





## ORIGINAL ARTICLE

# Extreme rainfall and its impacts in the Brazilian Minas Gerais state in January 2020: Can we blame climate change?

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## Abstract

In January 2020, an extreme precipitation event occurred over southeast Brazil, with the epicentre in Minas Gerais state. Although extreme rainfall frequently occurs in this region during the wet season, this event led to the death of 56 people, drove thousands of residents into homelessness, and incurred millions of Brazilian Reais (BRL) in financial loss through the cascading effects of flooding and landslides. The main question that arises is: To what extent can we blame climate change? With this question in mind, our aim was to assess the socioeconomic impacts of this event and whether and how much of it can be attributed to human-induced climate change. Our findings suggest that human-induced climate change made this event >70% more likely to occur. We estimate that >90,000 people became temporarily homeless, and at least BRL 1.3 billion (USD 240 million) was lost in public and private sectors, of which 41% can be attributed to human-induced climate change. This assessment brings new insights about the necessity and urgency of taking action on climate change, because it is already effectively impacting our society in the southeast Brazil region. Despite its dreadful impacts on society, an event with this magnitude was assessed to be quite common (return period of ~4 years). This calls for immediate improvements on strategic planning focused on mitigation and adaptation.

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Public management and policies must evolve from the disaster response modus operandi in order to prevent future disasters.

#### KEYWORDS

Brazil, climate change, disaster, extreme event attribution, precipitation

## 1 | INTRODUCTION

An extreme precipitation event took place in Southeast Brazil in between 23rd and 25th January 2020, leading to cascading effects of flooding and landslides, causing extensive material and human damage as well as exorbitant economic losses, especially in the state of Minas Gerais. Although this region experiences frequent extreme precipitation events that lead to flash flooding and population displacement (Marengo and Alves, 2012; Ávila et al., 2016), the January 2020 event was record-breaking with 320.9 mm of accumulated precipitation measured within 3 days at the state capital Belo Horizonte city (INMET, 2021). This corresponded to approximately 97% of the January (329.1 mm) climatological precipitation (INMET, 2021). The event gained much media attention after its cascading disasters, that is, floods and landslides, took the lives of at least 56 people, drove thousands of people into temporary homelessness, and caused millions of Brazilian Reals (BRL) in damaged properties and economic losses (S2ID, 2020).

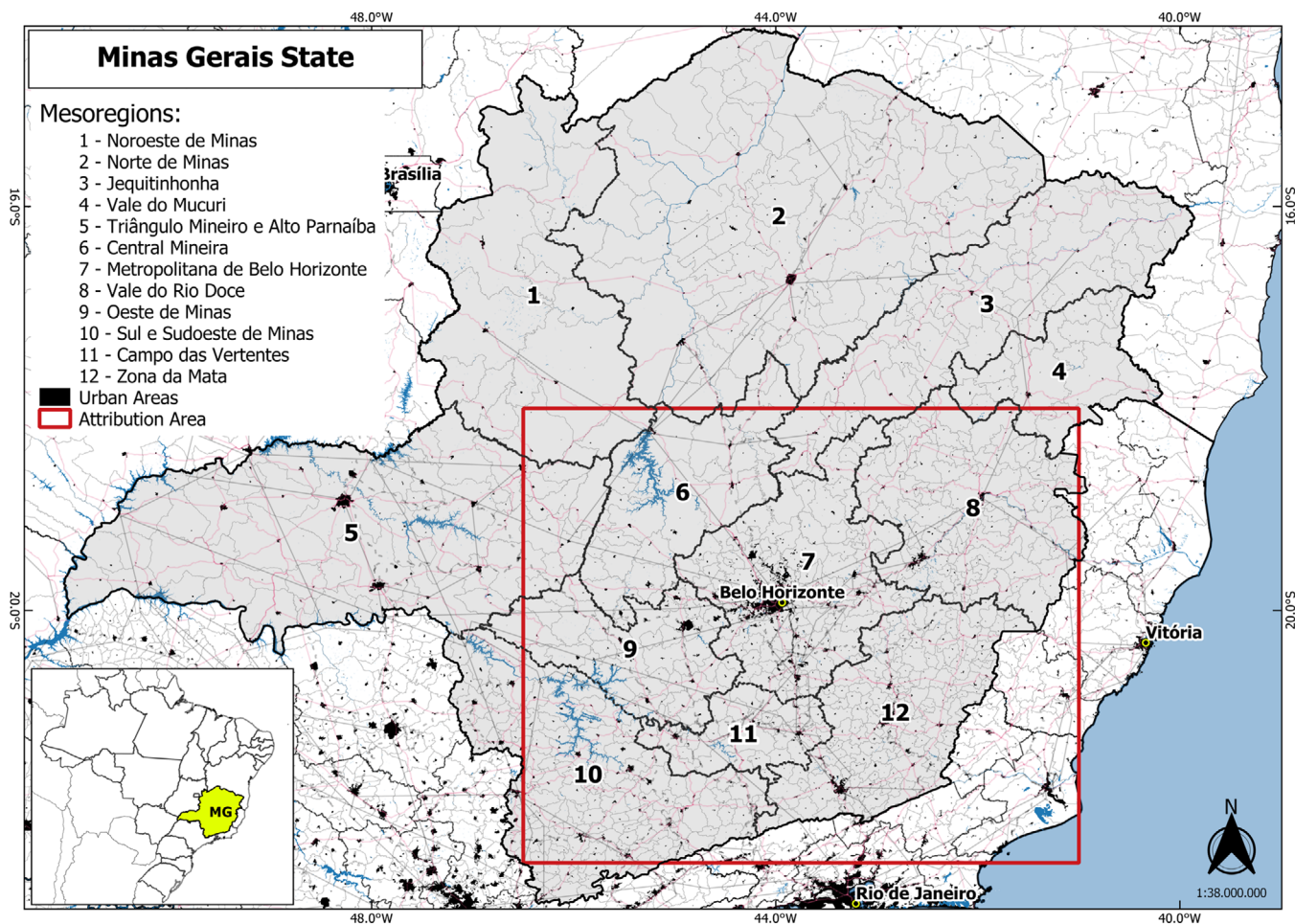
The event was caused by a combination of an intensified South Atlantic Convergence Zone (SACZ) and the emergence of the Kurumí subtropical cyclone (KSC) over the South Atlantic on the 23rd January 2020 (Marine Meteorological Service, 2020). Both processes contributed to the increase of moisture convergence across the region. Given the extreme impacts of this event, potential effects of human-induced climate change on these meteorological processes cannot be neglected, as climate change has been reported to be associated with increasing frequency and severity of extreme events around the world (Marengo et al., 2009).

Extreme event attribution helps quantify the potential effects of human-induced climate change on the occurrence of a determined event (Otto et al., 2016). The probability of an extreme event occurrence is compared between the world as observed under current climate conditions and a counterfactual world where human activities have not occurred. Climate model experiments with different external forcings are used to simulate these two worlds: the first uses all forcings, including anthropogenic ones. The second counterfactual world only uses natural

forcings, that is, those due to solar variability and volcanic activity. Given these scenarios, it is possible to calculate the probability ratio (PR), which represents the change in likelihood of occurrence of an extreme event, and the fraction of attributable risk (FAR), which assigns a fraction of the event probability of occurrence to human-induced climate change and can be used to estimate monetary losses (Otto et al., 2016; Stott et al., 2015; Otto, 2017; Frame et al., 2020).

Anthropogenic intensification of extreme rainfall events, especially with short duration and at local scale, has been reported worldwide (Fowler et al., 2021). However, for South America and more specifically for southeast Brazil, attribution studies assessing potential effects of anthropogenic climate change are still scarce (e.g., Otto et al., 2015; de Abreu et al., 2019). In one of the rare available studies, Otto et al. (2015) assessed the drivers of the 2014/15 water shortage in southeast Brazil and did not find evidence of anthropogenic climate change being the main driver of the event. Nevertheless, to support policymakers in making better adaptation decisions within the context of climate change and extreme events, and to inform the general public about climate change consequences, more studies are required. Given the impacts of the reported extreme precipitation event of January 2020, it is of utmost importance to understand and quantify the role that human-induced climate change played in this event and how it potentially exacerbated the socioeconomic damages.

Here, our aim was to assess the socioeconomic impacts of the extreme precipitation event over the Brazilian state of Minas Gerais in January 2020 and quantify how much can be attributed to human-induced climate change. To do that, we collected and analyzed official socioeconomics impact data for 194 municipalities of Minas Gerais state that were reported after the event, and conducted climate model experiments to analyze the likelihood of this extreme event occurring in a scenario with all forcings in comparison to the natural forcing scenario. Specifically, we aimed to answer these questions: (1) What were the socioeconomic impacts of this extreme precipitation event? (2) if and by how much this extreme precipitation event can be attributed to human-induced climate change?



**FIGURE 1** Study area location at the southeast Minas Gerais state, Brazil. The red line represents the spatial extent for the attribution analysis (Lon 46.5–41.0°W, Lat 22.5–18.0°S). The black patches represent urban cover. Location of Minas Gerais state within Brazil, shown in inset

## 2 | MATERIAL AND METHODS

### 2.1 | Study area

The study area was defined as the southeast region of the Brazilian state of Minas Gerais (Figure 1). The area is subdivided in 12 mesoregions, which are official Brazilian units of federation consisting of a group of cities that share characteristics of geographical and social organization (IBGE, 2017). The average annual rainfall of southern Minas Gerais is ~1600 mm (Viola et al., 2010; Souza et al., 2011; Reboita et al., 2015). The austral summer (December–January–February) represents the season with higher accumulated precipitation (600–800 mm), with an average of 350 mm occurring specifically during January (da Silva, 2014). The average elevation throughout the state is 700 m, ranging from 500 to 2000 m, and the terrain is often hilly (Ferreira et al., 2019). The natural land cover of the region is split between Cerrado savannas and tropical Atlantic forests (IBGE, 2004), with predominant land

being used for smallholding agriculture and cattle ranching (IBGE, 2018a). A total of 20 million people live in Minas Gerais, with 85% located in urban rather than rural areas (IBGE, 2011). Economy is diversified and based on agriculture, industry (mining and metallurgy), and services, producing 54% of the total Brazilian coffee production, together with corn, soy, and bean crops (IBGE, 2018a).

### 2.2 | Data

#### 2.2.1 | Observational data

We acquired the *Sistema Integrado de Informações sobre Desastres* (S2iD, Integrated Disaster Information System; S2iD, 2020) dataset, which compiles information on disasters in Brazil including location (municipality), type of disaster, date and time of occurrence, causes and effects, and human and material damage, along with public and private economic losses. This dataset information is recorded



on a specific form filled in by a member of the Brazilian Civil Defense Agency or locally responsible government agency, which must be sent within 10 days after the occurrence of the disaster (Brasil, 2020).

The human damage data used consist of: (i) the number of displaced people, who had to leave their residences temporarily due to the extreme event; (ii) homeless people, individuals who have had their residences completely destroyed by the extreme event; and (iii) sick and injured people. The material damage is related, predominantly, to real estate and facilities that have been damaged or destroyed as a result of a disaster. The economic losses consider the public and private data for the event period, where public economic losses are related to the collapse of some essential services aimed at serving the community, such as healthcare, drinking water supply, sewage systems, urban cleaning, and electricity generation and distribution; and private economic losses are related to the loss of economic activity in the industry, commerce, or agriculture, without directly affecting the community (Castro, 2020). In addition, we used the estimates of population count from the Gridded Population of the World, Version 4 (GPWv4) at 15 arc-minute resolution for the years 2000 and 2020 (CIESIN, 2016) to estimate the growth of human population (number of people per pixel), consistent with national censuses and population registers. In order to better match the spatial extent of the extreme rainfall event, all the socioeconomic data were aggregated into coarser spatial units of the aforementioned mesoregions.

To evaluate the vulnerability of municipalities to disasters, we used the main census variables associated with disaster vulnerability in the study area (de Assis Dias et al., 2018; de Souza et al., 2019), extracted from the Statistical Territorial Base of Risk Areas (BATER) dataset (IBGE, 2018b) (Supporting Information Table S1). It corresponds to sociodemographic data on the population exposure to the risk of mass movements, floods, and flash floods. This dataset is based on the 2010 population census from the Brazilian Institute of Geography and Statistics (IBGE) integrated with risk areas mapped by the Brazilian Geological Service between 2012 and 2015. The extracted variables include the number of people, children, and elderly, as well as information on the availability of water supply, sewage, and garbage collection for the dwellings (Supporting Information Text S1).

We used two datasets of gridded precipitation to better understand the spatial distribution of the daily precipitation in the study area and to have more robust estimations of the observed precipitation for the attribution analysis. The first was the CPC Global Unified Gauge-Based Analysis of Daily Precipitation data at  $0.5^\circ$  spatial resolution (Chen et al., 2008). The second was the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS)

at  $0.05^\circ$  spatial resolution, which integrates satellite imagery with in situ rain gauge station data (Funk et al., 2015). The CHIRPS dataset has been previously validated for the study region, showing very strong association ( $R^2 > 0.9$ ) with observed weather station data (Nogueira et al., 2018; Costa et al., 2019). Both datasets were resampled to the spatial resolution of N216, which is identical to the climate model that we use in our attribution analysis (Section 2.3.2). For Brazil, this broadly corresponds to gridboxes of size  $\sim 60$  km square. Moreover, to cover the common period between the observations and the model historical experiment (and thus related changes to atmospheric gas composition), the climatology considered for CHIRPS and CPC were from 1981 to 2013. We selected these two rainfall datasets due to the consistent representation of rainfall in space and time required for this application in contrast to the Brazilian weather station network, which has relatively low density and several stations have missing data in particular prior to 1995 (Xavier et al., 2015).

## 2.2.2 | Climate model and scenarios

The global climate model used for the attribution was the Hadley Centre Global Environmental Model version 3-A (HadGEM3-A), which is based on the atmospheric component of the HadGEM3 (Hewitt et al., 2011), run at an N216 horizontal resolution with 85 vertical levels (Ciavarella et al., 2018). The simulations were performed as part of the Met Office system for the attribution of extreme weather and climate events, with an increase of ensemble size of the experiments and resolution (Ciavarella et al., 2018) compared to the previous system (Christidis et al., 2013). HadGEM3-A is part of the HadGEM family of models and more information regarding its dynamical core and parametrization can be found in Davies et al. (2005).

Two experiments were conducted, in which the first considered both natural and anthropogenic forcing (ALL) and the second used only natural forcing (NAT). The external forcings are the variability in total solar irradiance at the top of the atmosphere, and the latitudinal variation of stratospheric aerosol optical depth, representing the volcanic activity, well-mixed greenhouse gases (GHG) and zonal-mean ozone concentrations, aerosol emissions, and land-use change. All these forcings were used in the ALL scenario, whereas only solar and volcanic historical forcings were considered in the NAT scenario, with the other forcings fixed at 1850 levels (Ciavarella et al., 2018).

The historical experiments for both ALL and NAT scenarios covered 1960–2013; however, we used the 1981–2013 period as the climatological reference to keep the analysis time periods consistent between estimates and models. The event period (January 2020) was analyzed by a

historical extension experiment, also considering the ALL and NAT scenarios, called historicalExt and historicalNatExt, respectively. The historical experiments had 15 members, whereas the historical extensions consisted of 525 members for ALL and NAT, respectively. The last pair of experiments with a larger ensemble is obtained in two steps: (1) after the historical period, an extension of seven members for each simulation is added ( $7 \times 15 = 105$  members) that is called historicalShort and historicalNatShort; (2) starting on January 1st of 2016, an additional five ensemble members are included ( $105 \times 5 = 525$  members) resulting in the 525 members for the historicalExt and historicalNatExt. The use of a large ensemble allows for the estimation of the model internal variability in each experiment and increases the confidence of statistical analysis, which is very useful when considering rare events at the tails of the distribution within a single scenario. More information about the ensemble generation and experiment setup can be found in Ciavarella et al. (2018).

## 2.3 | Analysis

### 2.3.1 | Impact and vulnerability assessment

Extreme events not only disrupt the affected areas but can represent a myriad of hazards to neighboring areas, as well as cause effects that can persist through time. These can range from public infrastructure damage to health-related impacts, losses of private property, and so forth. It is hard to exactly pinpoint the damages caused by these events, because such impacts tend to occur through synergistic effects. For example, if a person is disabled due to an extreme event, which is included as human damage, but it also has a larger economic consequence as the person may not be able to work in the future. Nevertheless, impacts should be always analyzed from an integrated approach, considering both human and economic aspects, to reflect the intersectoral nature of their impacts. Therefore, impacts in this work were analyzed both as human damage and economic losses (Dolman et al., 2018).

The human impacts were analyzed for each mesoregion of the Minas Gerais state and the percentages of sick and injured, displaced, and homeless people for the main affected mesoregions calculated. We also identified the five most affected municipalities within each mesoregion with the highest number of homeless people. The economic impacts include total material damage and total public and private economic losses, which were also analyzed by calculating the percentage of the damage in the five most affected cities in each mesoregion compared to the rest of the municipalities of the state of Minas Gerais.

Vulnerability was analyzed in terms of population exposure and official mapped vulnerable areas. Population growth has been reported to increase population exposure and social vulnerability in developing countries associated with poor urban planning (Blaikie et al., 2004). Thus, we quantified population exposure by calculating the growth in population between 2000 and 2020 for each mesoregion. To assess the vulnerable areas, we compared the most impacted cities with vulnerable areas defined by the BATER vulnerability dataset (IBGE, 2018b). We assessed whether mapped risk areas were more affected by the impacts than unmapped risk areas. This information can also be useful for civil defense in order to refine the risk maps. The criteria used for this analysis were the number of homeless people, by comparing the five most affected municipalities with the highest number of homeless people, with the municipalities mapped as vulnerable. All monetary impacts were reported in Brazilian Currency (BRL) and U.S. dollars (USD) given a 5.4:1 conversion rate (January 2021).

### 2.3.2 | Anthropogenic climate change attribution

One of the most challenging tasks in event attribution is the spatiotemporal definition of the extreme event (Otto, 2017). The task is more complex for precipitation cases because models usually present issues representing the spatial pattern of this meteorological variable, that is, the exact location of precipitation events (e.g., da Silva and de Camargo, 2018). Moreover, the complete analysis of the socioeconomic impacts requires a relation between the measured damages and the attribution estimation both spatially and temporally. Considering the previous assessment of the most-affected areas, we defined our event as the January spatial-maximum consecutive 5-day accumulated precipitation ( $RX5day_{max}$ ) within the southeast Minas Gerais state (red box in Figure 1). Several tests were done to find a reasonable metric regarding model performance compared with observational data in the region. For more details, please see Text S2 in the Supporting Information.

The event observed value, that is, the threshold for attributing the event probability change, was based on CPC and CHIRPS  $RX5day_{max}$  values for January 2020. These two observational datasets presented values closely related to a precipitation gauge in the state capital Belo Horizonte, within one of the most affected regions (Supporting Information Figure S1). A climatological analysis showed that the model is too wet in the region, with its empirical probabilistic functions (ePDFs) being more skewed to the right-hand side and, consequently, overestimating the

higher percentiles when compared to observations (Supporting Information Figure S3a and b). Therefore, the use of a correction method to remove the bias in the simulation before the attribution analysis was necessary. We employed a linear scaling correction, in which we adjust precipitation with a multiplier rather than an additive factor (e.g., Lenderink et al., 2007; Mendez et al., 2020). Although there are other elaborate methods for extreme values analysis, for example, quantile mapping (Mendez et al., 2020), they alter the distribution shape of the data, which might hide the model's inability to reproduce the event at hand, and make it difficult to achieve reliable attribution statements. Therefore, we prefer to use simpler methods that preserve the shape of the ePDF such as the linear scaling correction. Nevertheless, the linear scaling technique has shown to be effective for extreme analysis when using monthly or seasonal values (Shrestha et al., 2017), and it showed a good performance for our data (Supporting Information Figure S3c and d). The correction can be written as Equation (1):

$$Model_{corr}(t, m) = Model_{raw}(t, m) \times \frac{mean(Ob_{s_{clim}})}{mean(Model_{clim})}, \quad (1)$$

for  $t = 1, 2, \dots, T$  and  $m = 1, 2, \dots, M$ , where the  $Model_{corr}$  are the bias-corrected model values,  $Model_{raw}$  are the model raw outputs to be corrected,  $Ob_{s_{clim}}$  is the observed climatology, and  $Model_{clim}$  is the model climatology. The indices  $t$  and  $m$  correspond to time and ensemble members, respectively. The values here are all based in the  $RX5day_{max}$  for January and as we used just 1 month per year,  $T$  is equal to 33 for the observational ( $Ob_{s_{clim}}$ ) and model ( $Model_{clim}$ ) climatologies, which corresponds to the historical experiment period. The climatological adjustment, applied in the bias correction method evaluation, used the 15 available members ( $M = 15$ ) in the historical ensemble and  $Model_{raw} = Model_{clim}$  (see Figure S3). We removed the bias of January 2020 model raw values by using Equation (1) with the mean model climatology for January ( $mean(Model_{clim})$ ). In this case,  $T$  is 1 and  $M$  is 525 for each model scenario used as  $Model_{raw}(t, m)$ . The means in Equation (1) are computed over time for  $Ob_{s_{clim}}$  ( $T=33$ ) and over time and ensemble members for  $Model_{clim}$  ( $T=33, M=15$ ), considering the historical period as climatology.

To compare the likelihood of occurrence in the ALL and NAT scenario distributions, we calculated the PR (Equation (2)):

$$PR = P_{ALL}/P_{NAT}. \quad (2)$$

PR represents the increase in probability of exceeding the observed value (threshold) in the ALL scenario in comparison to the NAT scenario. To evaluate the PR signif-

icance, we conducted 10,000 bootstrap simulations with replacement to derive a 90% confidence interval using the 5th ( $PR_{0.05}$ ) and 95th ( $PR_{0.95}$ ) percentiles of the PR distribution.  $PR_{0.05}$  (the lower bound of the confidence interval) above 1.0 denotes a significant increase in likelihood of the extreme event in the ALL scenario in comparison to the NAT scenario. The PR calculation and significance test were done using both the ePDF and an adjusted gamma PDF. For the ePDF, the PR was calculated directly counting the number of occurrences above the threshold, whereas for the gamma distribution, the cumulative density function was used.

Given the PR values, we calculated the FAR as Equation (3):

$$FAR = 1 - (1/PR). \quad (3)$$

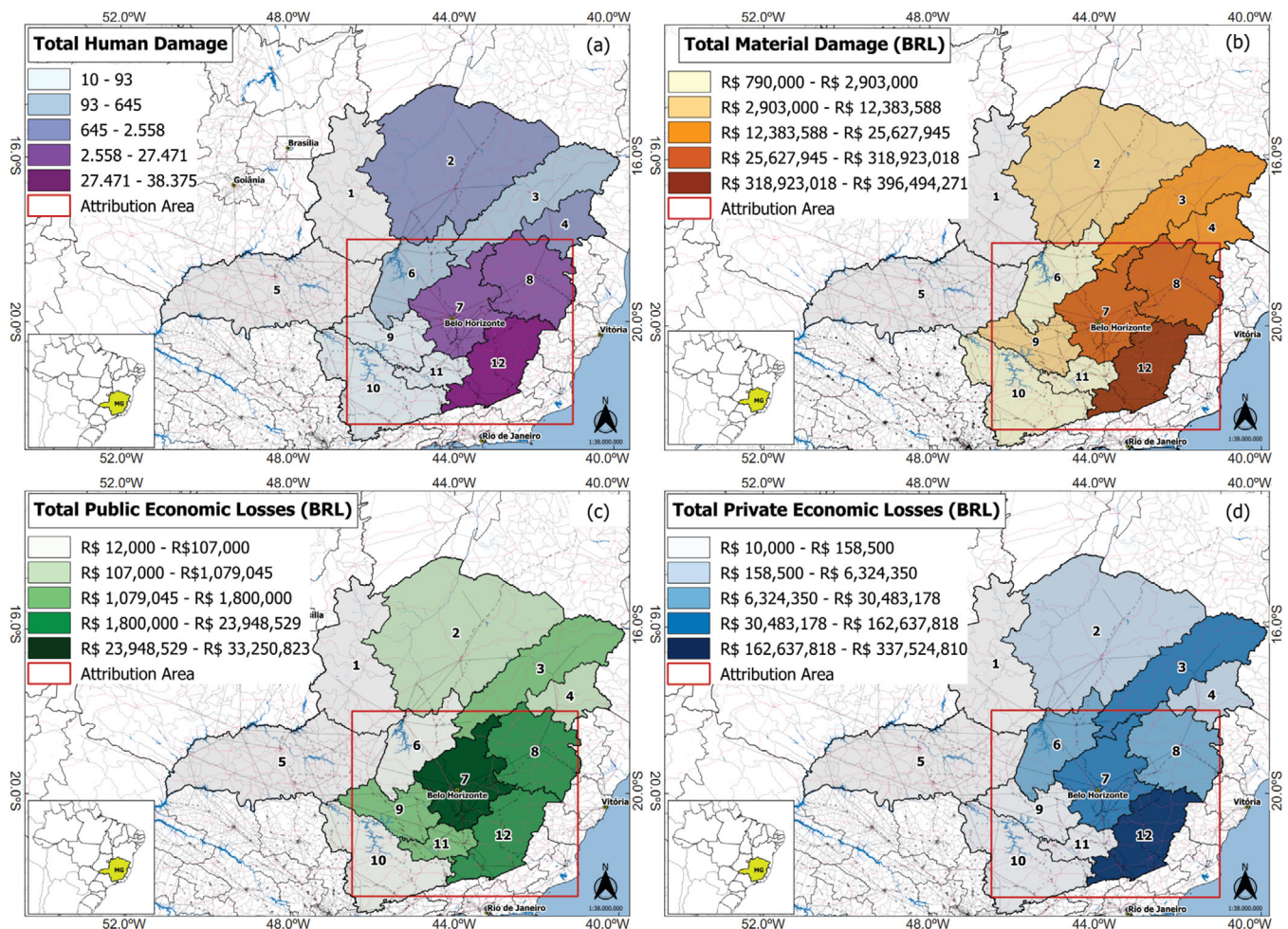
FAR corresponds to the fractional contribution of anthropogenic climate change to the event (e.g., Otto, 2017; Frame et al., 2020), from which we estimate the portion of socioeconomic damages attributable to anthropogenic climate change. Hence, a value near one implies that most of the observed event has been caused by altered atmospheric gas concentrations due to anthropogenic emissions.

### 3 | RESULTS

#### 3.1 | Socioeconomic impacts over Minas Gerais

The impacts of the extreme precipitation event of January 2020 over the entire state were: (i) 94,788 people affected, including displaced, homeless, and sick or injured (Figure 2a), (ii) BRL 881.33 million (USD 163 million) in total material damages (Figure 2b), (iii) BRL 48.29 million (USD 8.9 million) in total public economic losses (Figure 2c), and (iv) BRL 435.51 million (USD 80.6 million) in total private economic losses (Figure 2d). The impacts were more localized over the southeast of Minas Gerais (Figure 2). The most affected mesoregions were the Belo Horizonte Metropolitan Region, Vale do Rio Doce, and Zona da Mata. Together, they accounted for 91% of public economic losses, 93% of private economic losses, 92% of total material damage, 91% of the total displaced population, 95% of the total homeless population, and 99% of the sick and injured people from this extreme event. These mesoregions also showed the most concerning numbers regarding the disaster vulnerabilities of residents and dwellings in officially mapped risk areas. The mesoregions of Belo Horizonte Metropolitan, Vale do Rio Doce, and Zona da Mata concentrated the majority of the most vulnerable population groups according to age (up to 5 years





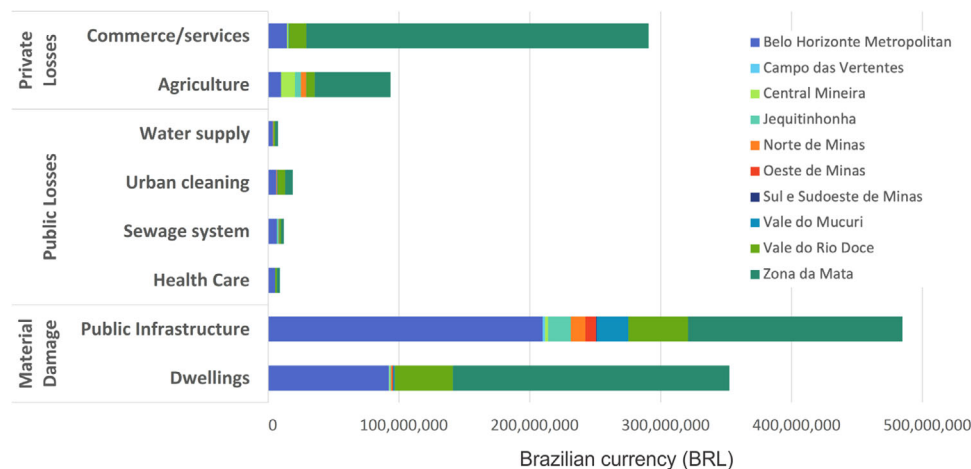
**FIGURE 2** Spatialized socioeconomic damage over Minas Gerais for the extreme rainfall event of January 2020. (a) Total human damage (absolute number of people), (b) total material damage (BRL), (c) total public economic losses (BRL), and (d) total private economic losses (BRL). The polygons represent the mesoregions (see Figure 1). Shading represents the severity of the damage

and over 60 years), and the highest number of inadequate dwellings (e.g., without basic sanitation) (Table S1). Besides, these three mesoregions experienced substantial population growth during the period from 2000 to 2020, exposing more people to this particular event (Figure S4). The most extreme example was the Belo Horizonte Metropolitan region, which had an increase in population of nearly 30% in 20 years. Rapid population increase in metropolitan regions is a common phenomenon observed throughout South America. In Brazil, the 2010 census indicated that 84% of the population lives in urban centres, consolidating an migratory process from rural areas, which started in the 1980s (IBGE, 2011). This rapid and unplanned population growth occurs with a lack of infrastructure and public service improvements, such as proper housing conditions, sanitation, transport, and so forth. Therefore, this increase observed in the Belo Horizonte Metropolitan mesoregion can be understood also as an increase in vulnerability. No data are available for the mesoregions

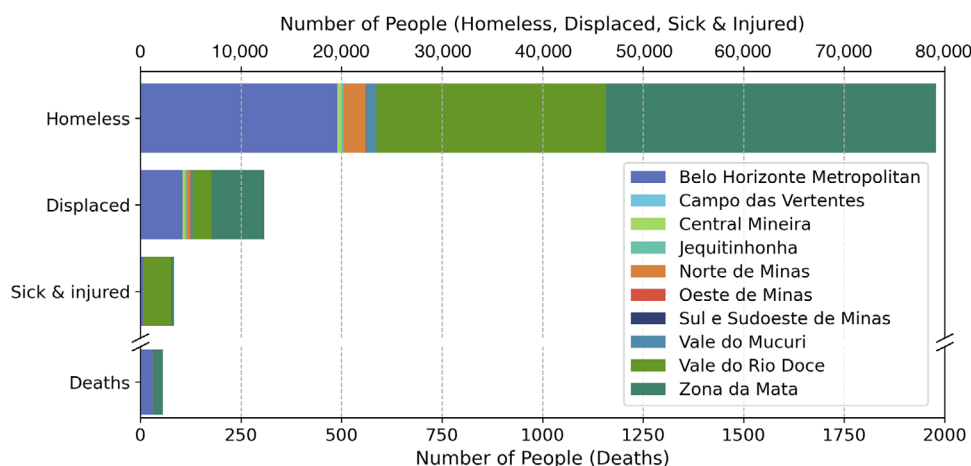
Noroeste de Minas and Triângulo Mineiro e Alto Paranaíba (Figures 1 and 2), located in the western sector of the state.

From the most affected mesoregions, 20% of municipalities were not mapped as vulnerable areas by the state civil defense: Conselheiro Pena and Taparuba (Vale do Rio Doce) and Raul Soares (Zona da Mata). These municipalities accounted for 5,217 displaced people, 360 homeless people, and BRL 4.01 million (USD 0.74 million) of material damage in destroyed households. This demonstrates the importance of constantly updating risk areas maps and the need for more strict vulnerability criteria to be defined and used by the authorities.

Although the public economic losses were considerable (38 million BRL), the most impacted sectors were material damage and private economic losses (Figure 3 and Table S2). The greatest impacts were observed on public infrastructure (BRL 484 million or USD 89.6 million), dwellings (BRL 352 million or USD 65.2 million), and commerce/services (BRL 290 million or USD 53.7 million).



**FIGURE 3** Breakdown of the economic impacts. Most impacted sectors related to material damage, public economic losses, and private economic losses as a consequence of the extreme precipitation event. All values are expressed in BRL (Brazilian currency)



**FIGURE 4** Breakdown of the social impacts per mesoregion. Human damage including deaths (number of people) as a consequence of the extreme precipitation event. Note that the x-axis scale is different for the number of deaths

These three subcategories accounted for >91% of the total monetary losses. Although public economic losses were the highest in Belo Horizonte, private economic losses peaked in Zona da Mata. This indicates that differential impacts observed between mesoregions also depend on their main activities. When looking at the impacts from an integrated approach, the values found in each category reveal the systemic nature of disaster impacts. As most of the material damage is related to public infrastructure, which comprises, predominantly, in the partial or total reconstruction of traffic routes and pipelines sections, this leads to public economic losses, such as providing water supply to the people affected, and the reestablishment of the sanitary sewage service, urban cleaning system, as well as garbage collection and disposal. Finally, the values observed in commerce/service reveal the interrup-

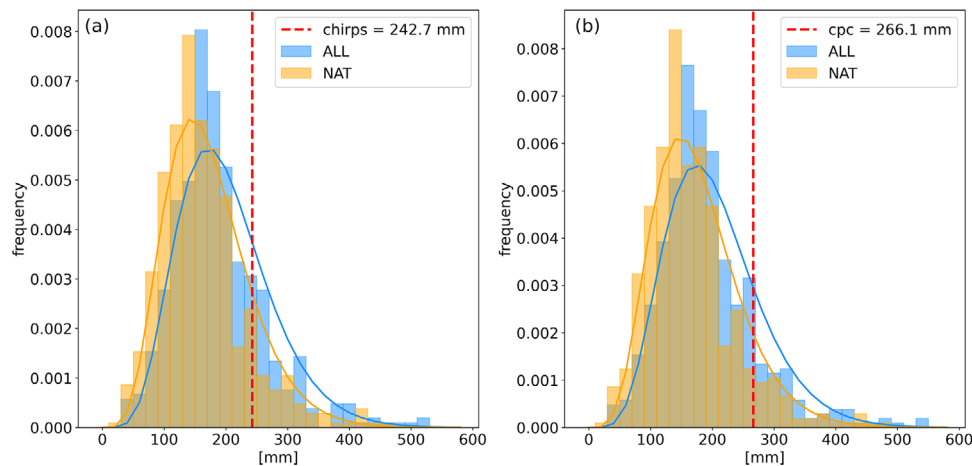
tion of businesses in the area, which sometimes might take weeks or months to recover, underscoring the long-lasting spatiotemporal effects of the impacts.

When partitioning the human damage caused by the extreme event between different categories, the official data recorded were the death of 56 people, caused 3328 people to become sick and injured, displaced 12,335 people, and left 79,125 people homeless (Figure 4 and Table S3). Homelessness was the most frequent category (83.4%) of human damage. We highlight here Belo Horizonte Metropolitan and Zona da Mata, the two mesoregions that had the majority of human damage including most deaths. Furthermore, the sudden increase in the number of sick and injured people as a result of the disaster often stresses the local public health system—which increases the chance of overall mortality due to the lack of available



**TABLE 1** Attribution metrics for the extreme precipitation event of Minas Gerais in 2020 based on the ALL and NAT scenarios, using the CHIRPS and CPC observed threshold. Probabilities and return periods were calculated using the fitted Gamma distribution. The 90% confidence interval (CI) was obtained by the 5th and 95th percentile using 10,000 bootstrap simulations

Metric	CHIRPS	CPC
	Estimate [90% CI]	Estimate [90% CI]
Event threshold (mm)	242.7	266.1
PR	1.70 [1.40, 2.10]	1.82 [1.42, 2.35]
FAR	0.41 [0.28, 0.52]	0.45 [0.30, 0.58]
NAT Return period (years)	6.67 [5.74, 7.99]	9.54 [7.92, 11.92]
ALL Return period (years)	3.92 [3.53, 4.43]	5.25 [4.60, 6.13]



**FIGURE 5** Histograms and gamma-fitted distributions of the spatial maximum RX5day in January 2020 for ALL (blue) and NAT (orange) scenarios using (a) CHIRPS and (b) CPC climatology for bias model correction. The thresholds for exceedance probability calculation in each case are shown in a dashed red line

treatment for everyone, and also leads to public economic losses in health care (Table 1)—mainly due to the urgent need to hire professionals. This highlights the importance of approaching disasters from a systemic point of view, in evaluating public or private economic losses, and assessing human or material damage.

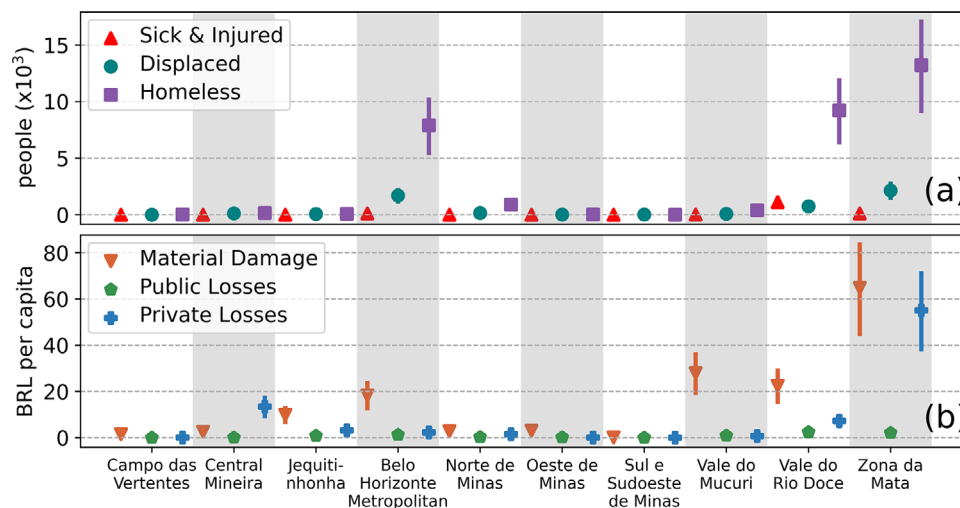
### 3.2 | Attribution analysis

The distribution of  $RX5day_{max}$  values in January 2020 for the ALL scenario was shifted to the right-hand side in comparison to the NAT scenario, indicating higher or more extreme values with anthropogenic climate change impacts (Figure 5). The event  $RX5day_{max}$  was similar in CHIRPS and CPC observations. Using these as the event threshold, the attribution metrics estimated from CHIRPS and CPC data also showed values with a similar range (Table 1). However, the PR estimate using CPC (PR = 1.82) was slightly higher than CHIRPS (PR = 1.70). Using the more conservative CHIRPS value, we estimated an FAR of 0.41 [0.28, 0.52] for this extreme event. This corre-

sponds to return intervals estimated at 6.67 years for the NAT scenario and 3.92 years for the ALL scenario, that is, anthropogenic climate change has increased the likelihood of occurrence/decreased the return interval for such an event.

### 3.3 | Attributable impacts to human-induced climate change

We estimated the attributable impacts to human-induced climate change for this extreme event based on the attribution analysis using CHIRPS (Figure 6) and CPC (Figure S5), to be 41% (FAR = 0.41). This fraction corresponds to the additional number of people affected and/or monetary losses incurred. We report here the main results based on the FAR estimated from CHIRPS, because it provided more conservative estimates. Belo Horizonte Metropolitan, Vale do Rio Doce, and Zona da Mata mesoregions reflect the most-affected human damage induced by climate change, especially regarding homeless people (Figure 6a). During the event, between 22,155 and 41,145 of



**FIGURE 6** Extreme event impacts attributable to human-induced climate change based on the attribution analysis using CHIRPS. Human damage categories are shown in (a) and monetary losses per capita are shown in (b). The markers and whiskers represent the estimate and a 90% C.I.

homeless people were likely attributable to anthropogenic climate change. For the total material damage, public and private losses (Figure 6b), the material damage is the category with higher monetary loss per capita, followed by the private losses. The private damage related to agriculture accounted for a total of BRL 93.45 million (USD 17.30 million), of which BRL 26.17–48.60 million (USD 4.84–9 million) were likely attributable to anthropogenic climate change. It is important to monitor the impacts on agriculture because they can interfere with the food security of this region and also of other more distant regions, where the food would be exported from this region. This shows the relevance of considering climate change impacts with an integrated and systemic perspective.

## 4 | DISCUSSION

Our findings show that human-induced climate change increased the likelihood of occurrence of this extreme precipitation event. The PR was estimated at 1.70 for the CHIRPS and 1.82 for the CPC, showing a good agreement and overlapping confidence interval between both datasets. The lower bound of the 90% confidence interval ( $PR_{0.05}$ ) was estimated at 1.40 and 1.42 for the CHIRPS and CPC datasets, respectively.  $PR_{0.05}$  greater than 1 indicates that this increase in occurrence is statistically significant and is independent of the observational dataset used in the attribution estimation. Therefore, our results suggest that the event was at least 70% more likely to occur due to human-induced climate change. We estimated that the event affected at least 90,000 people and caused more than BRL 1.3 billion (USD 240 million) of monetary losses. The

most expensive losses were derived from material damage (BRL 881 million or USD 163 million) and private economic losses (BRL 435 million or USD 80.5 million). From these estimates, our analysis indicates that at least 37,000 homeless and displaced people and more than BRL 550 million (USD 101.85 million) can be attributed to human-induced climate change. As a comparison, a study for all Brazilian regions found that the economic losses from extreme climatic events vary between 1.8 and 5.3 billion BRL (USD 330–940 million), when considering the accumulated economic loss of the entire year due to rainfall, flash floods, and so forth (GFDRR, 2020). This demonstrates the relevance of the event analysed in this work, adding up to BRL 1.3 billion loss (USD 240 million) but occurring over a period of only a few days.

The estimated return intervals for the event were relatively short for both scenarios, but even shorter in the ALL experiment (<5 years). This means that an event with high-magnitude impacts to society like the one herein reported is likely to occur every ~4 years in the real world, which is 70% more frequently than in a world without human influence. The decrease of the return period in a warmer world is in agreement with previous works based on observation that showed the reduction of extreme precipitation return period with time in the region (e.g., de Carvalho et al., 2014). Moreover, the return period found here is consistent with reports of frequent extreme precipitation events in the Minas Gerais region causing severe impacts to society (Marengo and Alves, 2012; Ávila et al., 2016).

Considering temporal trends worldwide, it is important to notice that a United Nation report on natural disaster and economic losses showed that the economic losses from natural disasters have been increasing in the last

20 years, and are likely to keep on increasing (UNDRR, 2019). Extreme climatic events represented 77% of the total economic loss from natural disasters in this period, and the most affected countries are in the developing world, particularly for the lack of adaptation to climate change impacts (Wallemacq et al., 2018).

Even though the event was extreme and climate change is expected to make it worse, the lack of urban risk management planning, mitigation, and adaptation strategies and infrastructure investment are yet key components for the extent of the impacts occurring over the study area. Consequently, the event most likely disproportionately affected the poorer population of the region that lives in high-risk situations, such as in areas with steep topography and poor housing conditions. Therefore, we interpret the impacts of this event as a socially constructed climatic disaster. Previous studies showed that the urban planning model implemented in this region, focusing solely on economic interests and leading to social exclusion and socioenvironmental vulnerability, were distinctive characteristics of the historical urban expansion of the Metropolitan Area of Belo Horizonte (Lages, 2020). While direct and immediate action on climate change requires international cooperation, it is still possible to minimize the scale of the impacts of similar events by improving city planning and through increasing public disaster prevention policies, focusing not only on improving an observational network for early warning system (e.g., the soil moisture network implanted and monitored by CEMADEN in risk areas) but also strengthening risk governance by organizing the role and responsibility of each institution that makes up this system. The use of green infrastructure, such as vegetated spaces, has been shown to decrease the likelihood and intensity of flash flood events, particularly on risk areas such as high slopes—where the most vulnerable populations reside (Rosa et al., 2020). In addition, the Sendai Framework for Disaster Risk Reduction recommends the development of mechanisms to involve civil society in building up a multihazard and people-centered early warning system approach, which takes into account the degree of vulnerability and capacity of people living in risk-prone areas, their needs in terms of gender, age, disability, mobility, status, language, and culture (Peek, 2008; Mustafa et al., 2015; UNISDR, 2015; Bennett, 2020). One important factor for disaster prevention that we highlight here is to keep track of population growth, that is, the location and rate of increase, because these factors usually are drivers to an increase in social vulnerability due to deficitary urban planning (Blaikie et al., 2004). Our results suggest that this process likely occurred in the Belo Horizonte Metropolitan region, which experienced the highest increase in population (30% in 20 years) among the states. Moreover, 20% of the most-affected mesoregions were not

previously mapped as vulnerable areas according to data from the civil defense. One of the unmapped municipalities (Raul Soares), however, was mapped as hydrological risk in another disaster monitoring system from the CEMADEN network. This finding highlights focal areas for pressing urban governance and resilience actions and the need for better exchange of information between institutions in order to prevent more human and material damage from future extreme events.

Although our numerical experiment results show significant human-induced climate change effects, and considerable damage caused by this extreme event, we caution for some potential uncertainties on our estimates. The overall impact numbers reported here were most likely underestimated due to data uncertainties and missing socioeconomics data for ~17% (2 out of 12 mesoregions) of the study area. The agricultural damage of most of 93 million BRL probably also has significant ramifications for regional food security, causing indirect effects such as the depletion of some trade goods in the markets and/or the rise in prices of main commodities that affects the urban populations. As previously indicated, agriculture is an important economic source for the region, especially for 15% of the state's population that live in rural areas (3 million people) and strongly depend on the production of their smallholder farming for their subsistence (IBGE, 2011). Additionally, although robust, the model results are not free of limitations. We point out uncertainties in the spatial and temporal scales which we have mitigated, and expect to have only marginally affected our results. Previous studies reported that models often misplace the SACZ over Southeast Brazil (e.g., da Silva and de Camargo, 2018). Climate model analysis also presented high inter- and intramodel variability in the region, increasing the uncertainties in precipitation values (Seth et al., 2009; Jones and Carvalho, 2013). However, the spatial aggregation approach that we conducted considering the domain of the southeastern Minas Gerais region likely minimized problems of capturing the exact position of the atmospheric phenomena, that is, we captured the most extreme event in the region during the event time frame. The same is pointed out for the temporal scale, in which it is not to be expected that global models accurately capture the exact timing of extreme events (e.g., Ciavarella et al., 2018). However, we expect to have minimized this limitation, when we used the  $RX5day_{max}$  as a metric for the attribution analysis.

We highlight the importance of having integrated disaster information systems such as the Brazilian S2iD, which conveys valuable and timely information that allows quantification of the impacts from extreme events. Specifically regarding this dataset, it was only recently created in 2012 and it has been used by civil defence agencies at national, state, and local level to inform disasters and request the



federal recognition of an emergency situation or a state of public calamity. It also allows users to consult the resource transfer processes for response and rebuild actions, and to seek information on occurrences, risk, and disaster management based on official data.

The climate modeling experiments used in the attribution analysis bring the possibility of disentangling the effects of humans to climate change, but there are still some caveats to this approach that can and should be improved upon for future studies. First, another bias correction method could be used instead of linear scaling. However, it is important to avoid techniques that alter the shape of the distribution, which may cause implications to the reliability of the attribution statement. Second, the use of a single model to assess extreme precipitation requires in-depth validation over the study region. HadGEM, HadCM, and HadAM model family has been shown to have good model performances in South America, regarding precipitation (e.g., Marengo et al., 2010; Chou et al., 2012; Llopart et al., 2014) and other extreme event precursors, such as extratropical cyclones (e.g., Reboita et al., 2018; Dias da Silva et al., 2021). However, given the narrow area where the extreme rainfall occurred in January 2020, the analysis would surely benefit from a model more calibrated and validated to the South American Monsoon System. Although regional institutes, such as the National Institute for Space Research (INPE), maintain climate models more adapted to the region (e.g., Eta-CPTEC), they do not have large ensembles available for attribution methods such as the ones used in this study. In fact, few institutions over the world produce this type of large ensembles, which narrows down the option of possible models to use for attribution studies. Large ensembles in climate models serve as a powerful tool to reduce uncertainty in climate projection and allow estimating climate change effects on a certain event. We believe that the scientific community, decision-makers, and society would benefit if more institutes can access funds and develop capacity to run climate model experiments with large ensembles.

## 5 | CONCLUSION

The present work aimed to assess the impacts of the extreme rainfall of January 2020 in the Brazilian state of Minas Gerais and the extent attributable to human-induced climate change combining multidisciplinary strands of extreme events analysis, economic and human cost of the precipitation, and event attribution to rising greenhouse gas concentrations, based on climate modeling. The extreme precipitation event over the Brazilian state of Minas Gerais in January 2020 was at least 70% more likely to occur due to human-induced climate change.

Over 90,000 people were affected by this extreme event, including those homeless, temporarily displaced, or sick or injured. Total monetary losses were estimated at more than BRL 1.3 billion (USD 240 million), divided between material damage, public, and private economic losses. We estimated that 41% of these impacts could be attributed to human-induced climate change. From the most-affected mesoregions, 20% of municipalities were not previously mapped as vulnerable regions. We highlight the importance of maintaining datasets such as the S2iD, which should, in principle, enable future assessments of the effectiveness of policy interventions in minimizing the impacts from similar future extreme events. Our findings can help to support policymakers on extreme events and climate change mitigation and management, and inform the general public about climate change consequences so that they can demand actions from the policymakers.

Future studies could investigate in more detail the disproportionate effects of extreme events over poor populations, from the perspective of environmental justice—because the disaster impacts are often stronger on the most marginalized populations, exacerbating inequality, and further perpetuating poverty. Such vulnerabilities translate into an unequal distribution of opportunities, reduced access to human rights resulting in decreased resilience for the disaster on a personal, community and regional level. Moreover, future research could also address the increasingly complicated interactions of human, economic and political aspects within ecological systems. This would probably require high-resolution data over some of the most-affected municipalities, with the integration of topographical information, hydrological modeling, and socioeconomic data. In addition, the attribution approach could also be used to evaluate the likelihood of the event from a dynamical perspective, evaluating the indices and metrics that measure the moisture transport and atmospheric instability over the region.

## DATA AVAILABILITY STATEMENT

We acknowledge CPC Global Unified Precipitation data provided by the NOAA/OAR/ESRL PSL, Boulder, Colorado, USA (<https://psl.noaa.gov/>) (Chen et al., 2008), CHIRPS data provided by Climate Hazards Center UC Santa Barbara (<https://www.chc.ucsb.edu/data/chirps>) (Funk et al., 2015), model data provided by the EUCLEIA (European Climate and Weather Events: Interpretation and Attribution; <https://cordis.europa.eu/project/id/607085>), and socioeconomic impacts data provided by the S2iD—*Sistema Integrado de Informações sobre Desastres* (<https://s2id.mdr.gov.br>) (S2iD, 2020).

## CONFLICT OF INTEREST

The authors have declared no conflict of interest.

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## SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of the article.

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