nature climate change

LETTERS

PUBLISHED ONLINE: 31 JULY 2017 | DOI: 10.1038/NCLIMATE3352

Less than 2 °C warming by 2100 unlikely

Adrian E. Raftery[1*], Alec Zimmer[2], Dargan M. W. Frierson[3], Richard Startz[4] and Peiran Liu[1]

The recently published Intergovernmental Panel on Climate Change (IPCC) projections to 2100 give likely ranges of global temperature increase in four scenarios for population, economic growth and carbon use[1]. However, these projections are not based on a fully statistical approach. Here we use a country-specific version of Kaya's identity to develop a statistically based probabilistic forecast of CO_2 emissions and temperature change to 2100. Using data for 1960–2010, including the UN's probabilistic population projections for all countries[2–4], we develop a joint Bayesian hierarchical model for Gross Domestic Product (GDP) per capita and carbon intensity. We find that the 90% interval for cumulative CO_2 emissions includes the IPCC's two middle scenarios but not the extreme ones. The likely range of global temperature increase is 2.0–4.9 °C, with median 3.2 °C and a 5% (1%) chance that it will be less than 2 °C (1.5 °C). Population growth is not a major contributing factor. Our model is not a 'business as usual' scenario, but rather is based on data which already show the effect of emission mitigation policies. Achieving the goal of less than 1.5 °C warming will require carbon intensity to decline much faster than in the recent past.

The IPCC has issued projections of climate change based on four different pathways for emissions and land use up to 2100, each one in turn based on a different socioeconomic scenario for the world's future and developed by a different research group[1,5]. They are called representative concentration pathways (RCPs) and were selected so as to represent the scientific literature as of 2007 and to span a range of radiative forcings by 2100. The RCP2.6 scenario was designed to represent very low greenhouse gas concentration levels[6], RCP4.5 and RCP6 are stabilization scenarios[7,8], and RCP8.5 represents rising radiative forcing[9]. The RCPs were not to be interpreted as forecasts[5].

The two key socioeconomic driving forces of the RCPs are population and GDP, and the RCPs drew on population information up to 2012[10]. The UN has recently issued new population projections to 2100, reflecting data up to 2015[2]. These are probabilistic projections based on a Bayesian model[3,4,11]. The UN's predictive distribution for world population in 2100 has a median of 11.2 billion and a 90% interval from 9.7 to 12.9 billion. Three of the four RCPs are based on population in 2100 below the lower fifth percentile of the UN's predictive distribution (9.7 billion); the only one higher is the high-emissions RCP8.5. This raises the question of the impact of the higher projected future population on climate.

The availability of probabilistic population projections now (unlike when the RCPs were formulated) makes it more feasible to develop a statistical forecasting model for the key drivers, as advocated by Moss and Schneider[12]. We use a simple form of the Kaya identity, which expresses future emission levels in a country as a product of three components: population, GDP per capita, and carbon intensity (CO_2 emissions per unit of GDP)[13,14]. This is a specific version of the IPAT equation, Impact = Population × Affluence × Technology. We use data from 1960 to 2010 on GDP per capita and carbon intensity for most countries. We build a joint Bayesian hierarchical statistical model for GDP per capita and carbon intensity in most countries, and combine it with the UN probabilistic population projections to produce a predictive distribution of quantities of interest to 2100. We develop a probabilistic forecast of global temperature increase by combining them with the relationship between cumulative CO_2 emissions and temperature used by the IPCC[15].

For GDP per capita we use a Bayesian hierarchical model for all countries based on the idea of a world technology frontier (represented by the US for the period of our data), towards which countries may converge[16]; see Supplementary Fig. 1. The frontier is modelled by a random walk model with constant drift[17,18]. This allows countries with high current growth rates to continue growing fast in the short to medium term, while avoiding unrealistically high long-term forecasts.

To model carbon intensity, we note that most countries have reached a peak intensity; subsequently their carbon intensity has been trending downwards, as illustrated in Fig. 1. Note that we posit a peak and subsequent decline in CO_2 emissions per unit of GDP; this is different from the Environmental Kuznets Curve hypothesis that CO_2 emissions per person rise and then decline, which has not been established despite much research[19]. We model carbon intensity using a Bayesian hierarchical model for most countries estimated using the post-peak data. For each country, intensity is modelled as a linear trend plus an autoregressive random process.

Our model incorporated a within-country correlation between model errors in GDP per capita and carbon intensity, estimated to be −0.16. We found no significant correlation between model errors in population and either of the other two components.

An advantage of a fully statistical model is that it can be assessed by prediction validation experiments; we carried out several. In the first one, we fitted the model using only data from 1950 to 1980, generated predictive distributions for the following 30 years, and compared them with what actually happened. We repeated forecasts through 2010 for data up to 1990 and 2000, respectively. Illustrative results for world CO_2 emissions are shown in Fig. 2. The results showed the model to be reasonably well calibrated. The largest deviation from our median forecast in these validation experiments is in prediction of the rapid uptick in CO_2 emissions from 2000 to 2010. This decade of rapid emissions, driven largely by China's exceptionally rapid growth, nevertheless lies within our 90% intervals for all three predictive validation experiments.

The results of these calibration exercises by country are shown in Supplementary Table 1, while the results for the five IPCC regions are shown in Supplementary Fig. 2. These indicate that the model is reasonably well calibrated at the regional (continental) and country

[1]Department of Statistics, University of Washington, Box 354322, Seattle, Washington 98195-4322, USA. [2]Upstart, PO Box 1503, San Carlos, California 94070, USA. [3]Department of Atmospheric Sciences, University of Washington, Box 351640, Seattle, Washington 98195-1640, USA. [4]Department of Economics, University of California, Santa Barbara, California 93106-9210, USA. *e-mail: raftery@u.washington.edu

 NATURE CLIMATE CHANGE DOI: 10.1038/NCLIMATE3352

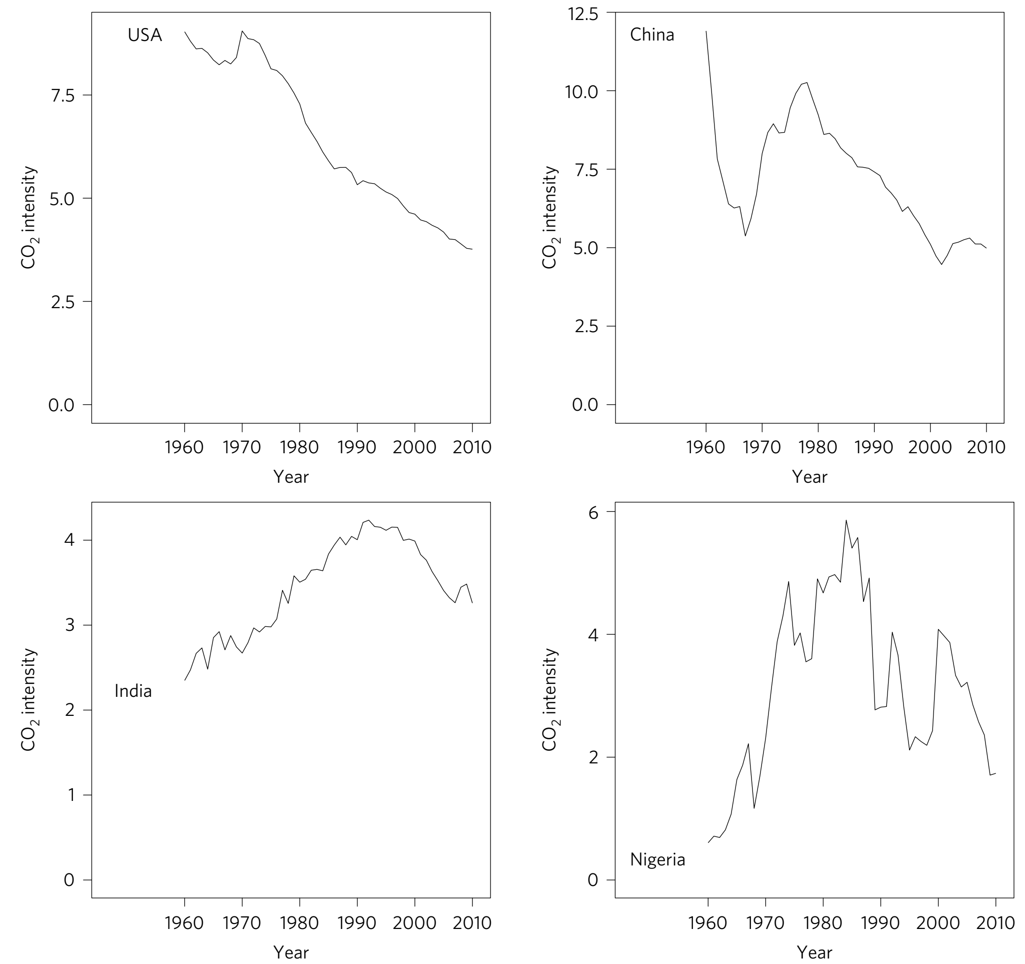

Figure 1 | Carbon intensity, expressed in tonnes of CO_2 per US$10,000 in 2010 Purchasing Power Parity for USA, China, India, and Nigeria. This illustrates the tendency of carbon intensity to decline after a peak has been reached.

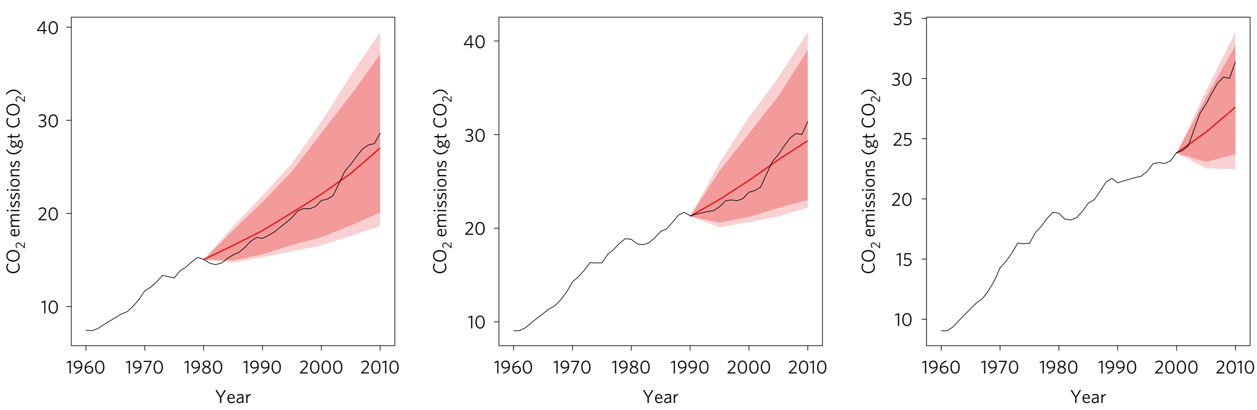

Figure 2 | Out-of-sample predictive validation of model for world CO_2 emissions. a, Model estimated from data from 1950 to 1980 and used to generate predictive distributions for 1980–2010, excluding countries in the former USSR due to lack of data. The solid red line is the predictive median, the heavily shaded region is the likely range (90% interval), the lightly shaded region is the 95% interval, and the black line shows the observations. **b**, Model estimated from 1950 to 1990 data, predictions for 1990–2010. **c**, Model estimated from 1950 to 2000 data, predictions for 2000–2010.

levels as well. Although these results are encouraging, it should be noted that they cover a prediction horizon of 30 years and 50 years of data overall, whereas we are projecting up to 90 years ahead. Thus our forecasts are best thought of as projections assuming that the general range of trends of the past 50 years continues into the future.

Figure 3 shows our predictive distributions of future world CO_2 emissions, by year and cumulatively, as well as of the Kaya components. The median projection lies between those of the two middle RCPs, RCP4.5 and RCP6. However, the plausible range of cumulative future emissions is wide, with a likely range from 2,300 to 5,700 Gt of CO_2 by 2100. The results suggest that cumulative emissions are likely to be higher than projected by the low-emissions RCP2.6 scenario, based on present evidence. Although they are likely to be lower than the 6,840 Gt projected by the high-emissions scenario RCP8.5, they could well reach 83% of that level based on

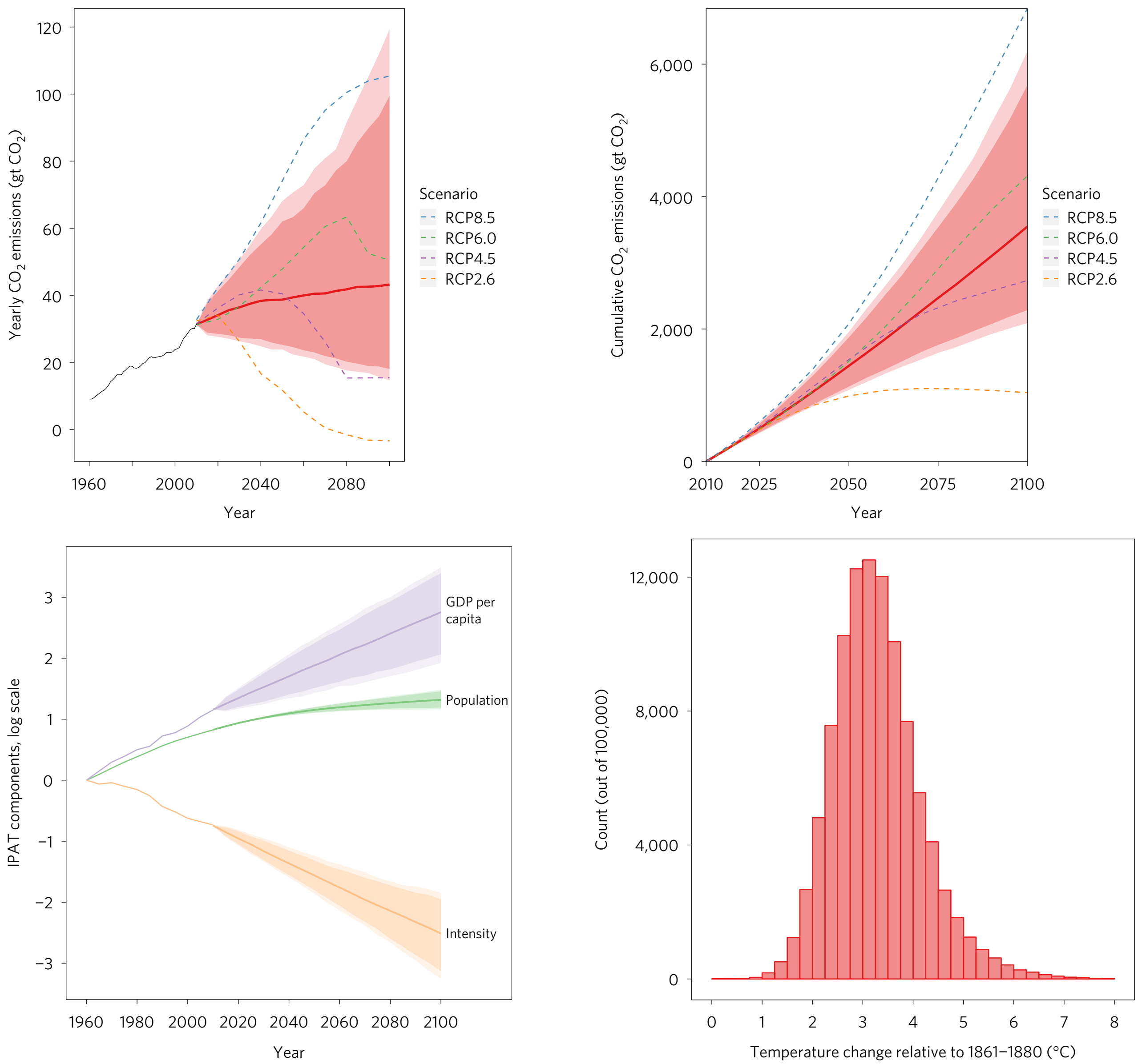

Figure 3 | Probabilistic forecast to 2100, with IPCC RCP scenarios. a, CO_2 emissions by year. **b**, Cumulative CO_2 emissions by year. **c**, Logarithm of the components of the Kaya identity by year, normalized to zero in 1960: population, GDP per capita, carbon intensity. **d**, Histogram of the predictive distribution of the global mean temperature increase relative to 1861–1880 (°C). In **a** and **b**, the solid red line is the predictive median, the heavily shaded region is the likely range (90% interval), the lightly shaded region is the 95% interval, and the IPCC RCP scenarios are the dashed lines.

trends to date. Predictive distributions for the five IPCC regions and 15 selected countries are shown in Supplementary Figs 3–6.

Figure 3c shows the Kaya components. Broadly, GDP per capita is expected to rise at around 1.8% per year, while carbon intensity is expected to decline by around 1.9% per year. These countervailing trends are likely to cancel one another out to a large extent. Our predictive distribution of future world GDP per capita largely spans the range of scenarios used by the IPCC[20–22], although there are large differences on a country-by-country basis. In particular, we project slower GDP growth in developing countries, due to weak or zero estimates of the rate of convergence to the world frontier.

The median UN population projection is for an increase of 4 billion to 2100, from the current 7.2 billion to 11.2 billion. A large portion of that increase is projected to be in Sub-Saharan Africa (SSA), whose population is projected to increase from its current 1 billion to 3.9 billion. Although GDP is projected to rise by around a factor of 21, CO_2 emissions from SSA are projected to be only about 6% of the world total at the end of the century. This reflects the very low current economic production in the region, and suggests that population increase will not be a major contributing factor to future increases in emissions this century.

We assessed the contribution of the three components to uncertainty about CO_2 emissions in 2100, as measured by predictive variance on the logarithmic scale. GDP per capita accounted for 50% of uncertainty, carbon intensity for 48%, and population for only 2%. Measures to reduce future emissions would need to target at least one of these components. Policies to reduce GDP per capita seem unlikely, and population increase will not be a major factor. This suggests that future policies should target carbon intensity.

Figure 3d shows the predictive distribution of global mean temperature increase to 2100, in the form of a histogram of random draws from the model. This is obtained by combining our predictive distribution of cumulative CO_2 emissions to 2100 with the relationship between cumulative CO_2 emissions and warming described by the IPCC[15]. The likely range is 2.0–4.9 °C, with a median of 3.2 °C. There is a 5% chance of less than 2 °C warming, and a 1%

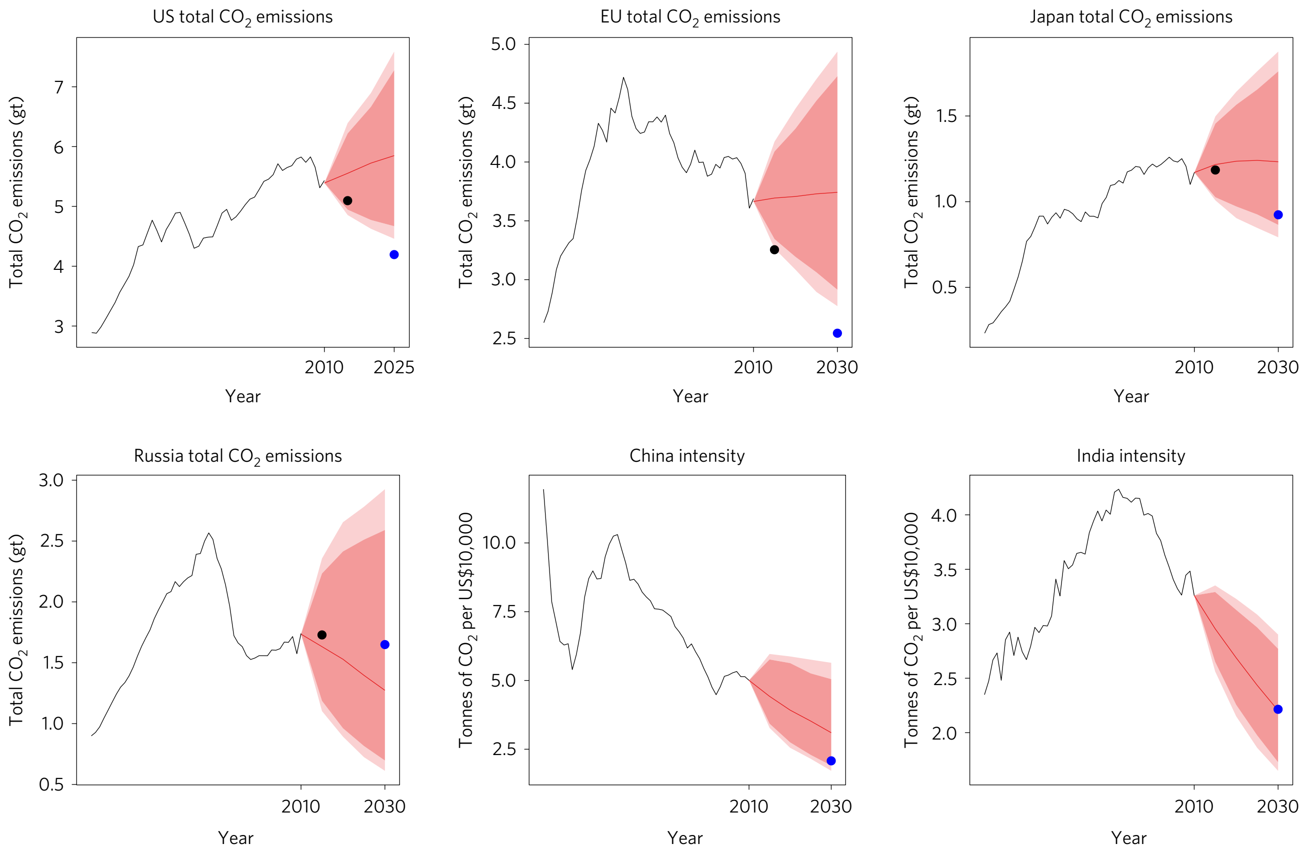

Figure 4 | Probabilistic CO_2 emissions forecasts for leading countries and regions, with Paris climate agreement targets. In each panel, the large black dot shows the preliminary estimate of CO_2 emissions for 2015, while the large blue dot shows the Paris climate agreement target for 2030 (2025 for the US). The targets for China and India are in terms of carbon intensity rather than total CO_2 emissions, and no comparable 2015 numbers for these two countries are available.

chance of less than 1.5 °C. This takes account of uncertainty in future population growth, economic growth, carbon intensity and climate sensitivity.

Figure 4 shows the predictive distributions to 2030 for five major countries and the European Union, compared with the 2015 Paris climate agreement intended nationally determined contributions (INDC)[23]. The INDCs were proposed with equity principles such as 'common but differentiated responsibilities' in mind, so these data should not be used to criticize countries' individual targets. These targets are well within the predictive intervals for Russia and India, towards the lower end but within the intervals for Japan and China, and well below the lower bounds for the USA and the EU. If China and India were to reach their intensity targets, it would probably result in decreases in carbon emissions in China, and relatively weak increases in India. This is in part due to a likely decrease in GDP growth rates in these countries.

Figure 4 also shows the preliminary report emissions for 2015 for the four major countries whose targets are expressed in terms of emissions rather than of carbon intensity. For Japan and Russia, these are very close to the median projections. For the US they are within the interval but at the low end, while for the EU they are below the bottom of the 95% interval, suggesting that the Paris Agreement targets could be reached. If the EU and the US alone were to meet their Paris Agreement targets, it would reduce our global emissions median forecast by nearly 3 Gt CO_2/year in 2030, down to a level similar to today's emissions. Rapid reductions in emissions would still be necessary thereafter to limit warming to 2 degrees[24]. Figure 3a suggests that the Paris Agreement's target of net zero emissions in the second half of the twenty-first century is unlikely to be reached.

Other probabilistic forecasting methods for emissions and temperature increase have been proposed, using combinations of statistical modelling, expert elicitation and scenarios[25–28]; in contrast, our approach is fully statistical. Our forecasting model does not explicitly incorporate future legislation that could change future emissions. It is based on past emissions, which implicitly account for accumulating legislation and regulation over the past 30 years since climate change became a global issue, and indeed carbon intensity has been improving steadily over that period. The model has performed well under cross-validation. We have also not accounted for the possibility that decreasing prices for alternative energy could cause a sudden massive shift to alternative energy. This would be speculative, especially given that the experience of the past 60 years is that carbon intensity has improved steadily in most countries past a certain point, rather than by abrupt large changes. The reverse is also possible due to decreases in fossil fuel prices, which have dropped in recent years.

Methods

Methods, including statements of data availability and any associated accession codes and references, are available in the online version of this paper.

Received 6 January 2017; accepted 22 June 2017; published online 31 July 2017

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Acknowledgements

This work was supported by NIH grants R01 HD054511 and R01 HD070936.

Author contributions

The first four authors wrote the manuscript and developed the statistical model. A.E.R. and D.M.W.F. designed the study. A.Z. and P.L. compiled and analysed data and wrote computer code.

Additional information

Supplementary information is available in the online version of the paper. Reprints and permissions information is available online at www.nature.com/reprints. Publisher's note: Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations. Correspondence and requests for materials should be addressed to A.E.R.

Competing financial interests

The authors declare no competing financial interests.

Methods

Data. For population, we used the estimates of population for all countries from 1950 to 2015 issued by the UN[2]. We produced probabilistic projections for all countries with the model used by the UN for its probabilistic projections[2–4]. The prediction intervals for future population from these projections are available at http://esa.un.org/unpd/wpp/Download/Probabilistic/Population.

GDP per capita data came from the Maddison Project, using data from 1960 to 2010[29]. We chose the Maddison Project data set for its completeness. The Maddison Project uses purchasing power parity (PPP) rather than market exchange rates to put GDP data on the same scale across countries and to adjust for inflation over time. GDP data are missing for countries in the former Soviet Union prior to 1990, and are missing for some countries in 2009 and 2010. The Maddison Project provides GDP data in 1990 US dollars, which we converted to 2010 US dollars by multiplying by 1.52 based on the OECD price deflator[30].

CO_2 emissions data came from the Global Carbon Budget[31]. We used data from 1960 to 2010. We used fossil fuel and cement production emissions for each country, excluding emissions from land-use change.

Our unit for carbon intensity is tonnes of CO_2 per US$10,000 in 2010 Purchasing Power Parity. For most countries carbon intensity has peaked and has seen a declining trend since the peak, and so we restricted the carbon intensity data we used to be post-peak for each country. We determined the peak for each country by finding the maximum of the intensity curve after smoothing the series using the loess smoother with span 0.25. We thus fitted our model to the decline phase of carbon intensity for each country, removing the earlier phase of non-declining carbon intensity. The United States and most Western European countries had declining carbon intensity throughout the data period 1960–2010. If carbon intensity had not peaked in a country by 2003, we determined that there was not enough evidence to determine that it had peaked yet.

There were 13 countries whose carbon intensity had not peaked by 2003, namely Angola, Benin, Bangladesh, Bolivia, Comoros, Honduras, Haiti, Morocco, Mauritius, Malaysia, El Salvador, Sao Tome and Principe, and Seychelles. There was also one country with fewer than 20 years of intensity data, namely Namibia. These 14 countries were excluded when estimating the intensity model, but not when projecting future emissions. We assumed that their intensity would start to decline immediately in 2010, a conservative assumption.

We removed North Korea, Qatar, Lesotho, Palestine, and Somalia from our data set due to the poor quality of the data for these countries. We restricted data for the United Arab Emirates, removing emissions data prior to 1969, and for Senegal, removing 1968 emissions data, also because of data quality concerns. After merging together these different data sources and removing these countries, we had 152 countries in our data set. The 49 countries with more than 100,000 inhabitants in the UN World Populations Projections (WPP) data set but not in ours had 93.7 million people in 2015. Countries we are not including with a population above 5 million people are North Korea (25 million people), South Sudan (12.3 million), Somalia (10.8 million), Papua New Guinea (7.6 million), and Eritrea (5.2 million). The countries included in our data set accounted for 98.7% of the world's population in 2015.

Model specification. We used Bayesian hierarchical models for each of the three components of the Kaya identity, estimated by Markov Chain Monte Carlo (MCMC)[32]. These are multilevel models in which each country has its own set of model parameters, and these parameters in turn are assumed to be drawn from a worldwide distribution. This yields estimates for individual countries that rely not only on the data for that country, but are also informed by the experience of other countries. This is particularly useful when data for a country are sparse or noisy.

We used the UN's official 2015 population projections for all countries, which are probabilistic and also based on Bayesian hierarchical models for fertility and mortality[2–4].

The model for GDP per capita has two components. There is a world frontier of GDP per capita, for which we use the United States as a proxy, and the GDP per capita of other countries converges to this world frontier at a country-specific rate. GDP per capita is modelled on the logarithmic scale, with the world frontier GDP per capita following a random walk with drift, also on the logarithmic scale. We represent the world frontier by the United States, allowing a different growth rate prior for 1960 to 1973, since during this time the United States experienced a period of high growth which has not persisted[33]. Note that our model does not allow a country's GDP to diverge systematically away from the frontier, although it may move further away from the frontier in any given time period.

We projected carbon intensity on the logarithmic scale for each country. We model the logarithm of carbon intensity as following a linear trend plus a first-order autoregressive process for each country.

We denote by F_t the logarithm of GDP per capita in the United States in year t, and by $G_{c,t}$ the logarithm of GDP per capita in country c in year t. We denote by $\tau_{c,t}$ the logarithm of carbon intensity in country c in year t. We use vague prior distributions for the world-level parameters. Our joint Bayesian hierarchical model for GDP and carbon intensity is then defined as follows:

GDP Component:

$$
\begin{aligned}
F_t &= F_{t-1} + \gamma + \gamma_{\mathrm{pre1973}} 1[t \leq 1973] + \varepsilon_t^{(f)} \\
F_t - G_{c,t} &= \phi_c (F_{t-1} - G_{c,t-1}) + \varepsilon_{c,t}^{(g)} \\
\varepsilon_{c,t}^{(g)} &\sim N(0, \sigma_c^{(g)2}) \\
\gamma &\sim \mathrm{Uniform}(0,1) \\
\gamma_{\mathrm{pre1973}} &\sim \mathrm{Uniform}(-0.1, 0.1) \\
\phi_c &\sim TN_{[0,1]}(\mu_\phi, \sigma_\phi^2) \text{ (truncated normal, to be in } [0,1]) \\
\mu_\phi &\sim \mathrm{Uniform}(0,1) \\
\sigma_\phi &\sim \mathrm{Uniform}(0,1) \\
\varepsilon_t^{(f)} &\sim N(0, \sigma^{(f)2}) \\
\sigma^{(f)} &\sim LN(-3, 20) \text{ (lognormal)} \\
\sigma_c^{(g)} &\sim LN(\mu^{(g)}, \sigma^{(g)2}) \\
\mu^{(g)} &\sim N(-6, 40) \\
\sigma^{(g)} &\sim \mathrm{Uniform}(0.05, 5)
\end{aligned}
$$

Carbon Intensity Component:

$$
\begin{aligned}
\tau_{c,t} &= \eta(t - \bar{t}) + \beta \tau_{c,t-1} - \delta_c + \varepsilon_{c,t}, \\
\eta &\sim N(0, 1/100), \\
\beta &\sim \mathrm{Uniform}(0,1), \\
\varepsilon_{c,t} | \varepsilon_{c,t}^{(g)} &\sim N\left(\rho \frac{\sigma_c}{\sigma_c^{(g)}} \varepsilon_{c,t}^{(g)}, (1-\rho)\sigma_c^2\right), \\
\delta_c &\sim N(\mu_\delta, \sigma_\delta^2), \\
\mu_\delta &\sim N(0,1), \\
\sigma_\delta &\sim LN(-5, 1.15^2), \\
\sigma_c &\sim LN(\sigma_\mu, \sigma_{\mathrm{SD}}^2), \\
\sigma_\mu &\sim N(-2, 100), \\
\sigma_{\mathrm{SD}} &\sim \mathrm{Uniform}(0.05, 5), \\
\rho &\sim \mathrm{Uniform}(-1, 1).
\end{aligned}
$$

Model estimation. We fitted our model using Markov Chain Monte Carlo (MCMC) sampling, as implemented by the JAGS package[34,35] in the R programming language[36]. Five chains were used, and each chain was run for 100,000 iterations after a burn-in period of 5,000 iterations; standard diagnostics indicated this to be sufficient to approximate the posterior distribution well.

To make projections we simulated many future trajectories of population, GDP per capita and carbon intensity jointly from their predictive distribution. To simulate one future trajectory, we proceeded as follows. We first sampled model parameters from the posterior distribution by choosing the parameters from one iteration of the MCMC algorithm chosen at random. Then, for each set of model parameters sampled, we sampled model random errors from their conditional distribution given the parameters sampled. Finally, we projected the future trajectory forward using the model, the sampled model parameters, and the sampled model random errors. These three steps were repeated many times, yielding many future possible trajectories. Prediction intervals were determined using quantiles of the resulting distribution.

We constrained intensity to a maximum of 50 tonnes of CO_2 per US$10,000 when projecting forward, a level higher than any seen historically, to constrain any unreasonably high projections for individual countries. This affected only some projections for Cameroon and the Republic of Congo. When sampled intensity for a country in a certain year would have exceeded this limit of 50, the intensity value was resampled for that country and year.

We were prepared to impose a hard upper limit on cumulative emissions based on the amount of fossil fuel in the ground, taken to be 11,000 Gt based on McGlade and Elkin[37], which is a conservative estimate relative to other estimates by the BGR, the IEA and the GEA (see Supplementary Table 5 in McGlade and Elkin[37]). However, none of our trajectories encountered this limit.

Model validation. Out-of-sample validation was used to check model bias and the calibration of our confidence intervals. The model was fitted only on data up to 1980, 1990, or 2000, and projections were made until 2010. This included determining when countries had peaked in intensity, with the restriction that the peak had to come at least 5 years before the last year of training data, mirroring model fitting in our primary analysis.

For each 5-year period, we checked the proportion of 90% and 95% intervals by country that included the true proportion of emissions for that country, along with the proportion of countries that had emissions above or below the median projected emissions.

We also performed out-of-sample validation by aggregating over the five IPCC regions in the RC5 classification[38]: OECD 1990 countries; Reforming Economies (REF), consisting of Eastern Europe and the former Soviet Union; Asia, consisting of non-OECD Asian countries, Middle East and Africa (MAF); and Latin America (LEM), consisting of countries of Latin America and the Caribbean. This also served as a check on cross-country correlation, since positive residuals between countries would lead to confidence intervals that are too narrow. In addition to checking interval coverage for CO_2 emissions, we also checked interval coverage by IPAT component.

Predictive distribution of temperature increase. Recent research has shown that temperature increase by 2100 is largely a linear function of cumulative carbon dioxide emissions[39,40]. We use the relation from Figure SPM.5 in the IPCC 2014 Synthesis Report[15] which relates cumulative emissions since 1860 to a probability density function of temperature change from 1861–80 to 2100, assumed to be conditionally Gaussian. This estimate takes into account uncertainty due to the carbon cycle, ocean heat uptake, and climate sensitivity.

Global temperature is also affected by emissions of other greenhouse gases such as methane, and the cleanup of aerosols, which affect the Earth's albedo. For the century-long global warming response, these factors become smaller in relative importance to CO_2. A full calculation of their relative effects is beyond the scope of this study.

Posterior distributions. The posterior medians and 95% intervals of the world-level parameters for the model of GDP and carbon intensity are shown in Supplementary Table 2. They are much tighter than the prior distributions, because the data provide substantial information about the world distribution as well as about the individual countries. In the GDP component of the model, perhaps surprisingly, the majority (110 out of 152) of the country-level ϕ_c values had a posterior median of 1, which corresponds to keeping pace with the frontier but not converging to it. However, these 110 countries accounted for only 39% of world population, so 61% of people were living in countries at the frontier or converging to it.

The posterior distribution of the parameter ρ describing the country-level correlation of residuals between the intensity and GDP models had a posterior median of 0.157, with a 95% interval of (0.127, 0.186). Note that by the model form, since the GDP model is expressed with a $-G_{c,t}$, this means that higher GDP per capita than expected corresponds to lower intensity than expected.

Data availability. The data and code used to produce the results in this article are available at https://github.com/PPgp/CO2projections.

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