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# Socio-climatic hotspots in Brazil

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**Abstract** Brazil suffers yearly from extreme weather and climate events, which can be exacerbated in a warmer climate. Although several studies have analyzed the projections of climate change in Brazil, little attention has been paid to defining the locations that can be most affected, and consequently have a more vulnerable population, in a spatially-explicit form. This study presents a spatial analysis of summarized climate change data and a joint investigation combining these possible climate changes and social vulnerability indicators in Brazil. The Regional Climate Change Index (*RCCI*), which can synthesize a large number of climate model projections, is used for the climate analysis, and the Socio-Climatic Vulnerability Index (*SCVI*) is proposed to aggregate local population vulnerabilities to the climate change information. The *RCCI* results show climatic hotspots emerging in Brazil, covering the western portion of the Northeast (NE), northwestern Minas Gerais state and center-western (CW) and northern regions (N), except northeast Pará and Amapá states. The *SCVI* analysis reveals major socio-climatic hotspots in the NE and several localized hotspots in some of the major Brazilian metropolitan regions, namely Manaus, Belo Horizonte, Brasília,

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Salvador, Rio de Janeiro and São Paulo. The two novelties of this study are a spatially detailed analysis of the *RCCI* in Brazil and the development of an index that can summarize the large amount of climate model information available today with social vulnerability indicators. Both indices may be important tools for improving the dialogue between climate and social scientists and for communicating climate change to policymakers in a more synthetic and socially relevant form.

## 1 Introduction

Projections indicate a considerable change in Brazil's climate within this century (Baettig et al. 2007; Marengo et al. 2009, 2010a), and there are several reasons to believe Brazil will be highly impacted by such climatic change: its economy depends heavily on exports of agricultural commodities (IPEA 2011); the provision of staple foods is strongly reliant on smallholder agriculture (responsible, for example, for 87 % of the national production of cassava, 70 % of dry beans, 46 % of maize, and 58 % of milk) (IBGE 2009); it has an energy matrix dominated by renewable energy, which is highly susceptible to climate variations (Lucena et al. 2009); and it still suffers widespread poverty, significant social inequality and epidemic outbreaks (IPEA 2003; Magrin et al. 2007; Confalonieri et al. 2009). The floods in São Paulo city in the summer of 2010 (Folha de São Paulo 2010), the landslides in the state of Rio de Janeiro in the summer of 2011 (Folha de São Paulo 2011), the annual dengue fever epidemics throughout the entire country, and the succession of intense droughts and floods events in Amazonia and Northeast (NE) Brazil (Marengo et al. 2011c, d; Ponce 1995) reveal how unprepared Brazil is for climate change.

Several studies have examined the effects of climate change in Brazil using different general circulation models (GCMs) and dynamical downscaling methods (e.g., Vera et al. 2006; Bombardi and Carvalho 2009; Marengo et al. 2010a, b, 2011a; Rusticucci et al. 2010). Despite the contribution of these studies to our knowledge of climate change, uncertainties about the regional climate impacts still remain. Moreover, the intrinsic uncertainties of climate change projections (Giorgi 2005; Knutti 2008) make the interactions between climate scientists and social scientists and, importantly, between scientists and policymakers, very difficult (Pidgeon and Fischhoff 2011). One possibility to improve the communication between climate scientists and others is the creation of climate change indices that aggregate various information and measures of uncertainty concisely and reliably (Giorgi 2006; Baettig et al. 2007; Xu et al. 2009). However, there is currently no scientific study showing where climate change hotspots (the word "hotspots" is used in this study to indicate areas with large regional climate changes and/or a highly vulnerable population) are located in Brazil and how these climate hotspots relate to population density and social conditions, such as poverty, education and health, in a country-wide perspective.

Therefore, this study addresses the need for straightforward and synthesized assessments of climate change and its probable social impacts in Brazil by presenting a spatially explicit analysis of Brazil's socio-climatic hotspots by relating more than one hundred climate projections with indicators of social vulnerability to climate change. The Regional Climate Change Index (*RCCI*) developed by Giorgi (2006) is applied specifically to Brazil and is incremented with social vulnerability proxies to compose what is defined here as the Socio-Climatic Vulnerability Index (*SCVI*). The *SCVI* is a timely approach to identifying the areas for which climate change projections have the most human/social relevance. This information can then be used to target areas where actions towards adaptation should be prioritized.

## 2 Methods

### 2.1 Climate simulation dataset

This study uses monthly precipitation and surface air temperature data simulated for the present climate (1961–1990) and projected to the end of this century (2071–2100) from 24 GCMs of the Coupled Model Inter-comparison Project Phase 3 (CMIP3) employed in the Intergovernmental Panel on Climate Change (IPCC) Fourth Assessment Report (IPCC 2007) (Table 1). Hereafter, the word change(s) refers to the difference between the mean values of the climate variables for the periods 2071–2100 and 1961–1990. Three sets of IPCC emission scenarios were used for the future period: SRES B1, A1B and A2, corresponding to equivalent $CO_2$ concentrations of approximately 550, 700 and 850 ppm, respectively, in the year 2100 (Nakicenovic et al. 2000). The models and simulations are described in more detail in Meehl et al. (2007).

The GCMs spatial resolutions vary from roughly 1–5 ° of latitude/longitude (Table 1). All GCMs were interpolated to a common 1 ° grid, using the conservative remapping scheme (Jones 1999; Giorgi and Bi 2005; Giorgi 2006; Xu et al. 2009), for inter-comparison

**Table 1** List of models, approximate model spatial resolutions, emissions scenarios and number of runs in the CMIP3 dataset used in this study. Models are ranked by their spatial resolution

| Models | Resolution (lat/lon) | 20C3M | A2 | A1B | B1 |
|---|---|---|---|---|---|
| INM-CM3.0 | 5 °×4 ° | 1 | 1 | 1 | 1 |
| GISS-EH | 5 °×4 ° | 5 | - | 3 | - |
| GISS-ER | 5 °×4 ° | 9 | 1 | 2 | 1 |
| GISS-AOM | 4 °×3 ° | 2 | - | 2 | 2 |
| CGCM3.1(T47) | 3.8 °×3.8 ° | 5 | 5 | 5 | 5 |
| ECHO-G | 3.8 °×3.8 ° | 5 | 3 | 3 | 3 |
| UKMO-HadCM3 | 3.8 °×2.5 ° | 2 | 1 | 1 | 1 |
| IPSL-CM4 | 3.8 °×2.5 ° | 1 | 1 | 1 | 1 |
| FGOALS-g1.0 | 2.8 °×3 ° | 3 | - | 2 | 3 |
| MRI-CGCM2.3.2 | 2.8 °×2.8 ° | 5 | 5 | 5 | 5 |
| CGCM3.1(T63) | 2.8 °×2.8 ° | 1 | - | 1 | 1 |
| CNRM-CM3 | 2.8 °×2.8 ° | 1 | 1 | 1 | 1 |
| MIROC3.2(medres) | 2.8 °×2.8 ° | 2 | 3 | 3 | 3 |
| PCM | 2.8 °×2.8 ° | 4 | 4 | 4 | 2 |
| GFDL-CM2.0 | 2.5 °×2 ° | 3 | 1 | 1 | 1 |
| GFDL-CM2.1 | 2.5 °×2 ° | 3 | 1 | 1 | 1 |
| BCCR-BCM2.0 | 1.9 °×1.9 ° | 1 | 1 | 1 | 1 |
| CSIRO-MK3.0 | 1.9 °×1.9 ° | 3 | 1 | 1 | 1 |
| CSIRO-MK3.5 | 1.9 °×1.9 ° | 3 | 1 | 1 | 1 |
| ECHAM5 | 1.9 °×1.9 ° | 4 | 3 | 4 | 3 |
| UKMO-HadGEM1 | 1.9 °×1.3 ° | 2 | 1 | 1 | - |
| CCSM3 | 1.4 °×1.4 ° | 7 | 4 | 7 | 9 |
| ECHAM4 | 1.1 °×1.1 ° | 1 | 1 | 1 | - |
| MIROC3.2(hires) | 1.1 °×1.1 ° | 1 | - | 1 | 1 |

purposes and to properly relate them with social datasets in a reasonable grid size. However, one might argue that the interpolation of models from the coarsest to the highest resolution in an ensemble is not ideal. An appropriate technique to downscale the results of climate models would be statistical downscaling or dynamical downscaling (Boulanger et al. 2006; Christensen et al. 2007). Nevertheless, these two techniques are too time-consuming and/or computationally expensive and their application is highly non-trivial. Because this study aims to present a new approach to combine climate and social information, a more suitable interpolation or downscaling technique for the climate change dataset can be applied in future studies.

For the *RCCI* calculation described in Section 2.2, all climate variables and statistics were computed as follows: 1) the change was calculated for each model simulation; 2) different runs using the same model (when available) were averaged; 3) the results were interpolated to a 1° latitude/longitude spatial resolution; 4) the ensemble average over the different available models was obtained; and 5) the three emission scenarios were averaged.

## 2.2 Regional climate change index

The *RCCI* is a qualitative index proposed by Giorgi (2006) to identify the regions in which climate change may be more prominent. This index is based on the temperature change in a specific region relative to the change in mean global temperature (or regional warming amplification factor, *RWAF*), change in mean regional precipitation ($\Delta P$, %) and change in the interannual variability of temperature ($\Delta\sigma_T$, %) and precipitation ($\Delta\sigma_P$, %), all of which are calculated separately for austral summer and winter. The *RCCI* is not affected by small changes below certain thresholds, while more intense changes receive heavier weights (Giorgi 2006).

In the *RCCI* formulation, the $\sigma_T$ and $\sigma_P$ indexes can represent a proxy for extreme climate conditions, such as excessively rainy or dry seasons, that could seriously affect human welfare and the environment. The interannual standard deviation of temperature was used as a measure of $\sigma_T$, and the coefficient of variation (i.e., the standard deviation divided by the mean) was used as a measure of $\sigma_P$. Both $\sigma_T$ and $\sigma_P$ were calculated for the selected 30 year periods after detrending the data to obtain unbiased variability estimates. The coefficient of variation was used as a measure of interannual precipitation variability because it removes the dependency of the standard deviation on the mean for zero-bounded variables such as rainfall (Räisänen 2002; Giorgi 2006).

However, it is worth mentioning that the process of estimating the occurrence of extreme events is non-trivial, especially for projections of the future climate (Frich et al. 2002; Meehl et al. 2005; Tebaldi et al. 2006 and citations quoted therein). The interannual variability calculated using the standard deviation and coefficient of variation are used only as a first approximation for such events (Räisänen 2002; Giorgi 2006 and Xu et al. 2009). A more suitable extreme climate calculation could be derived, for example, from a robust statistical estimate of the probability density function of daily temperature and precipitation data (Alexander et al. 2006) generated by an ensemble of higher-resolution models.

The *RCCI* was chosen for this study because it is a well accepted index in the literature to show where climate change could be, on a relative basis, more pronounced in a warmer climate based in a large set of climate models. Moreover, its results compare quite well with another well accepted index, the Climate Change Index, developed by Baettig et al. (2007), as will be discussed in Section 3.1.

### 2.3 Socio-climatic vulnerability index

This paper introduces an index that combines information about the magnitude of climate change in a specific region and social factors that could affect the vulnerability of the local population. We call this index the Socio-Climatic Vulnerability Index (*SCVI*) and define it as

$$SCVI = CI^{*}\sqrt[n]{\prod_{i=1}^{n} F_i},$$

where *CI* represents any climate change index suitable for the region, whereas the second element on the right-hand side of the equation represents the geometric mean of the normalized social vulnerability factors ($F_i$) that characterize the local social conditions.

The definition of vulnerability used here is based on that used by the IPCC: vulnerability is the degree to which a system (in this study, the Brazilian population) is susceptible to, and unable to cope with, adverse effects of climate change, including climate variability and extremes. Additionally, vulnerability is a function of the character, magnitude, and rate of climate change and the variation to which a system is exposed, its sensitivity and its adaptive capacity (glossary of IPCC AR4, [IPCC 2007]).

Similar to the *RCCI*, the *SCVI* is intended to be a relative index of vulnerability to climate change in which the most important is not the value itself, but how it compares from one region to another, ranking locations in which vulnerability is high or low in a comparative basis. Moreover, the *SCVI* can be applied on any spatial scale (assuming sufficient available data and a reasonable spatial scale for characterizing the analyzed region) and can incorporate as many distinct social variables as needed in the right-hand side of the equation above. Therefore, the *SCVI* can merge several indicators of a population's vulnerability (e.g., water resources and agricultural vulnerabilities) and climate change indexes based on a broad array of models.

The specialized literature includes dozens of indexes for indentifying a population's vulnerability to climate change on a country (e.g., Yohe et al. 2006; Diffenbaugh et al. 2007; Eriksen and Kelly 2007) or regional scale (e.g., Confalonieri et al. 2009 and Yusuf and Francisco 2009). For example, Preston et al. (2011) identified and reviewed 45 vulnerability mapping studies appearing in the literature until 2010. These studies differ from the present study in the following ways: several of the previous studies used observed climatology rather than climate change projections, nearly all of the previous studies were based on climate projections from solely one climate model and Brazil was always depicted using coarse spatial scales.

The *SCVI* was calculated for all of Brazil using a spatial resolution of 1 ° of latitude/longitude. The climate change index used here is the *RCCI* described in the previous section, but the use of other climate change indexes in addition to or instead of the *RCCI* could strengthen the reliability of the determination of climate change hotspots. The demographic density ($\rho$) (Goldewijk 2005) and the inverse of the Human Development Index (*HDI*) for all Brazilian municipalities (IPEA 2003) are used as the social vulnerability indicators (Fig. 1). Both social variables are normalized to the Brazilian domain and are representative of the year 2000. The original resolution of $\rho$ is 5 arc-minutes, whereas the *HDI* data are available at the municipal level. The transformation of these data to a 1° basis followed the procedures using the ArcGIS® software: first, the *HDI* data are transformed from a polygon shape into a 5 arc-min raster; second, both *HDI* and $\rho$ are converted into 1° latitude/longitude rasters using the "mean" neighborhood block statistics.

The employed *SCVI* formulation implies that the social vulnerability to climate change will be more pronounced in regions with higher $\rho$ and lower *HDI*, in agreement with several studies on social vulnerability to climate change (Adger 1999; Füssel and Klein 2006;

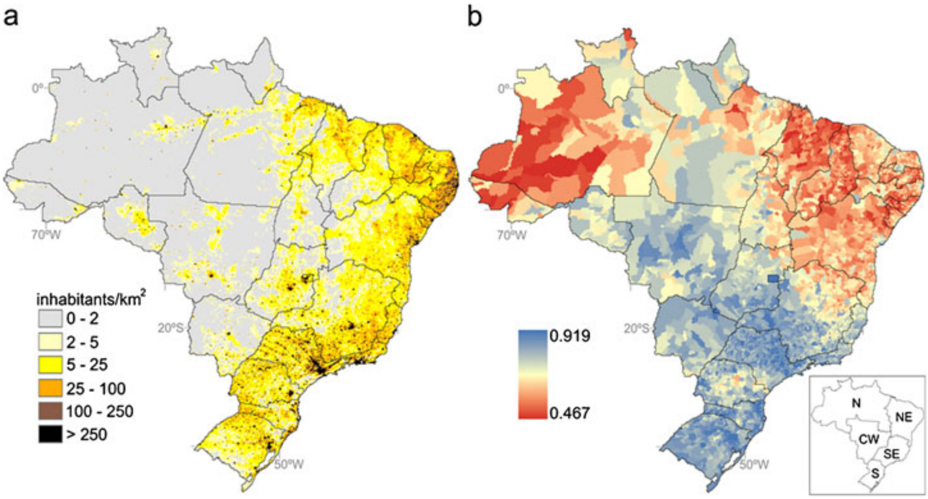

**Fig. 1** Year 2000 (**a**) Brazilian population density (inhabitants per km$^2$) and (**b**) Human Development Index (dimensionless). The bottom right-hand panel shows Brazil's 5 macro regions: North (N), Northeast (NE), Centre-West (CW), South (S) and Southeast (SE)

Eriksen and Kelly 2007; Magrin et al. 2007; Ionescu et al. 2009; Confalonieri et al. 2009). In general, these studies agree that social vulnerability is more pronounced in more heavily populated areas (justifying the use of $\rho$), and that sanitation/health, economic wealth and literacy levels influence exposure and sensitivity to climate change, and modulate the population's adaptive capacity for climate change. The *HDI* conveniently combines these three social indicators – health, income and education - into a single measure.

The most recent *HDI* information at the municipality level for Brazil was published in 2000 by the Brazilian office of the United Nations Development Programme in conjunction with the Ministry of Planning's Applied Economic Research Institute (IPEA) and the João Pinheiro Foundation (http://hdr.undp.org/en/reports/national/latinamericathecaribbean/brazil/name,3212,en.html). Unfortunately, more recent information at this level of detail is not available for either *HDI* or population density. However, although the values of *HDI* have changed from 2000 to 2011 (e.g., from 0.665 to 0.718 on the national level), it is reasonable to assume that the broad regional development patterns have not changed considerably. We assume the same for population density in terms of 2000–2011 changes in the spatial distribution pattern.

## 3 Results and discussion

### 3.1 *RCCI*

The analysis of the *RCCI* for Brazil (Fig. 2a) evidences the occurrence of climatic hotspots covering the western part of the NE region, the northwestern part of Minas Gerais state and the center-west (CW) and northern (N) regions of the country (except in northeast Pará and Amapá states).

In western NE and northwestern Minas Gerais state, the main factors that contribute to the higher values of the *RCCI* are the projected decrease of rainfall amounts during the austral

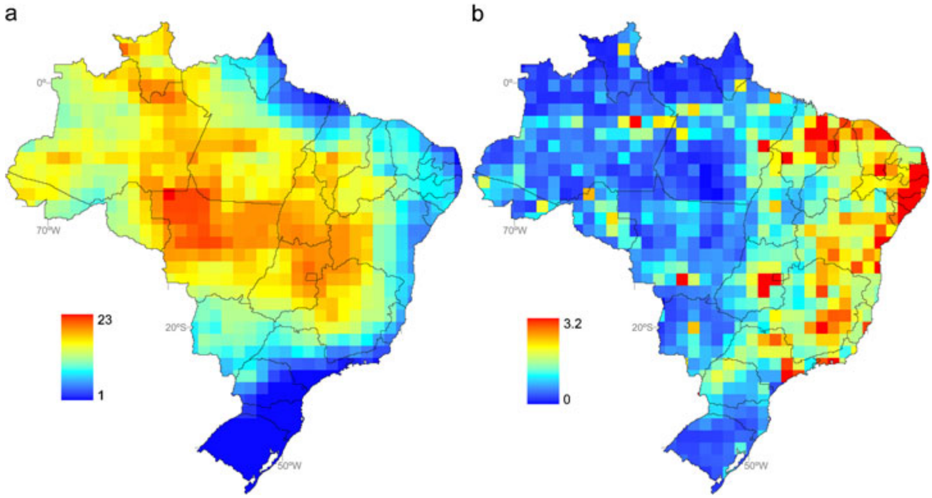

**Fig. 2** (**a**) Regional Climate Change Index (*RCCI*) and (**b**) Socio-Climatic Vulnerability Index (*SCVI*) for Brazil (both dimensionless)

winter and changes in the interannual variability of temperature and precipitation in both seasons (Table 2). In the CW region, high values of the *RCCI* are primarily caused by changes in both the mean and interannual precipitation variability in the austral winter and in the interannual temperature variability in the austral summer (Table 2). In N region the main contributors to high values of the *RCCI* are the changes in the interannual temperature variability in both the austral summer and winter and the interannual variability of rainfall and the *RWAF* during the austral winter (Table 2).

In general, the *RCCI* results agree with previous studies that use regional and GCM models to project climate change in South America (Boulanger et al. 2006, 2010; Vera et al. 2006; IPCC 2007; Bombardi and Carvalho 2009; Marengo et al. 2010a, 2011a). Moreover, the spatial pattern of the *RCCI* in Brazil compares well to the Climate Change Index

**Table 2** Mean values for the 5 Brazilian macro regions (see Fig. 1 for geographic reference) of the Regional Climate Change Index (*RCCI*) and its four components of climatic change: mean precipitation ($\Delta P$, % of present-day value), interannual variability of precipitation ($\Delta\sigma_P$, % of present-day value), mean surface air temperature relative to the global average temperature change (or Regional Warming Amplification Factor, *RWAF*) and change in regional surface air temperature interannual variability ($\Delta\sigma_T$, % of present-day value). Results are shown for the austral summer and winter (DJF and JJA, respectively), except for the *RCCI*

| | North | Northeast | Centre-West | Southeast | South |
|---|---|---|---|---|---|
| RCCI | 15.99 | 13.01 | 17.71 | 12.86 | 4.81 |
| $\Delta P$ (DJF) | 5.97 | 0.99 | 2.43 | 1.32 | 7.70 |
| $\Delta P$ (JJA) | −5.82 | −17.45 | −18.01 | −13.11 | 4.48 |
| $\Delta\sigma_P$ (DJF) | 5.00 | 10.10 | 8.39 | 10.01 | 1.06 |
| $\Delta\sigma_P$ (JJA) | 17.35 | 14.74 | 26.42 | 17.20 | 10.06 |
| *RWAF* (DJF) | 1.14 | 1.04 | 1.10 | 1.02 | 0.92 |
| *RWAF* (JJA) | 1.48 | 1.15 | 1.44 | 1.23 | 1.06 |
| $\Delta\sigma_T$ (DJF) | 16.11 | 12.40 | 21.15 | 18.10 | 6.11 |
| $\Delta\sigma_T$ (JJA) | 16.73 | 12.67 | 13.73 | 9.55 | 3.23 |

developed by Baettig et al. (2007), although the two indexes are calculated by different ensemble models and methodologies. Additionally, all areas indicated as hotspots by the *RCCI* were also predicted to suffer soil moisture deficits and an increase in the frequency of short-term (4–6 month duration) droughts by the end of the twenty-first century by Sheffield and Wood (2008). In the Amazon basin, the *RCCI* results are coherent with the well documented potential of climate change to enhance intense drought events in this region, such as the droughts of 2005 and 2010 (Malhi et al. 2008; Nobre and Borma 2009; Lewis et al. 2011; Marengo et al. 2011b, c, d; Davidson et al. 2012), which caused serious hydrological, agricultural and transportation problems, strongly affecting residents.

The lowest values of the climate index were found for Southern Brazil (S), in the states of São Paulo and Mato Grosso do Sul, and throughout the Brazilian coast. However, these low *RCCI* values should not be interpreted as indicating “no-change” or “no-impact” but rather as a smaller change relative to other regions of Brazil. For example, some studies indicate an increase in the frequency of extreme precipitation events in S during the last half of the twentieth century (e.g., Tebaldi et al. 2006; Rusticucci et al. 2010; Marengo et al. 2010b) and indicate a further increase in these events towards the end of the twenty-first century in a warmer climate (Tebaldi et al. 2006; Marengo et al. 2009). Thus, as mentioned in Section 2.2, future studies must improve the *RCCI* index calculation (i.e., using higher-resolution models and more advanced statistical techniques) to explicitly capture climate extreme events.

South America has the lowest *RCCI* values among the 26 averaged land regions of the world analyzed by Giorgi (2006). However, our study reveals that different climate change patterns are found inside each of the 3 (out of 26) boxes established to represent the South America climate change behavior in Giorgi’s study [“Amazon Basin” (20 S–10 N; 78.5–34.5 W), “Central South America” (40–20 S; 78.5–34.5 W) and “Southern South America” (56–40 S; 78.5–34.5 W)]. For example, the “Amazon Basin” box includes NE and Peru/Ecuador, regions with different predictions regarding precipitation change (Vera et al. 2006; Meehl et al. 2005). Differently, the results from the spatial analysis of the *RCCI* performed here emphasize the different projected climate change pattern when comparing N and NE regions.

### 3.2 *SCVI*

The *SCVI* analysis reveals major socio-climatic hotspots in NE Brazil and several widespread punctual hotspots in many of the major Brazilian metropolitan regions (Fig. 2b). The spatial pattern of the *SCVI* is quite different from that of the *RCCI*; it reveals an east–west gradient related to the historical occupation of the coastal lands and its vicinities in Brazil, which indicates that population density has a considerable weight in *SCVI* calculations. Therefore, the *SCVI* analysis shows that the designation of the most impacted areas by climate change can be quite different when translated into a social-vulnerability relevant form.

The large socio-climatic hotspots in NE result from a combination of low-to-medium *RCCI* values, relatively high $\rho$, and the lowest *HDI* levels in Brazil (Table 3). This result is in agreement with those shown of Confalonieri et al. (2009), who found that the NE region is the most vulnerable to public health impacts of climate change in Brazil, although those authors employed only past climatological observations in their analysis and presented their results on a state-level basis. However, the inclusion of the epidemiological vulnerability index presented by Confalonieri et al. (2009) in the *SCVI* calculation (making our results more comparable to those of Confalonieri et al.’s) did not change the relative socio-climatic vulnerability among the regions: NE remained as the most vulnerable area in the country, followed by SE, CW, S and N. This epidemiological vulnerability index was constructed by Confalonieri et al. (2009) using morbidity, mortality and health cost data related to seven

**Table 3** Mean values for the 5 Brazilian macro regions (see Fig. 1 for geographic reference) of the Socio–Climatic Vulnerability Index (*SCVI*, dimensionless), Human Development Index (*HDI*, dimensionless) and population density ($p$, inhabitants per km$^2$)

| | North | Northeast | Centre-West | Southeast | South |
|---|---|---|---|---|---|
| SCVI | 0.30 | 0.93 | 0.43 | 0.85 | 0.31 |
| HDI | 0.651 | 0.612 | 0.741 | 0.738 | 0.766 |
| ρ | 3.82 | 33.48 | 7.52 | 80.45 | 45.18 |

climate-sensitive endemic infectious diseases occurring in Brazil (e.g., dengue fever, cholera and malaria).

The other punctual socio-climatic hotspots covering some of the major Brazilian cities are Manaus (*SCVI*=3.2), Belo Horizonte (3.2), Brasília (3.1), Salvador (2.8), Rio de Janeiro (2.6) and São Paulo (1.7), as well as nearly all the NE capitals. Some of the values found for these cities are the result of high or very high *RCCI* values, as is the case for Manaus, Belo Horizonte and Brasília. For the other cities, even the relatively low *RCCI* values are not sufficient to avoid the high *SCVI* values, meaning that even a moderate climate change might bring serious consequences to these cities because of their high population densities. High $\rho$ values in Brazil indicate metropolitan areas, for which the *SCVI* formulation is able to correctly capture the effect of the pronounced social heterogeneity typical of the country's largest cities. As an example, let us consider the metropolitan area of São Paulo city, which in 2000 had an *HDI* of 0.828, suggesting a high human development level. However, a finer-scale analysis reveals that the São Paulo metropolitan region has several districts (especially in the city outskirts) with *HDI* values lower than 0.750, considered "moderate" human development, similar to many N and NE municipalities. A recent assessment of the overall vulnerability of the São Paulo metropolitan area to climate change shows that the residents of such districts would be affected most strongly by climate change through floods, landslides, and spreading diseases (Nobre et al. 2010). It is reasonable to apply the same conclusion to the other Brazilian metropolitan regions unveiled here as socio-climatic hotspots, as suggested by the neighborhood-level *HDI* analysis performed for other cities (e.g., SEPLAN et al. 2006 for Manaus; PNUD et al. 2006 for Salvador; IPP et al. 2003 for Rio de Janeiro).

In fact, the above-mentioned social impacts of climate change can vary dramatically by region and livelihood. For the NE, the major climatic constraint has always been linked to rainfall shortage and limited water availability for human consumption and subsistence agriculture (Kabat et al. 2003; Sahota 1968). The decomposition of the *RCCI* into separate components, given in Table 2, reveals that the future impacts of climate change on the NE population will be tied to aggravations of rainfall shortage and limited water availability. For metropolitan areas, these impacts will certainly be expressed by floods, landslides, heat waves, and possibly other events, which are closely linked to the urbanization pattern. It is important to note that some indirect impacts of climate change have not been included in this vulnerability assessment. Climate-driven agricultural losses can, for example, increase the vulnerability of a given population, even if the croplands are located in depopulated areas far from consuming centers. This issue is not addressed by this spatial analysis using only the *HDI* and $\rho$ as social vulnerability indicators, and will be tackled in future studies.

Finally, low *SCVI* values should not be interpreted as "no action needed". The *SCVI* index must be used as an auxiliary index in climate change debates rather than a substitutive to other specific vulnerability or impact indexes, such as the *RCCI*. Although it is reasonable to focus adaptation policies on regions where more people are affected, some adaptation measures are needed to strengthen the adaptive capacity of less dense, but no less important, areas. Let us take as an example the Brazilian Legal Amazon population of 23 million people, which is scattered over an area of more than 5 million km$^2$. If impacted by climate change, we may expect a south/eastward population migration, which would increase $\rho$ in already dense areas, thereby worsening the *SCVI* values in South/East Brazil, similar to the results of past dry spell events in Northeast Brazil (Yap 1976).

### 3.3 Final remarks

This study is a first-order spatially explicit evaluation of the social vulnerability to climate change in Brazil. Refinements should include the use of regional climate models (with spatial resolutions of 50 km or higher) or advanced statistical downscaling techniques and the consideration of other indicators of social vulnerability (such as fine-scale epidemiological information, data on susceptibility to landslides and floods, water availability, and agricultural risks).

That being said, the two major contributions of this study are the presentation of a more detailed analysis of the *RCCI* in Brazil (compared to the study by Giorgi 2006) and the development of a new index (*SCVI*) that merges the extensive number of IPCC global model projections on climate change with social vulnerability indicators. Moreover, this proposed index could be applied to other countries and regions. Both the *RCCI* and *SCVI* indexes have a simplistic and exploratory nature but can be useful for improving the dialogue between climate and social scientists and communicating climate change to policymakers in a more synthetic and socially relevant form.

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