Climate Change, Population Growth, and Population Pressure*

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Abstract

We develop a novel method for assessing the effect of constraints imposed by spatially-fixed natural resources on aggregate economic output. We apply it to estimate and compare the projected effects of climate change and population growth over the course of the 21st century, by country and globally. We find that standard population growth projections imply larger reductions in income than even the most extreme widely-adopted climate change scenario (RCP8.5). Climate and population impacts are correlated across countries: climate change and population growth will have their most damaging effects in similar places. Relative to previous work on macro climate impacts, our approach has the advantages of being disciplined by a simple macro growth model that allows for adaptation and of assessing impacts via a large set of climate moments, not just annual average temperature and precipitation. Further, our estimated effects of climate are by construction independent of country-level factors such as institutions.

1 Introduction

Climate change over the coming decades will affect the ability of land to support the lives and livelihoods of much of the world's population. In some cases, climate change will literally make land unlivable, for example by putting it underwater. Far more frequently, however, climate change will make land *less* livable or productive. This is most obvious in the case of agricultural productivity, which will be strongly affected by changes in rainfall and temperature. In addition, climate change may lower the quality of life in given regions or require the expenditure of additional resources to maintain a specific quality of life. Beyond reductions in the standard of living, these changes are expected to impact the frequency of conflict as well as flows of population, including migrants and refugees.

Many, though not all, of the economic and social effects of climate change can be understood through the lens of population pressure on fixed local factors of production. The distribution of population in space reflects heterogeneity in these factors: some places are more productive and easier to live in than others, and the places where life and production are easier tend to be where people concentrate. Climate change will alter some of these characteristics, making some locations more attractive and others less so. A decline in the services provided by local fixed factors, what we call the "quality" of land, means that the standard of living will decline or that some of people in a location will be induced to move elsewhere.

In this paper, we introduce a new methodology for projecting the economic impact of forecast changes in climate. Our methodology takes advantage of spatial variation in characteristics that will be altered by climate change in order to estimate weights on different climate components. Notably, we use a large set of climate indicators from global climate models that goes beyond simple annual averages of temperature and precipitation used in most existing research, to include intra-annual variation in both temperature and precipitation, frequency of temperature extremes, and suitability for many specific crops, among other measures. We econometrically assign weights to these multiple dimensions based on their effects on the within-country spatial distribution of population observed today. We pair the results of this econometric exercise with a macroeconomic growth model, which allows us to examine, among other things, the effects of within-country labor mobility.

Our paper makes two contributions. This first is the production of a new set of projections of the economic impact of climate change, at the grid cell, country, and world levels. The general tenor of the projections that we produce is in line with a good deal of previous work, specifically in finding that negative

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economic effects of climate change will be most severe in poorer and hotter countries, while several colder regions may benefit. But there are significant quantitative differences between our findings and previous research.

The second contribution is to bring together the analysis of climate change and population growth into a single framework, through the lens of population pressure on local resources. Population pressure rises when land quality declines or when population size rises. Our framework allows us both to study the combined impact of these two forces, and to compare their relative magnitudes. Many of the countries expected to suffer degradation in land quality due to climate change are also expected to see large increases in the population that will be reliant on that land, and the increase in population pressure due to having more people to support is on average larger than the increase due to degradation of land quality. Similarly, looking across the range of population and climate projections, uncertainty regarding the effect of population on economic outcomes appears to be bigger than uncertainty regarding the effect of climate.

The rest of this paper is structured as follows. Section 2 briefly reviews the literatures on the effects of both climate change and population growth on economic outcomes. Section 3 discusses our methodology for estimating land quality and how it will be affected by projected climate change. In section 4, we present our estimates of climate effects on land quality at the world, continent, and country levels. Section 5 lays out the economic model that is used to map from changes in climate and population into changes in GDP per capita, and also discusses the role of within-country labor mobility as means of adapting to climate change. Then section 6 presents projected country-level impacts from climate change alone as well as from climate and population combined. This section also discusses variability across climate and population projections. Section 7 aggregates projected damages from climate change to the world level, to facilitate comparison with other estimates. Section 8 concludes.

2 Previous Literature

2.1 Climate change

The economic effects of climate change are frequently summarized in the form of a damage function that relates the loss in GDP relative to what it would have been in the absence of climate change, on the one hand, to the extent of climate change, as summarized by as the increase in atmospheric carbon dioxide or the global rise in mean surface temperature, on the other. Broadly, there

are two approaches to estimating the damage function (Hsiang, 2016; Massetti and Mendelsohn, 2018). The first looks cross-sectionally to compare economic outcomes in locations with different climates in the present, and then interacts the estimated effects of climate differences with projected changes in climate in the future. This approach has the advantage of incorporating any adaptations to climate that are embodied in the current cross section. However, it faces the challenge that cross sectional variation in climate may be correlated with unobserved variables, such as institutions, that impact the economy. For this reason, research in this line tends to use within-country variation as a source of identification. Mendelsohn and Massetti (2017) review a large number of studies that use this approach in the case of agriculture, mostly looking at variation within a single countries. In the work most closely related to ours, Nordhaus (2006) applies this approach more broadly, regressing total GDP in grid cells covering the whole world on annual mean temperature and precipitation, geographical controls, and country fixed effects. His estimate is that in the scenario where global mean surface temperature rises by 3 degrees C, global output damage would be 3.0%.[1] In our estimation of climate damages we differ from Nordhaus (2006) in four dimensions: deploying more spatially disaggregated climate scenarios, considering changes in a broader set of climate attributes, using population rather than GDP as our dependent variable, and estimating a Poisson rather than long-linear model to relate geographic attributes to economic outcomes.

The alternative approach to estimating the damage function looks at the relationship between changes in outcomes such as temperature and precipitation, on the one hand, and output or other economic or social outcomes, on the other. The advantage of this approach is that it differences out any unobserved characteristics that may be correlated with climate. The greatest challenge it faces is dealing with adaptation. Hsiang (2016) and Lemoine (2021) discuss the assumptions required to estimate the effects in climate change through variation in weather.[2]

Dell, Jones, and Olken (2012) examine the effects of current and lagged annual average temperature on income growth in a panel data. They find a negative effect of temperature shocks on income growth in poor but not rich countries. They caution that, because their results are for short run fluctuations, they are not necessarily applicable to analyzing the effects of climate change, although they do find similar results in a medium-run analysis that

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[1]See also Costinot, Donaldson and Smith (2016), who focus on agriculture.

[2]Waldinger (2022) accounts for long run adaptation in a panel framework by using an historical event, Europe's Little Ice Age of the 16th and 17th centuries.

looks at 15 year differences. Burke, Hsiang, and Miguel (2015A) regress annual GDP growth on average annual temperature and its square in a panel of countries over the period 1960-2010. Plugging in projected future temperatures, they calculate income in each country-year relative to a baseline in which warming does not take place. They find dramatic effects. World GDP in 2100 is 23% lower than in the absence of warming. In almost all tropical countries, the projected shortfall larger than 80%, and in several (including India, Pakistan, and Nigeria) it is larger than 90%. Meanwhile Russia and the Nordic countries all experience gains of over 200%.[3]

Cruz and Rossi-Hansberg (2023) use a similar empirical strategy in estimating the damage function that serves as an input to their dynamic climate assessment model. Their starting point is a set of location-specific productivity and amenity values, which are derived from solving and inverting a spatial growth model that includes trade, migration, and local innovation, using grid cell data on wages, population, land, and energy prices. To separate productivity from amenities, they need to impose a particular cardinal utility function. These derived productivity and amenity values computed for 4 historical time periods, each five years apart, are then used as dependent variables in a panel regression. Climate variation is represented by the single variable of temperature (average January temperature in the northern hemisphere and average July temperature in the southern) for these time periods. It is not clear these short run fluctuations capture much in the way of how local productivity adapts to climate change.

A number of papers have compiled damage function estimates from several different sources and estimated an average worldwide damage function from them. For example, the DICE 2016 model (Nordhaus, 2018) embeds a damage function relating lost GDP to the square of the deviation of global average surface temperature from its historical mean. The damage coefficient is derived from fitting this model to 36 existing estimates of damages under different climate change scenarios. The coefficient implies that a rise in mean

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[3]Kahn *et al.* (2021) use a similar dataset to estimate autoregressive distributed lag models of the effect of temperature and precipitation deviations from their long run averages on annual income growth. Their central projection is that warming by 2100 under RCP 8.5 would reduce world GDP per capita by 7.2% relative to baseline. Tol (2021) uses a stochastic frontier model that allows for separate effects of weather shocks, on the one hand, and long-run climate change, on the other. These effects are estimated in 65 years of panel data on output per worker at the country level, with climate variation being estimated as the effect of changes in the thirty year averages of temperature and precipitation. He finds that a 3 degree C warming reduces global output by 5%. Most warm weather countries experience reductions in income of 10 to 20%, while many cold and temperate countries benefit. Russia's income rises by 60%. See also Newell, Prest, and Sexton (2021).

temperature of 3 degrees C would reduce world GDP by roughly 2.1%, and a 6 degree rise would reduce global income by 8.5%.[4] According to IPCC (2013), the rise in mean surface temperature by the period 2081-2100 is likely to fall into the range of 2.6-4.8 degrees under the RCP 8.5 emissions pathway where there is continuing high use of fossil fuels worldwide. Tol (2019) similarly pulls together 27 estimates of the damage function. For a 6 degree warming, the damage is 5% of welfare equivalent income. However, neither the Tol nor the Nordhaus compilations include the projections from Burke *et. al* (2015A), which are far larger. Tol and Nordhaus also both discuss the large uncertainty associated with damage function estimates.

Much of the recent literature discussing climate change in a spatial framework depends on these damage functions to incorporate warming in models. Desmet and Rossi-Hansberg (2015) uses a similar damage function to that of the DICE model in their spatial framework to examine the distribution of economic activity in the face of global warming. Krusell and Smith (2022) likewise embed climate change into their model as a U-shaped damage function representing the effect of temperature on total factor productivity. They calibrate their model at the regional level to match the global damage function estimate of Nordhaus.

In addition to the expected effects on GDP, research has also looked at impacts of climate change in many other dimensions, with two of the most notable being conflict and migration. Burke, Hsiang, and Miguel (2015B) and Harari and La Ferrara, (2018) examine the effect of climate on civil conflict. McGuirk and Nunn (2021) show that climate change has already driven increasing conflict between transhumant pastoralists and sedentary agriculturalists in Africa. Rigaud *et al.* (2018) project that as of 2050, 2.8% of the population in the group of developing countries that they study, or 143 million people, will have had to migrate internally. Similarly Burzyński *et al.* project that 62 million working age adults will have to move, most of them within their own countries, because of climate during the 21st century.[5] A 2021 U.S. government report predicted that over time an increasing fraction of this migration will be across national borders (White House, 2021).

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[4]A full welfare analysis would include non-market effects, for example species extinction. Nordhaus (2013), as a rough and ready approximation, adds 25% to the loss of GDP from climate change to account for these additional damages.

[5]See also Lustgarten (2020A, 2020B, 2020C).

2.2 Population Pressure

The literature studying the economic and social effects of climate change described above is mostly a product of the last several decades. By contrast, literature on the effects of natural resource congestion due to population growth is far older, going back at least to Malthus (1798). Authors such as Hardin (1968), and Ehrlich (1968) focused on the inability of existing natural resources to support ever-growing populations. More recent literature arguing that the resource congestion channel has an important impact on economic outcomes, particularly in poor countries, includes Young (2005), Acemoglu and Johnson (2007), and Kohler (2012). Das Gupta, Bongaarts, and Cleland (2011) point out that discussion of "sustainable development" at the country level is to a large extent simply a reformulation of the Malthusian concern with the ratio of population to resources. Paralleling the more recent literature on climate change and conflict, Acemoglu, Fergusson and Johnson (2020) show that higher growth in population resulted in increases in civil wars and other measures of social conflict. Similarly, pressure on natural resources due to population growth is a hypothesized driver of both internal and international migration.

Although research on this topic does not use the terminology of a damage function, there is no barrier to applying the same concept. For example, the IV estimates in Acemoglu and Johnson (2007) imply that a change in life expectancy that raised population by 1% would lower GDP per capita by 0.79%.[6] Similarly Ashraf, Weil, and Wilde (2013), using a simulation model parameterized to match Nigeria, find that an increase in fertility that raised population by 16.6% would reduce income per capita by 10.6%.[7]

Existing literature does not address the relative magnitude of economic stress due to climate change, on the one hand, and population growth, on the other. To the extent that the two issues are discussed together, it is often in the context of how population affects carbon emissions, and through this channel climate (Casey and Galor, 2017).[8]

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[6]Tables 8 and 9, column 1.

[7]Values for the year 2060, comparing the UN low and medium fertility projections.

[8]Vörösmarty *et al.* (2000) discuss the interaction of climate change and population growth in the particular case of demand placed on local freshwater resources.

3 Projecting Climate Impacts on Land Quality

Our approach follows broadly in the mode of the cross section approach discussed above, most notably Nordhaus (2006). The key insight is that one can infer the characteristics that affect land quality, and the appropriate weights to apply to them, by looking at current settlement patterns. In order to assess the effects of changes in land quality due to climate change and the effects of population pressure on both resource congestion and growth, we gather information for two periods: roughly current day, encompassing data from 1980 to 2010, and the future, for which we use projections for 2071 to 2100. For convenience, we refer to the former as 2010 and the latter as 2100.

3.1 Empirical Model

We outline a simple model of population allocation within a country that leads directly to our econometric specification. Production in grid cell i of country c is given by

$$Y_{i,c} = (Q_{i,c}Z_{i,c})^{\phi} K_{i,c}^{\alpha} (L_{i,c}B_c)^{1-\alpha-\phi} \tag{1}$$

where $Q_{i,c}$ is a measure of land quality, $Z_{i,c}$ is land area, B_c is a country-level measure of productivity due to non-land factors (institutions, technology, etc.), $K_{i,c}$ is physical capital, and $L_{i,c}$ is labor. Differences in human capital per worker could also be incorporated into B_c. Similarly, allowing for agglomeration economies would not affect the key results of the model for our purposes.[9] Although the regions that we use are all quarter-degree squares of latitude and longitude, they differ in their land areas both because lines of longitude converge away from the equator and because parts of some grid squares are covered with water.

Labor and capital are assumed to be perfectly mobile within countries to equalize their marginal products across grid cells. This implies that in equilibrium, within a country, grid cell density, $L_{i,c}/Z_{i,c}$, will be proportional

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[9]If we think that agglomeration economies come from density as in the classic Ciccone and Hall (1996) paper or more modern papers such as Combes *et al.* (2017) and Henderson, Kriticos and Nigmatulina (2020), then there should be a multiplicative argument on the right hand side of (1) equal to $(L_{i,c}/Z_{i,c})^{\eta}$. In this case, equation (4) is the same, except instead of estimating β, we are estimating $\beta\phi/(\phi - \eta)$. Using a typical value of 0.25 for (ϕ) as discussed below and $\eta = 0.04$ from the literature (see Rosenthal and Strange, 2004, or Combes and Gobillon, 2015), this factor is 1.19. While this affects the interpretation of the estimated coefficients in (4), it does not affect the fitted values from this equation that we focus on below.

to the quality of the land in the grid cell. Quality in turn is postulated to be a function of the vector of geographic characteristics, $x_{i,c}$, of the grid cell, $Q_{i,c} = exp(x_{i,c}\beta)$. Thus

$$L_{i,c}/Z_{i,c} = exp(x_{i,c}\beta)C_c, \qquad (2)$$

where C_c is a country fixed effect that ensures that we are identifying quality exclusively from variation in population density that is within-country and therefore not driven by differences across countries in institutions, technology, culture, or historical development.

Estimated land quality for each grid cell is the fitted value from (2), excluding country fixed effects. That is, we define

$$\hat{Q}_{i,c} = \exp(x_{i,c}\hat{\beta})\Big[\frac{\sum Z_{i,c}}{\sum \exp(x_{i,c}\hat{\beta})Z_{i,c}}\Big]. \qquad (3)$$

where $\hat{\beta}$ is the vector of estimated coefficients from equation (2). The term in brackets is a normalization such that the worldwide sum of quality-adjusted area $\hat{Q}_{i,c}Z_{i,c}$ is equal to the actual area of the world.[10]

3.2 Data and Specification

For the dependent variable in (2), we use the European Union's Global Human Settlements population layer (GHS-POP). In Appendix A we discuss the comparison of results using this population dataset with those obtained using two others: the Gridded Population of the World version 4 and LandScan.

Geographic characteristics, $x_{i,c}$, include elevation, latitude, ruggedness, distance to the coast, and a set of four dummies indicating the presence of a coast, a navigable river, a major lake, and a natural harbor within 25 km of a cell centroid, all from Henderson *et al.* (2018). From the U.N. Food and Agricultural Organization's Global Agro Ecological Zones v4 dataset (FAO's GAEZ) we add a selection of 33 characteristics that provide information on the thermal regime, moisture regime, and growing period of each grid square as well as suitability indices of 11 major crops for the time period 1981-2010.[11] To assess

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[10]It is straightforward to extend the model so that the vector of land characteristics affects not only the productivity but also the amenity value of a location. Let the amenity value of a grid square be given by $A_{i,c} = exp(x_{i,c}\gamma)$ and assume that mobility within a country equalizes the product of the average product of labor and amenities. In this case $E(\hat{\beta}) = \beta + \gamma$

[11]The FAO's GAEZ dataset can be accessed at: https://gaez.fao.org/. The 33 variables we use comprise the majority of continuous variables from Theme 2: Agro-climatic

the effect of climate variability, we include a measure of year-to-year volatility of daily temperature.[12] These data are collected for 237,023 quarter-degree grid squares in 164 countries.

Previous work (Nordhaus, 2006; Henderson, *et al.*, 2018) estimated the parameters in equation (2) by taking logs and including an additive error term. There are three key problems with this log-linear specification, however. First, 40% of grid squares in our data have zero reported population. While a strict application of the model suggests there should be no zeros, we believe the volume of zeros largely reflects measurement error (discussed in the appendix) as well as restrictions on where people are permitted to live.[13] A common approach to this problem is to replace these zeros with a small non-zero value.[14] Unfortunately, parameter estimates can be sensitive to the

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resources. We exclude variables that overlap in definition, are linearly dependent, assume irrigation, indicate beginning dates, are missing data for a significant area of the world, or have a value of 0 for more than 95 percent of observations. The variables that are dropped under these conditions are: annual temperature amplitude, quarterly P/PET ratios, net primary production with irrigation, beginning date of the longest component length of growing period, the beginning date of the earliest growing period, reference evapotranspiration deficit, snow stock at the end of calendar year, soil moisture condition at the end of the calendar year, and number of days with a maximum temperature of 45 degrees Celsius. We further exclude the number of consecutive days with average precipitation over 45 mm and the average annual sum of precipitation on such days; variation in these two measures is overwhelmingly concentrated in small regions of developing countries. The 11 crops (banana, cassava, maize, sweet and white potato, dryland and wetland rice, soybean, sorghum, wheat, and yam) are largest in terms of worldwide calorie production. GAEZ only provides crop suitability index projections assuming "high input," or commercialized agriculture, and so for consistency we use "high input" crop suitability indices for both periods.

[12]To construct this variable, we calculate the standard deviation of the linearly detrended daily average temperature over a 30-year period for each day in the calendar year. We then take the average of these 365 standard deviation values. Temperature values from 1981 to 2010 were used to calculate the 2010 variable, while projected values from 2071 to 2100 were used for the 2100 variable. This mimics measures of volatility used in environmental science papers such as Chan *et al.* (2020) while avoiding concerns about the difference in seasons between the northern and southern hemispheres. Other aspects of volatility are captured by variables in GAEZ: the number of days above 30, 35 and 40 degrees and below 15, 10 and 0 degrees; Annual temperature amplitude; Longest period of consecutive dry days in temperature growing period; Number of consecutive days with average precipitation over 30 mm; and maximum sum of precipitation on consecutive days when average daily precipitation is over 30 mm.

[13]According to the United Nations Environment Programme (2016), 14.7% of the world's land area is in "protected areas" such as national parks.

[14]For example, Henderson, *et al.* (2018), which examined lights data, assigned to every reported zero observation the minimum non-zero value in the dataset. In Nordhaus (2006), where output per square kilometer is the dependent variable, 3,170 of 17,409 grid squares in the regression sample have zero values for the dependent variable. Nordhaus imputes

value used for imputation, and are also sensitive to simply dropping zeros.

Second, as seen in Figures A1.A and A1.B, many grid cells in the world have extremely low population densities. For example, in the GHS data 75% have density less than 12 people per square kilometer, while 98.5% of the world's population lives in grid squares with density above this level. As discussed in Appendix A, data construction issues are likely to introduce a good deal of measurement error in sparsely populated regions, and even to the extent that density in these regions is correctly measured, its determinants are conceptually of less interest than the determinants of density in regions where most people live. The log-linear specification, however, ends up putting a lot of weight on regions with extremely low population densities.

Third, Santos, Silva, and Tenreyro (2006) show that OLS estimates of a log-linear version of (2) are inconsistent (and NLS inefficient) in the presence of heteroskedasticity, which is likely in our context. These issues are discussed more extensively in Appendix A.

For these reasons we estimate a Poisson model. The specific functional form is

$$E(L_{i,c}/Z_{i,c} \mid C_c, x_{i,c}) = exp(C_c + x_{i,c}\beta) \tag{4}$$

The Poisson specification is well-suited for outcome measures with many zeros and tiny values. As shown in Appendix Figure A2, predicted values of density from a Poisson specification are remarkably robust to using the two alternative population datasets noted above, while log-linear predicted values are not.

The stochastic component of the Poisson model is crucial for addressing the contingent nature of human settlement. There is a vast literature on multiple equilibria and accidents of history with agglomeration (e.g. Krugman, 1991; Arthur, 1989; Davis and Weinstein, 2002). More recent work has focused on dynamic development subject to stochastic processes that yield particular, unique equilibria as a way of encapsulating these accidents (Michaels, Rauch, Redding, 2012; Desmet and Rappaport, 2017). For example, in a model similar to ours but with a more complex production process, Desmet and Rappaport envision regions as being subject to initial large productivity/resource shocks and then to a series of accumulating independent draws over time. These accidents are important to understanding why, for example, the centre of Kolkata is not 50 kilometers further up or down the Hugli River or on a completely different river in historical Bengal. In that particular case, an initial arbitrary choice of a British East India Company employee, Job Charnock, and then a history of other choices and accumulations over 300 years, anchored that lo-

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values for 618 of these cells based on neighbors, and then assigns the remainder a value of one before taking logs.

cation and induced high density. Our reduced form specification summarizes the cumulative impact of such a succession of shocks. Since we are assuming a Poisson specification overall, we effectively assume that these shocks are a series of Poisson draws.

The country fixed effects in (4) control for factors like technology and national population relative to national land area. Identification of the determinants of land quality comes solely from within-country variation. In other words, β is not estimated by comparing the land characteristics of more and less densely populated countries, but rather by comparing variation in land characteristics and population density within countries.

3.3   Projecting Climate Impacts

Climate change will alter many of the characteristics that determine our measure of land quality. A key innovation in the present paper is to substitute projections of future characteristics into equation (3), allowing us to calculate expected future land quality at the grid cell level:

$$\hat{Q}_{i,c,2100} = exp(x_{i,c,2100}\hat{\beta}) \Big[\frac{\sum Z_{i,c}}{\sum exp(x_{i,c,2010}\hat{\beta})Z_{i,c}} \Big]. \tag{5}$$

In essence, to calculate grid-cell land quality for 2100, we apply the $\hat{\beta}$ coefficients from (4) estimated on 2010 data to future projections of the geographic characteristics. The term in brackets maintains the 2010 normalization from equation (3), so that global average Q in year 2100 is measured relative to 2010.

Projections of future climatic conditions are generated by global climate models. These are numerical representations of the earth's climate, in which future states of the world are derived from initial conditions using physical laws. As such, the outputs of these models are highly dependent on the assumed trajectory of carbon emissions from current day to the date of the projection. To ensure that these outputs are comparable, the Intergovernmental Panel on Climate Change (IPCC) has established four scenarios of future greenhouse gas concentrations, called Representative Concentration Pathways (RCPs), as standard inputs for the various models. The four scenarios are RCP 2.6, RCP 4.5, RCP 6.0, and RCP 8.5, where the number represents the increase in radiative forcing (in watts per square meter) relative to preindustrial conditions by 2100; RCP 2.6 traces the best-case trajectory while RCP 8.5 depicts conditions from sustained aggressive fossil fuel use. GAEZ provides projections for all four scenarios from five different climate models used

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in the IPCC's fifth assessment report.[15] Our main results rely on the grid-cell level mean of this five-model climate ensemble.[16] In Appendix B, we compare our predictions for changes in land quality between 2010 and 2100 under the 5 climate models with each other and with the ensemble mean. They are highly correlated with each other and, then, obviously with the mean. The larger deviations occur in countries where land quality is expected to improve dramatically, rather than in countries where land quality will deteriorate. We focus on the latter group, which includes nearly all poor and middle-income countries.

Our measure of quality is based on a worldwide grid square regression. A potential concern is that the value of specific land characteristics in determining economic outcomes may be a function of the level of a country's development. For example, a reduction in rainfall in an already dry climate could be devastating in a region reliant on smallholder agriculture, but in a richer region that imports its food from elsewhere it would have only a marginal effect. We address this concern in Appendix C, where we estimate equation (4) using a sample of grid squares solely from countries with below-median income. We then compare land quality predictions between this and our baseline. The results are highly correlated among the sample of below median income countries; larger deviations occur for countries where land quality is expected to improve dramatically.

4 Projected Effects of Climate Change on Land Quality

This section begins by reporting the estimated effects of climate change on land quality at the grid square level and then aggregates up to look at world, region, and country impacts on average land quality. Impacts are heterogeneous across the world: Some countries will experience improvements, while many others, especially poorer ones, will see significant deterioration.

4.1 Grid Cell, Global, and Regional Results

We start at the grid square level. The first panel of Figure 1 shows our estimated values of log 2010 land quality. The second panel then shows projected

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[15]The climate models available in GAEZ are HadGEM2, GFDL, IPSL, MIROC, and NorESM.

[16]Multi-model ensemble means tend to improve accuracy (Frankcombe *et al.*, 2018) and are used to generate headline predictions of climate change for IPCC assessment reports.

changes in land quality between 2010 and 2100 under RCP 8.5. In general, the areas with improvements in land quality are mountainous and/or distant from the equator. Land quality declines in almost all of Africa and Australia as well as large parts of South America and central, south, and southeast Asia. The northernmost parts of Europe are projected to benefit, along with most of Canada and Russia. There is a good deal of internal variation within larger countries. For example, within the United States, the Gulf coast suffers declines in land quality while in much of the mountain west it improves.

Figure 1: Log Land Quality

(a) Historical Log Land Quality
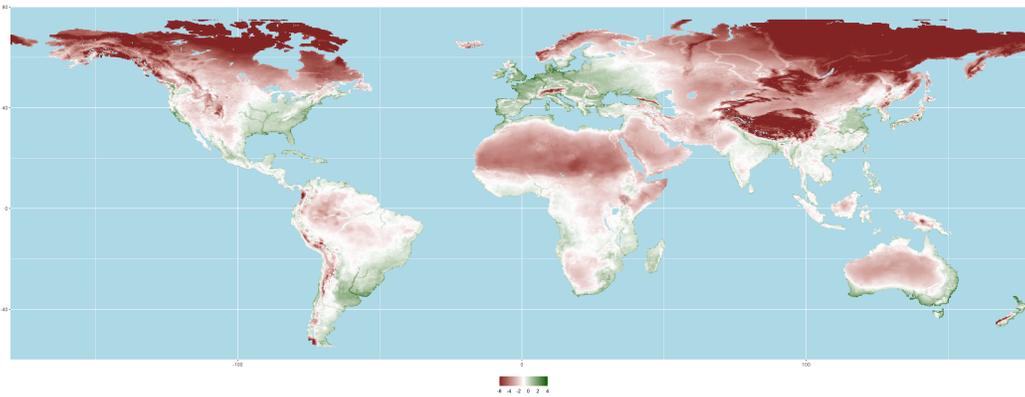
(b) Differences between Historical and 2071-2100 Log Land Quality under RCP 8.5
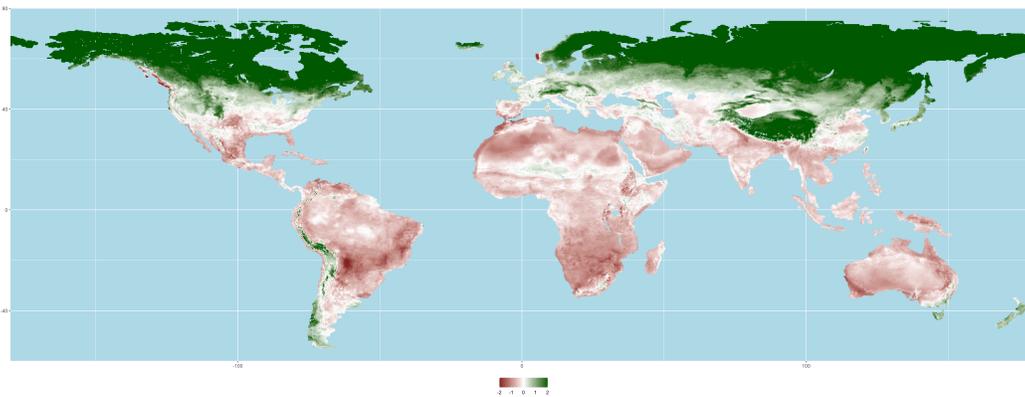
Notes: Data are censored at -6 and 4 and at -2 and 2 in the top and bottom panels, respectively, for visualization. Plate Carrée projection.

To examine heterogeneity in the distribution of projected changes in land quality, we plot in Figure 2 histograms for grid cells in countries whose 2010 GDPs were either above or below the median. In the left column, the vertical

axis represents the percentage of the country group's total land area that falls into each bin; in the right, it represents the percentage of the country group's total population. Among countries with below-median GDP per capita, 73% of the land area, hosting 84% of the current population, is expected to see a decrease in land quality. By contrast, among countries with above-median GDP per capita, only 48% of land area, hosting 55% of the population is expected to see such a decrease.

Figure 2: Histograms of Changes to Log Land Quality
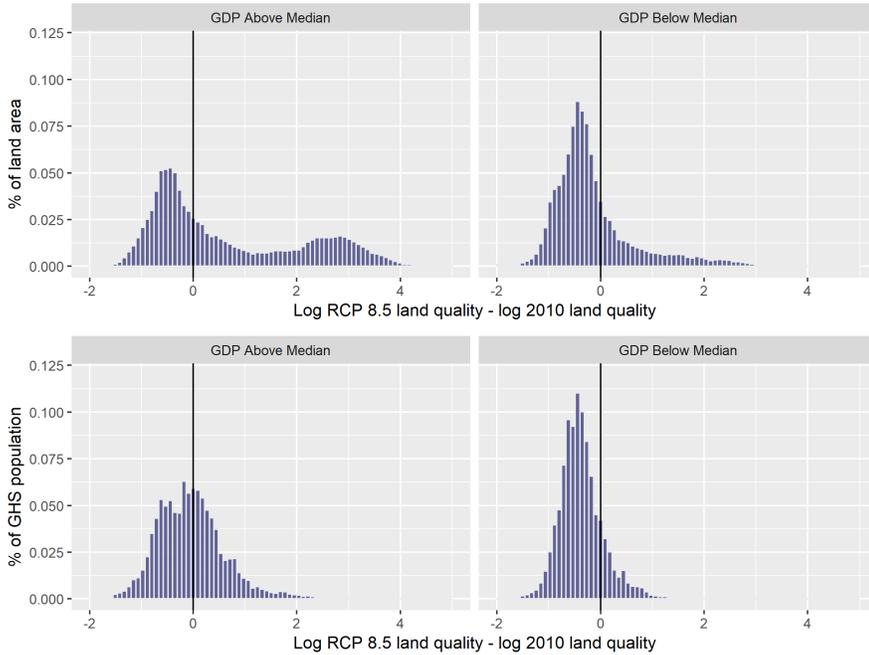
Notes: This figure depicts the distribution of cells in countries with above-median (left column) and below-median GDP (right column) in 2010. The histograms in the first row weight the cells by the percentage of total land area in their respective country group; the X axis is censored at -2 and 5. The histograms in the second row weight the cells by the percentage of total GHS population in their respective country group; the X axis is censored at -2 and 3.

To characterize global and regional impacts of climate change more formally, we define (area-weighted) Average Land Quality (ALQ) of region r as,

$$ALQ_{r,t} = \sum_{i \in r} \hat{Q}_{i,r,t} \frac{Z_{i,r}}{Z_r} \tag{6}$$

Thus, $ALQ_{r,t}$ is the sum of the quality index in equation (5) for each grid square multiplied by that grid square area, $Z_{i,r}$, all divided by regional land

area. A region can be a province, a country, a continent or the world. As we discuss below in section 5, area-weighting ALQ is what matters for income when labor is mobile.

The first column of Table 1, Panel (a) reports world- and continent-level ALQ. As noted above, world average land quality for 2010 is normalized to be one by construction from equation (5). Africa and Asia's ALQ are below the world average while Europe, the Americas, and Oceania's are above it.

In the remaining columns of Table 1, Panel (a), we repeat this exercise for 2100 under the four different RCP emissions scenarios. Here we keep the weights in Equation (5) and simply change the characteristics x according to each RCP scenario. At the world level, the change in average land quality is modest. Under all scenarios ALQ rises; and it rises across scenarios as we move from strong action on climate change mitigation (RCP 2.6) to continued aggressive use of fossil fuels (RCP 8.5). This overall world increase is driven by the rise of average land quality in Europe (including all of Russia), which increases by 30% in RCP 2.6 and 80% in RCP 8.5. There is little average change in the Americas, while there are modest declines in Asia and Oceania. Africa is the big loser, with a decline in average land quality of 13% in RCP 2.6 and 45% in RCP 8.5.

Table 1: World ALQ Change

(a) Area-weighted ALQ

Continent	Historical	RCP 2.6	RCP 4.5	RCP 6.0	RCP 8.5
World	1.000	1.015	1.040	1.046	1.049
Africa	0.722	0.627	0.555	0.521	0.395
Americas	1.133	1.073	1.085	1.072	1.078
Asia	0.755	0.731	0.709	0.691	0.656
Europe	1.305	1.701	1.954	2.076	2.352
Oceania	1.489	1.393	1.403	1.421	1.299

(b) 2010 Population-weighted *ALQ*

Continent	Historical	RCP 2.6	RCP 4.5	RCP 6.0	RCP 8.5
World	3.064	2.881	2.829	2.799	2.623
Africa	1.686	1.420	1.247	1.163	0.878
Americas	3.760	3.357	3.406	3.326	3.067
Asia	2.595	2.337	2.218	2.156	1.960
Europe	6.447	7.252	7.629	7.906	8.253
Oceania	18.025	15.626	16.281	17.190	14.524

The second panel of Table 1 repeats the analysis using population rather than area weights, replacing the Z's in equation (6) with 2010 populations. This allows us to look at how climate change will affect land quality experienced in the places where people currently live.

As would be expected, population-weighted *ALQ* at either the world or continent level in 2010 is far higher than area-weighted *ALQ*, given that people disproportionately live in higher-quality areas. The effects of climate change are noticeably different from this perspective. Weighted by where people currently live, worldwide average land quality declines by 14% by 2100 under RCP 8.5, rather than increasing as in the first panel. For Europe, the increase in population-weighted *ALQ* is only 28%, which is only about one-third as large as in the area-weighted case. The other regions see projected declines in *ALQ* that are larger than in the area-weighted case.

4.2   Country Level Results

Figure 3 shows that there is a strong relationship between countries' current levels of GDP per capita and projected changes in (area-weighted) land quality. Among countries with below-median GDP per capita, the average expected change in area-weighted land quality under RCP 8.5 is -27%; for those in the top half, the expected change is 41%. There is a good deal of variation among the richer countries, with some, such as Israel, Portugal, Greece, and the Gulf states doing poorly, while the Nordic countries, Japan, and New Zealand as well as Russia and Canada all do well. By contrast, among poor countries the projection is almost universally bad, with a few exceptions such as Lesotho, Tajikistan, and Moldova.

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Figure 3: 2010 GDP and Future *ALQ* Changes
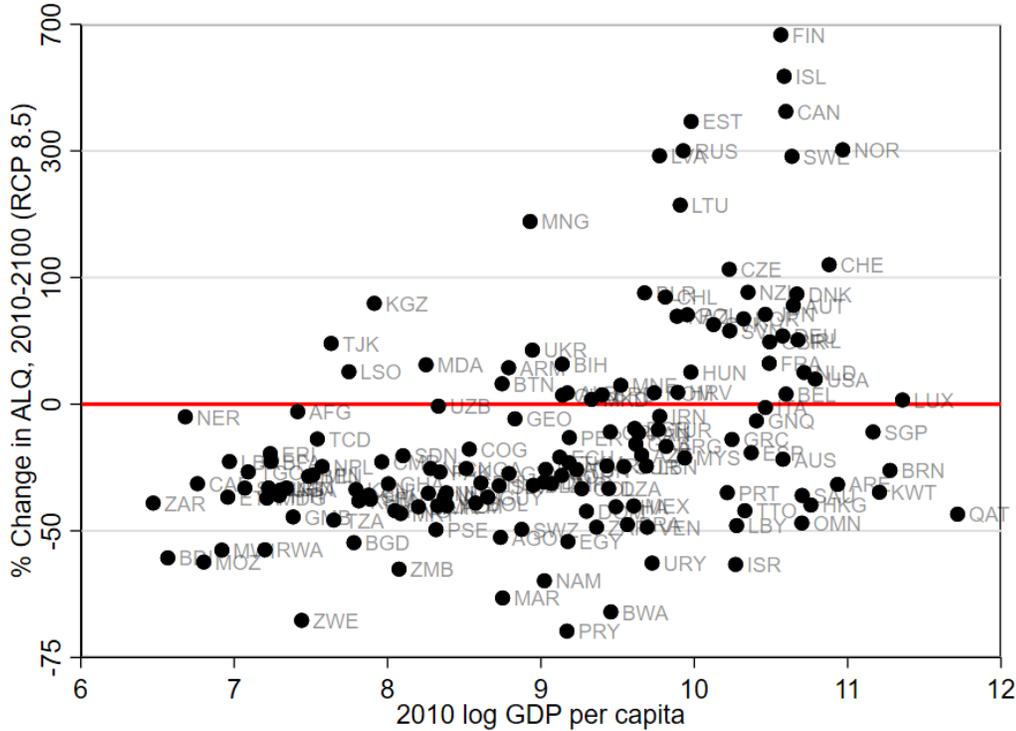
Note: Figure plots the percentage change in baseline area-weighted ALQ from 2010 to 2100 in RCP 8.5 in log scale against log 2010 GDP for the 156 countries with both values.

Taken by itself, this strong relationship between current income and expected effects of climate change on land quality would be a force pushing toward increased inequality among countries. If we instead look at population-weighted land quality, the average expected change remains steady at -28% for countries with below-median GDP per capita, while for the top half the increase in land quality shrinks dramatically to 17%. This suggests that increases to land quality in countries projected to benefit overall are concentrated in sparsely populated cells; internal migration will thus play a large role in determining whether actual gains are realized from these changes.

4.2.1   Population Growth

Declining land quality due to climate change is expected to have economic and social effects because it will mean a decline in the ability of the physical environment to provide support for the people who live in it. A moment's thought suggests that another contributor to this problem is changes in the

number of people. To a first approximation, we would expect a decline in land quality by 50%, holding constant the number of people living on it, to have the same economic effect as a doubling of the number of people, holding land quality constant.

Assessing this issue requires projections of future population. Unlike changes in ALQ, these are available only at the level of countries, not grid cells. We use population projections from the by the United Nations Population Division (UNPD, 2019). The UNPD provides a central forecast (the medium variant) as well as a range of probabilistic forecasts for each country. In this section, we use the medium variant projection for the year 2100, while in a later part of the paper we explore the full probabilistic range.

Figure 4: 2010 GDP and Future Population Growth
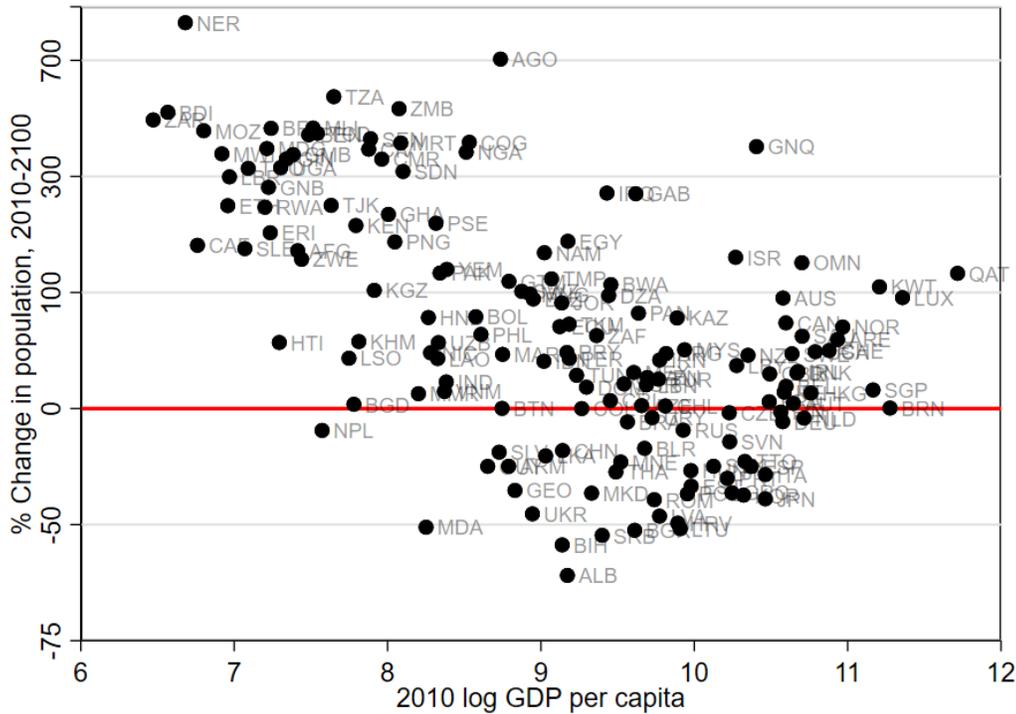
Note: Figure plots the percentage change in population from 2010 to 2100 in the U.N. medium variant projection using log scale against log 2010 GDP for the 156 countries with both values.

Figure 4 shows the relationship between current GDP per capita and expected population growth between 2010 and 2100 in the UNDP medium projection. The negative relationship is even more pronounced than the positive relationship between current GDP and expected changes in land quality shown

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in Figure 4. Many wealthy and middle income countries have negative projected population growth, and among the wealthy countries, those that do have positive projected growth generally have projected values of less than half a percent per year. The exceptions are mostly oil producers. By contrast, there are a significant number of poor countries where expected growth over this 90-year period is more than one percent per year, and many with expected growth near 1.5%. We now turn to analyzing the effects on expected economic growth of population pressure on land versus the impact of climate change on land quality.

5   Mapping Land Quality Changes and Population Growth into Income: Methodology

Changes in land quality and in the size of the population both act to change the degree of population pressure on natural resources. Following the existing literature on damage functions, our goal is to construct a quantitative measure of how income per capita in countries would differ in 2100 as a result of these changes, from what it would have been in their absence. Although the damage function approach is much more commonly applied in the case of climate change than in the case of population, we show that the two effects can be treated in parallel.

To measure the impacts of climate change and population growth we consider the comparison of specified baseline and alternative scenarios. Let $X_{i,Base}$ and $X_{i,Alt}$ be the 2100 values of quality-adjusted land in grid cell i under these two scenarios, with $L_{i,Base}$ and $L_{i,Alt}$ defined analogously. The choice of what baseline and alternative values to use will depend on the scenario being addressed. All other exogenous factors for each country, such as productivity, are assumed to evolve the same way in the two scenarios.

We analyze a simple growth model. Assume that output in grid cell i is produced with capital (K_i), labor (L_i), and quality-adjusted land, $X_i = Z_iQ_i$. The production function is

$$Y_i = X_i^{\phi}K_i^{\alpha}(eL_i)^{1-\alpha-\phi}, \tag{7}$$

We suppress the country subscript when there is no ambiguity. e is productivity that is the same throughout a country. We do not explicitly include human capital, but one can think of this as being incorporated into the productivity term.

We need to aggregate from this grid cell production term into a national output equation. To do so, we assume that capital is perfectly mobile, so that

the marginal product of capital is equalized across grid cells. It is simple to show that this leads to the capital-output ratio of each grid cell equaling the nationwide capital-output ratio. That is,

$$\frac{K_i}{Y_i} = \frac{K}{Y},$$

(8)

where K and Y are national magnitudes. We use equation (8) to write (7) as

$$Y_i = L_i \left(\frac{X_i}{L_i}\right)^{\phi/(1-\alpha)} \left(\frac{K}{Y}\right)^{\alpha/(1-\alpha)} e^{(1-\alpha-\phi)/(1-\alpha)}.$$

(9)

5.1 Labor Mobility

As shown above, climate change will have heterogeneous effects within countries. The extent to which this heterogeneity of climate impacts matters for aggregate output in a country depends on two factors. The first is the degree to which the spatial distribution of population can change in response to climate, which we refer to as labor mobility. The second is the empirical relationship between where population is located in the period prior to climate change, on the one hand, and the spatial distribution of climate impacts, on the other. This second factor is captured in the measure of population-weighted change in ALQ that we presented above.

We consider three cases. In the first ("mobile labor"), labor is perfectly mobile and thus the average product of labor is equalized across grid cells in both in the present and the future. In this case the distribution of land qualities within a country turns out to be irrelevant; all that matters is a country's total quality-adjusted area. The change in this area is captured by the area-weighted change in ALQ that we constructed above.

An issue with the approach in the mobile labor case is that the observed distribution of population in the initial period does not match the distribution predicted by our land quality measure. In the second case we address this issue by assuming that there are location-specific attributes that produce this residual variation in density, and further that these attributes will persist into the future. We thus call this case "perfect mobility with unmeasured quality."

Comparing the first and second cases gives insight into the importance of the heterogeneity of climate impacts. Some countries will turn out to be lucky in the sense that they have an unexpected concentration of population (beyond what would be predicted by pure geography) in regions that are expected to do unusually well as a result of climate change, while other countries have bad luck in this respect.

The third case is considered to highlight the importance of population mobility in response to heterogeneity of climate change impacts within a country. The starting point is the same as in the second case, specifically, we assume that there are unmeasured location-specific characteristics that, along with observed geographic attributes, perfectly explain the distribution of population in the initial period. Unlike the second case, however, we then assume that the relative populations of grid cells remain fixed over time. We call this case "prefect mobility today with unmeasured quality; no mobility going forward." Comparing the second and third cases, we can characterize the benefit of internal migration as a form of adaptation.

5.2   Mobile Labor

Equating the marginal product of labor across grid cells within a country implies that the ratio of labor to quality-adjusted land is equalized across grid cells, and is equal to this same ratio measured at the national level:

$$\frac{L_i}{X_i} = \frac{L}{X}. \tag{10}$$

Substituting equation (10) into (9), grid square output per worker is

$$\frac{Y_i}{L_i} = \frac{Y}{L} = \left(\frac{X}{L}\right)^{\phi/(1-\alpha)} \left(\frac{K}{Y}\right)^{\alpha/(1-\alpha)} e^{(1-\alpha-\phi)/(1-\alpha)}. \tag{11}$$

Through labor and capital mobility, grid-cell level output per capita is a function of national magnitudes and thus is constant across grid cells. We can aggregate labor, quality-adjusted land, and capital to the country-level in each period by simply summing. This corresponds to what we called the area-weighted case in calculating changes in land quality above.

Using (11) we can compare output per capita in the baseline and alternative scenarios:

$$\frac{\left(\frac{Y}{L}\right)_{alt}}{\left(\frac{Y}{L}\right)_{base}} = \left(\frac{\sum_i exp(x_{i,alt}\hat{\beta})Z_i}{\sum_i exp(x_{i,base}\hat{\beta})Z_i}\right)^{\frac{\phi}{1-\alpha}} \left(\frac{L_{Alt}}{L_{Base}}\right)^{\frac{-\phi}{1-\alpha}} \left(\frac{(K/Y)_{alt}}{(K/Y)_{base}}\right)^{\frac{\alpha}{1-\alpha}}. \tag{12}$$

The last term in this equation is derived as follows. We assume that capital is accumulated in the usual Solow model fashion

$$\dot{K} = sY - \delta K, \tag{13}$$

where δ is the rate of depreciation and the saving rate s is assumed to be fixed. Romer (2012) shows that if the rates of saving, depreciation, population growth, and technological progress are constant, then along the balanced growth path the capital-output ratio, which is the second term in equation (11), converges to a constant. Taking logs of (11), differentiating with respect to time, and then rearranging, we can solve for the growth rate of total output:

$$\hat{Y} = \frac{\phi\hat{X} + (1 - \alpha - \phi)[\hat{e} + \hat{L}]}{1 - \alpha} \tag{14}$$

We can similarly write the equation for the growth rate of capital as

$$\hat{K} = s\left(\frac{Y}{K}\right) - \delta. \tag{15}$$

Equating (15) to (14), the capital-output ratio along the balanced growth path is thus

$$\frac{K}{Y} = \frac{s}{\delta + \frac{\phi\hat{X} + (1 - \alpha - \phi)[\hat{e} + \hat{L}]}{1 - \alpha}}. \tag{16}$$

Thus

$$\left(\frac{(K/Y)_{alt}}{(K/Y)_{base}}\right) = \frac{\delta(1 - \alpha) + (1 - \alpha - \phi)[\hat{e} + \hat{L}_{Base}]\phi\hat{X}_{Base}}{\delta(1 - \alpha) + (1 - \alpha - \phi)[\hat{e} + \hat{L}_{Alt}] + \phi\hat{X}_{Alt}} \tag{17}$$

$\hat{L}$ and $\hat{X}$ are the annualized growth rates between 2010 and 2100 of population and aggregate land quality in either the baseline or alternative scenario.[17]

In the language of the climate change literature, (12) is one minus the damage function. Of the three terms on the right hand side of the equation, the first two have obvious interpretations in terms of population pressure on natural resources: output in the alternative case is lower than in the base case to the extent that land quality in the alternative is lower or that population is higher than in the base. The third term is a more complicated: it shows that to the extent that there is either land quality degradation (i.e. $\hat{X}_{Alt} < \hat{X}_{Base}$) or population decline (i.e. $\hat{L}_{Alt} < \hat{L}_{Base}$) the capital/output ratio in the alternative case will be higher than in the base case. This effect operates via the growth rate of total (not per capita) output along the balanced growth path. Below we show that quantitatively of very small importance.

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[17]This further assumes that growth of population and land quality are both constant on the balanced growth path.

5.3 Perfect Mobility with Unmeasured Quality

In this case, we continue to assume that labor is perfectly mobile in the present and the future. However, rather than assuming, as in the previous case, that year 2010 population is distributed according to our fitted measure of land quality, we instead assume that there is an unobserved dimension of land quality that explains the current population distribution.

Specifically, we define the multiplicative residual ϵ_i that makes our equation for land quality fit the distribution of population in every country exactly:

$$\frac{L_i}{Z_i} = \exp(\hat{C}_i + x_i\hat{\beta})\epsilon_i. \tag{18}$$

We assume that this residual ϵ_i represents unmeasured land quality, and that it is time invariant.

Our new measure of land quality for every grid square is then the fitted value from this equation, suppressing the country fixed effect:

$$\hat{Q}_{i,c} = \exp(x_i\hat{\beta})\epsilon_i. \tag{19}$$

The change in aggregate land quality is now

$$\left(\frac{X_{Alt}}{X_{Base}}\right) = \frac{\sum_i exp(x_{i,alt}\hat{\beta})\epsilon_i Z_i}{\sum_i exp(x_{i,base}\hat{\beta})\epsilon_i Z_i} \tag{20}$$

This in turn can be rewritten as

$$\left(\frac{X_{Alt}}{X_{Base}}\right) = \sum_i \left(\frac{L_{i,base}}{L_{base}}\right) \frac{exp(x_{i,alt}\hat{\beta})}{exp(x_{i,base}\hat{\beta})} \tag{21}$$

This is a weighted average of grid-cell specific changes in land quality, where the weights are the population of each grid cell in the baseline.

Equation (12) can now be rewritten as

$$\frac{\left(\frac{Y}{L}\right)_{Alt}}{\left(\frac{Y}{L}\right)_{Base}} = \left(\sum_i \left(\frac{L_{i,base}}{L_{base}}\right) \frac{exp(x_{i,alt}\hat{\beta})}{exp(x_{i,base}\hat{\beta})}\right)^{\frac{\phi}{1-\alpha}} \left(\frac{L_{Alt}}{L_{Base}}\right)^{\frac{-\phi}{1-\alpha}} \left(\frac{(K/Y)_{alt}}{(K/Y)_{base}}\right)^{\frac{\alpha}{1-\alpha}}. \tag{22}$$

5.4 Perfect Mobility Today with Unmeasured Quality; No Mobility Going Forward [incomplete]

We present one more case, which is useful for demonstrating the role of mobility in mitigating the effects of climate change. Our starting point is the same as in the previous case, which is specifically that the observed population distribution in 2010 is such that the average product of labor is equalized across grid cells, with unobserved quality ϵ_i explaining the deviation of the observed distribution from what would be explained by observed land characteristics and our estimated coefficient vector $\hat{\beta}$. Unlike the previous case, however, we now assume that there is no population mobility in the face of heterogeneous impact from climate change. More specifically, we assume that population in each grid cell in a country grows (or shrinks) at the same rate:

$$\frac{L_{i,Alt}}{L_{i,Base}} = \frac{L_{Alt}}{L_{Base}} \tag{23}$$

Unlike the previous two cases, output per worker will not be equalized across grid squares in the alternative case.

Aggregate output per worker is given by summing equation (9):

$$\frac{\left(\frac{Y}{L}\right)_{alt}}{\left(\frac{Y}{L}\right)_{Base}} = \left(\frac{L_{base}}{L_{alt}}\right) \left(\frac{(K/Y)_{alt}}{(K/Y)_{base}}\right)^{\frac{\alpha}{1-\alpha}} \frac{\sum_i L_{i,alt}^{\frac{1-\alpha-\phi}{1-\alpha}} [exp(x_{i,alt}\hat{\beta})Z_i\epsilon_i]^{\frac{\phi}{1-\alpha}}}{\sum_i L_{i,base}^{\frac{1-\alpha-\phi}{1-\alpha}} [exp(x_{i,base}\hat{\beta})Z_i\epsilon_i]^{\frac{\phi}{1-\alpha}}} \tag{24}$$

This can be rewritten (skipping several steps) as

$$\frac{\left(\frac{Y}{L}\right)_{alt}}{\left(\frac{Y}{L}\right)_{Base}} = \left(\sum_i \frac{L_{i,base}}{L_{base}} \left(\frac{exp(x_{i,alt}\hat{\beta})}{exp(x_{i,base}\hat{\beta})}\right)^{\frac{\phi}{1-\alpha}}\right) \left(\frac{L_{alt}}{L_{base}}\right)^{\frac{-\phi}{1-\alpha}} \left(\frac{(K/Y)_{alt}}{(K/Y)_{base}}\right)^{\frac{\alpha}{1-\alpha}} \tag{25}$$

The second and third terms of (25) are the same as in equation (22) above. The first term, representing the effect of the change in land quality, looks almost the same, except that the change in quality for each grid cell is raised to a power before being summed rather than after.

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6 Mapping Land Quality Changes and Population Growth into Income: Results

Equations (12), (22), and (25) provide parallel structures for estimating the effects of projected climate change and population growth under different assumptions about future labor mobility.

We start by examining the pure effect of climate change. After this, we examine the combined effects of climate change and population growth. For brevity we don't look at effects of different population growth scenarios, absent climate change.

To apply this framework, we need values for the production function parameters. A commonly used estimate for the natural resource share in production, ϕ, is 0.25. While this is probably too high for wealthy countries, we view it as reasonable for poorer countries, which are mostly reliant on local resources.[18] If we assume a one-third share for capital among inputs other than natural resources, we get $\alpha = 0.25$. We further assume that the annual growth rate of productivity, $\hat{e}$, is 1% and depreciation, δ, is 5%. However, these last two parameters are only relevant for the calculation of the offset terms in equations (12), (22), and (25). Appendix Table E3 shows that the offset term contributes extremely little to variation across countries in projected climate impacts, and is very insensitive to the choice of $\hat{e}$.

6.1 Climate Change Effects

To assess the pure effect of climate change, we project outcomes for 2100 under different climate scenarios, allowing for the same expected population growth. For all three equations, we set $X_{i,Base}$ equal to its 2010 value and $X_{i,Alt}$ equal to its 2100 value for each specified climate scenario. We set L_{Base} and L_{Alt} equal to the UN's 2100 median population forecast.[19] Thus we are comparing balanced growth outcomes in 2100 under different climate scenarios holding population growth constant across scenarios.

Appendix Table E2 shows country-level impacts calculated using our first two assumptions about labor mobility for all four RCPs. For comparison,

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[18]Hansen and Prescott (2002) assume a value of the fixed factor share of 30% for preindustrial economies. Cruz and Rossi-Hansberg (2023) use 0.20 as the natural resource share in production, although they also allow for a congestion cost in amenities. Ashraf, Lester, and Weil (2009), using data from Caselli and Feyrer (2007), calculate resources shares in national income that are as high as 25% in many poor countries, and exceed 30% in a few.

[19]Later, when aggregating to the world level, we will use 2100 populations from the Shared Socioeconomic Pathways to allow for comparisons with previous work.

the table also shows the RCP 8.5 projections from Burke *et. al* (2015A), which is probably the best known application of the panel-weather approach to estimating the impact of climate.[20] Since the Burke *et al.* results are based on population-weighted changes in climate, we compare them to our results under the assumption of perfect mobility with unmeasured quality. The correlation between their projections and ours (expressed in percent changes) is 0.76. However, the magnitudes are very different. In the Burke *et al.* projection, 20 counties suffer damage to GDP per capita of more than 90%, and 72 countries more than 80%. By contrast, our maximum loss is 32%. Similarly, in Burke *et al.* climate change increases GDP per capita in four countries by more than 300%, while in our estimates the biggest increase is 88%.

Figure 5: Country-Level Impacts from Climate Change with Mobile Labor
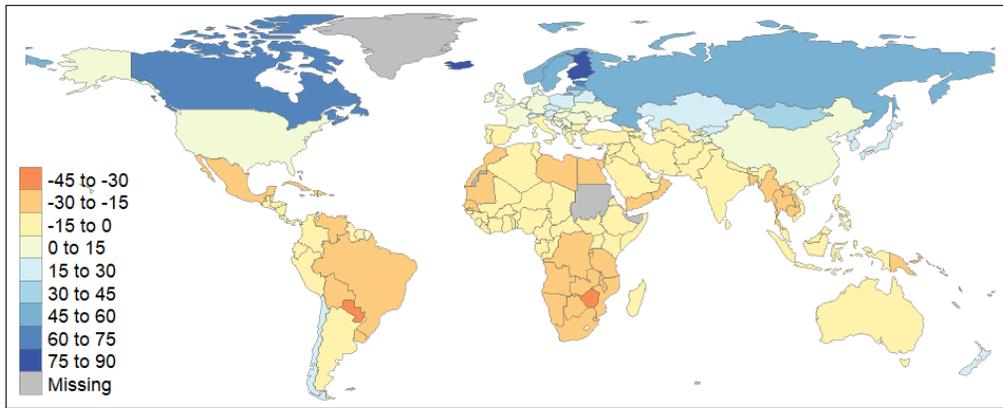
Notes: Countries are binned by the difference between GDP per capita under RCP 8.5 and no climate change under the assumption of mobile labor.

Figure 5 shows our results graphically for RCP 8.5 under the mobile labor assumption, i.e. equation (12). As expected, Nordic countries, Canada, and Russia gain while countries in or near the tropics typically lose. Among the most extreme projections, GDP per capita is respectively 31.0% and 32.1% below what it would be in the absence of climate change in Zimbabwe and Paraguay, with losses of over 25% in many African countries. On the other end, GDP per capita is 54.2% and 88.2% above baseline in Russia and Finland respectively.

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[20]Country-level projected per capita GDP with and without climate change from Burke, Hsiang, and Miguel (2015A) is provided here.

In Figure 6 we compare country level outcomes under the mobile labor assumption to that under the assumption of perfect mobility with unmeasured quality. It is immediately apparent that, while the two sets of predictions are highly correlated, points are scattered on both sides of the 45 degree line. These deviations from the 45 degree line are result from the unevenness of climate change impacts within a country and the extent to which particularly strong impacts take place in regions that are more or less populated than would be expected based on current land quality. Countries whose land quality increases the most in currently sparsely populated areas see far lower gains to output when unmeasured quality is taken into account; this is the case for Canada, Norway, and Iceland. The reverse holds true for countries like Peru and Bolivia, where for historical reasons many people live in mountainous areas and climate changes favor the places where economic activity is clustered. The estimated overall effect on GDP per capita for Bolivia is -16% under the mobile labor assumption and 20% under the unmeasured quality assumption.[21]

While the deviations from the 45 degree line of Figure 6 are interesting objects for study, we think that the most notable message of from this analysis is that for most countries, and certainly for most countries that are expected to suffer negative consequences for climate change, the assumption made regarding labor mobility makes little difference regarding the projected effect of climate change on GDP per capita. For that reason, in what follows we mostly present results for the mobile labor case, although the full set of results for alternate cases are given in the appendix.

Below, in Section 7, we calculate the world damage function by aggregating these country-level damages of climate change using projections of country-level GDP in 2100.

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[21]The vertical distance of countries from the 45 degree line in panel (a) of Figure 6 is closely related to the difference between the area-weighted and population-weighted change in ALQ discussed above (correlation coefficient of 0.62).

Figure 6: Comparisons of Country-Level Impacts from Climate Change
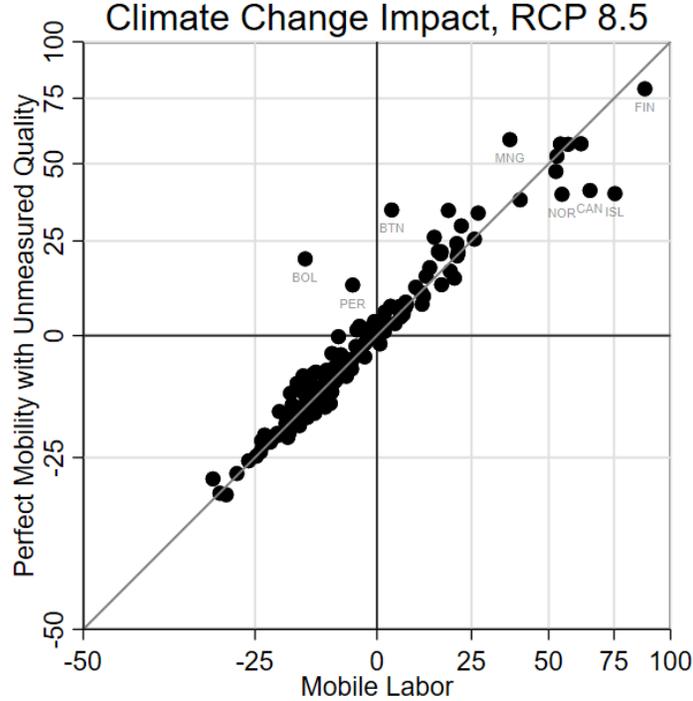
Note: Figure compares the percentage impact of climate change in 2100 under mobile labor assumptions against that under perfect mobility with unmeasured quality. RCP 8.5 and the U.N. medium variant population projection are used for each case; 164 countries are depicted in each panel.

6.2 Combined Impacts from Climate Change and Population Growth

In this section we look at the combined effects of climate change and population growth. In the next one, we then compare their relative magnitudes. Concretely, we will set $X_{i,Base}$ and $L_{i,Base}$ to their 2010 values and then use different combinations of projections to 2100 for $X_{i,Alt}$ and $L_{i,Alt}$. In both sections, we do our analysis only for the case of mobile labor, although results for the other case of labor mobility is shown in the appendix. As in Figure 6, the results are highly correlated.

Figure 7 shows the combined impacts from climate change under RCP 8.5 and population growth under the UNDP medium projection, against a base of no population growth and no climate change.

Because countries that are projected to suffer land degradation from climate change tend to also be the ones where population is growing fastest,

the size of impacts in Figure 7 tend to be much larger than those in Figure 5 where population growth does not differ between the base and alternative cases. Many countries, mostly poorer ones, experience losses well over 35% and many even over 50% in GDP under the combined population growth and climate deterioration, while with only climate change the maximum loss was under 32%. For example, Angola is projected to experience an impact of -20.6% from climate alone, but an impact of -63.4% from climate change combined with population growth. By contrast, many wealthy countries, particularly in northern Europe, are projected to see GDP per capita rise as a result of both climate change and falling population. The cross-country correlation between current log GDP of per capita and the projected impact of climate alone is 0.41, while the correlation between current log GDP and the the projected combined effects of climate and population is 0.55.

Figure 7: Impacts from Climate Change and Population Growth
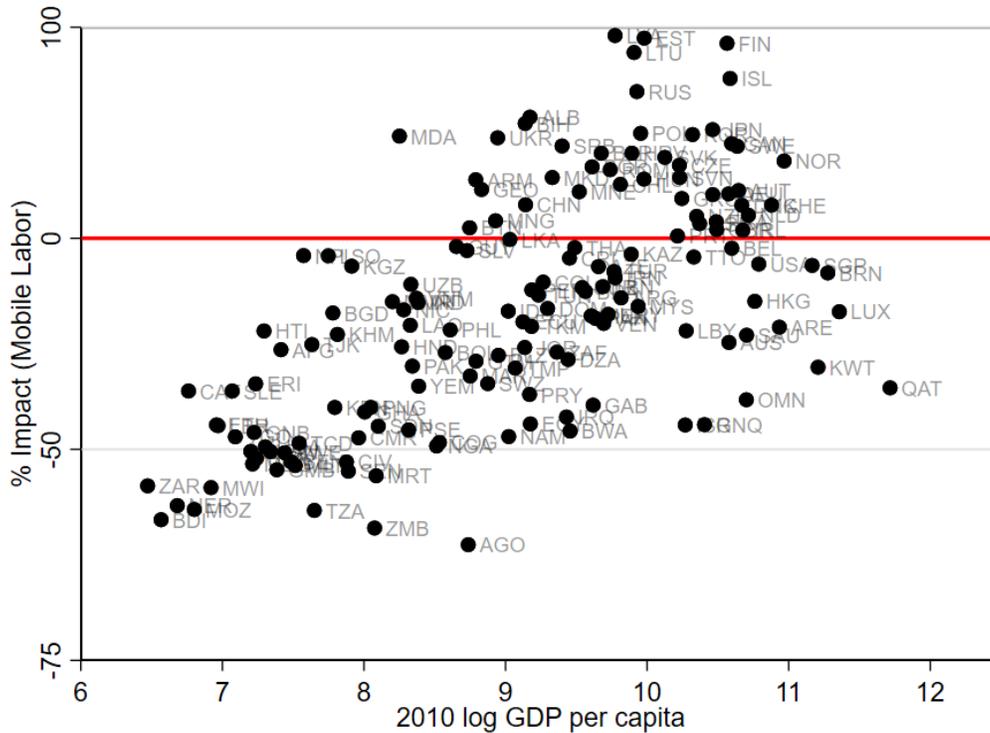
Note: The Y axis plots the percentage impact of climate change in 2100 using RCP 8.5 and the U.N. medium variant population projection under mobile labor assumptions in log scale. The X axis plots log 2010 GDP. 156 countries are shown.

6.3 Relative Importance of Climate Change and Population Growth

The analysis above naturally raises the question of the relative magnitude of effects from climate change and population growth. In equation (12), we want to compare the first term, $\frac{\sum_i exp(x_{i,alt}\hat{\beta})Z_i}{\sum_i exp(x_{i,base}\hat{\beta})Z_i}^{\frac{\phi}{1-\alpha}}$, to the second, $\left(\frac{L_{alt}}{L_{base}}\right)^{\frac{-\phi}{1-\alpha}}$. However, a complete answer to this question is complicated by the fact that both of these effects enter the third term in equation (12). Fortunately, in practice, as noted above and in Appendix Table E3 this third term is of relatively minor importance.

Figure 8 looks at how these two terms vary across countries. Each country is represented by a dot, with red dots indicating countries with GDP per capita below the median. The horizontal axis measures the first term (i.e. the impact of land quality change on GDP per capita) and the vertical axis measures the second (impact of population change on GDP per capita). A full set of country values appears in Appendix E.

Figure 8: Changing *ALQ* and Population
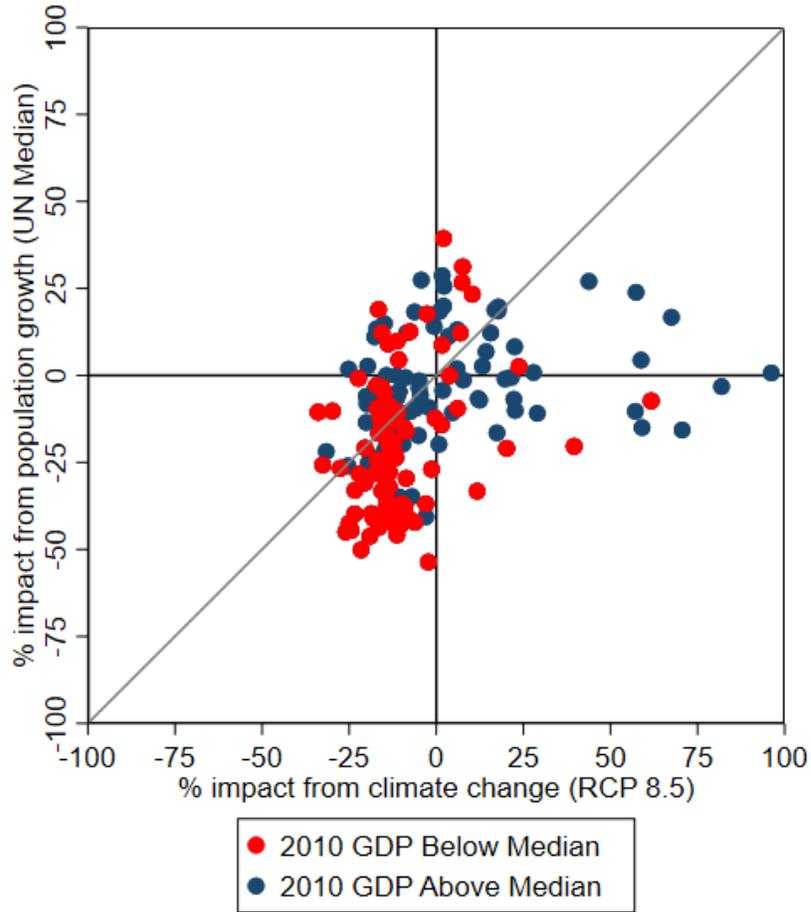
Note: Figure compares the effect of the the second term in equation (12), which represents the impact of population growth, against the first term, which represents the impact of climate change in 2100. Impacts are calculated in percentages under mobile labor assumptions using RCP 8.5 and the U.N. medium variant population projection; 164 countries are shown.

Countries on the 45 degree line are those for which the impacts of changes in land quality and population growth are equal. Countries below the 45 degree line have either more positive or less negative impacts of climate change than population growth, and vice versa for those above. Those negatively affected by climate change are to the left of the vertical line at 0 and are mostly low income countries, while those to the right of that line are disproportionately high income. Similarly looking at the horizontal line at 0, those countries

negatively affected by population growth are disproportionately low income countries. That is, low income countries tend to suffer losses from both population growth and climate change. Quantitatively, climate losses are all under 35%, while many countries have losses from population growth that are that in the 40–50% range. These countries are mostly poor and agricultural—that is to say, more prone to suffer from congestion and declining land quality, and in a worse position to deal with the consequences of these changes. Finally we note that the gains from climate change tend to exceed gains from population decline.

Figure 8 makes clear that for most of countries projected to experience high levels of damage from climate and population growth taken together, the biggest source of that damage is population growth. There are a few specific countries such as Paraguay and Morocco where effects from projected population increases are much smaller than for projected declines in land quality. But for the majority of countries, the major culprit is population growth. To give a typical example, in Tanzania, the impact of declining land quality is projected to be -18%, while the impact due to rising population is projected to be -46%.

It is worth recalling that all of this analysis is done using RCP 8.5, the most extreme climate scenario. As we explore further below, using projections from a less dire climate projection further elevates the relative importance of population growth as a driver of damages.

6.4   Variation Across Projections

In the analysis above, we focused on RCP 8.5, the most extreme of the four climate scenarios, along with the UN medium population projections. The fact that organizations like IPCC and the UNDP produce ranges of scenarios is indicative of the uncertainty regarding these projections. A natural implication of this is that one can learn something about the range of possible outcomes by looking at the range of scenarios.

In the case of the UNDP, they explicitly state that:

> In projecting future levels of fertility and mortality, probabilistic methods were used to reflect the uncertainty of the projections based on the historical variability of changes in each variable. The method takes into account the past experience of each country, while also reflecting uncertainty about future changes based on the past experience of other countries under similar conditions. The medium-variant projection corresponds to the median of sev-

eral thousand distinct trajectories of each demographic component derived using the probabilistic model of the variability in changes over time. Prediction intervals reflect the spread in the distribution of outcomes across the projected trajectories and thus provide an assessment of the uncertainty inherent in the medium-variant projection. [22]

Unlike the UNDP data, there are no probabilities assigned to the different RCPs used to assess the effects of changing climate, nor is there any claim that the actual path of climate change will fall within the span of the four commonly used RCPs. There is an additional layer of uncertainty in that RCPs only describe the path of radiative forcing values (in watts per square meter), while it then takes an entire climate model to generate projections of the physical outcomes of any RCP path.

All that being said, we would argue that there is still *some* information in the range of projections for each source. One might claim that in looking across the four RCPs, and similarly in comparing, say, the 5th to the 95th percentile probability population projections, one is in each case looking across the range of likely outcomes, and possibly getting some sense for the range of outcomes that different policies could achieve.

In conducting this analysis, we restrict ourselves to looking at individual countries, rather than trying to aggregate to the level of the world as a whole. We start with an example for a single country, India. Table 2 shows the percent change of GDP per capita in 2100, relative to a scenario where population and climate are unchanged. We consider four climate scenarios and five population scenarios, all under perfect population mobility.

Using the median UN forecast, India's GDP will be around 20% lower in RCP 8.5 than if both population and climate had remained the same. The main result in the table, however, is that moving across climate scenarios has a much smaller effect on the expected change in GDP per capita than does moving across population scenarios. For any given population scenario, the difference between the total impact of climate and population on GDP, comparing the most extreme climate scenarios, is about 10 percentage points. By contrast, for a fixed climate scenario, the range of impacts on GDP comparing

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[22]In addition to these probabilistic projections, the UNDP also provides "high" and "low" variant projections, which differ from the medium variant only setting the terminal level of the total fertility rate to be 0.5 above or below it. The relationship between these high and low variants, on the one hand, and the probabilistic bounds, on the other, varies by country. In general, in countries with high current fertility, the high and low projection variants fall within the 95% probability bounds, while the opposite it true in countries with low current fertility.

the highest to the lowest population growth scenarios is roughly 30 percentage points. Even comparing the 20th to the 80th percentile population growth number gives a range of impacts on GDP per capita of roughly 20 percentage points.

Table 2: Impact of Climate Change and Population on GDP per Capita in India

				Climate Scenarios			
				% Change in QAA, 2010-2100			
				RCP 2.6	RCP 4.5	RCP 6.0	RCP 8.5
				-15.96	**-16.95**	**-29.89**	**-38.45**
UN Pop. Projections	% Change in Pop., 2010-2100	5th Percentile	**-28.14**	7.35	6.95	1.48	-2.53
		20th Percentile	**-14.44**	0.48	0.11	-5.02	-8.78
		Median	**17.24**	-10.78	-11.11	-15.68	-19.03
		80th Percentile	**51.74**	-19.03	-19.33	-23.48	-26.53
		95th Percentile	**76.75**	-23.53	-23.81	-27.74	-30.62

Note: The numbers in bold in the first numerical column provide the percent change in population from 2010 to 2100 for each of the five population projections provided by the UNPD. The bold numbers in bold in the first numerical row provide the percent change in ALQ from 2010 to 2100 corresponding to each RCP. The 5×4 matrix provides the percent change to GDP per capita for each population projection-climate scenario pair according to equation (12))

In the perfect mobility case, we can use equation (12) to separate out variation in climate change and population growth in the total impact. As before, we ignore the small offset term.[23] Figure 9 expands this analysis graphically to look at 10 particularly interesting countries. Each country is represented by a colored rectangle. The horizontal dimension of the rectangle shows the range in projected impacts from land quality change (the first term in equation (12)), looking across all four RCPs. The vertical dimension of the rectangle is the range of the impact from population growth (the second term of equation

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[23]Values for country level damages inclusive of this term under all RCPs and population scenarios can be found in Appendix E.

(12)) going from the 5th to the 95th probability percentile estimate of the change in log population between 2010 and 2100.

Figure 9: Range of Impacts from Climate Change and Population for Selected Countries
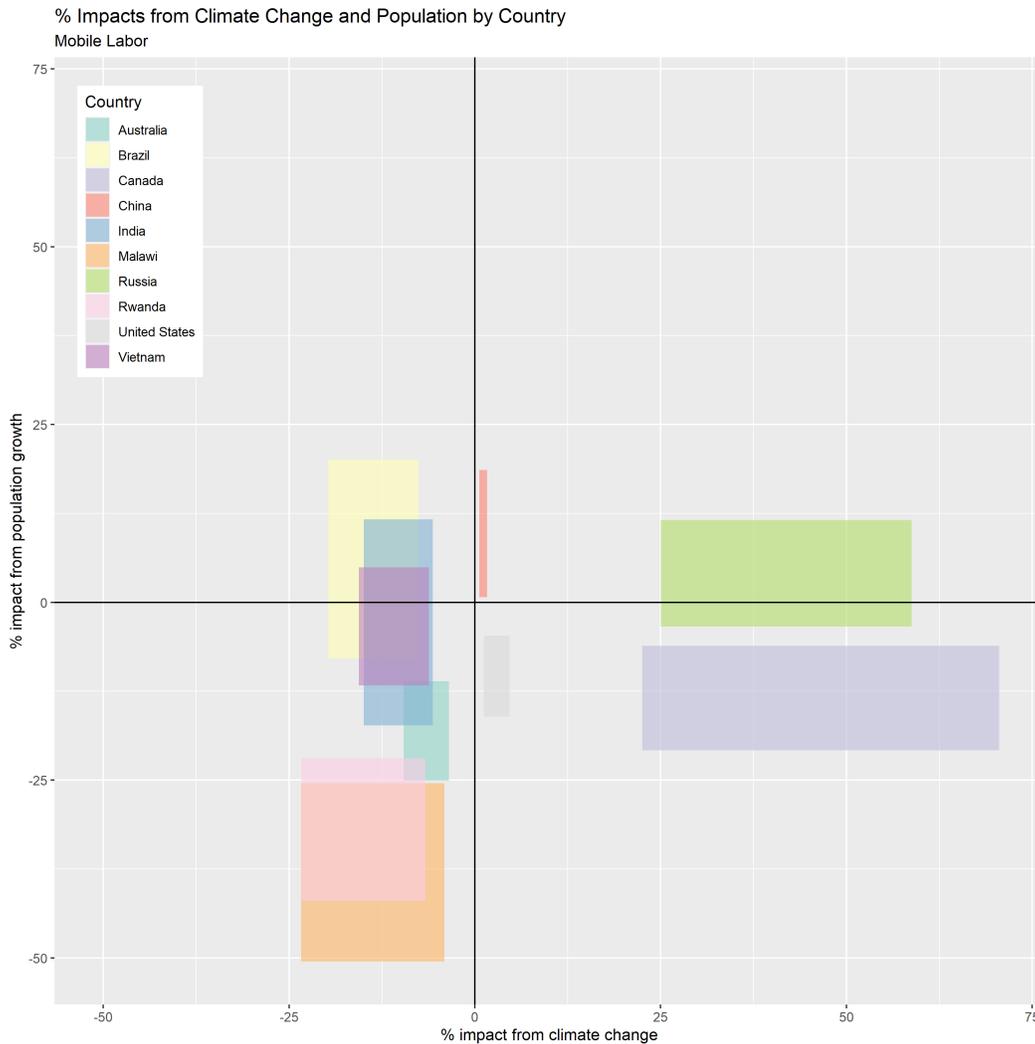
% Impacts from Climate Change and Population by Country
Mobile Labor

Note: This plot depicts the minimum and maximum impacts from climate change and population across different scenarios, represented by the first and second terms of equation (12)) as percent changes. The contribution from impacts attributed to climate change come from four RCP scenarios, and scenarios for log impacts from population comprise the 95th and 80th percent confidence intervals as well as the median from UN population projections.

As an illustrative example, for Malawi, the rectangle showing the range of GDP per capita losses is much taller than it is wide, indicating that there is less uncertainty regarding the effect of climate change than there is regarding

the effect of population change. The rectangle for Malawi is also entirely in the lower-left quadrant (rising population, falling land quality), indicating that, within the range of these estimates, all scenarios will lead to an increase in population pressure on quality-adjusted land. By contrast, the rectangle for Russia is wider than it is tall, i.e. there is more uncertainty about the effect of climate than about population. Russia also sits largely in the upper right quadrant, indicating that both forces will be pushing toward reduced population pressure on land.

Although we display only a limited number of countries in Figure 9 for illustrative purposes, looking over all poor countries there is a strong empirical regularity: Not only is expected damage from population growth larger than expected damage from climate change, but variation in damage among population scenarios is also larger than variation in damage across climate scenarios.[24]

7   The World Damage Function

In this section, we assess the damage from climate change aggregated to the world level. Our motivation for doing this is largely for comparability with existing literature.

Aggregating the country-level climate damages calculated in Section 6 to the world level requires an additional piece of information, which is the *level* of total output in each country in 2100 in the absence of climate change. So far we have avoided this issues of levels, and calculated percent losses or gains from whatever the level might be. Now we need the actual level to be comparable to the literature. Following other work in this area, we rely on the Shared Socioeconomic Pathways (SSPs; O'Neill *et al.*, 2014; Riahi *et al.*, 2017) for these projections. These are scenarios for how the world economy might evolve in the absence of both climate change and climate mitigation or adaptation policies. The different pathways embed particular assumptions about technological change, population and economic growth, and cross-country income convergence, among other dimensions. For example, SSP 5 features the following: rapid income growth at the world level combined with a large decline in income gaps among countries, and world population peaking around the year 2060 and then declining to around 7 billion in 2100. By contrast, in SSP 3, world income growth is slow, cross-country inequality falls only slightly, and high population growth in poor countries drives the world population to

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[24]Results for all countries can be accessed interactively at `https://bjang.shinyapps.io/appendix_countries/`.

12.6 billion in 2100. SSP 2 represents a continuation of historical social, economic, and technological trends, and falls roughly in the center of the range of the other pathways in terms of income and population growth.[25]

Table 3 shows the damage function at the world level, which aggregates country losses weighted by their 2100 GDP in the absence of climate change. These GDP weights vary considerably across the SSPs. The top rows show world GDP and population under the different SSP scenarios, as well as 2010 numbers. Then, in panels A and B, each entry shows the percentage change in world total GDP going from the case when climate change has no economic effects to the case where climate follows a specified RCP. Specifically, in Panel A, each entry is the weighted average of country-specific percentage changes in GDP under the particular SSP-RCP scenario assuming population mobility within countries as in equation (12) calculated above, where the weights are 2100 country values of total GDP under the specified SSP. Panel B shows analogous numbers for the case where there is an unobserved dimension of land quality that explains the current population distribution, as represented by equation (22).

Table 3: 2100 Impacts as Percentage of World GDP (OECD Env-Growth)

Year	2100					2010
Scenario	SSP 1	SSP 2	SSP 3	SSP 4	SSP 5	
	Sustainability – Taking the Green Road	Middle of the Road	Regional Rivalry – A Rocky Road	Inequality – A Road Divided	Fossil-fueled Development – Taking the Highway	Historical Data
World GDP	5.65e+14	5.38e+14	2.78e+14	3.53e+14	1.02e+15	6.73e+13
World Pop.	6.87e+09	8.98e+09	1.26e+10	9.25e+09	7.35e+09	6.85e+09
A. % Impacts: Mobile Labor						
RCP 2.6	-1.165	-1.088	-0.853	-0.162	-0.674	1.771
RCP 4.5	-1.588	-1.514	-1.260	-0.117	-0.796	2.768
RCP 6.0	-2.783	-2.661	-2.295	-0.878	-1.768	3.066
RCP 8.5	-5.278	-5.114	-4.566	-2.296	-3.727	3.584
B. % Impacts: Perfect Mobility, Unmeasured Quality						
RCP 2.6	-0.836	-0.731	-0.461	0.189	-0.404	2.032
RCP 4.5	-1.080	-0.958	-0.631	0.494	-0.372	3.285
RCP 6.0	-2.216	-2.047	-1.597	-0.258	-1.311	3.545
RCP 8.5	-4.821	-4.565	-3.866	-1.789	-3.509	3.706

Note: "World GDP" aggregates 160 countries for all SSP scenarios in 2100 and 143 countries for the 2010 column.

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[25]Projections of population, urbanization, and GDP that quantify the narratives of the Shared Socioeconomic Pathways are available in a database hosted by the International Institute for Applied Systems Analysis (IIASA) Energy Program at `https://tntcat.iiasa.ac.at/SspDb`. We use the projections of the Organization for Economic Co-operation and Development (OECD; Dellink *et al.*, 2017), considered the "illustrative" case. Population projections for each SSP are from Samir and Lutz (2017).

In each panel, RCP 8.5 unsurprisingly yields the most negative impacts to world GDP in the year 2100. Within each SSP, we see that the magnitude of impact increases moderately from RCP 2.6 to RCP 6.0, then jumps with RCP 8.5. It is worth noting that not all RCPs are plausible in each SSP. For example, it is highly unlikely that RCP 2.6 or even RCP 4.5 will be reached under the baseline SSP5 scenario. Comparison of RCPs across different SSPs must therefore be done with care. Impacts as percentage of world GDP in RCP 8.5 are higher in SSP1, the sustainability-focused scenario, than SSP5, the fossil fueled development scenario, due to the differences in convergence of world incomes under each narrative.

To compare these results to existing literature, Burke *et al.* (2015A) focus on the case of RCP 8.5 and SSP 5 to estimate that average global incomes would be reduced around 23%. By contrast, our projection is that world level GDP would fall by only 3.7% using the same scenarios and assuming perfect labor mobility. In Panel B, where unobserved quality is taken into account, these losses are slightly smaller at 3.5%.

8   Conclusion

This paper quantifies the projected effects of established climate change scenarios on characteristics that affect the carrying capacity of land, which we call land quality. Land quality tends to increase for select countries in currently colder climates and decreases in the tropics. Using this measure in a model of economic growth, we assess the effects of climate change against a counterfactual in which land quality is unchanged. Under the most extreme scenario of RCP 8.5, we estimate country-level impacts ranging from -32% to 88%, with a positive correlation between log GDP and climate change impact so that richer countries on average experience more positive impacts.

We further compare the effects of climate change against the effects of projected population growth, finding that the impact of the latter is consistently the larger of the two. Further, the difference in economic outcomes comparing the most extreme to the most modest climate scenarios is, for most countries, smaller than the difference in economic outcomes comparing the highest to the lowest population growth scenarios.

Our analysis of climate damages is closely tied to the output of global climate models, and thus shares any limitations that are present in these models. Notably, this means that our analysis may under weigh the importance of natural disasters that are likely to become more frequent with global warming.

One of our crucial findings is that climate change will make the natural

environment less supportive of human habitation in exactly the places where population growth is already working to raise the burden on that land. The intensification of population pressure disproportionately affects more vulnerable regions, becoming another driver for inequality in economic development.

A notable aspect of our analysis is that we allow for within-country labor mobility in response to climate change, but not for similar mobility between countries. While it is true that climate change will *ceteris paribus* raise the gap in income between rich and poor countries, the observable fact is that the income gap between these country groups is already quite large, and migration flows between them are relatively small. Further, while climate change will work to raise the income gap between rich and poor, other economic processes (embodied in the SSP scenarios discussed above) will lower the gap.[26]

A simple reading of our results would say "Don't worry about climate change–the bigger issue is population growth." This is not our interpretation, for several reasons. First, even a finding that population growth is a larger driver of environmental stress than climate change does not in any way lessen the damage being done by that climate change. Second, unlike the effects of population growth, the effects of climate change largely result from decisions and behaviors outside the country that is impacted. More concretely, in poor countries that will suffer the most from climate change, the vast majority of relevant emissions causing that climate change were the result of economic activity elsewhere in the world. Third, nothing in our analysis addresses the relative costs and unintended consequences of reducing population growth versus mitigating climate change. Finally, the welfare calculus regarding population growth differs markedly from that regarding climate change: having more warming, holding population constant, reduces the average welfare of a fixed set of people. By contrast, reducing population growth, holding climate constant, may raise welfare per capita but lower then number of people who experience that welfare.

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[26]Conte (2022) estimates that climate-induced international migration within sub-Saharan Africa between 200 and 2080 will be only 4 million individuals under the current regime of migration barriers. Absent those barriers, international migration within sub-Saharan Africe would increase by more than 100 million people.

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Appendices

A Comparison of Population Datasets and Cell-Level Specifications

In this appendix we first compare the distribution of population density in our main population data source, GHS-POP, to two alternatives, GPWv4 and LandScan. We then compare regression results using our baseline Poisson specification and a log-linear alternative, using all three datasets–a total of six variants. Specifically, we compare goodness of fit and fitted values in a regression of population on geographic characteristics. All three global datasets report population counts for 30-arc-second by 30 arc-second pixels in Plate Carrée (latitude/longitude) projection. The area of a pixel is 0.86 square km at the equator, decreasing with the cosine of latitude.

The Gridded Population of the World version 4 (GPWv4; CIESIN 2017) is the simplest of the three. The underlying data are population estimates for administrative regions (polygons) from censuses circa 2010. When there is no census in exactly 2010, values are extrapolated or interpolated from multiple censuses. Population is assumed to be distributed evenly within an administrative region. GPWv4's effective spatial resolution thus depends on what information individual countries provide, with richer countries typically providing data for finer regions, down to enumeration units, or even block level data. There is substantial variation within countries as well, with higher resolution in more densely populated regions. Of 12.9 million input polygons worldwide, only 2.4 million are from outside the United States. A grid cell crossing a polygon boundary is assigned a population density that is the areally-weighted average of its constituent polygons.

The European Union's Global Human Settlements population layer (GHS-POP; Schiavina *et al.* 2019; Freire *et al.* 2016) reallocates GPWv4 estimates within administrative polygons based on a companion dataset, GHS-BUILT (Corbane *et al.*, 2018, 2019) that defines built-up pixels as seen in Landsat 30-meter resolution satellite data circa 2015. In the rare cases where there is no built-up area visible in a region, it reverts to the GPWv4 estimates. Its land area measures are taken directly from GPWv4. More information about the GHS data can be found in Florczyk *et al.* (2019).

LandScan uses a proprietary algorithm to provide population estimates based on a much wider set of inputs that include census population data and satellite imagery at higher resolution than Landsat. While the algorithm is not publicly documented and changes from year to year, in the recent past input

data have also included information on elevation, slope, and land cover, as well as locations of road and rail networks, hydrologic features and drainage systems, utility networks, airports, and populated urban places. LandScan reports estimates of ambient population averaged throughout the day, whereas the other two datasets report nighttime (residential) population estimates. A recent explanation of LandScan for an academic audience can be found in Rose and Bright (2014).

We rely on GHS-POP as our primary source, and consider GPWv4 and LandScan for robustness here. GHS-POP's use of building cover to redistribute people within census units is very likely to provide more accuracy than GPWv4's assumption of uniform density within large administrative units.

LandScan aims to achieve the same goal of redistributing population based on built cover. However, as noted, it uses other information in making assessments, including higher resolution satellite imagery. LandScan may thus do a better job of finding the built environment in rural locations and it may have greater accuracy in dense but low income cities with coarse population data.

However LandScan has four main drawbacks. First, it has historically used coarse census data as a benchmark outside of the United States.[27] While better satellite imagery can better define the built environment, to convert that to population one still needs fine grained census population data. Second and more importantly, LandScan's algorithm uses physical features like elevation directly to predict population density. This raises the possibility that our regressions will end up simply predicting LandScan's algorithm rather than true population density. Third, LandScan's algorithm changes from year to year and is not documented. Finally LandScan measures the ambient population over the 24 hours of a day, making inferences about where people work and for how many hours of the day, without, as we understand it, much if any spatial economic census data which are unavailable for many developing countries anyway. This seems likely to add error without benefit for our purposes.

Figure A1 Panel A reports the cumulative distribution function (CDF) of log population density according to the three datasets, with zeros in each dataset replaced with that dataset's minimum nonzero value before logging. The figure shows that the three data sets treat grid squares with tiny densities very differently. For example GHS-POP registers about 40% of cells as having no people, with nonzero densities starting at $0.0000000033/km^2$, while

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[27]LandScan has not released details about its current census data, but as of its 2009 version: "Outside the USA LandScan used 79,590 administrative units for ambient modeling. By contrast, GPWv3 uses 338,863 units outside of the US." Source: https://sedac.uservoice.com/knowledgebase/articles/41665-what-are-the-differences-between-gpw-grump-and-la

Figure A1: Population Distributions by Grid Square Worldwide

A. CDFs of Grid-square Log Population Density

B. Cumulative Share of Population in Grid Squares by Log Density

— GHS — GPW — LandScan
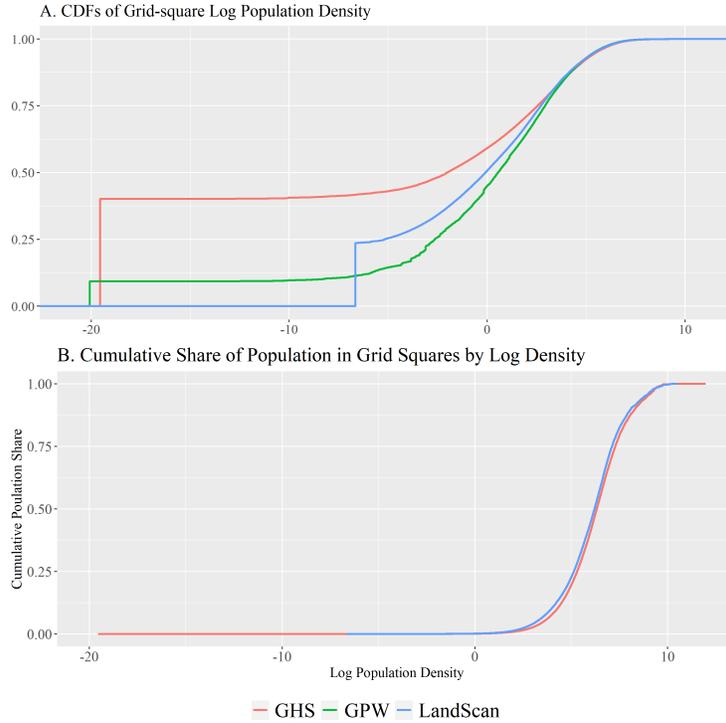
LandScan registers only about 24% of grid squares at 0, with non-zero densities starting at about 0.0013/km2. By population densities of about $50/km^2$ ($exp(3.9)$), the three lines converge, at which point about 85% of pixels have been accounted for. Panel B of Figure A1 analogously reports cumulative population by density. It shows that less than 10% of the world population lives at a density under $50/km^2$. However, since our unit of analysis is the grid square, these tiny densities potentially play an important role.

In implementing the log-linear specification, we assigned to such cells the population density of the least dense non-zero cell in the dataset before logging. We also experimented with creating versions of the logged GPWv4 and GHS-POP datasets in which cells with zero density are assigned the minimum nonzero density value in LandScan. As shown in Figure A1, LandScan's minimum value is much larger than the minimum non-zero density in the other two datasets.

Figure A2 compares cell-level predicted values across the three datasets. Using the Poisson specification (Equation (4)), Panel A shows that all three data sets give very similar predicted values. This is because the Poisson speci-

Figure A2: Predicted Values

(a) Poisson Specification
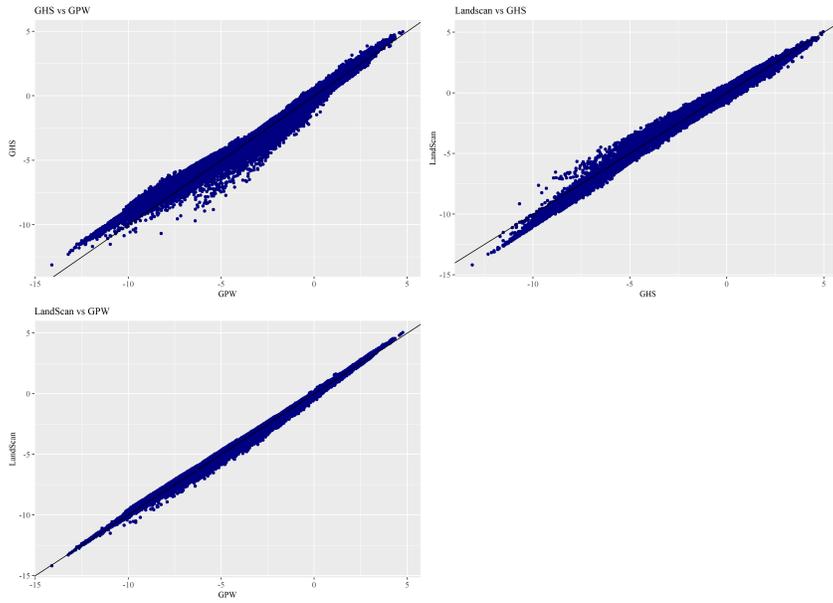
(b) Log Linear Specification
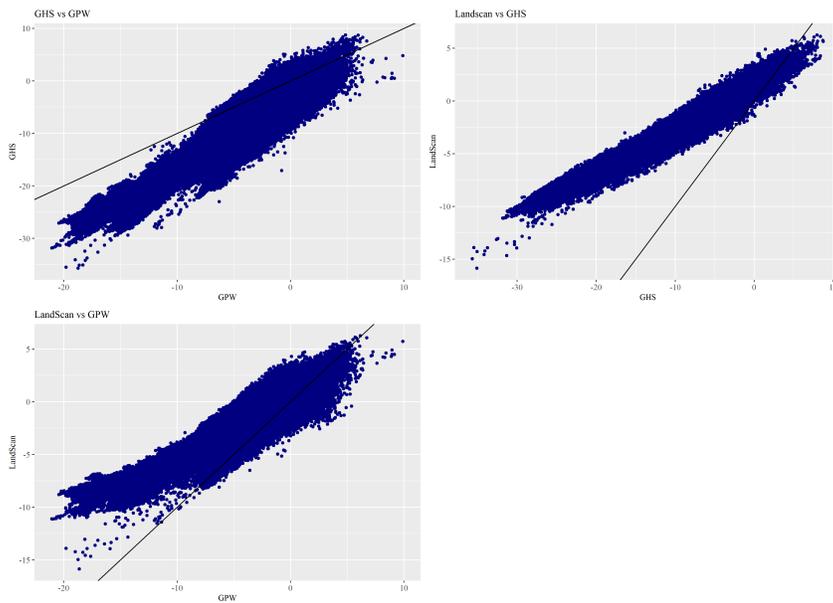
fication makes little distinction between cells that have moderately low density and those that have extremely low density. By contrast, in Panel B, there are large differences across datasets when using the log-linear specification, driven by the differing treatments of low density regions.

Table A1 reports goodness of fit measures for the log linear and Poisson specifications. In the first 3 rows zeros are assigned their dataset-specific minimum non-zero value. In rows 4 and 5 zeros in GHS-POP and GPWv4 are assigned the LandScan minimum value.

Table A1: Goodness of Fit for Grid Cell Level Regressions

	Log-linear	Poisson
GHS	0.597	0.567
GPW	0.758	0.621
LandScan	0.737	0.594
GHS Censored	0.659	0.567
GPW Censored	0.800	0.621

Note: The table reports R^2 values for the log-linear regressions and R^2_{DEV} for the Poisson specification.

Finally, Table A2 reports the main grid square Poisson estimation of equation (4) for a single climate model. Across climate models, historical values are identical for all but one variable: year-to-year volatility of daily temperature. Because we calculate year-to-year volatility using daily data from climate model historical backcasts, we run a regression for each climate model. Here we show the coefficients of the GFDL climate model; the results do not change noticeably across climate models.

Table A2: Grid Square Regression Coefficients

	Models
	GFDL
Ruggedness (000s)	−1.88e-06***
	(1.24e-07)
Abs(Latitude)	0.029***
	(3.84e-03)
Elevation (m)	−1.89e-04***
	(4.26e-05)
Distance to coast (000 km)	−7.15e-07***
	(3.4e-08)
Coast dummy	0.408***

	(0.028)
Harbor dummy	0.831***
	(0.025)
Navigable river dummy	0.751***
	(0.029)
Lake dummy	0.706***
	(0.147)
Adjusted LGP for evaluating agro-climatic constraints	5.59e-03***
	(5.62e-04)
Length of longest component LGP	2.26e-03***
	(3.97e-04)
Longest consecutive dry days in LGPt=5	−8.33e-04**
	(3.9e-04)
Number of dry days during LGPt=5	−8.8e-03***
	(1.49e-03)
Total number of growing period days	5.28e-03***
	(1.36e-03)
Total number of LGP days in component LGPs > 20 days	−7.7e-03***
	(1.1e-03)
Net primary production (rain-fed)	−4.53e-05***
	(3e-06)
Annual P/PET ratio (*100)	4.41e-03
	(2.75e-03)
P/PET (*100) for days with mean temperature > 5 deg. C	−0.021***
	(2.2e-03)
Seasonal P/PET ratio (*100) in summer	−2.41e-03***
	(6.31e-04)
Seasonal P/PET ratio (*100) in winter	−1.32e-03***
	(3.85e-04)
Number of consecutive days with average precipitation > 30 mm	0.111
	(0.122)
Total number of rain days (days with precipitation > 1 mm)	−7.53e-03***
	(1.4e-03)
Modified Fournier Index (mm)	2.77e-04***
	(3.44e-05)
Annual precipitation (mm)	2.61e-04**
	(1.31e-04)
Mean max. sum of precip. on consec. > 30 mm av. daily precip. days	−3.46e-03
	(4.08e-03)
Reference actual evapotranspiration (using AWC=100 mm/m)	9.91e-04***
	(1.81e-04)
Reference potential evapotranspiration (using AWC=100 mm/m)	−1.9e-03***
	(1.08e-04)
Number of days with max temperature > 35 deg. C	−1.22e-03***
	(4.28e-04)
Number of days with max temperature > 40 deg. C	3.92e-03***
	(7.74e-04)
Number of days with min temperature < 0 deg. C	−1.24e-03

	(8.33e-04)
Number of days with min temperature < 10 deg. C	−8.3e-04**
	(3.96e-04)
Number of days with min temperature < 15 deg. C	2.31e-03***
	(3.47e-04)
Number of days with mean temperature > 10 deg. C (LGPt=10)	−4.09e-03
	(2.79e-03)
Number of days with mean temperature > 5 deg. C (LGPt=5)	0.019***
	(3.15e-03)
Annual temperature amplitude (deg. C)	−0.046***
	(0.013)
Mean annual temperature (deg. C)	0.514***
	(0.035)
Snow-adjusted cold temperature limit	5.63e-04***
	(2.16e-04)
Temperature of coolest month (deg. C*100)	−1.4e-03***
	(2.97e-04)
Annual temperature sum for days with mean temperature > 10 deg. C	1.42e-03***
	(3.75e-04)
Annual temperature sum for days with mean temperature > 5 deg. C	−2.66e-03***
	(3.83e-04)
Air frost number	−0.381
	(2.407)
Snow-adjusted air frost number	0.627
	(2.521)
Maize suitability index; high input, rain-fed, CO2 fertilization	−6.25e-05***
	(9.71e-06)
Dryland rice suitability index; high input, rain-fed, CO2 fertilization	5.83e-06
	(5.94e-06)
Wetland rice suitability index; high input, rain-fed, CO2 fertilization	−2.03e-06
	(6.31e-06)
Wheat suitability index; high input, rain-fed, CO2 fertilization	7.75e-06
	(8.42e-06)
Cassava suitability index; high input, rain-fed, CO2 fertilization	−2.52e-05**
	(1.01e-05)
Soybean suitability index; high input, rain-fed, CO2 fertilization	8.72e-05***
	(8.8e-06)
White potato suitability index; high input, rain-fed, CO2 fertilization	3.85e-05***
	(9.69e-06)
Sorghum suitability index; high input, rain-fed, CO2 fertilization	6.76e-05***
	(7.99e-06)
Sweet potato suitability index; high input, rain-fed, CO2 fertilization	5.65e-05***
	(8.52e-06)
Yam suitability index; high input, rain-fed, CO2 fertilization	−9.58e-05***
	(9.75e-06)
Banana suitability index; high input, rain-fed, CO2 fertilization	2.48e-05***
	(8.35e-06)
Year-to-year volatility of daily temperature	−0.204***

	(0.024)
R^2_{dev}	0.567
Observations	237023

Note: LGP is the length of the growing period; LGPt=n is the temperature growing period, which provides the number of days with mean temperature over n degrees Celsius. P/PET is the ratio of precipitation to potential evapotranspiration. Goodness of fit measure is R^2_{DEV}. *p<0.1; **p<0.05; ***p<0.01

B   Variation Across Climate Models

As mentioned in the methodology, the main results in this paper rely on the ensemble mean of five climate model forecasts. Here we discuss the variation in projections across these forecasts in more detail. Appendix Figure B1 shows the grid-level standard deviation of our projected land quality measure across the five climate models included in this paper.

Figure B1: Changing ALQ and Population

(a) RCP 2.6
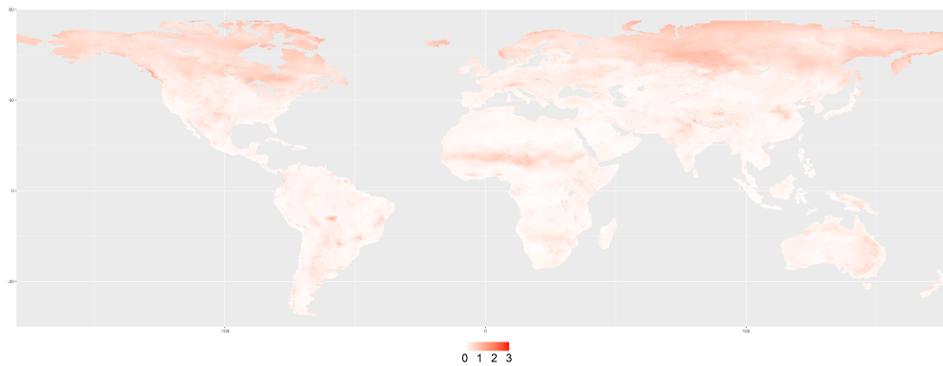
(b) RCP 4.5
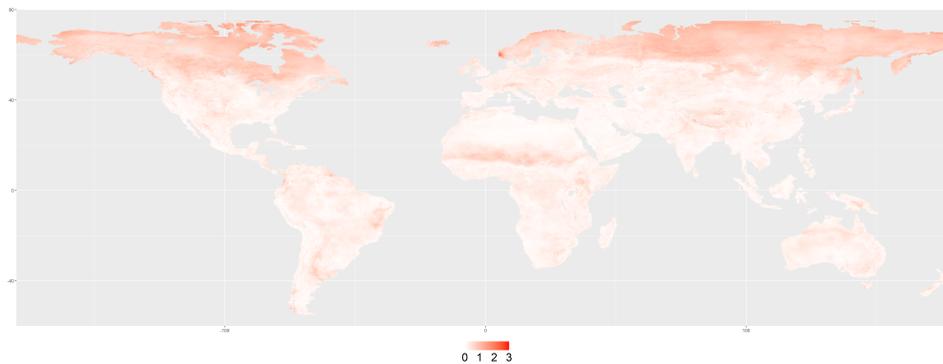
(c) RCP 6.0
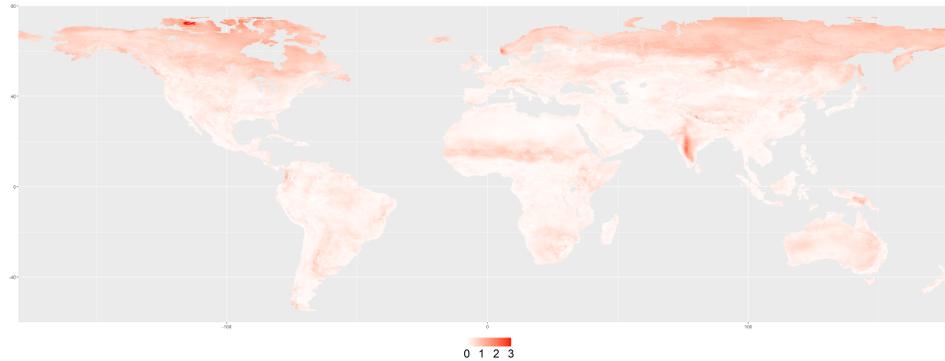
(d) RCP 8.5
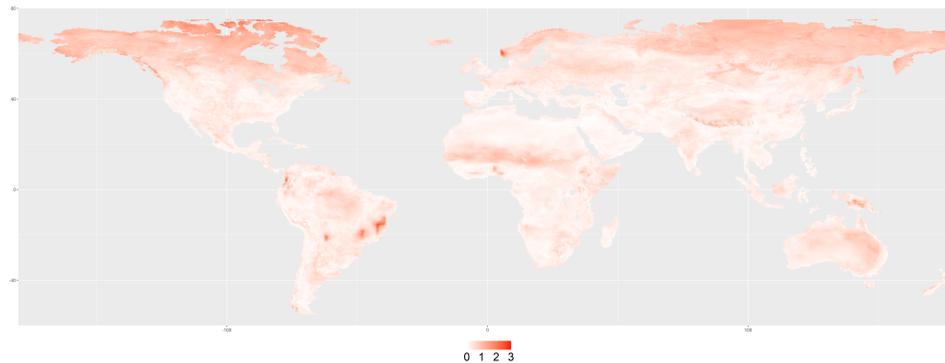
Note: Values are censored to 3 for visualization.

In general, the largest variation among models is in the northern part of the Northern hemisphere as well as the Sahara Desert, although there are other, more localized areas of disagreement as well in specific climate scenarios. Specifically, we see high variation in the Western Ghats for RCP 6.0 and in Minas Gerais in Brazil for RCP 8.5. Both of these are driven by unusually negative values from a single model (MIROC).

For each climate model we also calculate country-level projected changes in average land quality over the period 2010-2100 under the RCP 8.5 scenario. These are presented in Appendix Figure B2, where Panel (a) uses area-weighted ALQ, while (b) uses population-weighted ALQ. The two panels are similar. In general, these country level projections are highly correlated among the different climate models and each is well correlated with the ensemble mean. However, there are notably larger cross-models differences in projections for countries that are expected to have improved average land quality in the north-east of each graph, which also tend to be richer countries. Among countries where land quality is expected to decline, there is more accord among the models.

While within-model uncertainty–either from parameters or initial conditions–must also be acknowledged for each climate model, we are not equipped to address this additional source of uncertainty.[28]

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[28]The IPCC Assessment Report 4 discusses these issues and the degree of uncertainty

Figure B2: Comparison of changes to *ALQ* by Climate Model

(a) Area-weighted *ALQ*
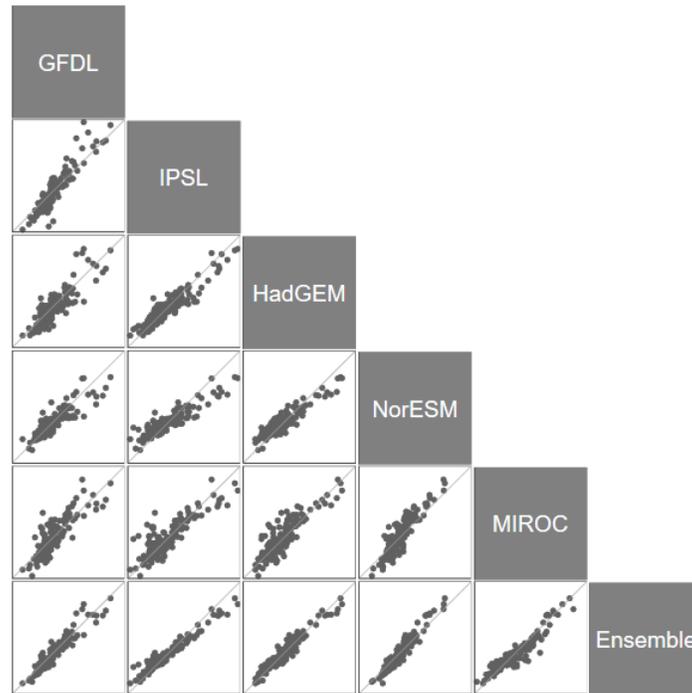
Note: Each cell of this matrix depicts a scatterplot comparing the log difference in ALQ from 2010 to 2100 projected by two different models. The range of each axis is fixed at -1.65 to 2.67. The diagonal represents the 45 degree line.

they impart in section 10.5. The confidence intervals reported for projections in IPCC Assessment Report 5 are estimated by assuming each model's point estimate is pulled from one normal distribution with same mean and standard deviation.

(b) 2010 Population-weighted *ALQ*
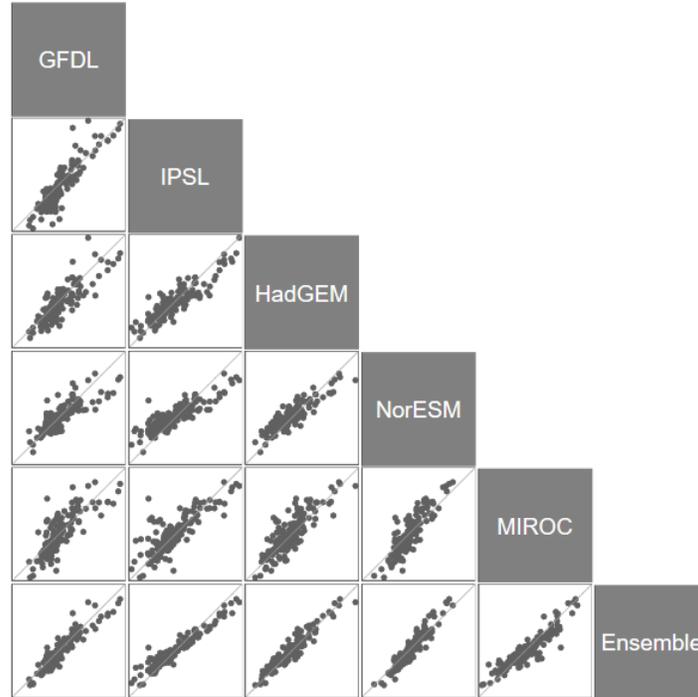
Note: Each cell of this matrix depicts a scatterplot comparing the log difference in ALQ from 2010 to 2100 projected by two different models. The range of each axis is fixed at -1.71 to 2.05. The diagonal represents the 45 degree line.

C Robustness of Measured *ALQ* Changes to Choice of Sample Countries.

One concern regarding our grid-cell regression is that countries may value the land characteristics included in our regression differently depending on their stage of development. As a robustness check, we replicate our main results on the effect of projected climate change on land quality, focusing on a sample of poor countries. Specifically, we re-estimate our grid-cell level Poisson regressions for measuring land quality on the sample of all countries with below-median GDP per capita, and then use estimated coefficients to form projections of the change in land quality due to climate change for this subsample of countries. The logic behind this exercise is that the value of specific land characteristics in determining economic outcomes may be a function of the level of a country's development. Correspondingly, the effect of a change in a particular characteristic will have a different effect in poor vs. rich countries. For example, a reduction in rainfall in an already dry climate could be devastating in a region reliant on smallholder agriculture, but in a developed region that imports its food from elsewhere it would have only a marginal effect.

The analysis above showed that it is generally in poor countries that climate change is expected to have the most negative effects. Furthermore, poor countries generally have fewer opportunities to substitute production away from climate-affected sectors, since they are heavily reliant on agriculture and primarily consume domestically produced food. Finally, large fractions of the populations of poor countries face high transportation costs in interacting with the broader world economy.

Figure C1: Log Land Quality, Countries with Below-Median GDP Only

(a) Historical Log Land Quality
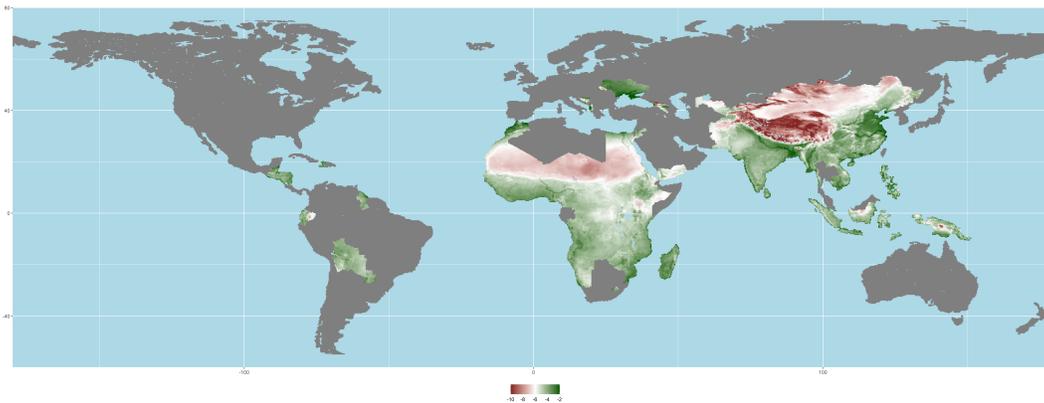
(b) Differences between Historical and 2081-2100 Log Land Quality under RCP 8.5
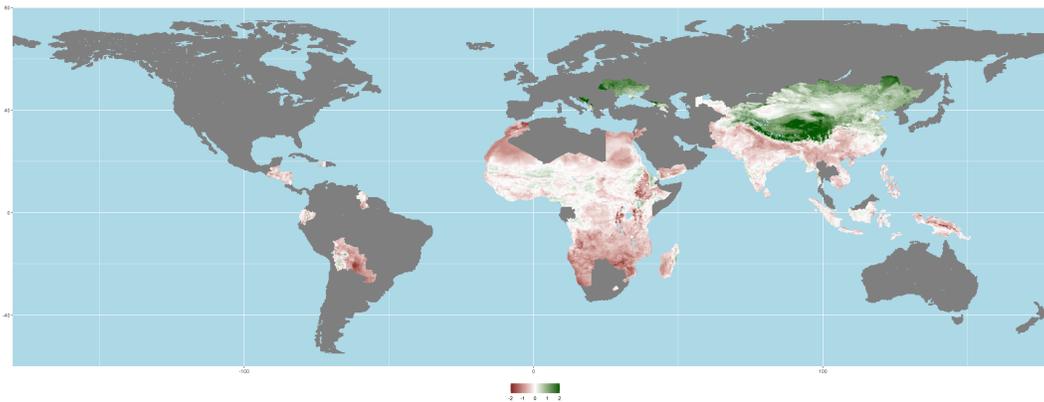
Note: Data are censored at -6 and 4 and at -2 and 2 in the top and bottom panels, respectively, for visualization. Plate Carrée projection.

Figure C1 is analogous to Figure 1, except that it bases estimates on and looks only at countries with current GDP per capita below the world median of $9,698. The first panel shows estimated values for grid-cell level land quality using this new estimation sample, while the second panel shows projected changes in land quality between 2010 and 2100

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under RCP 8.5. For the relevant countries, the (b) panels of Figures 1 and C1 seem very similar, with improvements in the Tibetan Plateau and parts of China and deterioration for most Africa and South and South-East Asia.

Figure C2 shows data on changes in land quality over the period 2010-2100 under RCP 8.5, comparing projections based on coefficients derived from the full sample (horizontal axis) and from the sample of below-median income countries (vertical axis). The data are aggregated to the country level using area weights. Doing this comparison using population-weighted projections yields a very similar result.

Figure C2: Comparing Change of Baseline *ALQ* and Below-Median GDP *ALQ*
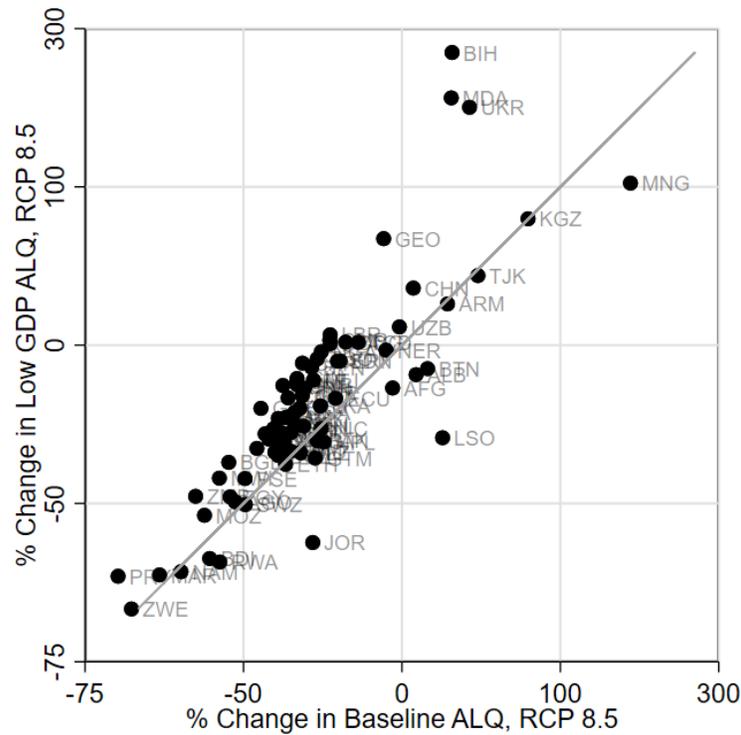
Note: Figure plots the percent change in baseline ALQ from 2010 to 2100 in RCP 8.5 against that of ALQ estimated using only countries with below-median GDP for the 78 countries with both values.

Overall, Figure C2 shows that the predicted effects of climate change are fairly similar using the two different approaches. There are 10 countries that are projected to have decreased *ALQ* using the full sample estimates but increased *ALQ* using the below-median sample estimates, and 3 countries that are expected to have the reverse. However in almost all of these cases, the projected changes in *ALQ* are not far from zero. Most countries that are projected to suffer severe declines in land quality under one measure are projected to suffer similar declines under the other. The correspondence between the two projections is fairly tight for the majority of countries that will experience deterioration, but more scattered among those where land quality will improve.

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Given this result, we use projections of the effect of climate change based on full-sample estimates for the main body of the paper.

D   Mapping Land Quality Changes and Population Growth into Income: Perfect Mobility with Unobserved Quality

This section provides figures and tables under the assumption of perfect mobility with unobserved quality that are analogous to Section 6

Figure D1: Country-Level Impacts from Climate Change: Perfect Mobility with Unobserved Quality
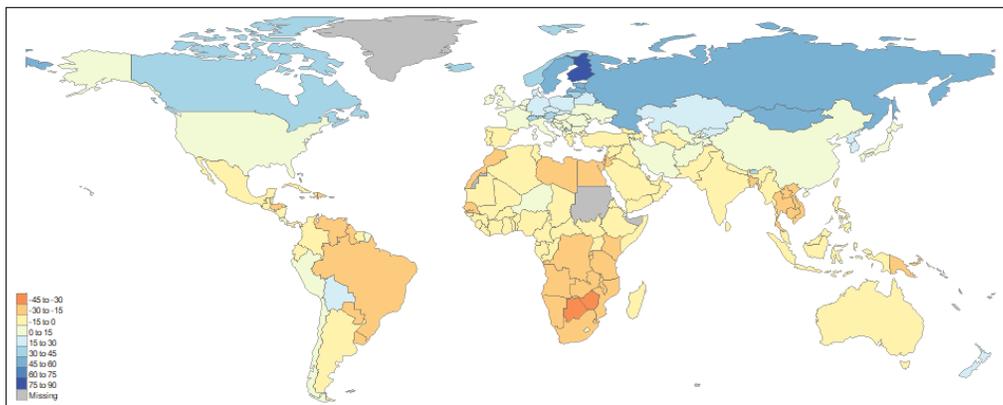
Notes: Countries are binned by the difference between GDP per capita under RCP 8.5 and no climate change under the assumption of perfect mobility with unobserved quality.

Figure D2: Impacts from Climate Change and Population Growth

Note: The Y axis plots the percentage impact of climate change in 2100 using RCP 8.5 and the U.N. medium variant population projection in log scale assuming perfect mobility with unobserved quality. The X axis plots log 2010 GDP. 156 countries are shown.

Figure D3: Changing *ALQ* and Population
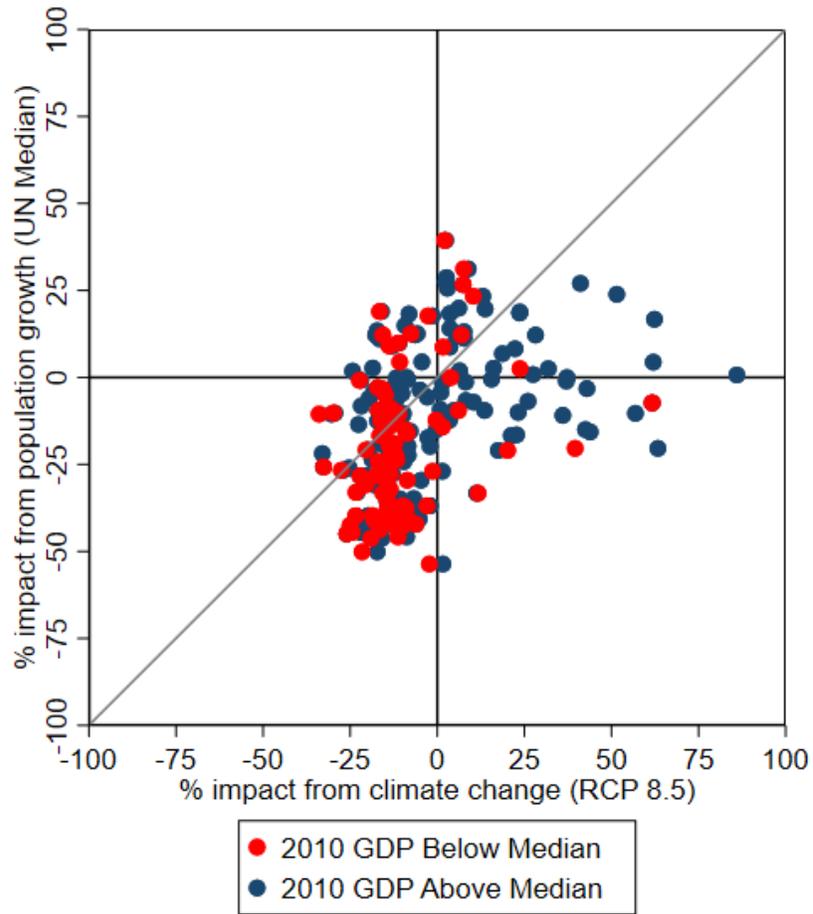
Note: Figure compares the effect of the the second term in equation (22), which represents the impact of population growth, against the first term, which represents the impact of climate change in 2100. Impacts are calculated in percentages assuming perfect mobility with unobserved quality using RCP 8.5 and the U.N. medium variant population projection; 164 countries are shown.

Table D1: Impact of Climate Change and Population on GDP per Capita in India

				Climate Scenarios			
				% Change in pop. wt. QAA, 2010-2100			
				RCP 2.6	RCP 4.5	RCP 6.0	RCP 8.5
				-21.51	-21.95	-32.03	-43.41
UN Pop. Projections	% Change in Pop., 2010-2100	5th Percentile	-28.14	7.50	7.24	1.44	-2.11
		20th Percentile	-14.44	0.63	0.38	-5.06	-8.39
		Median	17.24	-10.65	-10.87	-15.72	-18.68
		80th Percentile	51.74	-18.91	-19.11	-23.51	-26.21
		95th Percentile	76.75	-23.41	-23.60	-27.77	-30.32

Note: The numbers in bold in the first numerical column provide the percent change in population from 2010 to 2100 for each of the five population projections provided by the UNPD. The bold numbers in bold in the first numerical row provide the percent change in ALQ from 2010 to 2100 corresponding to each RCP. The 5×4 matrix provides the percent change to GDP per capita for each population projection-climate scenario pair according to equation (22))

Figure D4: Range of Impacts from Climate Change and Population for Selected Countries
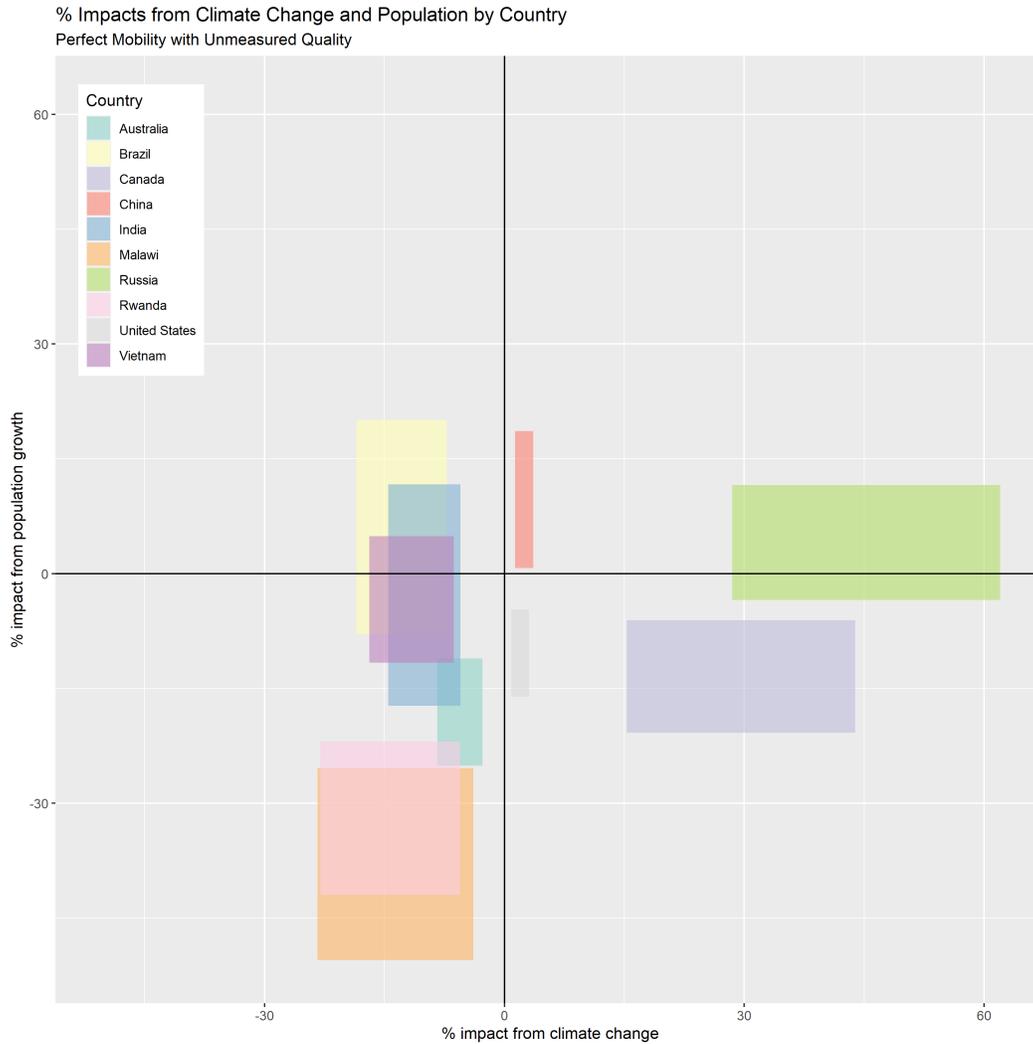
% Impacts from Climate Change and Population by Country
Perfect Mobility with Unmeasured Quality

Note: This plot depicts the minimum and maximum impacts from climate change and population across different scenarios, represented by the first and second terms of equation (22)) as percent changes. The contribution from impacts attributed to climate change come from four RCP scenarios, and scenarios for log impacts from population comprise the 95th and 80th percent confidence intervals as well as the median from UN population projections.

E   Data Tables

E.1   Baseline

Table E1: Changes in ALQ by RCP

Country	Historical ALQ	% Change in ALQ, 2010 - 2100							
		Area weighted				Pop. weighted			
		RCP 2.6	RCP 4.5	RCP 6.0	RCP 8.5	RCP 2.6	RCP 4.5	RCP 6.0	RCP 8.5
Afghanistan	0.20	12.66	2.20	3.97	-4.01	8.53	0.93	4.24	-1.99
Albania	2.62	-6.65	-5.72	-1.76	6.37	-10.96	-13.86	-8.27	2.95
Algeria	0.33	-14.42	-23.30	-26.89	-37.00	-17.76	-26.91	-31.80	-39.56
Angola	1.64	-23.71	-31.66	-36.47	-51.76	-27.20	-21.33	-27.33	-39.28
Argentina	2.83	-4.80	-10.71	-12.28	-20.62	-8.12	-14.07	-15.27	-22.47
Armenia	0.64	12.77	14.21	16.18	22.07	-4.41	-10.06	-5.54	-3.92
Australia	1.37	-10.16	-11.53	-12.84	-26.03	-16.66	-16.60	-15.10	-32.67
Austria	1.79	18.87	36.73	45.66	71.67	13.49	29.54	34.73	48.14
Azerbaijan	2.67	1.10	-16.82	-20.56	-24.26	-5.32	-21.63	-24.92	-30.21
Bangladesh	3.30	-25.24	-38.38	-36.69	-53.14	-26.52	-39.31	-37.56	-54.38
Belarus	3.48	40.24	66.05	74.89	83.90	35.54	57.48	65.23	75.17
Belgium	11.51	-11.69	-20.22	-7.49	5.72	-17.07	-26.49	-11.58	1.25
Belize	1.87	-24.13	-24.73	-25.70	-35.83	-25.74	-28.60	-28.04	-38.66
Benin	1.05	-7.98	-6.90	-16.29	-32.64	-12.76	-14.61	-25.66	-40.04
Bhutan	0.24	1.92	8.78	5.54	11.85	0.66	-0.71	-7.28	-12.73
Bolivia	0.87	-20.75	-22.95	-29.75	-41.80	7.38	14.22	11.14	6.93
Bosnia and Herzegovina	2.13	12.31	23.06	33.69	24.53	11.63	22.84	33.99	20.78
Botswana	0.50	-10.38	-45.57	-43.83	-67.93	1.38	-42.43	-37.76	-70.79
Brazil	1.09	-21.05	-25.19	-31.78	-48.26	-19.08	-19.79	-27.25	-43.71
Brunei	0.78	7.87	7.28	-7.48	-30.41	9.71	10.28	-5.76	-31.57
Bulgaria	4.52	12.95	13.99	14.29	-12.44	12.25	13.24	16.07	-11.11
Burkina Faso	0.39	-4.50	-8.79	-9.40	-26.96	-5.39	-11.13	-10.99	-30.20
Burundi	0.83	-23.37	-35.97	-41.45	-56.88	-22.86	-35.47	-41.30	-56.46
Cambodia	1.35	-18.05	-24.28	-29.99	-41.10	-19.24	-25.84	-31.63	-44.02
Cameroon	0.94	-8.29	-4.99	-14.28	-27.08	-6.11	-2.78	-11.22	-21.72
Canada	0.17	84.04	172.92	218.37	396.32	6.21	31.41	43.60	73.34
Central African Republic	0.48	-12.04	-12.84	-20.10	-35.29	-8.98	-9.26	-17.49	-33.75
Chad	0.11	1.90	0.76	2.36	-17.36	-2.84	-2.47	-2.43	-20.74
Chile	1.40	23.76	40.13	47.58	79.73	31.31	50.48	55.01	58.75
China	0.83	2.21	1.90	2.40	5.10	-4.42	-9.96	-10.32	-15.03
Colombia	0.59	-10.44	-14.71	-21.72	-37.06	-8.23	-15.13	-17.70	-37.78
Costa Rica	0.79	-10.71	0.33	-10.26	-14.07	-11.16	1.07	-9.12	-3.71
Croatia	5.95	10.60	18.54	26.27	6.73	10.55	17.64	25.34	2.88
Cuba	3.69	-21.60	-29.30	-31.00	-41.93	-17.83	-29.76	-32.97	-42.19
Czech Republic	3.31	43.26	64.75	74.88	109.24	36.02	54.63	62.14	88.14
Democratic Republic of the Congo	0.62	-11.08	-12.50	-22.33	-41.80	-13.05	-16.37	-24.93	-44.19

Country									
Denmark	12.66	38.18	55.29	72.88	82.73	47.40	66.17	83.65	95.88
Djibouti	0.22	0.67	-4.30	4.27	4.50	5.60	1.55	11.47	3.55
Dominican Republic	3.34	-26.29	-31.59	-33.26	-44.36	-28.39	-36.17	-38.37	-51.75
Ecuador	1.01	-2.36	-5.79	-9.87	-25.19	-7.35	-11.26	-14.00	-28.00
Egypt	0.33	-22.70	-33.99	-38.24	-52.84	-29.18	-40.92	-45.43	-58.95
El Salvador	1.20	-17.55	-20.62	-24.52	-36.02	-16.92	-17.84	-21.90	-34.05
Equatorial Guinea	1.01	-2.25	8.56	-0.42	-8.70	-1.28	7.06	-2.15	-13.15
Eritrea	0.32	-5.84	-18.33	-13.17	-23.71	-0.98	-20.18	-13.66	-28.87
Estonia	1.93	146.37	258.29	305.95	369.91	117.24	216.25	254.31	309.32
Ethiopia	0.71	-11.29	-21.78	-25.52	-39.89	-6.66	-19.81	-23.07	-41.77
Finland	0.73	141.49	296.31	396.01	655.08	99.39	192.27	268.64	369.08
France	6.91	-0.51	11.88	8.83	25.08	3.30	14.86	9.42	27.89
French Guiana	0.81	-3.43	2.60	-6.54	-8.69	-2.56	2.27	-6.18	-10.36
Gabon	1.06	-4.83	4.18	-4.54	-19.61	-5.73	3.06	-6.54	-17.60
Gambia	0.92	-16.38	-24.34	-30.46	-46.05	-18.17	-27.19	-32.01	-51.46
Georgia	1.73	4.30	-2.06	-3.50	-7.69	8.80	0.21	-1.15	-12.88
Germany	7.32	19.67	26.06	28.95	45.28	11.80	16.04	19.33	33.06
Ghana	1.16	-14.23	-12.81	-21.23	-35.34	-11.33	-12.18	-22.82	-41.18
Greece	4.63	-4.04	-9.22	-5.16	-17.54	-2.19	-12.47	-10.18	-27.13
Guatemala	1.22	-19.44	-22.09	-22.99	-31.60	-20.18	-20.26	-22.23	-31.39
Guinea	0.95	-17.52	-20.02	-25.95	-36.80	-17.22	-18.68	-25.62	-36.12
Guinea-Bissau	1.14	-3.47	-15.80	-19.31	-36.79	-3.15	-16.31	-19.72	-37.46
Guyana	1.04	-12.30	-21.05	-23.75	-39.89	-16.52	-28.08	-28.44	-46.10
Haiti	2.41	-19.67	-26.28	-27.53	-39.34	-18.49	-24.86	-28.14	-40.93
Honduras	1.41	-23.83	-26.72	-29.79	-38.56	-22.89	-28.91	-32.13	-42.63
Hong Kong	6.28	-14.68	-20.56	-28.94	-42.43	-15.27	-21.31	-29.45	-43.17
Hungary	4.83	22.53	36.61	45.39	19.16	24.70	38.53	46.75	22.55
Iceland	0.31	117.59	225.73	288.33	501.84	31.87	94.69	110.86	193.88
India	1.29	-15.96	-16.95	-29.89	-38.45	-21.51	-21.95	-32.03	-43.41
Indonesia	0.86	0.26	-4.08	-13.60	-34.74	-2.43	-6.62	-17.49	-41.15
Iran	0.41	7.64	-1.35	-1.88	-6.41	5.46	0.44	0.28	1.84
Iraq	0.50	2.06	-8.56	-14.02	-28.68	-1.79	-11.63	-17.84	-29.93
Ireland	5.72	16.00	25.85	39.38	42.15	13.74	20.92	29.43	28.97
Israel	2.51	-8.38	-29.95	-33.57	-58.41	1.50	-24.91	-29.13	-57.83
Italy	4.81	7.06	11.34	11.54	-1.82	11.26	16.43	15.80	-4.72
Ivory Coast	1.36	-16.23	-11.99	-21.72	-39.23	-15.09	-11.29	-18.64	-39.32
Japan	1.69	15.74	23.99	40.57	63.54	-2.30	-6.40	-0.70	6.65
Jordan	0.42	-7.79	-18.38	-19.16	-32.30	-5.99	-20.67	-22.51	-42.42
Kazakhstan	0.21	46.94	53.44	44.21	61.82	36.37	44.57	37.23	54.55
Kenya	0.68	-4.37	-12.21	-18.40	-37.31	-16.44	-26.38	-31.75	-49.38
Kuwait	0.34	-9.59	-20.74	-28.12	-38.24	-5.98	-18.94	-25.36	-36.16
Kyrgyzstan	0.08	36.59	53.36	53.62	73.66	26.74	38.87	32.53	42.40
Laos	0.95	-19.53	-31.76	-29.36	-42.65	-21.59	-33.74	-30.91	-44.08
Latvia	2.53	137.77	212.52	244.53	289.59	97.54	153.33	179.25	207.18
Lebanon	3.11	-4.25	-13.53	-14.03	-28.76	-8.47	-18.56	-19.31	-35.99
Lesotho	0.84	22.66	28.07	38.54	19.44	26.83	29.64	36.27	-4.24
Liberia	1.17	-4.58	-6.37	-16.97	-26.96	-4.31	-4.76	-14.72	-24.44

Libya	0.30	-18.70	-28.78	-33.64	-48.55	-18.85	-32.11	-40.07	-55.81
Liechtenstein	0.06	13.03	107.71	133.89	322.65	13.03	107.71	133.89	322.65
Lithuania	3.13	99.00	141.85	160.15	197.44	82.13	117.18	139.93	169.19
Luxembourg	4.25	9.66	5.37	-2.25	2.33	3.76	-5.57	-10.64	-7.07
Macedonia	1.88	7.34	10.61	18.55	2.68	8.61	11.92	20.88	5.04
Madagascar	2.51	-13.71	-20.70	-25.13	-40.20	-7.28	-13.56	-15.89	-31.69
Malawi	1.67	-11.84	-34.67	-39.91	-55.02	-11.38	-35.32	-40.43	-55.70
Malaysia	0.81	0.62	-0.90	-9.44	-25.48	0.10	-0.08	-9.79	-30.10
Mali	0.16	-3.64	-9.37	-11.74	-32.09	-5.69	-9.06	-13.01	-33.41
Mauritania	0.07	-12.69	-25.98	-26.18	-45.04	-6.63	-18.74	-14.18	-34.32
Mexico	1.55	-13.28	-23.15	-26.17	-42.69	-14.79	-11.75	-18.69	-39.91
Moldova	4.15	36.40	61.04	59.77	24.09	32.28	59.63	59.24	22.97
Mongolia	0.06	67.22	101.77	116.69	171.82	96.50	152.21	192.73	280.93
Montenegro	1.47	-10.86	-8.59	-7.73	10.94	-11.30	-10.01	-7.93	8.42
Morocco	1.34	-21.71	-41.21	-45.55	-65.38	-25.37	-45.24	-49.11	-72.71
Mozambique	2.01	-16.04	-32.87	-39.06	-57.86	-10.70	-28.34	-33.80	-54.15
Myanmar	1.55	-23.25	-33.05	-29.56	-42.98	-18.54	-29.11	-24.27	-35.61
Namibia	0.70	-21.70	-41.58	-42.47	-61.97	-16.69	-38.70	-39.46	-62.06
Nepal	0.69	-13.15	-10.83	-16.07	-28.92	-17.56	-18.25	-23.31	-39.41
Netherlands	21.85	-4.89	-12.54	-6.57	18.96	-9.55	-18.76	-13.34	13.69
New Zealand	5.86	19.03	34.88	55.91	84.53	-0.60	17.52	37.22	33.34
Nicaragua	1.28	-19.70	-7.26	-17.85	-29.70	-19.84	-21.17	-26.85	-40.47
Niger	0.06	14.12	11.34	15.64	-6.71	14.94	18.47	22.18	-5.62
Nigeria	0.84	-8.36	-9.03	-16.66	-29.71	-9.21	-10.53	-18.96	-33.37
North Korea	1.08	38.59	60.81	64.10	89.44	34.96	52.18	57.56	71.17
Norway	0.26	67.71	161.59	209.68	302.46	49.72	122.05	155.28	163.36
Oman	0.36	-24.34	-35.95	-36.74	-47.83	-16.34	-26.18	-29.00	-34.70
Pakistan	0.43	-7.42	-20.95	-20.78	-31.05	-15.43	-32.97	-32.62	-42.49
Palestine	2.13	-10.22	-24.84	-27.85	-49.68	-7.07	-20.95	-23.83	-46.09
Panama	1.23	-8.47	-2.03	-10.35	-14.59	-3.62	5.66	-4.87	-11.53
Papua New Guinea	0.83	-6.99	-12.76	-25.19	-44.16	-10.59	-18.12	-28.09	-46.61
Paraguay	1.44	-31.93	-34.80	-45.84	-71.12	-22.21	-24.46	-41.55	-66.91
Peru	0.69	-3.31	-4.62	-9.59	-16.72	-14.66	-17.58	-17.98	-21.71
Philippines	1.60	-10.95	-13.74	-23.06	-35.02	-15.07	-18.81	-27.63	-39.82
Poland	6.26	39.91	53.88	58.44	63.11	39.09	53.12	57.28	63.18
Portugal	8.33	-17.02	-21.75	-22.30	-38.39	-16.73	-21.54	-22.04	-38.23
Qatar	0.45	-19.86	-27.71	-33.76	-45.24	-20.47	-28.85	-34.63	-46.62
Republic of Congo	1.07	-0.62	5.77	-4.82	-21.83	1.41	2.77	-3.99	-22.19
Romania	4.44	21.25	23.88	27.55	6.41	17.97	19.21	20.43	-1.67
Russia	0.25	95.56	162.31	189.40	300.35	58.08	87.71	100.10	126.85
Rwanda	0.78	-18.63	-33.58	-40.18	-54.92	-18.14	-34.64	-41.29	-55.74
Saudi Arabia	0.18	-12.47	-23.84	-24.89	-39.32	-7.27	-18.97	-18.85	-32.26
Senegal	0.47	-12.88	-21.55	-23.66	-40.59	-20.86	-31.89	-34.42	-49.63
Serbia	3.59	17.08	27.30	40.67	5.30	16.49	26.02	41.39	1.05
Sierra Leone	1.00	-21.22	-24.62	-31.26	-36.84	-20.64	-23.38	-29.20	-35.28
Singapore	3.20	6.10	13.90	3.41	-14.10	6.10	13.90	3.41	-14.10
Slovakia	2.45	25.32	43.25	44.94	54.61	23.07	39.64	40.31	48.91
Slovenia	1.82	7.71	32.15	42.28	49.33	5.50	30.64	40.06	43.87

Somalia	0.24	-14.47	-27.31	-24.64	-30.21	-14.70	-27.54	-25.22	-36.04
South Africa	1.94	-2.34	-20.83	-21.23	-49.00	-11.61	-30.52	-31.55	-54.28
South Korea	1.98	38.27	49.98	62.82	59.53	43.16	54.42	67.07	66.58
Spain	3.69	-5.03	-10.64	-10.42	-23.36	-0.78	-6.51	-6.22	-23.62
Sri Lanka	1.73	-13.23	-14.75	-18.24	-30.00	-16.01	-18.17	-20.78	-31.60
Sudan	0.17	-7.92	-10.31	-7.70	-24.58	-6.30	-9.65	-5.49	-21.51
Suriname	1.00	-10.26	-14.26	-22.50	-28.94	-16.41	-20.77	-29.28	-34.65
Swaziland	2.99	-8.37	-25.09	-26.40	-49.61	-10.20	-26.13	-28.48	-50.08
Sweden	1.41	74.85	152.91	198.11	288.18	64.35	124.74	160.36	191.13
Switzerland	0.68	17.44	61.11	73.21	114.62	14.66	55.69	67.86	104.00
Syria	0.86	-9.96	-17.52	-16.34	-23.82	-12.82	-21.51	-17.69	-23.75
Taiwan	2.27	-2.79	-12.19	-14.19	-21.02	-5.67	-16.32	-17.09	-26.93
Tajikistan	0.19	13.41	20.27	25.30	39.44	7.97	14.27	18.32	30.53
Tanzania	1.31	-13.44	-24.96	-31.30	-46.98	-7.97	-16.71	-22.79	-38.49
Thailand	1.14	-22.98	-30.12	-32.11	-42.96	-24.18	-27.88	-34.84	-44.84
Timor-Leste	1.71	-12.36	-19.37	-21.90	-35.23	-12.30	-19.81	-22.95	-35.46
Togo	1.15	-9.05	-9.58	-20.04	-30.99	-8.22	-9.22	-20.57	-33.86
Trinidad and Tobago	3.23	-23.62	-19.75	-28.62	-44.18	-26.20	-22.96	-31.53	-44.82
Tunisia	1.88	-9.16	-15.36	-21.14	-30.13	-18.58	-25.31	-31.06	-39.78
Turkey	1.79	1.46	-4.59	-1.42	-13.02	-9.21	-13.61	-8.99	-16.04
Turkmenistan	0.34	-9.70	-16.59	-20.96	-27.45	-4.60	-9.67	-14.36	-21.93
Uganda	0.58	-16.93	-15.99	-25.49	-37.44	-21.07	-21.40	-29.95	-41.97
Ukraine	3.93	36.48	44.77	51.86	34.42	38.35	44.17	50.16	32.99
United Arab Emirates	0.25	-7.39	-16.75	-21.86	-35.54	-8.35	-22.46	-29.33	-41.33
United Kingdom	7.24	14.91	19.93	29.63	40.61	9.81	13.25	19.18	28.99
United States	1.44	3.68	7.27	7.55	14.69	-7.35	-3.65	-3.82	-4.80
Uruguay	9.18	-33.79	-44.49	-47.91	-58.09	-34.42	-50.40	-50.56	-60.20
Uzbekistan	0.27	-1.44	0.38	-1.51	-1.09	4.60	10.56	9.82	16.45
Venezuela	1.05	-19.21	-24.06	-30.82	-49.01	-20.79	-29.67	-35.57	-56.49
Vietnam	1.62	-17.34	-24.88	-26.41	-39.90	-19.02	-28.17	-29.63	-44.43
Yemen	0.35	-20.58	-33.28	-31.71	-42.65	-4.42	-17.92	-13.33	-24.37
Zambia	1.02	-21.66	-37.41	-42.45	-59.46	-20.83	-37.81	-42.71	-59.85
Zimbabwe	1.45	-20.98	-45.78	-49.16	-69.38	-26.68	-51.67	-55.17	-71.92

Table E2: Country-Level Impacts of Climate Change

	% Impact on 2100 GDP								
	Mobile Labor				Perfect Mobility, Unmeasured Quality				Burke et al. (2015)
Country	RCP 2.6	RCP 4.5	RCP 6.0	RCP 8.5	RCP 2.6	RCP 4.5	RCP 6.0	RCP 8.5	RCP 8.5
Afghanistan	3.81	0.69	1.23	-1.27	3.99	1.80	2.74	1.36	-35.96
Angola	-8.20	-11.34	-13.36	-20.57	-8.51	-8.41	-10.73	-16.42	-84.74
Albania	-2.10	-1.80	-0.54	1.92	-0.88	-1.07	0.16	2.23	-33.22
United Arab Emirates	-2.37	-5.57	-7.42	-12.82	-2.09	-6.78	-9.23	-14.44	-93.91
Argentina	-1.53	-3.48	-4.01	-6.96	-2.58	-4.47	-5.78	-9.15	-53.21
Armenia	3.80	4.21	4.77	6.39	2.96	3.04	3.70	5.15	89.79
Australia	-3.30	-3.76	-4.21	-9.01	-3.61	-2.75	-2.58	-7.91	-52.87
Austria	5.54	10.25	12.45	18.37	8.01	16.98	20.21	34.34	102.53
Azerbaijan	0.34	-5.57	-6.92	-8.29	-0.67	-5.67	-6.67	-7.98	-23.72
Burundi	-8.06	-13.12	-15.53	-23.29	-7.16	-11.40	-13.89	-20.92	-79.29
Belgium	-3.80	-6.80	-2.40	1.75	-4.33	-7.53	-2.76	0.94	29.85
Benin	-2.59	-2.23	-5.45	-11.71	-3.45	-3.71	-7.39	-13.52	-91.31
Burkina Faso	-1.44	-2.86	-3.06	-9.43	-1.23	-3.31	-3.08	-10.24	-86.88
Bangladesh	-8.66	-13.99	-13.26	-21.01	-8.08	-13.62	-12.56	-20.62	-89.81
Bulgaria	3.84	4.13	4.22	-4.02	5.48	7.06	8.66	2.23	29.55
Bosnia and Herzegovina	3.65	6.62	9.39	7.02	4.22	6.91	9.00	8.22	44.29
Belarus	11.10	17.10	19.00	20.88	11.11	16.51	18.41	20.71	170.25
Belize	-8.28	-8.51	-8.88	-12.96	-7.50	-8.41	-8.24	-12.81	-90.45
Bolivia	-7.02	-7.83	-10.46	-15.57	8.75	13.02	14.20	19.83	-69.14
Brazil	-7.09	-8.63	-11.21	-18.52	-6.73	-7.28	-9.92	-17.37	-82.77
Brunei	2.39	2.21	-2.39	-10.67	2.89	3.03	-1.79	-10.99	-87.83
Bhutan	0.59	2.66	1.70	3.55	8.52	17.39	18.41	34.49	-16.05
Botswana	-3.38	-17.34	-16.53	-29.93	0.24	-15.82	-13.99	-31.30	-89.61
Central African Republic	-3.95	-4.22	-6.80	-12.77	-2.92	-3.13	-5.89	-12.19	-90.77

Country								
Canada	246.69	40.81	29.48	25.35	14.32	65.34	43.79	36.99	21.06
Switzerland	120.91	33.52	20.66	17.33	3.87	27.00	18.75	16.09	5.15
Chile	31.96	14.51	13.15	11.49	7.46	20.07	12.90	11.09	6.87
China	-42.07	3.37	1.80	1.31	1.25	1.56	0.74	0.59	0.68
Ivory Coast	-90.71	-14.56	-6.52	-3.75	-5.15	-14.52	-7.43	-3.95	-5.43
Cameroon	-88.01	-7.40	-3.60	-1.21	-1.79	-9.47	-4.74	-1.60	-2.69
Republic of Congo	-88.69	-8.43	-1.55	0.92	0.34	-7.47	-1.55	1.78	-0.19
Colombia	-77.33	-8.25	-3.56	-2.63	-0.23	-13.42	-7.34	-4.84	-3.38
Costa Rica	-79.21	1.34	-2.00	1.27	-3.29	-4.62	-3.32	0.10	-3.47
Cuba	-83.77	-14.96	-10.75	-9.86	-6.13	-15.48	-10.86	-10.18	-7.26
Czech Republic	101.69	25.54	19.08	16.89	11.93	25.90	19.04	16.85	11.86
Germany	62.69	15.05	9.66	8.51	5.74	12.34	8.24	7.48	5.75
Djibouti	-84.51	0.90	3.17	0.11	1.62	1.39	1.32	-1.37	0.21
Denmark	86.18	24.25	21.80	18.33	13.65	20.73	18.66	14.74	10.63
Dominican Republic	-85.61	-17.15	-11.96	-11.33	-8.92	-16.69	-11.84	-11.16	-9.07
Algeria	-67.35	-11.57	-8.66	-7.07	-4.45	-13.47	-9.34	-7.97	-4.76
Ecuador	-69.25	-0.26	2.34	2.04	1.61	-8.67	-3.20	-1.85	-0.74
Egypt	-84.07	-21.04	-15.41	-13.65	-9.44	-21.00	-14.03	-12.22	-7.76
Eritrea	-87.46	-4.40	-0.84	-3.18	1.34	-8.15	-4.34	-6.16	-1.87
Spain	-46.36	-5.94	-1.87	-2.24	-0.28	-7.92	-3.36	-3.43	-1.59
Estonia	258.80	57.21	50.18	44.82	28.97	61.88	54.65	48.74	32.35
Ethiopia	-74.48	-13.63	-6.89	-5.79	-1.78	-14.78	-8.84	-7.43	-3.70
Finland	516.18	78.99	60.63	49.19	30.00	88.21	64.96	53.76	31.67
France	9.63	7.58	3.59	4.90	1.77	7.23	2.67	3.56	-0.16
Gabon	-89.05	-6.40	-2.04	1.09	-1.95	-6.63	-1.45	1.30	-1.54
United Kingdom	41.79	7.67	6.12	3.99	3.35	11.23	8.44	5.84	4.43
Georgia	7.72	-1.26	0.94	1.05	1.91	-2.45	-1.10	-0.64	1.31
Ghana	-90.15	-14.05	-7.13	-3.68	-3.87	-12.80	-7.22	-4.22	-4.71
Guinea	-91.75	-13.13	-8.93	-6.55	-5.87	-13.45	-9.03	-6.79	-5.89
Gambia	-88.71	-18.80	-10.58	-8.13	-5.31	-17.66	-10.81	-8.41	-5.48
Guinea-Bissau	-89.26	-13.71	-6.62	-5.36	-1.19	-13.44	-6.53	-5.27	-1.10
Equatorial Guinea	-84.51	-4.89	-0.93	1.60	-0.57	-2.83	-0.13	2.62	-0.72

Country								
Greece	-1.27	-2.95	-1.63	-5.80	-0.89	-3.49	-2.55	-7.56	-50.72
Guatemala	-6.55	-7.53	-7.86	-11.22	-5.90	-4.70	-5.58	-7.87	-83.34
French Guiana	-1.09	0.81	-2.11	-2.82	-0.18	1.72	-0.91	-1.90	
Guyana	-3.99	-7.07	-8.07	-14.60	-5.00	-9.05	-9.36	-16.59	-91.45
Hong Kong	-4.83	-6.92	-10.10	-15.80	-5.04	-7.20	-10.30	-16.15	-88.40
Honduras	-8.16	-9.27	-10.47	-14.13	-7.38	-9.52	-10.73	-15.34	
Croatia	3.17	5.40	7.49	2.04	2.79	6.17	9.48	2.70	-8.95
Haiti	-6.61	-9.08	-9.57	-14.45	-6.04	-8.36	-9.37	-14.14	-85.23
Hungary	6.51	10.18	12.33	5.59	7.62	11.13	13.14	7.15	25.17
Indonesia	0.08	-1.29	-4.46	-12.47	-0.03	-1.65	-4.92	-13.92	-85.07
India	-5.28	-5.63	-10.48	-14.04	-5.14	-5.37	-10.52	-13.66	-91.83
Ireland	4.74	7.44	10.93	11.61	4.11	6.40	9.32	9.72	47.28
Iran	2.33	-0.42	-0.59	-2.05	2.33	0.38	0.55	0.81	-58.15
Iraq	0.64	-2.78	-4.64	-10.08	-0.32	-3.83	-5.99	-10.16	-93.00
Iceland	27.49	44.65	52.84	75.37	9.04	22.78	25.94	39.79	512.92
Israel	-2.71	-10.56	-12.04	-24.03	-0.81	-9.42	-11.07	-23.99	-82.24
Italy	2.14	3.39	3.45	-0.57	3.07	5.68	6.12	3.39	-25.86
Jordan	-2.51	-6.16	-6.44	-11.49	-1.99	-6.97	-7.66	-15.53	-72.27
Japan	4.63	6.89	11.14	16.49	4.47	5.44	8.96	12.75	-35.15
Kazakhstan	12.81	14.35	12.15	16.27	14.44	17.32	15.58	21.27	208.29
Kenya	-1.39	-4.01	-6.19	-13.64	-4.43	-7.67	-9.78	-16.73	-73.29
Kyrgyzstan	10.27	14.35	14.41	18.90	9.89	13.55	13.07	16.41	169.58
Cambodia	-6.03	-8.32	-10.54	-15.24	-6.42	-8.88	-11.11	-16.16	-86.25
South Korea	10.57	13.40	16.33	15.60	13.67	17.15	20.36	21.91	-0.26
Kuwait	-3.11	-7.02	-9.83	-14.01	-2.01	-6.39	-8.79	-13.12	-95.56
Laos	-6.56	-11.24	-10.28	-15.92	-7.06	-11.74	-10.48	-15.99	-86.15
Lebanon	-1.35	-4.43	-4.60	-10.03	-2.52	-4.94	-5.11	-9.52	-39.92
Liberia	-1.46	-2.05	-5.69	-9.41	-1.41	-1.51	-5.05	-8.69	-88.38
Libya	-6.26	-10.05	-12.01	-18.71	-5.17	-9.77	-13.07	-20.54	-83.52
Liechtenstein	3.90	25.68	30.44	57.03	3.90	25.68	30.44	57.03	
Sri Lanka	-4.31	-4.83	-6.06	-10.48	-4.73	-5.81	-6.29	-10.25	-85.70
Lesotho	6.59	8.04	10.73	5.71	6.92	8.67	10.82	4.46	-2.41
Lithuania	23.77	31.49	34.51	40.23	21.37	28.77	32.12	37.74	156.57

Luxembourg	2.93	1.65	-0.71	0.73	1.39	-1.40	-3.18	-1.94	54.99
Latvia	30.83	42.44	46.84	52.57	27.44	38.12	42.04	47.28	190.08
Morocco	-7.36	-15.28	-17.27	-28.15	-7.09	-14.49	-16.58	-27.79	-66.98
Moldova	10.09	15.90	15.62	6.91	9.19	15.90	15.81	6.87	48.78
Madagascar	-4.54	-7.05	-8.72	-14.95	-1.84	-3.78	-4.67	-10.03	-73.39
Mexico	-4.35	-7.89	-9.03	-15.93	-3.73	-3.21	-5.34	-12.60	-73.41
Macedonia	2.22	3.18	5.42	0.82	2.73	4.35	6.56	3.35	35.55
Mali	-1.16	-3.06	-3.86	-11.49	-0.49	-1.63	-2.36	-10.36	-83.45
Myanmar	-7.91	-11.75	-10.34	-16.05	-5.73	-9.50	-7.62	-11.84	
Montenegro	-3.51	-2.75	-2.47	3.28	-0.77	1.64	1.57	7.17	
Mongolia	17.50	24.64	27.46	36.88	24.79	36.53	44.15	58.78	1413.40
Mozambique	-5.36	-11.81	-14.45	-23.83	-4.23	-10.58	-13.04	-21.98	-89.30
Mauritania	-4.19	-9.05	-9.12	-17.18	-0.78	-4.53	-3.08	-10.65	-80.44
Malawi	-3.89	-12.55	-14.82	-22.23	-3.66	-12.51	-14.78	-22.21	-87.06
Malaysia	0.19	-0.28	-3.05	-8.77	0.78	0.51	-2.43	-9.48	-87.44
Namibia	-7.39	-15.51	-15.92	-26.13	-3.75	-12.96	-13.03	-25.59	-88.74
Niger	4.27	3.46	4.71	-2.18	6.37	7.83	9.10	1.54	-80.27
Nigeria	-2.71	-2.94	-5.58	-10.51	-2.28	-2.71	-4.91	-10.47	-91.49
Nicaragua	-6.62	-2.33	-5.96	-10.42	-6.36	-6.71	-8.90	-14.78	-91.55
Netherlands	-1.55	-4.08	-2.09	5.56	-0.71	-2.64	-1.33	5.98	30.88
Norway	17.58	35.18	42.53	54.77	12.31	25.94	33.54	39.56	249.29
Nepal	-4.29	-3.50	-5.30	-10.07	-2.65	-1.60	-1.90	-4.13	-85.26
New Zealand	5.59	9.81	14.90	21.12	4.93	10.80	16.16	21.65	-8.97
Oman	-8.38	-13.04	-13.37	-18.45	-4.74	-8.75	-9.74	-12.73	-94.38
Pakistan	-2.39	-7.10	-7.04	-11.00	-2.39	-7.10	-6.76	-10.82	-92.55
Panama	-2.73	-0.64	-3.36	-4.82	-1.20	1.67	-1.40	-2.52	-85.41
Peru	-1.05	-1.47	-3.10	-5.55	2.78	6.12	7.77	12.67	-50.66
Philippines	-3.56	-4.51	-7.87	-12.60	-4.27	-5.34	-8.82	-13.61	-83.57
Papua New Guinea	-2.25	-4.20	-8.71	-16.71	-3.43	-6.11	-9.58	-19.14	-74.92
Poland	10.98	14.31	15.35	16.40	13.94	17.71	19.28	21.84	87.90
North Korea	10.70	15.96	16.69	22.04	12.22	20.32	20.29	29.55	
Portugal	-5.62	-7.32	-7.53	-13.94	-3.40	-3.82	-3.83	-8.65	-41.02
Paraguay	-11.31	-12.50	-17.42	-32.09	-7.28	-8.09	-14.52	-28.68	-84.18

Palestine	-3.33	-8.58	-9.74	-19.39	-2.16	-6.92	-7.82	-17.15
Qatar	-6.70	-9.67	-12.11	-17.19	-6.93	-10.08	-12.40	-17.70	-91.60
Romania	6.15	6.86	7.84	1.95	7.36	9.24	10.00	5.74	49.57
Russia	23.25	35.09	39.30	54.19	26.42	38.91	42.82	57.12	419.15
Rwanda	-6.28	-12.07	-14.91	-22.14	-5.24	-11.62	-14.50	-21.84	-78.35
Saudi Arabia	-4.08	-8.16	-8.56	-14.45	-1.82	-6.30	-6.24	-11.58	-95.74
Sudan	-2.56	-3.37	-2.49	-8.50	0.20	-2.34	0.63	-6.01	-86.80
Senegal	-4.25	-7.37	-8.16	-15.13	-6.55	-10.45	-11.28	-17.56	-89.13
Singapore	1.86	4.14	1.05	-4.63	1.86	4.14	1.05	-4.63
Sierra Leone	-7.21	-8.49	-11.10	-13.42	-6.95	-8.05	-10.64	-13.04	-91.00
El Salvador	-5.82	-6.92	-8.37	-12.95	-5.44	-5.66	-7.05	-12.06	-85.40
Somalia	-4.81	-9.58	-8.54	-10.73	-3.26	-7.56	-6.65	-8.36
Serbia	5.00	7.75	11.14	1.61	4.75	7.48	10.87	2.45	30.70
Suriname	-3.32	-4.68	-7.64	-10.10	-5.14	-6.95	-10.01	-12.43	-92.19
Slovakia	7.26	11.82	12.23	14.51	11.67	17.41	19.70	26.11	90.78
Slovenia	2.34	9.06	11.60	13.29	1.87	10.92	13.43	17.38	79.85
Sweden	19.10	33.70	40.78	52.94	19.55	34.28	42.02	52.68	210.20
Swaziland	-2.70	-8.65	-9.15	-19.31	-2.91	-8.40	-9.22	-18.77	-77.62
Syria	-3.23	-5.85	-5.43	-8.16	-3.64	-6.80	-5.72	-8.23	-71.71
Chad	0.60	0.24	0.74	-5.84	0.61	-0.02	0.94	-5.86	-86.43
Togo	-2.94	-3.12	-6.80	-11.02	-1.75	-2.01	-4.99	-9.33	-89.66
Thailand	-7.78	-10.52	-11.32	-15.97	-7.82	-9.78	-11.76	-16.15	-90.00
Tajikistan	4.04	5.98	7.35	11.03	3.71	5.72	6.88	10.62	-14.84
Turkmenistan	-3.14	-5.52	-7.09	-9.55	-1.55	-3.22	-4.91	-7.30	-60.31
Timor-Leste	-4.05	-6.53	-7.45	-12.72	-3.82	-6.54	-7.70	-12.72
Trinidad and Tobago	-8.02	-6.60	-9.94	-16.54	-8.66	-6.98	-10.37	-15.54	-81.73
Tunisia	-2.95	-5.07	-7.14	-10.58	-3.20	-5.54	-7.71	-11.10	-76.34
Turkey	0.45	-1.45	-0.45	-4.26	0.29	-0.95	0.14	-2.67	-16.62
Taiwan	-0.88	-3.96	-4.64	-7.06	0.58	-2.94	-3.06	-5.39
Tanzania	-4.45	-8.66	-11.17	-18.14	-3.19	-6.36	-8.77	-15.11	-83.83
Uganda	-5.68	-5.34	-8.85	-13.73	-5.59	-4.88	-8.26	-13.27	-83.14
Ukraine	10.12	12.15	13.82	9.60	11.99	13.89	15.52	12.08	81.51

Uruguay	-12.04	-16.72	-18.35	-23.68	-10.81	-16.35	-17.03	-22.85	-54.70
United States	1.14	2.22	2.30	4.38	0.80	2.60	2.63	2.88	-36.28
Uzbekistan	-0.45	0.12	-0.48	-0.34	0.69	2.29	1.78	3.26	-45.49
Venezuela	-6.44	-8.23	-10.85	-18.93	-6.68	-8.12	-10.05	-18.39	-90.96
Vietnam	-5.76	-8.53	-9.12	-14.66	-5.94	-9.06	-9.77	-15.86	-87.50
Yemen	-6.97	-11.91	-11.27	-15.99	-2.36	-6.37	-5.02	-9.07	-87.96
South Africa	-0.74	-7.04	-7.19	-18.96	-1.82	-9.53	-8.94	-21.35	-66.19
Democratic	-3.64	-4.13	-7.66	-15.69	-4.23	-5.21	-8.57	-16.71	-87.92
Republic of the									
Congo									
Zambia	-7.41	-13.74	-16.00	-24.77	-7.06	-13.65	-15.90	-24.77	-86.80
Zimbabwe	-7.12	-17.46	-19.10	-30.96	-7.31	-17.76	-19.46	-31.06	-83.83

Table E3: Variance Decomposition of Impact Estimates

| $\hat{e}$ | Variance | | | | $2 \times$ Covariance | | |
	$\frac{Y}{L}$	X	L	Offset	X, L	X, Offset	L, Offset
0 %	0.150	0.039	0.059	0.001	0.037	-0.000	0.014
1 %	0.148	0.039	0.059	0.001	0.037	-0.000	0.012
2 %	0.146	0.039	0.059	0.001	0.037	-0.000	0.011

E.2 Interactive Country-Level Data Tables

`https://bjang.shinyapps.io/appendix_countries/`