Regional Impacts of Future Climate Change on Health and Labor in Brazil

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1 Introduction

Global climate and environmental change have aggravated in the last decades (Nordell, 2007). Increased health stress is one of the most alarming consequences of these changes. The impacts of climate change on human health is complex, ranging from more direct consequences, such as increase in the prevalence of climate-sensitive diseases and in the demand for health care, to more indirect impacts, such as loss in labor supply (temporary through morbidity or permanent through deaths) and productivity (Pattanayak et al., 2009).

Although many studies have tried to estimate the direct and indirect consequences of a warmer and dryer environment for the economy, both at the global and the local scales, a smaller number of studies have addressed the mid and long term health implications of these changes at a regional level. Some studies are notable exceptions, such as the simulation of the economy-wide consequences of future climate change for human health conducted by Bosello et al. (2006). In Brazil, some studies have suggested climate-sensitive future scenarios of regional vulnerability (Barbieri et al., 2015), migration (Barbieri et al., 2010), agriculture productivity (Domingues et al., 2016), and infectious diseases (Barcellos et al., 2009). None of these studies, however, evaluates the health and wealth impacts of climate change as a dynamic process. Pattanayak et al. (2009) is one of the few exceptions, although their model do not compute the climate impact on labor supply through morbidity and mortality losses (gains) at a regional scale. Nor they recursively compute deaths due to climate in their population projection estimates.

Building on their previous work, this study takes a multi-stage approach to estimate the climate-related consequences on cardiovascular/respiratory and infectious/vector-borne diseases, morbi/mortality, and labor supply in Brazil. Combining Spatial Bayes Smoothing, Spatial Econometrics, data on the Global Burden of Disease, and a Regional Com-

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putable General Equilibrium (CGE) model, we estimate the future development of climate-sensitive health disorders, their implications for loss (gain) in morbidity and mortality, and the consequences for labor supply, family consumption, and economic growth for the Brazilian states and regions from 2010 to 2040. As far as we know, this is the only study estimating the impact of climate change on health and economic development at the regional level.

2 Materials and Methods

To evaluate the impact of climate change on the Brazilian economy as a result of its impacts on the labor supply through health, we combine different sources of data and analytical strategies. Population health was proxied by two groups of variables: *disease notifications* (dengue, malaria, and leishmaniosis) and *hospitalizations* (circulatory, respiratory, and infectious diseases). These health indicators were derived from administrative health records by municipality. Climate parameters were proxied by *precipitation* (total amount of rain within one year and its standard deviation) and *temperature* (12-month average). The climate scenario used in this analysis was the Representative Concentration Pathways 8.5.

The effect of climate change on the labor supply was obtained by a two-step strategy. The first step estimates the relationship between climate change and health. Building on Bosello et al. (2006) and Pattanayak et al. (2009), the second step analyses to what extent health losses due to climate change affects the labor supply based on the Global Burden of Disease parameters (WHO, 2016). The change in the number of cases estimated for the working age population (labor supply) was used in a computable general equilibrium model to verify the effect of climate change on the Brazilian economy by 2040. Our IMAGEM-B (Integrated Multiregional Applied General Equilibrium Model - Brazil) incorporates detailed data for the Brazilian economy, yielding the climate impact on the main macroeconomic variables, such as Gross Domestic Product (GDP), employment, and family consumption. These impacts are reported at both national and state levels and are evaluated as the percentage cumulative deviation from a base scenario without considering the change in the climate parameters (*business-as-usual*).

2.1 Data and Variables

2.1.1 Climate Parameters

Historical Climate Data

In this study, we use data provided by the Center of Weather Forecast and Climate Studies (CPTEC), at the Brazilian Institute for Spatial Research (INPE). Measured on a daily basis by municipality from 1900 to 2010, the climate data were transformed into annual averages.

Precipitation data were classified as *precipitation intensity* and *precipitation dispersion.* Precipitation intensity was measured as the total amount of precipitation within a year. Precipitation dispersion was measured as the standard deviation of the monthly precipitation within a year. Although many studies use precipitation intensity only (Bosello et al., 2006), we included precipitation dispersion in order to capture the effect of the rainfall distribution throughout the year on climate-sensitive diseases (Hashizume et al., 2008; Pattanayak et al., 2009). Our temperature parameter represents the annual average temperature by municipality. For the econometric models testing the effect of these climate parameters on climate-sensitive health measures we use data for 2005 (base year). Figure 1 summarizes these measures and how they were applied to the econometric analysis.

Variable	Information available	Variable used in the econometric analysis	Measurement unit	Available years	Base year
Temperature	Monthly average temperature by year and municipality	**Annual average temperature:** average value of the monthly temperature averages within a year	°C	1900-2010	2005
Precipitation	Monthly cummulated precipitation by year and municipality	**Total anual precipitation:** sum of monthly precipitation over the year	mm		
		Standard deviation of precipitation within a year			

Figure 1: Definition of climate variables used in the econometric models for health measures

Future Climate Scenarios

To simulate the impact of climate change on health, we use the Representative Concentration Pathways (RCP) 8.5 climate scenario provided by INPE. Based on the Model for Energy Supply Strategy Alternatives and their General Environmental Impact (MESSAGE), the RCP 8.5 scenario assumes future economic growth, increased emission of greenhouse gases (GHG), and the absence of effective climate policies. Data for this scenario were based on the EtaHG2ES global circulation model with a spatial resolution of 0.2 degrees. In this scenario, the lack of effective climate mitigation policies leads to a considerable increase in GHG emissions over time, resulting in a radiative forcing of 8.5 W/m^2 by 2100 (Riahi et al., 2011).

Figure 2 shows the spatial distribution of annual average temperature for Brazil in 2010 and 2040, based on the RCP 8.5 climate scenario. Overall, municipalities experience a steady increase in temperature over time, with a larger number of municipalities scoring average temperatures above 24 degrees Celsius. Increase in temperature would be mostly concentrated in the Center-West, west of Minas Gerais, Maranhão, Piauí, and a large portion of the Eastern Brazilian Amazon. In contrast, the South region would have little variation, with some municipalities experiencing declining temperatures.

Figure 3 represents the spatial distribution of total annual precipitation over the same period. Along with increased temperature, most municipalities would experience a drier environment by 2040. The reduction in total rainfall would be mostly felt in a long corridor stretching from the Northeast *sertão* to the north part of Minas Gerais. São Paulo and large areas of the Brazilian Amazon would also be affected. In the South of Brazil, however, rainfall would increase.

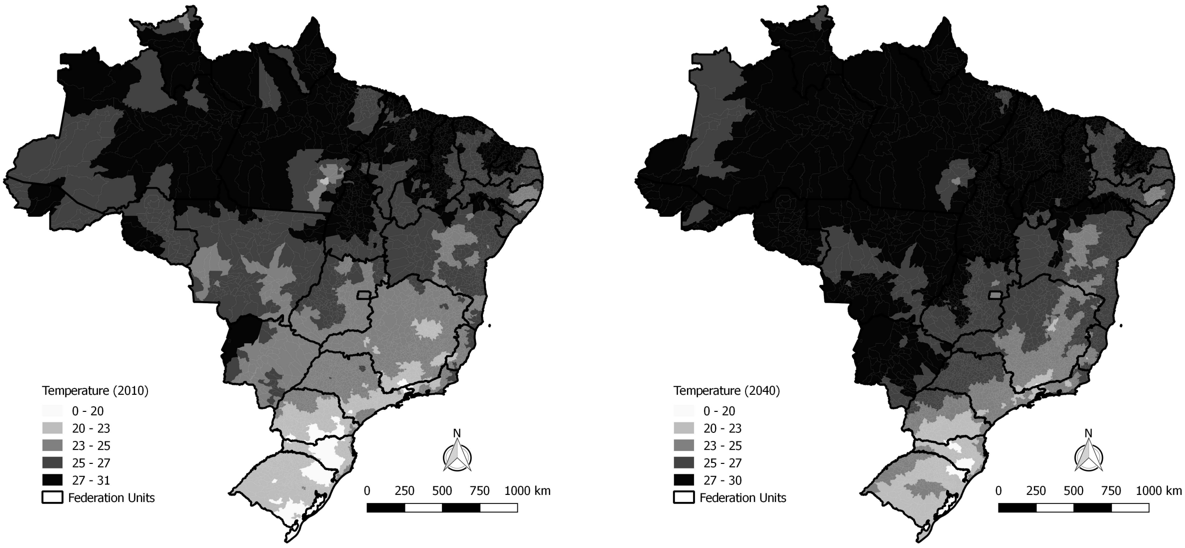

Figure 2: Spatial distribution of the annual average temperature from 2010 to 2040 - Brazil, RCP 8.5 Climate Scenario

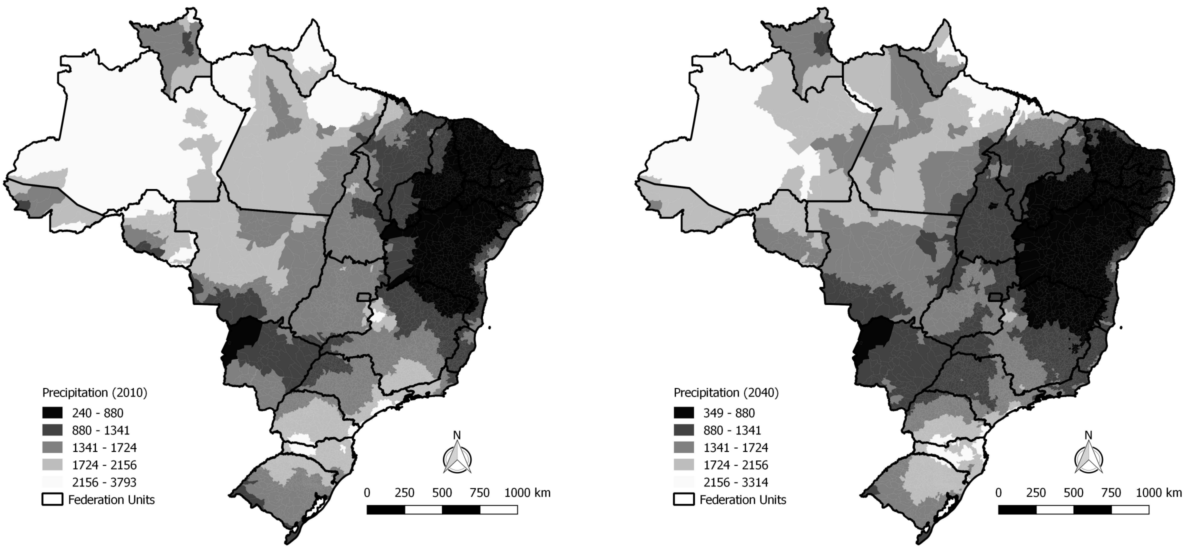

Figure 3: Spatial distribution of the total annual precipitation from 2010 to 2040 - Brazil, RCP 8.5 Climate Scenario

2.1.2 Population Health Measures

We use two groups of climate-sensitive health indicators as summarized in Figure 4: indicators of hospitalizations by selected causes and disease notifications. Data on hospitalizations are provided by the Authorization Forms for Hospital Admittance. This information refers to in-patient care received in the Brazilian Public Health Care System, which responds for 66% of total hospitalizations in the country (IBGE, 2014). Data on disease notifications are provided by the Notifiable Disease Information System. All health data were obtained at the municipality level, using the municipality of residence instead of municipality of occurrence as the criterion of data selection.

Disease counts are based on a 5-year average centered in 2012. The population used to calculate the baseline rates of climate-sensitive diseases by municipality are the 2012 population estimates from the Brazilian Bureau of Statistics[1]. These rates represent number of cases by 1000 persons, and were corrected by the Spatial Empirical Bayes smoother to reduce potential small-area estimation bias (Anselin and Rey, 2014).

Population Health Indicator		Source
Number of Hospitalizations (per thousand persons)	Infectious and parasitic diseases (Ch. I ICD-10)	Health Ministry/Hospital Information System/ Authorization Forms for Hospital Admittance
	Diseases of the circulatory system (Ch. IX ICD-10)	
	Diseases of the respiratory system (Ch. X ICD-10)	
	Diarrhea and gastroenteritis of presumed infectious origin or other intestinal infectious diseases (ICD-10 codes A09; A02; A04-A05; A07-A08)	
Number of Disease Notifications (per thousand persons)	Dengue	Health Ministry/ Notifiable Diseases Information System
	Malaria	
	Visceral Leishmaniasis and American Cutaneous Leishmaniasis	

Figure 4: Population Health Indicators measured at the municipality level

2.1.3 Sociodemographic Measures

Health indicators are sensitive to key demographic and socioeconomic characteristics of the population (Dahlgren and Whitehead, 1991). To account for these confounding effects on the relation between climate and health, we include the following variables in our econometric analysis: proportion of individuals 0 to 14 years old, proportion of individuals 60 years old and above, proportion of women, proportion of individuals in urban areas, mean *per capita* household income, Gini Coefficient, and *per capita* health expenditures. All control variables are estimated at the municipality level. Data were obtained from the 2010 Demographic Census, except for the *per capita* health expenditures. The latter was provided by the Information System on health public budgets (SIOPS, in Portuguese).

2.2 Methods

2.2.1 Estimating the impact of climate change on labor supply through its impact on health

Model 1: Impact of climate on health

Assessing the relationship between climate change and health requires information on both indicators covering a sufficiently long time span. The Intergovernmental Panel on Climate Change (IPCC, 1990), for instance, defines climate change as a statistically significant variation in a climate parameter over a long period, typically measured in decades.

[1]For dengue notifications, data were only available until 2012, so we used an average centered in 2010. Because of that, data on population used to estimate dengue prevalence was based on the 2010 Demographic Census.

Although we have reliable longitudinal data on climate, time series for health measures in Brazil are uncommon. The few longitudinal health data available in the country lack reliability, especially before the 1990's when the Brazilian Public Health System was created. A commonly used strategy to overcome this limitation is to estimate relations between health and other parameters (such as climate) using cross-sectional data at the municipality level. This strategy allows us to capture heterogeneity for the indicators used, since the Brazilian municipalities are highly diverse in their socioeconomic, health, and climate attributes (Barbieri et al., 2015).

In this study, we estimate the relation between climate and health using econometric analysis of cross-sectional data for all 5.565 Brazilian municipalities. The dependent variable is a measure of the average population health (log of the rates of hospitalization and disease notifications). Our key independent variables - the climate parameters - were measured in 2005 (our base year). The models control for socioeconomic and demographic characteristics, as explained in Section 2.1.3. The association between climate and health in this study is described by the following generic function:

$$ln\Theta_{k,m} = f(R_m, \sigma(R_m), T_m, E_m) \tag{1}$$

where:

- $ln\Theta_{k,m}$ = log of the k-th morbidity rate in municipality m
- R_m = annual total rainfall in municipality m
- $\sigma(R_m)$ = standard deviation of rainfall in municipality m
- T_m = average temperature in municipality m
- E_m = vector of sociodemographic attributes of municipality m

Ordinarily Least Square (OLS) models are routinely applied (Pattanayak et al., 2009). However, OLS estimators are biased in the presence of spatial dependence of error terms, violating the assumption of a diagonal error matrix. This is particularly true in the case of health and climate parameters. Vector-borne diseases, for instance, tend to cluster spatially due to vector mobility (Winters et al., 2010). Climate parameters and their variation are also similar in space (Khormi and Kumar, 2015). In this case, it is likely that the association between health and climate and unobserved factors affecting both will cause spatial dependency on the error term of the model (Anselin and Rey, 2014; Khormi and Kumar, 2015).

The main spatial econometric models for cross-sectional data are the Spatial Autoregressive Model (SAR) and the Spatial Error Model (SEM). While the SAR model includes the spatially lagged dependent variable as an independent variable, the SEM model includes the spatial dependence of unobserved influences in the error term only. The most common criterion to choose between the two specifications is the Robust Lagrange Multiplier (LM) statistics. If the LM statistics is significant for both specifications, Anselin and Rey (2014) suggest the use of the smaller value as the best model choice. This is the strategy used here. Models for dengue, malaria, and leishmaniosis were based on SAR estimates, while circulatory, respiratory, and infectious and parasitic diseases where modeled using the SEM specification. The spatial models were estimated in the GeoDaSpace software version 1.0 (GeoDa, 2016), using a Queen spatial weight matrix of order 1[2].

Model 2: Impact of health on labor supply

The first step to obtain the impact of health on labor supply due to climate change is to calculate counter-factual rates of diseases. The rates are based on predicted values from our spatial regressions. For the SEM model, predicted values are linear projections, as in a traditional OLS model. For the SAR models, the predicted value of k-th health indicator for the m-th municipality is given by:

$$ln\hat{\Theta}_{k,m} = (I_n - \hat{\rho}W)^{-1} X_m \hat{\beta} \tag{2}$$

where I_n is a $n \times n$ identity matrix, n is the number of municipalities, $\hat{\rho}$ is the coefficient for the spatially lagged dependent variable, W is the Queen matrix for spatial weights, X_m is the matrix of covariates, and $\hat{\beta} = (X_m X_m)^{-1} X_m (I_n - \hat{\rho}W) ln\Theta_{k,m}$.

Although the models were directly estimated by the GeoDaSpace software, values for Eq.(2) had to be estimated by a script developed by the authors in the R environment[3] (R Core Team, 2016). These values were exponentiated to get the predicted rates for the k-th morbidity. The predicted values of counter-factual rates of diseases ($\Theta^{cf}_{p,k,m}$) were calculated by replacing the climate parameters (based on the year 2005) for their respective projections in 2010 and 2040[4], as defined by the following equation:

$$\Theta^{cf}_{t,k,m} = \hat{\Theta}_{k,m} \times \left(\sum_{C} (\Delta C_{t,c,m} \times \hat{\beta}_{c,k}) + 1 \right) \tag{3}$$

where $\Delta C_{t,c,m} = C_{t,c,m} - C_{c,m}$ for $t = 2010, 2040$. The $\Delta C_{t,c,m}$ represents the change in each of the climate parameters (temperature, precipitation level and dispersion) between the t-th and the base years.

The incidence of persons affected by the k-th morbidity in the t-th year can be obtained by multiplying the difference between the predicted prevalence rate at the base year and the counter-factual prevalence rate in year t by the projected population in the same year ($P_{t,m}$)[5]. The formula is given by:

$$\Gamma_{t,k,m} = \left(\Theta^{cf}_{t,k,m} - \hat{\Theta}_{k,m} \right) \times P_{t,m} \tag{4}$$

Eq.(4) provides the expected number of additional cases for the k-th morbidity in year t due to climate change. These additional cases can be decomposed into deaths (*permanent*

[2]Two cases of islands were found among the 5,565 Brazilian municipalities. To avoid exclusion of these islands when using Queen matrices for spatial weights, we imputed their weights based on the 4-nearest neighbors.

[3]The script is available upon authors' request.

[4]We actually estimated all the results for quinquennial intervals. We decided to report results for 2010 and 2040 to avoid cluttering the text with excessive information. Results are available upon authors' request.

[5]The population projections for 2010 and 2040 by municipality are updated figures based on the small-area estimations provided by the Center for Development and Regional Planning at the Universidade Federal de Minas Gerais (CEDEPLAR, 2014). Since some individuals would die due to climate change between 2005 and the t-th year, the population exposed to reproduction changes. To incorporate this change in exposure, we recursively projected the population at each quinquennial time interval, excluding individuals aged 15 to 49 years old who would die from climate-sensitive morbidities. This updating will affect primarily the $\Gamma_{t,k,u}$ parameter described in Eq.(4).

loss) and disability (*temporary loss*) for the total population, using the following parameters from the Global Burden of Disease project: Disability-Adjusted Life Year (DALY) and its components (WHO, 2016). The DALY is the sum of the years of life lost (YLL) due to premature death and the years lost due to disability (YLD). The YLL is the product of the number of deaths and the life expectancy at the age of death. The YLD is the product of the number of incident cases, the mean duration of disability, and the weight of disability (Leite et al., 2015). These parameters are available by age, sex, country, and groups of morbidities, including the ones used in this study. The most recent estimates provided by the project for Brazil corresponds to 2015.

The first component of DALY (YLL) provides the permanent lives lost in the total population. In Eq.(5), factor $\boldsymbol{A}$ represents the total number of deaths from the k-th morbidity among the total population for each sex. Since we are interested in the labor loss only, this factor is weighted by the proportion of deaths (D) among the working age population (π) due to the k-th morbidity for each sex (factor $\boldsymbol{B}$). The outer summation combines these permanent labor losses for each sex, given the final permanent labor loss for the working age population:

$$YLL^{\pi}_{t,k,u} = \sum_{s} \left(\underbrace{\sum_{a=0}^{80+} \left(\Gamma_{t,k,u} \times \frac{YLL^{a,s}_{k}}{DALY^{a,s}_{k}} \right)}_{\mathbf{A}} \times \underbrace{\zeta_{s,k,u}}_{\mathbf{B}} \right) \tag{5}$$

where a stands for age, s for sex, u for state, and $\zeta_{s,k,u} = \frac{\sum_{a=15}^{69} D^{a,s}_{k,u}}{\sum_{a=0}^{80+} D^{a,s}_{k,u}}$.

Data on mortality by age and sex was provided by the Latin American Human Mortality Database (Urdinola and Queiroz, 2013). The most updated data refers to 2010, available for the following morbidity groups used in this study: infectious and parasitic diseases, and diseases of the circulatory and respiratory system. Since information for dengue, malaria, and leishmaniosis is not available, we assume that the age profile of deaths for these morbidities is the same as the one for the infectious and parasitic diseases. We further assume that all age profiles of mortality by cause remain constant by 2040. The incidence parameter ($\Gamma_{t,k,m}$) had to be aggregated at the state level due to lack of information by municipality[6]. This is why it is represented in Eq.(5) as $\Gamma_{t,k,u}$.

The second component of DALY (YLD) provides the temporary years of life lost in the total population due to disability. In Eq.(6), factor $\boldsymbol{A}$ represents the total number of life years temporarily lost due to disability among the population for each sex. As in the first component, we need to restrict these figures to the labor force. We do so weighting factor $\boldsymbol{A}$ by the proportion of hospitalizations / notifications (H) among the working age population for each sex (factor $\boldsymbol{B}$). The outer summation combines these temporary labor loss for each sex, given the final temporary labor loss for the working age population:

$$YLD^{\pi}_{t,k,u} = \sum_{s} \left(\underbrace{\sum_{a=0}^{80+} \left(\Gamma_{t,k,u} \times \frac{YLD^{a,s}_{k}}{DALY^{a,s}_{k}} \times w^{a,s}_{k} \times d^{a,s}_{k} \right)}_{\mathbf{A}} \times \underbrace{\varphi_{s,k,u}}_{\mathbf{B}} \right) \tag{6}$$

where w_k is the disability weight, d_k is the duration of disability, and $\varphi_{s,k,u} = \frac{\sum_{a=15}^{69} H^{a,s}_{k,u}}{\sum_{a=0}^{80+} H^{a,s}_{k,u}}$.

[6]This aggregation does not cause loss of information, because it is a sum of number of cases.

The percentage change in the labor force ($\psi^{\pi}_{t,k,u}$) between the t-th and base year is given by:

$$\psi^{\pi}_{t,k,u} = \left(\frac{YLL^{\pi} + YLD^{\pi}}{\sum_{15}^{69} P_{k,u}}\right) \times 100 \quad (7)$$

2.2.2 The impact of climate induced change in labor supply on the Brazilian economy

The last step in our methodological strategy is to estimate the regional economic impact of changes in the labor supply due to climate change. To do that, we use the IMAGEM-B (Integrated Multi-regional Applied General Equilibrium Model - Brazil). IMAGEM-B is a computable general equilibrium (CGE) model of multiple regions for Brazil. The model follows the basic theoretical structure of the TERM model - The Enormous Regional Model - described in several other works (Horridge et al., 2005).

IMAGEM-B is a bottom-up CGE model that covers all 27 states in Brazil. Bottom-up models allow the simulation of policies with region-specific price effects, such as when wage labor increases in specific regions. They also allow us to model imperfect factor mobility between regions or between sectors. Thus, increased labor demand in one region may be both choked off by a local wage rise and accommodated by migration from other regions. Each regional CGE model is fairly conventional: producers choose a cost-minimizing combination of intermediate and primary factor inputs, subject to production functions structured by a series of constant elasticity of substitution (CES) "nesting" assumptions. Two high-level aggregates, of primary factors and of intermediate inputs, are each demanded in proportion to the industry output (Leontief assumption). The primary factor aggregate is a CES composite of capital, land, and a labor aggregate. The aggregate intermediate input is again a CES composite of different composite commodities, which are in turn CES composites of commodities from different sources (regions). Industry outputs are transformed into commodity outputs via a constant elasticity of transformation (CET) mechanism. The industries have constant-returns-to-scale technology and price at the marginal cost[7].

Figure 5 illustrates the details of the IMAGEM-B system of demand sourcing for a single commodity (*Food*) by a single user (*Households*) in a single region (*Minas Gerais* state). The diagram depicts a series of 'nests', indicating the various substitution possibilities allowed by the model. The same diagram would apply to other commodities, users, and regions. At the top level, households choose between imported (from another country) and domestic food. A CES or Armington specification describes their choice. Demands are guided by user-specific purchasers' prices with typical elasticity of substitution between domestic and imported composites. Demands for domestic food in a region

[7]The use of increasing returns to scale in regional / structural CGE models is not a usual hypothesis, unlike the reduced econometric models of the New Economic Geography. Theoretically, the introduction of this hypothesis into a general equilibrium model can cause problems of existence or multiplicity of equilibria (Mas-Colell et al., 1995). A parametric approach to increasing returns in a regional CGE model for Brazil can be found in Haddad and Hewings (2005). In this work, however, only 8 economic sectors were specified and the return parameters were estimated in a cross-section for one Brazilian state. There are currently no econometric estimates for returns to scale at the sectoral and regional level for Brazil, justifying the theoretical and practical reasons for the hypothesis of constant returns used here. It can be considered at first that the results obtained from the simulations correspond to the lower results bound. Homogeneous returns in the regional sectors would tend to increase the positive impacts and minimize the negative impacts due to the hypotheses of fixed factors in the short or long term.

are summed over users to yield its total value. The usage matrix is measured in "delivered" values, which include basic values and margins (trade and transport), but not the user-specific commodity taxes.

The second level treats the origin of the domestic compound across the various regions. A matrix shows how this compound is divided among the source regions (Minas Gerais, São Paulo, and Rio de Janeiro in the example). Again, a CES specification controls this allocation. The CES implies that regions with lower production costs will tend to increase their market share. The sourcing decision is made on the basis of delivered prices, which include transport and other margin costs. Hence, even with growers' prices fixed, changes in transport costs will affect regional market shares. The variables at this level are not user specific, since the decision is made on an all-user basis as if wholesalers, not final users, decided where to source food products. The implication for our example using Minas Gerais is that the proportion of food which comes from São Paulo is the same for households, intermediate, and all other users. This feature is in agreement with the database available for the Brazilian interstate trade, which does not specify the use of flows by destination state.

The next level down shows how a "delivered" food product from Rio de Janeiro is a Leontief composite of basic food products and the various margin goods. The share of each margin in the delivered price is specific to a particular combination of origin, destination, commodity, and source. For example, we should expect transport costs to form a larger share for region pairs that are far apart, or for heavy or bulky goods. Under the Leontief specification we preclude substitution between Road and Retail Margins and incorporate a CES specification to accommodate Road/Rail switching.

The bottom part of the substitution hierarchy shows that margins on food passing from Rio de Janeiro to Minas Gerais could be produced in different regions. The figure shows the sourcing mechanism for the road and retail margins. We might expect this to be drawn more or less equally from the origin (Rio de Janeiro), the destination (Minas Gerais), and regions in between. There would be some scope for substitution (elasticity of $\varepsilon = 0.5$), since trucking firms can relocate depots to cheaper regions. For retail margins, on the other hand, a larger share would be drawn from the destination region, yielding less scope for substitution ($\varepsilon = 0.1$). Once again, this substitution decision takes place at an aggregated level, implying that the share of, say, São Paulo, in providing Road margins on trips from Bahia to Santa Catarina is the same, whatever good is being transported. Parallel system of sourcing is also modeled for imported food products, tracing them back to port of entry instead of region of production.

The composition of household demand follows the linear expenditure system (LES). There is a set of representative families[8] in each region, consuming domestic goods (from the regions of the national economy) and imported goods. The treatment of household demand is based on a combined CES / Klein-Rubin preference system. The demand equations are derived from a utility maximization problem whose solution follows hierarchical steps. At the first level there is CES substitution between domestic and imported goods. At the subsequent level there is a Klein-Rubin aggregation of composite goods. Thus, utility derived from consumption is maximized by this utility function. This specification gives rise to the LES, in which the share of expenditure above the subsistence level for each good represents a constant proportion of the total subsistence expenditure of each household.

"Investors" are a category of use of the final demand, responsible for the production

[8]Families and households are used interchangeably.

of new units of capital. These investors choose the inputs through a process of minimization of costs, subject to a hierarchical technology structure. As in production technology, capital goods are produced by domestic and imported inputs. Exports from each region's port to the world face a constant elasticity of demand. The standard small country assumption is assumed, implying that Brazil is a price-taker in import markets. However, because the imported goods are differentiated from the domestically produced goods, the two varieties are aggregated using a CES function, based on the Armington assumption. Exports are linked to the demand curves negatively associated with domestic production costs and positively affected by an exogenous expansion of international income. Government consumption is typically exogenous and can be associated or not with household consumption or tax collection. Stocks accumulate, following the changes of production.

Our IMAGEM-B is a multi-period model with recursive-dynamic mechanisms. These mechanisms are: (i) a stock-flow relation between investment and capital stock, which assumes a one year gestation lag; (ii) a positive relation between investment and the rate of profit; and (iii) a relation between wage growth and regional employment, implying that unemployment rates vary, at least in the short run. The model is solved using the GEMPACK (Horridge et al., 2012), and contains a large database that tracks flows of interregional and international purchases of each commodity from each region of origin to each destination region. IMAGEM-B database is based on the 2005 Brazilian National Input-Output tables, along with other regional data sources. The database covers 55 sectors/products and the 27 Brazilian states. We use the model to construct a base forecast for future states of the economy, to which different policy scenarios can be compared. The new scenarios differ from the base only via shocks on labor force due to future climate change, which generate deviations from the base. These deviations can be directly interpreted as the effect of climate-induced change in labor supply through health on the main macroeconomic variables for the Brazilian economy and its states: Gross Domestic Product (GDP), labor, and household consumption.

3 Results

Figures 6 and 7 present the results from the expected partial impact of climate change on disease prevalence (Figure 6), morbi-mortality, and labor supply (Figure 7) by region and disease groups. Prevalence of circulatory diseases is expected to decline from 2005 to 2040 due to the projected increase in average temperature across most municipalities in Brazil (Figure 7 - Panel B). Consequently, the morbi-mortality rate from circulatory disease is expected to decline, yielding an increase in the labor supply by 2040. This pattern holds for all the Brazilian regions, with higher impacts in the South. Different from the circulatory diseases, prevalence of respiratory disease is expected to increase marginally, with a small increase in morbi-mortality and loss in the labor force across regions.

The impact of future climate change on vector borne and infectious diseases is higher in magnitude when compared to the chronic conditions. Overall, prevalence of infectious diseases, and dengue is expected to increase across all regions, resulting in higher morbi-mortality rates and significant loss in the labor force by 2040. Change in the prevalence of all three diseases will be higher in the North (ranging from 14% for infectious diseases to 55% for dengue) and Center-West (ranging from 18% for infectious diseases to 68% for dengue). Despite the increase in the prevalence, rates themselves are low in magnitude (but high if compared to other countries). Therefore, additional morbi-mortality and loss in the labor force due to climate change would increase only marginally. Change in rates

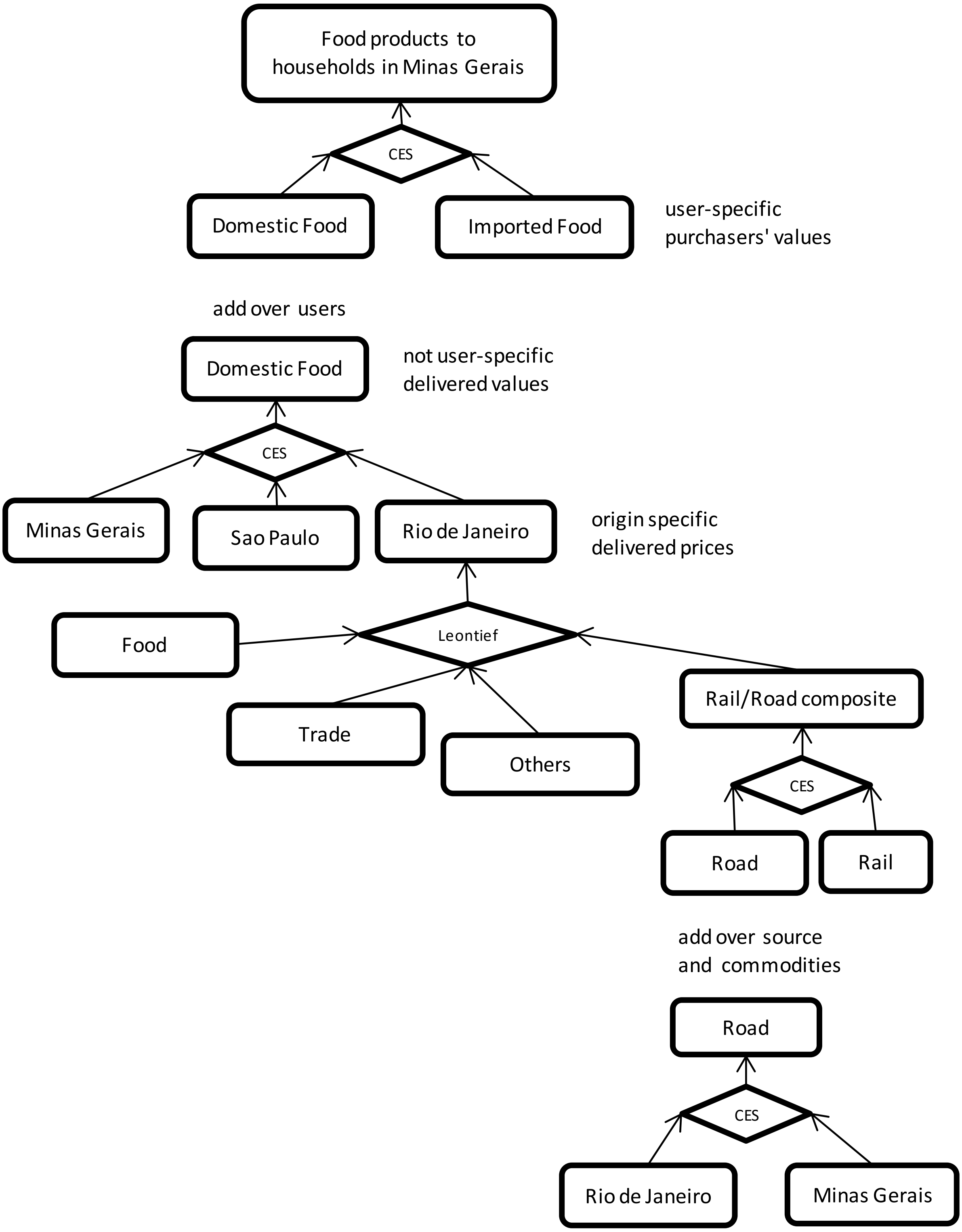

Figure 5: IMAGEM-B system of demand sourcing

is the lowest for leishmaniosis.

Figures 8, 9, and 10 present the effect of climate change on employment, family consumption and economic growth, respectively, by the Brazilian states when partial and indirect effects through the economy are simultaneously considered (from the regional general equilibrium model). Different from the impacts suggested by Figures 6 and 7,

Region	Circulatory	Respiratory	Infectious	Diarrhea	Dengue	Leishmaniosis
Relative risk ratio of disease prevalence (2040/2005) - 95% Confidence Interval in brackets						
North	0.999	1.059	1.142	1.372	1.552	0.971
	(0.991; 1.007)	(1.056; 1.063)	(1.137; 1.147)	(1.357; 1.387)	(1.495; 1.609)	(0.948; 0.993)
Northeast	0.982	1.042	1.09	1.24	1.128	0.994
	(0.979; 0.985)	(1.039; 1.045)	(1.085; 1.094)	(1.230; 1.250)	(1.114; 1.143)	(0.983; 1.004)
Center-West	0.97	1.058	1.179	1.495	1.681	1.133
	(0.962; 0.972)	(1.055; 1.061)	(1.174; 1.183)	(1.483; 1.507)	(1.668; 1.693)	(1.117; 1.150)
Southeast	0.982	1.03	1.109	1.267	1.533	1.19
	(0.979; 0.984)	(1.028; 1.031)	(1.107; 1.111)	(1.265; 1.270)	(1.518; 1.549)	(1.184; 1.196)
South	0.896	1.031	1.107	1.354	0.915	1.377
	(0.894; 0.898)	(1.029; 1.032)	(1.105; 1.110)	(1.340; 1.357)	(0.905; 0.925)	(1.372; 1.382)

Source: Author's own calculations. Based on simulated rates of diseases due to RCP 8.5 climate change scenario (INPE), WHO (2016), and regional economically active population projections for Brazil (Cedeplar, 2014). Estimates from counterfactual rates derived from spatial econometric models.

Figure 6: Impact of Climate Change (temperature and precipitation) on Disease Prevalence by Region and Disease - Brazil, 2040 (Base year = 2005)

Panel A: Number and rate (‰) of additional Deaths in 2040 by Region and Disease

Region	Circulatory		Respiratory		Infectious		Diarrhea		Dengue		Leishmaniosis	
	N	Rate	N	Rate	N	Rate	N	Rate	N	Rate	N	Rate
North	-2,718	-0.12	22,782	1.00	84,614	3.70	69,456	3.04	54,565	2.39	-8,655	-0.38
Northeast	-27,119	-0.42	38,902	0.61	131,006	2.05	112,628	1.76	-7,121	-0.11	1,090	0.02
Center-West	-11,219	-0.70	19,036	1.18	58,246	3.62	45,509	2.83	149,083	9.26	1,756	0.11
Southeast	-74,910	-0.78	54,601	0.57	138,494	1.44	54,521	0.57	131,670	1.37	1,268	0.01
South	-157,019	-4.88	33,545	1.04	63,755	1.98	55,366	1.72	-352	-0.01	1,107	0.03

Panel B: Number and rate (‰) of additional Years of Life Diseased in 2040 by Region and Disease

Region	Circulatory		Respiratory		Infectious		Diarrhea		Dengue		Leishmaniosis	
	N	Rate	N	Rate	N	Rate	N	Rate	N	Rate	N	Rate
North	-262	-0.01	19,596	0.86	13,519	0.59	36,213	1.58	37,853	1.66	-40	0.00
Northeast	-2,614	-0.04	33,461	0.52	20,932	0.33	58,722	0.92	-4,940	-0.08	5	0.00
Center-West	-1,081	-0.07	16,374	1.02	9,306	0.58	23,727	1.47	103,424	6.42	8	0.00
Southeast	-7,221	-0.08	46,964	0.49	22,128	0.23	28,426	0.30	91,344	0.95	6	0.00
South	-15,136	-0.47	28,853	0.90	10,187	0.32	28,867	0.90	-244	-0.01	5	0.00

Panel C: Number and rate (‰) of Labor Supply Loss due to Morbi-Mortality in 2040 by Region and Disease

Region	Circulatory		Respiratory		Infectious		Diarrhea		Dengue		Leishmaniosis	
	N	Rate	N	Rate	N	Rate	N	Rate	N	Rate	N	Rate
North	-920	-0.06	7,381	0.45	47,742	2.88	39,565	2.39	28,671	1.73	-4,972	-0.30
Northeast	-7,630	-0.17	11,100	0.25	65,854	1.48	56,591	1.28	-640	-0.01	554	0.01
Center-West	-4,301	-0.38	5,679	0.51	30,148	2.69	23,693	2.12	78,174	6.99	1,027	0.09
Southeast	-26,667	-0.42	14,967	0.24	76,155	1.20	29,865	0.47	74,066	1.17	710	0.01
South	-46,780	-2.24	9,230	0.44	40,186	1.93	34,610	1.66	-276	-0.01	683	0.03

Source: Author's own calculations. Based on simulated rates of diseases due to RCP 8.5 climate change scenario (INPE), WHO (2016), and regional economically active population projections for Brazil (Cedeplar, 2014). Estimates from counterfactual rates derived from spatial econometric models.

Figure 7: Health impacts of climate change in Brazil by Region and Disease by 2040

these include change in production costs due to climate-induce loss (gain) in the labor supply. The regional impacts vary significantly, and is different by group of diseases.

Figure 8 shows the regional variation in the cumulated percentage change in employment by 2050. For the respiratory and circulatory disease, increase in unemployment due to the climate induced shocks on the labor supply would be mostly concentrated in the Southeast and parts of the Northeast. South, Center-West, and most of the North region would be benefited with increase in employment rates because of the expected increase in temperature, reducing the incidence of these chronic conditions. For the vector borne and infectious diseases, higher losses in job creation would concentrate in the South, Center-West, and North regions. Despite the large regional differences, the final impact on employment would be modest, and mostly due to change in the labor loss caused by the increased incidence of infectious and vector borne diseases.

Figure 9 shows the regional variation in the accumulated percentage change in family consumption by 2050. Different from employment, family consumption would stay vir-

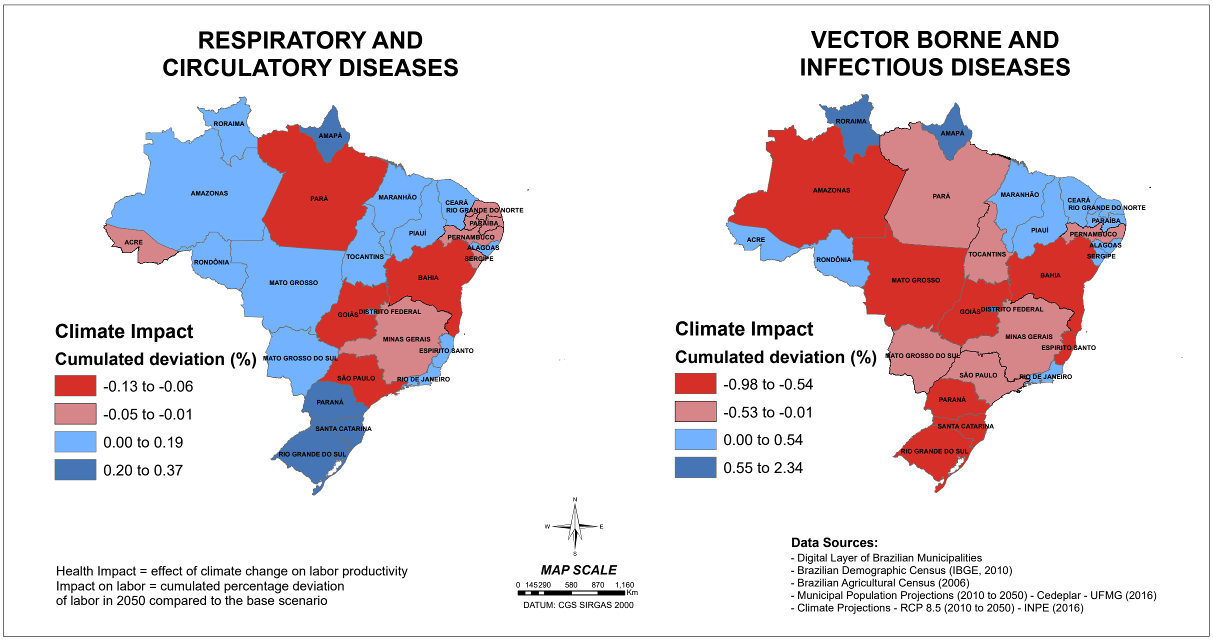

Figure 8: Change in State-level employment due to change in labor supply from climate-sensitive diseases - Brazil, 2015 to 2050

tually unaltered if the climate-induced change in labor supply affected the economy only through the expected change in respiratory and circulatory disease. This trend would hold for all states, with expected increase in consumption due to the climate shock on respiratory and circulatory diseases ranging from 0.004% to 0.5% in 35 years. For the vector borne and infectious diseases, however, most states would experience reduction in family wellbeing. Most Northeastern states and and four Northern states (Roraima, Amapá, Acre, and Rondônia) these impacts would be less felt. The most impacted states would experience an average decline in family consumption of 2.5% by 2050 due to the expected labor loss in response to increased incident of vector-borne and infectious diseases only.

Figure 9 shows the regional variation in the accumulated percentage change in family consumption by 2050. Different from employment, family consumption would stay virtually unaltered if the climate-induced change in labor supply affected the economy only through the expected change in respiratory and circulatory disease. This trend would hold for all states, with expected increase in consumption due to the climate shock on respiratory and circulatory diseases ranging from 0.004% to 0.5% in 35 years. For the vector borne and infectious diseases, however, most states would experience reduction in family well-being. Most Northeastern states and and four Northern states (Roraima, Amapá, Acre, and Rondônia) these impacts would be less felt. The most impacted states would experience an average decline in family consumption of 2.5% by 2050 due to the expected labor loss in response to increased incident of vector-borne and infectious diseases only.

The expected change in economic performance of the Brazilian states is similar to the regional trend found for employment (Figure 10). Growth in the regional GDP would be mostly due to expected labor shocks from vector-borne and infectious diseases. The most affected states would be the ones in the Brazilian agribusiness belt (Center-West), Bahia, and Amazonas. The South region would follow, with expected decline in economic growth of around 2% to 3% by 2050.

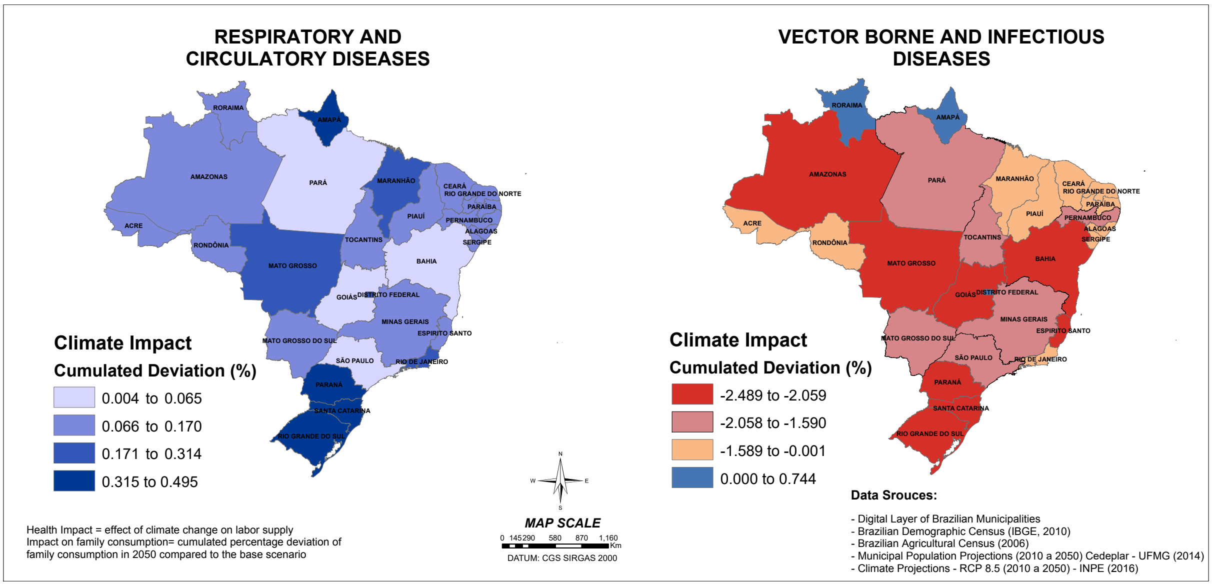

Figure 9: Change in State-level family consumption due to change in labor supply from climate-sensitive diseases - Brazil, 2015 to 2050

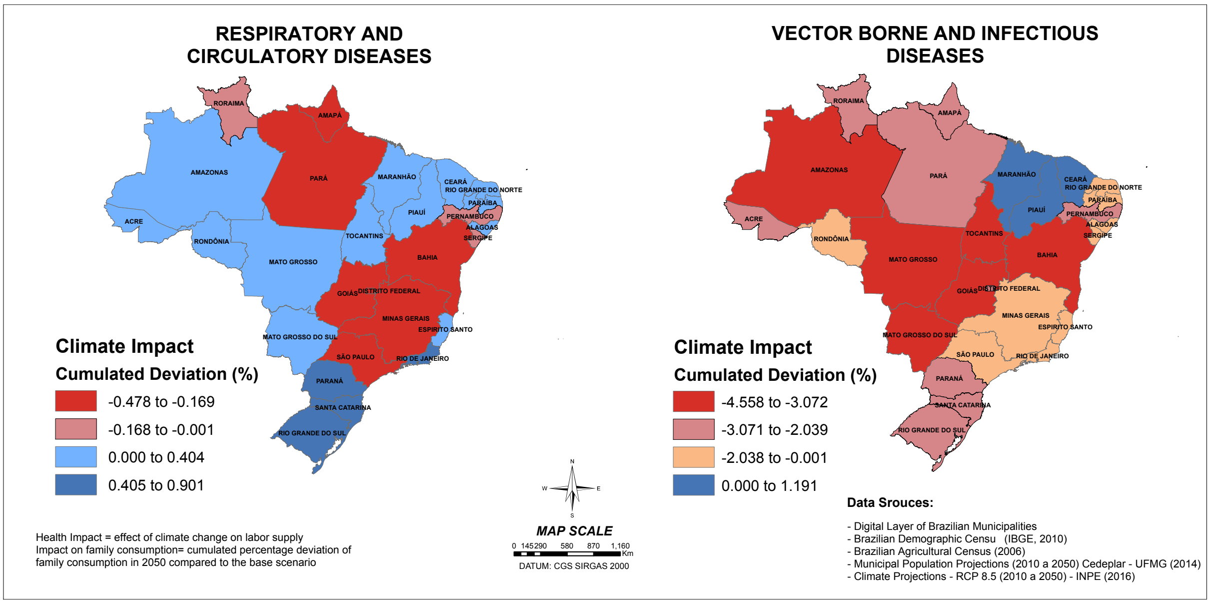

Figure 10: Change in State-level Gross Domestic Product due to change in labor supply from climate-sensitive diseases - Brazil, 2015 to 2050

4 Concluding Remarks

Global climate and environmental change have increased in the last decades. Increased health stress is one of the most alarming consequences of these changes. Although many studies have tried to estimate the direct and indirect consequences of a warmer and drier environment for the economy, both at a global and local scale, a smaller number of studies have addressed the mid and long term health implications of these changes at a regional level and as a dynamic process. Pattanayak et al. (2009) is one of the few exceptions, although their model do not compute the climate impact on labor supply through morbidity and mortality losses (gains) at a regional scale. Nor they recursively compute deaths due to climate in their population projection estimates.

Building on their previous work, this study has taken a multi-stage approach to estimate the climate-related consequences on cardiovascular/respiratory and infectious/vector-borne diseases, morbi/mortality, and labor supply in Brazil. Combining Spatial Bayes Smoothing, Spatial Econometrics, Global Burden of Disease data, and a Regional Computable General Equilibrium model, this study estimated the future development of climate-sensitive health disorders, their implications for morbi-mortality, and the consequences for labor supply and productivity for the Brazilian states and regions from 2010 to 2040.

We found a link between between climate change and health, although this relation varies by disease and by region. The prevalence of circulatory diseases is expected to decline from 2005 to 2040 due to the projected increase in average temperature across most municipalities in Brazil. Consequently, the morbi-mortality rate from circulatory disease is expected to decline, yielding an increase in the labor supply by 2040. This effect is more pronounced in the South.

The impact of future climate change on vector borne and infectious diseases is higher in magnitude when compared to the chronic conditions. Overall, prevalence of infectious diseases, wit large, and dengue more specifically, is expected to increase across all regions, resulting in higher morbimortality rates and significant loss in the labor force by 2040. Change in the prevalence of all three diseases will be higher in the North and in the Center-West. Despite the increase in the prevalence, rates themselves are low in magnitude (but high if compared to other countries). Therefore, additional morbi-mortality and loss in the labor force due to climate change would increase only marginally.

The impact of the projected climate change on labor (from the demographic model) is higher than its computed effect in the economy (from the computable regional general equilibrium model). The CGE result shows that increased morbi-mortality and labor loss would be higher for vector-borne and infectious than for non-communicable diseases, and mostly concentrated in less developed regions of the country.

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