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A Longitudinal Study on the Drivers of Forestation

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A LONGITUDINAL STUDY ON THE DRIVERS OF FORESTATION

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ABSTRACT

This paper studies the effects of population growth, income levels, and governance on forestation using longitudinal data covering 161 countries from 1996-2015. The study begins with a review of the empirical literature on deforestation and preservation of environmental quality. Then, we conduct our own empirical analysis through log differencing and analysis of annual percentage changes in forest area. We find evidence that these factors matter, but that the relationships are weak. The estimated effects do differ between our groupings of countries with regard to income levels as well as forest area sizes. Population growth generally leads to a reduction in forest area. Conversely, rising incomes slow deforestation and increase the chances of reforestation and afforestation. We witness the disappearance of a Kuznets curve relationship across all groups after individual country effects are included. A bettering of perceived rule of law, political stability, and reduction in corruption is also correlated with more positive forestation rates.

TABLE OF CONTENTS

TABLES AND REGRESSIONS

INTRODUCTION

Economists, prompted by the growing concern among natural scientists, began studying global forest loss in the late 1970s and 1980's. Concerns about biodiversity in tropical regions drove these studies. Different methodologies have been used to investigate the drivers of forestation. Forestation, as used throughout the paper, is a neutral term which refers to the change in forest area due to deforestation, reforestation, and afforestation. The first studies used demographic data such as population growth and economic growth to explain the variance in forestation both between and within countries. The second wave of research focused more on land-use decisions related to institutional and governmental policy. Some have attempted to synthesize these two main areas of study, but many past inquiries from the 1980's and 1990's suffered from unreliable and inconsistent data.

Since the bulk of these studies have been conducted, the global environment has changed drastically. The world endured incredible political reformation following the collapse of the Soviet Union and fall of communism, entered into the internet age, and both governments and other organizations have increased the flow of information across great distances to larger audiences. These factors have completely changed the way we live our everyday lives, as well as the way we view both the environment and governmental responsibility. On top of previous biodiversity concerns, media sources, governments, and non-governmental organizations have paid increasing attention to the global preservation of forest lands due to their vital role in regulating climate change. Forests act as carbon sinks; however, when harvested or cleared they release much of their stored carbon into the atmosphere. An increase in the quantity and severity of natural disasters thought to be influenced by the amount of carbon dioxide in the atmosphere has amplified this attention. In response to climate threats and mounting worry, some governments and many NGO's have initiated large-scale forest protection and reforestation acts.

This paper aims to contribute to the growing literature examining the main drivers of deforestation and main factors that encourage afforestation and reforestation. To do this, we seek to answer three specific questions. How do the effects of population growth on forestation change between wealthier and poorer nations? How do forestation rates change based on per capita income, specifically, do forestation rates follow a U-shaped or S-shaped relationship with income per capita often referred to as the Environmental Kuznets Curve? How do governance measures such as property rights security and political stability directly affect, and jointly with population and income variables, affect forestation?

Some scholars have argued that population growth increases deforestation rates in tropical, temperate, and boreal forests by increasing demand for forest products, spurring greater agricultural land expansion and increasing rural migration (Allen and Barnes 1985; World Bank 1992; Rosero-Bixby and Palloni 1998). "Forest conversion to large-scale agriculture (32%) and small-scale local agriculture (26%), as measured by a stratified random sample of 10% of tropical forests is estimated to be the largest driver of deforestation globally" (FAO 2001). Developing regions frequently use resources inefficiently. For example, poorer nations often have open-access forest resources which allow migrants to occupy and deforest insecure land (Lopez 1998). Agricultural expansion with regards to land area is intensified in poorer countries where use of irrigation, advanced mechanized farming methods, and fertilizers is low, causing lower crop yield (FAO 1997, 2003). Rudel (1989) found that countries with smaller rainforests (Burundi, Rwanda and Haiti in comparison to Brazil), were more at risk of deforestation due to population growth and migration of low-income farmers than countries with large rainforests. Similarly, Arrow et al. (1995) predicted that the effect of population growth on deforestation will be greater in lower income countries than in high-income countries due to the fact that low-income countries tend to be more agrarian compared to service-centric economies. It is important to note that there is some opposing literature that examines cases in which population growth occurs concurrently with improving soil and water resources such as Tiffin et al. (1994) and Boyd and Slaymaker (2000). However, these results vary greatly between countries and sometimes within districts in a country. Therefore, we do not expect this to be a reliable global trend.

A large literature explores whether environmental "bads" or disamenities worsen linearly with economic development, or if there is a point where environmental "bads" either improve or become environmental goods. This common theory regarding the switch from bad to better or good is called the Environmental Kuznets Curve (EKC) and originally stems from Kuznets work in income inequality (Kuznets, 1995). Under this framework countries with relatively low GDP per capita have low deforestation rates, but with economic growth, these rates increase. Then, once a certain level of growth is achieved, deforestation slows down or even becomes reforestation. Clearly deforestation is not always inefficient, but in the case of rapidly deforesting countries, the clearing of forested areas is usually in exchange for unmechanized agriculture (Deacon 1994). This implies a U-shaped parabola with GDP per capital on the X-axis and a measure of environmental change, in this case forestation rate, on the Y-axis. If a full reversal from negative forestation to positive forestation occurs, this would be an incomplete horizontal S-shaped graph with a zero-forestation rate being the horizontal axis[1].

If environmental amenities can be usefully thought of as a normal good, we can expect an income effect that increases demand for environmental quality. This demand is often visible through governmental and institutional reform. Positive income elasticity holding true, poorer people may be willing to sacrifice environmental quality in exchange for income. For example, a typical farmer in Central America may be willing to clear a patch of forest if that land can be used to support his family, while a family in the United States may choose to preserve the foliage if offered the equivalent monetary value. There are several possible explanations for why the relationship between economic growth and forestation could be nonlinear. The World Bank's *World Development Report* (1992, pg. 39) states that, "As incomes rise the demand for improvements in environmental quality will increase, as will the resources available for investment." The same article affirms that the intensity of this phenomena depends on the strength of institutions and alignment of incentives to use "scarce resources sparingly" when deciding their use. Arrow et al. (1995) proposes that this pattern could reflect countries' general progression from agrarian focused economies, to manufacturing-heavy industries, then to advanced service economies. In their generational long-term stock resource model of environmental quality, Pecchenino (1994) predicts that environmental quality degrades until it induces positive investment. At which point, environmental quality improves, creating a V-

[1] See appendix for reference.

shaped graph. Others, like Suri and Chapman (1998) examine trade between high-income and developing countries and attribute the increase in environmental quality in wealthier countries to their exportation of natural resource dependent and polluting manufacturing processes.

The existence and causality of these U-shaped curves has been disputed in recent years in part due to statistical methodology and in part due to varying results dependent on the measure of environmental quality. Researchers suspect that GDP per capita explanatory variables are endogenous to the model due to both omitted variable and simultaneity bias (Paudel et al. 2014). Omitted variables could be cultural or geographic factors that affect both environmental quality and the economy. The simultaneity bias arises because poor environmental quality may also reduce economic success. Arrow et al., (1995) point out that this nonlinear relationship has been proven somewhat valid "for pollutants involving local short-term costs (for example sulfur, particulates, and fecal coliforms), not for the accumulation of stocks of waste or for pollutants involving long-term and more dispersed costs." Studies including Paudel et al. (2014) have shown a non-linear relationship between income and resource pollutants such as water quality while controlling for improvements in political variables. Barbier (2004) and Culas (2007) study deforestation and identify the presence of a U-shaped relation between GDP per capita and forestation rates[2] while examining institutional variables and agricultural land expansion. However, there is conflicting evidence Koop and Tole (1999), Copeland and

[2] This is a distinction from claiming that wealthier countries will have better environmental quality compared to both themselves in previous time periods and other countries, as their past behavior may have greatly reduced forest area. Those with lower income levels may have higher deforestation rates, but at this point in time, those deforestation trends may not have had a large effect on overall forest area.

Taylor (2004), Stern (2004) suggesting that this relationship only holds when “extreme assumptions are made about the commonality of structure across countries.”

Population size and income are likely connected to both the effectiveness of government implemented policies as well as the strength of institutions. We observe a clear correlation between nation wealth and the nature of institutions, but determining which direction causality flows between the two is unclear (Acemoglu and Robinson 2012).

Factors influencing forestation rates are often complementary to one another rather than competing (Casse and Milhoj 2002). Many have conducted studies related to governmental policy and their related environmental outcomes. For example, Bohn and Deacon (2000), and Mendohlson (1994) use default risk models which demonstrate that weaker property rights reduce the investment rate. This reduction, in turn, increases deforestation rates on the basis that forest preservation is an investment that yields future streams of income. Alston, Libecap, and Schneider (1996) demonstrate these differences in agriculture investment due to land titling processes. Rudel (1995) focuses on micro-level interactions governed by informal social controls on a frontier and find that strengthening local populations may be the most effective control in locations with unrestricted areas of forest. Araujo, et al. (2011) use an instrumental variables approach and find that the enforceability of property rights and quality of legal institutions judged by number of violent conflicts and expropriation procedures is the driver of deforestation in the Brazilian Amazon. They bring up an earlier point made by De Soto (2000) that Western property law is not applicable to developing countries, further complicating appropriate environmental policy. The effects of direct government action, such as privatizing forest lands, has been shown as a method to reduce deforestation indirectly by reducing corruption in the forestry industry by Koyuncu and Yilmaz (2013). Despite these numerous studies we have not seen a common practice emerge globally. It is predicted that better measures of governance will correlate with positive (or less negative) levels of forestation, but it is uncertain whether these measures affect forestation directly or are only significant when examined jointly with other factors.

DATA

In order to provide valuable tests that relate forestation to population, income, and institutional quality, we needed a clear and consistent measure of year-to-year forest area as well as reliable year-to-year data on population, income, and governance. In this paper we use forest area data as reported by the Food and Agriculture Organization of the United Nations for the years 1990-2015 in the quinquennial Forest Resources Assessment. Their assessment is composed from two main sources, "Country Reports prepared by National Correspondents and remote sensing that is conducted by FAO together with national focal points and regional partners." The FAO defines *Forest Land* as "land spanning more than 0.5 hectares with trees higher than 5 meters and a canopy cover of more than 10 percent, or trees able to reach these thresholds"[3] and is evaluated in units of 1000 hectares. This definition of forest land is a land-use definition, differing from other studies that only examine the presence of tree cover. Tree stands in agricultural systems such as fruit trees, oil palm plantations, and Christmas trees are excluded. However, areas that may be currently unstocked due to sustainable forestry

[3] See full definition in appendix.

practices and natural disaster mitigation are included if they are expected to regenerate within five years. This specification naturally excludes regions with sparse trees, deserts, and grasslands.

These data are, of course, imperfect. The usual criticisms are that the FRA uses "data-poor country reports, lack of comparable long-term trend data by Mather (2005), Grainger (2008), Harris et al. (2012) as cited by MacDicken (2015), and assumptions that remotely-sensed data are inherently superior to forest statistics reported by sovereign nations by Grainger (2008), Harris et al. (2012), and Hansen et al. (2013) as cited by MacDicken (2015)." However, even with these imperfections, the FRA is the most complete database of forest area and related variables available[4].

GDP and population data were both drawn from The World Bank and cover years 1995-2016. They are displayed in units of 1000's of people and 1000's of 2019 U.S. dollars throughout the paper when used as a continuous variable. This paper only includes countries with a population greater than 300,000 in 2016.

All aforementioned variables are also used categorically. The study divides the sample into countries based on per capita GDP levels (in 2019 US$) where "High Income" denotes those with incomes greater than $12000, "Middle Income" between $2000 and $12000, and "Low Income" less than $2000. These income group

[4] The prospect of perfect, long-term forest data regarding countries that differ greatly in economic and technological resources is attractive, but highly impractical (MacDicken 2015). In the 2015 edition of the FAO's FRA they imposed a new data-quality tiered system. About 60% of the data reported was classified as Tier 3, the highest quality, while only about 11% was classified as Tier 1, the lowest quality (Keenan et al. 2015). Countries who report data of only Tier 1 quality do tend to be lower-income countries. Of the 12 countries who reported Tier 1 quality data and had over 5 million hectares of forest area (combined only equal to 9% of global forest area) in 2015, 10 were in Africa. The lower quality data may be less precise than higher quality tiers, but we do not expect this to bias our estimates as there is no evidence that countries with less accurate data systematically report either higher or lower forest areas. That being acknowledged, this is still an improvement over earlier FRA reports, so the most recent reports should be seen as more reflective of the global forest situation than previous. Additionally, after country reports were compiled, they were each independently reviewed by FAO staff and other external experts and necessary adjustments were made before their incorporation into the 2015 FRA database (MacDicken 2015).

classifications use similar to the thresholds as the World Bank. We divide the sample into groups based on change in forest area; "High Deforestation" means a country lost 15% or more of their forest over the course of the study. "Low Deforestation" signifies that a country lost between 0-15% of total forest area over the course of the study. "Reforestation" classifies those who regenerated forest area. Finally, countries are sorted into those with over 15,000,000 hectares of forest area, marked "Large Forest Area". Those with less than 15,000,000 hectares are placed in the "Smaller Forest Area" group.

Finally, The World Governance Indicators provide several measures of perceived governance that cover the most countries over our course of study compared to other competitive measures. More importantly, there is a well-defined system by which Kaufmann, Kraay, and Mastruzzi (1996-2015) standardize their estimates to account for varying methods of reporting across regions. These indicators measure three factors titled *Political Stability and Absence of Violence, Rule of Law,* and *Control of Corruption*[5] which encompass different aspects of governance which may affect forestation rates. These values are updated every two years from 1996-2002, then annually from 2002-current. They are aggregate indicators developed by combining over 30 individual sources from private sector firms, international organizations, expert reporters, think tanks, and in-country surveys. In order to aggregate this wide variety of data, they first sort each individual measure in each survey into one of their six indicators. Then, they are preliminarily rescaled so that each measure is put onto a 0-1 scale[6]. Due to the fact

[5] See definitions in appendix.
[6] In order to correct for sample biases and ensure comparability between sources, Kaufmann and Kraay subject the data to an Unobserved Components Model. The model assumes that the observed data from each source are linear for the signaled but unobserved level of governance plus error. They then weight each data point according to its correlation between data sources to more accurately reflect the true unobserved measure. The composite measures are normally distributed with a mean of zero, a standard deviation of 1, and range from -2.5 to 2.5 with higher values reflecting better governance.

that the research database uses studies that may not encompass all reported regions, not every source is used for every country (Kaufmann, Kraay, and Mastruzzi 2010). These indicators are measures of perceived governance by a variety of sources. However, perceived governance is expected to be more accurate than measuring actual governance using any other source due to the widely differing strategies used to quantify governance and likely potential bias from within country sources.

DEFINING FORESTATION

$$A_{i,t} = F(E_i)L(\phi_{i,t}; \beta)$$

A is forest area for country i in year t. The model assumes that forest area for each country is determined by a combination of environmental factors, E, such as rainfall, temperature, severity of seasons, and levels of socio-economic factors, ϕ, such as population, income, and property rights security. β is a parameter vector which may change from one time period to the next due to factors such as World Bank lending changes or varying time-dependent levels of global attention on deforestation among others (Deacon 1994). E is assumed constant for each country over the period of the study for simplification although global climate change may affect each country in our sample differently. If environmental conditions are indeed a time independent variable, their effects on forestation can be removed by taking the first difference between time periods so that the change in forested area, CFA, is equal to:

$$CFA_i = log\left(A_{i,t}\right) - log\left(A_{i,t-1}\right)$$

$$CFA_i = \left(log(L\left(\phi_{i,t}; \beta_t\right))\right) - \left(log(L\left(\phi_{i,t-1}; \beta_{t-1}\right))\right)$$

If we allow the parameter vector to change between years, likely for reasons stated above, the model becomes:

$$CFA_i = \beta_t log(\phi_{i,t}) - \beta_{t-1} log\ (\phi_{i,t})$$

This equation defining forestation area can be simply altered to measure forestation rate, FR, in each country in each year. Positive values translate as positive forestation, negative rates mean deforestation.

$$FR_{i,t} = ((A_{i,t} - A_{i,t-1})\ /\ A_{i,t-1}) * 100$$

A possible model for a cross-country and time series analysis of factors on forestation rates looks like:

$$FR_{i,t} = B_0 + B_1 PopulationGrowth_{i,t} + B_2 LagPopulationGrowth_{i,t} + B_3 GDPperCapita_{i,t} + B_4 GDPperCapita^2_{i,t} + B_{5-7} GovernanceFactor_{i,t} + \alpha_i + \varepsilon_{it}$$

Here, α_i is the country specific, time invariant factor that measures qualities such as climate, country specific traditions, soil quality, etc. These factors can of course change over time, but transformations of these varieties tend to be slow-developing.

METHODOLOGY

We examine both the annual forestation rate and the direct differences in logged forest area between observed time periods. Neither functional form is likely to be an exact representation of the relationship in our data, but both provide helpful insights. The annual forestation rate depicts how a change in population growth rates or income will affect national deforestation rates, while the direct difference in logged forest area reports elasticities to be interpreted as proportional changes.

It is probable that countries will have individual heterogeneity, and it is likely that the unobserved effects will also be correlated with our independent variables such as income per capita and population growth. This paper explores several econometric approaches to handling said heterogeneity bias. For our estimates of the change in annual percentage change in forest area, first, we use a pooled OLS estimator. This model imposes the restriction that a change in one explanatory variable will have the same effect on the change in forest area for all countries. Then, we compare those estimates to pooled OLS run on time-demeaned data, also known as a within or fixed-effects estimator. It is fairly certain that our original OLS estimates will be biased as our observations are not independent because we are using longitudinal data. We also run a random-effects estimator and compare the results to our previous fixed-effects estimator. These account for positive serial correlation in the error term that can make pooled the OLS standard errors incorrect (Woolridge 2013). The random-effects estimator differs from the fixed-effects estimator in that it assumes α_i to be uncorrelated with our other explanatory variables. Although these methods impose a similar assumption that all countries in our sample will have a common structure, the fixed-effect and random-effect estimators allow for these to be shifted due to individual differences. This may be reasonable as it is likely that countries share more in common with themselves in past years than other countries in the same time period. For our models with the dependent variable log change in forest area, the first differencing procedure should remove the bias caused by excluding environmental and cultural variables.

To begin, we first run somewhat naïve regressions using population growth, income, and our governance indicators to establish an idea of the basic patterns. These initial regressions estimate select independent variables while excluding other relevant factors. We assess the quality of the different estimation methods by comparing F-Statistics, Wald-Chi Squared statistics, and using a Hausman test before dividing the complete set into smaller samples based on forest land area or income per capita levels. This division allows insight into if and/or how different factors affect countries with varying common characteristics. Finally, we proceed to incorporate these variables into a synthesized model in order to see how they interact.

SUMMARY STATISTICS

Table 1

	Complete Sample	High Income	Low or Medium Income
Forest Area (1000's Hectares)	24891.1 (85345.8)	26157.7 (74656.3)	25299.4 (90602.7)
Annual Percentage Change in Forest Area	-0.0559 (1.340)	0.460 (1.169)	-0.233 (1.368)
Percentage Change in Forest Area 1990-2015	2.944 (33.61)	19.75 (44.99)	-2.174 (27.81)
GDP per Capita	9755.1 (15005.7)	31421.5 (16756.2)	2804.1 (2919.4)
Annual Percentage Change in GDP per Capita	5.315 (10.23)	4.080 (4.730)	6.465 (7.697)
Population (1000's)	39337.747 (138056.6)	26341.499 (51923.9)	45078.6 (158727.5)
Annual Percentage Change in Population	1.591 (1.412)	1.189 (1.687)	1.709 (1.260)
Rule of Law	-0.125 (1.017)	1.174 (0.705)	-0.544 (0.642)
Political Stability and Absence of Violence/ Terrorism	-0.168 (0.976)	0.753 (0.612)	-0.461 (0.843)
Control of Corruption	-0.110 (1.030)	1.206 (0.847)	-0.537 (0.614)
N	161	49	112

mean coefficients; sd in parentheses

Table 1 shows that forest area is evenly split between high-income and medium/low-income countries, however the wealthier countries have a trend to reforest, while the less wealthy countries deforest. The mean GDP per capita of our set is $9755.10. One can see that lower income countries have around twice as many people as higher income countries and are growing more quickly. As expected, the governance measures are highly correlated with our measures of income, higher incomes yielding better governance measures.

Table 2

	Complete Sample	Large Forest Area	Smaller Forest Area
Forest Area (1000's Hectares)	24891.1	92665.0	3518.0
	(85345.8)	(156141.8)	(3875.9)
Annual Percentage Change of Forest Area	-0.0559	-0.186	-0.0147
	(1.340)	(0.685)	(1.487)
Percentage Change in Forest Area 1990-2015	2.94439	-2.79741	4.718291
	(33.69637)	(14.08347)	(37.62331)
GDP per Capita	9755.1	9843.5	9727.1
	(15005.7)	(14427.8)	(15195.8)
Annual Percentage Change of GDP per Capita	5.315	5.302	5.320
	(10.23)	(11.31)	(9.868)
Population (1000's)	39337.7	108353.1	17573.1
	(138056.6)	(266393.0)	(28302.5)
Annual Percentage Change of Population	1.591	1.568	1.598
	(1.412)	(0.974)	(1.526)
Rule of Law	-0.125	-0.206	-0.0990
	(1.017)	(1.117)	(0.983)
Political Stability and Absence of Violence/ Terrorism	-0.168	-0.316	-0.122
	(0.976)	(0.935)	(0.985)
Control of Corruption	-0.110	-0.167	-0.0919
	(1.030)	(1.125)	(0.998)
N	161	39	122

mean coefficients; sd in parentheses

When the data set is divided between countries with large forest areas versus countries with smaller forest areas, we see that countries with larger forest areas deforest a higher percentage of their forest lands. This is concerning from a global forest area and carbon sequestration perspective but does not mean those countries are necessarily using their forest lands inefficiently. Measures of GDP per capita and population growth are fairly even between the two samples, while the countries with smaller forest areas have better governance measures on average.

Table 3

	Annual Forestation Rate (OLS)	Annual Forestation Rate (FE)	Annual Forestation Rate (RE)
Annual Percentage Change in Population	-0.0188	0.00828	-0.0219
	(0.31)	(0.13)	(0.45)
5-Year Lagged Annual Percentage Change in Population	-0.144*	-0.0736	-0.115*
	(1.98)	(1.05)	(2.24)
Constant	0.194	0.0391	0.153
	(1.57)	(0.22)	(1.12)
F-Statistics for Significance (P-Values)	1.53 (0.1966)	0.64 (0.6365)	
F-Statistics for Pooled Model (P-Values)		6.8 (0.000)	
Wald Chi-Squared (P-Values)			8.07 (0.0889)
Hausman Statistics (P-Value)			0.86 (0.9306)
N	483	483	483

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3, our first examination of the effect of population growth on annual forestation rate, shows that generally, when populations grow, forest areas negatively impacted. The row labeled 'F-statistics for Pooled Model' shows that we reject the null that individual effects, when taken together, are no different than zero. Both the fixed-effects estimator, and the random-effects estimator are preferred over our pooled OLS estimates. Based on our Hausman statistic, we fail to reject the null that the unique errors are uncorrelated with the regressors. Therefore, it suggests the use of the random-effects estimator. Its results are jointly statistically significant at a confidence level of about 9%. The random-effects estimates of the entire data set show that a growth in population of that same year leads to a decrease in annual forestation rate, but the effect is much stronger when we examine the population growth rate five years prior. This finding coincides with Deacon's (1994) earlier conclusion.

Table 4

Random Effects	Annual Forestation Rate	Annual Forestation Rate if High Income	Annual Forestation Rate if Medium Income	Annual Forestation Rate if Low Income	Annual Forestation Rate if Large Forest Area	Annual Forestation Rate if Small Forest Area
Annual Percentage Change in Population	-0.0219	0.0408	-0.0661	-0.217	-0.0596	-0.019
	(0.45)	(1.06)	(0.57)	(1.18)	(0.48)	(0.34)
5-Year Lagged Annual Percentage Change in Population	-0.115*	-0.0985*	-0.157	0.0321	-0.0292	-0.123*
	(2.24)	(2.18)	(1.34)	(0.21)	(0.23)	(2.08)
Constant	0.153	0.382*	0.319	-0.0502	-0.0651	0.187
	(1.12)	(2.57)	(1.71)	(0.13)	(0.37)	(1.18)
Wald Chi-Squared (P-Values)	8.07 (0.0889)	6.49 (0.1652)	8.72 (0.0684)	2.34 (0.6731)	0.94 (0.6238)	5.40 (.0673)
N	483	133	179	161	116	367

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4 shows the use of the random-effects estimator when the data set is split into different groups with regard to their income-per-capita and forest areas. We see that for our lower income countries, the negative effects of population growth in the same year are more severe assuming previous growth rates held constant. Population growth negatively impacts annual forestation rates for both countries with large and small forest areas, but ceteris paribus, this effect is most intense for countries with less forest area if population growth occurred five years previously. It is likely that countries with less forest area also are smaller in size, thus an increase in population may increase population density by a greater factor.

Table 5

OLS	Log Change Forest Area	Log Change Forest Area if High Income	Log Change Forest Area if Medium Income	Log Change Forest Area if Low Income	Log Change Forest Area if Large Forest Area	Log Change Forest Area if Small Forest Area
Log Change Population	-0.175***	0.227**	-0.153*	-0.269***	-0.195***	-0.172***
	(4.76)	(3.05)	(2.36)	(4.24)	(4.03)	(3.87)
Constant	0.0137**	0.0173*	0.0187**	-0.000181	0.0077	0.0159*
	(2.73)	(2.00)	(2.77)	(0.02)	(1.28)	(2.55)
F-Statistics for Significance (P-Values)	22.63 (0.000)	9.29 (0.027)	5.55 (.0194)	18.01 (0.000)	16.28 (0.0001)	14.94 (0.0001)
R-Squared	0.034	0.0546	0.0246	0.0693	0.0962	0.0298
N	644	163	222	244	155	489

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5 reveals that a 1% increase in population growth yields a proportional .175% reduction in forest area. This result supports our previous examination on population growth's effect on annual percentage changes in forest areas with the exception of high-income countries, where population growth is related to an increase in forest area. The negative effect on low-income countries is stronger than that on medium-income countries. This finding seems to support FAO (1997, 2003) and others' hypothesis that population growth drives more agrarian expansion in low-income countries than in wealthier ones. We do not find conclusive evidence in support of Rudel's (1989) hypothesis that countries with smaller forested areas are more susceptible to population pressures. Regardless of how the data is split up, the coefficients of the log change in population are significant at least at an .05 level, however the explanatory power of this model is low with R-Squared estimates ranging from .024-.0962.

Table 6

OLS	Log Change Forest Area	Log Change Forest Area if High Income	Log Change Forest Area if Medium Income	Log Change Forest Area if Low Income	Log Change Forest Area if Large Forest Area	Log Change Forest Area if Small Forest Area
Log Change Population	-0.0552	0.122	-0.122	-0.252	-0.089	-0.0543
	(0.92)	(1.82)	(1.18)	(1.53)	(0.94)	(0.77)
5-Year Lagged Log Change Population	-0.082	-0.0129	-0.0638	0.016	-0.0464	-0.0856
	(1.96)	(0.22)	(0.87)	(0.2)	(0.81)	(1.71)
Constant	0.00902*	0.0089	0.0170**	-0.00345	0.00208	0.0111*
	(1.98)	(1.76)	(2.83)	(0.20)	(0.37)	(1.98)
F-Statistics for Significance (P-Values)	7.43 (0.0007)	2.88 (0.0595)	4.06 (0.0189)	1.49 (0.2277)	16.28 (0.0001)	14.94 (0.0001)
R-Squared	0.037	0.0425	0.0441	0.0186	0.0507	0.029
N	483	133	179	161	116	367

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

When the lagged log change in population value is included, the signs of our coefficients and the rankings of magnitude remain the same but are no longer significant at a .05 level. When both the log change in population and lagged log change in population variables are included, the coefficients are interpreted as if the other is held constant. In this case a 1% increase in population in the same year yields a proportional .0552% reduction in forest area, while a 5-year previous 1% increase in population reduces forest area by .082%.

Table 7

	Annual Forestation Rate (OLS)	Annual Forestation Rate (FE)	Annual Forestation Rate (RE)
GDP per capita ($1000s)	.0481***	-0.0178	0.0269**
	(4.25)	(1.17)	(2.84)
GDP per capita-squared	-0.000523***	0.0000852	-0.000282*
	(3.69)	(0.53)	(2.26)
Constant	-.377***	0.106	-0.236*
	(3.11)	(0.9)	(2.18)
F-Statistics for Significance (P-Values)	9.36 (0.0001)	1.3 (0.2732)	
F-Statistics for Pooled Model (P-Values)		7.02 (0.000)	
Wald Chi-Squared (P-Values)			8.34 (0.0154)
Hausman Statistic (P-Values)			14.13 (0.0009)
Kuznets?	No	Yes	No
Turning Point		$104,460.09	
N	629	629	629

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7 depicts ambiguous results depending on the model. Using the fixed-effects model[7], and thus incorporating the individual country specific effects under the assumption that these effects are correlated with GDP per capita, we see that the relationship between annual forestation rate and GDP per capita, although insignificant, does imply an U-shaped relationship. This is noted in the row labeled ‘Kuznets?’. However, the turning point GDP per capita value is much higher than almost all countries studied.

[7] The ‘F-Statistics for Pooled Model’ and the ‘Wald Chi-Squared’ statistic test for the model’s validity against the OLS regression. In this case the OLS estimates are thought to be biased. The Hausman statistic compares the fixed-effects estimator against the random-effects estimator and in this case, we reject the null in favor of the fixed-effects estimator.

Table 8

Fixed-Effects	Annual Forestation Rate	Annual Forestation Rate if High Income	Annual Forestation Rate if Medium Income	Annual Forestation Rate if Low Income	Annual Forestation Rate if Large Forest Area	Annual Forestation Rate if Small Forest Area
GDP per capita ($1000s)	-0.0178	-0.0475**	-0.0383	0.296	-0.00331	-0.0226
	(1.17)	(2.86)	(0.28)	(0.39)	(0.15)	(1.19)
GDP per capita-squared	0.0000852	0.000353*	0.00415	-0.166	-0.000000496	0.000115
	(0.53)	(2.18)	(0.41)	(0.45)	(0.001)	(0.6)
Constant	0.106	1.531***	0.182	-0.652*	-0.152	0.186
	(0.9)	(4.4)	(0.45)	(2.04)	(1.04)	(1.26)
F-Statistics for Significance (P-Values)	1.3 (0.2372)	5.1 (0.0077)	0.23 (0.7911)	0.11 (0.8932)	.09 (.9112)	1.2 (.3103)
F-Statistics for Pooled Model (P-Values)	7.02 (0.000)	8.80 (0.000)	4.22 (0.000)	4.13 (0.000)	7.54 (0.000)	6.8 (0.000)
Kuznets?	Yes	Yes	Yes	No	No	Yes
Turning Point	$104,460.09	$67,280.45	$4,614.45			$98,260.86
N	629	163	222	244	479	150

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

When the sample is divided into countries based on income groups and forest areas, only the countries with high incomes exhibit a significant Kuznets curve relationship. However, the turning point of $67,280.45 per capita is greater than the current GDP per capita of most countries in the sample. For medium-income and small-forest area countries, the Kuznets relationship is insignificant, while low-income and large-forest area countries do not follow this curve.

Table 9

OLS	Log Change Forest Area	Log Change Forest Area if High Income	Log Change Forest Area if Medium Income	Log Change Forest Area if Low Income	Log Change Forest Area if Large Forest Area	Log Change Forest Area if Small Forest Area
Log Change GDP per Capita	0.0308***	0.0517	0.0218	0.0331**	0.0142	0.0354***
	(3.7)	(1.77)	(1.81)	(2.67)	(1.48)	(3.4)
Constant	-0.0124**	0.0214*	-0.00144	-0.0456***	-0.0159**	-0.0110*
	(2.85)	(2.25)	(0.20)	(6.89)	(3.33)	(2.01)
F-Statistics for Significance (P-Values)	13.66 (0.002)	3.15 (.0780)	3.26 (0.0723)	7.12 (0.0082)	2.2 (0.1401)	11.56 (0.0007)
R-Squared	0.0213	0.0192	0.0146	0.029	0.0146	0.0237
N	630	163	222	240	151	479

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Rather than examining levels of GDP per capita, our log differenced model looks at the impacts of a change in income. A 1% increase in GDP per capita reflects a proportional .031% increase in forested area. Across all groups, increasing GDP per capita growth has positive effects on changes in forested area. These effects are stronger for countries with smaller forest areas. The explanatory power of this model remains low, but the F-Statistics show that most samples examined are jointly significant.

GOVERNANCE AND FORESTATION

Table 10 presents summary statistics for our governance indicator variables. The mean values of each are compared across groups of countries which exhibit different forestation behaviors. As expected, the values for highly deforesting countries are lower than those who deforest less, and much lower than those who reforest. This comparison of values seems to support previous studies like Bohn and Deacon (2000) and Mendohlson (1994) which argue that preserving forests is an act of investment, so is more likely to occur under regimes with strong property rights and effective enforcing institutions.

Table 10

	High Deforestation	Low Deforestation	Reforestation
Rule of Law	-0.79	-0.339	0.366
	(0.621)	(0.939)	(0.989)
Political Stability and Absence of Violence/ Terrorism	-0.659	-0.291	0.177
	(0.854)	(0.961)	(0.916)
Control of Corruption	-0.76	-0.313	0.367
	(0.555)	(0.938)	(1.052)
N	148	208	288
mean coefficients; sd in parentheses			

Table 11

	Annual Forestation Rate (OLS)	Annual Forestation Rate (FE)	Annual Forestation Rate (RE)
Rule of Law	0.222	0.262	0.301
	(0.66)	(1.11)	(1.62)
Control of Corruption	0.107	-0.182	-0.0543
	(0.35)	(0.82)	(0.31)
Policital Stability and Absence of Violence/ Terrorism	0.0752	0.217^{*}	0.162
	(0.61)	(2.02)	(1.79)
Constant	-0.0108	-0.0105	0.00471
	(0.11)	(0.26)	(0.05)
F-Statistics for Significance (P-Values)	8.23 (0.00)	2.69 (0.0459)	
F-Statistics for Pooled Model (P-Values)		7.31 (0.000)	
Wald Chi-Squared (P-Values)			25.39 (0.000)
Hausman P-Value			1.62 (.6548)
N	626	626	626

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 11 shows the results of a simplistic regression of our governance indicators on annual forestation rates. The majority of the coefficients are individually insignificant at a .05 level, but still demonstrate that better governance raises the annual forestation rate. The individual significance takes a second seat to the joint significance as these variables are highly correlated. For instance, better control of corruption leads to stronger rule of law, and strengthening the rule of law allows for more political stability etc. We ran significance tests for combinations of these indicator variables and F-tests suggest for each combination they remain strongly jointly significant. Again, the fixed-effects and random-effects estimates are thought to be more accurate than the pooled OLS estimates.

SYNTHESIS

Table 12

	Annual Forestation Rate (OLS)	Annual Forestation Rate (FE)	Annual Forestation Rate (RE)
Annual Percentage Change in Population	0.0212	-0.0162	-0.0108
	(0.34)	(0.24)	(0.21)
5-Year Lagged Annual Percentage Change in Population	-0.108	-0.0861	-0.0857
	(1.68)	(1.17)	(1.58)
GDP per Capita	0.0188	0.0108	0.0168
	(1.3)	(0.41)	(1.1)
GDP per Capita Squared	-0.00025	-0.00000695	-0.000157
	(1.81)	(0.03)	(0.94)
Rule of Law	0.0515	0.0621	0.128
	(0.13)	(0.19)	(0.54)
Control of Corruption	0.14	-0.158	-0.00639
	(0.41)	(0.56)	(0.03)
Political Stability and Absence of Violence/ Terrorism	0.0343	0.0463	0.0424
	(0.25)	(0.32)	(0.39)
Constant	-0.0278	-0.0378	-0.0231
	(0.16)	(0.12)	(0.12)
F-Statistics for Significance (P-Values)	3.01 (0.0054)	0.38 (.9165)	
F-Statistics for Pooled Model (P-Values)		6.39 (0.000)	
Wald Chi-Squared (P-Values)			17.37 (.0152)
Hausman P-Value			2.24 (.9451)
Kuznets?	No	No	No
N	466	466	466

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 12 is a beginning synthesis including population growth, GDP per capita levels, and our governance indicators. The governance measures examine our three separate measures that are all useful as proxies for overall governmental quality. After examining our tests of pooled-model significance and our Hausman Statistic, the random-effects estimates are favored. The coefficients follow the trends of our original naïve regressions in that population growth is correlated with deforestation while income growth is correlated with reforestation. The Kuznets relationship disappears in our synthesis model. This result supports Koop and Tole (1999), Copeland and Taylor (2004), Stern (2004) that the relationship is only apparent under strict commonality assumptions. As expected, a bettering in our governance indicators, especially *Rule of Law,* increases forestation rates.

Tables 13 and *14* respectively divide our synthesis model into countries based on income levels and forest areas. When the sample is split into income groups, we observe same trends noted above. Immediately the results hint that low-income countries may exhibit a Kuznets curve relationship, but jointly our independent variables are insignificant for that group. Countries with large forest areas display an unexpected result with regards to our governance indicators. Improving property rights, measured by our 'Rule of Law' variable improves the annual forestation rate. Conversely, bettering 'Control of Corruption' worsens forestation rates. The explanation for why this may be is uncertain as it directly conflicts with Koyuncu and Yilmaz's (2013) findings. It is possible that in countries with larger sized forest areas, the corruptive powers hold interests in forest lands, but further study will be necessary.

Table 13

Random Effects	Annual Forestation Rate	Annual Forestation Rate if High Income	Annual Forestation Rate if Medium Income	Annual Forestation Rate if Low Income
Annual Percentage Change in Population	-0.0108	0.0389	-0.0472	-0.245
	(0.21)	(1.01)	(0.40)	(1.30)
5-Year Lagged Annual Percentage Change in Population	-0.0857	-0.0927*	-0.139	0.0317
	(1.58)	(2.02)	(1.19)	(0.19)
GDP per Capita ($1000s)	0.0168	0.0156	0.079	-0.846
	(1.1)	(0.9)	(0.5)	(0.82)
GDP per Capita-squared	-0.000157	-0.000114	-0.00427	0.357
	(0.94)	(0.72)	(0.38)	(0.74)
Rule of Law	0.128	0.124	0.0751	0.447
	(0.54)	(0.42)	(0.21)	(0.89)
Control of Corruption	-0.00639	0.0319	0.0392	0.0339
	(0.03)	(0.14)	(0.12)	(0.07)
Political Stability and Absence of Violence/ Terrorism	0.0424	0.0419	0.142	-0.123
	(0.39)	(0.22)	(0.88)	(0.58)
Constant	-0.0231	-0.19	0.12	0.657
	(0.12)	(0.56)	(0.24)	(0.87)
Wald Chi-Squared (P-Values)	17.37 (0.0152)	11.17 (.1313)	10.42 (.1662)	4.15 (.7620)
Kuznets?	No	No	No	Yes
Turning Point				$1184.87
N	466	133	175	158

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 14

Random Effects	Annual Forestation Rate	Annual Forestation Rate if High Forest Area	Annual Forestation Rate if Low Forest Area
Annual Percentage Change in Population	-0.0108	-0.0134	-0.0148
	(0.21)	(0.10)	(0.25)
5-Year Lagged Annual Percentage Change in Population	-0.0857	0.0514	-0.0921
	(1.58)	(0.38)	(1.48)
GDP per Capita ($1000's)	0.0168	0.0288	0.02
	(1.1)	(1.35)	(1.05)
GDP per Capita-Squared	-0.000157	-0.000356	-0.000192
	(0.94)	(1.13)	(0.96)
Rule of Law	0.128	0.680^{**}	-0.0133
	(0.54)	(2.88)	(0.04)
Control of Corruption	-0.00639	-0.524^{*}	0.148
	(0.03)	(2.54)	(0.55)
Political Stability and Absence of Violence/ Terrorism	0.0424	-0.162	0.0658
	(0.39)	(1.45)	(0.48)
Constant	-0.0231	-0.486	0.00517
	(0.12)	(1.70)	(0.02)
Wald Chi-Squared (P-Values)	17.37 (.0152)	17.15 (0.0165)	14.30 (0.0461)
Kuznets?	No	No	No
N	466	112	354

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 15 investigates the effects of both changes in population and in GDP per capita. These results underline previous results showing that a growth in population is, in general, harmful to changes in forested area, while a growth in GDP per capita is beneficial. If growth in both population and GDP per capita were to happen concurrently they would partially offset each other, except for in the wealthiest countries. Even though most of the variation across countries is not accounted for by the included variables, the significance of most variables at least at a .05 level, and its concurrence with previous estimates increase the reliability of the results.

Table 15

OLS	Log Change Forest Area	Log Change Forest Area if High Income	Log Change Forest Area if Medium Income	Log Change Forest Area if Low Income	Log Change Forest Area if Large Forest Area	Log Change Forest Area if Small Forest Area
Log Change Population	-0.158***	0.222**	-0.135*	-0.250***	-0.190***	-0.149**
	(4.15)	(3.00)	(2.05)	(3.90)	(3.84)	(3.25)
Log Change GDP per Capita	0.0245**	0.0484	0.017	0.0255*	0.0104	0.0285**
	(2.92)	(1.7)	(1.39)	(2.09)	(1.13)	(2.71)
Constant	0.00494	0.00699	0.0102	-0.00907	0.00419	0.0055
	(0.83)	(0.67)	(1.12)	(0.80)	(0.60)	(0.74)
F-Statistics for Significance (P-Values)	15.63 (0.000)	6.15 (0.0027)	3.76 (0.0248)	11.37 (0.000)	8.59 (0.0003)	11.18 (0.000)
R-Squared	0.0475	0.0713	0.0332	0.0876	0.104	0.0449
N	630	163	222	240	151	479

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 16 includes our governance variables in the synthesis log differences regression. Most of the governance variables are insignificant individually, except for *Rule of Law* and *Control of Corruption* in countries with large forest areas. The coefficient values for population growth and GDP per capita growth change by a small value, but the interpretation of their effects is unchanged.

Table 16

OLS	Log Change Forest Area	Log Change Forest Area if High Income	Log Change Forest Area if Medium Income	Log Change Forest Area if Low Income	Log Change Forest Area if Large Forest Area	Log Change Forest Area if Small Forest Area
Log Change Population	-0.0808*	0.251**	-0.122	-0.252***	-0.0941	-0.0795
	(2.04)	(3.18)	(1.81)	(3.81)	(1.83)	(1.67)
Log Change GDP per Capita	0.0263**	0.0553	0.0142	0.0236	0.0173*	0.0294**
	(3.15)	(1.90)	(1.13)	(1.90)	(1.13)	(2.71)
Rule of Law	0.0101	0.0320	-0.00477	0.00901	0.0545***	0.000667
	(0.81)	(1.00)	(0.28)	(0.40)	(3.92)	(0.04)
Political Stability and Absence of Violence/ Terrorism	0.00462	-0.0111	0.0107	-0.0000460	0.00235	0.00323
	(0.77)	(0.76)	(1.24)	(0.00)	(0.37)	(0.43)
Control of Corruption	0.0107	-0.0138	0.00958	0.0275	-0.0405**	0.0241
	(0.90)	(0.52)	(0.59)	(1.11)	(3.12)	(1.64)
Constant	-0.000964	-0.00902	0.0131	0.0198	-0.00339	0.0000012
	(0.16)	(0.48)	(1.38)	(1.25)	(0.49)	(0.00)
F-Statistics for Significance (P-Values)	15.22 (0.00)	2.85 (0.0171)	2.37 (0.0402)	5.98 (0.000)	10.55 (0.000)	11.29 (0.000)
R-Squared	0.1108	0.0833	0.0530	0. 0969	0.2680	0.1091
N	617	163	218	233	150	467

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

ALTERNATIVE SPECIFICATIONS

To test whether the main findings are robust to changes in the econometric specifications, we considered the following. First, we added some additional variables that plausibly could affect forestation, including population density and percentage of total population which lives in urban areas. The direct values of these variables as well as the change in values of these variables between time periods were examined. Second, we analyzed their effects on forestation and the coefficients of our other predictors using both naïve regressions and by incorporating them into our synthesis model.

When included in a naïve regression using logged difference in forest areas, population density is statistically significant. The model predicts that an increase of 10 people per square kilometer yields a proportional .000465% reduction in forest area. Conversely, percentage of total population living in an urban area appears insignificant. When added to the regression portrayed in *Table 16*, neither population density nor urban population percentage is significant. Additionally, the inclusion of these variables does not alter the values of our previous coefficients meaningfully.

CONCLUSION AND DISCUSSION

This paper sought to provide updated descriptive statistical results for use in comparison with previous studies which examined the drivers of forestation. To do so, we examined both direct logged differences in forest areas as well as annual forestation rates in 161 countries from the years 1996-2015. Our results support previous studies that current and prior population growth increases forest loss, while improving GDP per capita increases preservation and reforestation. We did not find that countries follow a traditional Kuznets curve after individual country effects included. Improving governance measures, specifically strengthening property rights, lessening corruption, and maintaining political stability, are beneficial for forest preservation. Although Mendelsohn (1994) warns that deforestation will only cease when forests are more valuable than other land uses, he also concludes that secure property rights are a step towards "prudent management of the world's scarce resources."

We find evidence that institutional quality matters when predicting forestation. Our governance indicators are jointly significant, but it is difficult to separate the individual effects as they are highly correlated with one another. Additionally, measures of governance do trend closely with incomes. Wealthier countries often have stronger institutions and more reliable governments, but it is uncertain which direction causality flows. The division of countries into groups based on income levels and forest area size provides additional insight into their heterogeneity. We discover different estimated effects of a change in all of our independent variables depending on income level as well are forest area size. We attribute this mainly to the income effect for environmental quality as well as the different spatial challenges regarding enforcement of regulation that accompany large forests.

It is clear for both research and for future policy that continually improving forest data will ensure greater accuracy in these studies, especially in lower-income areas of the world. Moreover, these assessments should be continually updated to keep close track of in the moment trends to provide proactive solutions rather than purely reactive ones. This study was based on just one measure of forest area, the FAO's land-use definition, but depending on research goals, a narrowing or expansion on the definition of forest area, e.g., biomass, forest area including grasslands and foliage used in certain types of farming, distinguishing between primary tropical forest and regenerated temperate forest, may be more applicable. Forests' role in greater environmental policy is multifaceted due to their ability to sequester carbon, provide havens of biodiversity, provide medicines and crops of the future, and return sustainable forest goods. Likewise, however, the threats to forest areas are complex. Moreover, the drivers of forestation are likely "determined endogenously" so the "unraveling of the chain of causation" is central to any policy aimed at affecting forestation (Deacon 1994). This leads to belief that the most effective environmental policies will likely take on a portfolio approach of conservation of existing areas, regeneration of degraded areas, and promoting sustainable land uses.

APPENDIX

Forest Area: "land spanning more than 0.5 hectares with trees higher than 5 meters and a canopy cover of more than 10 percent, or trees able to reach these thresholds. Excludes land that is predominantly under agricultural or urban land use, and land that is predominantly used for maintenance and restoration of environmental function… Forest land is determined both by presence of trees and by the absence of other predominant land uses. The trees should be able to reach a minimum height of 5 meters in situ. Includes areas with young trees that have not yet reached but that are expected to reach a canopy cover of 10 percent and tree height of 5 meters. It also includes areas that are temporarily unstocked owing to clear-cutting as part of a forest management practice or natural disasters, and that are expected to regenerate within five years. Local conditions may, in exceptional cases, justify the use of a longer time frame. Includes forest roads, firebreaks, and other small open areas. May include forest land in national parks, nature reserves, and other protected areas, such as those of specific environmental, scientific, historical, cultural, or spiritual interest. Includes windbreaks, shelter belts, and corridors of trees with an areas of more than 0.5 hectares and width of more than 20 meters. Includes abandoned shifting cultivation land with a regeneration of trees that have, or is expected to reach a canopy cover of 10 percent and tree height of 5 meters. Includes areas with mangroves in tidal zones regardless of whether this area is classified as land area or not. Includes areas with bamboo and palms provided that land use, height and canopy cover criteria are met. Some agroforesty systems such as the taungya system, where crops are grown only during the first years of the forest rotation should be classified as forest. Excludes: tree stands in agricultural production systems, such as fruit-tree plantations, oil palm plantations, rubber and Christmas trees, and agroforestry systems when crops are grown under tree cover." Measured in 1000's of hectares. http://www.fao.org/faostat/en/#data/GF

Population: Measured in 1000's of people
https://data.worldbank.org/indicator/SP.POP.TOTL

GDP: Measured in 1000's of 2019 US dollars
https://data.worldbank.org/indicator/NY.GDP.MKTP.CD

GDP Per Capita: GDP/Population

Population Density: People per square km of land area
https://data.worldbank.org/indicator/EN.POP.DNST

Urban Population: Percent of total population living in an urban area
https://data.worldbank.org/indicator/SP.URB.TOTL.IN.ZS

Annual Percentage Change Variables: $= ((X_{i,t} - X_{i,t-1})\ /\ X_{i,t-1}) * 100$

Rule of Law: "Rule of law captures perceptions of the extent to which agents have confidence in and abide by the rules of society, and in particular the quality of contract enforcement, property rights, the police, and the courts, as well as the likelihood of crime and violence."

Control of Corruption: "Control of corruption captures perceptions of the extent to which public power is exercised for private gain, including both petty and grand forms of corruption, as well as "capture" of the state by elites and private interests."

Political Stability and Absence of Violence/ Terrorism: Political stability and absence of violence/terrorism measures perceptions of the likelihood of political instability and/or politically motivated violence, including terrorism."
https://info.worldbank.org/governance/wgi/#home

Forest Area > 15000000 Hectares	High-Income	Medium-Income	Low-Income
	Argentina	Angola	Cameroon
	Australia	Bolivia	Central African Republic
	Canada	Brazil	Congo
	Chile	China	Democratic Republic of the Congo
	Finland	Colombia	India
	France	Gabon	Mozambique
	Japan	Guyana	Myanmar
	Spain	Indonesia	Sudan
	Sweden	Lao PDR	Tanzania
	United States	Malaysia	Zambia
	Venezuela, RB	Mexico	Zimbabwe
		Papua New Guinea	
		Paraguay	
		Peru	
		Russian Federation	
		Suriname	
		Thailand	
Forest Area < 15000000 Hectares	**High-Income**	**Medium-Income**	**Low-Income**
	Austria	Albania	Afghanistan
	Bahamas	Algeria	Bangladesh
	Bahrain	Armenia	Benin
	Belgium	Azerbaijan	Burkina Faso
	Brunei Darussalam	Belarus	Burundi
	Cyprus	Belize	Cambodia
	Denmark	Bhutan	Chad
	Estonia	Bosnia and Herzegovina	Comoros
	Germany	Botswana	Djibouti
	Greece	Bulgaria	Ethiopia
	Hungary	Costa Rica	Gambia
	Iceland	Croatia	Ghana
	Ireland	Cuba	Guinea
	Israel	Dominican Republic	Guinea-Bissau
	Italy	Ecuador	Haiti
	Kuwait	Egypt	Kenya
	Latvia	El Salvador	Kyrgyzstan
	Lithuania	Equatorial Guinea	Lesotho
	Luxembourg	Fiji	Liberia
	Malta	Georgia	Madagascar
	Netherlands	Guatemala	Malawi
	New Zealand	Honduras	Mali
	Norway	Iran	Mauritania
	Oman	Iraq	Nepal
	Panama	Jamaica	Niger
	Poland	Jordan	Pakistan
	Portugal	Kazakhstan	Rwanda
	Puerto Rico	Lebanon	Senegal

	Saudi Arabia	Libya	Sierra Leone
	Singapore	Maldives	Somalia
	Slovakia	Mauritius	South Sudan
	Slovenia	Mongolia	Syrian Arab Republic
	South Korea	Montenegro	Tajikistan
	Switzerland	Morocco	Togo
	Trinidad and Tobago	Namibia	Uganda
	United Arab Emirates	Nicaragua	Yemen
	United Kingdom	Nigeria	
	Uruguay	Philippines	
		Romania	
		South Africa	
		Sri Lanka	
		Timor-Leste	
		Tunisia	
		Turkey	
		Turkmenistan	
		Ukraine	
		Uzbekistan	
		Vietnam	

High-Deforestation	Low-Deforestation	Reforestation	
Argentina	Afghanistan	Algeria	Romania
Belize	Albania	Austria	Russian Federation
Benin	Angola	Azerbaijan	Rwanda
Botswana	Armenia	Bahrain	Slovakia
Burkina Faso	Australia	Belarus	Slovenia
Cambodia	Bahamas	Belgium	Spain
Cameroon	Bangladesh	Bhutan	Sweden
Chad	Bolivia	Bulgaria	Switzerland
Comoros	Bosnia and Herzegovina	Chile	Syrian Arab Republic
South Korea	Brazil	China	Tajikistan
El Salvador	Brunei Darussalam	Costa Rica	Thailand
Equatorial Guinea	Burundi	Croatia	Tunisia
Ethiopia	Canada	Cuba	Turkey
Guatemala	Central African Republic	Cyprus	Ukraine
Haiti	Colombia	Denmark	United Arab Emirates
Honduras	Congo	Dominican Republic	United Kingdom
Indonesia	Democratic Republic of the Congo	Egypt	United States
Kyrgyzstan	Djibouti	Estonia	Uruguay
Liberia	Ecuador	Fiji	Uzbekistan
Malawi	Guinea	Finland	Vietnam
Mali	Guinea-Bissau	France	
Mauritania	Guyana	Gabon	
Myanmar	Jamaica	Gambia	
Namibia	Jordan	Georgia	
Nepal	Kazakhstan	Germany	
Nicaragua	Kenya	Ghana	
Niger	Libya	Greece	
Nigeria	Madagascar	Hungary	
Pakistan	Malaysia	Iceland	
Paraguay	Maldives	India	
Somalia	Mauritius	Iran	
Sudan	Mexico	Iraq	
Tanzania	Mozambique	Ireland	
Timor-Leste	Norway	Israel	
Togo	Oman	Italy	
Uganda	Panama	Japan	
Zimbabwe	Papua New Guinea	Kuwait	
	Peru	Lao PDR	
	Portugal	Latvia	
	Saudi Arabia	Lebanon	
	Senegal	Lesotho	
	Sierra Leone	Lithuania	
	Singapore	Luxembourg	
	South Africa	Malta	
	South Sudan	Mongolia	
	Sri Lanka	Montenegro	
	Suriname	Morocco	
	Trinidad and Tobago	Netherlands	

	Turkmenistan	New Zealand	
	Venezuela, RB	Philippines	
	Yemen	Poland	
	Zambia	Puerto Rico	

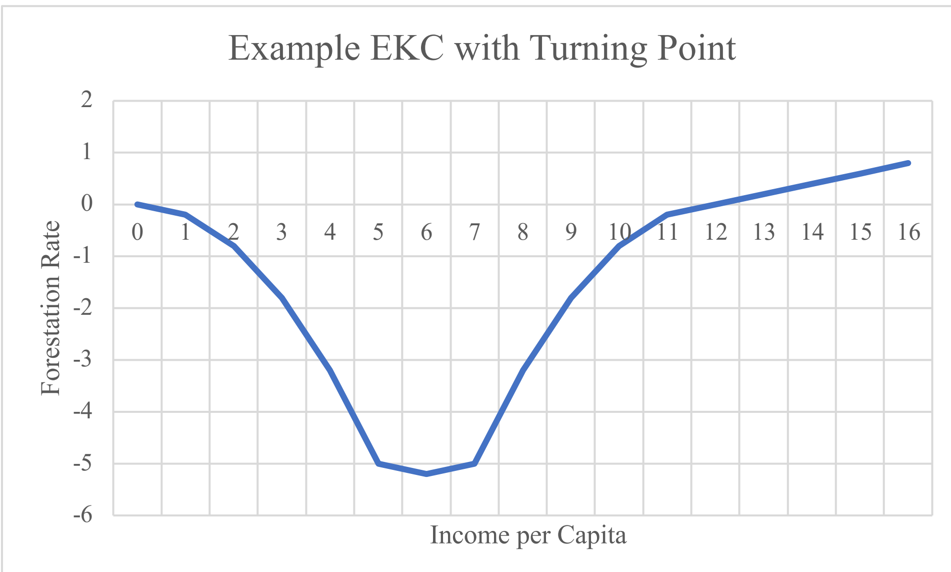
Country	**GDPPC 1990 (2019 US $)**	**GDPPC 2015 (2019 US $)**	**Change Rule of Law 1996-2015**	**Change Political Stability 1996-2015**	**Change Control of Corruption 1996-2015**
Afghanistan		590.0765	0.2743922	-0.1310353	-0.0465902
Albania	617.2304	3952.831	0.6805531	0.8841076	0.3782352
Algeria	2394.42	4162.852	0.3428156	0.34185	0.2750315
Angola	922.5501	4170.731	0.5813732	1.534685	0.1279316
Argentina	4318.775	13698.29	-0.6208894	-0.0845734	-0.3549264
Armenia	637.8557	3617.936	0.0907152	0.4312557	0.225724
Australia	18214.84	56644.04	0.0738213	-0.4495726	-0.0411556
Austria	21680.99	44176.67	0.0128917	0.3192526	-0.2899529
Azerbaijan	1266.021	5500.31	0.4762866	0.1006286	0.370656
Bahamas	12350.98	30483.82	-0.7196963	-0.3726216	-0.2125545
Bahrain	8528.983	22688.88	0.126598	-1.129314	-0.2421469
Bangladesh	297.568	1210.159	0.1604128	-0.4875087	0.3003679
Belarus	2124.84	5949.106	0.3208702	0	0.0483848
Belgium	20710.64	40431.95	0.1233938	-0.5432821	0.07651
Belize	2197.185	4905.537	-0.8509462	-0.1397851	-0.0414144
Benin	393.6862	783.9631	-0.378562	-0.8119107	-0.0871599
Bhutan	557.9722	2616.01	0.3888814	0.4840753	0.0346277
Bolivia	709.9488	3077.026	-0.7535415	-0.0329324	-0.2361522
Bosnia and Herzegovina		4584.243	0.3307984	0.1240077	0.1672694
Botswana	2750.95	6521.146	0.0007639	-0.0308607	0.0184484
Brazil	3093.038	8750.222	0.0613788	-0.5181978	-0.4366821
Brunei Darussalam	13604.16	30967.89	-0.1299799	-0.0595924	0.1998174
Bulgaria	2366.53	6993.783	0.0240047	-0.3626332	-0.1313106
Burkina Faso	351.9793	575.3145	0.0933203	-0.6703568	-0.2124309
Burundi	209.0516	304.3742	0.1874633	0.0756481	-0.4382077
Cambodia		1163.19	0.080656	0.8405814	-0.1595994
Cameroon	951.8883	1353.924	0.2234787	-0.4267792	0.1180636
Canada	21371.29	43327.17	0.1476878	0.1062319	-0.228985
Central African Republic			-0.4041191	0	-0.131411
Chad	291.8662	781.3311	-0.0915051	0.1613898	-0.2574654
Chile	2500.646	13736.64	0.0213802	-0.053527	-0.3060505
China	317.8847	8069.213	0.1173662	-0.3413606	-0.0638098
Colombia	1396.029	6085.21	0.6212614	0.5345342	0.0985885

Comoros	1043.801	1271.057	0.4759959	-0.2546613	0.3870574
Congo	1146.812	1712.121	0.3374799	0.3940077	-0.074169
Costa Rica	1844.863	11393.03	-0.1297324	-0.1891333	-0.1244875
Croatia		11773.26	0.1695742	0.312602	0.317784
Cuba	2706.976	7602.279	0.3405086	0.3964084	-0.3069449
Cyprus	7293.28	16951.66	-0.0000114	0.0353964	-0.1138271
Democratic People's Republic of Korea	6516.305	27105.08	0.0511388	-0.2370481	0.0509961
Democratic Republic of the Congo	270.1106	497.6298	0.3328753	0.3256967	0.2637575
Denmark	26891.44	53254.85	0.203644	-0.6056606	-0.1837111
Djibouti	766.1409	1761.61	-0.0358604	-0.2016989	0.2887745
Dominican Republic	984.6914	6534.909	0.0976536	0.2208679	-0.0970211
Ecuador	1491.402	6150.156	-0.3885139	0.4301866	0.2229962
Egypt	748.6023	3547.713	-0.5833038	-1.549755	-0.0890617
El Salvador	916.7567	3669.879	0.1547925	-0.3491613	0.0914313
Equatorial Guinea	262.6695	11213.48	-0.0374911	-0.1642109	-0.2193624
Estonia		17412.45	0.6782535	-0.2796719	0.4542668
Ethiopia	253.193	645.465	0.4202958	-0.5542265	0.0006087
Fiji	1834.99	4889.462	0.0156471	0.2801555	-0.1436682
Finland	28380.55	42494.66	0.0785847	-0.6807855	-0.1677957
France	21690.63	36613.38	-0.0460855	-0.6803097	-0.0626053
Gabon	6251.018	7448.716	-0.3441222	-0.6153347	-0.0026323
Gambia	345.8558	704.9741	-0.5172762	-0.513595	-0.382963
Georgia	1614.64	3756.378	1.204759	0.3472104	1.687782
Germany	22219.57	41394.66	0.1571263	-0.7131249	-0.0231977
Ghana	402.5889	1783.061	-0.0125563	0.3277444	-0.0968364
Greece	9600.185	18167.77	-0.6165673	-1.038986	-0.7358942
Guatemala	825.8074	3923.573	-0.0658066	0.1129504	0.0208356
Guinea	441.4128	727.3025	0.2279369	1.522689	-0.0385793
Guinea-Bissau	241.0025	591.8062	0.0315531	-0.1682725	-0.3786843
Guyana	533.5362	4160.265	-0.0533486	0.3488216	-0.2398848
Haiti	436.1136	814.5464	0.2827579	-0.0414777	0.0057243
Honduras	993.478	2341.275	0.0630164	-0.3903738	0.3881992
Hungary		12503.68	-0.506198	-0.170866	-0.639045
Iceland	25008.85	52428.6	-0.1593684	-0.267774	-0.3281795
India	368.8848	1606.953	-0.3775331	0.0496362	-0.0064573
Indonesia	585.0011	3334.549	0.2952441	1.381059	0.4607178
Iran	2219.842	4862.3	-0.4159789	-0.1993751	-0.2033464
Iraq	10297.43	4914.728	-0.0296024	-0.5244091	0.1317245
Ireland	14048.11	61908.79	0.2073034	-0.6771151	0.1825856

Israel	12658.15	35855.27	0.1375302	-0.0532668	-0.1103383
Italy	20757.09	30170.52	-0.5855449	-0.5421516	-0.7128887
Jamaica	1894.293	4925.416	0.1720217	-0.0902941	-0.2577051
Japan	25359.35	34567.75	0.2029774	-0.1337769	0.2951959
Jordan	1168.349	4096.099	0.0703244	-0.6064621	0.1762743
Kazakhstan	1647.463	10510.77	0.6680815	-0.1257681	0.2713436
Kenya	366.3009	1355.055	0.3846631	-0.1761558	0.0474015
Kuwait	8776.741	29109.07	-0.5716999	-0.9657716	-0.8156893
Kyrgyzstan	609.1729	1121.083	-0.1181648	-0.6992404	-0.2465679
Lao PDR	203.256	2159.433	0.1894057	1.120425	-0.0256082
Latvia		13639.69	0.5972629	0.0275545	0.5403876
Lebanon	1050.118	8529.513	-0.6603574	-1.263847	-0.3410231
Lesotho	371.8442	1154.355	-0.3158742	-0.4035146	0.0717652
Liberia		706.0595	1.144015	1.133919	0.8475857
Libya	6514.321	4465.49	-0.6397546	-1.899634	-0.7495794
Lithuania		14291.91	0.7159725	0.3352448	0.2602176
Luxembourg	34645.15	100428.4	0.0292896	-0.1667362	0.0482221
Madagascar	265.6761	402.0883	-0.4427088	-0.5879866	-0.3982779
Malawi	199.2859	362.6582	0.1704921	0.3589552	-0.4902951
Malaysia	2440.592	9655.138	0.2288138	0.1647676	-0.1019447
Maldives	963.5956	9821.691	-0.6443148	-0.7586983	-0.0978499
Mali	316.8166	749.918	-0.3875969	-1.925552	0.1538084
Malta	7191.924	23715.53	-0.2551247	-0.5229726	-0.0571032
Mauritania	502.2318	1158.256	-0.4424511	-0.9820089	-0.469558
Mauritius	2506.179	9260.448	-0.127984	0.241886	-0.0829422
Mexico	3060.685	9298.244	-0.0644786	-0.6005339	-0.5202909
Mongolia	1172.443	3946.962	-0.3736253	-0.1071369	-0.181825
Montenegro		6514.273	-0.2834197	0.1407977	0.0397436
Morocco	1213.069	2907.188	-0.2182577	-0.2758926	-0.1106018
Mozambique	189.6245	528.313	-0.1214007	-0.3888497	-0.3177779
Myanmar		1138.993	0.1874025	0.5092305	0.5514502
Namibia	1969.167	4803.283	-0.0314299	0.9873396	-0.2614917
Nepal	193.4761	747.1604	-0.423954	0.1670813	0.0886492
Netherlands	21019.12	45175.23	0.1701648	-0.8339831	-0.3223571
New Zealand	13670.2	38649.38	0.1760882	0.1631416	0.0238285
Nicaragua	243.5613	2073.498	0.1551228	-0.0226243	0.1212136
Niger	309.5865	362.7522	0.1440276	-1.191339	0.2405193
Nigeria	567.1859	2729.763	0.1377978	-0.4692993	0.1349664
Norway	28242.94	74521.57	0.1501065	-0.3722035	0.051198
Oman	6448.132	16410.61	-0.1811686	-0.3391783	-0.5286098

Pakistan	371.5726	1428.638	0.1620786	-1.379676	0.0303003
Panama	2603.781	13627.69	0.0454791	0.1331233	-0.0492023
Papua New Guinea	746.5074	2605.946	-0.0248966	-0.2117799	-0.1074625
Paraguay	1379.324	5447.119	0.3205161	1.009516	0.4327772
Peru	1210.006	6053.113	0.2042643	0.5911598	-0.1408247
Philippines	715.3106	2878.338	0.0323454	0.5332677	0.0570351
Poland	1731.21	12556.36	0.0878825	0.5657262	-0.0413225
Portugal	7885.394	19252.63	-0.0788862	-0.4798861	-0.2253895
Puerto Rico	8652.508	29764.06	-0.2465391	0.5937448	-0.8094644
Romania	1680.706	8977.499	0.3624702	0.5715001	0.4736389
Russian Federation	3485.112	9463.809	0.333922	0.3674365	0.0461076
Rwanda	352.4401	711.774	1.273567	1.706062	1.238542
Saudi Arabia	7204.729	20732.86	0.2685056	-0.8529071	0.2418042
Senegal	957.8437	1186.327	-0.175172	0.4740584	0.1369713
Sierra Leone	150.6512	582.9362	0.5330521	1.766608	0.0951771
Singapore	11864.28	54940.86	0.5149704	0.1704745	-0.115859
Slovakia	2395.565	16182.3	0.1614578	0.2126947	-0.0479507
Slovenia		20873.16	-0.0611973	0.0674397	-0.1118069
Somalia		478.7848	-0.0249715	-0.4314797	-0.0464252
South Africa	3076.455	5742.988	-0.1137391	0.0124917	-0.5928316
South Sudan		917.9214	-1.85548	-2.375689	-1.687486
Spain	13767.38	25817.39	-0.532804	-0.2107701	-0.791097
Sri Lanka	463.5132	3844.514	-0.1149738	1.995154	-0.1611471
Sudan	615.8875	2513.885	0.38846	0.0817821	-0.6203782
Suriname	953.1943	8617.762	-0.1726626	0.0462747	-0.716935
Sweden	30162.32	50832.55	0.2076782	-0.4457919	-0.0557289
Switzerland	38428.39	82081.6	-0.0317023	-0.2401881	0.0218947
Syrian Arab Republic	988.9486		-0.9290832	-2.795851	-0.5195997
Tajikistan	497.6401	918.8119	0.3348739	0.7661246	0.1496021
Tanzania	167.2745	879.3362	-0.0248889	0.2860325	0.1230894
Thailand	1508.286	5846.395	-0.728817	-1.449741	-0.3064004
Timor-Leste		2501.577	-1.413793	-0.7088967	-0.5216166
Togo	430.0115	563.4754	-0.0971676	0.0630477	0.0346184
Trinidad and Tobago	4147.639	17941.24	-0.57028	0.1335411	-0.5412604
Tunisia	1492.879	3827.73	0.154265	-1.284895	0.1589935
Turkey	2794.353	10984.8	-0.1012248	-0.6937157	0.04284
Turkmenistan	865.7897	6432.684	-0.0894957	-0.0947758	-0.2128834
Uganda	246.8273	675.1211	0.4003982	0.4431561	-0.1781921
Ukraine	1569.739	2016.01	0.2952543	-1.551573	0.170068
United Arab Emirates	27256.29	39122.05	-0.0359611	-0.215564	0.955012

United Kingdom	19095.47	44472.15	0.1170177	-0.5175367	-0.2629595
United States	23954.48	56803.47	0.0033685	-0.4064458	-0.2608402
Uruguay	2989.991	15524.84	0.1219621	0.0732082	0.3916984
Uzbekistan	651.4192	2137.577	0.1135504	0.9337683	-0.2095504
Venezuela, RB	2446.804		-1.17096	-0.21983	-0.7177974
Vietnam	94.8802	2065.169	0.0230937	-0.3395519	0.1421463
Yemen	468.367	1693.908	0	-1.536711	-0.4226674
Zambia	409.258	1313.89	0.2521993	0.1177915	0.3761703
Zimbabwe	862.5866	1265.294	0.0239528	0.7047499	-0.322019



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