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Setting Sustainable Development Goals – A Dynamical Systems Approach

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Abstract

Employing a novel dynamical system modeling approach with global data, our best-fit model identifies the mechanisms for reducing global greenhouse gas emissions to under 44 gigatonnes of carbondioxide equivalent ($GtCO_2e$) by 2020. Our results show that with a business-as-usual scenario the global emissions will reach 61 $GtCO_2e$ by 2020. We test the estimated parameters to suggest options to set the Sustainable Development Goals in the post-2015 scenario. The analysis shows that a democratic equal reduction in the total emissions of all countries would imply a reduction of about 27.6% . The burden of reducing emissions, however, would not change much if the top 25 global emitters (includes, China, India, United States, Canada, Germany etc.) bear the full burden of this reduction. In a business-as-usual scenario where no global emission cuts are implemented, the model suggests that the emission-reduction technology should improve by at least 2.6 percent and tastes and preferences should improve by 3.5 percent, if the global emissions reduction target is to be met.

JEL Classifications: C51, C52, C53, C61, Q01, Q50.

Keywords: Sustainable Development Goals, dynamical systems, Bayesian, greenhouse gases

1 Introduction

Increased production of goods and services lead to growth of Green House Gas (GHG) emissions, particularly carbon dioxide (Granados, Ianides and Carpintero, 2012; Raupach et al., 2007; Quadrelli and Peterson, 2007; Roca and Alcantara, 2001; Tol et al., 2009), which is one of the strongest predictors of temperature increase. Scientists agree that unless this global temperature increase

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is capped to under 2 degree Celsius, irreversible climate change will occur, leading to crisis, conflicts and large losses in GDP (IPCC, 2007). Recognising this the Copenhagen Accord, 2009, agreed to cooperation in peaking (stopping from rising) the global and national greenhouse gas emissions but it was in Cancun at the COP/16/CMP6 in 2010, that the United Nation Framework Convention on Climate Change (UNFCCC)Parties agreed to limit a rise in global average temperature to 2 degrees Celsius above the pre-industrial levels. United Nations Environment Program (2011) estimates that to achieve this GHGs should be reduced to less than 44 gigatonnes of carbon dioxide equivalent ($GtCO_2e$) by 2020. With the Sustainable Development Goals (SDGs) [1] for the post-2015 development agenda still under formulation and the slow pace of global environmental strategy - meeting this target by 2020 would be challenging unless some drastic measures are introduced.

Our objective in this paper is to quantify the gap between the scientifically stipulated target of 44 $GtCO_2$ equivalent and the predicted GHG emissions by 2020, if the business-as-usual scenario persists. We also identify and test mechanisms to suggest policy options to reduce this gap.

Without making any a priori assumptions, we use an innovative dynamical system modeling approach, to identify interactions between GHG emissions and Gross Domestic Product per capita (we use GDP per capita in international dollars, fixed 2005 prices and measure it in the log scale and represent it by GDP or G through the rest of this paper) by analysing data for 134 countries for 1990-2005. First, we fit equations for the rate of change of each indicator as a function of the level of the indicator itself and the level(s) of other indicator(s). The nonlinear dynamics and effects are captured by the polynomial terms that cover diverse linearities and nonlinearities (Ranganathan et al., 2014). The intention here is to use the theoretical literature as a guide to identify relationships and variables, and investigate all the plausible interactions. Second, we use the best-fit model to predict the total GHG emissions for the year 2020. Third, based on our best-fit model, we test and identify mechanisms which may be used to suggest options to achieve the 44 $GtCO_2$ equivalent target by 2020.

The main contribution of our paper is that the model we present provides robust predictions for the business-as-usual scenario based on the available data and the interacting variables. Further, the model also provides clear mechanisms for reducing emissions by controlling different factors such as technology and environmental quality preferences. The best-fit model thus enables us to test the effects of adopting legally binding reductions for countries or the influence

[1] The SDGs broadly aims at reducing the global greenhouse gas emissions, achieving a more equitable and sustainable management and governance of natural resources while promoting dynamic and inclusive economic and human development. Instead of being prescriptive in terms of specific development strategies or policies, this integrated post-2015 UN framework suggests enablers that overlap between the fundamental principles of Sustainability and the four core dimensions. These core dimensions include: sustainable use of natural resources; managing disaster risk and improving disaster response; affordable access to technology and knowledge; providing sustainable energy for all; coherent macroeconomic and development policies supportive of inclusive and green growth; sustainable food and nutrition security; managing demographic dynamics; and conflict prevention and mediation (UN 2012).

of economic prosperity in people's environmental preferences and delivers policy suggestions that may be implemented to reach global emission reduction targets.

We find three main results. First, our best-fit model shows that GHG emission decreases as the product of GDP and GHG emissions increases. This could be attributed to the greater awareness, education or preference for better environmental quality in countries, as the GDP rises (or conversely, concern for the environment due to increasing emissions beyond a certain level). It thus suggests that GHG emissions might be brought down through mechanisms of better technology/efficiency and by bringing about greater changes in the education/awareness or preferences of citizens towards better environmental quality. We also find a non-linear effect of GHG emission on itself. This is in line with recent literature that does not find supportive evidence for the Environmental Kuznets Curve (EKC) that suggests that after a country reaches a certain economic level, its environmental degradation begins to reduce. Based on the fact that a majority of the developing countries are in their initial phase of development our results suggest that countries will continue to have a greater increase in emissions.

Second, our analysis shows that if we continue with the business-as-usual scenario the predicted global GHG emissions will be nearly 61 $GtCO_2e$ by 2020. This is 17 $GtCO_2e$ above the recommended 44 $GtCO_2e$ to keep the increase in temperature under 2 degrees Celsius in this century. (These numbers are not absolute and there are minor revisions in recent IPCC reports but we use the 44 $GtCO_2e$ as a useful target in this paper).

Third, based on our data and estimated parameters, we test and suggest various policy options that may work in the short run to achieve the impending targets for reduction in GHG emissions by 2020. Our results show that a democratically equal cut in emissions by all countries would require an overall reduction of about 27.6% . We also demonstrate that this burden in emissions reduction would not change much if we focus on the 25 most polluting countries. In the absence of any emission cuts, our model suggests that the technology should improve by at least 2.6 percent and the tastes and preferences should improve by 3.5 percent, if the global emissions reduction target is to be met.

The paper is organized as follows. In the following section we present the theory and literature on the relationship between economic growth and environment. Section 3 presents the analytical tools and methods that we use to capture the relation between our indicators. We then discuss the data that we use in the next section. Section 5 presents the empirical results with the best-fitted model and discusses its implications for the relationship between economic performance and GHGs. It also makes the prediction for the global GHG emission in 2020, based on the business-as-usual scenario. Section 6 tests options to achieve the 44 $GtCO_2e$ GHG emissions target. Section 7 concludes with a discussion of the results and suggested policies.

2 Theory and empirical evidence

The literature on the relationship between economic growth and environmental degradation is dominated by the Environmental Kuznets Curve (EKC) that hypothesizes an inverted U-shaped relationship between income growth and environmental degradation. During the initial stage of development, a certain amount of environmental degradation is inevitable, but as income rises there are greater incentives and preferences to improve environmental quality (Grossman and Krueger, 1991, 1995; Shafik and Bandyopadhyay, 1992; Panatayou,1993; see Dinda 2004 for a survey; World Bank, 1992).[2]

Based on various assumptions the researchers have theoretically derived the EKC relationship between environmental quality and income(Dinda, 2002; John and Pecchenino, 1994; Selden and Song, 1995; Stokey, 1998). A few theoretical studies such as Lopez (1994) argue that income growth is driven by accumulation of production factors, which increase firms' demand for polluting inputs. Simultaneously, demand for environmental quality rises with income, as the willingness to pay for a clean environment increases. From a basic comparative static analysis of the costs and benefits for an improved environmental quality, the EKC can be derived from the technological link between consumption of a desired good and abatement of the 'bad' produced as a by-product (Andreoni and Levinson, 2001).

Specifically, we know that GDP growth is largely unaffected by the emissions, though there may be a negative effect due to the imposition of 'green technologies.' The change in the total GHG emissions of a country is affected by the economic state of the country - its GDP. The yearly change in the total GHG emissions depends on: the GDP; on its current emissions level; the efficiency in technology; and also on the current 'taste' or environmental concerns of the population.

Empirical estimation of the EKC soon recognised that in such a reduced form model, income proxies for too many other determinants, for example, level of economic activity, regulatory capability and incentives etc. (Stern, 2004, 2007; Dijkgraaf and Vollebergh, 1998, 2005; Holtz-Eakin and Selden, 1995; Richmond and Kaufmann, 2006; Füller-Fürstenberger and Wagner, 2007; He, 2007; Hossain, 2011). There was therefore a potential for bias arising from variables omitted from the model (Galeotti et. al, 2009). This recognition led to attempts to extend the model by including variables relating to the structure of the economy, energy prices, trade openness and occasionally political rights and civil liberties (Dasgupta and Maler, 1995; Barrett and Graddy, 2000; Harbaugh et al., 2002; Narayan and Narayan, 2010).

[2]Some researchers argue that increase in environmental deterioration is transient and with greater economic growth, environmental quality will improve (Beckerman, 1992; Lomborg, 2001; Barlett, 1994; Bhagwati, 1993). Others insist that trade liberalization re-distributes pollution from rich countries to poor countries, as the pollution-intensive industries move to developing countries (Suri and Chapman, 1998; Ekins, 1997). Arrow et al.(1995) believe that economic growth is neither a necessary nor a sufficient factor to induce environmental improvement.

Bi-directional causality between income and carbon dioxide emission has also been found by several empirical studies (Coondoo and Dinda, 2002; He, 2006; Shen, 2006). Over 100 studies published in the last 25 years show the following three effects. The scale effect (all else equal, an increase in output means an equi-proportionate increase in pollution), the composition effect (all else equal, if the sectors with high emission intensities grow faster than sectors with low emission intensities, then composition changes will result in an upward pressure upon emission), and the technical effects that describe the decrease of sector emission intensities as resulting from the use of more efficient production and abatement technologies (Grossman and Krueger, 1991; Antweiler et al., 2001; Stern, 2002; Brock and Taylor, 2005).

More recent literature shows that increase in world output leads to an increase in carbon dixide emission (Granados, Ianides and Carpintero, 2012; Raupach et al., 2007; Quadrelli and Peterson, 2007; Roca and Alcantara,2001; Tol et al., 2009). For instance, Raupach et al. (2007) estimate that the CO_2 global emissions increased at an annual rate of 1.1% in 1990s to that of over 3% in 2000-2004. Most EKC empirical studies use cross-country data. Others use multi-function system estimation methods for panel data that enables them to assign country-specific random coefficients to the income and the squared income terms (List and Gallet, 1999; Koope and Tole, 1999; Halkos, 2003). Country specific EKC derived from international experience are deemed “descriptive statistics” by Stern et al. (1996), who suggests that the relationship between economic growth and environmental impact should be analysed by examining the historical experience of individual countries, using econometrics and qualitative historical analysis. Only a few studies have done this (Roca et al., 2001; Friedl and Getzner, 2003; Lindmark, 2002).

Based on this theoretical and empirical understanding, we try to build a parsimonious model that identify common patterns in the available data for countries over time, in terms of their economic performance and GHG emissions.

3 Methods

We use a novel data-driven mathematical modelling approach to analyse dynamic relationships in the yearly changes of the indicators of interest (Ranganathan et al., 2014). Our main intent is to understand the interactions between indicators in terms of the change in one variable between times t and t+1 as a function of all included model variable(s) at time t. We use a Bayesian model selection approach to identify the best model.

In our approach ordinary differential equations are fit to country-level data on indicators. For instance, consider the indicators log GDP per capita (G) and total GHG emissions (E). We attempt to find the best-fit model for changes dG and dE as a function of G and E, that is,

$$\frac{dG}{dt} = f_1(G, E) \quad (1)$$
$$\frac{dE}{dt} = f_2(G, E) \quad (2)$$

We restrict our model space (defined by the possible functions f_1, f_2 to comprise polynomials in G and E with the interacting terms, that capture various linear and nonlinear effects. In order to test a wide range of possible interactions, we fit models of the form:

$$f(G, E) = a_0 + \frac{a_1}{G} + \frac{a_2}{E} + a_3G + a_4E + \frac{a_5}{GE} + \frac{a_6E}{G} + \frac{a_7G}{E} + a_8GE + +a_9G^2 + a_{10}E^2 + \frac{a_{11}}{G^2} + \frac{a_{12}}{E^2}$$

Selecting a specific model is equivalent to choosing a subset of non-zero coefficients $a_0, ..., a_{12}$ and the corresponding terms while setting the other coefficients to zero. If we allow m polynomial terms in our model specification, we get a total of $\binom{13}{m}$ models. Note that due to our choice of model terms the number of models we have to evaluate computationally is sufficiently small while the terms comprising products of variables and higher order terms capture non-linearities in the system. These higher order terms typically result in multi-stable states for the dynamical system, which are characteristic of the realistic socio-economic systems.

Also, each of the terms lends itself to interpretation in terms of actual economic factors. For instance, the term $\frac{G}{E}$ may be interpreted as the emission efficiency of a country's economic output and its inverse $\frac{E}{G}$ then corresponds to the emission inefficiency of the economy. The EG term (and its inverse) may be interpreted as the environmental concern or environmental preference variable.

A model's complexity is defined in terms of the number of terms in it and we use a two-stage fitting algorithm to select the least complex model that fits the data well. In the first stage of the model selection algorithm, we find the maximum-likelihood model for each possible number of terms m. We fit the changes in the indicator variables using multiple linear regression over all $8,192$ possible models $f_1(G, E)$ (and similarly for $f_2(G, E)$). We find the models with the greatest likelihood value as a function of number of terms in the model. Thus $M_1, M_2, ...$ represent the best models with 1 term, 2 terms and so on.

The log-likelihood value of the best fit for dG models with m terms is given by

$$L_G(m) = \log P(dG|G, E, \phi^*_{i,m}) \quad (3)$$

where dG, G, E are all the observations from the dataset and $\phi^*_{G,m}$ is the set of unique parameter values obtained for the model with the highest log-likelihood value among all models with m terms.

The ranking of the models according to log-likelihood values shows us which models best fit the data. However, there is an overfitting effect where more complex models (more terms in the model) rank high on this scale but are not the most robust for the available dataset. This is because the maximum log-likelihood value increases monotonically with additional terms, since each term allows an extra degree of freedom on curve fitting but there is a dminishing returns effect once the essential information from the dataset has already been captured by a model. Thus reliance on the log-likelihood value alone can lead to overfitting the data by selecting too many terms. Accepting a model may accurately fit the existing data but this may generalise poorly to unseen data and hence have little predictive power.

To address this problem we use the Bayesian approach (Jeffreys, 1939; Berger, 1985; Jaynes, 2003; MacKay, 2003) to evaluate the fit of these models in the second stage of our model selection algorithm. We calculate the Bayes factor also called the Bayesian marginal likelihood (MacKay, 2003). The Bayes factor compensates for the increase in the dimensions of the model search space by integrating over all parameter values, i.e.,

$$B_G(m) = \int_{\phi_{G,m}} P(dG|G, E, \phi_{G,m})\pi(\phi_{G,m})d\phi_{G,m} \tag{4}$$

The Bayes factor is thus the likelihood value averaged over the parameter space with a prior distribution defined by $\pi(\phi_{G,m})$. We choose a non-informative prior distribution (Ley and Steel, 2009). For example, $\pi(\phi_{i,m})$ can be chosen to be uniform over the range of feasible parameter values. In our method, this range of values is chosen to include most feasible values (we test this numerically by looking at the parameters that maximise the log-likelihood value and then choose a large enough range around this value) but also to be small enough for the integral to be computed using Monte Carlo methods.

4 Data

The data used in the paper has primarily been taken from the World Bank 'World Development Indicators' dataset. This contains data for nearly 200 countries for a period of more than 50 years. Specifically, to obtain the value of total GHG emissions in kt of CO_2 equivalent, we add the values given for CO2 emissions, the other greenhouse gas emissions, HFC, PFC and SF_6 (kt CO_2 equivalent), Methane emissions (kt CO_2 equivalent) and Nitrous oxide emissions (kt CO_2 equivalent). The corresponding per capita emissions data is also available in the same dataset.We have this data for 134 countries for the years from 1990 to 2005 in this dataset. The CO_2 emissions dataset is more complete (we also have CO_2 emissions data for years before 1990 for many countries). For other gases we have to rely on interpolations to get yearly values.

The data in the World Bank indicators set is itself sourced from Carbon Dioxide Information Analysis Center, Environmental Sciences Division, Oak Ridge National Laboratory, Tennessee, United States and the International Energy Agency statistics, according to notes in this publicly available dataset. We use the data from the 2009 dataset in this study.

We decided to use total emissions data in our models to test the model predictions against the global targets set by the IPCC. In addition, we also tested models using total emissions per capita but the model parameter estimation was distorted by the presence of outliers in the form of sparsely populated and/or oil-producing countries which had extremely high emissions per capita.

For the economic indicator, we use the GDP per capita (in international dollars, fixed 2005 prices) from the publicly available Gapminder dataset, which itself uses publicly available data and uses extrapolation methods to provide GDP values for certain countries from the beginning of the nineteenth century. Documentation for this is provided at www.gapminder.org. In the years of interest for us (roughly 1950-2009), the data is virtually identical to the World Bank dataset.

The data clearly shows that while there is a small increase in the median values of both the total emissions and the GDP per capita, much of it is driven by large outliers. In the case of total emissions, in which we are especially interested, the outliers are mainly the United States of America, China, India and a few other countries. In fact, the top 5 emitters contributed more than 50 per cent in every year in the dataset[3]. This contribution went from nearly 53 per cent in 1990 to around 51 per cent in 1992-1993, which was its lowest, before increasing again. In the last 4 years (2002-2005) the proportional contribution has been increasing nearly exponentially. China overtook the United States as the highest emitter in 2005, and India bypassed Russia as the third largest emitter in 1998. There has also been a significant movement within the top 10 emitters as countries such as Mexico, Indonesia, Brazil improve their economy and emit more.

5 Results

5.1 Economic Growth and Greenhouse gas emissions

An important consideration in the sustainable development paradigm is the effect of economic growth on the environment. A large body of literature has grown on this subject both in economics and ecology but it is still not clear if a specific mechanism may be attributed to the interaction between the key indicator variables - GDP and total greenhouse gas emissions. Given the set of all possible two variable models relating GDP (G) and greenhouse gas emissions (E) to the rate change in GDP and the rate of change in greenhouse gas emissions, we find that the model with the largest Bayes factor is (coefficients rounded off):

$$\frac{dG}{dt} = 0.014 \tag{5}$$

$$\frac{dE}{dt} = E + 7.3x10^{-6}E^2 - 3.8E/G - 0.06EG \tag{6}$$

[3]In 2005 the top 5 total emitters were China, United States, India, Russian Federation and Japan.

The model in Equation 5 indicates that the GDP growth is unaffected by the total emissions, suggesting that any effort to cut down emissions may not have a significant effect on the economy. At the same time, this is not conclusive evidence as other models which include interaction terms also perform nearly as well as the best model presented here in terms of model fit. Note that even with the simple model, the mechanism for emissions reduction could still have a secondary effect since the growth rate (the parameter in the GDP model) may be changed by specific mechanisms.

According to the EKC, in the initial stages of development, economic growth leads to environmental degradation. This is represented by the first two terms in Equation 6. However, as income increases, the preference for better environmental quality also increases (Grossman and Krueger, 1991,1995; Shafik and Bandyopadhyay, 1992; Panatayou,1993; see Dinda 2004 for a survey; World Bank, 1992). This corresponds to the EG term having a negative coefficient in Equation 6. An emission inefficient economy which uses polluting technologies, for instance, would have high increase in emissions year on year as it grows. This would imply that the emission inefficiency term $\frac{E}{G}$ be positively correlated with yearly increase in emissions. We see this effect in the data but Equation 6 suggests that this term is actually negatively correlated with increase in emissions. This seeming contradiction is due to the effect of interactions with other terms. The emission inefficiency term $\frac{E}{G}$ by itself is positively correlated with yearly increase in emissions but in combination with the other terms, its effect is negative on the overall yearly change.

As countries like China, India, Brazil and Indonesia develop, their total emissions continue to increase the total emissions (as captured by the E and E^2 terms). With the increase in their GDP per capita, the $\frac{E}{G}$ interaction term implies a decline in the decrease in the change in the total carbon dioxide emissions. This might be due to the choice of technology, efficiency, institutions, macro policies as also several social and political factors. As these countries will continue on their economic development path our model suggests that the EG interaction term kicks in with greater taste and preference for better environmental quality. The result of these two terms taken together is that first there is an increase in emissions with increasing GDP followed by a decrease due to the preference term.

We can see from the data phase portrait Fig. 1 that countries with higher GDP per capita have more GHG emissions and vice versa. Fig. 2 shows the phase portrait of the dynamical system given by our model in Equations 5 and 6. We can see that the two phase portraits are similar, confirming that the model predicts the data reasonably well.

5.2 Model Validation and GHG emission projection in the short run

The system of equations 5 and 6 provide the description of the most probable dynamics between economic growth and GHG emissions, in 1990-2005. If the patterns of growth that were current until 2005 were to continue with a business-

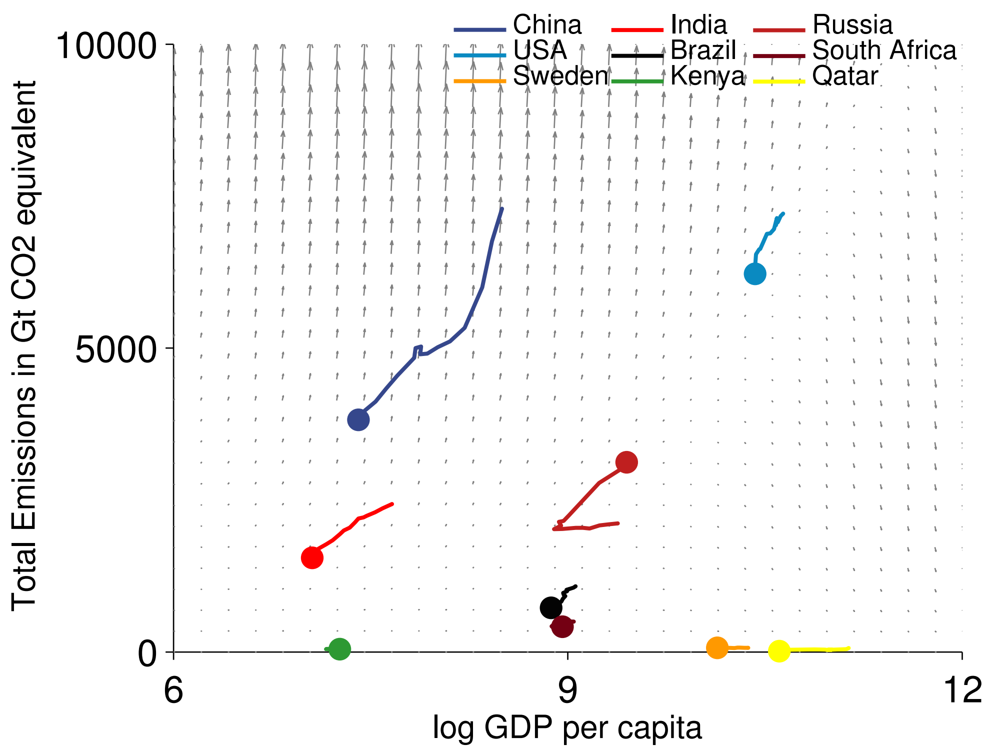

Figure 1: Total emissions against log GDP per capita for all countries from 1990-2005. The black vector lines show the average yearly changes (magnitude and direction) in log GDP and total emissions as a function of current log GDP and total emissions. The coloured vector lines show representative country trajectories in the same time period.

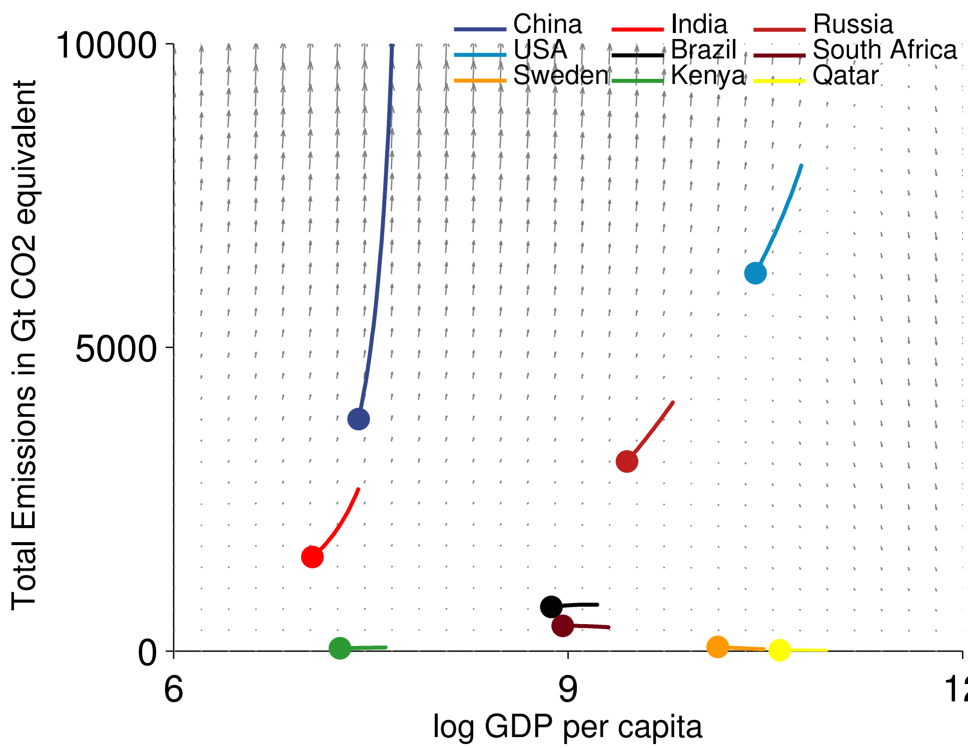

Figure 2: The model predictions for total emissions against log GDP per capita for all countries from 1990-2005. The coloured vector lines show the predicted country trajectories starting from 1990 initial conditions for the same time period.

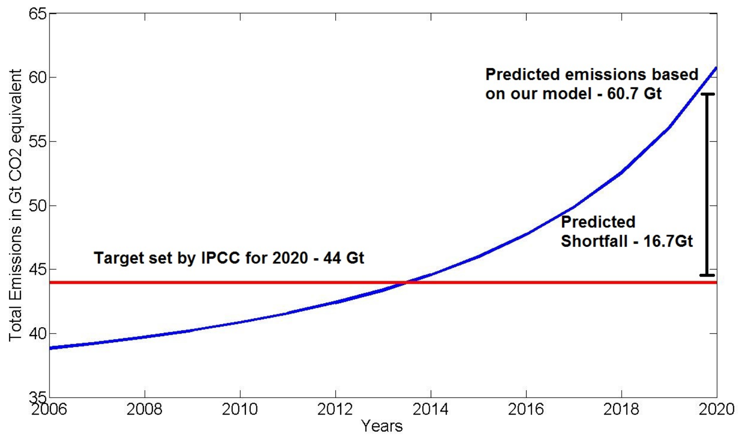

Figure 3: Predicted Total Emissions with the IPCC target for 2020 to keep global temperature increase below 2 degrees C

as-usual scenario, our global projections for GHGs show that the GHGs rise from around 35.7 $GtCO_2e$ to nearly 61 $GtCO_2e$ equivalent in 2020 (Fig. 3). Our projections are very close to the UNEP (2011) business-as-usual projections. According to UNEP the global emissions could reach around 56 $GtCO_2e$ in 2020.

We test the robustness of our best-fit model by checking the predictions for 2008 and 2010, against the actual data. Our model predictions for the total emissions are 39.70 $GtCO_2e$ in 2008, while the actual recorded value was 41.12 $GtCO_2e$. In 2010, the predicted total emissions are 42.73 $GtCO_2e$ while the actual total emissions were 40.84 $GtCO_2e$. Investigating the country-wise prediction we find that United States, for example, will emit less than what the model predicts (about 7.6 $GtCO_2e$ in 2010 is predicted by the model) whereas historically, since 2005, it has reduced emissions (actual in 2010 is 6.61 $GtCO_2e$). We find similar evidence for the developed countries. On the other hand, fast growing developing economies like China, emit more than what our model predicts (actual emission in 2010 was 10.7 $GtCO_2e$, predicted: 9.94 $GtCO_2$). Overall these effects balance each other globally to an extent and our model leads to a somewhat conservative estimate that nearly reflects the actual emissions.

Even if we go by the more conservative target (target-band) of 44 GtCO2e (range: 39-44 GtCO2e) by 2020, the projected business-as-usual scenario in our model leaves a gap of 17 $GtCO_2e$ with the IPCC target in the global emissions. What makes the task of reducing this gap challenging is that the reduction in the GHG needs to be achieved while enhancing access to energy. About 1.4 billion people lack modern energy services (UNEP 2011). Add to that the energy demands of the fast growing economies, like China and India, and the task becomes even more difficult.

6 Testing ways to Reduce Greenhouse Gas Emissions

Many proposals have been suggested to reduce emissions to acceptable levels. Our model allows us to test different scenarios based on changes to the different model parameters. We also test options by imposing the global target of 44 $GtCO_2e$ and find the set of model parameters that can achieve this target.

6.1 Proportional Reduction in Emissions

One simple option to achieve emissions reduction is to impose a proportional reduction in emissions on all countries. In this regime, we know that our global business-as-usual projection for total emissions is 60.77 $GtCO_2e$, which is 16.77 $GtCO_2e$ above the 44 $GtCO_2e$ target. To eliminate this emission gap, each country could aim for a total reduction in 2020 of 27.6% of its predicted emissions.

One objection to this "democratic" scheme of reducing emissions across different countries is that the poorer countries need to reduce emissions in the same proportion as the more developed countries. This may set back their development as the initial stages of economic development present additional challenges and reducing energy consumption and hence greenhouse gas emission might be a difficult proposition to achieve. On the other hand, emissions per capita numbers show that some developed countries (when we exclude very under-populated countries such as Aruba or the Caribbean islands, for instance) have a much larger share of emissions relative to the population they support. Some developing countries such as China and India, even though they support huge populations, also contribute very heavily to the global emissions.

Of the total predicted emissions of 60.77 $GtCO_2e$, the top 25 emitters which includes rapidly developing countries such as China, India, Brazil, Indonesia, Mexico, Turkey etc. and developed countries such as the United States, the United Kingdom, Canada, Japan, Germany, Italy etc. contribute 54.5 $GtCO_2e$, or nearly 90% of the total emissions. If the load of reducing the 16.77 $GtCO_2e$ in 2020 is shared only by the top 25 emitters, then they have to reduce their emissions by 30.8% each while the others can continue along their historical trajectories. Table 4 presents the predicted 2020 emissions for the top 10 emitters. Regime I presents the reduction in $GtCO_2e$ if all countries democratically reduce their emissions in the same proportion to achieve the global target of 44 $GtCO_2e$. In contrast, Regime II presents the same proportional reduction in the emissions by the top 25 emitters in the world, in order to meet the global targets. According to our prediction estimates, with the exception of China, for other countries this would not result in a significant increase in the required reduction to meet the global targets in the short run. Thus, one possible strategy could be to focus on the top GHG emitters.

Country	2005 Emissions (Gt CO2eq)	% of total global emissions	Predicted 2020 emissions (Gt CO2 eq)	% of total global emissions	Regime I Reductions (Gt CO2 eq)	Regime II Reductions (Gt CO2 eq)
China	7.2916	18.94	29.8151	49.05	8.2289	10.1531
USA	7.2114	18.73	8.5433	14.06	2.3580	2.9093
India	2.4325	6.32	3.8387	6.3	1.0595	1.3072
Russia	2.1150	5.49	2.2401	3.6	0.6183	0.7628
Japan	1.3891	3.61	0.9170	1.51	0.2531	0.3123
Brazil	1.0796	2.80	1.1199	1.84	0.3091	0.3814
Germany	0.9785	2.54	0.6185	1.02	0.1706	0.2106
Canada	0.7256	1.89	0.4193	0.69	0.1157	0.1428
United Kingdom	0.6622	1.72	0.3996	0.066	0.1103	0.1361
Mexico	0.6393	1.66	0.5791	0.095	0.1598	0.1972

Figure 4: Table showing the top 10 emitters in 2005 and their predicted emissions in 2020 based on model predictions. Regime I reductions correspond to proportionally equal reductions for all countries based on estimated overshoot of 16.77 Gt CO2 equivalent in 2020. Regime II reductions correspond to the top 25 emitters of 2020 sharing the burden of reducing all the excess emissions.

6.2 Effect of Emission Cuts, Technology and Preferences in Business as Usual Scenario

The model parameters in Equations 5 and 6 represent the business-as-usual scenario. If policy changes are allowed, they are reflected by changes in the model parameters. In general, we can rewrite the two equations as

$$\frac{dG}{dt} = 0.014 \times \delta \tag{7}$$

$$\frac{dE}{dt} = \alpha(E + 7.3 \times 10^{-6} E^2) - \beta \times 3.8E/G - \gamma \times 0.06EG \tag{8}$$

where changes in the estimated coefficients in the original model due to policy interventions are represented by changes in the parameters $\alpha, \beta, \gamma, \delta$. Here δ represents changes in economic growth rate, α represents the cutoff rates of emission imposed on countries, β is the improvement in technology and γ is the change in environmental preference.

If only one parameter can be changed, we see that total emissions decreases when α decreases and when β and γ increase.

In the real world scenario policymakers make multiple interventions simultaneously. It is therefore more interesting to look at combinations of policy interventions where two or more parameters are simultaneously changed. This analysis enables us to identify the most effective combination among the imposed reductions, technological change and change in environmental preference, and to choose the best option to invest in among them.

The three figures 5,6 and 7 show the predicted emissions as a function of changes in two of the parameters keeping the third constant at 1 which corre-

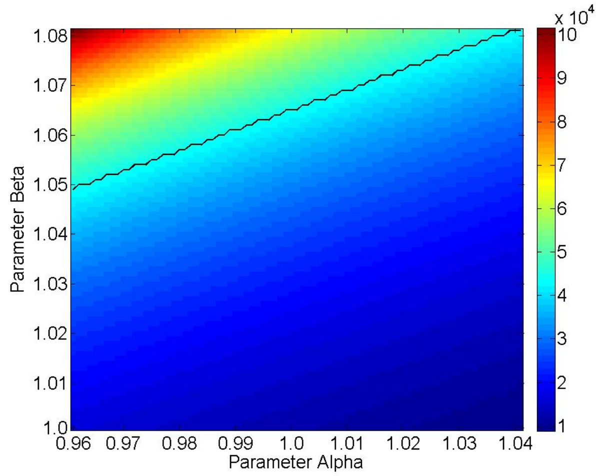

Figure 5: Predicted total global emissions in 2020 shown as a function of changing the parameters α and β. The mapping of colour to amount of emissions is shown as a colourbar in units of mega tonnes of CO_2 equivalent. The black line represents the desired target of 44 GtCO$_2$e.

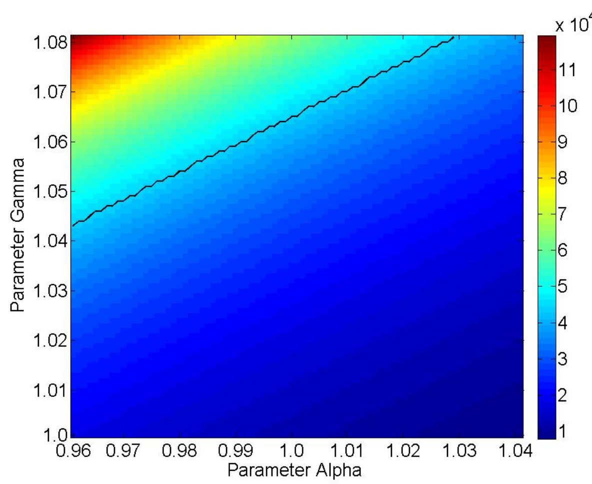

Figure 6: Predicted total global emissions in 2020 shown as a function of changing the parameters α and γ. The mapping of colour to amount of emissions is shown as a colourbar in units of tonnes of CO_2 equivalent. The black line represents the desired target of 44 GtCO$_2$e.

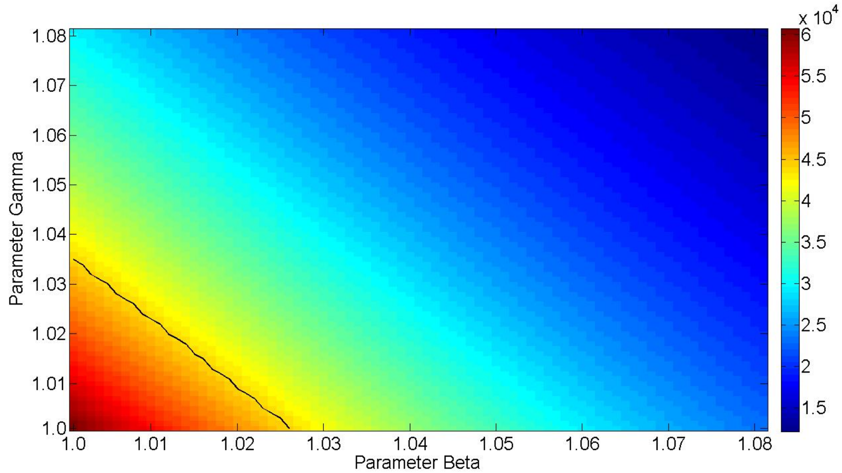

Figure 7: Predicted total global emissions in 2020 shown as a function of changing the parameters β and γ. The mapping of colour to amount of emissions is shown as a colourbar in units of tonnes of CO_2 equivalent. The black line represents the desired target of 44 $\mathrm{GtCO_2e}$.

sponds to the business-as-usual scenario for that variable. Instead of using a 3-D plot, we use a heatmap to show the predicted emissions in 2020 as a function of the two parameters while the third is constant at 1. The mapping of colour to amount of emissions is shown in the colour bar in units of mega tonnes of $\mathrm{CO_2}$ equivalent. The grading is such that blue (and shades of blue) correspond to low values while red and shades of red correspond to high values. Since we are not concerned here with the exact values for every set of parameters but only those parameter values that yield the desired target (shown by the black lines on the plots), the heatmap is an efficient way to condense the information. Note that the scales are different in the three figures and so the same shade of colour represents slightly different value of predicted emissions.

We see from the figures that different parameter combinations yield the same predicted emissions (same colours on the heatmap). Specifically, the black lines on the three figures show the values of the parameters for which predicted emissions in 2020 is 44 $\mathrm{GtCO_2e}$. Numerical simulations are used to obtain these heatmaps and hence the black lines represent the numerically closest values to 44 $\mathrm{GtCO_2e}$. Mathematically we can see that the curves of constant predicted emissions on these planes are straight lines.

The region below the black lines in Figures 5 and 6 and the region above the black line in Figure 7 are the desirable set of parameters which will lead to achieving the target of less than 44 $\mathrm{GtCO_2e}$ in 2020. It is clear from Figure 5 that if the environmental quality preference is business-as-usual, improvements in technology will be required to meet the desired target even if emissions are cut-down. For instance, a global-emissions cut of 4 percent would still require a 5 percent improvement in technology by 2020 to meet the required target. If however, the technology scenario remains business-as-usual (figure 6), meeting the global emissions target for 2020 would be impossible without improvements in preferences for environmental quality. This is already a sign of the difficult task ahead in controlling emissions. A result that is supported by the literature that shows that the developing countries have a harder time improving environmental quality (for example,compare the results in Stern and Common 2001 and Selden and Song 1994; Cole et al. 1997 and Kauffman et al. 1998).

The model provides clear directives on how to attain global emission targets if no clear emission cuts are agreed upon and implemented by countries, especially the top emitters. In such a business-as-usual scenario (Figure 7), we would require an improvement of about 3.5 percent in preference for better environmental quality and about 2.6 percent improvement in technology. It is worth emphasising that changes below these thresholds will not result in desired outcomes.

7 Discussion and Conclusions

In the post-2015 scenario, the scientific evidence pointing towards the imminent dire consequences of GHG emissions need to be translated into actionable goals that may be globally implemented with immediate effect. These SDGs need to be simple, clear, achievable and easily monitored. We use dynamical systems models to investigate the interaction between GHGs and GDP and test some intuitively plausible options that can potentially be formulated into SDGs. Predicting the total GHG emissions for the year 2020 our best-fit model suggests that the emissions might be brought down through mechanisms of better technology/efficiency and by bringing about greater changes in the education/awareness or preferences of citizens towards better environmental quality. According to our estimation, the business as usual global GHG emission prediction is about 61 $GtCO_2e$ by 2020. This is nearly 17 $GtCO_2e$ above the recommended 44 $GtCO_2e$ for 2020 to keep the increase in temperature under 2 degree in this century.

We test and suggest three potential SDGs. The first SDG option is a democratic equal reduction in the total emissions of all countries. This would imply a total reduction in 2020 of 27.6% of its predicted emissions between now and 2020. The second SDG option is to focus on the top emitters. Rapidly developing countries such as China, India, Brazil, Indonesia, Mexico, Turkey etc. and developed large economies such as the United States, the United Kingdom, Canada, Japan, Germany, Italy etc. account for the majority of the future global emissions till 2020. We find that if the top 25 emitters bear the full load of meeting the global emissions reduction target, their burden in reducing emissions does not change by much. Thus, focussing on a few key global emitters in the short-run might be a more effective strategy.

Our results from Figure 7 suggest that under a business-as-usual scenario where no global emission cuts are implemented, the world would have to see an improvement in its emission-reduction technology by atleast 2.6 percent and also alter its tastes and preferences by about 3.5 percent. This provides us with the third SDG option, as any improvements below these thresholds would not be sufficient to achieve the desirable emissions target by 2020.

While our best-fit model provides us insights into setting of SDGs, the real world is fraught with political, social and institutional hurdles. A suggestion to focus on the set of most 25 polluting countries in the very short run might make logical sense but in terms of implementation might turn out to be a political and diplomatic mine-field. At best, the suggestions in this paper may be treated as normative directives to identify the immediate threat of the process of economic growth and global GHG emissions and insights into how they may be effectively contained, at least in the very short run.

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