Assessment of global climate change impacts on labour productivity

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Abstract

This study assesses the impact of climate change on outdoor labour productivity at the regional-scale and across the globe. It uses five impact models that describe observed relationships between labour productivity and temperature, with climate model simulations from five Global Climate Models (GCMs) under a high emissions scenario (RCP8.5), i.e. 25 climate-impact model combinations. To the authors' best knowledge this is the first assessment of the heat stress and labour productivity to use multiple impact models with multiple climate models. Impacts are estimated for the end of the century (2070-2099) and near-term (2021-2050), relative to present-day (1981-2010). Impacts are assessed without adaptation.

Globally, at the end of the century, the spread in the magnitude of decline in labour productivity across all 25 climate model-impact model combinations is 2-21%.

The impacts of climate change are felt heterogeneously across the globe. At the end of the century the greatest impacts are projected for Mexico, Central America and the Caribbean, and South Africa, where the spreads are 3-32%, 2-32% and 3-31% respectively. The UK and Ireland, and northern Europe, experience the lowest impacts: 0-11% and 0-13% respectively.

Economic implications assessed under a static-comparative framework indicate that mean annual global GDP losses could reach 0.2% in the 2030s and 0.6% by the end of the century. The respective welfare losses are estimated at 0.3% and 1%, respectively. The mean values hide significant heterogeneity across global regions, socio-economic characteristics and the 25-member ensemble of impact projections.

An important conclusion is that the magnitudes of climate uncertainty and impact model uncertainty are comparable for most regions. For example, for India at the end of the century, for one impact model the spread of the decline in labour productivity is 13-22% across climate models; whilst for one climate model, the spread is 3-27% across different impact models. For several regions of the globe, impact model uncertainty is larger than climate model uncertainty. It is strongly recommended, therefore, that future assessments use multiple impact models to sample some of the range in uncertainty that can arise from using different impact models.

Contents

1 Introduction

Climate conditions have an influence on the productivity of workers. Empirical evidence from ergonomics studies show that most forms of human performance, hereafter referred to as labour productivity, generally deteriorate under increasing air temperature beyond a threshold (Hancock et al., 2007; Hancock and Vasmatzidis, 2003; Pilcher et al., 2002; Ramsey and Morrissey, 1978; Witterseh et al., 2004). Wet Bulb Globe Temperature (WBGT), instead of dry-bulb air temperature, is normally used when assessing the relationship between temperature and labour productivity (Budd, 2008).

Evidence for the detrimental effects of increasing temperature on labour productivity are largely from studies conducted within specific working environments, involving office, factory, or outdoor workers respectively (e.g. Federspiel et al., 2002; Jeremiah et al., 2016; Lin and Chan, 2009; Link and Pepler, 1970; Niemelä et al., 2002; Niemelä et al., 2001). There has so far been no effort to design a study that provides empirical evidence for changes in labour productivity with temperature across multiple working environments, locations and countries, using a consistent methodology.

Despite the well-known association between increasing temperature and declining labour productivity, there have been few assessments of the impact of climate change on labour productivity, which combine climate projections with exposure response functions (ERFs) that relate changes in labour productivity to WBGT. Some studies have used ERFs derived from empirical studies in distinct locations (Kjellstrom et al., 2009; Kjellstrom et al., 2013), whilst others have used ERFs developed from meta-analyses (Burke et al., 2015; Hsiang, 2010). In the latter case, the ERF was derived from a meta-analysis of 22 ergonomics studies by Pilcher et al. (2002).

Zivin and Neidell (2015) explore the effects of high temperature on the optimal allocation of time for individuals. The rationale is that higher temperatures can affect the optimal decision regarding the allocation of overall time between labour and leisure, in the edn, leading to productivity losses. That scheme has been used in the US study of climate impacts of Hsiang et al. (2017). The recent analysis of the Climate Impact Risk Assessment 2 (CIRA2) project of the US EPA (Martinich and Crimmins, 2019) follows a similar methodology based on the optimal allocation of time, based also on the analysis of Zivin and Neidell (2015).

Regarding global estimates of labour productivity and climate change, Takakura et al. (2017) compute the cost of preventing heat-related illness when the recommended breaks to reduce the effects of high temperatures are strictly followed. The recommended breaks depend on the work intensity and a measure of heat stress, which depends both on temperature and precipitation. The authors consider that all sectors of the economy are affected. The losses in terms of lower labour are translated into GDP losses with the use of a Computable General Equilibrium (CGE). With a dynamic framework, where economies and population growth, they conclude that under a high emission scenario the global losses could range between 2.6 and 4% of GDP. Those losses would become much less under the 2C scenario, estimated at 0.5%.

A key feature of this study was setting up an ensemble of several published ERFs and various climate models. The ensemble allowed to critically evaluate the utility of different impact models that relate WBGT to labour productivity loss for estimating climate change impacts on labour productivity. The exercise can be viewed as a model inter-comparison sensitivity analysis which illustrates performance of the different impact models when used with a consistent climate signal. Further, thanks to use of the numerous climate models, the results also illustrate behaviour of the impact models under different future climate paths, to provide a measure of climate uncertainty implications on labour productivity.

With exception to Burke et al. (2015) and Houser et al. (2015), climate model uncertainty has been relatively under-sampled in climate change impact assessments for labour productivity. The number of climate models employed in other assessments include: 1 (Dunne et al., 2013; Kjellstrom et al., 2016; Kjellstrom et al., 2013), 2 (Kjellstrom et al., 2009) and 3 (Kjellstrom et al., 2014). Estimates of the impacts of climate change have been shown to be highly sensitive to the driving climate data from climate models so it is important that this source of uncertainty is adequately accounted for. No previous studies have accounted for impact model uncertainty, however, i.e. the application of multiple impact models/ERFs for estimating impacts – the assessment presented here is the first.

In this study the economic welfare effects of declining labour productivity are estimated with the CGE Model, CAGE (Climate Assessment General Equilibrium). The CGE analysis follows a static comparative approach (as in e.g. Aaheim et al., 2012; Hertel et al. 2010; and Ciscar et al. 2012), estimating the counterfactual of future climate change (2030s and 2080s) occurring under current socioeconomic conditions. Therefore, the climate shock-induced changes occur as if in the economy of today.

The document is organised in five additional sections. Section 2 presents the methodology of the study. Section 3 analyses the labour productivity results, while section 4 discusses the key aspects of the methodology affecting the results. Section 5 focuses on the economic analysis of the impacts due to labour productivity changes. Finally, Section 6 concludes with the main take home messages.

2 Methods

2.1 Overall approach

The study used simulations of climate variables from 5 different GCMs to compute daily outdoor WBGT, for the period 1981-2100, on a 0.5° grid across the globe. The WBGT estimates were then used as input to five separate labour productivity-WBGT ERFs to compute daily declines in labour productivity for outdoor workers respectively on the grid. This was done for the following time periods:

- Present-day: 1981-2010
- Near-term: 2021-2050
- End of the century: 2070-2099

The difference in labour productivity between the present period and the climate change period was calculated and represents changes in labour productivity attributable to climate change. Data on present-day population for each grid cell was used to calculate the population-weighted mean regional difference (from present) in outdoor daily average labour productivity due to climate change, for each impact model and GCM.

2.2 Climate models

The study provides a comprehensive assessment of the sensitivity of labour productivity impacts to climate model uncertainty by computing impacts with five GCMs (HadGEM2-ES GCM, IPSL-CM5A-LR, MIROC-ESM-CHEM, GFDL-ESM2 and NorESM1-M), all run under a high emissions scenario (RCP8.5). The choice of the emission scenario allows to consider impacts at higher warming levels which typically exceed 3^{o}C warming at the end of the current century. This set of GCMs has been used in numerous impact assessments as part of the Intersectoral Impact Model Intercomparison Project (ISIMIP) to demonstrate the spread in impacts that can arise from climate modelling uncertainty (Warszawski et al., 2014).

The climate variables from each GCM were bias-corrected towards an observation-based dataset (Weedon et al., 2011), using an established method (Hempel et al., 2013), specifically designed to preserve long-term trends in temperature projections to facilitate climate change impact assessments. The GCM data could therefore be used for the present-day and future time periods in the impact assessment.

NetCDF files for daily maximum surface air temperature, daily minimum surface air temperature, and daily mean relative humidity were downloaded for each GCM from the Earth System Grid Foundation (ESGF), for 1981-2100.

2.3 Calculating WBGT

WBGT was calculated for outdoor (WBGTod) conditions without direct sun exposure (ie: no short wave radiation), from indoor WBGT (WBGTid), following the approximation described by Kjellstrom (2014):

$$\text{WBGTod} = \text{WBGTid} + 3^{0}\text{C}$$

Daily WBGTid was calculated for every 0.5° grid cell from the psychrometric wet bulb temperature (Tw) and daily maximum temperature (Tmax), following the method described by Lemke and Kjellstrom (2012):

$$WBGTid = 0.67Tw + 0.33Tmax$$

Tw was not available from the GCMs so it was estimated empirically from Tmax and daily mean relative humidity (RHmean), following Stull (2011)[1]:

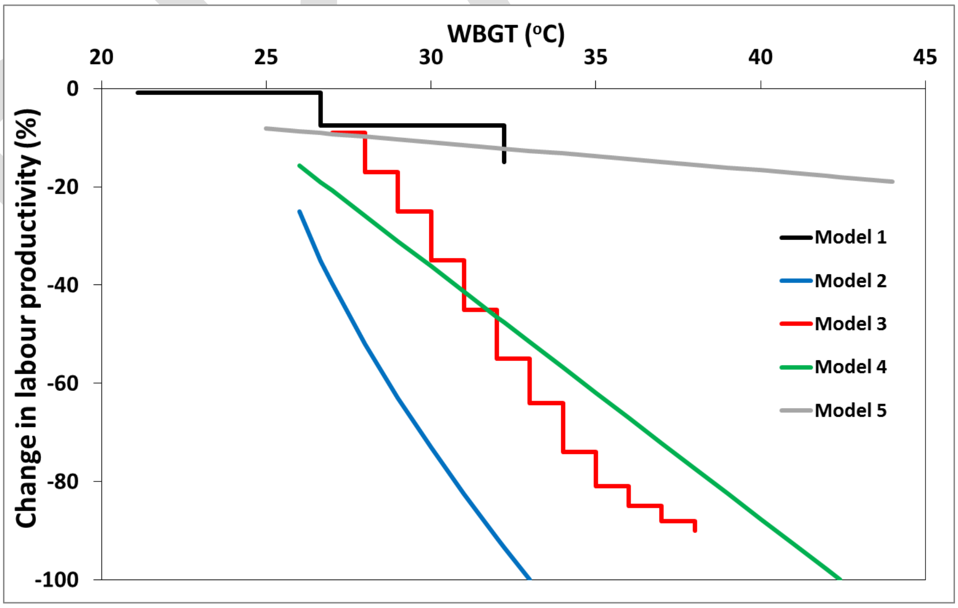
$$Tw = Tmax\ atan[0.151977(RHmean+8.313659)^{1/2}] + atan(Tmax+RHmean) - atan(RHmean-1.676331) + 0.00391838(RHmean)^{3/2}atan(0.023101RHmean) - 4.686035$$

2.4 Impact models

A number of past studies (e.g. Dunne et al. 2013; Burke et al. 2015; Hsiang et al. 2010) have employed different labour productivity impact models for the purpose of labour productivity climate change impact assessment. This study extends the relevant research by bringing together several impact models previously used in climate change impacts assessments.

The impact models are ERFs that describe relationships between labour productivity and WBGT. The application of different impact models for the first time provides a demonstration of the uncertainty in impact projections that can arise from using different ERFs. Five impact models were employed in the study, with significant heterogeneity. Figure 1 represent the ERF for all the impact models; the vertical axis refers to the productivity loss in percentage terms, while the horizontal scale displays the WBGT in degrees Celsius. The threshold temperatures above which labour productivity starts to decline are where the lines begin on the left. At the end of each line on the right, it is assumed that the line becomes horizontal with increasing WBGT.

Figure 1. The five impact models.



[1] This equation combines the maximum daily temperature and average daily relative humidity as only the average humidity data was available. This data limitation could lead to an overestimation of the psychometric wet bulb temperature as the two constituents are inversely related in the diurnal cycle and, optimally, a sub-daily data on the relative humidity should be used. In this study, however, this does not translate to a systematic overestimation in the effects of climate change on labour productivity, because the climate change impacts were estimated relatively, i.e. compared to present-day simulated labour productivity, and because the impact models are not highly non-linear.

The first impact model (model 1, black line in Figure 1) is an ERF developed by Pilcher et al. (2002), which has been used in two recent climate change impact assessments (Burke et al., 2015; Hsiang, 2010). The ERF is a step-function developed from a meta-analysis of 22 studies that report associations between labour productivity and WBGT. A more recent meta-analysis (Hancock et al., 2007) was consulted but crucially it does not present the results as an ERF.

The ERF described by Pilcher et al. (2002) does not differentiate between the intensity of work being undertaken by the worker – other ERFs do, e.g. the third model used in this study (Kjellstrom et al., 2014). This is because the meta-analysis only considered how certain types of task were effected by increases in WBGT. The ERF covers four types of tasks: reaction time tasks, attentional or perceptual tasks (e.g., vigilance, tracking or acuity tasks), mathematical tasks (e.g., multiplication or adding tasks, identifying lower versus higher numbers), and reasoning, learning, or memory tasks (e.g., logic tasks, word recall tasks). Therefore the first ERF is quite different from the other four used in this study, because the other four have been created to specifically describe the relationship between WBGT and physical labour. Nevertheless, the ERF defined by Pilcher et al. (2002) is used in this study because of its application in two recent prominent assessments of the impacts of climate change on labour productivity (Burke et al., 2015; Hsiang, 2010). Moreover, it is the only ERF used in this study that is derived from a systematic meta-analysis of empirical evidence published in the peer-reviewed literature.

The second impact model (blue line in Figure 1) is an ERF developed by Dunne et al. (2013), which is based upon National Institute for Occupational Safety and Health (NIOSH) standards and combines light, moderate and heavy labour into a single metric by a non-linear regression equation along a continuum from 25°C to 32.2°C (Figure 1). The decline in labour productivity is calculated as:

$$\text{Decline in labour productivity (\%)} = 100 - (100 - (25 \times \max(0, \text{WBGT} - 25)^{2/3}))$$

If WBGT is less than 25°C then there is no loss in labour productivity. If WBGT is greater than 33°C, then the decline in labour productivity is 100%.

Dunne et al. (2013) notes that the ERF derives from a comprehensive attempt by NIOSH (1986) to synthesize available knowledge on the effect of temperature on productivity in hot and humid conditions, to yield a single recommendation on work limits with general applicability. This resulted in the establishment of safety thresholds applicable to healthy, acclimated labourers, sustainable over an 8-hour work period.

The second impact model displays the highest sensitivity of all the impacts models employed in this assessment (Figure 1). Beyond the 33°C limit, the threshold implies that no amount of labour can be safely sustained over a typical 8 hour work period. Dunne et al. (2013) explains that this has been observed in several studies described by NIOSH (1986) including a study of iron, ceramics, and quarry workers (Nag and Nag, 2009) that showed beyond the exercise regime of around 1 hour, the threat of heat exhaustion and other medical effects requires a switch in the mode of labour, away from the sustainable thresholds they define in the ERF, and towards a focus on more short-term thermal stress accumulation where the labourer is closely monitored and allowed to actively dissipate accumulated heat stress over long periods of recovery. As far as can be ascertained, the original ERF applied by Dunne et al. (2013), and the method by which it was derived, is not described in a peer reviewed journal.

The third impact model (red line in Figure 1) uses one of three ERFs developed by Kjellstrom et al. (2014), which are based upon three ISO standard work intensity levels (Parsons, 2006): 200 W (assumed to be office workers in the service industry, engaged in light work indoors), 300 W (assumed to be industrial workers, engaged in moderate work indoors) and 400 W (assumed to be construction or agricultural workers, engaged in heavy work outside), and three studies that report observed declines in labour productivity with increasing temperature (Nag and Nag, 1992; Sahu et al., 2013; Wyndham, 1969). The ERF for heavy work only is used in this assessment because it corresponds to the type of work conducted by the study participants that were used to develop all the other impact models (except the first model). A limitation with the third impact model is that the empirical evidence used to develop the ERF is from studies in highly distinct locations, including a gold mine (Wyndham, 1969), 124 rice harvesters in West Bengal in India (Sahu et al., 2013), and six women observed in a climatic chamber (Nag and Nag, 1992).

To explore how impacts estimated from one of the ERFs that informed the third impact model, compares with estimates from it, and the other impact models, the fourth impact model is based upon empirical evidence reported by Sahu et al. (2013) (green line in Figure 1). The authors investigated high heat exposure during agricultural tasks in India. They observed that worker productivity reduced by approximately 5.14% for each 1°C increase in WBGT above 26°C. Sahu et al. (2013) developed a linear regression model that is applicable for workers who have worked for 5-hours or more. The loss in productivity can be calculated for all WBGT values greater than or equal to 26°C and less than 42.4°C (above 42.4°C the decline is 100%). The decline in labour productivity is calculated as:

$$\text{Decline in labour productivity (\%)} = 100 - ((-5.14 * \text{WBGT}) + 218)$$

The fifth impact model (grey line in Figure 1) uses some of the latest empirical evidence on how labour productivity is affected by high temperatures. Li et al. (2016) observed a 0.57% decrease in productivity for every 1°C rise in WBGT above 25°C, for re-bar workers (heavy labour) in China. The decline in labour productivity can be calculated for all WBGT values greater than or equal to 25°C as:

$$\text{Decline in labour productivity (\%)} = 100 - ((-0.57 * \text{WBGT}) + 106.16)$$

Whilst the fourth and fifth impact models are derived from empirical evidence, reported in peer reviewed journals, they are specific to certain types of heavy labour, within distinct climates, and with particular workers. In contrast, the first and third impact models were derived from multiple sources of empirical evidence.

The present assessment assumes that relationships between WBGT and labour productivity observed at the local scale, for distinct locations, types of labour and specific individuals (e.g. 16 rebar workers in China (Li et al., 2016)), can be scaled-up for all types of labour, the general population, and across the globe. Thus it is assumed that the estimated impacts for outdoor labour productivity are applicable to all economic sectors that involve moderate to intense outdoor working, including agriculture and construction.

In order to allow implementation of the impact models until the end of the current century when the temperature increase reaches beyond 3^{o}C, some of the ERFs were extended beyond their calibration range. Extrapolation of Models 4 and 5 was necessitated by the fact that in practice, labour productivity would decline further beyond the upper temperature of the calibration limit – stopping at the calibration limit would likely have underestimated the effect of WBGT on labour productivity loss. It is for this reason that previous climate change health studies have extrapolated temperature-health relationships beyond the empirical calibration limits (e.g. Gasparrini et al. 2017; Dessai 2003; Gosling et al. 2009,2016).

Model 4 (Sahu et al. 2013) was calibrated between 26-32°C and extrapolated here to 100% decline in labour productivity, which occurs at 42.4°C, for the same reasons as outlined for Model 5. Inspection of Figures 3 and 4 from Kjellstrom et al. (2014) suggests that linear extrapolation of the linear function from Sahu et al. (2013) would still broadly follow the S-shape of other functions however, so it is likely that any difference in labour productivity loss relative to using an S-function is minor. Model 5 (Li et al., 2016) was extrapolated beyond its calibration limits (25-29°C), assuming a linear growth, because there was no evidence to indicate the shape of an S-curve for this study. The assumption of the linear growth beyond 29°C built on other climate change impact studies (e.g. Hsiang et al. 2010) which have used linear functions up to over 35°C.

Nonetheless, as the true relationships could be S-shaped, it is possible that labour productivity loss is still underestimated. Other factors that could mean the impacts of WBGT on labour productivity are underestimated include the effects of an ageing population and population general health (e.g. personal fitness), which were not accounted for in the projections.

2.5 Population data

Present-day population data on a 0.5° resolution grid that matched the GCM grid was obtained from the Socioeconomic Data and Applications Centre (SEDAC) Gridded Population of the World (SEDAC, 2017). In line with some past climate change impact assessments for labour productivity (e.g. Dunne et al., 2013), population remained stationary at present-day levels under the climate change scenarios.

The gridded population data was used to calculate mean regional population-weighted labour productivity impacts attributable to climate change. The regions and countries that comprise them are displayed in Table 1.

Table 1. The regions and comprising countries that were used for the computation of mean regional population-weighted labour productivity impacts attributable to climate change.

Region	Countries included in region
China	China
Japan	Japan
Korea	Korea
Indonesia	Indonesia
Russia	Russia
India	India
USA	USA
Canada	Canada
Mexico	Mexico
Brazil	Brazil
South Africa	South Africa
UK & Ireland	UK, Ireland
Northern Europe	Denmark, Estonia, Finland, Lithuania, Latvia, Sweden
Central Europe (North)	Poland, Netherlands, Luxembourg, Germany, Belgium
Central Europe (South)	Austria, Czech Republic, France, Hungary, Romania, Slovakia, Slovenia, Croatia
Southern Europe	Bulgaria, Cyprus, Spain, Greece, Italy, Malta, Portugal
Australasia	Australia, New Zealand, rest of Oceania
South Asia	Bangladesh, Iran, Sri Lanka, Nepal, Pakistan, rest of South Asia
Sub-Saharan Africa	Botswana, Cote d'Ivore, Cameroon, Ethiopia, Ghana, Kenya, Madagascar, Mozambique, Mauritius, Malawi, Namibia, Nigeria, Senegal, Tanzania, Uganda, South Central Africa, Central Africa, rest of Eastern Africa, Rest of South African Customs Union, Rest of Western Africa, Zambia, Zimbabwe
Rest of Europe	Albania, Switzerland, Norway, Rest of Eastern Europe, Rest of EFTA, Rest of Europe
Rest of South-east Asia	Cambodia, Laos, Mongolia, Malaysia, Philippines, Singapore, Thailand, Taiwan, Vietnam, Rest of East Asia, Rest of Southeast Asia, Rest of the World
Rest of Former USSR	Armenia, Azerbaijan, Belarus, Georgia, Kazakhstan, Kyrgyzstan, Ukraine, Rest of Former Soviet Union
Middle East & North Africa	United Arab Emirates, Bahrain, Egypt, Israel, Kuwait, Morocco, Oman, Qatar, Saudi Arabia, Tunisia, Turkey, Rest of North Africa, Rest of Western Asia
Central. America & Caribbean	Costa Rica, Guatemala, Honduras, Nicaragua, Panamá, El Salvador, Rest of Central America, Caribbean, Rest of North America
Rest of South America	Argentina,Bolivia, Chile, Colombia, Ecuador, Peru, Paraguay, Uruguay, Venezuela, Rest of South America

Note: The choice of regional aggregation (25 regions) was decided according to the following criteria. Firstly, the major individual countries in the climate negotiations have been included separately; therefore Brazil, Canada, China, India, Indonesia, Japan, Korea, Mexico, Russia, South Africa and the USA are included individually. The European Union has been split into five regions: UK and Ireland, Northern Europe, Central Europe (North), Central Europe (South) and Southern Europe. The remaining regions have been split geographically and are Australasia, Rest of South Asia, Rest of sub-Saharan Africa, Rest of Europe, Rest of South-East Asia, Rest of Former Soviet Union, Middle East & North Africa, Central America & Caribbean and South America.

2.6 Impact model evaluation

The five impact models are based upon empirical evidence of associations between labour productivity and WBGT, and/or safety thresholds for conducting work in hot and humid environments. Thus they are conceptually different from physically based impact models such as hydrological models and crop yield models, which tend to be based upon model parameters that represent physical processes and therefore require calibration and evaluation for tuning model parameters. The labour productivity models are synonymous with other human health impact models that are not generally evaluated, such as temperature-mortality models, which are constructed from empirical data for specific locations, using established epidemiological statistical techniques (Baccini et al., 2008; Gasparrini et al., 2015). Moreover, the labour productivity models cannot be evaluated for the locations where they were derived because this would involve evaluating the models against their training data. Furthermore, the original datasets from which the models were derived are not readily available, which precludes an evaluation of the impact models with techniques such as split-sample evaluation.

3 Results

3.1 Outdoor labour productivity

Table 1 shows regional differences (from present) in outdoor labour productivity for the near future (2030s) and end of century (2080s) time horizons.

Table 1: Regional differences (from present) in daily minimum, average and maximum outdoor labour productivity due to climate change, from the ensemble of 25 climate-impact models combinations.

Region	2030s			2080s		
	min	**mean**	max	min	**mean**	max
China	-0.6	-3.2	-7.5	-1.7	-9.3	-19.7
South-east Asia	-0.6	-3.9	-9.7	-1.5	-10.1	-24.8
South-west Asia	-0.8	-4.2	-8.8	-2.3	-12.5	-24.2
India	-0.6	-4.3	-9.3	-2.2	-13.1	-26.7
Indonesia	-0.5	-3.4	-10.1	-1.1	-8.4	-24.9
Japan	-0.4	-2.4	-5.8	-1.6	-8.1	-18.1
Korea	-0.6	-3.1	-7.5	-1.6	-9.1	-19.0
Australia and Oceania	-0.6	-2.8	-6.0	-1.6	-8.5	-18.3
USA	-0.7	-3.5	-7.6	-2.2	-10.2	-20.5
Canada	-0.4	-1.9	-5.2	-1.1	-6.9	-17.6
Mexico	-1.0	-5.6	-12.8	-2.6	-15.6	-32.3
Central America and Caribbean	-0.8	-5.8	-13.5	-2.1	-15.2	-31.8
South America	-0.8	-3.9	-8.5	-2.2	-11.3	-22.0
Brazil	-0.5	-4.8	-10.7	-2.1	-14.2	-28.9
Sub-Saharan Africa	-0.7	-4.9	-11.7	-2.0	-13.8	-29.9
Middle East & North Africa	-0.8	-4.2	-9.4	-2.2	-12.0	-25.2
South Africa	-0.9	-4.8	-10.9	-2.9	-15.1	-31.0
Northern Europe	-0.2	-0.9	-4.2	-0.4	-3.5	-12.6
UK & Ireland	-0.1	-0.8	-3.4	-0.4	-2.9	-10.3
Central Europe North	-0.4	-1.6	-4.7	-0.9	-5.6	-16.1
Central Europe South	-0.5	-2.4	-6.6	-1.3	-7.5	-19.9
Southern Europe	-0.5	-2.8	-8.1	-1.6	-8.4	-21.4
Rest of Europe	-0.4	-1.9	-5.0	-1.2	-6.2	-16.9
Rest of FSU	-0.5	-2.6	-6.6	-1.6	-7.8	-19.8
Russia	-0.4	-1.8	-5.3	-1.0	-5.8	-17.2
Global	***-0.7***	***-3.7***	***-7.5***	***-1.9***	***-10.8***	***-20.5***

Figure 2 shows, for the end of the century, the mean regional differences (from present) in daily average outdoor labour productivity due to climate change. Figure 3 shows the results for near future.

The impacts of climate change on labour productivity are larger at the end of the century than they are in the near-term. For the three most sensitive impact models (Models 2, 3 and 4), the impacts are around 10% points larger at the end of the century than in the near-term. For the two least sensitive impact models (Models 1 and 5), the impacts are around 3% points larger at the end of the century.

There is large uncertainty in the impacts as a result of using different impact models. The impacts are smallest with the two least sensitive impact models. At the end of the century, the impact of climate change on labour productivity is typically less than a 5% decline in all regions. The impacts are considerably larger according to the other three impact models and are generally within the range of 10-30% declines in labour productivity due to climate change.

A similar degree of uncertainty regarding the productivity impacts is due to using multiple GCMs. Moreover, the magnitudes of GCM and impact model uncertainty are comparable for most regions. For example, for India at the end of the century, for one impact model (Model 2) the spread of the decline in labour productivity is 13-22% across climate models; whilst for one climate model (HadGEM2-ES), the spread in impacts is 3-27% across different impact models.

There is significant variation in the magnitude of impact across regions at the end of the century. The three regions that experience the largest impacts are Mexico, Central America and the Caribbean, and South Africa, where the spread in the magnitude of decline in labour productivity across all 25 climate-impact model combinations is 3-32%, 2-32% and 3-31% respectively. In contrast, the two regions that experience the least impacts are UK and Ireland, and northern Europe, where the spreads of declines in labour productivity are 0-11% and 0-13% respectively. For comparison, the spread in impacts globally is 2-21%.

Figure 2. End of century mean regional differences (from present) in daily average outdoor labour productivity due to climate change.

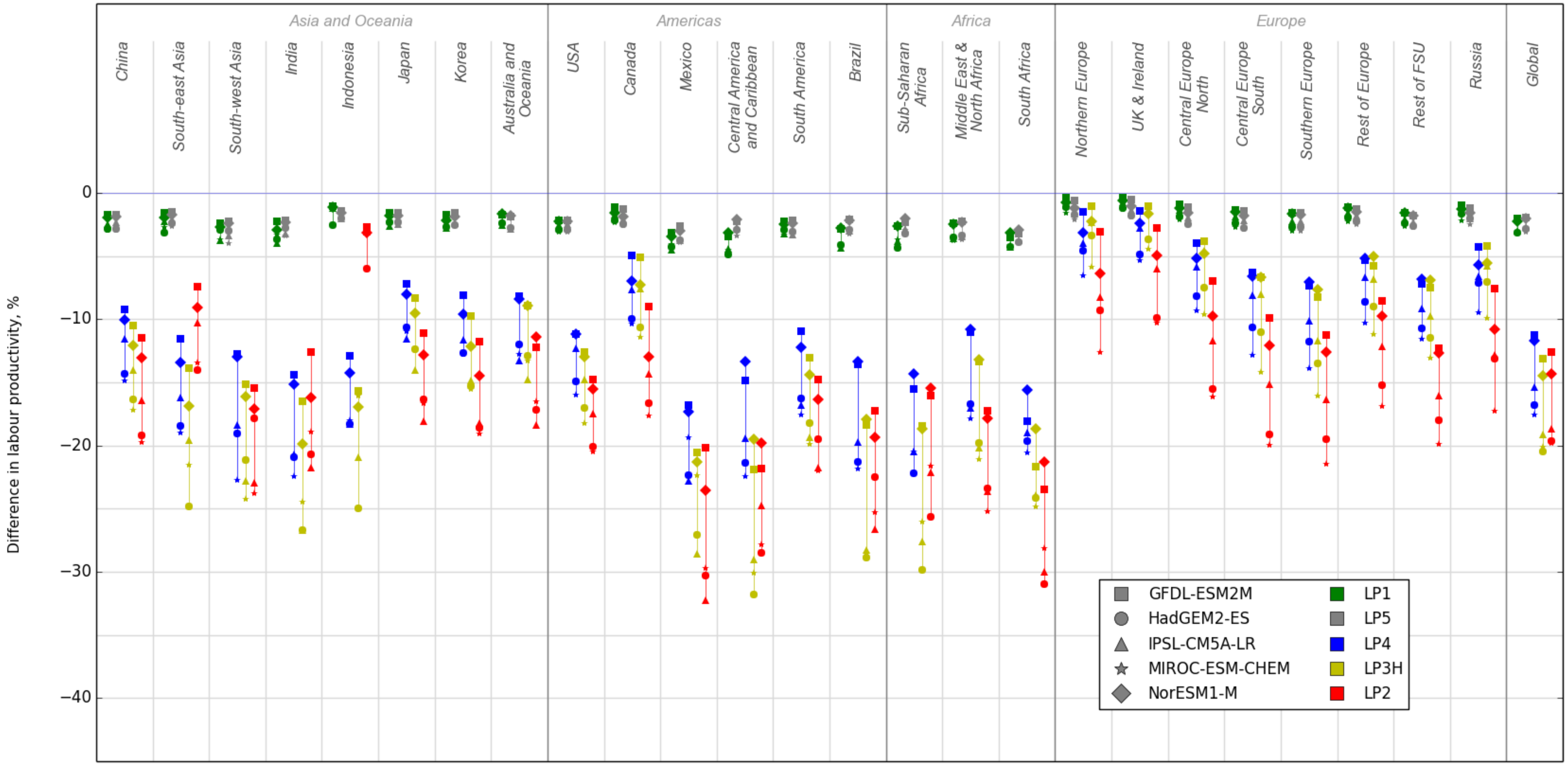
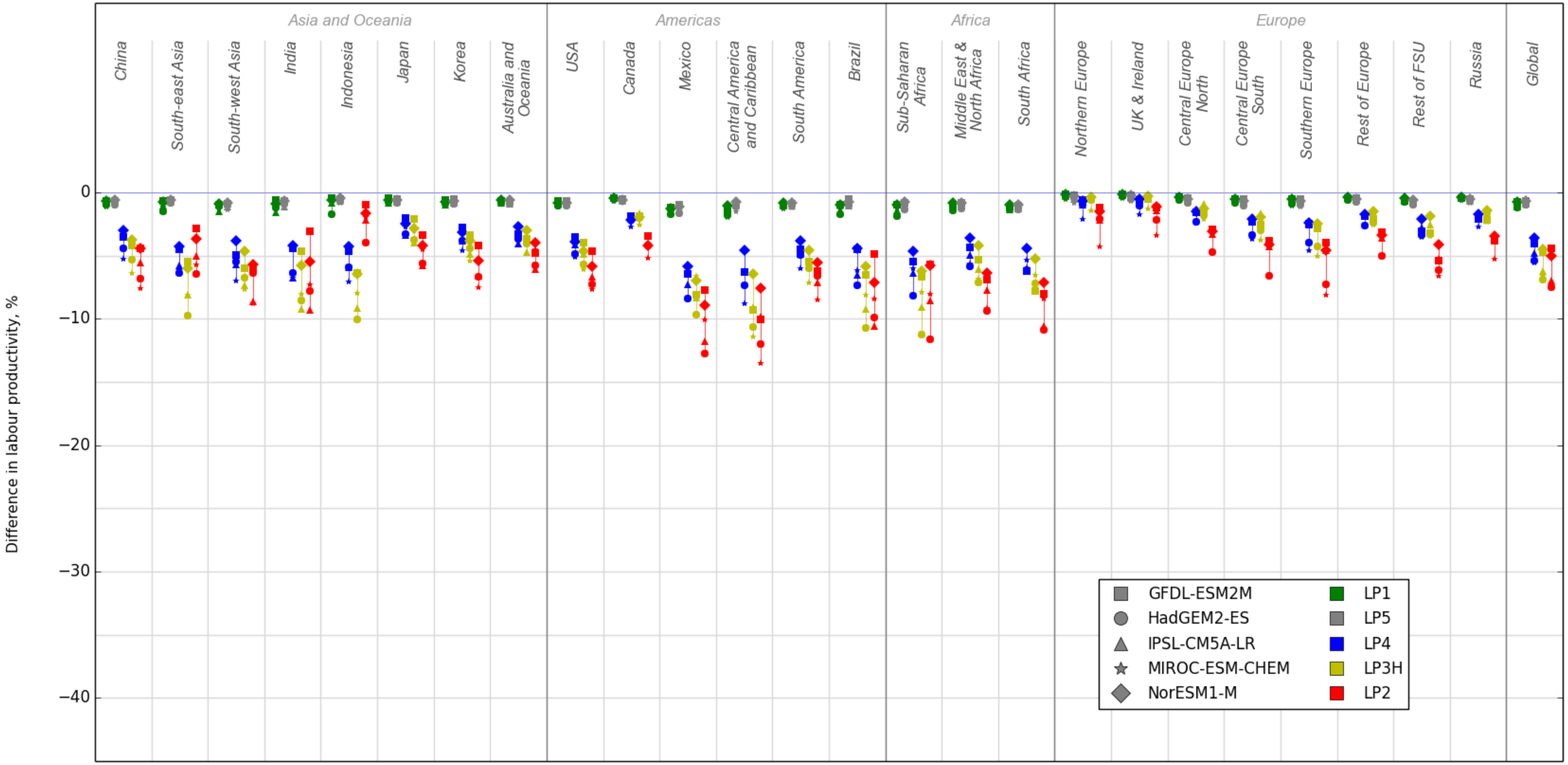


Figure 3. Near future mean regional differences (from present) in daily average outdoor labour productivity due to climate change.



4 Economic implications

This section presents estimates of economic implications of changes in labour productivity for near term (2030s) and end of century (2080s) scenarios. The results reflect changes in productivity of labour in construction and agriculture sectors. The analysis of climate impacts follows a static comparative approach, estimating the counterfactual of future climate change occurring under the current socioeconomic conditions. Therefore, the changes induced by climate shock would occur in the economy as of today. The economic model is run for the full ensemble of all 25 climate-impact model combinations. The mean, minimum and maximum estimates from the ensemble are discussed here.

4.1 The economic model

The economic simulations have been performed with the CAGE[2] Computable General Equilibrium (CGE) model, which is a static multi-country, multi-sector CGE model of the world economy linking the economies through endogenous bilateral trade. The CAGE database is mainly based on the Global Trade Analysis Project (GTAP) database, version 8 (Narayanan et al., 2012). The model's overview is provided in the Appendix and the full model description and mathematical model statement is provided in the Annex of Pycroft et al. (2015).

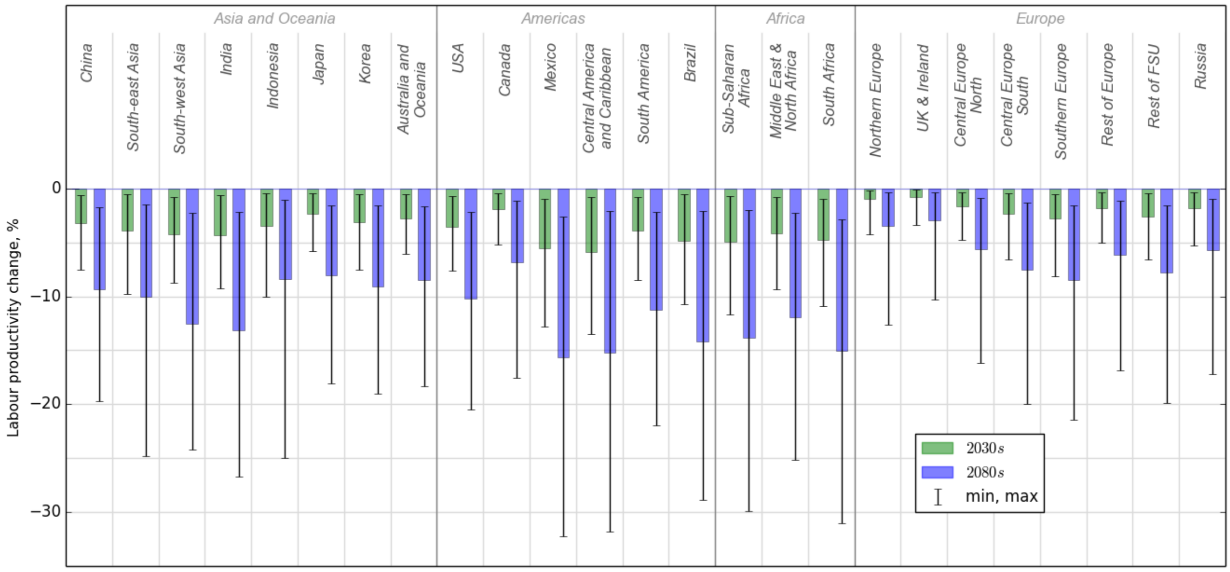
4.2 Integration with economic model

The direct impact represents the productivity change of a unit of labour, and it is integrated within production process in the economic model as the change in productivity of labour endowment. The sectors affected by the labour productivity shocks are construction and agriculture. In those sectors labour is subject to intensive physical work performed outdoors. The magnitude of the economy-wide impact will depend, inter alia, on the labour intensity of the affected sectors and the relative sizes of the sectors in the economy.

Figure 4 summarises the shocks introduced to the CGE model, representing percentage loss in labour productivity for the world regions (reflecting the labour productivity loss discussed in section 3.1).

[2] See Appendix. The full model description and mathematical model statement is provided in the Annex of Pycroft et al. (2015).

Figure 4: Change in labour productivity (the bars represent mean values). %.



4.3 Economic results

The change in labour productivity constitutes the shock to the CAGE CGE model. The model was solved separately for each of the 25 impact-climate model combinations, and the results present the maximum, mean and minimum of each of the set of results.

Table 2 and Figure 5 show GDP losses of the world regions for the 2030s and the 2080s. In the 2030s the mean global GDP reduction is 0.22%, equivalent to more than €100 billion. However, there is a large range in the loss across the 25-member ensemble. When taking the maximum estimate of loss in labour productivity from the ensemble, the GDP reduction more than doubles compared to the mean value, to €258 billion.

The end-of-century (2080s) sees far more significant impacts of labour productivity losses on GDP than in the near future, with a mean global GDP loss of €348 billion, up to a maximum of €822 billion. The mean value represents 0.7% of GDP, a lower estimate that the cost of Takakura et al. (2017). That might be due to several reasons: first, this study assumes that only the agriculture and construction sectors are affected, rather than all economic sectors as in the Takakura et al. study; second, this assessment is static while that of Takakura et al. is dynamic, where GDP and population change in time.

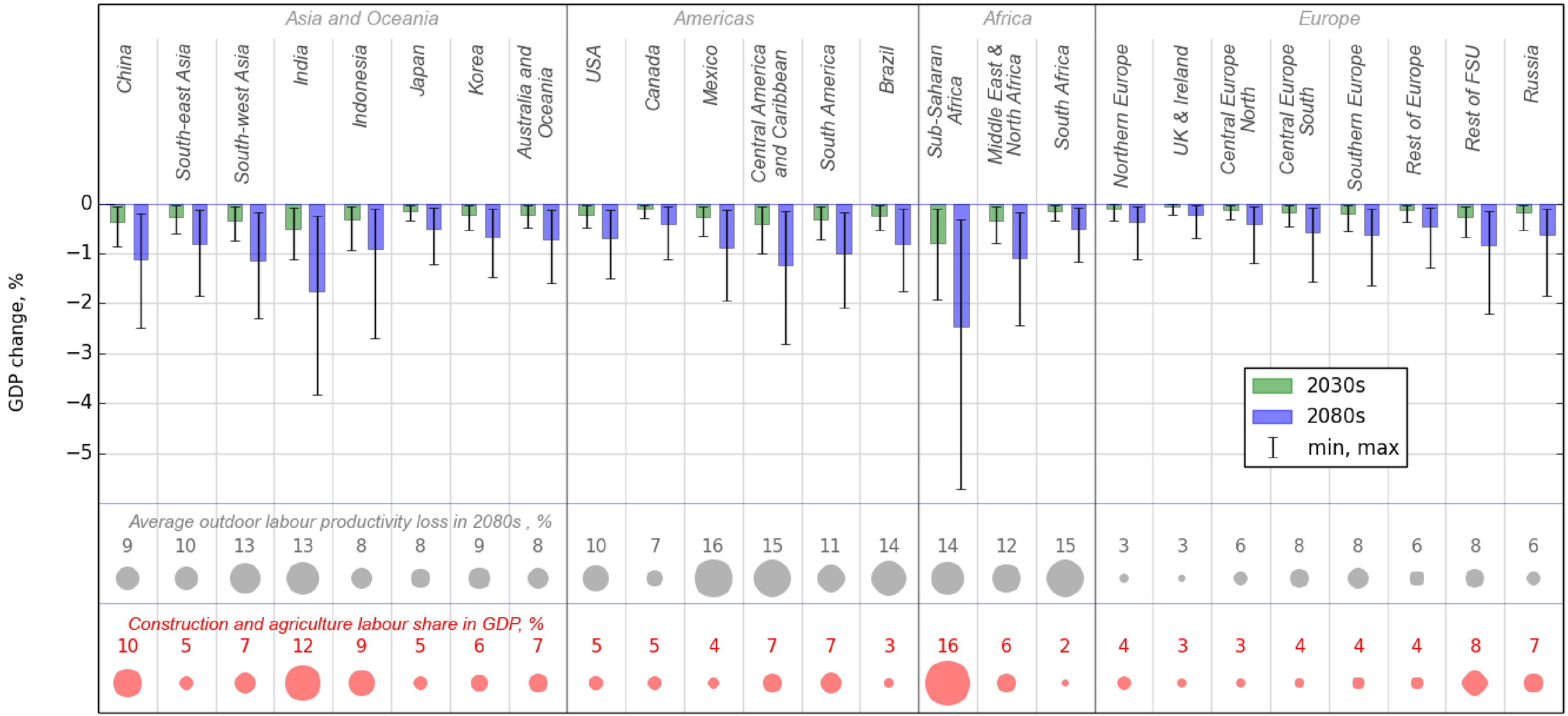
Table 2: Change in GDP for different scenarios

Region	percentage change						bn €					
	2030s			2080s			2030s			2080s		
	min	**mean**	max	min	**mean**	max	min	**mean**	max	min	**mean**	max
China	-0.1	-0.4	-0.8	-0.2	-1.1	-2.5	-2	-11	-27	-6	-35	-78
South-east Asia	0.0	-0.3	-0.6	-0.1	-0.8	-1.8	0	-3	-7	-1	-9	-20
South-west Asia	-0.1	-0.3	-0.7	-0.2	-1.1	-2.3	0	-2	-4	-1	-5	-11
India	-0.1	-0.5	-1.1	-0.2	-1.8	-3.8	-1	-5	-12	-3	-19	-40
Indonesia	0.0	-0.3	-0.9	-0.1	-0.9	-2.7	0	-1	-4	0	-3	-10
Japan	0.0	-0.1	-0.3	-0.1	-0.5	-1.2	-1	-5	-13	-3	-20	-47
Korea	0.0	-0.2	-0.5	-0.1	-0.7	-1.5	0	-2	-5	-1	-6	-13
Australia and Oceania	0.0	-0.2	-0.5	-0.1	-0.7	-1.6	0	-2	-4	-1	-7	-14
USA	0.0	-0.2	-0.5	-0.1	-0.7	-1.5	-5	-27	-61	-16	-88	-188
Canada	0.0	-0.1	-0.3	-0.1	-0.4	-1.1	0	-1	-4	-1	-5	-14
Mexico	0.0	-0.3	-0.6	-0.1	-0.9	-1.9	0	-2	-6	-1	-8	-18
Central America and Caribbean	-0.1	-0.4	-1.0	-0.1	-1.2	-2.8	0	-1	-3	0	-4	-10
South America	-0.1	-0.3	-0.7	-0.2	-1.0	-2.1	-1	-3	-7	-2	-9	-19
Brazil	0.0	-0.2	-0.5	-0.1	-0.8	-1.8	0	-3	-6	-1	-10	-21
Sub-Saharan Africa	-0.1	-0.8	-1.9	-0.3	-2.5	-5.7	-1	-4	-10	-2	-13	-29
Middle East & North Africa	-0.1	-0.3	-0.8	-0.2	-1.1	-2.4	-1	-7	-15	-4	-21	-48
South Africa	0.0	-0.1	-0.3	-0.1	-0.5	-1.2	0	0	-1	0	-1	-3
Northern Europe	0.0	-0.1	-0.3	0.0	-0.4	-1.1	0	-1	-3	0	-3	-11
UK & Ireland	0.0	-0.1	-0.2	0.0	-0.2	-0.7	0	-2	-6	-1	-6	-20
Central Europe North	0.0	-0.1	-0.3	-0.1	-0.4	-1.2	-1	-6	-15	-3	-19	-54
Central Europe South	0.0	-0.2	-0.5	-0.1	-0.6	-1.6	-1	-6	-15	-3	-19	-52
Southern Europe	0.0	-0.2	-0.5	-0.1	-0.6	-1.6	-1	-7	-20	-4	-23	-62
Rest of Europe	0.0	-0.1	-0.4	-0.1	-0.5	-1.3	0	-1	-3	-1	-4	-11
Rest of FSU	0.0	-0.3	-0.7	-0.2	-0.8	-2.2	0	-1	-2	0	-3	-7
Russia	0.0	-0.2	-0.5	-0.1	-0.6	-1.8	0	-2	-6	-1	-7	-20
Global	-0.04	-0.22	-0.49	-0.12	-0.70	-1.57	-19	-106	-258	-57	-348	-822

In terms of relative GDP losses (i.e. percentage terms), Sub-Saharan Africa is the most affected region, both in the 2030s (0.8%) and 2080s (2.5%). It is also the only region to potentially undergo a loss greater than 2% of its GDP by the end of the century. Regions which have more than 1% GDP loss by the 2080s are China (1.1%), India (1.8%), Central America and Caribbean (1.2%), and Middle East and North Africa (1.1%). In Europe the effects of climate change are greater at lower latitudes compared to higher latitudes, e.g. at end of the century 0.2% in UK and Ireland compared with 0.6% in Southern Europe.

In terms of absolute GDP losses (i.e. €) around 40% of global GDP losses occur in the Americas, with a further 30% lost in Asia and Oceania, 20% in Europe, and 10% in Africa.

Figure 5. Change in GDP, %



The magnitude of economy-wide impact will depend, inter alia, on labour productivity loss in each of the regions (Figure 4), and on the labour intensity of the affected sectors and their relative sizes in the economy.

The complementary information presented at the lower part of Figure 5 assists in explaining the regional economic effects. The grey circles indicate the average labour productivity loss in the 2080s and the red indicators show a share of each region's GDP contributed by the affected labour in the construction and agricultural sectors.

The region with the largest GDP loss, Sub-Saharan Africa, does not experience the biggest productivity reductions but it has a very large share of its workforce, 16%, employed in the two affected economic sectors. Other regions with high labour productivity losses, e.g. Mexico (16%), Central America and Caribbean and South Africa (15%), have a much smaller proportion of their workforce employed in construction and agriculture, hence the 'weight' placed on the productivity loss is smaller and the resulting GDP loss is also smaller.

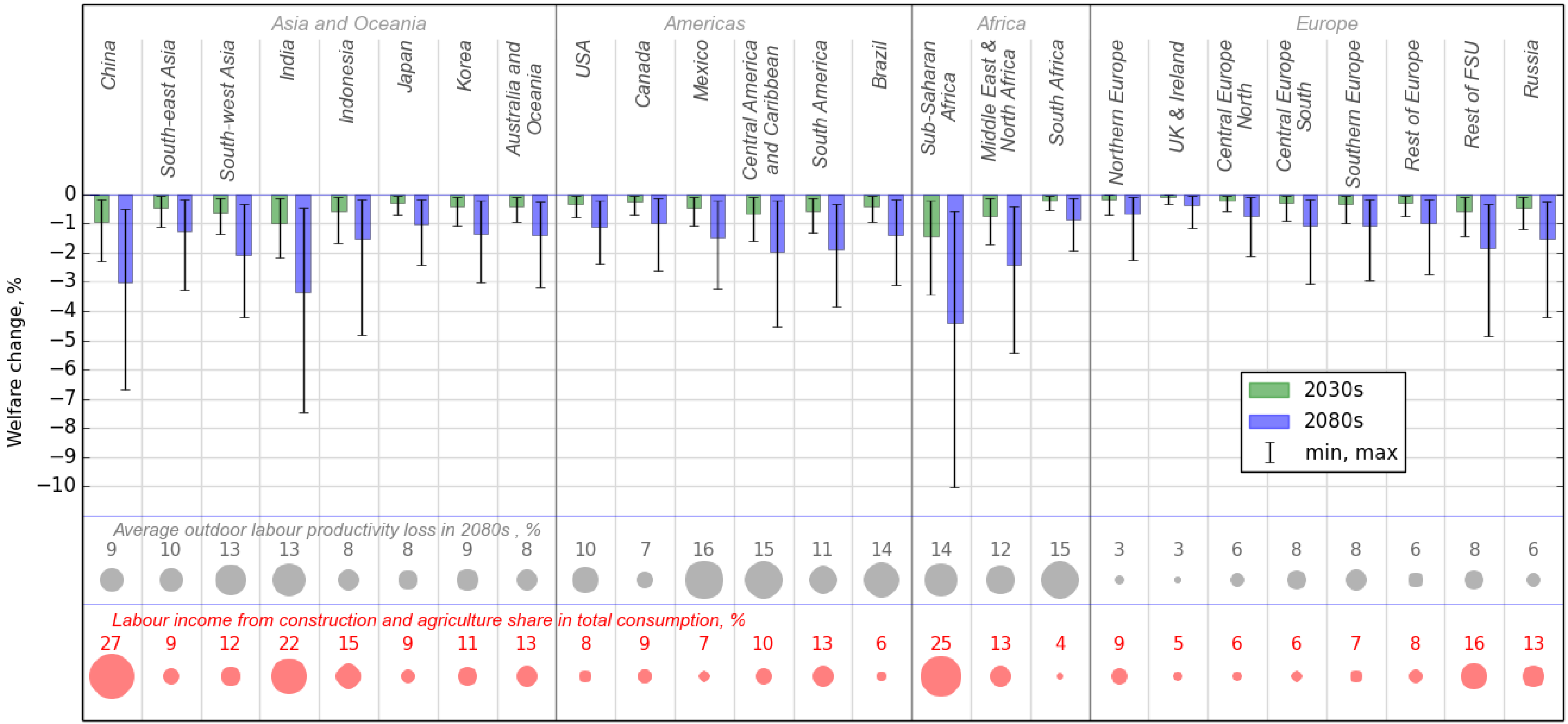
The welfare effects (Table 3 and Figure 6) are similar in value terms to the GDP losses, however they are much larger when expressed in proportional terms because the households' consumption (against which the welfare loss is measured) is only one of the components of GDP. Taking the mean declines in labour productivity from the 25-member ensemble, the global welfare reductions are 0.4% in the 2030s and 1.3% in the 2080s. If the maximum productivity losses are assumed, then the welfare losses are 0.9% and 2.9% respectively.

Table 3: Change in welfare for different scenarios

Region	percentage change						bn €					
	2030s			2080s			2030s			2080s		
	min	**mean**	max	min	**mean**	max	min	**mean**	max	min	**mean**	max
China	-0.2	-1.0	-2.3	-0.5	-3.0	-6.7	-2	-11	-27	-6	-35	-78
South-east Asia	-0.1	-0.4	-1.1	-0.2	-1.3	-3.3	0	-2	-6	-1	-7	-18
South-west Asia	-0.1	-0.6	-1.3	-0.3	-2.1	-4.2	0	-2	-4	-1	-6	-12
India	-0.1	-1.0	-2.2	-0.5	-3.4	-7.4	-1	-6	-13	-3	-20	-44
Indonesia	-0.1	-0.6	-1.7	-0.2	-1.5	-4.8	0	-1	-4	0	-3	-10
Japan	-0.1	-0.3	-0.7	-0.2	-1.0	-2.4	-1	-6	-14	-4	-21	-49
Korea	-0.1	-0.4	-1.1	-0.2	-1.4	-3.0	0	-2	-5	-1	-6	-14
Australia and Oceania	-0.1	-0.4	-0.9	-0.2	-1.4	-3.2	0	-2	-4	-1	-7	-15
USA	-0.1	-0.3	-0.8	-0.2	-1.1	-2.4	-5	-28	-62	-17	-89	-190
Canada	-0.1	-0.3	-0.7	-0.1	-1.0	-2.6	0	-2	-5	-1	-6	-17
Mexico	-0.1	-0.5	-1.1	-0.2	-1.5	-3.2	0	-2	-6	-1	-8	-18
Central America and Caribbean	-0.1	-0.7	-1.6	-0.2	-2.0	-4.5	0	-2	-4	-1	-5	-11
South America	-0.1	-0.6	-1.3	-0.3	-1.9	-3.8	-1	-3	-7	-2	-10	-20
Brazil	0.0	-0.4	-1.0	-0.2	-1.4	-3.1	0	-3	-6	-1	-9	-20
Sub-Saharan Africa	-0.2	-1.4	-3.4	-0.6	-4.4	-10.0	-1	-4	-11	-2	-14	-32
Middle East & North Africa	-0.1	-0.8	-1.7	-0.4	-2.4	-5.4	-1	-7	-17	-4	-24	-53
South Africa	0.0	-0.2	-0.6	-0.1	-0.9	-1.9	0	0	-1	0	-1	-3
Northern Europe	0.0	-0.2	-0.7	-0.1	-0.6	-2.3	0	-1	-3	0	-3	-10
UK & Ireland	0.0	-0.1	-0.4	0.0	-0.4	-1.1	0	-2	-6	-1	-6	-19
Central Europe North	0.0	-0.2	-0.6	-0.1	-0.7	-2.1	-1	-5	-14	-3	-18	-53
Central Europe South	-0.1	-0.3	-0.9	-0.2	-1.1	-3.1	-1	-6	-16	-3	-19	-55
Southern Europe	-0.1	-0.3	-1.0	-0.2	-1.1	-2.9	-1	-7	-21	-4	-23	-62
Rest of Europe	-0.1	-0.3	-0.8	-0.2	-1.0	-2.7	0	-1	-3	-1	-5	-12
Rest of FSU	-0.1	-0.6	-1.5	-0.3	-1.8	-4.9	0	-1	-3	-1	-3	-9
Russia	-0.1	-0.5	-1.2	-0.2	-1.5	-4.2	-1	-2	-7	-1	-8	-23
Global	-0.1	-0.4	-0.9	-0.2	-1.3	-2.9	-19	-108	-266	-58	-355	-845

Regionally, the largest welfare losses are in Sub-Saharan Africa (1.4% in 2030s and 4.4% in 2080s), India (1% in 2030s and 3.4% in the 2080s), China (1% in 2030s and 3% in 2080s), and in Middle East and North Africa (0.8% and 2.4%). Other world regions see welfare losses below 1% in the 2030s. By the end of the century, most of the regions in the Americas and in Africa lose between 1-2% of welfare. In Europe the welfare loss is below 1.5% with exception to Rest of the FSU where the loss is 1.8%.

Figure 6. Welfare change, %



Since welfare, as measured here, reflects changes in real consumption, it will depend not only on the size of the productivity reduction among workers employed in construction and agricultural sectors, but also on the share of total consumption financed from construction and agricultural wages.

For example Sub-Saharan Africa's mean welfare loss is 4.4% by the 2080s, which results from 14% productivity reduction in construction and agricultural labour and from a high share of consumption financed by labour from those two sectors (25%). By contrast, South Africa faces a 15% reduction in outdoor labour productivity but because only 4% of income comes from outdoor employment, the 'weight' placed on the productivity loss is much smaller and the aggregate welfare loss is 0.9%.

It should be stressed that the reported GDP and welfare results reflect regional averages, which is underpinned by more heterogeneous effects that vary nationally and sub-nationally, across sectors and across demographics.

5 Discussion

5.1 Selection of impact models

A large spread in impacts is projected with the different impact models, for any given climate model. This highlights the likely underestimation of impacts in earlier studies that have used only one impact model (e.g. Burke et al., 2015; Hsiang, 2010). Whilst the approach used in this study is not exhaustive, because not every ERF ever developed was applied, the study does show for the first time, the choice of impact model can have a significant effect on the projected impacts of climate change on labour productivity. Other researchers are therefore encouraged to account for this significant source of uncertainty in future work.

Nevertheless, it is acknowledged that more impact models could have been used, such as those reported by Graff Zivin and Neidell (2014) and used by Houser et al. (2015). However, a balance needs to be struck between several competing factors: the number of impact models included, computational resources, and the form of the impact models. This is why only five impact models were used here. More specifically, all the impact models applied here, describe the relationship between WBGT and percentage changes in labour productivity. The model described by Graff Zivin and Neidell (2014), for instance, differs from these five in two fundamental ways: 1) it is based upon identifying the incremental influence of daily maximum temperature, not WBGT; and 2) it estimates the effects of maximum temperature on the number of minutes individuals work, not specifically a change in productivity in percentage terms. This is no more an advantage or a disadvantage over the approach used in the present assessment; it is a different methodology. However, to maintain a degree of consistency between the impact models used in the present study, only models that report changes in labour productivity in percentage terms and with WBGT were included.

5.2 Calculation of WBGT

Daily maximum WBGT and daily minimum WBGT was calculated from daily maximum temperature and minimum temperature respectively, with mean daily relative humidity in both cases, because daily maximum and minimum relative humidity was not available from the GCMs. However, this inherently assumes that the daily peaks and troughs respectively, in temperature and humidity, occur at the same time of the day. They could, however, occur several hours apart. The highest temporal-resolution data available from the GCMs employed in this study was daily. It was not possible, therefore, to estimate WBGT more precisely. An alternative approach to estimating WBGT more precisely could involve calculating it from daily mean vapour pressure, which could be calculated from dewpoint temperature and daily maximum temperature, following Buck (1981). There is very little diurnal cycle in vapour pressure and so it is suitable for calculating WBGT at maximum temperature (Eurocontrol, 2011). However, bias corrected daily dewpoint temperature was not available from the GCMs used.

Thus there is likely to be a small error in the magnitude of daily maximum and minimum WBGT estimated from the climate models relative to what would actually be observed. To understand the magnitude of this error requires an evaluation using higher temporal resolution empirical data, ideally at hourly or 15-minute resolution. The magnitude of error could vary spatially across the globe, so the errors would need to be evaluated across the global domain, for multiple locations, to facilitate a robust analysis. This would require significant resource, because weather observations from multiple meteorological stations across the globe would need to be downloaded, quality controlled, and analysed. The magnitude of error between bias corrected simulated WBGT and observed WBGT would also need to be compared. The variety of methods that can be used to estimate WBGT (Lemke and Kjellstrom, 2012) would compound the evaluation further. Such an evaluation is beyond the remit of this study. The authors are not aware of a study that has conducted such an evaluation, so this is a worthwhile avenue for further research.

5.3 Economic analysis

The economic analysis benefits from the richness of the ensemble's labour productivity results as the economic model is implemented for each of the climate-model impact-model combinations. This rage of results provides a measure of how the uncertainty in the climate and impact models translates into socio-economic results. Use of the economic model allows to simulate climate-induced regional labour productivity changes within the specific regional economic circumstances viz. bring into the analysis factors such as the actual amount of the labour affected, relative size of the construction and agricultural sectors, and a share of household income due to wages from those sectors. Importance of consideration of the economic environment is demonstrated by illustrating how a similar change in labour productivity can imply different welfare and GDP effects in different regions.

The economic model is implemented in a static comparative mode - consistent with the labour productivity computations – and basically answers the question 'what the current economy would look like if the future climate occurs today?' The static approach does not account for dynamic effects such as changes in composition of economy, changes in population and labour characteristics or capital investment. On the other hand it allows to avoid bringing into the analysis an additional uncertainty associated with development of future economic projections.

Finally, the economic modelling accounts for private[3] adaptation by having firms and households reacting to changes in price signals resulting from the productivity shock. The modelling does not account, however, for any planned adaptation or technical progress which would alleviate negative consequences of the increased heat stress.

[3] Also referred to as autonomous or automatic adaptation.

6 Conclusions

This is the first global-scale climate change impact assessment for labour productivity using multiple climate models with multiple impact models. It is also the first to assess the economic impacts in such a way.

This approach has yielded an important conclusion: impact model uncertainty and climate model uncertainty are comparable in magnitude. Moreover, for several regions of the globe, impact model uncertainty is larger than climate model uncertainty. It is strongly recommended, therefore, that future assessments of both labour productivity and its economic impacts use multiple impact models to sample some of the range in uncertainty that can arise from using different impact models.

Climate change is associated with declines in labour productivity across the globe but the magnitude of impact is heterogeneous. The largest impacts are seen in Mexico, Central America and the Caribbean, and South Africa, whilst the least impacts are seen in the UK and Ireland, and northern Europe.

The economic impacts of declining labour productivity with climate change could be substantial. The uncertainty range is large, however. The ensemble of 25 climate-impact models suggests a reduction in global GDP by the end of the century of between €57-822 billion.

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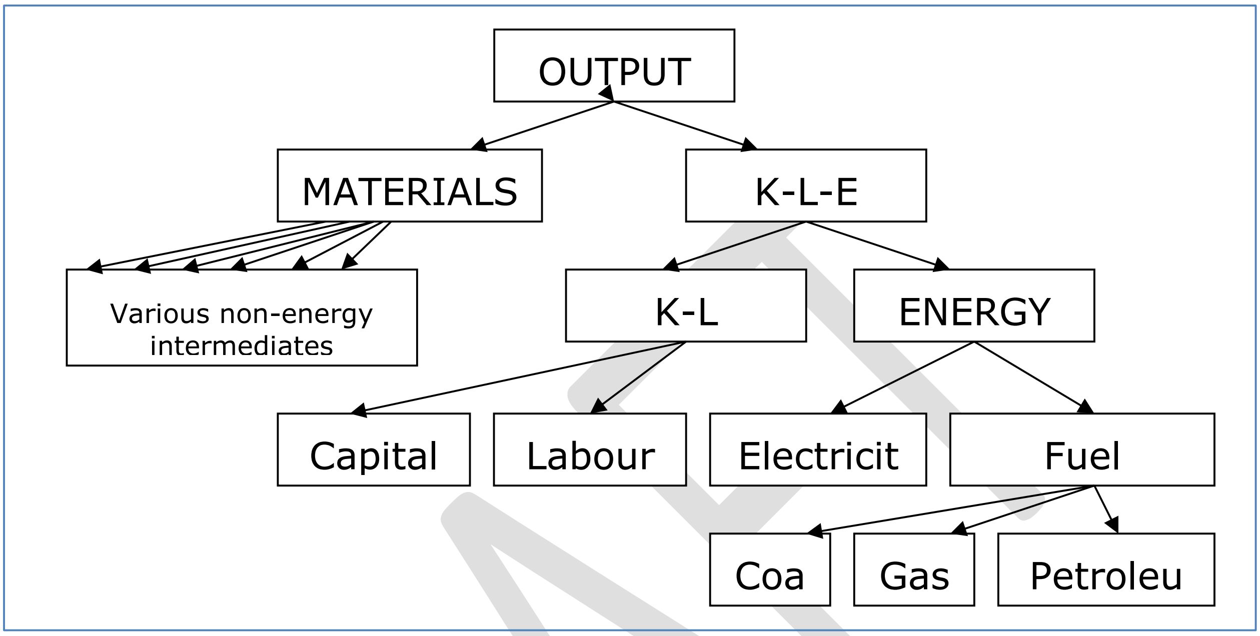
7 Appendix: Description of the CAGE-GEME3 model

Producers seek to maximise profits subject to their production technology and the cost of inputs. The production technology is modelled using a nested constant elasticity of substitution (CES) function which is summarised in below.

Figure 7: Production structure in the CAGE model



Note: K-L-E refers to the capital-labour-energy bundle and K-L to the capital-labour bundle.

As shown, output is produced by combining capital (K) and labour (L) with energy (E) and other intermediate inputs. All combinations of inputs are treated as imperfect substitutes, as governed by CES functions (though some are given low elasticity values to reflect low levels of substitutability).

All commodities enter the marketplace. Production from each country can be sold either within that country or exported. Similarly, the purchase of goods and services can be either of domestic production or imports. Total domestic demand consists of that from households, government, investment, intermediate inputs, and inputs for transport margins used for trade. The extent to which this domestic demand is satisfied by imports or domestic production is governed by a two-level constant elasticity of substitution function reflecting the imperfect substitutability at both levels. On the lower level, imports from different regions are combined, and on the upper level, the composite import commodity is combined with domestic production (the Armington function, Armington, 1969).

The economic institutions included in the model are households, government, firms and the rest of the world. Households purchase marketed commodities at market prices, meaning that the prices include commodity taxes. Households maximise their utility or well-being based on their preferences and the relative prices of goods and services, subject to their income constraints. Household consumption also has a nested structure, with households first choosing between energy and non-energy commodities and then on consumption within these categories. Substitutability within each nest is determined by a constant elasticity of substitution function.

There are general constraints to the system (which are not directly considered by any of the particular economic agents). The zero profit constraint in production is imposed as firms are assumed to operate in a competitive environment. There are also zero profit constraints on domestic economic institutions – households, governments and investment – which mean that all income to institutions must be accounted for with either spending or saving. With respect to imports and transport margins, the zero profit conditions imply that their prices are also constrained to match their costs, inclusive of margins and taxes, as appropriate.

The macroeconomic closure rules govern the savings-investment behaviour, aggregate government finances, the behaviour of factor markets and the trade balance between each country and the rest of the world. The savings-investment closure maintains a constant volume of investment, and any change in the price of investment goods is adjusted for by changing the value of household savings. The government closure allows public consumption to be flexible in terms of quantity, then any additional revenue to government raises government income, and hence raises government expenditure. In that case, government consumption is modelled with a Leontief function, i.e. an increase (fall) in government expenditure proportionally increases (decreases) consumption of all commodities. The factor-market closure fixes the aggregate volume of both capital and labour at the regional level. Both capital and labour can move between sectors, however capital and labour are immobile across regions. Thus, returns to capital and wage rate of labour adjust to clear the market, and the wage and capital prices are region specific. The rest-of-the-world closure fixes the current account balance between regions at the benchmark level, with prices adjusting to ensure that all production from each region is either consumed domestically or exported.

Table 4: List of region-codes and geographical aggregation.

Region	***List of countries***
China	China
Japan	Japan
Korea	Korea
Indonesia	Indonesia
Russia	Russia
India	India
USA	USA
Canada	Canada

Mexico	Mexico
Brazil	Brazil
South Africa	South Africa
UK & Ireland	UK, Ireland
Northern Europe	Denmark, Estonia, Finland, Lithuania, Latvia, Sweden
Central Europe (North)	Poland, Netherlands, Luxembourg, Germany, Belgium
Central Europe (South)	Austria, Czech Republic, France, Hungary, Romania, Slovakia, Slovenia, Croatia
Southern Europe	Bulgaria, Cyprus, Spain, Greece, Italy, Malta, Portugal
Australasia	Australia, New Zealand, rest of Oceania
South-west Asia	Bangladesh, Iran, Sri Lanka, Nepal, Pakistan, rest of South Asia
Sub-Saharan Africa	Botswana, Cote d'Ivore, Cameroon, Ethiopia, Ghana, Kenya, Madagascar, Mozambique, Mauritius, Malawi, Namibia, Nigeria, Senegal, Tanzania, Uganda, South Central Africa, Central Africa, rest of Eastern Africa, Rest of South African Customs Union, Rest of Western Africa, Zambia, Zimbabwe
Rest of Europe	Albania, Switzerland, Norway, Rest of Eastern Europe, Rest of EFTA, Rest of Europe
South-east Asia	Cambodia, Laos, Mongolia, Malaysia, Philippines, Singapore, Thailand, Taiwan, Vietnam, Rest of East Asia, Rest of Southeast Asia, Rest of the World
Rest of Former Soviet Union	Armenia, Azerbaijan, Belarus, Georgia, Kazakhstan, Kyrgyzstan, Ukraine, and other countries from the rest of Former Soviet Union
Middle East & North Africa	United Arab Emirates, Bahrain, Egypt, Israel, Kuwait, Morocco, Oman, Qatar, Saudi Arabia, Tunisia, Turkey, Rest of North Africa, Rest of Western Asia
Central. America & Caribbean	Costa Rica, Guatemala, Honduras, Nicaragua, Panamá, El Salvador, Rest of Central America, Caribbean, Rest of North America
Rest of South America	Argentina, Bolivia, Chile, Colombia, Ecuador, Peru, Paraguay, Uruguay, Venezuela, Rest of South America

Table 5: List of sector codes and sectoral aggregation

Aggregation	***Constituent sectors***
Agriculture	Bovine cattle, sheep and goats, horses, animal products nec, raw milk, wool, silk-worm cocoons, fishing
Crops	Paddy rice, wheat, cereal, grains nec, vegetables, fruit, nutsv oil seeds, sugar cane, sugar beet, plant-based fibers, crops nec
Forestry	Forestry
Coal Mining	Coal
Crude Oil Extraction	Oil
Natural Gas	Gas, gas manufacture, distribution

Refined Oil	Petroleum, coal products
Electricity	Electricity
Metals	Ferrous metals, metals nec, metal products
Chemicals	Chemical, rubber, plastic products
Energy Intensives	Minerals nec, paper products, publishing, mineral products nec
Electronic equipment	Electronic equipment
Transport Equipment	Motor vehicles and parts, transport equipment nec
Other Equipment	Machinery and equipment nec, manufactures nec
Consumer Goods	Bovine meat products, meat products nec, vegetable oils and fats, airy products, processed rice, sugar, food products nec, beverages and tobacco products, textiles, wearing apparel, leather products, wood products
Construction	Construction
Transport	Transport nec, water transport, air transport
Market Services	Water, trade, communication, financial services nec, insurance, business services nec, dwellings
Non-market Services	Recreational and other services, public administration, Defense, Education, Health

List of abbreviations and definitions

ERFs: exposure response functions

ESGF: Earth System Grid Foundation

GCMs: Global Climate Models

ISIMIP: Intersectoral Impact Model Intercomparison Project

NIOSH: National Institute for Occupational Safety and Health

RCP: Representative Concentration Pathway

RHmean: daily mean relative humidity

Tmax: daily maximum temperature

Tw: psychrometric wet bulb temperature

WBGT: Wet Bulb Globe Temperature

WBGTid: indoor WBGT

WBGTod: outdoor WBGT