



Extreme Rainfall and Hydro-Geo-Meteorological Disaster Risk in 1.5, 2.0, and 4.0°C Global Warming Scenarios: An Analysis for Brazil

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With the inclusion of demographic characteristics of the population living in vulnerable areas, a combination of empirical and climate models was used to project changes to climate and in hydro-geo-meteorological disasters in Brazil. This study investigated the effect of extreme rainfall changes and the risk of floods and landslides under 1.5, 2.0, and 4.0°C global warming levels (GWLs). Projections from a large ensemble of pre-CMIP6 models and different warming levels show a remarkable change in heavy precipitation. As a result, with increasing warming this enhances the risk of landslides and flash floods in the context of climate change. Comparisons of vulnerability and change in potential impacts of landslides and floods show that three regions, highly densely populated areas, are the most exposed to landslides and floods. The Southern and Southeastern of Brazil stand out, including metropolitan regions with high economic development and densely populated, which may be those where disasters can intensify both in terms of frequency and magnitude. The eastern portion of the Northeast is also signaled as one of the affected regions due to its high vulnerability and exposure since the present period, although the projections of future climate do not allow conclusive results regarding the intensification of extreme rainfall events in scenarios below 4°C. The main metropolitan regions and tourist resorts, and key infrastructure in Brazil are located in those regions. This study highlights the importance of environmental policies to protect human lives and minimize financial losses in the coming decades and reinforces the need for decision-making, monitoring, and early warning systems to better manage disasters as part of disaster risk reduction risk management.

Keywords: climate extremes, climate-related disasters, climate change, disaster risk reduction, vulnerability

INTRODUCTION

Present and future climate extremes imply adverse impacts on natural and human systems. These extreme events are anticipated to be among the potentially most harmful consequences of a changing climate. However, it is very difficult to translate changes in the intensity, duration, and frequency of weather and climate extremes (i.e., hazards) into actual risks for specific sectors and/or locations, or, even further, to express these in quantitative terms, mainly because we lack sufficient knowledge of the socioeconomic and environmental implications, including data on vulnerabilities and exposure (IPCC, 2012). Disasters triggered by climate extremes pose severe societal challenges across a range of sectors (IPCC, 2012, 2013, 2014, 2019; Moreno et al., 2020; Sillmann and Sippel, 2020). Climate risks are distributed unevenly between regions and generally higher in developing countries with low income (De Coninck et al., 2018). For example, the state of São Paulo in southeastern Brazil experienced profound water shortages in 2014–2015 due to severe drought (Otto et al., 2015; Nobre et al., 2016). On the other hand, intense rainfall has increased in southern Brazil (Dunn et al., 2020), and in the Metropolitan Region of São Paulo this increase in the last seven decades caused disruption to transport, flooding and landslides (Marengo et al., 2020a,b).

The United Nations Office for Disaster Risk Reduction considers disaster as a severe disruption of a community's functioning or a society (UNISDR, 2015). This involves widespread human, material, economic, or environmental losses and impacts. About 90% of all climate related disasters are caused by weather-climate-related hazards. Among them are floods, flashfloods, landslides, and droughts (UNISDR, 2015; EM-DAT, 2019). Intense rainfall followed by a flash flood or landslides has strong impacts on population.

The majority of climate-change impact assessments have been framed in future time horizons, e.g., impacts by the middle or end of the twenty-first century using the Special Report Emission Scenarios (SRES) or the Representative Concentration Pathways (RCPs) emission scenarios (IPCC, 2007, 2014). According to the IPCC's Special Report on Global Warming of 1.5°C—if we exceed 1.5–2°C, it is likely an increase in the risk of impacts consequence of extreme rainfall events and rising sea levels (IPCC, 2019). It was during the 2015 United Nations Climate Change Conference COP-21 held in Paris that the boundary of 1.5–2.0°C warming has been regarded as the most desirable, to avoid strong impacts of climate change on natural and human systems (Hulme, 2016). Prior to the Paris Agreement, the IPCC AR5 (IPCC, 2014) and World Bank (2014) presented synthesis diagrams with impacts of 1.0–6.0°C warming levels above pre-industrial conditions. However, these were based on expert judgment rather than quantitative impact assessments. The Stern Review of the Economics of Climate Change (Stern, 2016) included an early assessment of possible impacts of various warming levels.

Various studies have documented some impacts of different global warming levels (GWLs), but few of them deal with South America or specifically, with Brazil. These show that there is regional differentiation in both future climate risks and vulnerabilities to incremental

increases in global-mean temperature. In addition, the magnitude of global warming at the level of 1.5, 2.0°C or higher can lead to more extreme and severe climatic conditions (HELIX project-www.helixclimate.eu, IPCC, 2018, 2019).

Limited research on the consequence of GWLs of 1.5 and 2°C was conducted for risk of disasters due to increase in rainfall extremes. For these systems, climate is one of many drivers that result in adverse outcomes. The risk of natural disasters depends also on non-climatic factors that are not included in the climate projections. Among them they used land use, drainage systems, relief, slope, road density, and hydrography, and socioeconomic information.

In Brazil, a pioneer work developed by Debortoli et al. (2017) use IPCC AR5 models to assess risk of landslides, floods, flashfloods, and drought for the present and future. The authors developed empirical models that use these climate projections together with official statistics and environmental information to project risk of water-related natural disasters at the municipality level. They found a large increase in risk of landslides and flash floods in Brazil in the context of climate change by 2050. Regions already considered to be of high vulnerability will become even more vulnerable, such as the mountainous region of Rio de Janeiro, interior and southern Minas Gerais, and various locations on the Brazilian coast in southeast Brazil. Southern Brazil is the region with the most impressive increments (50%) of risk of landslides, changing from a “low” vulnerability to a “high” vulnerability class late in the century.

These and other studies (Brasil, 2016; De Almeida et al., 2016; EM-DAT, 2019; Marengo et al., 2020a,b; Moreno et al., 2020; Travassos et al., 2020) consistently report that climate change exacerbates climate hazards and amplifies the risk of water related disasters at the local and regional level. They identify Brazil's hot spots of vulnerability to hydro-geo-meteorological disasters using a combination of projected indices of climate extremes, and environmental data, including land use, drainage systems, relief, slope, road density, hydrography, and socioeconomics. In Brazil, the increase in the frequency and intensity of extreme rainfall combined with population exposure has triggered disasters such as landslides, floods, and flashfloods in various regions of Brazil (Ávila et al., 2016; Alvala et al., 2019; Marengo et al., 2020a,b).

Adaptation to a world with 1.5°C global warming will require environmental policies that consider extreme weather conditions and reduce risk of climate-related disasters (IPCC, 2018, 2019). Key synergies between international agreements have been explored for sustainable development and disaster risk reduction a stronger integration between agendas of sustainable development (e.g., Agenda 2030; United Nations, 2015, 2016), disaster risk reduction (e.g., Sendai Framework, UNISDR, 2018) and the 2015 Paris Agreement (UNFCCC, 2016a,b). Past and current experiences in dealing with climate variability and extreme events, irrespective of attribution to climate change, hold valuable lessons to inform adaptation and mitigation policy. Global warming above 2.0°C is projected to further increase the risk of climate extremes which will increase the difficulty meeting Sustainable Development Goal (SDG) 13 on Climate Action. This will also strongly self-reinforce interactions between

climate and water management problems, threatening SDG 6 (Access to Clean Water and Sanitation), reduce agricultural production and food security and threatening (SDG 2, Zero Hunger), increasing health risks (threatening SDG 3, Good Health and Wellbeing), and damaging critical infrastructure (SDG 9, Industry, Innovation, and Infrastructure).

To date, from a Brazilian perspective, there are no studies that assess disaster risk under potential impacts of regional climate change under different GWLs. Therefore, the objective of this study is to provide projections and assess uncertainties of disaster risk for flash floods and landslides. This is done to identify hot spots of the vulnerability of such disasters in Brazil for different GWLs: 1.5, 2, and 4°C above pre-industrial temperatures. For this we use Vulnerability-Exposure indices, climatic hazards (based on extreme rainfalls), and the potential impact derived from an ensemble of climate models.

CONCEPTS AND TERMS USED IN THIS STUDY

For this study, we define a **potential impact** of climate and geophysical hazards. This potential impact is the combination of the exposure and sensitivity on physical assets, natural resources, and systems. The concept of potential impact is based on the definition proposed by the IPCC AR5 (IPCC, 2014), which refers to the effects on the natural and human systems caused by extreme meteorological and climatic events and also by climate change. That this definition incorporates any impact that may come from meteorological events, whether these are the results of natural climate variability or the interference of climate change.

IPCC AR5 presented a framework focused on the concept of “climate risk,” which is given by the interaction of the dimensions defined as “hazards,” “exposure,” and “vulnerability.” **Climatic hazards** represent the potential for the occurrence of meteorological events that cause significant impacts on human systems and their activities. **Vulnerability** refers to the propensity or predisposition of an element to be adversely affected by some hazard, and includes only the variables that represent sensibility and susceptibility to the events of flash floods and landslides. **Exposure** refers to people’s presence and their activities that can be adversely impacted by the events of flash floods and landslides. The focus of this work is the impacts caused in urban areas and, therefore, this dimension represents the exposure of people within this territory.

METHODS

Models

This study assesses changes in risk of natural disasters (landslides and flashfloods) as a consequence of changes in extremes of temperature and heavy precipitation under GWLs of 1.5, 2, and 4°C in Brazil. GWLs represents the variation of the global average anomaly of the air temperature at the surface in relation to the pre-industrial period (approximately 1,870–1,899), that is, the increase or reduction in temperature in relation to that period.

Projected future climate change were taken from six simulations with the HadGEM3A-GA3.0 Atmospheric General Circulation Model at a resolution of N216 (~60 km in mid-latitudes), performed as part of the research project HELIX (High-End cLimate Impacts and eXtremes). This is a predecessor of the version of the HadGEM3 model used in the 6th Coupled Model Intercomparison Project (CMIP6) and hence is considered a “pre-CMIP6” model. The HadGEM3A-GA3.0 simulations ran from 1971 to 2100, driven by greenhouse gas and aerosols concentrations from the RCP8.5 scenario and prescribed sea surface temperatures (SSTs) and sea ice concentrations (SICs) from six projections from the earlier 5th Coupled Model Intercomparison Project (CMIP5) (Betts et al., 2018). The different SST and SIC patterns drove different patterns of atmospheric circulation change, allowing different patterns of regional climate change to be examined. Land cover patterns were fixed at the present-day state, so biophysical impacts of land use change or vegetation responses to climate change were not considered.

GWLs of 1.5, 2, and 4°C were defined on the basis of the global mean temperature anomaly in the driving CMIP5 models relative to those models’ simulations of global mean temperature in 1,870–1,899. The climate state in a particular simulation at each GWL was defined as the first 20-year period with that global mean temperature anomaly. This meant that the time of passing a particular GWL was different in the six projections (**Table 1**).

As GWLs increase, greater changes can be expected in the corresponding climate scenarios, which are likely to produce even more pronounced impacts. A previous study with this six-member HadGEM3A-GA3.0 ensemble (Betts et al., 2018) shows relatively large changes in extreme precipitation across many parts of Brazil compared to other world regions at GWL 1.5 and GWL 2.0, with both increases and decreases being seen in different parts of the country. There are also substantial differences between the individual ensemble members at local scales, even in the sign of the change. Nevertheless, when averaging over the IPCC reference regions (Iturbide et al., 2020), there is a strong consensus between several different climate model ensembles on an increase in extreme precipitation over all regions of Brazil at 1.5 and 2°C global warming (Uhe et al.,

TABLE 1 | Set of global simulations with the HadGEM3A model and the corresponding CMIP5 forcing models.

Atmospheric model	CMIP 5 forcing model	GWL 1.5	GWL 2.0	GWL 4.0
HadGEM3A	IPSL-CM5A-LR	2006–2036	2020–2050	2056–2086
HadGEM3A	GFDL-ESM2M	2021–2051	2037–2067	*
HadGEM3A	HadGEM2-ES	1998–2028	2018–2048	2056–2086
HadGEM3A	IPSL-CM5A-MR	2005–2035	2020–2050	2055–2085
HadGEM3A	MIROC-ESM-CHEM	2000–2030	2017–2047	2053–2083
HadGEM3A	ACCESS1-0	2012–2042	2024–2054	2066–2096

Also listed are the time periods when GWLs of 1.5, 2.0 and 4.0°C are reached, using the RCP8.5 scenario.

*This realization did not reach the GWL 4.0 by 2100.

2021). That comparison of different climate model ensembles included the six HadGEM3A-GA3.0 projections as part of a larger ensemble of projections from HELIX.

Debortoli et al. (2017) used a different approach where climate change impacts assessment models for flash floods and landslides were framed in long-term future time horizons (by the middle or end of the twenty-first century) by using downscaled scenarios using the Eta 20 km regional model from two CMIP5 global models. In this paper, the focus is Brazil at various GWL from a high-resolution HadGEM3A global model. The impact models developed for landslides and flash floods in this work (different from those derived by Debortoli et al., 2017 using RCP4.5 and 8.5) are fed by the rainfall extremes projections from the HadGEM3A-GC3.0 projections at the three GWLs shown in **Table 1**.

Climate Extremes Indices

To assess future risk of floods and landslides we used a subset of extreme precipitation indices devised by Expert Team on Climate Change Detection and Indices (ETCCDI, Frich et al., 2002). These indices are:

- Consecutive wet days (CWD): the annual maximum number of consecutive humid (rainy) days found within a year (in days),
- Maximum 1-day precipitation (Rx1D): the annual maximum recorded in 1 day precipitation total that could lead to flooding (in mm),
- Maximum 5-days precipitation (Rx5D): the annual maximum consecutive 5 days precipitation total that could lead to flooding (in mm),
- Extreme rainfall (R95P): the annual total precipitation, when precipitation is >95th percentile of the 1961–1990 daily precipitation distribution (in mm),

For this study these indices were calculated annually and grouped for the historical period (1971–2010) and for the periods found for each GWL scenario. The result used for each index is the average of all annual values found for each period.

The CWD index can be useful to identify areas subject to gradual flooding. When this index is low (values around 7 days) and coincides with high extreme indexes such as Rx5day, it can indicate that extreme precipitation phenomena occur in a short period of time, facilitating the triggering of landslides and sudden floods.

Indices for Floods and Landslides

These indices (**Table 2**) are based on three components: (i) climatic simulations and projections, expressed by the combination of extreme rainfall indices from section Flash Floods derived from the HELIX models; (ii) socioeconomic, represented by the combination of socioeconomic indices provided by IBGE (2011); (iii) physical-environmental, based on the crossing of different thematic maps, physical, and environmental variables that reflect the susceptibility of each geographical area to trigger floods or landslides.

As in Debortoli et al. (2017), we tested different combinations of significance weights for each of the variables used, until an

TABLE 2 | Indices used to assess flash floods and landslides (adapted from Debortoli et al., 2017).

Index	Explanation
Potential Impact Index (PI)	A composite indicator that aims to provide a comparative assessment between Brazilian cities regarding the impacts that may be caused by geo-hydrological hazards (flash floods and landslides) triggered by meteorological events. This is the main index of this study and represents the potential for negative impacts associated with the triggering of flash floods or landslides, taking into account the climatic, physical, environmental, and demographic characteristics of each Brazilian city. The higher the index, the greater the probability and magnitude of impacts caused by geo-hydrological events
Climatic Hazards Sub-Index (CH)	Represents the potential for flash floods or landslides to occur, in terms of probability and magnitude, taking into account the precipitation extreme indices and the equations developed by Debortoli et al. (2017)
Vulnerability-Exposure Sub-Index (VE)	It represents the relationship between the dimensions of vulnerability and exposure, incorporating the variables representative of susceptibility (considering the particularities of flash floods and landslides events) and also of urban population density

empirical equation was reached that could be applied throughout the national territory and, as a final result, obtained a map similar to the one presented in the Brazilian Atlas for Natural Disasters (CEPED-UFSC, 2013b). This step was carried out with the climatic data of the present period (1971–2010), so that it could arrive at a close result and with the same pattern as the disaster maps of the Atlas, which refers to the period 1990–2010. The same empirical equation was used for future projections, where variables of the social and physical-environmental dimensions were kept constant, so that only climatic data (as represented by the extreme climate indexes previously shown) are modified.

This basic premise for such extrapolation is based on the following arguments: (i) physical and environmental conditions will remain the same in future periods or will undergo minor changes that can be considered irrelevant in the context; (ii) using the social data of the present in modeling future vulnerability allows to identify regions where the climate will intensify it and, in this way, it is possible to provide information for the reflection and creation of public policies that improve the social aspects in these places and, thus, can reduce vulnerability as a whole, accelerate the adaptive process and/or mitigate possible impacts.

In this study, the vulnerability assessment in the form of an index does not incorporate metrics related to adaptive capacity due to the lack of representative data on the analysis scale (municipalities). In other words, vulnerability contemplates only the variables that represent sensibility and susceptibility to the events of flash floods and landslides. For exposure: this term refers to the presence of people and their activities that can be adversely impacted by the events of flash floods and landslides. The focus of this work is the impacts caused in urban areas and,

therefore, this dimension specifically represents the exposure of people within this territory.

Potential impacts are evaluated separately for the historical and future time-slices because the level of potential impact may change as exposure changes over time. It is important to first evaluate historical trends and current baselines to understand the conditions and trends under which water systems are currently operating. To calculate the Potential Impact Index PI for historical (present 1971–2010) and future (until 2100), we use the ensemble of the six climate simulations.

Calculation of the Potential Impact Index

In this subsection we show details about the variables used in each index / sub-index, for each type of hazard (flash floods and landslides), as well as the equations to calculate such indices.

For the Potential Impact, two different indices were calculated, one for flash floods and the other for landslides. In each case, specific variables that have a cause and effect relationship with each type of hazard were used. However, the equation that defines the two indexes has the same relational structure between its dimensions, according to Equation (1):

$$PI = VE * (1.0 + CH) \quad (1)$$

The first term on the right side of Equation (1) (VE) aggregates the concepts of Vulnerability and Exposure in a single sub-index, based on the characteristics of susceptibility to each of the hazards and their interaction with the number of people coexisting in these conditions (more details next item). The second term on the right side of Equation (1) (CH) incorporates the issue of the climate hazard, which represents the intensity and frequency of the rains potentially triggering such processes. It is important to emphasize that the interaction of these dimensions through multiplication makes the rains only amplify the pre-existing condition given by the dimensions of Vulnerability and Exposure. This ensures that there are no false positive results with a high potential impact in places where rainfall is very intense, but that there are not enough physical conditions for the outbreak of the assessed hazards (e.g., lowland regions where there is a lot of severe rainfall signaling high potential impact in case of landslides).

The PI index was calculated from the model ensemble for both the historical reference period (1971–2010) and future periods defined by the warming scenarios GWL 1.5, 2.0, and 4.0. However, the only dimension that varies in future periods is the climatic dimension (CH), keeping the others (VE) constant. The strategy used was to present the results of the ensemble of the models for each period of analysis (baseline, GWL 1.5, 2.0, and 4.0). That is, first all CHs were calculated separately, and then the results were aggregated in the form of an ensemble, following the logic presented in the following Equation:

$$PI_{\text{mean}} = \frac{1}{N} \sum_{n=1}^N PI_n \quad (2)$$

One way of presenting the results of future climate projections is through maps of relative changes of the PI index. This strategy was adopted to highlight the regions where the climate changes

are more accentuated in relation to the reference period and that only the map of the Potential Impact Index with absolute value does not allow to identify due to the subtle changes of color scale between each period. Therefore, maps of relative changes ($PI_{\text{rel. change}}$) were prepared that show the increments of the potential impact index for each future period (PI) in relation to the reference period (PI_{ref}), according to the following Equation (3):

$$PI_{\text{rel. change}} = \frac{PI - PI_{\text{ref}}}{|PI_{\text{ref}}|} * 100 \quad (3)$$

To assess the uncertainties related to the results of the PI ensemble, maps of the standard deviation were also generated for each period of analysis ($PI_{\text{std. dev.}}$), According to Equation (4):

$$PI_{\text{std. dev.}} = \sqrt{\frac{1}{N-1} \sum_{n=1}^N (PI_n - PI_{\text{mean}})^2} \quad (4)$$

Another way of presenting the results was through the evaluation of agreement between the models in pointing out a positive or negative trend of the PI rel. change (rel. Change). In some situations, this type of information may be more important for sensitizing decision makers in formulating public policies for adaptation and disaster risk reduction (DRR). Equation (5) represents the way in which this parameter was calculated for each future scenario (GWL 1.5, 2.0, and 4.0):

$$PI_{\text{sign agrmt.}} = \frac{1}{N} \sum_{n=1}^N SA_n * 100 \begin{cases} \text{if } PI_n > 0: SA_n = 1 \\ \text{if } PI_n < 0: SA_n = -1 \end{cases} \quad (5)$$

This indicator of convergence in the tendency (sign agreement) shows what percentage of models exhibit the same tendency. +100%/-100% shows that all six models show increase/decrease in tendency of change. This is independent on the magnitude of the change.

Climatic Hazards Sub-indices

Some extreme indices, such as the annual maximum daily precipitation amount or the maximum annual wind speed, have traditionally been modeled with different distributions of values considered “extreme” in engineering applications. However, the “extremes” used as indicators of climate change have a much broader context. While some of the indexes fall within the traditional definition, most have no direct causal relationship with the impacts to be analyzed. Therefore, it is important to make this distinction when analyzing the rates of climatic extremes, since only a very small number of events can be assumed to be a really extreme value distribution (IPCC, 2012).

As presented, each index in section Flash Floods reflects the characteristics of a locality in receiving a certain type of extreme event, with its particularities and reference units. For this reason, these indices needed to be reworked so that they can be related to each other, in order to explain the CH of the potential impact. Debortoli et al. (2017) suggest the linear normalization of these indexes (between 0.00 and 1.00) and proposed the following Equations (6 and 7). These normalized indices are included in the risk analysis of landslide disasters (CH_L) and flash floods

(CH_{FF}), respectively. In this study we use the same equations by them defined:

$$CH_L = \frac{0.4 * RX1day + 1.0 * R95pTOT + 1.3 * RX5day + 1.3 * (1 - CWD)}{4} \quad (6)$$

$$CH_{FF} = \frac{1.75 * RX1day + 0.5 * R95pTOT + 0.5 * RX5day + 0.25 * CWD}{3} \quad (7)$$

For landslides (Equation 6), the Rx5day indices and the inverse of CWD were those that had the greatest relevance for defining the CH of vulnerability. This means that places that receive rain events with large volumes that accumulate in up to 5 days, and that do not usually have many consecutive days of rain (that is, severe events in a short period) are those with the greatest potential to trigger landslides. In the case of flash floods (Equation 7), the indexes with the most relevance were Rx1day and R95p, indicating that the intense rains that happen within a period of 24 h (or less) and the locations where the “very humid” days are characterized by high rainfall volumes are the main climatic factors that are associated with impacts of this nature.

A key feature of this work is that all the indices and sub-indices presented were developed considering the limits of urban areas, because in Brazil more than 90% of deaths caused by landslides and floods occur in urban areas (database from CEMADEN, between 2014 and 2020). That is, all variables used (climatic or not) were considered only for the condition in which they are within the domain defined by the urban areas of each municipality. This is due to the fact that the two types of disasters assessed occur mainly in urban areas. The database of urban areas used in this work comes from the work by <http://www.wudapt.org>. On the other hand, the visual representation of the results only for the urban domain becomes unfeasible, since they are very small areas compared to the continental dimension of Brazil. For that, it was necessary a series of adjustments that would allow the presentation in a more adequate way.

Most of the calculation steps to establish the indices were made from spatial data in Raster format, specifically through the Map Algebra tool from the Spatial Analyst Tool of the ESRI ArcGIS 10.1 software. In this way, the indices and variables used are presented spatially in grid points, where each point has a numerical value of its attribute. Consequently, within the same urban area polygon it is possible to have several values for a given variable, sub-index, or index. However, as one of the objectives is to find the most critical cities and regions in Brazil, some procedures were adopted to calculate average values:

- Given a given variable (or index) that is in Raster format, a new TIFF file is created with dimensions of 1×1 km, regardless of its original resolution (**Figure 1A**);
- From this TIFF file, a point shapefile (Conversion Tools, Raster to Points tool) is generated, where each generated point represents the centroid of a grid box of points of dimension 1×1 km (**Figure 1B**).
- The average of all points that are within the domain of the polygons that define urban areas is calculated, allowing the

search for points that are within 500 m beyond this domain. For this step, the Spatial Join tool is used, with the Merge Rule configured for the Mean condition. This step takes place between **Figures 1B,C**.

- The final result is a new shapefile for urban areas, exactly identical to the original, but now with a new attribute that refers to the average of the variable or index in question (**Figure 1C**).

Given the size of the Brazilian territory, any maps that present their entire extension do not allow the proper visualization of urban areas. So, to overcome this limitation, an extrapolation was made so to transfer the information obtained to urban areas to the municipal polygon (**Figure 1D**).

Vulnerability-Exposure Sub-index

This sub-index represents the non-CHs associated with the impacts caused by flash floods and landslides. Different indices were elaborated for each type of hazard, considering representative variables for each case. As previously described, vulnerability in this study only contemplates the dimension of “sensitivity,” given by the characteristics of susceptibility to flash floods and landslides. The variables that make up the sensitivity dimension are the same ones proposed in Figure 3 of Debortoli et al. (2017). In addition, the concept of “exposure” was incorporated based on data from the urban population density of 2010 National Census (IBGE, 2011) for each Brazilian municipality, which were weighted according to **Table 3**. This same database was used to calculate both VE_L and VE_{FF} . The way in which this dimension is related to the vulnerability data is detailed in the upcoming sections.

Vulnerability-Exposure to Landslides Index (VE_L)

Landslides can be classified as geological and geotechnical process related to soil downward movement, rocks, debris and/or organic material under the effect of gravity. Landslides are described as gravitational mass movements of soil that occur rapidly (De Vita et al., 1998). These mass movements can occur in various formats such as rotational, translational, or shallow landslides and debris flow. In Brazil, they often occur in slope areas occupied by cutting slopes, embankments, or natural slopes exacerbated by human activities. Landslide disasters have been responsible for the highest death toll in the country (Carvalho et al., 2007; CEPED-UFSC, 2013a,b; Alvala et al., 2019). Since they are typically induced by human activities, these disasters are therefore called mixed disasters.

The main factors in the aggravation of landslide risks are: the release of waste water, the outflow from water supply networks, the concentrated release of storm water, water infiltration, embankment cuts with excessive steepness and height, inadequate landfill execution, improper disposal of waste, and uncontrolled removal of forest cover (De Vita et al., 1998). Thus, to assess the vulnerability of the environmental dimension considering landslides, we have established a spatial database that could represent the phenomenon at the national level, with direct and indirect factors linked to its occurrence. The variables

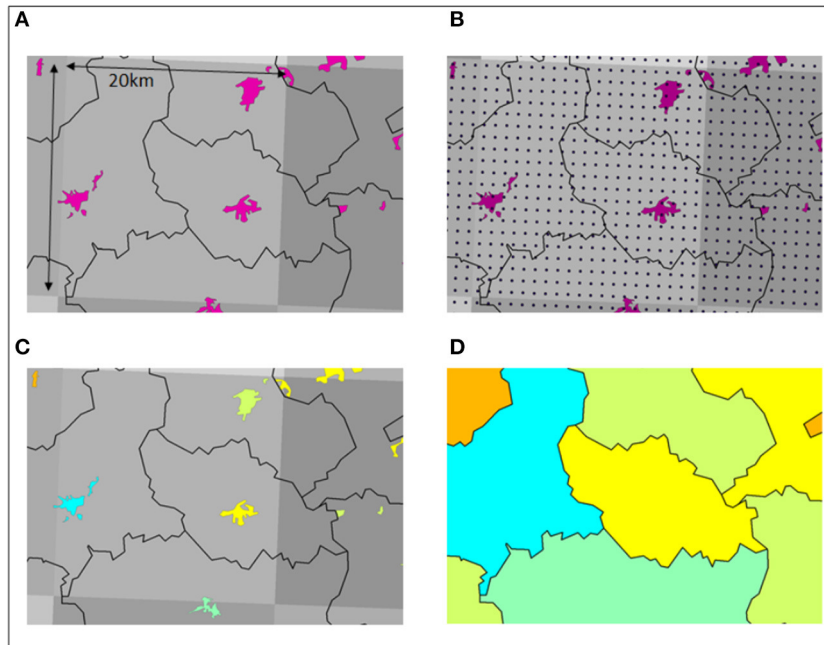


FIGURE 1 | Illustrative example of the aggregating spatial information process from the Raster format (gray squares in **A–C**) into polygons referring to the political division of Brazilian municipalities (**D**).

TABLE 3 | Weighting of the Urban Population variable, which defines the Exposure dimension.

Urban population	Exposure
> 1,000,000	1
500,000–1 min	0.95
250,000–500,000	0.75
100,000–250,000	0.5
< 100,000	(Pop)/200,000

considered are defined by Debortoli et al. (2017) and can be summarized as:

- **Slope:** the NASA/SRTM data set was calculated with the same spatial resolution as the original—90 m, generating a raster with continuous values ranging from 0° to 30°. It is worth noting that the result of the slope map with 90-m resolution does not allow a good representation of terrain characteristics and has been unable to identify a direct relation to susceptibility to landslides under purely geotechnical criteria that normally would be based on slope calculation directly from the slopes. When calculating the slope using the SRTM, the highest values found refer to slopes between 25° and 30°, which correspond to small areas, almost points, and do not represent well the regions with steep terrain. On the other hand, 90% of the country has a slope of <5° according to this resolution. Only southern and southeast Brazil and northern Roraima state display slopes greater than these values. In these mountain regions, the change in the slope is very abrupt, taking place within small

geographical spaces, which cannot be reflected on this map (and are precisely where landslides occur more frequently). Therefore, it was necessary to develop a slope categorization taking into account such aspects, because slopes >30° and 45° are considered critical to landslide triggering but are not detected at this resolution. A continuous data adjustment was performed to later attribute weights to classify degrees of slope.

- **Landforms:** This data set was developed by the Directorate of Geosciences (IBGE/DGC) and Embrapa soil. In the database, there are about 167 landform units, which have been identified with the use of different types of sensors (radar imagery and Landsat satellite images), remote sensing technology, digital image processing, and GIS. However, to calculate the index of vulnerability to landslides, we have used only seven (7) landform classification compartments. The criterion to define weights was determined by the relationship of landform to topographic features, ranked according to ability to trigger landslide outbreaks. Similar to the other variables used in calculating the vulnerability index, weights were assigned from 0.00 to 1.00.

Based on these two variables and the weighting of the classes of urban population (Table 3), Equation (8) was defined, which defines the VE_L :

$$VE_L = \left(\frac{\text{Slope} + \text{Landforms}}{2} \right) * (1 + \text{Exposure}) \quad (8)$$

Vulnerability-Exposure to Flash floods Index (VE_{FF})

Flash floods in this study is defined as a hydrological process in which runoff has a high and concentrated energy transmission.

The phenomenon is described as an overflow above the maximum capacity of the main river channel, usually caused by heavy rains concentrated in steep regions. These conditions cause a sudden and violent rise in flow rates, and consequently, overflow (De Castro et al., 2003). In urban areas, flash floods usually result from a deficiency of water drainage systems, which may or may not be associated with river overflow. When causing minor impacts, flash floods are defined by the momentary accumulation of water in a given area, usually due to poor drainage systems. To assess the vulnerability to flash floods dimension, we have established a spatial database that could represent the phenomenon at the national level, with direct and indirect factors linked to its occurrence. This includes public database maps related to runoff coefficients and the natural dependence of the regions on their drainage network system. A detailed description of the variables and processing can be found in Debortoli et al. (2017):

- Roads (density): road maps provided by the IBGE with an original scale of 1:250,000. The shapefile obtained from these data divides the road into two classes: paved and unpaved.
- Natural Drainage System (density): hydrography maps provided by IBGE with the original scale of 1:250,000. It was calculated directly from its linear vector (streams) density (km/km^2). The final map is normalized on a scale of 0.00 to 1.00.
- Flooding vulnerability Mapping (density): Flooding Vulnerability Atlas provided by the National Water Agency—ANA (Agencia Nacional de Aguas—ANA, 2014) was prepared from the orthorectified hydrology cartographic base at a scale of 1:1,000,000.

$$VE_{FF} = \left(\frac{1.5 \cdot VFMap + 0.5 \cdot RdDens + 0.25 \cdot DDens}{2.25} \right) * (1 + Exposure) \quad (9)$$

Where: VFMap is flooding vulnerability mapping, RdDens is the road density and DDens is the drainage system density.

As in the case of Equation (8) (VE_L), the first term on the right side of Equation (9) refers exactly to the model that was proposed by Debortoli et al. (2017), with the exception of the land use variable that was not included in the present study, which is focused on urban areas. The second term in Equation (5) refers to the urban population that, in this model, will be able to increase the sensitivity by up to 100% for cases where the municipalities have more than one million inhabitants.

RESULTS AND DISCUSSIONS

In Brazil, about 85% of disasters are related to rainfall or a lack of it. Flash floods and landslides have resulted in more than 10,000 deaths in the last five decades. Southern Brazil is the most exposed and vulnerable to climate-related disasters triggered by extreme rainfall (Ávila et al., 2016; De Almeida et al., 2016; Debortoli et al., 2017; Alvala et al., 2019).

Before presenting the results, some important aspects are highlighted to understand the maps with relative changes. The

indices used in this study were validated for the reference period (1971–2010). This was done by comparing with a history of disasters provided by CEMADEN and Federal Civil Defense at the municipality considered level. Similar intercomparison was done visually with the maps from the Atlas of Natural Disasters (CEPED-UFSC, 2013b) by Debortoli et al. (2017). After the validation, the potential impact model was fed with data from the ensemble of future climate projections from the model for the three GWLs. The intention was not only to understand where there may be an increase in impacts of flash floods and landslides, but to identify if this tendency to increase in the future is detected in places where critical condition is already observed in the present.

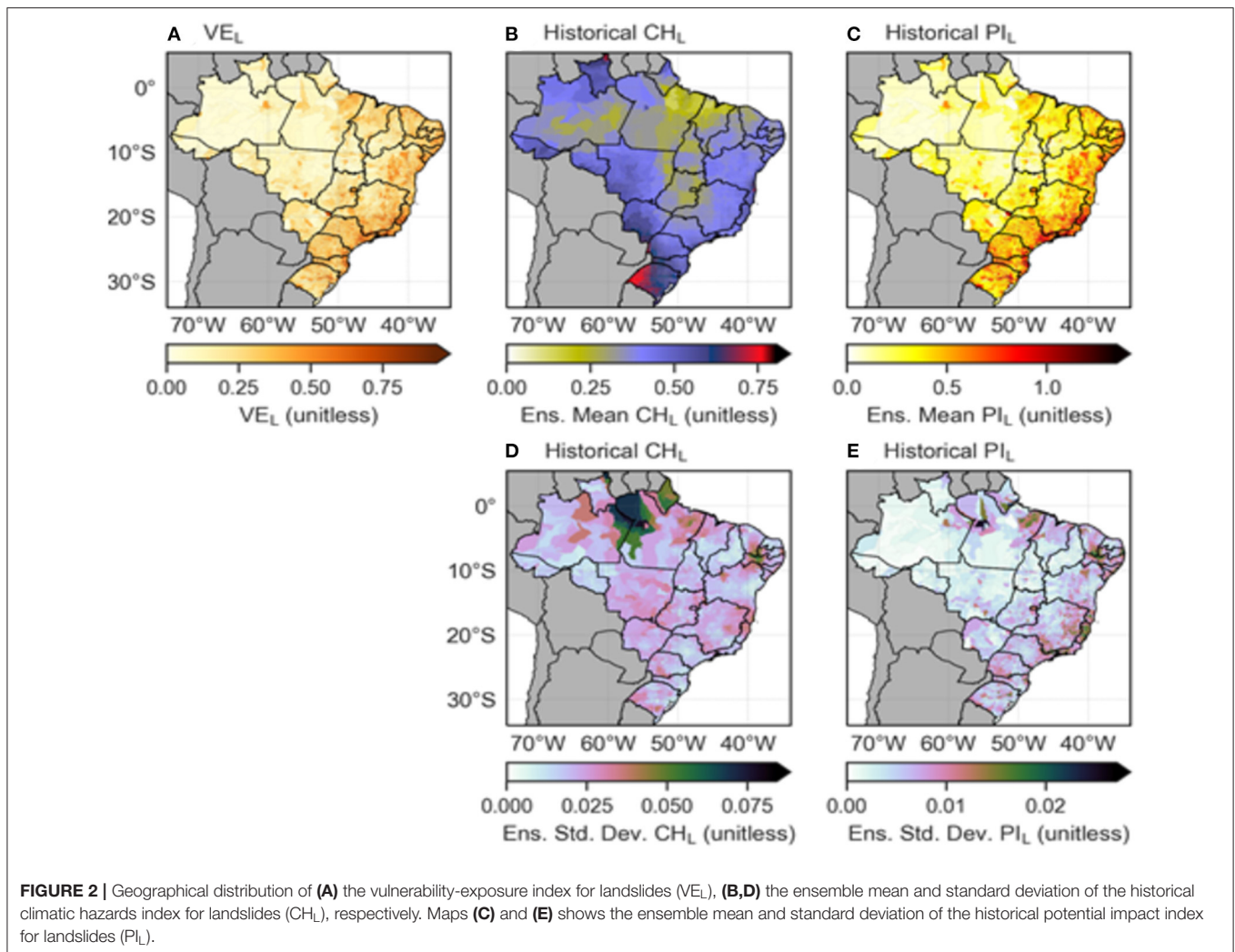
Landslides

Figure 2 exhibits the results referring to the analysis for landslides, for the reference period. **Figure 2A** shows the Vulnerability-Exposure sub-index for landslides (VE_L). The cities with high urban population density are shown (in darker tones) and are inserted in mountainous and/or more rugged terrain regions. The most susceptible areas with the highest population density are on the east coast. This is mainly detected in the Southeast and Southern regions of the country. This is consistent with Debortoli et al. (2017), specifically the physical-environmental dimension presented by the authors.

Figure 2B shows the ensemble for the Climatic Hazard sub-index for landslides. The maps represent the spatial distribution of climatic conditions that potentially trigger landslides. That is, the shades of dark red represent regions with more intense and severe rains that happen in a 5-day period ($Rx5day$). The dark blue shades the rain regimes do not characterize a sequence of consecutive very long rainy days (CWD).

The regions with the largest changes are the extreme south, southwest and northwest sections of the country. This map has some patterns similar to those observed by Debortoli et al. (2017) when they assessed the CH of vulnerability. However, at the time, the authors used other models (Eta-MIROC and Eta-HadGEM2 ES), that also highlighted much of the country's east coast. This is a feature not observed in the present study. **Figure 2D** represents the standard deviation of the model ensemble (**Figure 2B**), highlighting in lighter tones (light blue and pink) the locations where there is a consensus among climate models and. On the other hand, the darker tones (green and dark blue) indicate where there is the greatest divergence. For much of Brazil the standard deviation is relatively low. However, the northern part of the country show signals of greater inter model fluctuations relative to the average.

However, **Figures 2A,B** are not enough to represent where the impacts caused by landslides are more frequent and severe. This is because the necessary condition to identify these impact scenarios must consider environmental, demographic and climatological attributes. This joint assessment is represented by the spatialization of the potential impacts index for landslides (**Figure 2C**). This map identifies some “hotspots” in the eastern sections of the Southern, Southeastern and Northeast Brazil regions. These are the regions historically impacted by disasters related to landslides, consisting with findings by Debortoli



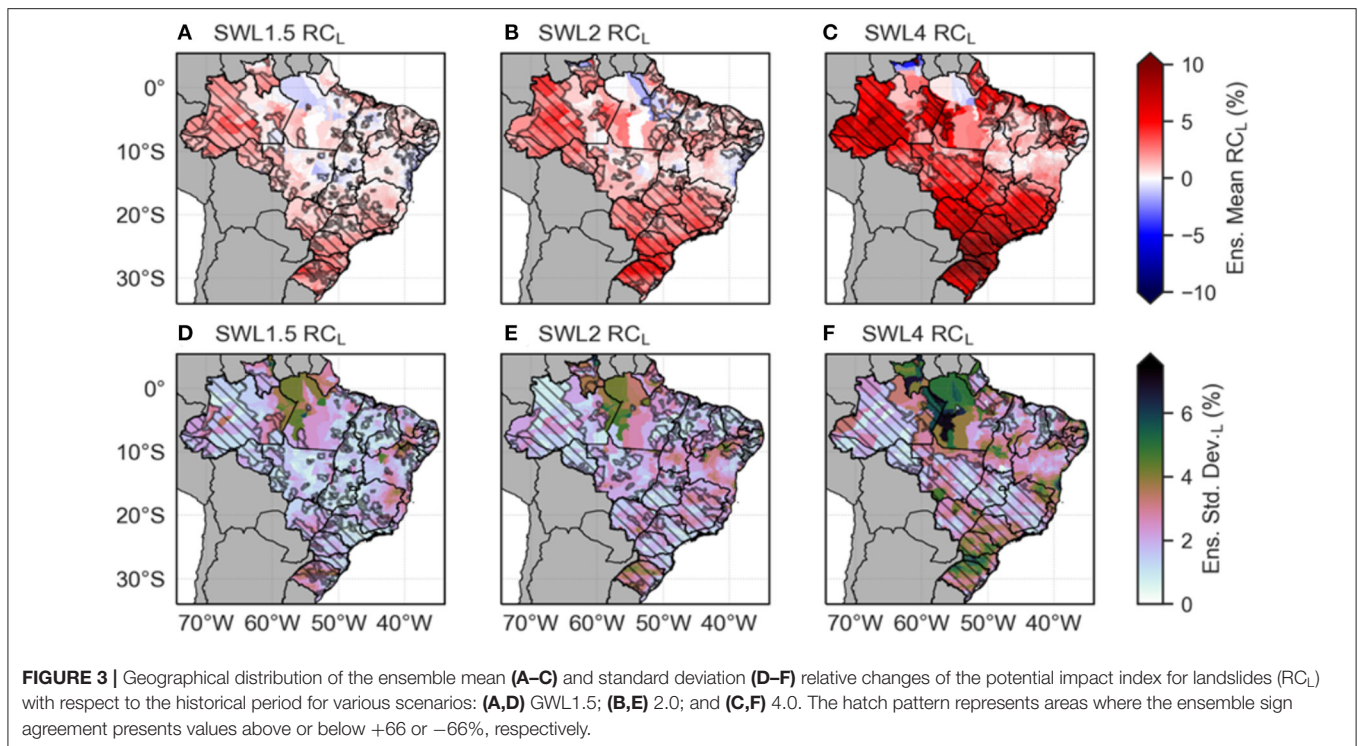
et al. (2017) and the Natural Disaster Atlas (CEPED-UFSC, 2013b). The most affected are the states of Santa Catarina, São Paulo, Rio de Janeiro, and Espírito Santo in southern and southeastern Brazil and in the states of Bahia and Pernambuco in northeast Brazil.

The PI_L map (Figure 2C) shows the model ensemble of the VE_L sub-index for the six different model runs. As this interaction is not linear (see Equation 1), the distribution of the standard deviation associated within this ensemble (Figure 2E) was calculated. In general, this map indicates that the hotspots identified by the PI_L (Figure 2C) have low or medium standard deviation, with the exception of a portion of the east of the Southeast region (state of Espírito Santo). The lowest values of the standard deviation refer to the regions with the lowest PI_L . This characteristic is in accordance with the conceptual structure of the potential impact index for landslides (Equation 1). This shows that vulnerability and exposure (VE_L) are the limiting factors for the impact. The CH can only amplify this potential condition. That is, although there is a great divergence between the models (as in the extreme North, shown in Figure 2D, the

influence of CH_L will be small in the value of PI_L . This makes the standard deviation of the potential impact index for landslides also small, as observed in great part of the north-central portion of the country.

Figure 3 shows the results of the ensemble of projections of relative changes of PI_L for the various GWLs. The maps represent how much the future indexes increased or decreased relative to the baseline. The individual model maps are not presented because it would be difficult to visually identify changes in the absolute values of the index. The upper part of Figure 3 shows the maps of relative changes for each heating scenario, being (Figure 3A) for the GWL 1.5 (Figure 3B) 2.0 and (Figure 3C) 4.0. At the lower panel standard deviation maps (Figures 3D–F) are shown. The hatched areas show regions where there is a consensus among models >66% (positive or negative signals) for the projected change.

It is noted that in almost all of the Brazilian territory there is a signal of an increase in the PI_L , with small exceptions in part of the central and northern regions of the country. In general, this increase is more explicit in the most critical scenarios (GWL



2.0 and 4.0). This is detected in Southern and Southeastern regions and in the Western Amazon. Moreover, the risk scenario observed for the Southern and Southeastern regions is more critical. This is because these are densely populated regions very susceptible to landslides (Figure 2C). These regions require special attention and require disaster risk reduction policies and adaptation strategies. In addition to the clear signs of increased potential impact, these regions show consensus (hatched regions) among models. This characterizes less uncertainty of the results and, therefore, provides subsidies for directing more assertive strategies to reduce future impacts.

The interpretation of an increase in the PI_L value of 10%, for example, does not mean that future losses and impacts may be 10% greater than those observed in the past. The social structure of human systems within Brazil cannot be expressed in the scale of analysis adopted. This means that the real impacts can be much greater than this 10%, because in practice the impacts do not follow a linear logic. Considering that this system is non-linear, such disturbances could take proportions never before observed due to certain thresholds being overcome. It is recommended that these relative values be understood only as a spatial reference. These shows contrasts between different regions. These may be more or less impacted in the future, and not as a way to predict the future impact itself.

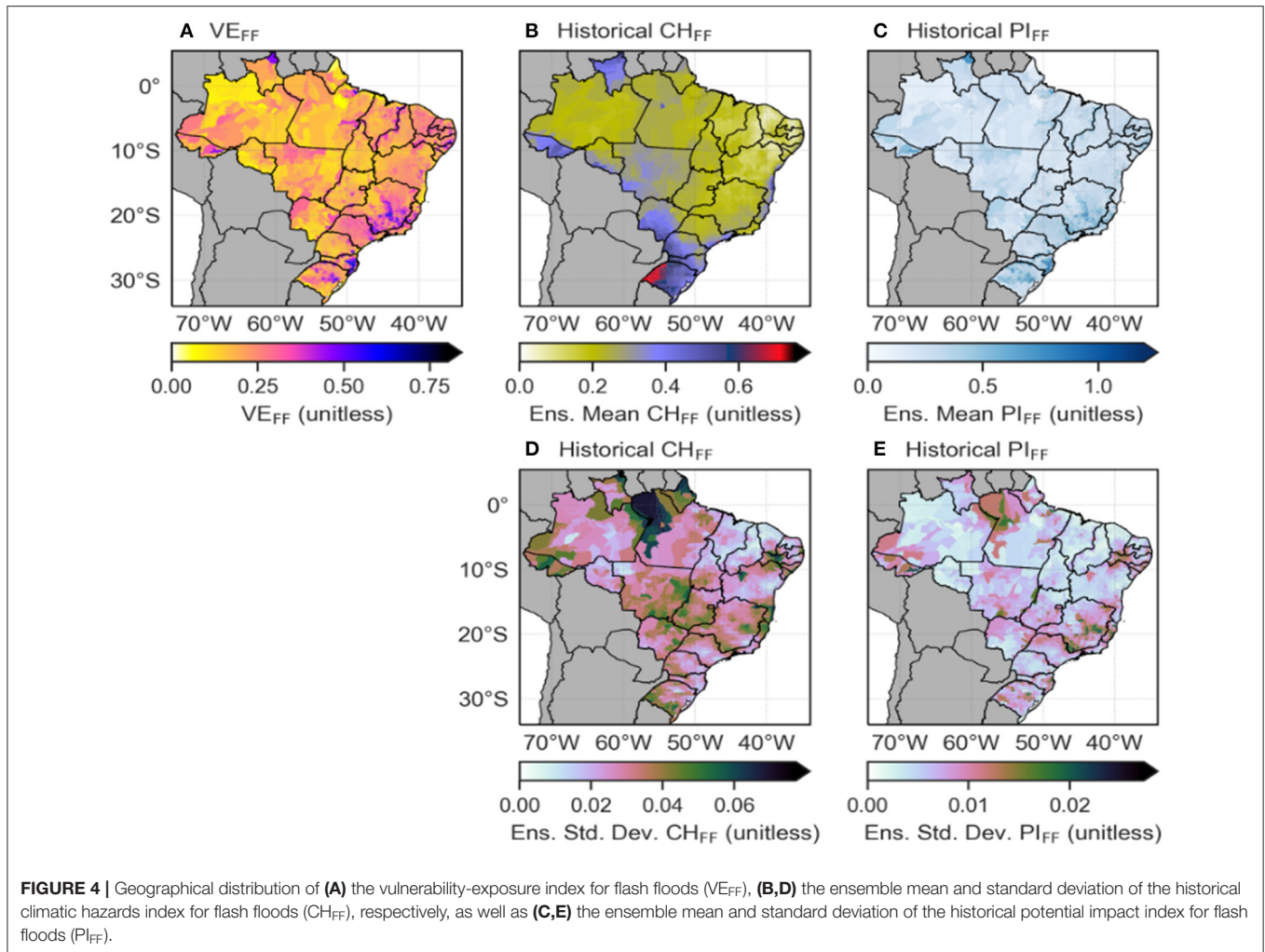
The standard deviation in the previously mentioned regions shows the lowest values where the largest changes in PI_L are observed. This means that there is not much fluctuation between the resulting values for each member and suggests a good reliability of the results. Only in the GWL 4.0 scenario, higher values of the standard deviation are projected in the southern region (in green tones), but it can also be attributed to the fact

that the absolute values of the PI_L are also high. Large part of the country exhibits low values of standard deviation, in all scenarios, extending from Western Amazonia all the way to West Central Brazil to the Southern and Southeastern regions. The coastal region of northern Brazil also shows significant increases in the PI_L as suggested by the consensus among models. However, this is not a region with a history of disasters related to landslides. In general, the Northern Brazil region does not present conclusive or expressive results regarding the intensification of impacts caused by landslides. This may be linked to the lack of skill of climate models in predicting the future changes in rainfall extremes.

The metropolitan regions in eastern portion of Northeast Brazil are recurrently impacted by landslide events. Bandeira and Coutinho (2015) showed that in the Metropolitan Region of Recife landslides caused a total of 214 deaths between 1984 and 2012. More recently, according to newspapers, the city of Recife was affected by a landslide that killed 8 people on July 24 2019 (<https://riotimesonline.com/brazil-news/rio-politics/heavy-rainfall-kills-at-least-eight-and-causes-landslides-and-flooding-in-recife/>), 7 people in December 24 2019 (<https://www.theguardian.com/world/2019/dec/24/seven-die-in-landslide-in-brazilian-city-of-recife>). It is suggested that more detailed studies on impacts of climate-related disasters should be done for this region.

Flash Floods

The maps in Figure 4 shows the results flash floods for the baseline. Figure 4A exhibits the Vulnerability-Exposure (VE_{FF}) sub-index, where cities with high urban population density are highlighted (in darker tones) and in regions more susceptible to



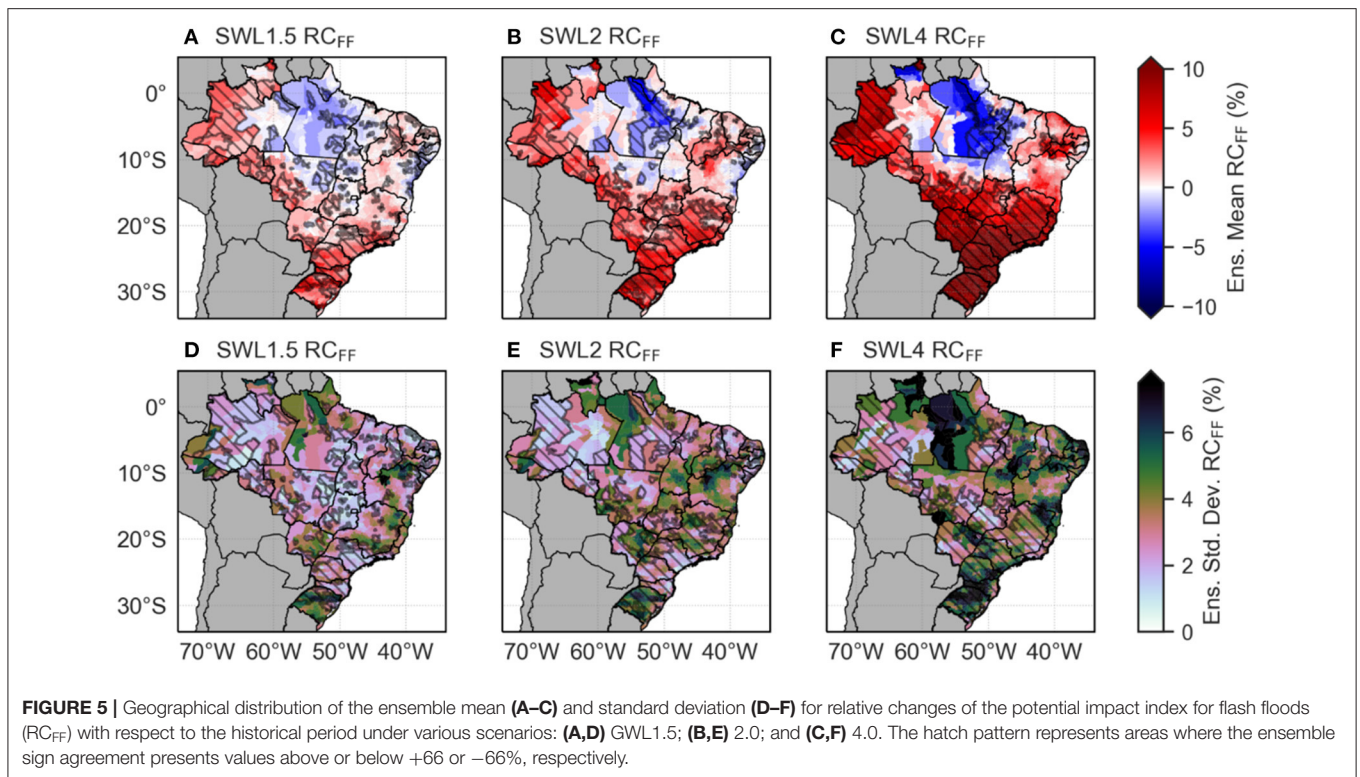
flashfloods. The regions with highest vulnerability and exposure are located in the South and Southeastern regions of Brazil and in some sections of the eastern coast of Northeast Brazil. This result is consistent with similar maps from Debortoli et al. (2017), when compared with the physical-environmental dimension used by the authors. This would be equivalent to VE_{FF} . These regions show positive trends in heavy rainfall, in terms of frequency and magnitude during the 50 years or so (Sillmann et al., 2013; Magrin et al., 2014).

Figure 4C represents the potential impact index for flash floods PI_{FF} as a composite of **Figures 4A,B**. The spatial patterns observed are similar to those in **Figure 4A**, with the difference that the highest values are in the Southern and Southeastern regions. These show large population density, where urban development coexists with a series of infrastructure problems. This favors the occurrence of disasters caused by flashfloods. These results are also similar to the spatial patterns observed by the vulnerability index proposed by Debortoli et al. (2017), with a difference that they show also high PI_{FF} in the Northeast Brazil. The results of **Figure 4C** are consistent with the Atlas of Natural Disaster occurrences (CEPED-UFSC, 2013b) used as a reference for validation in the work of Debortoli et al. (2017).

Furthermore, **Figure 4B** shows the spatial distribution of heavy rainfall rains that potentially can trigger flashfloods, as shown by the CH_{FF} index. In this map, the extreme south of Brazil stands out, together with the state of Acre in Western Amazonia, and the state of Amapá in the extreme northern Amazonia. The quality of these results is more linked to the skill of the models used to represent the climatic behavior in the Brazilian territory.

Figure 4B shows the spatial distribution of heavy rainfall rains that potentially can trigger flashfloods (CH_{FF}). In this map, southern Brazil, Western and extreme northern Amazonia show the highest CH_{FF} . The quality of these results is more linked to the skill of the models used to represent present climate. In the lower panels, **Figures 4D,E** show the standard deviation of **Figures 4B,C**, respectively. The above-mentioned regions exhibit the greatest divergence among models. This may be linked to variability in the regional climate due to the different forcing SSTs linked to representation of extreme rain events. This can be explained due to the scarce number of rainfall stations that makes the validation process of the models difficult.

Figure 4E shows that the PI_{FF} variability is relatively less than that of **Figure 4D**. This is because of the potential impact



index for flash floods is more linked to the characteristics of vulnerability and exposure (VE_{FF}), and in less degree to the CH given by CH_{FF} sub-index (see Equation 2). Some municipalities in the Southeast region show high standard deviation, with the high largest values in the state of Minas Gerais where the highest PI_{FF} index is found.

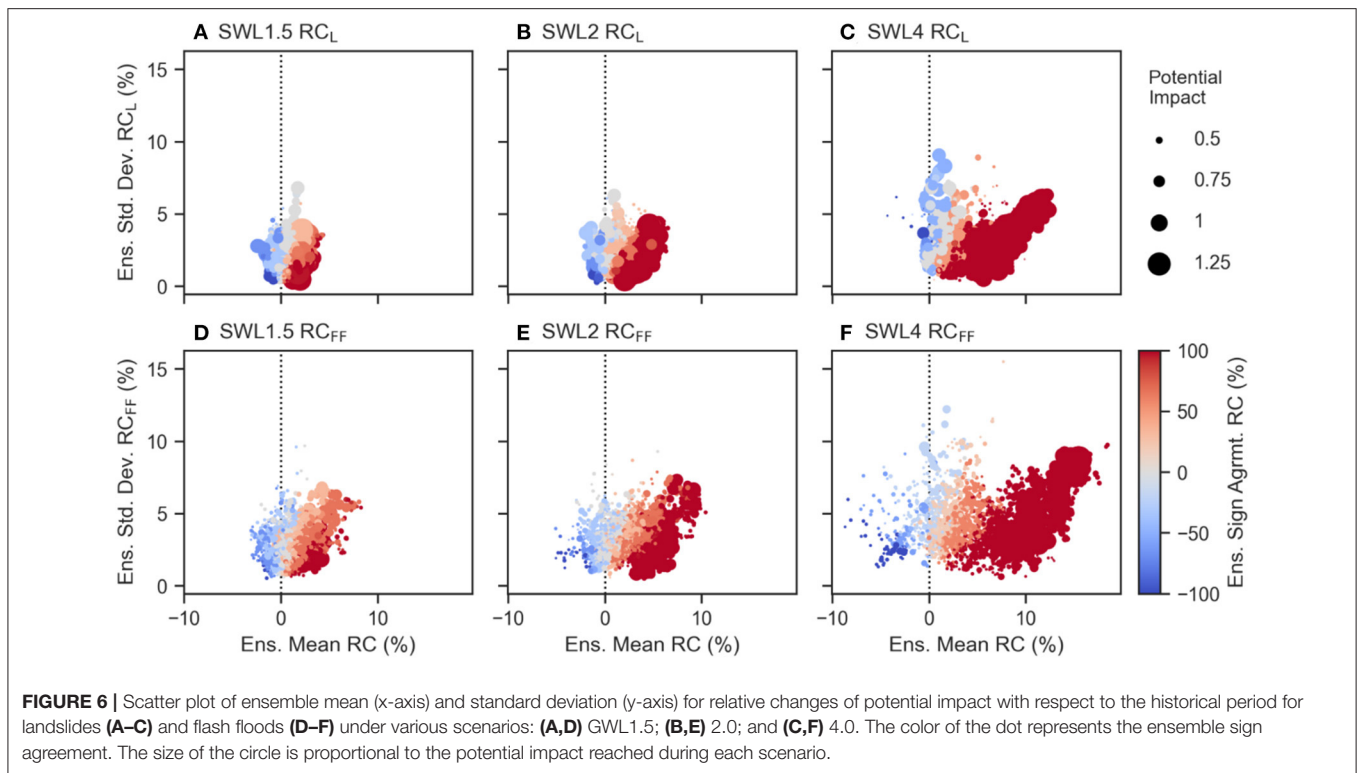
The maps in **Figure 5** show the results of the relative changes (RC_{FF}) of the PI_{FF} index for the three warming scenarios. In the lower panels the respective standard deviation maps are shown. As expected, the patterns shown in the RC_{FF} map are similar to those for landslides shown in **Figure 4**. This makes sense, since the same rainfall extreme indices were used ($Rx1day$, $Rx5day$, CWD , and $R95p$), even if the equations were different (Equations 1 and 2). The southern region of Brazil exhibits the highest values for relative changes since the GWL 1.5 scenario. This pattern is intensified in the warmer scenarios (GWL 2.0 and 4.0), covering a larger area that including Southeastern Brazil. This projected pattern follows exactly the same trend identified by Debortoli et al. (2017). Western Brazil also shows high values of RC_{FF} , suggesting that extreme short-term precipitation events may be intensified throughout this region in the future. In all these regions, there is consensus among models, suggesting an increase in extreme rainfall events (hatched areas).

In the semiarid Northeast Brazil, there are high values of the RC_{FF} , mainly from GWL 2.0. However, there are divergences among models in signaling this significant increase. This does not allow for any conclusion for this region for flash floods in the future. This region shows a tendency for drought conditions and aridification in the future in warming scenarios (Marengo

et al., 2020a,b). The regions with the highest values of RC_{FF} are precisely the large urban centers and metropolitan regions of cities of the Southern and Southeastern Brazil. These regions already show a high PI_{FF} in the present (**Figure 5C**) and exhibit a history of recurring disasters related to flashfloods (Nobre et al., 2011; Xavier et al., 2014). Moreover, these cities have more resources and adaptive capacity, which would facilitate the implementation of adaptation measures to reduce disaster risk.

The results presented in this work may serve as a basis to justify the need for future actions focused on disaster risk reduction. It is necessary to mention that in these same regions there is a large number of smaller municipalities with less documented history of disasters. In any case, these the results suggest that they will also be more impacted by extreme rainfall events. It is difficult to predict whether such events will cause disasters in the future, but the evidences are enough to mobilize stakeholders in order to organize human systems and activities. With these measures it would be possible to increase their capacity to cope with possible severe flashfloods. In general, there is a potential risk for increasing impacts caused by flashfloods, both in spatial scope and in absolute values.

The standard deviation maps (**Figures 5D–F**) show high values projected in the in extreme southern Brazil. In this case, while the models show convergence in the tendency of increasing impacts (hatched regions), there is a large intermodel variability relative to the mean. In other words, although the average of the RC_{FF} is around 10% in these regions, some models have much higher values (close to 20%), while others have lower values. This represents some uncertainty regarding the absolute



value of the RC_{FF} . The maps suggest a future intensification of extreme rainfall events in this region. Impacts would be more significant if there are no adaptation measures to reduce the risk of these disasters. In addition, as explained in the case of landslides, the value of the RC_{FF} must be observed only as a way of understanding the different potential impacts in Brazil.

Integrated Analysis

Figure 6 shows an assessment of the statistical distribution of relative changes of PI_L and PI_{FF} in relation to the respective standard deviations for urban areas. It is noted a similar pattern for both landslides and flashfloods. With higher warming levels the number of cities that have high relative change in both potential impact indices increase. In addition, the greater is the agreement among models (shades in red at the right side). It is important to note that in the GWL 4.0 scenario there is a significant increase in the higher relative change values, in some cases beyond 10%.

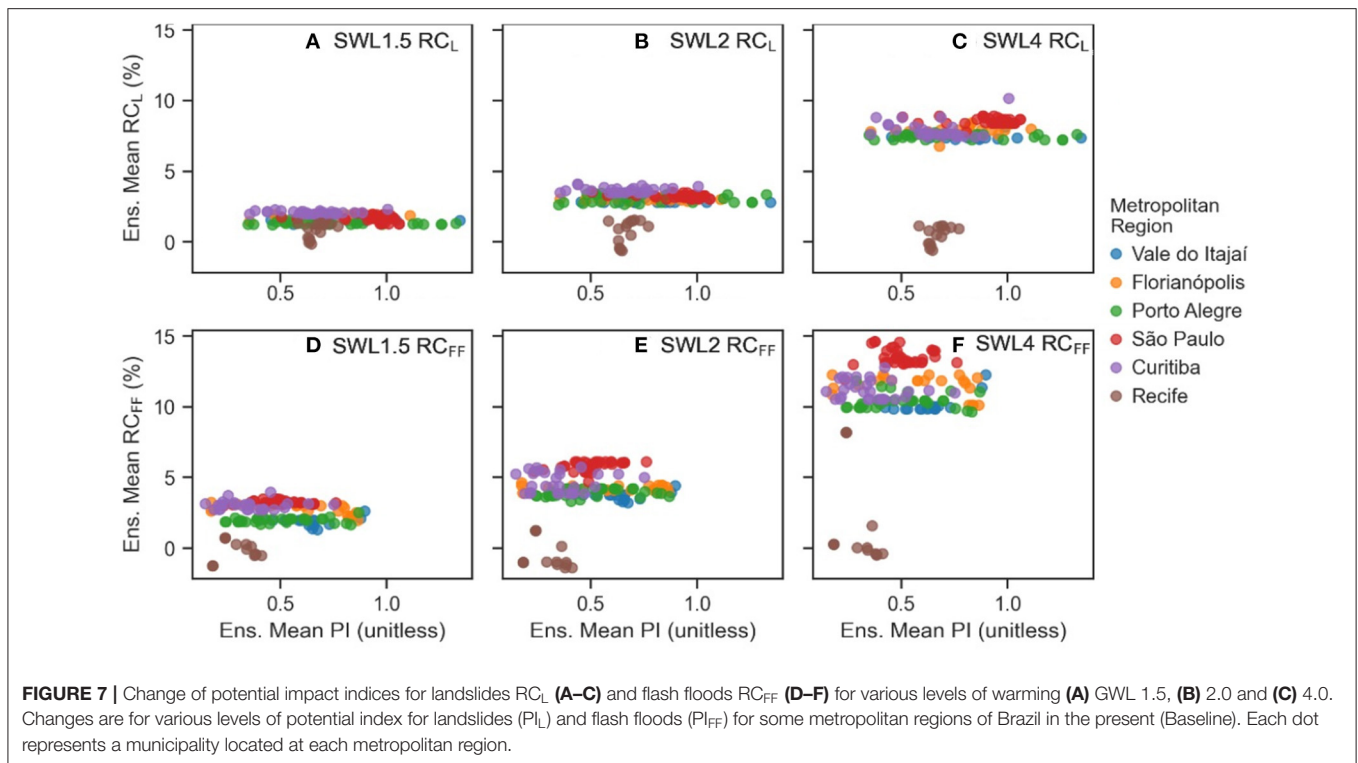
The observed spread also allows us to identify that the cities with high absolute values (larger circles) exhibit high relative change in the potential impact index. This can be considered critical as they are cities that at the present show high-risk of hydro-geological disaster. This risk tends to increase in future warmer climate scenarios, mainly due to the intensification of extreme rain events.

Based on the analysis of **Figures 6, 7** shows changes in the PI_L and PI_F (RC_L and RC_{FF} , respectively, in the y axis) relative to the PI_L and PI_{FF} for the present (x axis). This plot of some metropolitan regions of Southern and Southeastern Brazil and

in the Eastern Coast of Northeast Brazil that are vulnerable and exposed to the impacts of landslides and floods in present.

The population living in large cities in Southern and Southeastern Brazil, as well as on the coast of Northeast Brazil are commonly stricken by natural hazards, especially floods and landslides. Fatalities occur due to the presence of housing in areas susceptible to flooding and landslides, and in all these situations, existing government structures have not been sufficient to prevent deaths, as in the Metropolitan Area of São Paulo (Nobre et al., 2011; Di Giulio et al., 2018; Young et al., 2019; Marengo et al., 2020a; Travassos et al., 2020), in the Itajaí Valley in the state of Santa Catarina (Marengo, 2009; Xavier et al., 2014), in the state of Rio de Janeiro (Marengo and Alves, 2012) and Recife (Bandeira and Coutinho, 2015). In Santa Catarina state in southern Brazil, 22–24 November 2008 saw heavy rainfall over, which caused severe floods and deadly mudslides with 120 fatalities reported (Marengo, 2009). In the highlands of Rio de Janeiro, in January 2011, heavy rainfall sparked flash flooding and mudslides claimed the lives of 916 people while 345 are still missing, and 35,000 people were left homeless (Marengo and Alves, 2012).

In **Figure 7**, the horizontal axis represents the PI_L and PI_{FF} for the baseline period. The further to the right, the greater the risk in that region considering the baseline. We emphasize the values of horizontal axis are fixed for all GWL scenarios. The vertical axis refers to the values of the relative changes (RC) between the IP of the future scenarios and the baseline. The purpose of this graph is evaluating that some regions already have a high risk at the present time and may be more impacted in the future, depending on the warming scenario. In the case of landslides (**Figures 7A–C**), it is noted that practically all the



regions have a similar increase in potential impact, in the three scenarios, with the exception of Recife, which practically remains without significant increments. São Paulo and Curitiba are the metropolitan regions that require attention, as they are those in which there is an increase of approximately 10% in the IP in the GWL 4.0. On the other hand, Porto Alegre and Vale do Itajaí also require special attention because they are the regions with the highest absolute IP value (points on the far right) and increments ranging from 2 to 7% depending on the scenario.

The results for flashfloods show similar patterns to landslides. The main differences refer to the higher values of the increments in future scenarios, although the absolute values of the IP are lower. For flash floods, São Paulo stands out as the metropolitan region with the largest increases (close to 15%), although its absolute PI for the baseline is not as high as other regions analyzed. In this sense, the Florianópolis region also stands out, as it is the one with the highest number of points on the extreme right and with increments that exceed 10% in GWL 4.0. Even highlighting these two cases, we reiterate that all the metropolitan regions evaluated, with the exception of Recife, they present results that deserve the attention of the public authorities, since the absolute values of IP already in the baseline are above the national average and all the results of future scenarios suggest a significant increase in future risk.

DISCUSSIONS AND CONCLUSIONS

The impacts of natural disasters in the population are mainly concentrated on poorest and most vulnerable people, living in the outskirts of large cities are the ones more exposed to landslides and flash floods (CEPED-UFSC, 2013b). Our results show that the highly densely populated regions Southern and Southeastern

Brazil as well as the coastal section of Northeast Brazil are the most exposed to landslides and floods. This is in agreement with Hummell et al. (2016) who showed a concentration of the most socially vulnerable cities in the Northeast Brazil region, as well as the social vulnerability of metropolitan areas and state capitals in the South and Southeastern regions. This pattern seems to persist and to aggravate in the future for warming above 2.0°C.

In Brazil, measures to cope with the impacts of landslides and flash floods and have been post-disaster on the risk management side. This suggests that a more proactive approach in terms of monitoring and predicting risk is need, so to protect life and properties. Improving the knowledge of risk, and monitoring and early warning, dissemination and communication, and disaster preparedness are and must be mandatory. There is a need to improve adaptive capacity of metropolitan regions in the three most affected regions in the present and in the future by mapping risk areas and improving the alert system. In the present, early warning systems have been proposed as a strategy for reducing the vulnerability of populations living in at-risk areas (Alvala et al., 2019).

In the future, with warming above 1.5°C these impacts may be stronger. The scenario of more intense and frequent heavy rainfall from middle twenty-first century induces a high risk of landslides and floods in those regions. Densely populated metropolitan regions and capitals in the present experience losses due to hydro-geological-meteorological disasters. In a warmer future these urban areas may be more exposed to such events, affecting regional economies, key infrastructure, and people prone to such disasters. In this paper, we improve our knowledge of risk and disaster preparedness, with the inclusion of sociodemographic characteristics of the population living in vulnerable areas together with information on climate risk.

Lastly, model projections at various warming levels indicate a large increase in Brazil's vulnerability to landslides and flash floods in the context of climate change, particularly with warming above 2.0°C. Comparison of vulnerability and change in potential impacts of landslides and floods from ensemble of HELIX models shows that they converge in the three regions above mentioned. This highlights the importance of environmental policies to protect human lives and to minimize financial losses in the coming decades. These processes involve decision-making, monitoring, and early warning systems needed for a better management of disasters that can also be of service in future climate scenarios as part of disaster risk reduction and risk management. This shows the need for collaboration between scientists and decision makers to address emergent risks and extreme events toward disaster risk reduction and strengthened societal resilience.

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

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AUTHOR CONTRIBUTIONS

JM, PC, LA, and RB idealized the paper and wrote it. PC and FD elaborated and made the analysis of the maps of risk of natural disasters. RB provided with the HELIX data and helped in the analysis of the climate change scenarios. All authors contributed to the article and approved the submitted version.

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