ECONOMIC COSTS OF HEAT STRESS INDUCED REDUCTIONS IN WORKER PRODUCTIVITY DUE TO CLIMATE CHANGE IN A DEVELOPING COUNTRY

Mariana Conte Grand and Matías Soria

World Bank and UCEMA

We provide evidence on the likely benefits of reducing the burden of heat in the labor market. We consider two different measures of wet bulb globe temperature ($WBGT$) to estimate heat stress under the *shade* and the *sun* for 5 climate models and two future scenarios as of 2035, 2050 and 2100. Using Paraguay's household survey, we calculate the share of people employed per working age population in agriculture and construction, industry, and services. Then, we consider a standard workability-temperature loss function for the average worker of each sector and exposure to WBGT and level of work effort. Using the discounted present value added per worker along with GDP projections, we assess the productivity losses attributed to climate change. When comparing 2050 with 2020, productivity losses due to climate change are 1.4% for agriculture and service, 0.3% for industry and 0.05% for services under the mildest scenario, and 3.7%, 1.1% and 0.2%, respectively if the future is hotter. Losses vary geographically and across climate models. When forecasting people employed and value added per worker, productivity losses attributable to climate change, when comparing 2050 with 2020, range between 1.4% and 2.1% of GDP under the mildest and harshest climate scenarios, respectively.

Keywords: heat stress, productivity costs, climate change, Latin America, Paraguay

JEL: J01, J08, J28

1. Introduction

Hot days are projected to increase in duration, frequency, and intensity with climate change (Legg, 2021). As labor contributes to a large share of a country's GDP, climate effects on labor are considered to be among the most important drivers of total economic costs of climate change (Dasgupta et al., 2021).[1] Heat's impact on workers has economic consequences that originate in several factors. First, heat can affect health in two ways: a direct one, that goes from heat rash to heat stroke (usually referred to as "occupational health illnesses"); and an indirect one, related not to hot temperatures themselves but to injuries that result from working in the heat. Second, high temperatures can induce direct productivity losses because workers, even if they go to work, could become less efficient and produce less. Third, because of policies designed to cope with heat stress, there may be overtime payments (workers may be asked to work outside usual hours) and additional staff (because workers may be allowed to work less hours to decrease exposure to heat[2]). Since heat can cause economic losses, estimating them is key both for employers, who would like to attenuate that burden, as well as for policy makers, who would like to protect workers and see the impact that this may have on fiscal accounts.

There are several literature reviews on the link between heat and productivity losses. Borg et al. (2021) analyze the results of studies written in English, without limits in the time of publication, and find 18 that calculate heat related productivity costs. The estimated global costs from lost worktime are USD 311 billion in 2010 (≈0.5% of GDP), 2.4–2.5 trillion in 2030 (>1% of GDP) and up to 4% of GDP by 2100.

[1] According to ILO Stats (https://ilostat.ilo.org/topics/labour-income/), the share of labor over GDP in Paraguay is 46.1% in 2019, which is high, but lower than comparatives: world 52.6%; World Upper-middle income countries 49.4%; Americas Upper-middle income nations 48.1%; Latin America and the Caribbean Upper-middle income countries 48.1%.

[2] Nevertheless, according to Watts et al. (2019), as a reaction to heat workers generally decrease their work intensity or reduce the time they work while at the workplace rather than asking for leave.

Zhao et al. (2021) evaluate heat related productivity losses in 30 English-written articles from 1990 to 2020. Results are diverse, but the authors conclude that "Even with adaptation measures, the reduction in global GDP from reduced labor productivity is still 2.6% (1.4–4%) by 2100 if the global mean temperature rise is 3.7 °C (under the RCP8.5 scenario), while the value is approximately 0.31% (0.14–0.5%) if the global temperature rises below 2 °C (under the RCP2.6 scenario)".[3]

Those reviews rely on studies at different geographic levels. For example, for all regions in the world, Orlov et al. (2020) find an average reduction of 0.5% of global GDP for 2050 and 2100 in RCP2.6, and 0.7% for 2050 and 1.8% for 2100 under RCP8.5. At the other extreme of geographic coverage is the work of Morabito et al. (2020) for a wine and honey farm in Florence, Italy. However, as expected, the results differ by region, as these are several times larger in West Africa and South Asia.[4] In terms of sectors, estimated costs are generally higher in agriculture (Orlov et al., 2020), construction (Costa & Floater 2015; Takakura et al., 2017), manufacturing (Costa & Floater 2015; Xia et al. 2018) and mining activities (Takakura et al. 2018; Xiang et al., 2018). According to Borg et al. (2021), costs are larger for workers in outdoor industries, medium-sized businesses, males, and aged 25–44 years.

The existing evidence points to several knowledge gaps. First, geographical coverage is low. Borg et al. (2021) and Zhao et al. (2021) reviews find a focus on Europe, the US, China or India, and there are also a few studies at the subnational level.[5] As made explicit by Zhao et al. (2021), estimates for high heat risk regions in low African income countries are insufficient. The same assessment holds for Latin America. This is important not only because heat risks are geographically diverse but also because adaptation options also differ. Second, a few studies consider demographic changes, and changes in the structure of labor force and industry in the future (Zhao et al. 2021). As an example, Parsons et al. (2021) assume that future population and earnings are static. These aspects are particularly important, since future population is expected to rise and get older. Third, in general, impacts are assessed for each specific sector, and do not consider the indirect effect that losses have on other sectors. In the few cases that this indirect effect is considered, it is large. For example, Xia et al. (2018) estimate for China a 0.7% of direct product loss and 4.4% of indirect output loss. Overall, results differ according to the methodology used. Zhao et al. (2021) estimate that heat related output losses are 1.7, 1.4, 0.7 and 0.6% by using respectively: general equilibrium models; only input-output tables; econometric estimates that link heat to output; and the human capital approach (that simply multiplies hours lost by wages[6]). Fourth, almost no study analyzes who bears the cost of productivity losses; and there is also a lack of evidence as to what extent the workers suffer the cost (because their pay depends on productivity) and to what extent the firms face it. Fifth, only few papers (3, i.e., 10% of those reviewed by Zhao et al. 2021) quantify how adaptation reduces economic losses (Takakura et al. 2018; Morabito et al. 2020; Orlov et al. 2020), and the results go from 22 to 68%, which is not marginal.

Within this existing knowledge, this note describes a back-of-the-envelope calculation to approximate productivity impacts of climate change in Paraguay.[7] We follow usual procedures in the literature (in particular, Morabito et al. 2020; Orlov et al. 2020; Parsons et al. 2021). Our contribution is

[3] Without adaptation, those costs are 2.9% and 0.44% of global GDP respectively.

[4] See https://unu.edu/publications/articles/productivity-losses-ignored-in-economic-analysis-of-climate-change.html

[5] More precisely, Borg et al. (2021) includes evidence from European countries, Canada, Australia, and Malaysia, China and India, as well as some global studies. Zhao et al. (2021) reports global studies, and at the national level for European countries, China, or South-East Asia.

[6] The International Organization of Standardization (ISO) developed guidelines on the required duration and frequency of breaks at work depending on heat levels (https://www.iso.org/obp/ui/#iso:std:iso:7933:ed-2:v1:en). And these type of studies calculate the cost by estimating the gap between usual hours worked and those worked under this type of standard (Orlov et al., 2020).

[7] The choice of this country has to do with the timing of the elaboration of the Country Climate and Development Report, that is an analytic product of the World Bank, for which the authors of this document have contributed.

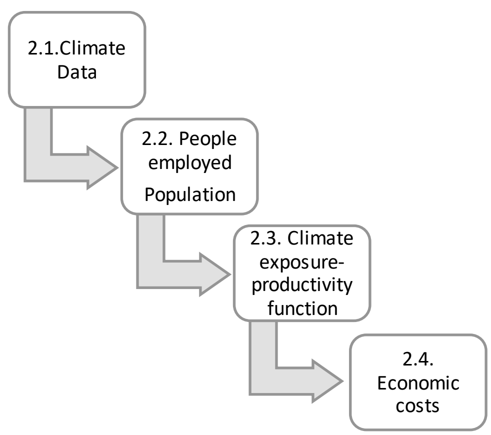
to advance knowledge for a developing country using very high climate resolution data as well as local household surveys, to consider future changes in population structure, and to cover all sectors of the economy.

The remainder of this paper is organized as follows: Section 2 describes the methodology, assumptions and data employed; Section 3 presents the results and discusses them; and the final section concludes, states the caveats behind the calculation that can help the interpretation of our results to guide future work, and points out to possible policy recommendations.

2. Methodology and data

The methodology that we use combines climate, epidemiological, and economic data. As described in Figure 1, it follows 4 steps. First, we consider two different measures of wet bulb globe temperature ($WBGT$) to estimate heat stress both in the shade ($WBGT_{shade}$) and in the sun ($WBGT_{sun}$), where *shade* refers to indoor without air conditioning (or outdoor under the shade) and *sun* refers to outdoor. The former is estimated following Lemke & Kjellstrom (2012) and captures how changes in temperature and humidity affect exposure to heat (Section 2.1). The latter is based on Liljegren et al. (2008) and allows to consider additional variables –such as wind speed and solar radiation levels– that also affect heat stress when individuals are exposed to direct sunlight in open spaces.

Figure 1. Summary of empirical methodology



Source: Own elaboration.

Then, after obtaining these indices, assumptions are made on how many hours people spend under minimum, mean and maximum temperatures. Second, based on household surveys, we calculate the share of people employed in the base year in terms of the working age population (in both cases, people over 15 years old). After that, with population projections, we forecast employment levels based on those shares (Section 2.2). Third, we consider a standard workability-temperature loss function for the average worker of each sector (Section 2.3). Finally, using the discounted present value added per worker along with GDP projections (Section 2.4), we assess the productivity losses attributed to climate change.

2.1. Climate data

Five climate variables are required as inputs to estimate $WBGT_{shade}$ and $WBGT_{sun}$: temperature in °C, relative humidity ($hurs$) in %, wind speed ($sfcwind$) in m/s and solar radiation ($rsds$) in W/m^2, daily mean temperature (tas) and daily maximum temperature ($tasmax$) in °C. The last two allow us to capture that individuals are exposed to various levels of heat at different times of the day.

Climate variables data were obtained from the Coupled Model Intercomparison Project version 6 (CMIP6), with a downscaled adjustment proposed by Noël et al. (2022), except for *rsds*, that is from the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP), because it was not available in the CMIP6-adjust database.[8] To consider climate projections' uncertainty, we include five forcing climate models in our analysis: GFDL-ESM4, IPSL-CM6A-LR, MPI-ESM1-2-HR, MRI-ESM2-0 and UKESM1-0-LL.[9] The two climate scenarios we analyze are SSP1 2.6 – sustainability scenario – and SSP5 8.5 – fossil fuel development scenario.[10] We do so for a window around the years 2020, 2035, 2050 and 2100,[11] where 2020 is intended to represent current conditions.

The heat stress indices themselves are calculated on a daily basis for each grid cell ($0.5° \times 0.5°$ of latitude and longitude[12]) for Paraguay using the R package "HeatStress", written by Casanueva et al. (2019). They are weighted sums of different measures of temperature, with the following specifications:

$$WBGT_{shade,l} = \frac{2}{3} \cdot T_{pwb,l} + \frac{1}{3} \cdot T_{as,l}$$

$$WBGT_{sun,l} = 0.7 \cdot T_{nwb,l} + 0.2 \cdot T_{g,l} + 0.1 \cdot T_{as,l} \tag{1a}$$

where the subindex l refers to the level for each variable, which could be mean or maximum.

Starting with $WBGT_{shade,l}$, one-third of this variable is explained by the *near surface* air temperature $(T_{as,l})$, and two-thirds are explained by the psychometric wet bulb temperature $(T_{pwb,l})$. This last variable is obtained by combining $T_{as,l}$ and dewpoint temperature $(dewp_l)$, which is itself obtained by combining $T_{as,l}$ and $hurs$ (Lemke & Kjellstrom 2012). Moving on to $WBGT_{sun,l}$, only 10% of this variable is explained directly by $T_{as,l}$, while 70% is explained by natural wet temperature $(T_{nwb,l})$ and the remaining 20% is explained by globe temperature $(T_{g,l})$. These last two variables are calculated by combining $T_{as,l}$, $dewp_l$, $rsds$ and $sfcwind$, following an iterative process in the context of a model based on fundamental principles of heat and mass transfers (Liljegren et al., 2008).

To match the climate data with the socioeconomic data for Paraguay, we use the household survey (*Encuesta Permanente de Hogares Continua*, EPHC). The concrete data source is the Socio-Economic Database for Latin America and the Caribbean (SEDLAC) that has information for 24 countries of the region, including Paraguay.[13] For the 2019 fourth quarter[14], the last one before the COVID pandemic, there is data on the following departments of Paraguay: Asunción (where the capital city is located), San Pedro, Caaguazú, Caazapá, Itapúa, Alto Paraná, Central and the rest of the country. Those, except Caazapá, are the 6 most populated ones. As shown in Table 1, the 7 areas that are detailed by name in the EPHC, account for 74.8% of the population of the country and 76.6% of GDP.

Table 1. Population per department in Paraguay

[8] Concretely, the data we used belong to https://theclimatedatafactory.com/ and are in https://esgf-node.ipsl.upmc.fr/projects/esgf-ipsl/

[9] We used all the climate models available in the CMIP6-Adjust experiment (https://esgf-node.ipsl.upmc.fr/projects/cmip6-adjust/), that are the debiased data at higher resolution available.

[10] We cannot consider the SSP2 4.5 because solar radiation (*rsds*) is not available from ISIMIP for that scenario.

[11] Concretely, we do the analysis for the following years: 2016-2025, 2026-2040, 2046-2055, 2096-2100. We then average for each period. So, when we refer to 2020, we are in fact talking about an average for the 10 years window around that year.

[12] The only exception is the variable *rsds*, that is only available for $1° \times 1°$ for the five models we use, so we adjust the grid to fit the rest of the variables.

[13] https://www.cedlas.econo.unlp.edu.ar/wp/estadisticas/sedlac/.

[14] For poverty calculations, the fourth quarter is the one taken as the reference for each year.

Code-Departments (*d*)	Population	*Share of Population*	*Share of GDP*
0 - Asunción	522,286	*7.4%*	*9.1%*
2 - San Pedro	429,921	*6.1%*	*5.4%*
5 – Caaguazú	557,758	*7.9%*	*6.9%*
6 - Caazapá	189,567	*2.7%*	*1.9%*
7 - Itapúa	608,223	*8.6%*	*9.2%*
10 - Alto Parana	819,586	*11.6%*	*13.5%*
11 - Central	2,158,246	*30.5%*	*30.6%*
20 - Rest of the country	1,783,740	*25.2%*	*23.4%*
Total	**7,069,327**	**100%**	**100%**

Source: Own elaboration.
Notes: region_est2 is the variable for department in Paraguay EPHC 2019Q4. The geographical disaggregation of GDP comes from an estimate by McCord & Rodriguez-Heredia (2022)

Hence, equation (1a) can be more precisely defined as:

$$WBGT_{i,l,s,t,m,d} = \begin{cases} \frac{2}{3} \cdot T_{pwb,s,t,m,d} + \frac{1}{3} \cdot T_{as,l,s,t,m,d} & \text{if } i \text{ is shade} \\ 0.7 \cdot T_{nwb,s,t,m,d} + 0.2 \cdot T_{g,s,t,m,d} + 0.1 \cdot T_{as,l,s,t,m,d} & \text{if } i \text{ is sun} \end{cases} \quad (1b)$$

i (exposure dimension): shade, sun
l (levels): mean, max
s (scenarios): SSP1.2.6, SSP5.8.5
t (days): 365 days in 2019, 2035, 2050, 2100
m (models): IPSL-CMGA-LR; MPI-ESM1-2-HR; GFDL-ESM4; UKESM1-O-LL; and MRI-ESM2-0
d (departments): Asunción, San Pedro, Caaguazú, Caazapá, Itapúa, Alto Paraná, Central and the rest of the country

So, for *WBGT*, there are 2 exposure dimensions (*i*) for 2 levels (*l*), for 2 climate scenarios (*s*) for 365 days in 4 years (*t*) for 5 models (*m*), and 8 departments (*d*). This is, 2x2x2x4x5x8=1280 variables with values for 365 days each.

Having the WBGT defined, as is usually calculated in the literature following Kjellstrom et al. (2018), WBGT daily average follows a so-called “4+4+4” formula: if working hours were 12, 4 occur at mean, 4 at maximum, and for 4 at an average between mean and maximum WBGT:

$$WBGT_{i,s,t,m,d} = \left(\frac{4}{12}\right) \cdot WBGT_{i,max,s,t,m,d} + \left(\frac{4}{12}\right) \cdot WBGT_{i,mean,s,t,m,d} + \left(\frac{4}{12}\right) \cdot WBGT_{i,AvgMeanMax,s,t,m,d} \quad (2)$$

This means that it is assumed that one third of the working day is spent at the mean temperature, another third at the maximum temperature and the remaining third at an average between the two. Hence, since the two levels (*l*: mean and max) were combined after making this assumption, the variables remaining are 640 (i.e., 2x2x4x5x8). Each one has data for 365 days.

2.2. People employed in each sector in each region in the present and as percentage of working-age population for the future

We calculate the share of people working within each sector in each of the departments in Paraguay at the present and use it to forecast employed in the future, applying those shares to projected population.

In particular, the shares (*e*) of people in working age (15 and over), who work in each department and each sector of activity are:

$$e_{t_o,d,a} = \frac{E_{t_0,d,a}}{WPop_{t_0,d,a}} \quad (3)$$

where $E_{t_{o,d,a}}$ is people in working age (15 and over), in the last year pre COVID (t_o= *2019 Q4*), who work in each department and each sector of activity; and $WPop_{t_0,d,a}$ is all working age population (if they work or not). These shares refer to the present and remain fixed in time, because we do not have, as now, estimates for the future.

Most of the workers surveyed declare the sector of activity of their main occupation (i.e., over 99% of the total), so we can properly assign them to activities. In Paraguay, 68.6% of inhabitants 15 years old or older work (Table 2), and, considering the whole country, of those who work, 61.5% do so in activities related to services, 27.6% work in agriculture and construction and 10.9% in the manufacturing sector.

Table 2. Share of working age population who work in each department by branch of activity (2019 Q4)

Departments	Agriculture and construction	Industry	Services	Do not declare*	All sectors
ASUNCION	5.2%	7.5%	56.1%	0.1%	*68.9%*
SAN PEDRO	40.5%	6.4%	23.3%	0.0%	*70.2%*
CAAGUAZU	28.1%	5.0%	38.4%	0.0%	*71.5%*
CAAZAPA	46.9%	2.3%	24.5%	0.0%	*73.7%*
ITAPUA	25.8%	6.1%	38.9%	0.0%	*70.8%*
ALTO PARANA	13.3%	5.3%	48.4%	0.0%	*67.0%*
CENTRAL	8.0%	10.2%	48.5%	0.1%	*66.9%*
Rest of the country	26.3%	7.0%	35.6%	0.0%	*68.9%*
Share of total people who work over total working age population					*68.6%*

Source: Own calculations based on EPHC 2019Q4 for Paraguay SEDLAC 2022 (https://www.cedlas.econo.unlp.edu.ar/wp/estadisticas/sedlac/).

Those shares of employed people over working age population per department ($e_{t_{o,d,a}}$) from equation (3) are applied to working-age population along time (population 15 years and over, as shown in Table 3). To get the expected workers per year, department, and activity sector (note that population projections do not change across climate models or scenarios), we do:

$$E_{y,d,a} = e_{t_o,d,a} \cdot WPop_{y,d} \tag{4}$$

where y = 2020, 2035, 2050 and 2100. This means that we are left with *t* x *d* (i.e., 4x8=32) variables for all sectors of activity (*a*).

Table 3. Working age population per department per scenario per year

Departments	2020	2035	2050	2100
ASUNCION	540,591	675,771	795,789	922,610
SAN PEDRO	284,616	351,634	402,827	405,492
CAAGUAZU	387,486	478,563	548,482	555,535
CAAZAPA	124,458	153,511	175,533	175,725
ITAPUA	374,820	461,867	529,278	540,370
ALTO PARANA	500,457	621,750	722,523	786,970
CENTRAL	1,241,063	1,558,436	1,840,301	2,138,796
Rest of the country	1,232,073	1,519,044	1,740,750	1,766,901
Total	*4,685,564*	*5,820,575*	*6,755,482*	*7,292,399*

Source: Own calculations based on the geospatial distribution from SSP2 scenario, adjusted to the totals from UN projections (https://population.un.org/wpp/).

2.3. Exposure-response functions

We chose the *Hothaps* (*High Occupational Temperature Health and Productivity Suppression*) exposure-response functions, that come from observational data originally derived in Kjellstrom et al., (2009), based on epidemiological studies. The *Hothaps* function states how much workability aptitude people would have under different WBGT, depending on the intensity of their work. This workability function takes the following shape:

$$Workability = 0.1 + \frac{0.9}{1+\left(\frac{WBGT_i}{\alpha_1}\right)^{\alpha_2}} \tag{5a}$$

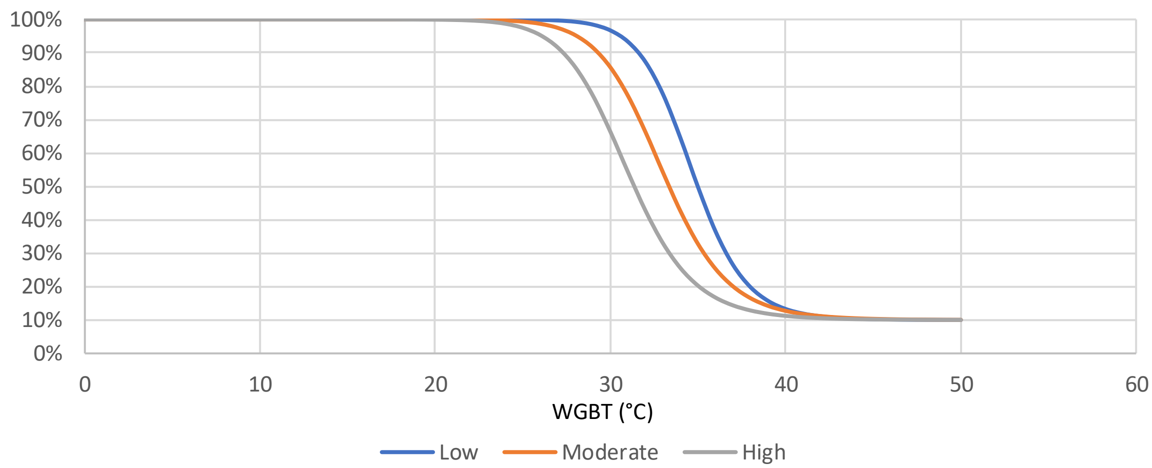
where the α_s parameters refer to different work intensities. Table 4 reports the values for those parameters, and Figure 2 shows the shape of the curves depending on the intensity of work.

Table 4. Workability depending on intensity of work

Intensity of work	α_1	α_2
Low	34.64	22.72
Moderate	32.93	17.81
High	30.94	16.64

Source: Own elaboration based on Orlov et al. (2020).

Figure 2. Workability per type of work as a function of WBGT



Source: Own elaboration based on Orlov et al. (2020).

Each sector work is assigned a *WBGT* and intensity of work (Table 5) as in Kjellstrom et al. (2009).

Table 5. Exposure and intensity of exposure per sector of activity

Sector	WBGT	Intensity
Agriculture and construction	Sun	High
Manufacturing	Shade	Moderate
Services	Shade	Low

Source: Own elaboration based on Kjellstrom et al. (2009).

The Paraguay household survey (EPHC) includes several sectors of activity:

- **Primary** (agriculture livestock hunting and fishing)
- **Secondary** (manufacture and construction)
- **Tertiary** (Commerce; restaurants and hotels; utilities; finance, insurance, and real state; public administration; education and health; domestic servants; and transportation)

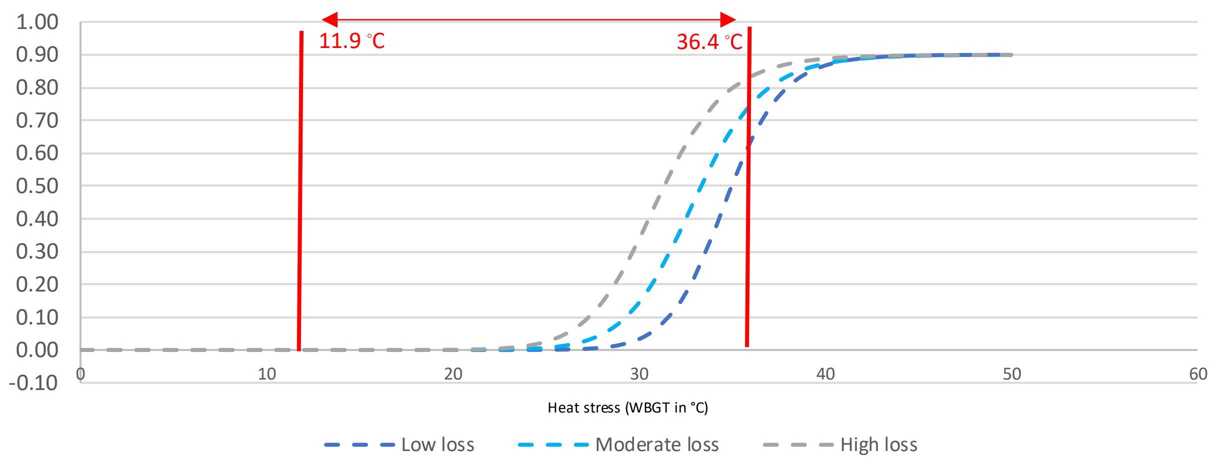
We organize people in sectors to match the type of WBGT which they are exposed to, as well as the intensity of their work. Since, by Table 5, construction has the same treatment as agriculture, branches of activities are aggregated in those three sectors: *s* = Agriculture and Construction, Manufacture or Industry, and Services.

Then, *workability lost* (*L*) factor can be denoted as:

$$L_a = 1 - \text{Workability} = 0.9 - \frac{0.9}{1+\left(\frac{WBGT_{ia}}{\alpha_{1a}}\right)^{\alpha_{2a}}} \quad (5b)$$

This means that workability functions from Figure 2 are now the workability loss functions as shown in Figure 3. What this Figure 3 depicts is that, if wet bulb globe temperature is, for example, 32 degrees, there would be a productivity loss of 13%, 34% and 57% for low intensity, moderate, and high intensity works, respectively. Vertical lines in Figure 3 show minimum and maximum values the mean WBGT shade and sun in our daily data per department in the years considered.

Figure 3. Workability loss as function of wet bulb globe temperature



Source: Own elaboration based on Orlov et al. (2020) and our constructed database.
Note: Vertical lines in red show minimum and maximum values among all WBGTs shade and sun in our daily data per department in all years all scenarios and all models considered in this study.

This function is usually referred to as logistic (for example, by Orlov et al. 2020), but it is indeed an expression of the Morgan-Mercer-Flodin growth equation, which has 4 parameters (Morgan et al., 1975). Here, the upper asymptote is 0.9 and the value of the function at $WBGT = 0$ is 0, while α_1 and α_2 influence the rate of growth and the point of inflection of the curve. Hence, at lower temperatures, there would be no productivity loss and, at extremely high ones, the maximum loss is 90%.[15]

To fit our data to the productivity impact calculations with the equation (5b), the workability loss factor (*WLf*) can be expressed as:

$$WLf_{s,t,m,d,a} = 0.9 - \frac{0.9}{1+\left(\frac{WBGT_{s,t,m,d,ia}}{\alpha_{1a}}\right)^{\alpha_{2a}}} \tag{5c}$$

We denote *ia* the WBGT associated to activity and the same holds for α_{1a} and α_{2a}. We have then 960 workability loss variables (i.e., 2x4x5x8x3) for 365 days each. When we add over 365 days, we get the annual number of days lost per worker due to heat. We can then calculate the percentage of days lost per worker per year by dividing by 365.

Productivity losses (*PL*) per year are obtained by combining equations (4) and (5c) into:

$$PL_{s,t,m,d,a} = \frac{WLf_{s,t,m,d,a}}{\#days_{s,t,m,a}} \cdot E_{y,d,a} \tag{6}$$

This implies that the number of people employed is assumed to be constant during the whole year. The results of equation (6) are, for each scenario, for each day, for each model, for each department and for each sector, the average productivity workers loose due to the different WBGT levels. This can be interpreted as equivalent employed lost.

[15] As explained by Kjellstrom et al. (2018), there in any circumstances, no matter temperature, 10% of productivity losses when taking micro-breaks during the time of work.

2.4. Valuation of productivity losses using annual value added

There are several ways to value productivity losses. One usually considered (for example, in Parsons et al., 2021) is to assign to each worker the value added in its sector. Based on the number of workers derived with equation (4), the value added per sector in guaranies and their conversion to 2015 US dollars (US$), the value added per sector corresponding to 2019 is reported in Table 6. [16]

Table 6. Value added per worker per sector

Year 2019	Real GDP, millions of (2014) guaranies	Workers	VA constant 2015 US$ per worker
Agriculture and construction	35,880,609	1,003,087	6,987
Manufacture	39,972,696	390,990	19,969
Services	116,960,700	2,245,481	10,174
Ratio LCU 2014 to USD 2015			0.0002

Source: Own elaboration based on Paraguay National Accounts and EPHCQ4.
Note: Note that workers in the Table are all in the ECH2019Q4. However, when limited to those age 15 and considering working age population over 15, the corresponding numbers are slightly different: 897,059; 344,016; and 1,976,832 respectively.

What Table 6 shows is that even if there are less workers in manufacture, their value added is higher than in services, where workers work in highest numbers.

For projections of value added to 2035 and 2050, we use the World Bank assumptions for the GDP per capita, and we build a logarithmic trend for 2100. We assume that the share of each sector will remain constant (i.e., each sector will grow at the same rate).

Hence, what we calculate as value of productivity losses per year (y) is:

$$VL_{s,y,m,d,a} = \left(\sum_{t=1}^{365} PL_{s,t,m,d,a}\right) \cdot VApW_{s,y,d,a} \cdot (1+g_t) \tag{7}$$

where g is the rate of growth from each year in the future with respect to 2020.

Then, the impact of climate change on the value of productivity losses results from the difference between annual losses from 2035 to 2020, 2050 to 2020 and 2100 to 2020 in the two scenarios (s) for the 5 models (s) in the 8 departments (d) for the 3 branches of activities (a).

3. Results

This section shows the results for each step described in Figure 1: climate data (WBGTs), people employed, productivity losses per worker, and value of productivity losses.

3.1. Wet bulb global temperature

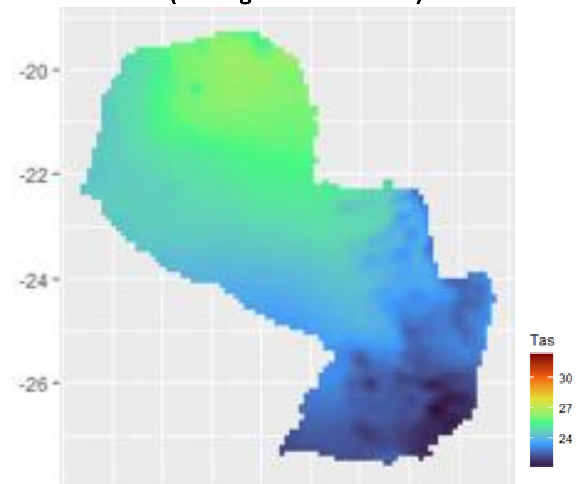
As stated above, $WBGT_{shade}$ and $WBGT_{sun}$ are heat stress indices that are obtained by applying equations (1b) and (2) to the gridded data for the five selected climate variables.[17] Given that the part of the country that do not correspond to the department named in the EPHC has different climate characteristics, we decided to divide the "Rest" (as named in the household survey) in three different areas grouping several departments: Northwest (Alto Paraguay, Boquerón and Presidente Hayes); Northeast (Concepción, Amambay and Canindeyú); and South (Cordillera, Guairá, Misiones, Ñeembucú and Paraguarí). Figure 4 illustrates for 2020 how is the average temperature along the country as of 2020.

Figure 4. Geographic differences in heat

[16] The numbers in Table 6 are of a similar order of magnitude than those reported for Paraguay in the World Development Indicators database in constant US$: 5,954 for agriculture (does not include construction), and 22,037 for industry (it includes construction) and 9,541 for services.
[17] Annex A reports, in different graphs, the levels of all the climate variables used as inputs to calculate the WBGTs.

a) Paraguay departments

b) Mean near surface air temperature $(T_{as}, °C)$: 2020 (average 2016 to 2025)



Source: a) https://www.abc.com.py/edicion-impresa/suplementos/escolar/2022/06/14/mapa-del-paraguay-division-politica/ b) own elaboration.

Then, Table 7 shows it is the case that, for the same years and department, the SSP585 scenario yields higher (or almost equal) WBGT for both sun and shade than the milder SSP126. However, in scenario SSP126 the WBGTs increase along time, except in 2100 where it decreases 0.2 degrees with respect to 2050, because mitigation actions are taken, climate improves and so heat stress decreases. This is not the case of SSP585, where wet bulb temperature increases heavily by 2100 (i.e., it is approximately 2.8 degrees higher than in 2050). Finally, the Northwest region is the hottest place to work and Itapúa the coolest one.

In terms of climate models used to forecast climate variables, the highest WBGT are derived by the UKESM1-0-LL model and the lowest most often come from the MPI-ESM1-2-HR, while IPSL-CM6A-LR always present intermediate values (see Table B.1 in Appendix B for details on derived WBGT per model, averaging across departments).

Table 7. ***$WBGT_{shade}$*** **and** ***$WBGT_{sun}$*** **by climate scenario, departments, and years, for mean across models**

	Years	ASUNCIÓN	ALTO PARANÁ	CAAGUAZÚ	CAAZAPÁ	CENTRAL	ITAPÚA	NORTHWEST	NORTHEAST	SAN PEDRO	SOUTH
WBGT shade (°C)											
SSP126	**2020**	22.89	22.55	22.80	22.36	22.89	22.01	24.15	23.73	23.66	22.41
	2035	23.18	22.81	23.06	22.62	23.18	22.26	24.47	24.02	23.93	22.69
	2050	23.58	23.24	23.49	23.05	23.58	22.69	24.86	24.45	24.36	23.09
	2100	23.39	23.03	23.29	22.85	23.39	22.49	24.66	24.22	24.16	22.89
SSP585	**2020**	22.92	22.55	22.80	22.39	22.92	22.05	24.15	23.73	23.65	22.45
	2035	23.48	23.12	23.37	22.94	23.48	22.57	24.75	24.33	24.24	23.00
	2050	24.02	23.74	23.98	23.52	24.02	23.14	25.26	24.92	24.82	23.53
	2100	26.82	26.61	26.86	26.33	26.82	25.88	28.13	27.89	27.75	26.23
WBGT sun (°C)											
SSP126	**2020**	23.40	23.21	23.44	23.02	23.40	22.63	24.65	24.40	24.30	22.94
	2035	23.67	23.47	23.70	23.27	23.67	22.87	24.96	24.69	24.57	23.21
	2050	24.09	23.90	24.14	23.71	24.09	23.32	25.34	25.12	25.00	23.62
	2100	23.89	23.68	23.92	23.50	23.89	23.12	25.15	24.89	24.80	23.42
SSP585	**2020**	23.42	23.20	23.43	23.03	23.42	22.66	24.64	24.38	24.28	22.97
	2035	23.96	23.73	23.98	23.55	23.96	23.16	25.22	24.96	24.85	23.49
	2050	24.50	24.35	24.57	24.13	24.50	23.73	25.73	25.55	25.42	24.02
	2100	27.24	27.18	27.41	26.89	27.24	26.42	28.54	28.46	28.30	26.69

Source: Own calculations.
Note: 2020 comes from models, not actual data, and that is why climate variables (and so, WBGTs) differ among climate models.

3.2. Employed population per sector along time

Then, using data in Tables 2 and 3 and equations (3) and (4), we calculate the number of people employed, reported in Table 8. The highest number of workers in agriculture are in Caaguazú and San Pedro, those working in manufacturing are in large part in the Central department and population working in services is concentrated in Asunción and the Central department. Remember that, as we stated before, the shares of the working population are assumed to be constant, so the number of workers increase only because population increases. The total number of workers per sector evolves as shown in Figure 5.

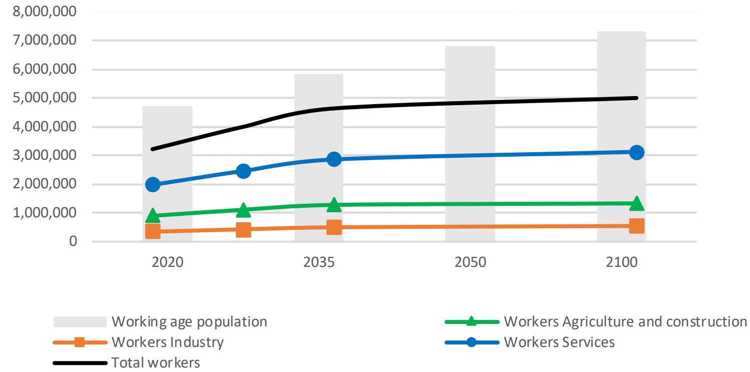
Table 8. People employed by department by year

	2020	2035	2050	2100
Agriculture				
ALTO PARANA	66,390	82,480	95,848	104,398
ASUNCION	28,042	35,054	41,280	47,858
CAAGUAZÚ	108,907	134,505	154,157	156,139
CAAZAPÁ	58,424	72,063	82,401	82,491
CENTRAL	99,526	124,978	147,582	171,519
ITAPÚA	96,827	119,314	136,728	139,594
NORTHWEST	33,918	41,588	47,673	48,377
NORTHEAST	97,971	120,625	137,809	137,669
SAN PEDRO	115,329	142,485	163,229	164,309
SOUTH	191,724	236,775	271,740	278,045
Sub Total	*897,059*	*1,109,868*	*1,278,447*	*1,330,398*
Industry				
ALTO PARANA	26,417	32,819	38,138	41,540
ASUNCION	40,739	50,926	59,970	69,527
CAAGUAZU	19,348	23,896	27,387	27,739
CAAZAPA	2,869	3,539	4,046	4,051
CENTRAL	127,089	159,589	188,453	219,020
ITAPUA	22,719	27,995	32,081	32,753
NORTHWEST	9,089	11,145	12,775	12,964
NORTHEAST	26,254	32,325	36,930	36,892
SAN PEDRO	18,115	22,380	25,639	25,808
SOUTH	51,378	63,451	72,821	74,510
Sub Total	*344,016*	*428,064*	*498,239*	*544,805*
Services				
ALTO PARANA	242,398	301,146	349,956	381,171
ASUNCION	303,029	378,805	446,081	517,171
CAAGUAZU	148,971	183,986	210,867	213,578
CAAZAPA	30,489	37,606	43,001	43,048
CENTRAL	601,630	755,482	892,122	1,036,824
ITAPUA	145,871	179,747	205,982	210,299
NORTHWEST	45,909	56,291	64,527	65,479
NORTHEAST	132,607	163,269	186,528	186,339
SAN PEDRO	66,425	82,066	94,014	94,636
SOUTH	259,503	320,482	367,807	376,341
Sub Total	*1,976,832*	*2,458,881*	*2,860,884*	*3,124,885*
Total	**3,217,907**	**3,996,813**	**4,637,570**	**5,000,088**

Source: Own elaboration.

Note: The number of workers was calculated for the 7 most populated departments, while the rest of the country was split into 3 subregions: Northwest (Alto Paraguay, Boquerón, Presidente Hayes), Northeast (Concepción, Amambay y Canindeyú) and South (Cordillera, Guairá, Misiones, Ñeembucú y Paraguarí).

Figure 5. Total number of workers per sector per selected year



Source: Own elaboration.

3.3. Productivity losses per worker

Table 9 depicts the annual days lost per worker per year due to heat for all scenarios, all years, per district and branch of activity for the mean across climate models, compared to the situation where temperatures are low enough that there is no productivity loss according to the exposure-response functions in Figure 3. What the results in that table mean is that, for example, in Asunción, losses per worker in the agriculture sector are such that, if the SSP12.6 scenario is what the future looks like, it is as if the employed workers worked 5%, 6.1% and 6.2% less of their time in 2035, 2050, and 2100, compared to the situation when WBG temperature is comfortable (around less than 20 degrees Celsius). The share of work lost because of heat is considerably larger for agricultural and construction workers than for industry and services workers, which was an expected result, since the former work in the sun and the latter work in the shade. In addition, losses in the SSP58.5 model are always larger than those in the SSP2.6 model. For the former scenario, losses are higher as time goes by, since climate change is forecast to be highly damaging, while for the most optimistic SSP12.6 climate forecast, the share of work losses increase slowly (on average) until 2100.

Considering the whole country, of the 3,2 million estimated people over 15 years old employed in 2020, the productivity work losses with respect to a temperature below 20 degrees are equivalent to 45,000 who do not work. This is 1.4% of employment. The "workers lost" for 2020 correspond to the agriculture and construction sectors (88.8% of the total), and the remaining pertain slightly more to industry (6.7%) than to services (4,4%).

Table 9. Annual days lost per worker in Paraguay with respect to temperatures with no heat stress: by scenario, year, scenario, departments and sectors, for average across climate models

Annual days lost (WLf) per worker per year	2035 SSP12.6	2035 SSP8.5	2050 SSP12.6	2050 SSP8.5	2100 SSP12.6	2100 SSP8.5
Agriculture and construction						
ALTO PARANA	14.48	17.20	17.85	23.91	17.91	77.98
ASUNCION	18.34	21.90	22.40	29.63	22.76	85.72
CAAGUAZU	16.39	19.54	20.24	27.03	20.37	84.25
CAAZAPA	14.84	17.78	18.39	24.49	18.51	76.35
CENTRAL	18.34	21.90	22.40	29.63	22.76	85.72
ITAPUA	12.66	15.26	15.78	21.00	15.83	67.38
NORTHWEST	28.31	33.28	33.95	43.16	33.74	112.23
NORTHEAST	22.95	27.20	28.21	36.69	27.71	105.47
SAN PEDRO	24.50	28.99	29.85	38.55	29.90	105.14
SOUTH	15.29	18.29	18.70	24.75	18.66	74.56
Industry						
ALTO PARANA	2.54	3.24	3.21	4.95	3.48	28.49
ASUNCION	3.88	4.91	4.87	7.32	5.35	36.85
CAAGUAZU	3.01	3.83	3.81	5.86	4.16	32.70
CAAZAPA	2.66	3.39	3.37	5.14	3.68	28.21
CENTRAL	3.88	4.91	4.87	7.32	5.35	36.85
ITAPUA	2.26	2.88	2.88	4.33	3.11	23.72
NORTHWEST	6.53	8.23	8.18	11.76	8.58	56.63
NORTHEAST	4.38	5.54	5.59	8.40	5.81	45.44
SAN PEDRO	4.92	6.24	6.21	9.30	6.70	46.95
SOUTH	3.08	3.89	3.85	5.74	4.12	29.60
Services						
ALTO PARANA	0.28	0.38	0.37	0.67	0.45	7.92
ASUNCION	0.50	0.67	0.65	1.15	0.81	12.03
CAAGUAZU	0.35	0.48	0.46	0.84	0.57	9.76
CAAZAPA	0.31	0.41	0.40	0.72	0.50	7.99
CENTRAL	0.50	0.67	0.65	1.15	0.81	12.03
ITAPUA	0.25	0.34	0.33	0.58	0.40	6.25
NORTHWEST	0.93	1.28	1.23	2.08	1.41	23.56
NORTHEAST	0.54	0.74	0.73	1.30	0.83	15.75
SAN PEDRO	0.65	0.89	0.86	1.53	1.04	16.88
SOUTH	0.37	0.50	0.48	0.84	0.58	8.77

Source: Own calculations.

Note: WLf is the workability loss factor described in equation (5c).

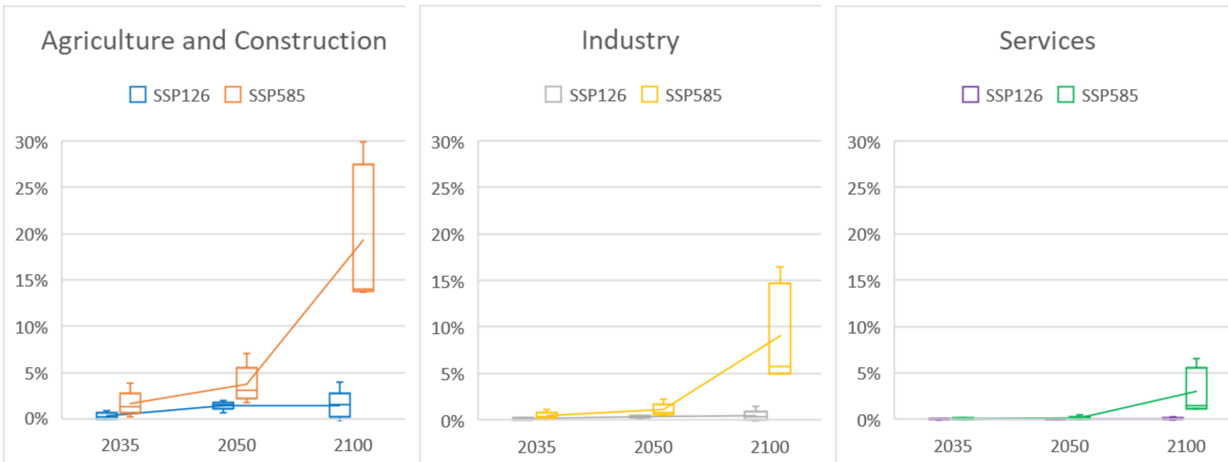
3.4. Damages in productivity losses attributable to climate

3.4.1. Productivity losses per worker due to heat stress differences because of climate change

To assess productivity losses attributable to climate change, we calculate the difference between productivity losses with respect to the no-heat temperatures in Table 9 and those in 2020 under the different climate scenarios and models. Figure 7 summarizes those results for aggregates per sector and total, using as weights the number of people employed (average 2020, 2035, 2050, 2100). As can be seen in Figure 7, the highest productivity losses from climate change occur in the agriculture and construction sectors, and the lowest occur in the activities related to services.

When comparing 2050 with 2020, mean (across climate models) productivity losses due to climate change are 1.4% for agriculture and construction, 0.3% for industry and 0.1% for services under the mildest SSP12.6 scenario. Those losses go up to 3.7%, 1.1% and 0.2%, respectively, if SSP58.5 is the future that occurs. Those losses vary depending on the models that project climate. For example, for agriculture and construction in the worse scenario (SSP58.5), productivity losses per worker as of 2050 could be as high as 7.1%, according to the UKESM1-0-LL model.

Figure 7. Difference productivity per worker with respect to 2020: weights by employed per department

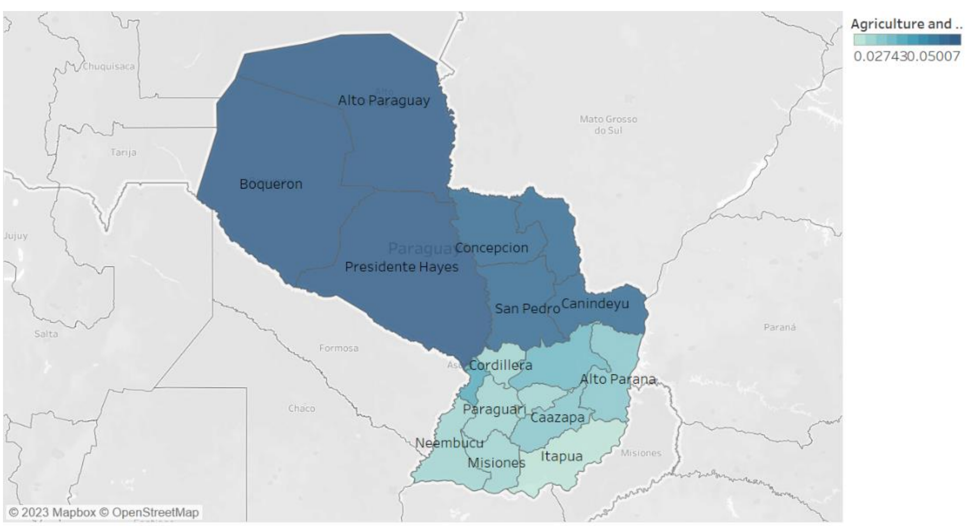


Source: Own elaboration

Note: the range of values is given by the different estimates of each of the 5 climate models.

When weighing by total employment in each sector, productivity losses per worker for the whole country for 2035, 2050 and 2100, as compared to 2020, are 0.11%, 0.47%, and 0.51% under SSP12.6, and 0.53%, 1.26%, and 8.19% under SSP58.5.

Figure 8. Productivity losses per worker per department: agriculture and construction sector, SSP8.5, average across models, difference 2050 to 2020



Map based on Longitude (generated) and Latitude (generated). Color shows sum of Agriculture and construction SSP585. The marks are labeled by Departamento. Details are shown for Country and Departamento.

However, there is geographic diversity. Considering the difference between 2050 and 2035 for the agriculture and construction sector in the SSP58.5 scenario, as Figure 8 shows, productivity losses per worker are higher in the Northern departments than in the Southern ones. While, for the overall country, productivity losses are 3.7%, they are 5.01% for those agriculture and construction workers in the North, 4.74% for those employed in San Pedro, and 2.74% for those in Itapua. Note that while productivity losses are high in the North, the working population in some of those departments is quite low. For example, in Boquerón and Alto Paraguay live only 1% of all working-age inhabitants.

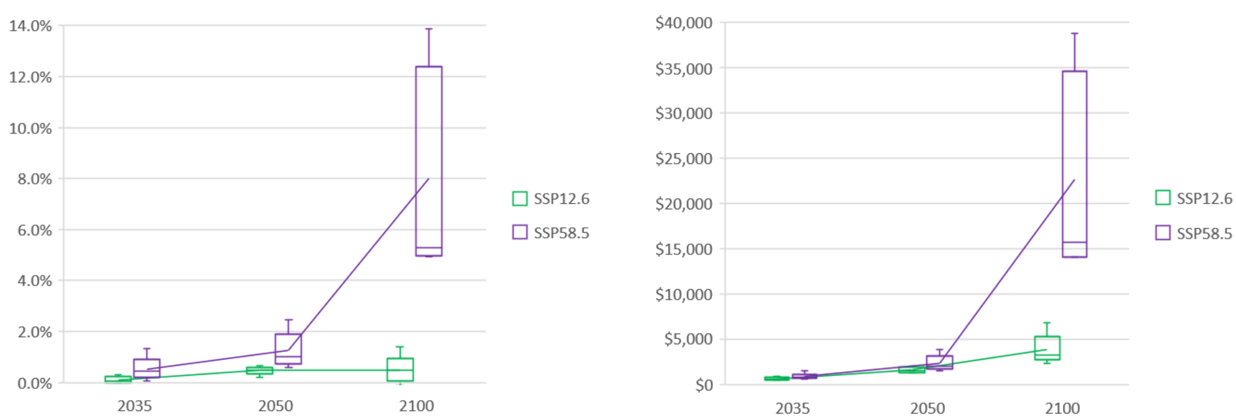
3.4.2. Productivity losses due to heat stress differences if climate remained the same as in 2020

To calculate monetary damages attributable to climate change that consider future modification of population and value added per worker, we build a Base Case where WBGT remains the same as in 2020 while population grows as well as GDP, and an Alternative Case where all variables, including WBGT, do change. The results of that difference in the productivity losses per worker (equation (5c)) and the value of productivity losses for all workers (equation (7)) is as seen in Figure 9, Panel a).

As can be seen in Figure 9, changes in productivity losses per worker due to climate changes (shifts in WBGT), considering the whole country (i.e., using weights to add across departments and sectors based on employed in each year), increase substantially by 2100 for the worst climate scenario (SSP58.5). In such circumstances, workers are between 4.9% and 13.9% less productive, depending on the climate model, than if climate did not change. For this most pessimistic climate scenario, agricultural and construction workers are 19.3% less productive, manufacturing workers lose 9% of their productivity, and services ones lose 3.0%. On the other extreme, for the milder climate scenario (i.e., SSP12.6), changes in productivity between the climate change and no climate change cases peak in 2050 and range from 0.20% to 0.64%, depending on the climate model.

Figure 9. Productivity losses

a) Per worker due to climate: average for whole country **b) Value of productivity losses for the whole country (millions of 2015 USD)**



When considering forecasts of people employed and value added per worker, the value of all productivity losses in 2100 for SSP58.5 ranges between 14 billion 2015 US dollars (i.e., 6.3% of GDP) and 38.9 billion 2015 US$ in the worst model estimate, which is equivalent to 17.5% of Paraguay's projected GDP (Figure 9, Panel b). However, Paraguay and central South America in general is expected to suffer more heat stress than other parts of the of the world under SSP58.5 (Legg, 2021), so the estimate obtained is likely. García-León et al. (2021), for example, find that the total estimated damages attributed to heatwaves comparing hot years (2003, 2010, 2015, and 2018) to the historical period 1981–2010 amounts to 0.3–0.5% of European gross domestic product (GDP), but asserts that by 2060 impacts might increase by a factor of almost five compared to the historical period 1981–2010 if no further mitigation or adaptation actions are taken.

4. Conclusions and policy recommendations

Present and future heat is estimated to have an impact on workers' productivity in Paraguay, with the consequent economic losses. There are some caveats in our analysis of the heat direct impacts on productivity, in addition to the fact that it does not include indirect general equilibrium effects (in that sense, it differs from other analysis as Orlov et al. 2020) and workability functions could be different from Paraguay than for those studies behind the Hothaps function. First, the geographical details of the household survey are limited to information of Asuncion and 6 departments (instead of Asuncion and 17 departments), and the remaining one is aggregated under "rest of the country", that we divided in three sections. So, even if the climate data is gridded, the share of employed people per activity is much less granular. This is an issue since, as shown in Figure 4, that rest covers a large area of the territory with different climates. We cannot change that limitation of the household survey, but we believe that it does not undermine our analysis, since the 6 departments plus Asunción identified by the survey are home of 75% of the total population of Paraguay, and generate around that same percentage of GDP (McCord & Rodriguez-Heredia, 2022).[18]

Second, we assume that all workers follow the "4+4+4" rule, which means that, if they work 12 hours a day, they remain 4 hours in mean, max and average between mean and max temperatures. As in the literature, workers allegedly work 365 days a year. We could vary the fractions hours worked in each level of exposure, instead of using 1/3. Our assessment overestimates the impact since, according to the WDI data based on EPHC, in 2019, 32.5% of workers work part-time, and we are assuming that they all work all day.[19] Adjustments can be made to change this assumption.

Third, we group activities, which have 11 branches of activity under the EPHC in 3 main sectors. We do so because productivity loss functions are at that level, but we could keep the 11 sectors and apply to each of them the exposure functions corresponding to each of the 3 sectors (for example, for commerce, apply services, and the same for restaurants and hotels). Some individuals in Asunción and Central department of the people employed do not declare the branch of activity in which they work (this accounts for 0.21% of those employed). For the moment, we omit them instead of assigning them to branches of activities, making a guess that the proportion is the same. Therefore, we are slightly underestimating the productivity impact. We could assign them proportionally to each branch in a new round of calculations. Moreover, individuals´ activity branch is that of their main occupation. Of those employed, 14.4% declare a secondary occupation. And, when considering those who declare their branch of activity belong those who declare it, 70.1% work for the same sector in the primary and the secondary occupation. This assumption could also be changed.

Fourth, we assume that population changes along time but not across scenarios (this was a decision made to match this with the macro modeling), that the share of people employed in each sector

[18] The parameters of the hothaps function could be modified so that with high heat, workers loss all productivity instead of 90%.

[19] Note that, from the EPHC, the number of hours worked varies per sector. Monthly hours worked are: 39 for Agriculture and Construction 39, 46 for Manufacturing and 44 for Services.

is constant along time, and that the number of people employed is constant all the days of the year. If data becomes available, those assumptions could also be changed.

Fifth, in the literature it is standard to use 15 years to determine workability, so we use the same threshold, even if 1.6% of people that appear as employed in the EPHC are between 10 and 14 years old. According to the Paraguay law (https://conaeti.mtess.gov.py/index.php/trabajo-adolescente-protegido/en-que-horario-pueden-trabajar-los-adolescente), citizens between 14 and 15 years can work 4 hs per day, 24 hs a week; between 16 and 17 years they can work 6 hs per day and 36 hs a week; and over 18 years they can work 8 hours per day and 48 hs per week. Hence, it would be possible to change that assumption.

Sixth, value added per worker per sector follow the same growth trajectory as the whole economy. There is no assumption on how the structure of the economy changes along time. This assumption can change if more detailed projections become available.

Finally, adaptation to heat already can be occurring and more is likely to happen. However, we do not have information for Paraguay to take it into account in our calculations, and that implies an overestimation. This happens in many studies on this topic since, as shown by (Zhao et al., 2021b), only in a few cases (3 out of 30 papers reviewed), adaptation can be quantified.

In addition to refining the analysis by considering those caveats, when possible, there are at least three other extensions that we can foresee. One is to perform a Montecarlo sensitivity simulation on the different parameters. Another, more ambitious one, would be to extend this work to other countries so that we can benchmark productivity losses in Paraguay with respect to those happening in other places of the world. It would be relatively easy to do so for those countries in the Socio-Economic Database for Latin America and the Caribbean (SEDLAC), that has information for other 23 countries of the region.[20] This work could also derive in a distributive analysis. Since workers in agriculture and construction have generally lower skills (and, consequently, lower incomes), heat stress impact on those sectors could exacerbate income inequality.

In terms of policy recommendations, voluntary and induced adaptation to heat in labor conditions is possible, and there are several alternatives that have been considered. One is that, whenever possible, people work in the shade instead of the sun (Morabito et al., 2020 and Orlov et al., 2020). One way to do that is to reduce sun exposure in agriculture through mechanization.[21] Another way is the shifting work schedules: working 2 hs earlier (from 8am-5pm to 6am-3pm) reduces costs (Morabito et al., 2020). Parsons et al. (2021) estimates that shifting working hours could imply savings of up to 30% for heavy tasks. A similar result is obtained by working overtime instead of normal hours (Orlov et al., 2020). Takakura et al. (2018) estimates the effect of shifting outdoor work 3 hours earlier: projected GDP losses decreased from 2.8% (1.7%–3.8%) to 1.6% (1.0%–2.4%) under RCP8.5, and from 0.44% (0.41%–0.92%) to 0.14% (0.12–0.47%) under RCP2.6. An alternative for adaptation is to increase training awareness programs, appropriate clothing, or adequate water consumption (Day et al., 2019; Nunfam et al., 2020). In that sense, workplace guidelines are important for minimizing occupational heat stress. Finally, there are options to increase resilience by increasing air conditioning access, solar blinds, indoor ventilation, or insulation through glazing. Air conditioning was potentially the most effective adaptation for industrial

[20] Those countries are: Argentina; Bahamas; Belice; Bolivia; Brazil; Colombia; Costa Rica; Chile; Dominican Republic; Ecuador; El Salvador; Guatemala; Guyana; Haiti; Honduras; Jamaica; Mexico; Nicaragua; Panama; Peru; Suriname; Uruguay; and, Venezuela.

[21] There is a variable in the World Development Indicators database that could be used for mechanization in agriculture, which is the number of tractors per 100 kilometers squares of arable land, but it is quite outdated for all countries in general. For Paraguay, the last information is for 2008.

activities, according to Costa & Floater (2015), who compare the latter four actions in addition to the change in working schedules.

Paraguay has legislation to attenuate occupational risks caused by thermic stress. Decree 390/1992 and law 5804/2017 specifically include a definition of what heat limit is depending on the intensity of the work, the type of protection the employers have to provide depending on water availability, time to rest, availability of specific clothes, etc. However, the share of people informally employed in Paraguay is around 70% as of 2021. This means that, even if legislation for heat stress considerations exist, it covers a small percentage of population. Moreover, even if formality were higher, having labor norms coverage might attenuate the impact of climate change on workers' well-being, but it did not avoid productivity losses that occurred at high level of temperatures. With respect to air conditioning or similar appliances, there is information that approximately 75% of households have air conditioning appliances, but that share is around 20% for Caazapá.[22] In addition, as shown by Davis et al. (2021) for Paraguay, penetration of air conditioning is considerably lower for low income households than for high income ones. Hence, climate change could increase well-being inequality due to differences in access to air conditioning. That type of data is not available for workplaces, but one would expect a similar pattern where small and medium forms have less penetration of air conditioning than large ones.

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Annex A. Input variables

Figure A.1 Relative humidity (%)

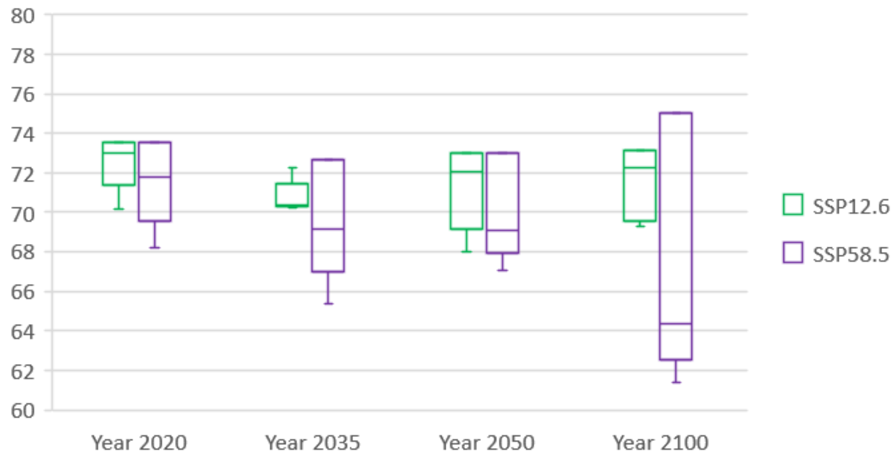


Figure A.2 Wind speed (m/s)

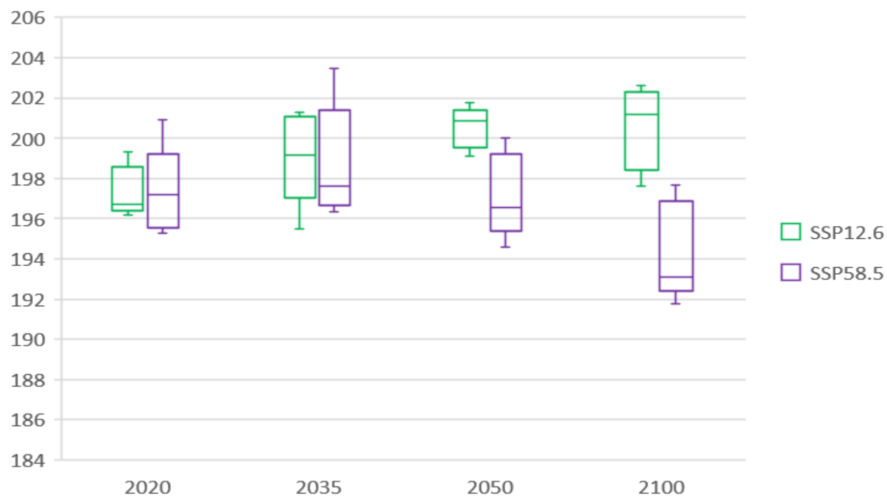
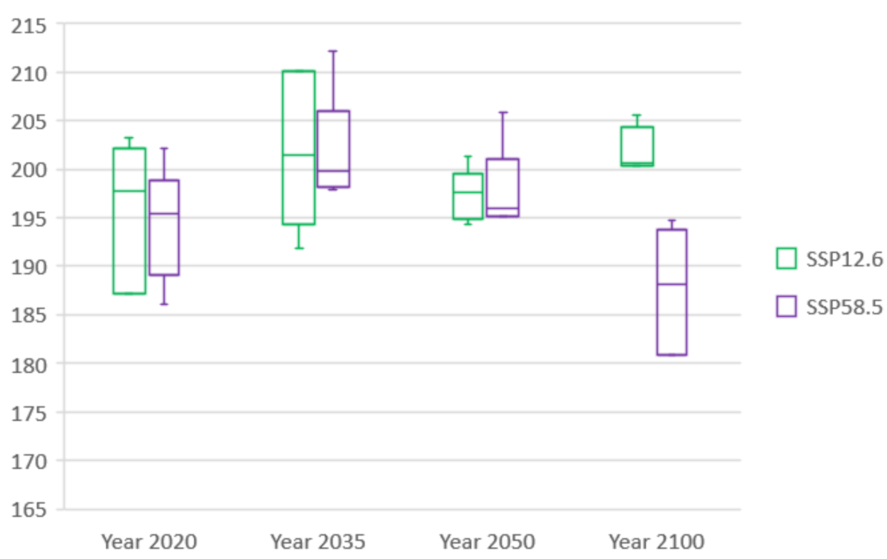


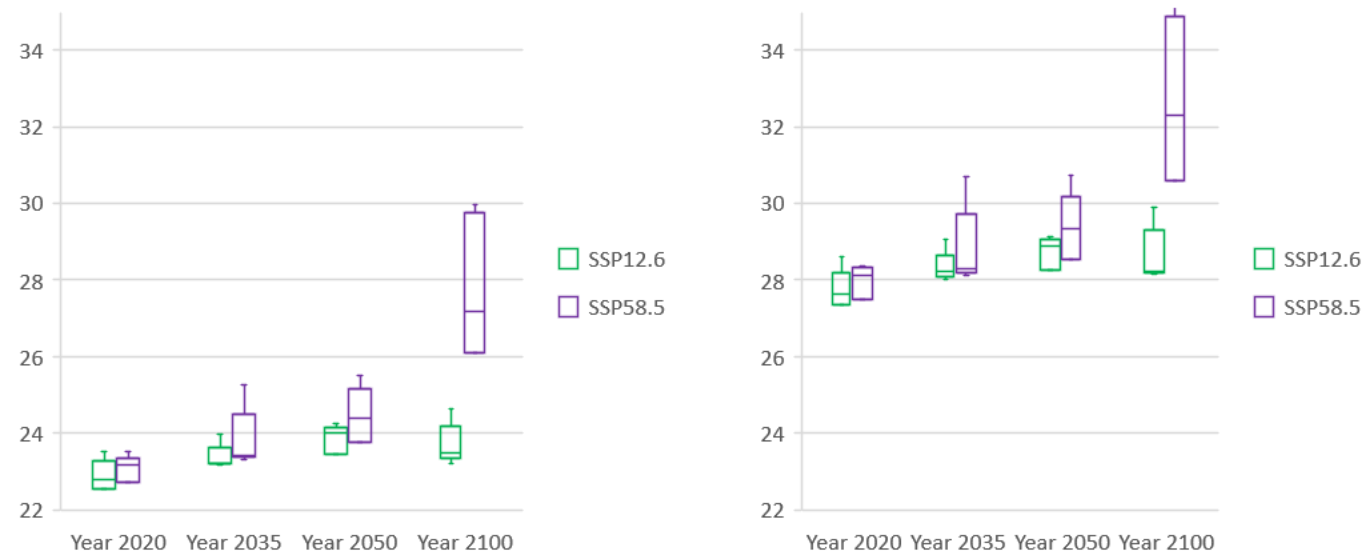
Figure A.3 Solar radiation (W/m2)



Source: Own elaboration.

Figure A.4. Temperature levels

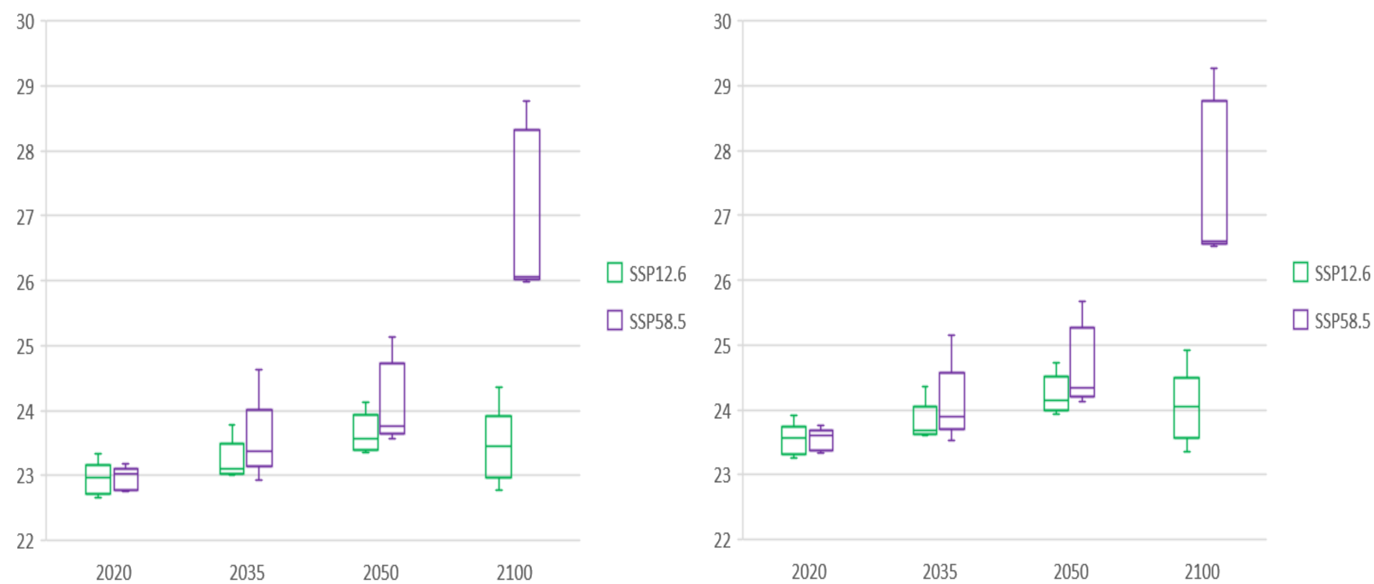
a) Mean temperature (°C) **b) Max temperature (°C)**



Source: Own elaboration.

Figure A.5. WBGTs

a) WBGTShade (°C) **b) WBGTSun (°C)**



Source: Own elaboration.

Anexo B. Additional results

Table B.1. WBGTs per scenario, years for mean across departments: differences across models

		GFDL-ESM4	IPSL-CM6A-LR	MPI-ESM1-2-HR	MRI-ESM2-0	UKESM1-0-LL
WBGT shade (°C)						
SSP126	**2020**	22.78	23.01	22.98	22.65	23.35
	2035	23.00	23.19	23.11	23.06	23.79
	2050	23.56	23.75	23.36	23.44	24.14
	2100	23.16	23.49	22.77	23.46	24.35
SSP585	**2020**	23.04	23.04	22.76	22.81	23.19
	2035	22.94	23.37	23.35	23.41	24.63
	2050	23.76	24.34	23.58	23.73	25.14
	2100	26.04	27.87	26.07	26.01	28.80
WBGT sun (°C)						
SSP126	**2020**	23.40	23.61	23.57	23.27	23.93
	2035	23.61	23.77	23.69	23.68	24.38
	2050	24.16	24.33	23.95	24.07	24.74
	2100	23.79	24.07	23.37	24.09	24.92
SSP585	**2020**	23.62	23.62	23.34	23.42	23.78
	2035	23.54	23.91	23.90	24.02	25.17
	2050	24.32	24.86	24.13	24.36	25.69
	2100	26.55	28.29	26.60	26.62	29.29

Source: Own elaboration.
Note: Red is for maximum and blue for minimum WBGT across models in each year.