito de este artículo es evaluar la vulnerabilidad al cambio climático a nivel local en la Cuenca del Río de la Plata en Uruguay. Para ello elegimos un conjunto de indicadores y una metodología que puede aplicarse a cualquier proyecto de desarrollo y es apta para la replicación a diferentes escalas, dinámicas y diversidad regional. Nuestra evaluación de vulnerabilidad difiere de otros estudios en el sentido de que la agregación no se basa en pesos subjetivos o basados en expertos sino en el comportamiento de los datos. Los resultados muestran la distribución norte-sur de las localidades más vulnerables en las áreas centrales de la Cuenca. Los perfiles de vulnerabilidad están formados principalmente por la capacidad de adaptación (en forma de acceso a sistemas de tratamiento de aguas residuales) y los peligros relacionados con la precipitación y la temperatura.*

**Palabras claves:** *Exposición, sensibilidad, capacidad de adaptación, adaptación, mitigación.*

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## Abstract

*Vulnerability assessments to climate change have a long history on multidisciplinary research. The focus on constructing assessments has shifted from relying only on biophysical and climatic features toward a more integrated approach including social and economic aspects of human communities. This expansion on scope has converted assessments on useful tools to inform policy making and public expenditure on mitigation and adaptation to climate change. However, there is no consensus on the appropriate modelling to be followed given uncertainty on weighting and aggregation mechanisms. The purpose of this paper is to assess vulnerability to climate change at local level for the Rio de la Plata Basin in Uruguay. For this we choose a set of indicators and a methodology that can be applied to any development project and is suitable of replication to different scales, dynamics and regional diversity. Our vulnerability assessment differs from other studies in the sense that aggregation does not rely on subjective or experts-based weights but on the behavior of data. Results show north-south distribution of the most vulnerable localities in the central areas of the Basin. The vulnerability profiles are shaped mainly by adaptive capacity (in the form of access to sewage treatment systems) and hazards related to precipitation and temperature.*

***Keywords:*** *Exposure, sensitivity, adaptive capacity, adaptation, mitigation.*

## 1. Introduction

Vulnerability has a particular long history in the risk hazards and geography literature, where it has been defined from a biophysical point of view as the potential for loss because of a natural disaster (Mitchell et al., 1989) and is often understood to have two sides, namely, an external side related to the shocks and perturbations to which a system is exposed; and an internal side regarding the ability (or lack thereof) to adequately respond to and recover from external stresses (Chambers, 1989).

The applications that are given to assessments and indicators range from informing decision-making processes in complex environments, to the allocation of funds to adaptation and mitigation strategies in at-risk regions. Among these regions there may be communities that suffer of food, health and environmental insecurity, gender inequalities, weak security and governance, lack of infrastructure and education, and lack of access to appropriate resources and capacities to deal with extreme events (Bele, Tiani, Somorin, & Sonwa, 2013). From mid-1990's research on vulnerability changed from an exclusive focus on meteorological and biophysical factors towards a multidisciplinary approach overlapping social, economic and political issues related to climate change (Fernandez et al. 2015). Hence, research on vulnerability during the last 20 years has focused not only in meteorological and biophysical factors, whose frequency and historical distributions determine the level of exposure and sensitivity of a region and are considered stress factors of a system but also research has extended to the socio-economic and political structures as well as institutions (or lack thereof) that make societies vulnerable (Blaikie et al., 1994; Bohle et al., 1994; Cutter, 1996; Ribot, 1996; Kelly and Adger, 2000).

The Intergovernmental Panel on Climate Change (IPCC) in the Second Assessment Report defines vulnerability as "the extent to which climate change may damage or harm a system" and it added that vulnerability "depends not only on a system's sensitivity, but also on its ability to adapt to new climatic conditions" (Watson et al. 1996). In addition, Watson et al. (1998) argue that the vulnerability of a region depends to a great extent on its wealth and development conditions because poverty levels limit adaptive capabilities, economic flexibility to cope with climatic hazards and deter adoption of technologies to protect production systems. Therefore, socioeconomic systems are more vulnerable in developing countries where economic and institutional circumstances are less favorable. That is, the position of the IPCC is aligned with that of Blaikie et al. (1994) in the sense that vulnerability highly depends on the level of economic and institutional development of a region (Fernandez et al. 2015).

Hence, vulnerability assessments provide a starting point to determine the effective means of promoting remedial action to limit impacts by supporting coping strategies and facilitating adaptation. The purpose of this paper is to assess vulnerability to climate change at local level for the Rio de la Plata Basin in Uruguay. For this we choose a set of indicators and a methodology that can be applied to any development project and is suitable of replication to different scales, dynamics and regional diversity. Our vulnerability assessment differs from other studies in the sense that aggregation does not rely on subjective or experts-based weights but on the behavior of data. In addition, we take an integrated approach by not relying only on biophysical indicators but also on components related to the socioeconomic context. Results show north-south distribution of the most vulnerable localities in the central areas of the Basin.

The vulnerability profiles are shaped mainly by adaptive capacity (in the form of access to sewage treatment systems) and hazards related to precipitation and temperature.

This paper is organized as follows: Section 2 discusses the details of the methodology behind the assessment. Section 3 presents the results. Section 4 concludes.

## 2. Methodology

### 2.1. Vulnerability

Kelly and Adger (2000) defined vulnerability as “the ability or inability of individuals or social groupings to respond, recover from or adapt to any external stress placed on their livelihoods and well-being.” Thus, vulnerability to climate change is a multidimensional process affected by a large number of indicators which are rooted in four disciplines, namely, biophysics, meteorology, economics and ecology. A typical approach to quantifying vulnerability under this approach is to define a set of proxy indicators (Luers et al., 2003) and assess vulnerability through their aggregation. Indicators are useful for monitoring and studying trends and exploring conceptual frameworks and are also applicable across different scales including district, regional and national levels (Gbetibouo et al., 2010). They are useful tools on projecting vulnerability based on an adequate understanding of current conditions, trends, and causalities (Moser, 2010).

In this paper we characterize vulnerability in terms of its three components, namely (Watson et al. 1996):

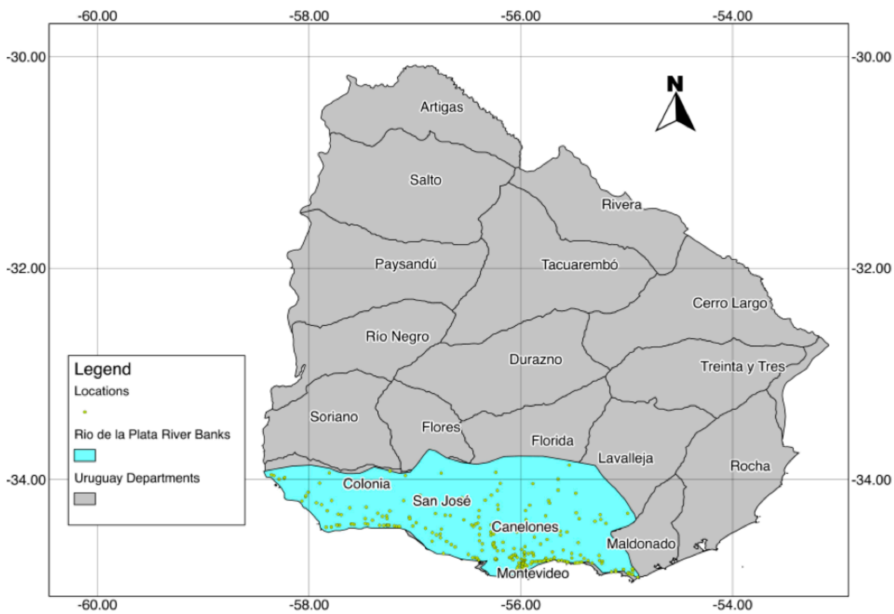
1. **Exposure:** the condition of disadvantage due to the location, position or location of a subject, object or system at risk.

2. **Sensitivity:** the degree of internal fragility of a subject, object or system to meet a threat and receive a possible impact due to the occurrence of an adverse event.

3. **Adaptive capacity:** the capacity of a system, community or society exposed to hazards to cope, absorb, and recover from the effects of an adverse event timely and effectively, considering the preservation and restoration of its essential basic structures and functions.

There is no systematic methodology to determine vulnerability in the context of multiple stressors (O’Brien et al., 2004). The basic setup for climate change vulnerability assessments is the assumption that climate change exposure (i.e., on-going and future exposure) will affect current sensitivity, either positively or negatively, and that individuals or communities will respond given their adaptive capacity. Thus, the vulnerability profile is constructed by combining indicators for adaptive capacity, sensitivity indicators as well as indicators related to exposure to climate variables (O'Brien et al., 2004). The assessment is applied to all locations that are geographically exposed to the Rio de la Plata Basin and examines the importance of drainage infrastructure as a component for reducing vulnerability to climate change. We use 243 localities in the departments of Canelones, Colonia, Flores, Florida, Lavalleja, Maldonado, San Jose and Montevideo (Figure 1).

**Figure 1:** Study Area – Rio de la Plata Basin




Source: Construction and Aggregation of the Vulnerability Indicators

We use a number of indicators not only based on biophysical terms but also on the socioeconomic context of the basin. In order to construct the vulnerability indicator we aggregate the exposure and sensitivity indicators following Fernandez et al. (2015), Hiremath (2013) and Iyengar et al (1982). Let $X_{id}$ denote the value of the $i^{th}$ vulnerability indicator in the $d^{th}$ locality (i.e. $i = 1,2, \dots ,m$; $d = 1,2, \dots n$). For normalization we set $y_{id} = \dfrac{X_{id} - Min_d X_{id}}{Max_d X_{id} - Min_d X_{id}}$ if it is assumed that the indicator is positively associated to vulnerability, and $y_{id} = \dfrac{Max_d X_{id} - X_{id}}{Max_d X_{id} - Min_d X_{id}}$ otherwise.

The scaled values, $y_{id}$, vary from zero to one, such that from the matrix of scaled values, $Y = (y_{id})$, we construct a measure of vulnerability for each locality as follows:

$$y_d = w_1 y_{1d} + w_2 y_{2d} + \cdots + w_m y_{md} \qquad \textbf{(3)}$$

Where $w_i$ are weights reflecting the relative importance of the individual indicators with the following properties $0 < w_i < 1$ and $w_1 + w_2 + \cdots + w_m = 1$. We assume the weights vary inversely as the variation in the respective indicators of vulnerability as follows:

$$w_i = \frac{k}{\sqrt{Var\,(y_i)}}$$

$$\text{Where } k = \left( \sum_{i=1}^{m} \frac{1}{\sqrt{Var\,(y_i)}} \right)^{-1}. \qquad \textbf{(4)}$$

This weighting mechanism ensures that large variation in any of the indicators will not dominate the contribution of the rest and distort comparisons.

A meaningful characterization of the vulnerability profiles should be in terms of a fractile classification based on an assumed distribution of $y_d$ (Iyengar 1982). We assume that $y_d$ follows a Beta distribution in the range (0, 1) which is skewed and relevant to characterize positive valued random variables. This distribution has the probability density as follows:

$$f(z) = \frac{z^{a-1}(1-z)^{b-1}dx}{B(a,b)}, \quad 0 < z > 1 \text{ and } a,b > 0$$

$$\textbf{(5)}$$

$$\text{Where } B(a,b) = \int_0^1 x^{a-1}(1-x)^{b-1}\,dx$$

The parameters (a,b) can be estimated by solving the following simultaneous equations:

$$(1 - y)a - yb = 0 \qquad \textbf{(6)}$$

$$(y - m)\,a - mb = m - y \qquad \textbf{(7)}$$

Where, y is the overall mean of the localities indicators and m is defined as:

$$m = s_y^2 + y^2 \qquad \textbf{(8)}$$

Where $s_y^2$ is the variance of the indicators by locality.

Let (0, z1), (z1 , z2 ), (z2 , z3 ), (z3 , z4 ), (z4 , z5 ) be the linear intervals such that each one has the same probability weight of 20 per cent. The cut-off points (z) can be obtained from tables of the Beta function. These fractal groups can be used to classify the vulnerability categories as follows:

1. Less vulnerable if $0 < y_i < z_1$
2. Moderately vulnerable if $z_1 < y_i < z_2$
3. Vulnerable if $z_2 < y_i < z_3$
4. Highly vulnerable if $z_3 < y_i < z_4$
5. Very high vulnerability if $z_4 < y_i < 1$

## 2.2 Climate Indicators

Similar to Fernandez et al (2015) we choose temperature, humidity, wind intensity and precipitation as climate (exposure) indicators. These are part of the Essential Climate Variables (ECV) identified by the Global Climate Observing System (GCOS) as relevant to understand the climate system (Mason et al. 2010). We focus on climate variability using a dataset which contains the ECVs in a monthly basis for a range of 40 years (1971-2011).

This range is sensible because that particular trends in warming, ocean precipitation anomalies, average of maximum zonal-mean wind stress and other effects are well-defined since 1970 (IPCC 2014).

The climate variables in this study are common to the computational models used by the IPCC to simulate the climate change scenarios. These variables are available in different reanalysis datasets such as NCEP/NCAR Reanalysis Project (CDAS) and Modern Era Retrospective-Analysis for Research and Applications (MERRA) from NASA. For the latter type of data it is necessary that all units of analysis are located as close as possible to a weather station; however this is not usually possible. Also, these parameters vary significantly even within a region due to physical factors (e.g. terrain slope), limiting the use of interpolation because of likely biases. For that purpose we propose to use reanalysis climate datasets within a specific range of time and area. Thus, we extract climate data through a regular grid over the areas of interest (i.e. spatial map) for each time step available. Then we classify some locations with similar or different climate patterns, and identify areas with well-regulated seasonal patterns. It is inferable that the latter puts a particular location in a more vulnerable position to climate change.

In practice, climate data are usually found in time series of spatial maps (2-3 dimensions) which imply very large datasets. Then we need to summarize the variability in a manageable set of indicators. Therefore, we make use of a principal component analysis (PCA) which is known in the oceanography literature as empirical orthogonal function (EOF) (Emery and Thomson 2001). This technique permits to characterize dominant spatial patterns and temporal indexes of variability with few first modes. However, these modes may not be necessarily linked to dynamical or physical modes, but they represent the covariance structure of the dataset. In our approach, we assume that these modes are linked to climate patterns in the areas of study. Hence, our exposure index is linked to the correlation coefficient between the time series and the specific location with the principal component of the entire dataset (Mearns et al., 1997). The EOFs have a physical interpretation, which could lead to identify possible spatial patterns in order to make sensible comparisons between regions (Lorenz, 1956).

Following Bjornsson et al. (1997), a climate dataset is formed by a matrix X(t,j,i) of 3 dimensions (time, longitude, latitude), the first dimension corresponds to time, and the other two correspond to space. The dataset is re-arranged in a matrix A(x,t) with dimension NxM, where M is the number of elements in spatial dimension, and N is the temporal dimension. The matrix A(x,t), could be represented by a linear combination of their eigenfunction, F(x), and eigenvector, a(t):

$$A(x,t) = \sum_{n=1}^{N} a_n(\mathrm{t}) F_n(x) \qquad \textbf{(1)}$$

The matrix A(x,t) is demeaned to get an anomaly matrix; then it is decomposed by the singular decomposition method in order to get non-singular values which correspond to the EOF and PC of the data (i.e. the spatial and temporal patterns in the area of interest). The EOF gives a map of the variance of the modes in the dataset.

We relate the value for a particular location with the corresponding PC linked to a temporal pattern in the parameter. The exposure indicator will be formed by the extracted EOF (cEOF) and the variance of the time series (vTS) of the parameter in a particular location (x,y) in the map such that:

$$EI=cEOF*vTS \qquad \textbf{(2)}$$

In order to avoid different results because of the order of variables or modification in locations number, all the process is carried over the original dataset, that is, the X(t,j,i) is rearranged in A(x,t).

### 2.3. Sensitivity and Adaptive Capacity Indicators

As in previous studies (Antwi-Agyei et. al. 2012, Luers et. al. 2003, Lardy et. al. 2012, Ionescu et. al. 2009) we separate vulnerability into its three components, namely, exposure, sensitivity and adaptive capacity. The set of indicators we use are given in Table 1. The exposure indicators also come from the Climate Forecast System Reanalysis (CFSR) monthly products, developed by the National Center for Environmental Prediction (NCEP), for the date range from 1979 to 2010 and extracted in a rectangular grid (36S-29S, 60W-52W). The rest of indicators belong come from the 2011 Population and Household Census (PHC).

**Table 1:** Vulnerability Indicators

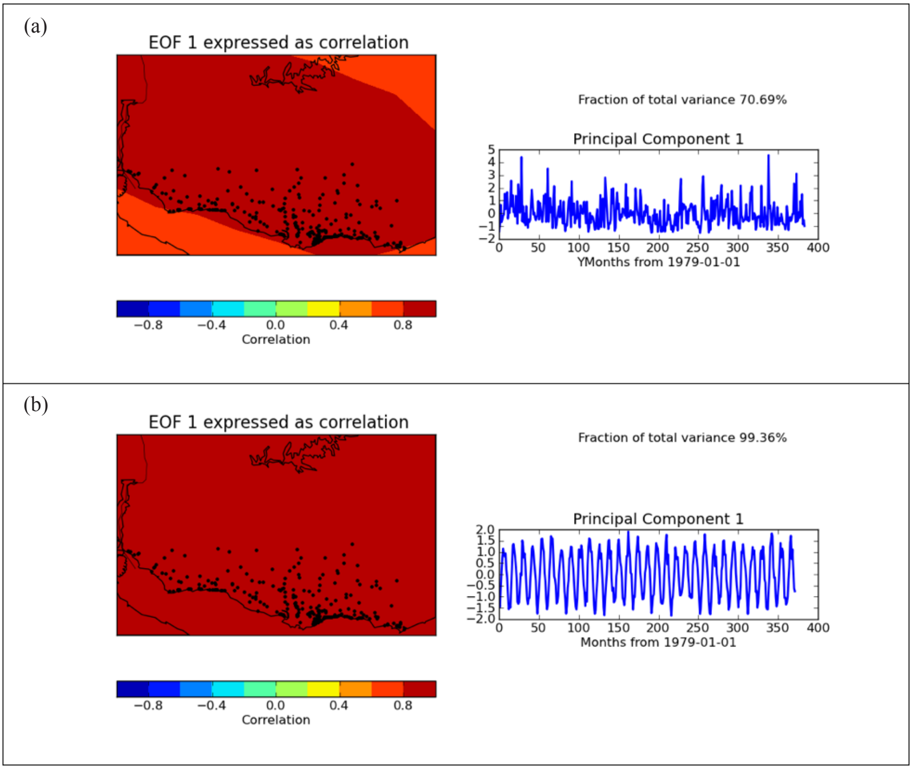
| Focus | Indicators | Source |
|---|---|---|
| | **Exposure** | |
| Climate | Precipitation (+) | NCAR |
| | Relative humidity (+) | NCAR |
| | Wind velocity (+) | NCAR |
| | Temperature (+) | NCAR |
| | **Sensitivity** | |
| Demographics | Illiteracy rate (+) | PHC |
| | Population density (+) | PHC |
| | Unemployment rate (+) | PHC |
| Socially vulnerable groups | Average number of children per household (+) | PHC |
| | Proportion of crowded households (+) | PHC |
| | Proportion of population 0-5 years (+) | PHC |
| | Proportion of population 65 years or older (+) | PHC |
| | Proportion of population with low schooling (+) | PHC |
| | Proportion of population with permanent disability (+) | PHC |
| | **Adaptive Capacity** | |
| Physical infrastructure | Proportion of households receiving water through piped system (-) | PHC |
| | Proportion of households with access to computer (-) | PHC |
| | Proportion of households with electricity service (-) | PHC |
| | Proportion of households with land phone service (-) | PHC |
| | Proportion of households with proper sanitary facilities (-) | PHC |
| | Proportion of households with sewage treatment service (-) | PHC |
| | Proportion of houses with exclusive room for kitchen (-) | PHC |
| | Proportion of houses with exclusive sanitary facilities (-) | PHC |
| | Proportion of population with internet access (-) | PHC |
| | Proportion of population with mobile phone access (-) | PHC |

Notes: PHC - Population and Household Census and NCAR – National Center for Atmospheric Research (USA). +/- denote the association between the indicator and vulnerability

## 2.4. Results

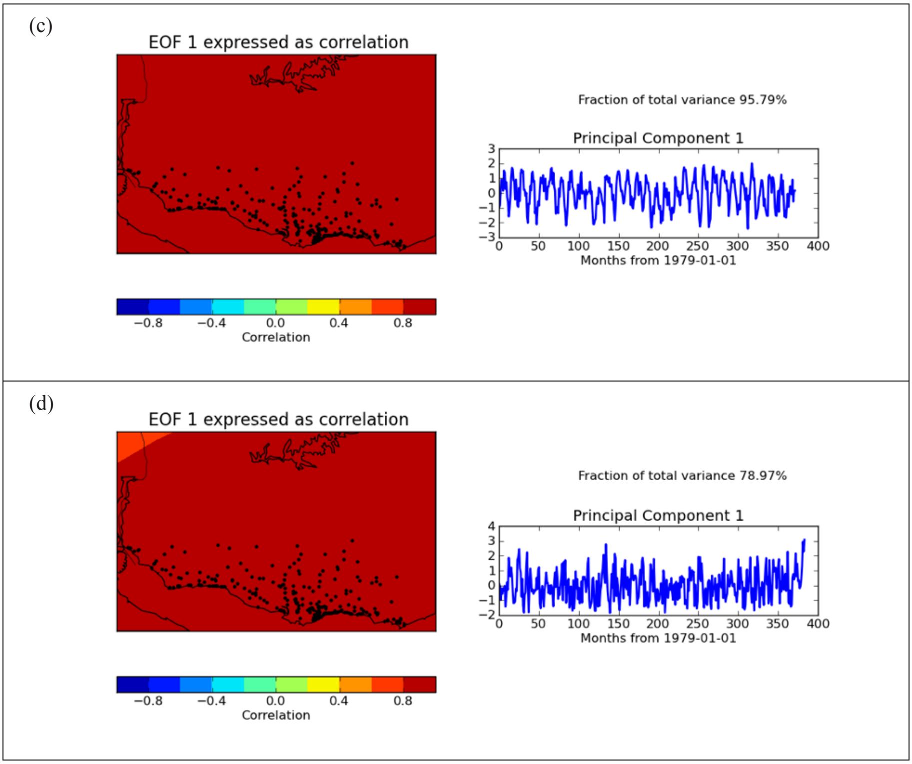
The EOFs and their principal components may be interpreted as a climate pattern and serve to extract a map correlation value for a particular location. Figure 2 shows the EOF analysis for all the exposure indicators. In every case the temporal and spatial correlations are around 0.8 which reflects this approach is reliable to proxy climatic behavior within the context of the assessment. However, given the location of all localities with respect to the basin and the homogeneous geographic conditions, exposure to climatic features does not show sharp differences across localities. In addition, the EOFs and PCs also contain a significant share of the climatic variance (Table 2).

**Figure 2:** EOF analysis: (a) Precipitation, (b) Temperature, (c) Relative humidity, (d) Wind velocity




Note: In the EOF panel, dots represent the localities where correlation with PC is extracted.

**Figure 2 (continued):** EOF analysis: (a) Precipitation, (b) Temperature, (c) Relative humidity, (d) Wind velocity




Note: In the EOF panel, dots represent the localities where correlation with PC is extracted.

**Table 2:** Percentage of Explained Variability - EOF Mode

| Indicator | Percentage of variability |
|---|---|
| Precipitation (+) | 70.69% |
| Relative humidity (+) | 95.79% |
| Wind velocity (+) | 78.96% |
| Temperature (+) | 99.30% |

## 3. Vulnerability Assessment

The estimated parameters *a* and *b* of the Beta distribution are 26 and 33, respectively, and the cut-off points are $z_1$ = 0.387, $z_2$=0.424, $z_3$=0.457 and $z_4$=0.495. Table 3 shows the weights of each indicator towards the formation of the aggregate vulnerability indicator. There is strong contribution mainly from exposure and adaptive capacity indicators.

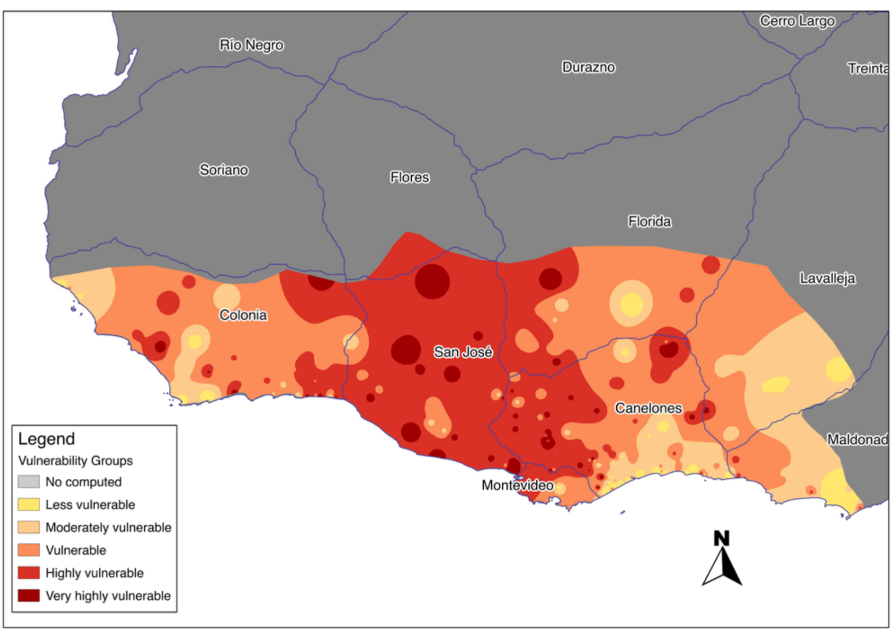
The largest weights correspond to the proportion of households with sewage treatment service, and precipitation. In the area there used to be, by the time of data collection, important works on drainage infrastructure to control floods. Thus, precipitation and runoff are key variables related to those works that may shape the vulnerability profile of the localities. Other climate-related variables are among the top ten indicators, as follows, temperature ($3^{rd}$), relative humidity ($6^{th}$) and wind velocity ($7^{th}$). From the five indicators with the highest weights, one of them is the proportion of population with low schooling ($4^{th}$) and another is related to physical infrastructure, namely, the proportion of houses with exclusive room for kitchen ($5^{th}$). On the other hand, the indicators with the lowest weights correspond to the proportion of houses with exclusive sanitary facilities, the proportion of households receiving water through piped system, and the proportion of population with permanent disability. Intermediate values appear for some of the sensitivity indicators such as the illiteracy rate ($9^{th}$), the proportion of population 65 years or older ($10^{th}$), and the proportion of population 5 years or younger ($12^{th}$).

**Table 3:** Weights of the Vulnerability Indicators

| Indicator | Weight |
|---|---|
| Proportion of households with sewage treatment service | 0.0955 |
| Precipitation | 0.0848 |
| Temperature | 0.0720 |
| Proportion of population low schooling | 0.0678 |
| Proportion of houses with exclusive room for kitchen | 0.0656 |
| Relative humidity | 0.0633 |
| Wind velocity | 0.0628 |
| Proportion of households with land phone service | 0.0606 |
| Illiteracy rate | 0.0597 |
| Proportion of population 65 years or older | 0.0588 |
| Proportion of population with internet access | 0.0547 |
| Proportion of population 1-5 years | 0.0456 |
| Proportion of households with electricity service | 0.0450 |
| Proportion of households with proper sanitary facilities | 0.0396 |
| Proportion of population with mobile access | 0.0344 |
| Proportion of houses with exclusive sanitary facilities | 0.0342 |
| Proportion of households receiving water through piped system | 0.0296 |
| Proportion of population with physical disability | 0.0260 |

Figure 3 maps the vulnerability categories to the Basin. The least vulnerable localities are spread across the departments of Colonia, Canelones, Florida, Lavalleja and Maldonado. There is no uniform pattern apart from the economic conditions of those areas. On the contrary, most of the high and very high vulnerability localities concentrate in San Jose. Vulnerability in these areas is shaped mainly by economic disadvantage, in terms of low schooling and housing conditions, in interaction with precipitation and temperature, and related hazards, e.g. floods, droughts. Intermediate levels of vulnerability are found around Montevideo, Uruguay's capital and largest city. Though Montevideo is located in areas with greater climatic hazards, infrastructure and agglomeration externalities appear to mitigate any of the exposure indicators. Hence, results agree with Blaikie et. al. (1994) in the sense that the multi-dimensional perspective about vulnerability is grounded on the idea that a climatic disaster occurs when unsafe conditions in the socioeconomic system converge with the biophysical factors that favor the exposure of a natural hazard. Therefore, unlike the biophysical vision where vulnerability depends exclusively on the frequency and geographical distribution of disasters, the scope of our vulnerability assessment involves the number of people that experience a hazard and suffer serious damage and/or disruption of their subsistence system.

**Figure 3:** Mapping of Vulnerability to Climate Change



### 3.1. Decomposition of the Composite Vulnerability Indicator

We separate the individual indicators and apply the aggregation procedure in order to obtain three separate indicators for exposure, sensitivity and adaptation.

Panel (a) of Figure 4 shows that the localities with the least adaptive capacity are located in the western area of the Canelones department and around Montevideo. Thus, Montevideo turns out to be moderately adaptable to climate change. Other localities with high adaptive capacity appear in El Pinar and Villa Argentina (Canelones department), and Santa Regina (Colonia department). Panel b shows that the highly sensitive localities are found in the departments of San Jose, the western portion of Canelones and the eastern part of Lavalleja. Moderately vulnerable localities are sprawled across the Basin where clear concentration arises. This is more noticeable for the least sensitive localities which are located to the west of Montevideo and concentrated in the south and coastal part of the Basin. Panel c shows that the highest exposed localities are also found in a North-to-South pattern. Furthermore, the highly and very highly exposed localities are concentrated in the San Jose Department. It includes Montevideo and the surrounding areas which in Panel b correspond to the less sensitive localities. In turn, the least vulnerable and moderately vulnerable localities are located in the west part of the Basin.

**Figure 4:** Adaptive Capacity Indicator at Locality Level: (a) Adaptive Capacity

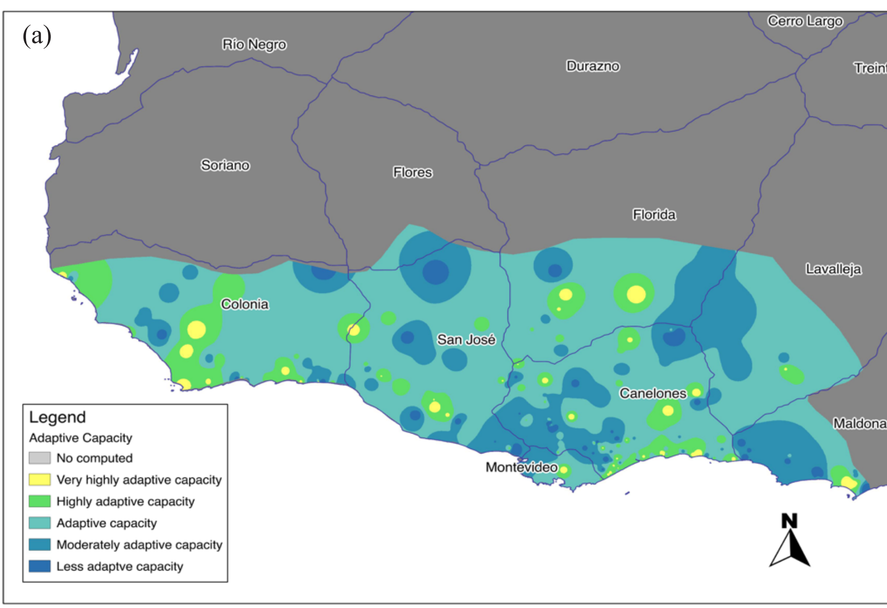


**Figure 5:** Adaptive Capacity Indicator at Locality Level: (b) Sensitivity

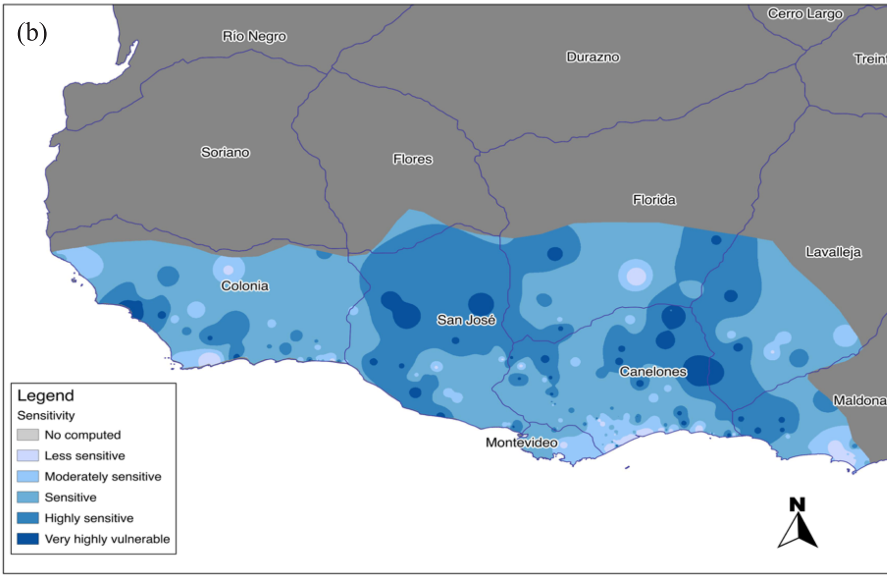
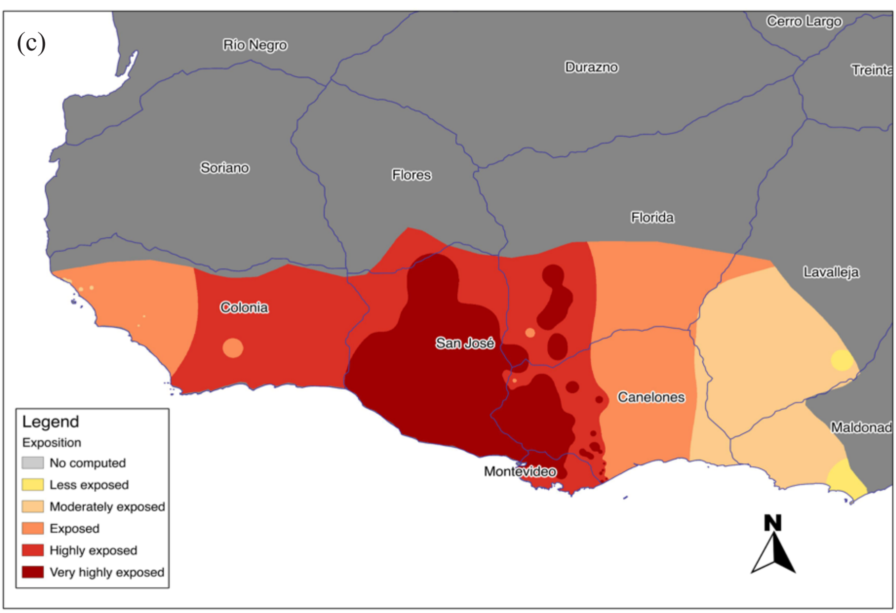



**Figure 6:** Adaptive Capacity Indicator at Locality Level: (c) Exposure



## 4. Discussion

Following the vulnerability concept, our approach presents a methodology to quantify the level of exposure in function of the geographic location. We have chosen a method that considers the statement of IPCC 2001, which recommended that the exposure should be represented by the variability of climate conditions. The adequate representation of these factors is important as climate change is not only a defined and specific natural event. Also, climate change effects are globally different, and the short and long-term effects are barely understood. Thus, even though we can have some expectations about how climate change will affect the frequency or intensity of some hazards (e.g. flooding and droughts), uncertainty remains about location and variability. In our approach, given that small changes in variance and mean of climate variables produce changes in the frequency and intensity of hazards, the use of climate indicators allows us to incorporate the relative sources of the extreme weather events, (Gutowski et al. 2008; Kevin E. Trenberth 1999).

For IPCC (2001), both climate variability and climate extremes are described through statistical distributions of precipitation and temperature. It is remarkable that changes in the mean values cannot explain adequately the extreme events occurrence. Plus, changes in the variance alone cannot explain high values during extreme events either. This leads us to use a method that incorporates both the mean and the variance of the climate variables for adequate explanation of the level of exposure to climate changes effects. We disregard the use of single values of means for a particular locality, since we will compare multiple variables from different places. For this reason we include the spatial pattern, which could be interpreted as the mean value for all localities clustered in the same regions. We also include in our analysis the value of monthly and yearly variance for the different locations. This approach (mean and variance) lets us consider the vulnerability of communities to extreme weather events and their effects rather than more or less precipitation, humidity and wind intensity, or minimum or higher temperatures.

We have found some difficulties to apply a standard method to analyze the climate parameters, for instance, we used yearly averages instead of monthly average for the precipitation amount in the EOF computation. It was remarkable for us to find that the spatial and temporal pattern of climate conditions obeys to different factors that affect their behavior in the area of study.

We use reanalysis data, which is the outcome of numerical models and observational data assimilation, from which we aim to get a standard dataset for the analysis and comparison between different locations. This method is convenient in countries where it is not easy to get meteorological information, due to the lack of meteorological stations or the difficulty on processing this information. At the same time, reanalysis models can satisfactorily reproduce the natural variability (Tett, Johns, and Mitchell 1997) and yield reliable results for inter seasonal variability.

In this paper we have also identified that population size does not necessarily imply that infrastructure will accompany their development such that vulnerability be reduced. A future economic or demographic impact analysis would complement the extent of the implications of this study. Similar to O'Brien et al. (2004) we present a method for mapping vulnerability to stressors at the sub-national level. We operationalize the IPCC definition of vulnerability in a sub-national assessment to show how different factors that shape vulnerability vary within one country. The approach places the social and economic well-being of society at the centre of the analysis, focusing on the socio-economic and institutional constraints that limit the capacity to respond. From this perspective, the vulnerability of any locality is determined by resource availability and by the entitlement of individuals and groups to call on these resources (Kelly & Adger, 2000).

The importance of social capital is difficult to capture in geo-referenced data, vulnerability requires integration of both physical, ecological, and social variables, however the challenge remains on identifying those factors that are relevant in each case (Moser, 2010). Plus, it is an open research endeavour to assess how different weighting of indicators influence interpretation and be usefully linked to planning, prioritization, and decision-making; as well as to determine what infrastructure is required to ensure monitoring over time given the dynamic nature of vulnerability. The latter is important specially if we know that anticipating or adapting to climate change impacts become vital in order to minimize their consequences on human well-being and on the environment (Bele, Tiani, Somorin, & Sonwa, 2013).

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