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Plastic pollution and economic growth: the influence of corruption and the lack of education

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Abstract: Green economic growth fed by technological solutions is often mentioned to mitigate plastic pollution. But economic growth appears to be in contradiction to planetary boundaries. By developing two worldwide socio-economic models based on non-technological solutions, economic production, social, and policy data, we demonstrate the adverse ecological impact of the lack of regulatory process and educational environmental programs. Our results support other studies that observe the effect of several key factors on behaviors in favor of the environment: *i*) improving the quality of democracy with better regulation in all country income categories, *ii*) implementing long-term educational programs to increase environmental awareness in low and middle income countries, *iii*) limiting urbanization and urban sprawl, which generates disconnection from the environment and reduces opportunities for personal experiences with the ecosystem. All these key factors feature industrial responsibility, environmental awareness and willingness to engage in ethical production, consumption and plastic waste management. Our results show a 1% increase in education or corruption control policies reduces annual inadequately managed plastic waste by 0.97% and 0.18% respectively. As a result, progressively raising the number of schooling years to 12 and implementing tighter corruption control policies would reduce by 44% and 28% respectively the global amount of inadequately managed plastic waste discarded into the global ecosystem in 2050 as compared to 1990. Otherwise, this amount is predicted to increase from 61-72 million tonnes per year in 1990 to 61-110 million tonnes per year in 2050.

Key words: plastic pollution, global economic model, gross domestic product (GDP), socio-economic scenarios, waste management, governance factors.

1. Introduction

The increase in plastic marine litter is evident, as are its harmful effects on marine ecosystems (*inter alia*, Ostle et al., 2019; Baztan et al., 2018). A growing number of studies provide estimates of the global annual amount of plastic entering the ocean from land-based sources (Jambeck et al., 2015; Lebreton et al., 2015; Schmidt et al., 2015). For example, Jambeck et al. (2015) estimate that in 2010 between 4.8 and 12.7 million tonnes of plastic entered the ocean. This relatively wide range shows further studies are needed to improve its accuracy.

One step in that direction is improving understanding of key factors determining plastic production, waste generation and mismanagement. Barnes (2019) modeled the relationship between mismanaged plastic waste and income per capita for 151 countries. His results suggest that as income per capita increases in a country, environmental pollution such as mismanaged plastic waste per capita also increases up to certain level of individual income. After this turning point, mismanaged plastic waste per capita will decrease due to an increase in environmental improvement efforts, while average inhabitant income continues increasing (Barnes, 2019). Such a relationship is known in environmental economics as the environmental Kuznets curve. Additionally, Barnes (2019) argues growing economies have more financial means available for technological innovations to reduce pollution (Dinda, 2004), reduce materials used in production (Lindmark, 2002), and reduce the amount of polluting inputs per outputs (Stern, 2004).

Here we use a recent database from the World Bank (2018) providing data observed in 2011-2017 to design two models demonstrating plastic waste generation is not exclusively a function of GDP per capita. It also strongly depends on factors such as geographic location, policy measures (e.g., corruption control policies), market regulations favoring the private sector, and education levels (e.g., the average number of years of schooling) (Hidalgo-Ruz et al., 2018). Regarding corruption, the definition used in this paper comes from the World Bank (2018a) and Kaufmann et al. (2010) in that corruption occurs when public power is exercised for private gain, including petty and grand forms of corruption, as well as the "capture" of the state by elites and private interests.

2. Method

2.1. Selection of available data

We designed two models to calculate how global economic growth, corruption control policies, market regulations in favor of the private sector, geographic location, urbanization, demography, and education influence inadequately managed plastic waste generated annually in all 217 countries and territories in the world. Model 1 focuses on the influence of corruption control policies and is made of Eq. 1, 2 and 3. Model 2 focuses on the influence of education policies. It is made of Eq. 1, 2 and 3bis (see equations below). Economic growth is measured by annual changes in global GDP per capita. Inadequately managed plastic waste is measured by the annual generation of plastic waste for which waste treatment consists of landfilling in open dumps or collective discarding in waterways and marine areas. Inadequately managed plastic waste is a useful variable to study because it includes plastic waste that could eventually enter the ocean via inland waterways, wastewater outflows, storm drains, and transport by wind or tides. Plastic waste is sometimes also directly discarded at sea by fishing, aquaculture, and shipping activities but our models do not take that into account. Data is difficult to find since direct littering at sea is forbidden by international legislation. Plastic waste is also sometimes directly littered on the ground by individuals. This is why the variable studied by Barnes (2019) is mismanaged plastic waste: it includes plastic waste directly littered by individuals in addition to inadequately managed plastic waste. However, direct individual littering is difficult to estimate due to the lack of data. Barnes (2019) applies to all countries a constant coefficient from Jambeck et al. (2015) who estimate littered plastic waste is 2% of total municipal solid waste, based on United States national data for the year 2008, which is not representative of all countries.

In several countries, a substantial portion of plastic waste is not categorized by any kind of waste treatment; the World Bank (2018) database categorizes these cases as "unaccounted for" or "others." Our models take into account that a proportion of these wastes are likely inadequately managed. We designed the model equations to compute inadequately managed plastic waste (i.e., Eq. 3 and 3bis) based on a subset of data from 122 countries. We selected these countries because they reported percentages lower than 25% (and less than 5% for most of them) of total municipal solid waste listed in both categories, assuming that such countries reported on their waste management more rigorously. The validation of our models (Section 2.3) shows they behave as if waste registered in both categories were inadequately managed exclusively in the 136 low-, middle-, and upper middle-income countries. This follows aggregation rules 3 and 4 developed by Uehara and Cordier (2019). The best fit between observed data and modelled estimations is obtained with Model 2 (Fig. 3). Thereby, we calculated with Model 2 that among the global annual amount of plastic waste registered as "waste unaccounted for" and "other waste treatment" by the 217 countries in 2011-2017, 85% was inadequately managed.

We selected the explanatory variables in our models based on an exploratory approach. For that purpose, we tested available data (Kaza et al., 2018; World Bank, 2018; World Bank, 2019; World Bank, 2019a) to identify variables that might explain plastic waste generation per capita and inadequately managed plastic waste percentages. The variables tested were pre-selected based on literature from the social sciences, which proposes various predictors to explain waste generation and management:

- values, norms, and habits (Peattie, 2010): partly captured by geographic dummy variables in Models 1 and 2 (Tables 1, 2 and 3),
- urbanization (Kiessling et al., 2017; Kolekar, 2016; Karak et al., 2012): captured by the percentage of the total population living in urban areas in Models 1 and 2 (Table 1),
- standard of living (Bandara et al., 2007; Karak et al., 2012): partly captured by GDP per capita in Models 1 and 2 (Tables 1, 2 and 3),
- education and knowledge (Hidalgo-Ruz et al., 2018; Kolekar, 2016; Morren and Grinstein, 2016; Karak et al., 2012; Peattie, 2010): education is partly captured by the average number of years of schooling in Model 2 (Table 3),
- Environmental awareness (Kiessling et al., 2017; Hidalgo-Ruz et al., 2018; Karak et al., 2012; Peattie, 2010): indirectly included in Models 1 and 2 by the percentage of the total population living in urban areas (Table 1),
- governance (Karak et al., 2012; Milfont and Markowitz, 2016): captured in Model 1 by corruption control policy estimates (Table 2) and in Models 1 and 2 by market regulatory quality percentile rank (Table 1),

- income levels (Bandara et al., 2007; Kolekar, 2016): captured by GDP per capita in Models 1 and 2 (Tables 1-3),
- cultural patterns (Bandara et al., 2007; Vicente-Molina et al., 2013) and geography (Peattie, 2010): partly captured by geographic dummy variables in Models 1 and 2 (Tables 2-3),
- demography (Kolekar, 2016; Peattie, 2010): captured by the number of inhabitants per country at the moment of running the full equation of Models 1 and 2 (Eq. 1).

2.2. Equation development

The statistical tests show that among the explanatory variables listed above, those entered in the model equations (Tables 1, 2 and 3) are all statistically significant; *p*-values < 0.05, the highest R^2 (for linear equations), and the lowest AIC scores (for equations based on a logit model) across all models tested are included in the supplementary materials (Tables S1 to S19). Models 1 and 2 are divided each into three equations based on these explanatory variables: one equation for plastic waste generation per capita (Table 1), one equation for percentage of municipal solid waste that is inadequately managed (Table 2 and 3), and one equation combining all (Eq. 1). While the equation based on Table 1 variables is estimated using a linear regression, the equation based on Table 2 and 3 variables is estimated using a logistic regression following Jambeck et al. (2015). Each equation is calculated country by country.

Equation 2 calculates the amount of plastic waste generated per capita and Equation 3 (and 3_{bis}) calculates the percentage of this waste that is inadequately managed. The final output of the models is generated by Equation 1, which multiplies the results from Eq. 2 and Eq. 3 for Model 1 (or Eq. 3bis for Model 2) with the total population of each country. The result is the annual amount of inadequately managed plastic waste discarded by the world population in million tonnes per year over the period 1990-2050. The results shared here are for the global scale, obtained by summing the results from each of the 217 countries and territories.

We estimate the amount of plastic wastes (in tonnes per year) that are inadequately managed in a country as follows:

$$Inadequately\ managed\ plastic\ wastes = \\ Plastic\ waste\ per\ capita \times Inadequately\ managed\ waste\ \% \times population \qquad \textbf{(1)}$$

Where $Plastic\ waste\ per\ capita$ is computed in Eq. 2 and represents the amount of plastic waste individuals generate in one year (in kg/person/year), $Inadequately\ managed\ waste$ % is computed in Eq. 3 and 3_{bis} and represents the percentage municipal waste that is inadequately managed either because the waste treatment consists in landfilling in open dumps or collective discard in waterways or in marine areas, $population$ is the number of people living in the country. Eq. 1 is calculated for each country.

$Plastic\ waste\ per\ capita$ is computed as follows (the statistical tests in Table 1 show the explanatory variables are all statistically significant):

$$Plastic\ waste\ per\ capita = EXP\left(1.573\ ln(GDP\ per\ capita) - 0.080\ \left(ln(GDP\ per\ capita)\right)^2 + 0.562\ very\ small\ island + 0.012\ urban\ population + 0.008\ Market\ regulatory\ quality - 5.347\right) \quad \textbf{(2)}$$

Where ln is the natural logarithm, $GDP\ per\ capita$ is the Gross Domestic Product of the country divided by its population and is expressed in purchasing power parity (PPP) in constant 2011 international $ per person, $very\ small\ island$ is a dummy variable which takes the value of 1 if the country is a small island and 0 if it is not, $urban\ population$ is the percentage of the population living in urban areas, and $Market\ regulatory\ quality$ is expressed in percentile rank that captures perceptions of the ability of the government to formulate and implement sound policies and regulations that permit and promote private sector development. Percentile rank indicates the country's rank among all countries covered by the aggregate indicator, with 0 corresponding to lowest rank, and 100 to highest rank. In Eq. 2, the correlation between GDP per capita and plastic waste generation per capita is very good, given that the more purchasing power people gain from their income (estimated by GDP per capita), the more they increase their overall material consumption, which increases the amount of plastic waste they discard at the end of a product’s life (Wilson et al., 2012). The indicator measuring market regulatory quality is a governance variable capturing perceptions of the ability of governments to formulate and implement sound policies and regulations permitting and promoting private sector development (World Bank, 2018a; Kaufmann et al., 2010). We include this variable in the model assuming such regulation enhances consumption of products and thus increases plastic waste generation per capita. Governance indicators are one of the most important factors enabling effective environmental management (Bennett and Satterfield, 2018). The geographical variable “small islands” is also influential since larger amounts of wastes are generally generated per capita on small islands, plastic waste included (Eckelman, 2014).

Table 1. Linear regression model computing LN (plastic waste generation per capita) as a linear function of LN (GDP per capita), [LN (GDP per capita)]^2, small islands, urban population percentage, and market regulatory quality (Equation 2 applied in Models 1 and 2).

Variable	Coefficient	Std. Error	*p*-Value	
LN (GDP per capita)	1.57291	0.5879081	0.008	***
(LN (GDP per capita))^2	-0.080482	0.0329161	0.016	**
Small islands	0.5617574	0.1541988	0.000	***
Urban population	0.0122711	0.0038205	0.002	***
Market regulatory quality	0.0079495	0.0036527	0.034	**
Constant	-5.347286	2.578574	0.040	**
R^2	0.4804			
Adjusted R^2	0.4623			
N	149			

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

$Inadequately\ managed\ waste$ % is computed in Eq. 3 as follows (the statistical tests in Table 2 show these variables are all statistically significant):

$$Inadequately\ managed\ waste\ \% = \frac{EXP(-1.159\ ln(GDP\ per\ cap.) - 1.244\ Corr.control + 2.216\ MEA + 3.057\ LAC - 1.684\ Small\ islands + 9.926)}{1 + EXP(-1.159\ ln(GDP\ per\ cap.) - 1.244\ Corr.control + 2.216\ MEA + 3.057\ LAC - 1.684\ Small\ islands + 9.926)} \quad \textbf{(3)}$$

Where $Inadequately\ managed\ waste$ % is a percentage expressed in nominal value (from 0 to 1), $GDP\ per\ cap.$ is GDP per capita as in Eq. 2, $Corr.control$ is an estimate for corruption control policies which captures perceptions of the extent to which public power is exercised for private gain, including petty and grand forms of corruption along with "capture" of the state by elites and private interests. The estimate ranges from -2.5 (low level of control of corruption) to 2.5 (corruption is highly controlled by proper policies). MEA is a dummy variable which takes the value of 1 if the country is from Middle East or Africa and 0 if it is not; LAC is a dummy variable as the previous one for countries from Latin America. In Eq. 3, there is a statistically significant correlation between GDP per capita and inadequately managed plastic waste (*p*-values < 0.01), which follows an environmental Kuznets curve, although not as closely as suggested in Barnes (2019). Figure 1 shows GDP per capita only explains 11% ($R^2 = 0.11$) of variation in inadequately managed plastic waste. This is why we include additional variables in the model such as a governance indicator reflecting corruption control policies. This indicator captures perceptions of the extent to which public power is exercised for private gain, including both petty and grand forms of corruption, and "capture" of the state by elites and private interests (World Bank, 2018a; Kaufmann et al., 2010). We selected this variable assuming that in countries where corruption control is low, the plastic industry and other corporate interests may exert an influence on environmental legislation in favor of plastic products and against preventive measures to reduce plastic waste and mismanagement – a list of preventive measures is available in Cordier and Uehara (2019).

Table 2. Logit model computing the percentage of inadequately managed waste as a logistic function of LN (GDP per capita), corruption control policies (estimate), and dummy variables [0, 1] for Middle Eastern and African, Latin American, and Small island countries (Equation 3 applied in Model 1).

Variable	Coefficient	Std. Error	*p*-Value	
LN (GDP per capita)	-1.159099	0.4099703	0.005	***
Corruption control policies (estimate)	-1.243777	0.5616087	0.027	**
Middle-East and African countries	2.21588	0.9259708	0.017	**
Latin-American countries	3.056826	0.8849186	0.001	***
Small islands	-1.684385	0.8090709	0.037	**
Constant	9.926191	3.682973	0.007	***
Pseudo R^2	0.5411			
Log likelihood	-38.80185			
AIC	89.6037			
N	122			

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

We tested another set of data to design an alternative version of Eq. 3 (Eq. 3_{bis}), assuming education level in a country might influence the amount of inadequately managed plastic waste. The explanatory variables in Eq. 3_{bis} are the following: (i) the natural logarithm of GDP per capita; (ii) average number of years of schooling for people ≥ 25 years old; and (iii) geographic indicators for Latin American countries. The model using Eq. 3_{bis} is Model 2 (based on education) whereas the model using Eq. 3 is Model 1 (based on corruption control policies). The education indicator based on the average number of years spent at school by individuals 25-years-old or older was selected assuming that more education leads to greater environmental concern, which would be reflected by support for decision-makers who implement adequate plastic waste management. In Eq. 3_{bis}, $Inadequately\ managed\ waste\ \%$ is computed as follows (the statistical tests in Table 3 show these variables are all statistically significant):

$$Inadequately\ managed\ waste\ \% = \frac{Exp(-1.385\ ln(GDP\ per\ cap.) - 0.437\ years\ of\ school\ +\ 3.287\ LAC\ +\ 16.179)}{1 + Exp(-1.385\ ln(GDP\ per\ cap.) - 0.437\ years\ of\ school\ +\ 3.287\ LAC\ +\ 16.179)} \tag{3_{bis}}$$

Where $years\ of\ school$ is the average number of years of schooling in a country for individuals ≥ 25 years old.

Table 3. Logit model computing the percentage of inadequately managed waste as a logistic function of the number of years of total schooling, LN (GDP per capita), and dummy variables [0, 1] for Latin American countries (Equation 3_{bis} applied in Model 2).

Variable	Coefficient	Std. Error	*p*-Value	
Years of school	-0.437077	0.1741331	0.012	**
LN (GDP per capita)	-1.385286	0.3867209	0.000	***
Latin-American countries	3.286815	1.11963	0.003	***
Constant	16.17896	3.716624	0.000	***
Pseudo R^2	0.6140			
Log likelihood	-26.74853			
AIC	61.49706			
N	100			

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

2.3. Validation of the model

The validation process consists in comparing observed data with model estimations over the period 2011-2017. The blue diamonds shaped in Figures 1-3 are based on observed annual data for 141 countries in 2011-2017 for 80% of them except for 17% (observed in 2000-2010) and 3% of the countries (observed in 1993-1996) (Kaza et al., 2018; World Bank, 2018; World Bank, 2019; World Bank, 2019a). Countries with non-available data for plastic wastes generation, plastic waste treatment or GDP have been discarded from the graphs. Among the 141 countries, there are 30 countries with non-available data for the number of school years (used in Model 2). They have been estimated with a linear model calculating the number of school years as a linear function of *ln* (GDP per capita) and geographic location variables ($R^2 = 0.73$ and all *p*-values < 0.05). The model is available in supplementary materials (Table S19). Observed data for inadequately managed plastic waste do not exist *per se*, several raw data points have to be summed for that value. The observed data displayed in Figures 1-3 have been summed from the World Bank (2018) database on plastic waste following the aggregation rules developed by Uehara and Cordier (2019). Rule 3 was followed for Fig. 1 and Fig 3, and Rule 4 for Fig. 2 because it provides the best fit between observed data and estimations from the models across all aggregation rules tested.

In a first analysis, Figure 1 seems to confirm the existence of an environmental Kuznets curve (represented by the orange dots on the graph) as found by Barnes (2019), describing a U-inverse relationship between observed GDP per capita and observed plastic wastes inadequately managed per capita (Dasgupta, 2002; Stern, 2004). The equation of the environmental Kuznets curve, which has been used to compute the orange dots in Fig. 1, is the following: plastic waste inadequately managed per capita = 61.56 *ln* (GDP per capita) - 3.64 [*ln* (GDP per capita)]^2 - 235.10. However, a statistical analysis of the U-inverse curve displayed in Figure 1 reveals that although the environmental Kuznets curve equation is statistically significant (all *p*-value < 0.01), GDP per capita only explains 11% of the variation in the generation of plastic waste inadequately managed per capita ($R^2 = 0.11$). Moreover, the Mean Absolute Error (MAE) of the environmental Kuznets curve equation is relatively high (MAE = 15.05 kg/person/year).

Results from Models 1 and 2 better fit with observed data (Figures 2 and 3). Models 1 and 2 succeed explaining 48% of plastic waste generation per capita ($R^2 = 0.48$) estimated with Eq. 2, and their estimation of the percentage of plastic waste per capita with Eq. 3 and 3bis have the lowest AIC scores (AIC = 89.6 and 61.5 respectively) of all the models tested in supplementary materials (all *p*-values < 0.05, displayed in Tables 1 and 2). Moreover, the MAE = 13.09 and 11.86 kg/person/year for Models 1 and 2, respectively, which is lower compared to the environmental Kuznets curve equation.

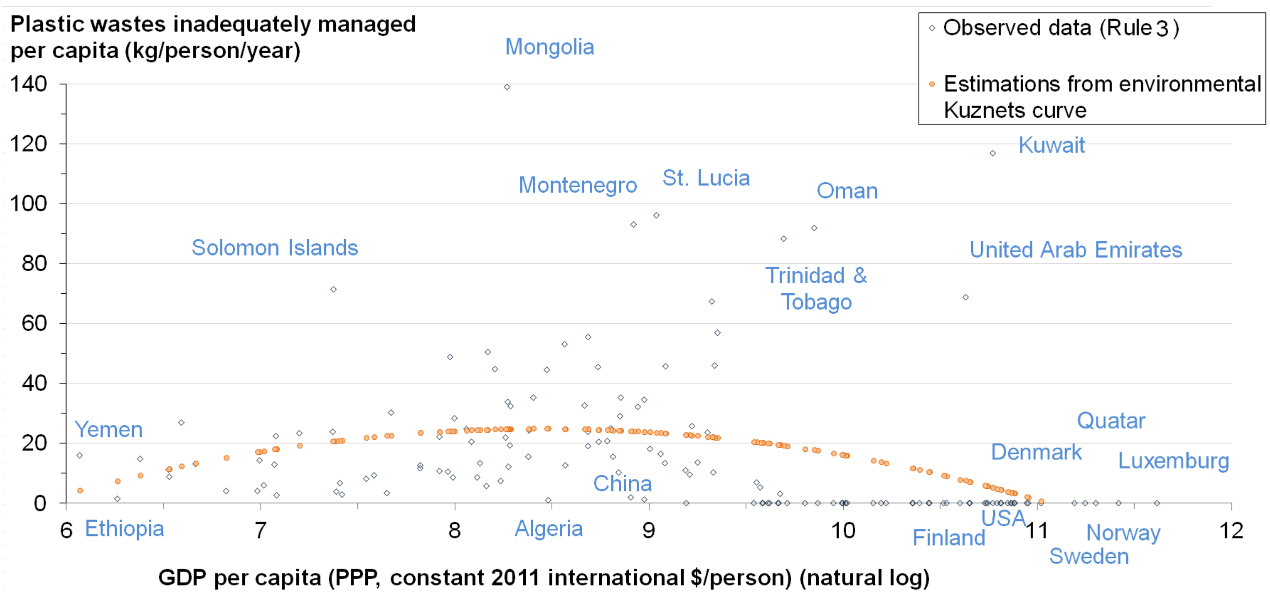

Fig. 1. Environmental Kuznets curve estimations compared to observed data of inadequately managed plastic waste generated per capita in 141 countries in 2011-2017.

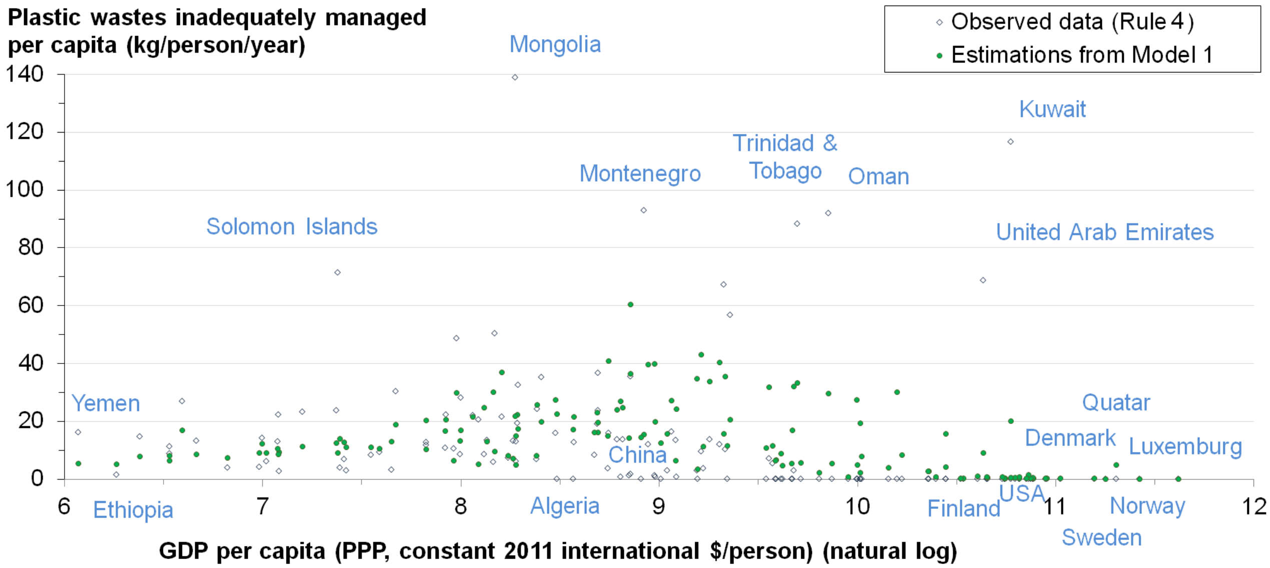

Fig. 2. Model 1 estimations compared to observed data of inadequately managed plastic waste generated per capita in 141 countries in 2011-2017.

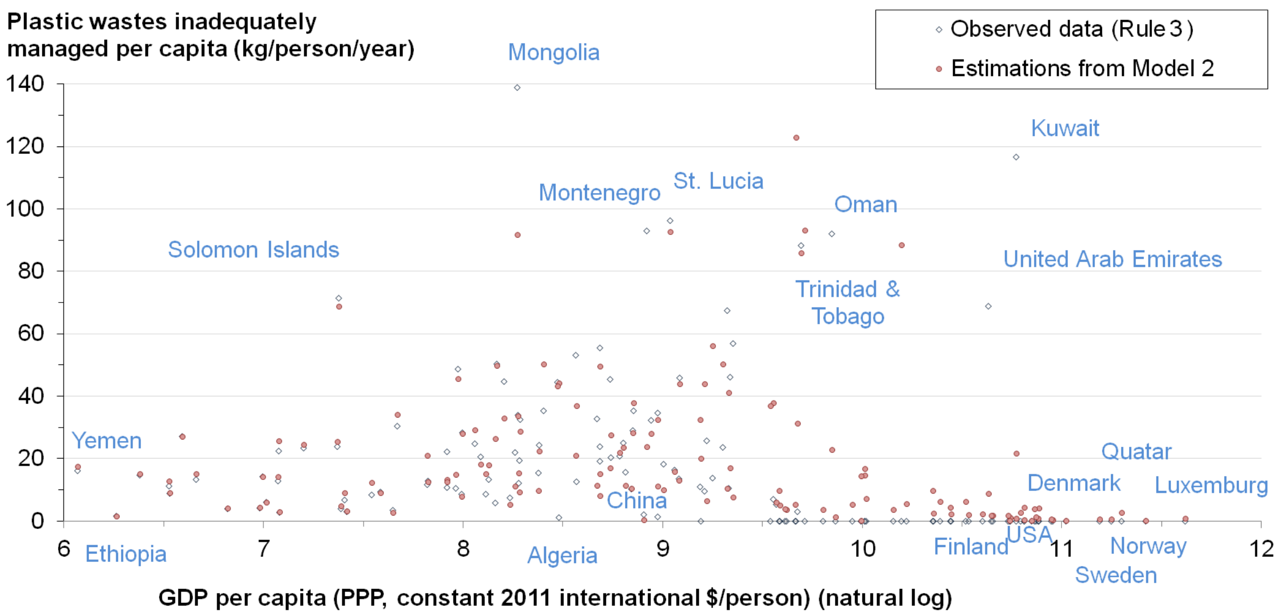

Fig. 3. Model 2 estimations compared to observed data of inadequately managed plastic waste generated per capita in 141 countries in 2011-2017.

3. Results

All scenarios displayed below were computed using observed data in Models 1 and 2 to simulate the period 1990-2017 and extrapolated data to simulate the period 2018-2050.

3.1. Business-as-usual scenario

The business-as-usual scenario (BAU) forecasts explanatory variables based on past trends observed from 1996-2017 (Fig. 4). The forecast relies on a linear regression calculated country by country. Regarding GDP per capita, we used forecasts from OECD (2019) and Hawksworth et al. (2017), which provide long-term forecasts of GDP per capita for 55 countries.

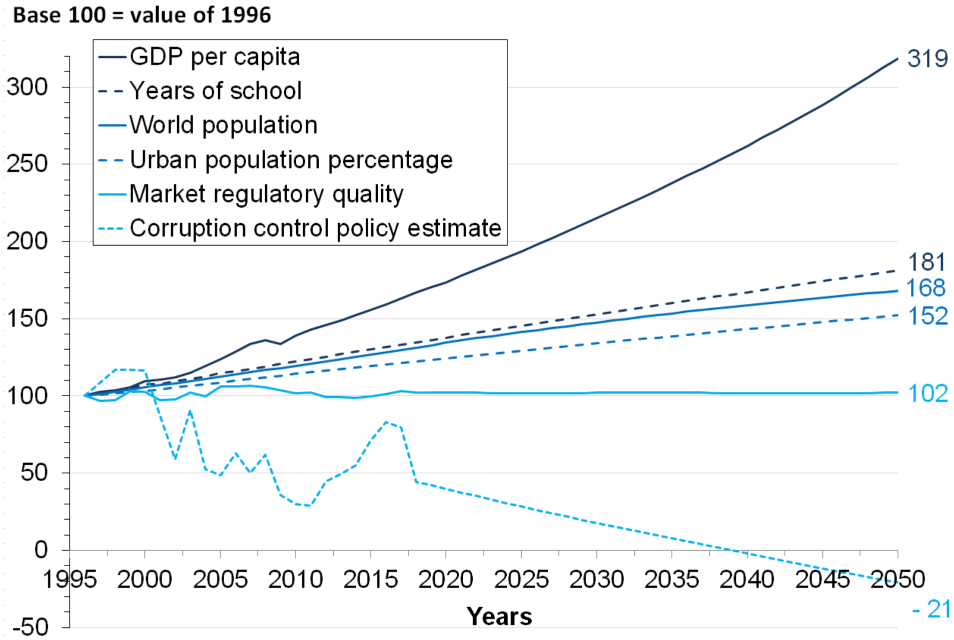

Fig. 4. Evolution of variables explaining global inadequately managed plastic waste in the BAU scenario. Observed data from 1996-2017; extrapolated data from 2018-2050. All values standardized in base 100 = 1996, that is, the amounts in the year 1996 have been set to 100 and any variation is added to 100 in percentage increase.

Model 1 shows that under the BAU scenario, annual amounts of inadequately managed plastic waste generated globally increase from 61 million tonnes per year in 1990 to 110 million tonnes per year in 2050 (Fig. 6 (scenario *BAU (Model 1)*).

Model 2 tells a different story. It estimates that under the BAU scenario, the annual amounts of inadequately managed plastic waste globally will decrease from 72 million tonnes in 1990 to 61 million tonnes in 2050 (Fig. 6 (scenario *BAU (Model 2)*).

From the BAU scenarios simulated with Models 1 and 2, we estimate that in the worst case the growth in the annual amount of inadequately managed plastic waste globally is expected to slow over the period 2020-2050 and keep a slight increase trend. In the best case, it will moderately decrease over 2020-2050 (Fig. 6). If we sum the annual amount of inadequately managed plastic waste generated since 1990 in the BAU scenario, Models 1 and 2 estimate the cumulative stock to 2264-2514 million tonnes in 2017 and to 5109-5678 million tonnes in 2050. Both models show the cumulative stock will continue drastically increasing by 2050 (Fig. 5).

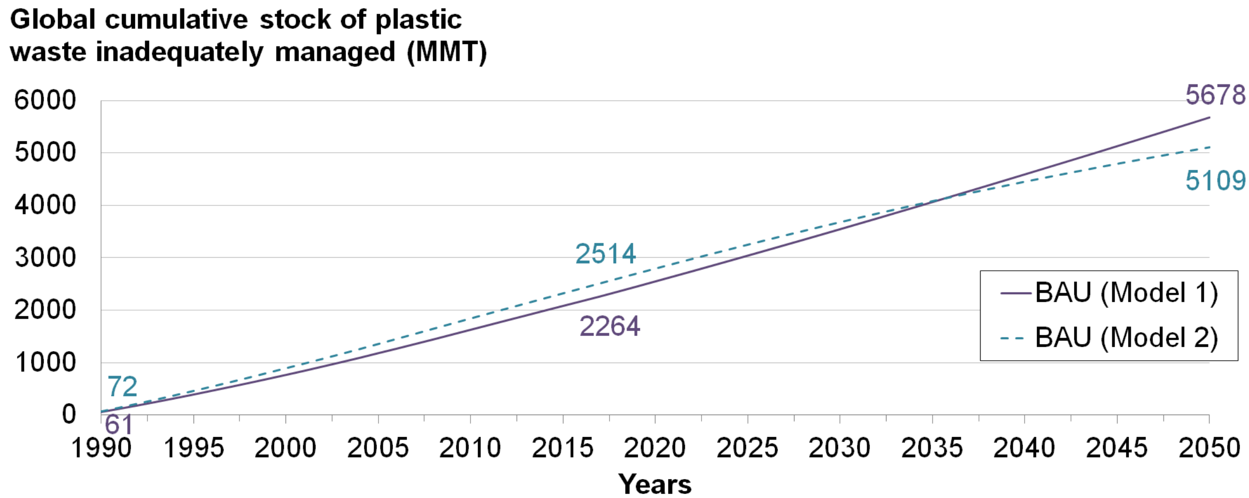

Fig. 5. The total stock of plastic waste inadequately managed accumulated over 1990-2050 in the global ecosystem is expected to more than double over the period 2017-2050 (BAU scenario). Note: MMT: million metric tonnes; BAU: business-as-usual scenario; Model 1: takes into account the weakening trend of corruption-fighting policies; Model 2: takes into account the increasing trend in the number of schooling years.

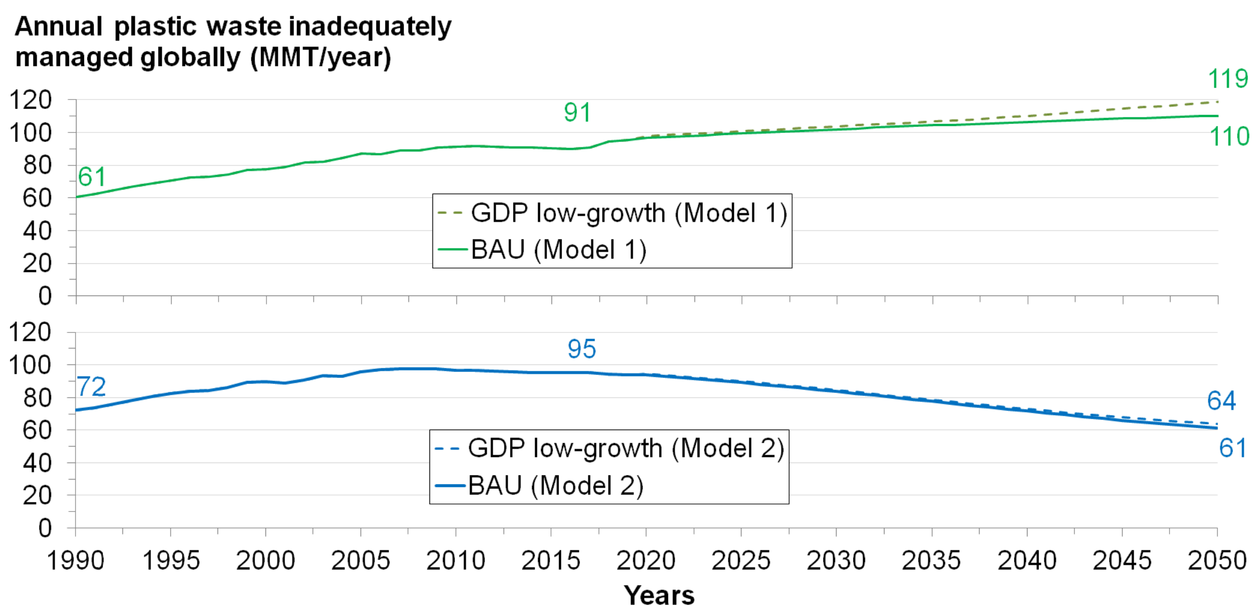

Fig. 6. By 2050, global generation of inadequately managed plastic waste will increase by 80% at worse (upper graph) or decrease by 15% at best (lower graph) compared to 1990 levels in the absence of significant environmental policies (BAU scenario).

3.2. Mitigation scenario 1: capping GDP

In all mitigation scenarios presented below, we only modify the explanatory variable under analysis (e.g., GDP per capita in sub-section 3.2). All other variables follow the BAU trend displayed in Fig. 4.

Several authors propose an economic slowdown policy as an intervention to reduce global environmental issues (Victor, 2018; Krausmann et al., 2009). The GDP low-growth scenario (Fig. 6) simulates such an economic slowdown capping GDP per capita in all countries at a maximum of $30000 (international $ at 2011 constant prices) over the period 2020-2050. Without such a cap (BAU scenario), half the countries of the world will probably achieve a GDP per capita greater than $30000 by 2050 with a world average value at $30268. With the cap (GDP low-growth scenario), the GDP per capita world average would achieve a level of $21784 in 2050. We set the cap at $30000 because it is the GDP per capita threshold beyond which the level of life satisfaction does not increase much[1]. Our results show that with such a cap the annual amount of inadequately managed plastic waste slightly increases and reaches 64-119 million tonnes/year in 2050 (results from Models 2 and 1 respectively) instead of 61-110 million tonnes/year in the BAU scenario (Fig. 6).

3.3. Mitigation scenario 2: extending education

In the education scenario, we simulate a situation in which the 43 countries ranked as generating the most inadequately managed plastic waste (Table 4) would implement education policies ensuring individuals ≥ 25-years-old will have received 12 schooling years at least by 2050 progressively starting from 2020. Such an educational target is not easy to achieve; it will be a political and economic challenge. According to the BAU scenario, if current trends continue, only 14 countries in the top 43 will have reached an average number of school years of at least 12 by 2050. The top 43 countries' inadequately managed plastic waste encompasses 91% of the total discarded in the world in 2017 (estimated 91-95 million tonnes per year – results from Model 1 and Model 2 respectively). Among the top 43 countries, 30 of them have an average number of schooling years less than 8 (Table 4). Fig. 7 shows the education scenario reduces by 34% the amount of inadequately managed plastic waste in 2050 (40 million tonnes/year) compared to the BAU scenario (61 million tonnes/year).

[1] Authors' own calculation based on data published by Ortiz-Ospina and Roser (2017).

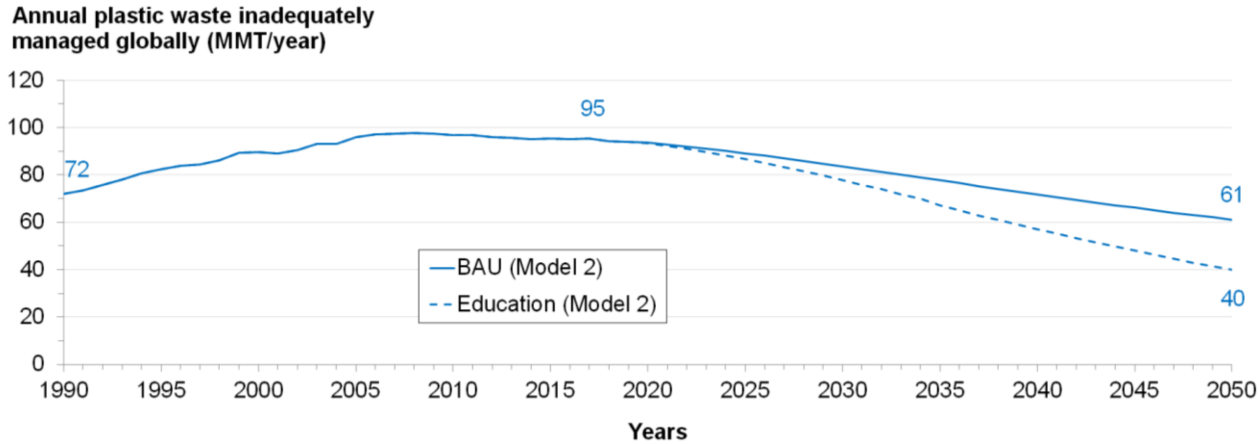

Fig. 7. Raising education levels succeeds in reducing globally inadequately managed plastic waste discarded by the world population annually.

3.4. Mitigation scenario 3: fighting corruption

In the fighting corruption scenario, corruption control policies are implemented over 2020-2050 in the top 43 countries as in previous scenario. With Model 1, we estimate fighting corruption reduces the global annual amount of inadequately managed plastic waste by 28% in 2050 compared to 1990 levels. This means implementing policies to prevent public power to be used for private gain, including petty and grand forms of corruption and the capture of the state by elites and private interests (World Bank, 2018a; Kaufmann, 2010). To reach 28% abatement by 2050, the top 43 countries should progressively raise their corruption control policies close to the level of countries such as Uruguay in 2016 or France and Estonia in 2017, that is, a corruption control estimate of 1.24. If such a scenario were implemented (Fig. 8), the estimated global amount of annually inadequately managed plastic waste would fall to 44 million metric tons per year in 2050 instead of 110 million tons per year as in the BAU scenario.

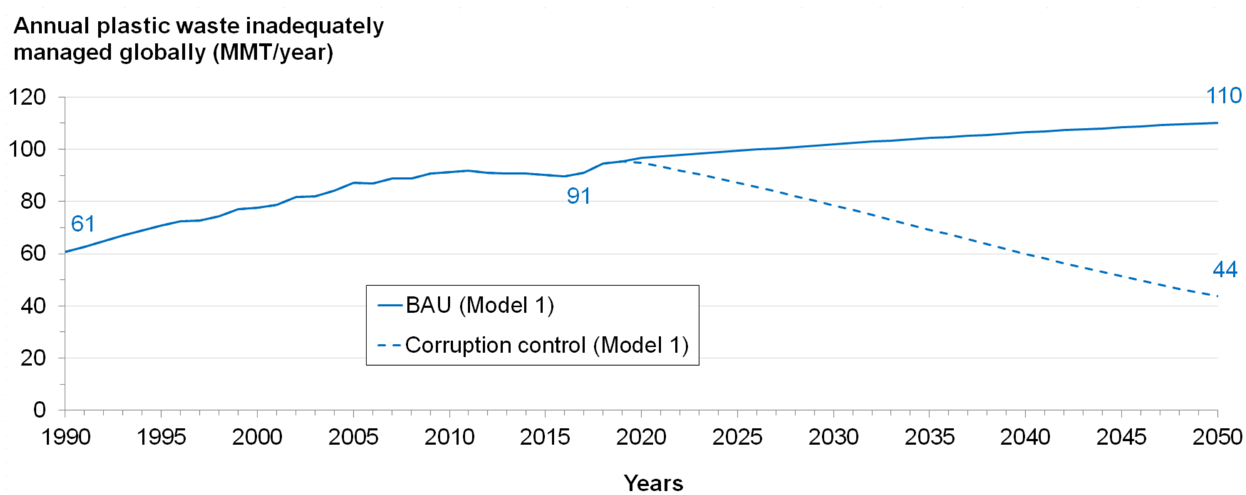

Fig. 8. Corruption control policies succeed to reduce globally inadequately managed plastic waste discarded by the world population annually.

Table 4. **Characteristics of the top 43 countries ranked by mass of inadequately managed plastic waste in 2017**. MMT/yr = million metric tonnes per year. HIC = High Income Country; UMC = Upper Middle income Country; LMC = Low Middle income Country; LIC = Low Income Country. Corruption control policy estimates range from -2.5 (total lack of public policies to fight corruption) to +2.5 (corruption completely impeded by public policies). Europe - 28: European Union of the 28 member States. N.A.: non-available data. Line 35: Dom. Rep. = Dominican Republic. Line 24: Congo DRC = Democratic Republic of Congo (Congo-Kinshasa).

Observed data from World Bank (*2018a, 2019*)							BAU scenario (Results from Model 2) (in the ranges, results from Model 1 are in *italic*)			
Country	Income cate-gory	Corruption control policy estimate		Years of schooling		Popu-lation (million)	Plastic waste generation rate (kg/person/yr)	% Inadequately managed waste	Inadequately managed plastic waste (MMT/yr)	Inadequately managed plastic waste (MMT/yr)
(Years) →		**1996**	**2017**	**1995**	**2010**	**2017**	**2017**	**2017**	**2017**	**2050**
1 India	LMC	-0.38	-0.24 ↗	3.51	5.39 ↗	1338.7	20.2	79.6%	*13.85* – 21.57	4.50 – *8.98*
2 China	UMC	-0.27	-0.27 →	5.69	7.12 ↗	1386.4	31.0	32.2%	*12.38* – 13.82	1.71 – *10.05*
3 Brazil	UMC	-0.02	-0.53 ↘	4.84	7.66 ↗	207.8	44.8	94.0%	*8.64* – 8.75	5.11 – *8.66*
4 Mexico	UMC	-0.51	-0.93 ↘	6.48	8.33 ↗	124.8	45.0	85.1%	4.78 – *5.29*	1.80 – *7.46*
5 Indonesia	LMC	-0.86	-0.25 ↗	4.21	7.26 ↗	264.6	30.1	53.7%	*2.89* – 4.28	*0.78* – 0.80
6 Pakistan	LMC	-1.22	-0.78 ↗	2.77	4.45 ↗	207.9	17.8	90.8%	*2.77* – 3.37	3.46 – *3.49*
7 Nigeria	LMC	-1.19	-1.07 ↗	N.A.	N.A.	190.9	19.4	80.5%	*2.91* – 2.98	7.76 – *7.99*
8 Bangladesh	LMC	-0.97	-0.83 ↗	3.29	4.91 ↗	159.7	15.5	92.1%	*2.01* – 2.29	1.57 – *1.69*
9 Colombia	UMC	-0.51	-0.37 ↗	6.09	8.45 ↗	48.9	46.6	92.8%	*2.10* – 2.12	1.98 – *3.20*
10 Argentina	HIC	-0.10	-0.26 ↘	8.34	9.48 ↗	44.0	44.3	79.4%	*1.70* – 1.55	0.56 – *1.57*
11 Vietnam	LMC	-0.49	-0.58 ↘	4.60	7.45 ↗	94.6	19.6	69.9%	*1.16* – 1.30	0.23 – *0.67*
12 Philippines	LMC	-0.36	-0.48 ↘	7.12	8.18 ↗	105.2	27.0	44.3%	1.26 – *1.54*	0.15 – *1.16*
13 Peru	UMC	-0.40	-0.50 ↘	7.25	8.68 ↗	31.4	45.5	86.8%	1.24 – *1.34*	0.32 – *1.75*
14 Egypt	LMC	-0.47	-0.54 ↘	4.05	6.55 ↗	96.4	19.7	53.8%	1.02 – *1.68*	0.13 – *2.29*
15 Ethiopia	LIC	-0.93	-0.56 ↗	N.A.	N.A.	106.4	9.6	97.6%	*0.90* – 1.00	*0.92* – 1.20
16 Morocco	LMC	-0.11	-0.13 ↘	2.66	4.24 ↗	35.6	29.8	84.6%	0.90 – *0.93*	0.53 – *1.45*
17 Chile	HIC	1.45	1.04 ↘	8.40	9.71 ↗	18.5	61.2	72.3%	*0.59* – 0.82	0.24 – *0.44*
18 Venezuela	UMC	-0.86	-1.36 ↘	5.5	8.16 ↗	29.4	31.2	89.1%	0.82 – *0.88*	0.38 – *1.09*
19 Turkey	UMC	-0.15	-0.19 ↘	4.81	6.56 ↗	81.1	40.4	24.4%	*0.56* – 0.80	0.08 – *0.17*
20 Europe - 28	HIC	1.18	1.09 ↘	9.13	11.23↗	512.2	49.7	3.1%	0.80 – *1.01*	0.07 – *1.13*
21 Tanzania	LIC	-0.70	-0.48 ↗	4.09	5.12 ↗	54.7	15.0	93.1%	*0.65* – 0.77	1.64 – *1.65*
22 Myanmar	LMC	-1.50	-0.56 ↗	2.71	4.09 ↗	53.4	15.8	90.6%	*0.55* – 0.76	*0.05* – 0.15
23 Thailand	UMC	-0.36	-0.39 ↘	4.33	7.30 ↗	69.2	30.4	35.2%	*0.64* – 0.74	0.06 – *0.55*
24 Congo DRC	LIC	-1.65	-1.42 ↗	2.92	3.61 ↗	81.4	8.6	99.3%	*0.69* – 0.70	*2.86* – 2.97
25 Kenya	LMC	-1.16	-0.96 ↗	4.54	6.19 ↗	50.2	15.8	87.5%	*0.68* – 0.69	0.56 – *1.37*
26 Ghana	LMC	-0.34	-0.23 ↗	5.66	6.76 ↗	29.1	25.5	75.3%	*0.48* – 0.56	0.16 – *0.46*
27 Sudan	LMC	-1.24	-1.54 ↘	1.97	3.13 ↗	40.8	14.0	95.2%	*0.51* – 0.55	0.81 – *1.12*
28 Algeria	UMC	-0.57	-0.61 ↘	4.17	5.98 ↗	41.4	27.2	48.1%	0.54 – *0.97*	0.17 – *1.52*
29 Angola	LMC	-1.17	-1.41 ↘	N.A.	N.A.	29.8	23.1	76.4%	0.53 – *0.57*	2.37 – *2.70*
30 Uganda	LIC	-0.72	-1.04 ↘	3.38	5.42 ↗	41.2	13.0	97.4%	*0.49* – 0.52	1.26 – *1.33*
31 South Afric.	UMC	0.73	-0.01 ↘	8.22	9.43 ↗	57.0	37.8	22.8%	0.49 – *0.59*	0.06 – *1.64*
32 Côte d'Ivoi.	LMC	-0.26	-0.52 ↘	2.50	4.22 ↗	24.4	21.2	94.2%	*0.39* – 0.49	0.71 – *0.74*
33 Guatemala	UMC	-0.86	-0.74 ↗	3.41	4.30 ↗	16.9	25.3	99.3%	*0.42* – 0.43	0.81 – *0.79*
34 Cameroon	LMC	-1.33	-1.18 ↗	4.15	5.96 ↗	24.6	19.3	87.5%	0.41 – *0.42*	0.53 – *1.08*
35 Dom. Rep.	UMC	-0.42	-0.74 ↘	5.92	7.56 ↗	10.5	42.2	92.5%	0.41 – *0.42*	0.21 – *0.62*
36 Iran	UMC	-0.48	-0.81 ↘	5.26	8.17 ↗	80.7	27.9	18.1%	0.41 – *1.91*	0.02 – *2.88*
37 Ecuador	UMC	-0.68	-0.60 ↗	6.71	7.44 ↗	16.8	24.8	95.3%	0.40 – *0.40*	0.44 – *0.52*
38 Iraq	UMC	-1.60	-1.37 ↗	4.17	6.38 ↗	37.6	26.5	37.8%	0.38 – *0.93*	0.05 – *1.70*
39 Afghanistan	LIC	-1.29	-1.52 ↘	1.86	3.47 ↗	36.3	9.7	98.7%	*0.34* – 0.35	0.90 – *0.95*
40 Yemen	LIC	-0.74	-1.59 ↘	0.65	2.60 ↗	27.8	12.3	98.9%	0.34 – *0.34*	0.73 – *0.75*
41 Senegal	LIC	-0.14	-0.09 ↗	2.06	1.95 ↘	15.4	21.6	98.4%	*0.22* – 0.33	*0.51* – 0.90
42 Nepal	LIC	-0.64	-0.75 ↘	2.24	3.31 ↗	27.6	12.0	97.4%	*0.28* – 0.32	*0.31* – 0.34
43 Mozambiq.	LIC	-0.42	-0.86 ↘	0.80	1.14 ↗	28.6	10.9	99.7%	*0.29* – 0.31	*1.02* – 1.13
Total 43 countries									***77.3* – 86.9**	**49.6 – *90.9***
Total world (217 countries)									***91.0* – 95.4**	**61.2 – *110.2***

4. Discussion

4.1. Discussing the explanatory variables of the model

Growing wealth is usually associated with a higher per capita waste production (Hoornweg and Bhada-Tata, 2012), although this does not necessarily translate into higher waste emission into the ecosystem because of more efficient and alternative disposal strategies (e.g., controlled landfilling, recycling, composting) (Kiessling et al., 2017). Pro-environmental behavior is generally higher in developed countries (Morren and Grinstein, 2016). Models 1 and 2 confirm these assertions and estimate that an increase of GDP per capita by 1% in all countries compared to the BAU scenario, *ceteris paribus*, would reduce annual inadequately managed plastic waste discarded globally by 0.28% (Table 5). At the same time, it would increase by 0.02% the global annual amount of plastic waste generated (adequately and inadequately managed), which would increase ecological side-effects of waste treatments (e.g., fossil fuel consumption for recycling processes). Focusing the entire solution on economic growth policies is not a solution. Even with the impressive growth of the GDP per capita forecast in the BAU scenario (Fig. 4), 61 million tonnes per year of inadequately managed plastic waste will still be discarded globally by 2050 in the best case (Fig. 7). This is only slightly below 1990 levels estimated at 72 million tons per year by Model 2.

If economic growth cannot significantly solve the problem of plastics, it is due to multiple offsetting factors that counterbalance the effect of the growing GDP per capita. The first factor is world population growth, which plays a major role in Equation 1. The world population is expected to multiply by 1.68 in 2050 compared to 1996 (Fig. 4) in the BAU scenario, which will tremendously increase the global amount of inadequately managed plastic waste discarded annually. Second, it is due to the increasing percentage of population living in urban areas, which is expected to multiply by 1.52 by 2050 compared to 1996 (Fig. 4) and will increase plastic waste generation per capita. Third, this is due to the weakening of corruption control policies in many countries (Table 4). The world average for the corruption control policy estimate decreased from -0.19 in 1996 to -0.23 in 2017. With such a trend, the estimate is expected to reach a value of -0.41 by 2050 in the BAU scenario (which equates to -21 in base 100 = value of 1996 in Fig. 4). This might lead in the worst case – as estimated by Model 1 – to an increase in annual inadequately managed plastic waste from 61 million tonnes per year in 1990 to 110 million tonnes per year in 2050 (Fig. 8).

Table 5. Effect of a 1% variation in each key factor individually on the reduction of annual plastic waste inadequately managed generated in 2017 (simulated with Models 1 and 2)

Key factors	Change in key factors in all countries compared to BAU scenario	Impact on annual plastic waste inadequately managed globally	Impact on annual plastic waste globally (adequately and inadequately managed)
Number of schooling years	+ 1%	- 0.97%	–
Urban population percentage	- 1%	- 0.68%	- 0.77%
GDP per capita	+ 1%	- 0.28%	+ 0.02%
Corruption control policies	+ 1%	- 0.18%	–

In countries with the lowest Human Development Index (HDI) and Education Index (EI), there is a tendency of anthropogenic marine debris abundances to increase, while in the countries with the highest HDI and EI, there is a tendency of decreasing litter abundance (Hidalgo-Ruz et al., 2018). Our results are in the same vein. Model 2 confirms that education offers an effective solution to plastic waste since it estimates an increase in all countries of the number of schooling years by 1% compared to BAU scenario, *ceteris paribus,* would reduce annual inadequately managed plastic waste discarded globally by 0.97% (Table 5). This result is in the same order of magnitude as the one found by Vicente-Molina et al. (2013) for Spain and the USA. They estimated that a 1% increase in objective environmental knowledge increases pro-environmental behaviours by 0.40%. However, they found the opposite for Brazil and Mexico where a 1% increase in objective environmental knowledge decreases pro-environmental behaviours by 0.40%. Model 2 takes this effect into account since when education increases by 1 schooling year in a country, the annual amount of inadequately managed plastic waste is reduced in Eq. 3bis via a coefficient of -0.44. However, if this country is from Latin America, an additional +3.29 coefficient is added to Eq. 3bis (Table 3).

Vicente-Molina et al. (2013) found education is one of the most important variables identified by researchers to explain high levels of environmental behaviour. However, as highlighted by Vicente-Molina et al. (2013), although education and environmental knowledge seem to be significantly and directly related, it is not clear how they affect actual pro-environmental behaviour (Zsóka et al., 2012).

Our results from Model 2 are based on a sample of 100 countries, covering their entire population. These populations have an average level of education lower than a university degree. In this sample, 88% of the countries have an average number of schooling years below 12 for individuals 25 years old or more, even while half of the sample covers high-income countries. This means a substantial portion of the population in these countries never finished secondary school (i.e., schools covering ages from 12 to 18 years old). This might explain the significant statistical relationship we found between the number of schooling years and inadequately managed plastic waste discarded annually.

Fortunately, correct knowledge has been shown to predict pro-environmental behaviors, recognizing knowledge is a necessary but not sufficient condition for decision-making (Gifford and Nilsson, 2014). Beyond the minimum knowledge required, which might be defined by the threshold of 12 schooling years, additional factors influence pro-environmental behavior as identified, *inter alia*, by Vicente-Molina et al. (2013): the type of information contained in environmental content, the type of studies/degree (social sciences, science, engineering), the number of subjects addressing environmental issues, among others.

The number of schooling years is not the only influencing factor. Otto and Pensini (2017) evaluated the effect of nature-based environmental education on students from 9- to 11-years-old. They found increased participation in nature-based environmental education was related to greater ecological behaviour, mediated by increases in environmental knowledge and connectedness to nature. Connectedness to nature explained 69% and environmental knowledge 2% of the variance in ecological behaviour. It is essential to identify the types of knowledge and experiences that effectively encourage environmental behaviour in school educational programs (Vicente-Molina et al., 2013).

The importance of connectedness to nature analysed by Otto and Pensini (2017) explains the influence of urban areas on pro-environmental behaviours. Kiessling et al. (2017) demonstrate that a region with an 'attractive' landscape that enables individuals to have meaningful interactions with nature will foster higher environmental awareness and willingness to engage in managing coastal litter pollution. In urban areas, the opportunities to develop such connections with nature are reduced, which is likely to decrease environmental awareness of urban populations and to generate a lack of interest in ecosystems and their preservation (Kiessling et al., 2017; Miller, 2005). In urban areas, there are also more packaged products, food waste and manufacturing, which generates higher rates of plastic waste per individual (Hoornweg and Bhada-Tata, 2012; Hoornweg et al., 2013; Salhofer, 2008). Our results are in line with these studies. Models 1 and 2 (Eq. 2 and Table 1) estimate that a decrease of urban population by 1% in all countries compared to the BAU scenario, *ceteris paribus*, would reduce annual inadequately managed plastic waste discarded globally by 0.68% (Table 5).

Biswas et al. (2012) observed that corruption can increase pollution by affecting the stringency of environmental regulation and enforcement, but it can also reduce polluting emissions by lowering economic activity. Cole (2007) evaluates the magnitude of these two countervailing effects of corruption on pollution and shows that, for the majority of countries, the reduction effect of corruption outweighs the increasing impact on pollution. However, the statistical model designed by Biswas et al. (2012) shows it is more complex; the final net effect of corruption on pollution depends on the size of the shadow economy. The shadow economy comprises production activities – from legal or illegal firms – that avoid government regulation or taxation and as such are not following environmental standards and norms. Estimations from Biswas et al. (2012) show the marginal impact of an increase in corruption on polluting emissions is significantly positive when the size of the shadow economy is above the sample average. At the mean and maximum size of the shadow economy, a 1% increase in the corruption index increases polluting emissions per capita by 0.10% and 0.50% respectively. This is in line with our results from Model 1: decreasing corruption-control policies by 1% (i.e., corruption is likely to increase) in all countries compared to the BAU scenario, *ceteris paribus*, increases annual inadequately managed plastic waste discarded globally by 0.18% and vice versa (Table 5). This is within the range of 0.10-0.50% calculated by Biswas et al. (2012). This might mean that for the sample of 122 countries in 2011-2017 on which Model 1 has been designed (Table 2), the size of the shadow economy was already beyond the threshold under which corruption lowers economic activities and plastic waste generation. These 122 countries perhaps already had a sufficient shadow economy size in which higher corruption allowed firms to continue their operations by bribing monitoring bureaucrats and exerting lobbying pressures on deputies to reduce environmental legislation stringency, thus allowing the generation of more plastic waste. Biswas et al. (2012), and others such as Damania et al. (2003), conclude that controlling corruption significantly moderates the destructive effects of the shadow economy in terms of polluting emissions.

Reducing the level of corruption through control policies could ease the design of stricter regulations to change the global community's relationship with producing and purchasing plastic products, improve environmental awareness regarding plastic pollution, reduce the generation of plastic wastes and improve their management. Global governance solutions such as an international plastic treaty could impede industries' abilities to resist government regulations on plastic waste, deflect accountability, and advocate in favor of corporate self-regulation (e.g., CSR). Such an international treaty could counteract the intent of plastic industries to make final consumers responsible for plastic pollution (Dauvergne, 2018). The current version of our models does not address regulation solutions yet. However, further analysis on that topic can be found, *inter alia*, in Vince and Hardesty (2018).

Places with large tourism flows compared to the limited size of local population, as is the case for small islands, generate massive amounts of plastic waste per capita (Eckelman, 2014). This is reflected in Models 1 and 2 via Eq. 2 (Table 1), where the coefficient for small islands is large and positive. However, Kiessling et al. (2017) have observed that on small islands, the isolated geographic location, the unique cultural identity and biodiversity, the small size of the local community, and international tourism exert internal and external pressures that favor environmental awareness and engagement on the coastal litter problem by local populations and promote pro-environmental behaviors in the context of waste management (Kiessling et al., 2017). Our results support these observations. The negative coefficient for small islands in Eq. 3 and Table 2 demonstrates that, *ceteris paribus*, small islands generate less inadequately managed plastic wastes than continental countries.

4.2. Data reliability and limits of quantitative intents

An important limit relates to observed data. The waste identified by the global database of the World Bank (2018) – used to design our models – exclusively includes quantitative data on municipal solid waste generated by households at home (Kaza et al., 2018). Following annual reports from industry associations of plastic producers (PlasticsEurope, 2018), in Europe 40% of plastic goes to packaging, 20% to building and construction, 17% to appliances, mechanical engineering, medical uses, furniture and other applications, 10% to automotive uses, 6% to electrical uses and electronics, 4% to household uses, leisure and sports, and 3% to agriculture. This means in Europe approximately 50% of plastics are produced for use by households at home and regulated by the Waste Framework Directive (2008/98/EC) (European Parliament and Council, 2008). Europe has the world's most regulated waste management system and only 25% of plastic household waste enters the recycling loop. Waste mismanagement rates (mismanaged waste = inadequately managed wastes + wastes directly littered by individuals) in other countries can reach 80% - 100%. Our study of plastic pollution is based on very conservative estimates; we are confident the actual amount of plastic waste is larger than our estimates and therefore the extent of plastic pollution is greater too.

5. Conclusion

In contrast to the environmental Kuznets curve theory, our model shows that keeping GDP per capita growing as it is in most countries (BAU scenario) will not be sufficient to resolve plastic waste management issues by 2050. Additionally, there is increasing evidence that unlimited economic growth is less and less viable in a limited global ecosystem. By developing two worldwide models based on social, political, market regulatory, and governance data, we demonstrate the impact of non-technological solutions to discarded plastic waste. Corruption control and education are able to reduce inadequately managed plastic waste; they must be part of implemented interventions. Additional research should investigate how combining the policy measures suggested in this paper can achieve the highest reduction in mismanaged plastic waste with the lowest effort. Future research should also investigate additional policy options. For example, Models 1 and 2 could be used to study scenarios for policies addressing urban and rural planning as well as birth policies to limit world population (e.g., education policies reduce the number of children per family). Another way to design policy interventions to reduce plastic waste is by investigating the plastic waste policies implemented in the countries appearing in the lower-right of Fig. 1-3 such as tax systems making repaired and reused products cheaper than new ones. Such policies directly address planned product obsolescence and single-use plastic products by favoring longer-lasting, repairable products (Cooper, 2016) and reduce plastic waste discards. Strict regulations of the plastic-producing industry have the potential to bring about significant solutions (e.g. return and deposit systems for plastic bottles, enforcing extended producer responsibility). However, these require higher environmental awareness driven by educational programs especially addressed to children (Kiessling et al., 2017), and a tremendous increase of corruption-control policies in most countries (Table 4). Otherwise, plastic regulations will see their stringency reduced by industrial lobbies (Candau and Dienesch, 2017; Biswas et al., 2012; Milfont and Markowitz, 2016; Damania et al., 2003).

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Author contributions (follows the CRediT taxonomy)

M. C., T. U., J. B. and B. J. participated to the conceptualization of this study and wrote the manuscript text. M. C. and T. U. contributed to data curation, formal analysis and the methodology. J. B. contributed to the project administration and organized field observations. J. B. and B. J. contributed to the validation of the results as well as to the review and editing of the manuscript text.

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