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Analyzing Green Growth and Environmental Quality of Life

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Abstract

Green Growth entails fostering economic progress while safeguarding natural resources to ensure environmental sustainability and uphold our well-being. To assess how environmental factors and associated risks influence the quality of life and well-being of the Indian populace, we conducted an analysis focusing on the environmental dimension, utilizing mortality rates and exposure to harmful pollutants as key indicators. This research relies on OECD data to investigate the impact of environmental conditions on human welfare. Various statistical and mathematical analysis techniques, including time series models such as ARIMA and AR, were employed to examine mortality rates attributed to PM2.5, lead, and ozone. Additionally, the study explored future trends in these mortality rates. Towards the study's conclusion, we conducted a direct comparison between GDP growth rates and the GDP decline rate resulting from the loss of human resources due to environmental risks. The findings indicate that in 2000, for every 100 USD earned, 0.057 was lost due to deaths caused by select environmental risks. By 2019, this figure rose to 0.1 per 100 USD, suggesting that endeavors aimed at boosting GDP are exerting adverse effects on the environment. Recognizing that green growth encompasses both economic and sustainable development policies, it addresses these dual imperatives concurrently. Achieving sustainable economic growth necessitates a comprehensive approach that minimizes environmental harm, underscoring the importance of adopting holistic strategies.

Key words: Environmental, OECD, ARIMA, GDP, underscoring

Introduction

Green Growth focuses on encouraging economic growth, while ensuring that natural assets continue to deliver the environmental resources and services on which our welfare relies. To indicate how environmental conditions and risks associated with them is affecting the quality of life and well-being of people of India. We will analyse environmental dimension of quality of life by mortality rates and exposure to harmful matters. Green growth pillars are anchored on five dimensions which are natural resource base, socio-economic outcomes, environmental productivity, environmental-related policy responses, and quality of life. The OECD in 2009 defined these terms as achieving sustained economic development while reducing the negative environmental externalities including climate change, loss of biodiversity, and natural resource exploitation [1] (https://doi.org/10.1038/s41597-023-02319-4) The quality of the local living environment has a straight impact on human health. A healthy environment is a source of satisfaction, improves mental well-being, and allows people to recover from the stress of everyday life to perform physical activities. Essential aspect of quality of life includes access to resources, green spaces, forests as economies rely not only on healthy and productive workers, but also on natural resources.

Mortality from exposure to ambient ozone

Ozone occurs both in the Earth's upper atmosphere (Stratosphere) and also at ground level. Depending on where it is found it can be classified as good or bad Ozone. Tropospheric ozone created by chemical reactions between oxides of nitrogen (NOx) and volatile organic compounds (VOC) and this happens when pollutants emitted by cars, power plants, industrial boilers, refineries and other sources react chemically to form ozone at ground level in the presence of sunlight.

Mortality from exposure to ambient ozone is expressed in deaths per million inhabitants. Ambient (or ground-level) ozone (O3) has serious consequences for human health, contributing to, or triggering, respiratory diseases like asthma and reduced lung function (as per WHO). Ozone exposure is highest in emission-dense countries with warm summers. The most important determinants are background atmospheric chemistry, climate, anthropogenic and biogenic emissions of ozone precursors and the ratios between different emitted chemicals.

Mortality from exposure to lead

Lead can be added to soils and sediments through deposition from sources of lead air pollution. Elevated lead in the environment can result in decreased growth and reproduction in plants and animals, and neurological effects in vertebrates. Sources that contribute to lead in the ambient air include smelters, mining operations, waste incinerators, battery recycling, and the production of lead shot and fishing sinkers. Lead is also released by the burning of coal, oil, solid waste, and the use of leaded aviation gasoline in piston engine powered aircraft [2].

Mortality from exposure to lead is expressed in deaths per million inhabitants. it is a toxic metal found in the Earth's crust and its extensive use has resulted in wide-ranging environmental contamination and significant public health problems in the various parts of the world. Chief sources of environmental lead contamination include mining, manufacturing and recycling activities, and, in some countries, the continued use of leaded paint, gasoline, and leaded aviation fuel.

Mortality from exposure to residential radon

Mortality from exposure to residential radon is expressed in deaths per million inhabitants. Radon (Rn) is a radioactive gas that arises as a by-product of the decay chain of uranium, occurring naturally within the Earth's crust. Some fraction of this natural radon escapes into the atmosphere, where it forms at low concentration unless build-up is caused by enclosed spaces like homes, mines or caves. It is widely acknowledged that soil gas infiltration is the primary source of residential radon. Although there are other sources such as building materials and well water, they are generally considered less significant. Radon is a significant contributor to the ionizing radiation dose that the general population is exposed to and is considered the second leading cause of lung cancer, after smoking. Numerous epidemiological studies have established a clear link between indoor radon exposure and lung cancer, even at low levels commonly found in residential buildings.

Methodology

In this section we will discuss about: handling data set, Time series Analysis, Stationarity, Seasonality and different types of forecasting model.

Dataset:

Here we are using open-source OECD estimated "Environmental dimensions of quality of life" data for our analysis. The dataset contains last 20 years annual estimates of death due to PM 2.5, Lead, Ozone and Radon. We will explore and clean the data before using it for the analysis.

Data cleaning plays a crucial as it ensures the accuracy and reliability of the data used for further analysis and modeling. Data cleaning in time-series analysis involves the following steps:

1. Missing values: Missing values can occur in time-series data due to various reasons, such as sensor failures, data transmission issues, or human errors. It can be handled through various methods like interpolation, forward filling, backward filling, or dropping rows with missing values.
2. Outlier detection and treatment: Outliers are extreme values that depart significantly from the usual patterns in the time series. Identification of outliers and handling them properly is important to avoid bias in the study.
3. Unpredictable data: data may contain inconsistent or incorrect values, such as inconsistent units, invalid data types, or data entry errors. Different ways to handle functionalities to clean and correct such data inconsistencies, including data type conversion, data normalization, or applying business rules to identify and correct erroneous data.

By examining the data and handling the imperfections through data cleaning steps, we ensure the reliability of the time-series data for accurate and expressive analysis.

Time Series Analysis:

Time series Analysis involve examining past data to unearth pattern, trends & other valuable Insights. It plays an important role in understanding the behavior of time dependent data & making predictions for the future. Understanding data trends and patterns enable us to gain valuable insights and make an informed decisions and predictions based on the available information.

Stationarity:

Stationarity refers to a concept in time-series analysis where the statistical properties of a dataset, such as mean and variance, remain constant over time. Stationarity of the data can be checked through Augmented Dickey-Fuller (ADF) test. Other available method for the same purpose is Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test, and visual inspection of time series plots.

Seasonality:

Seasonality refers to the recurring patterns in a time series that arise at regular intervals. It introduces likely variations in the data over precise periods. Seasonality and stationarity represent different aspects of time series behavior. Seasonality can be tested through techniques such as decomposition analysis and autocorrelation function (ACF) plots. Another way to test for seasonality involves decomposing the time series and analyzing the seasonal component through plots and graphs.

Autocorrelation and partial autocorrelation:

Autocorrelation quantifies the correlation between a variable's current value and its past values at different time lags. On the other hand, partial autocorrelation measures the direct relationship between a variable's current value and its past values, excluding the effect of intermediate-lagged variables.

Different Types of forecasting models

There are various forecasting models in Time series with its own merits, restrictions, and aptness for different kind of data. Some common types of forecasting models are mentioned below:

Moving Average (MA):

This model calculates the average of previous observations to forecast upcoming values. It helps in eliminating the short-term fluctuations and recognize underlying trends in the data.

Autoregressive (AR):

This model assumes that the future values depend on the past values with some amount of lag and uses past observations in linear regression equation to calculate future values.

Autoregressive Moving Average (ARMA):

The ARMA model combines the autoregressive and moving average models, considering both past observations and the average of past errors to make predictions.

Autoregressive Integrated Moving Average (ARIMA):

The ARIMA model is the extension of the ARMA model. Along with other parameters of ARMA is incorporating differencing also to make the time series stationary. It is appropriate for non-stationary data with trends and seasonality. ARIMA is a widely used approach that combines the three components to capture the patterns in time-series data Autoregression (AR), Differencing (I) and Moving Average (MA).

SARIMA:

An extension of the ARIMA model that takes the seasonal patterns in the data also in the account through some additional terms to represent the seasonality, making it suitable for timeseries data with repeated patterns. The seasonal ARIMA model can be implemented in the same way to the ARIMA model but with additional seasonal parameters.

Once the model is fitted, we can use it to forecast future values by specifying the start and end dates for the forecast period.

We have further Quantified the economic impact of these hazards so that policymakers to prioritize mitigation efforts and allocate resources effectively. One proposed method for comparative analysis involves juxtaposing the economic losses attributed to environmental hazards with the GDP growth rate of a country. This method aims to provide insights into the relative magnitude of economic losses in comparison to the overall economic performance of the nation.

Steps involved in the calculation are as follow:

1. We summed the mortalities from different environmental risks to get total Human resource loss due to environmental hazards.
2. Let total mortality from environmental risk per million be 'x', then
3. Mortality due to environmental risks in year 'n' (Mtn) will be

$$Mt_n = \frac{x}{1000000} \times (\text{Populaion in year n})$$

4. If GDP per capita of the country in year n is' y', then GDP loss in year n will be

$GL_n = (MT_n) \times (y)$

5. Similarly, we will find GDP loss for all the years
6. Then, we compare the GDP LOSS RATE with GDP GROWTH RATE by taking the initial as origin year (here, it is year 2000).
7. GDP LOSS RATE for year n1 (GLRn1) where base year is n0 will be:

$$GLR_{n1} = \frac{GJ_{n0} - GL_{n1}}{GL_{n1}} \times 100$$

GDP LOSS RATE for n_1 (GGR_{n1})

$$GGR_{n1} = \frac{GDP_{n1} - GDP_{n0}}{GDP_{n0}} \times 100$$

Similarly, we will find growth and decay for each year in comparison to year 2000 and compare them to get overall scenario of economy growth.

8. GDP loss percent (GLP) – This indicates the amount we loss due to environmental degradation for every 100 rupees earned in the form of GDP, each year.

$$GLP_{n1} = \frac{GL_{n1}}{GDP_{n1}} \times 100$$

Results and Discussion

We have used OECD 20 years of estimated data on mortality per million due to PM 2.5, Lead, Ozone & Radon. The data shows in the last 20 years India has recorded around 518 deaths per million due to PM 2.5, 83 deaths per million due to Ozone, 156 due to lead & nearly 2 people per million die annually due to Radon (Fig. 1). The mortality rate due to each of 4 elements has been increasing but the rate of increase due to PM2.5 has been alarming. if talk about relative dispersion in the mortality numbers then PM 2.5 has a 0.24 coefficient of variation, whereas it is 0.22 for Ozone, 0.06 for Lead & 0.13 for Radon.

After ensuring that there were no outliers or irrelevant entries in our data, we proceeded with Time series analysis. Through the Augmented Dickey fuller test, we check the stationary due to all four pollutants (Fig. 2a, 2b, 2c and 2d).

Through the above test reports, we can conclude that other than lead all other pollutants data is nonstationary and this detail needs to be taken care of while fitting the time series model. We can decompose the data further to get the look of Trend, seasonality, and randomness (Fig. 3a, 3b, 3c and 3d).

Table 1: Other vital statistics related to the given can be checked

Variable	Mean population exposure to PM 2.5	Mortality from exposure to mbient PM 2.5	Mortality from exposure to ambient ozone	Mortality from exposure to lead	Mortality from exposure to residential radon
Count	12.00000	20.000000	20.00000	20.000000	20.000000
Mean	83.551462	517.918800	85.20305	156.169050	2.221350
Std.	7.948600	124.246921	19.16144	9.713394	0.353068
Min.	70.645470	363.672000	64.47600	138.848000	1.808000
25%	79.928215	395.341000	67.80600	147.983000	1.886750
50%	83.257620	484.352000	80.23950	155.408000	2.142500
75%	89.198638	650.362000	98.64700	165.193500	2.462500
Max	95.836600	717.172000	122.97500	170.210000	2.906000

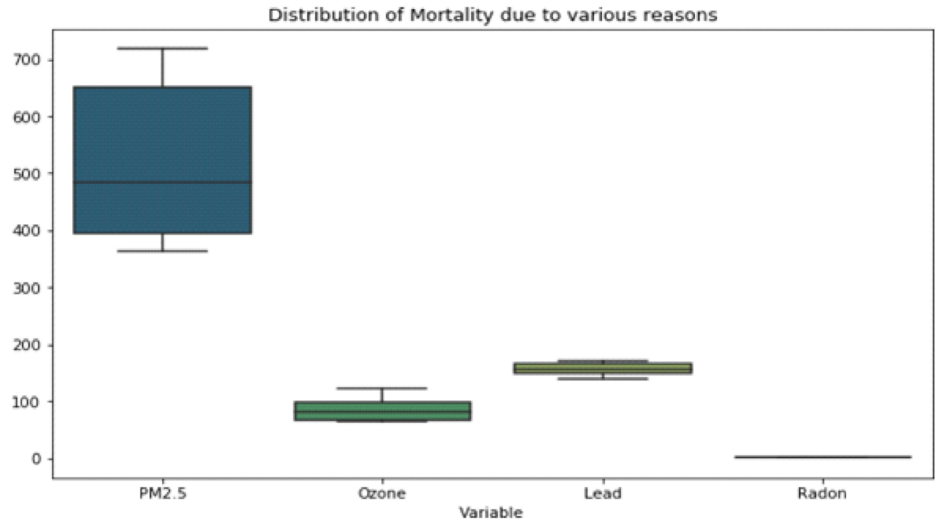


Fig 1: Box plot showing the distribution of data

```
Augmented Dickey-Fuller test :
ADF test statistic       2.466602
p-value                  0.999038
#lag-value               8.000000
#nobs                   11.000000
critical value (1%)     -4.223238
critical value (5%)     -3.189369
critical value (10%)    -2.729839
dtype: float64
Weak evidence against the null hypothesis
Fail to reject the null hypothesis
Data has a unit root and is non-stationary
```

Fig 2a: PM2.5

```
Augmented Dickey-Fuller test :
ADF test statistic       1.677045
p-value                  0.998071
#lag-value               8.000000
#nobs                   11.000000
critical value (1%)     -4.223238
critical value (5%)     -3.189369
critical value (10%)    -2.729839
dtype: float64
Weak evidence against the null hypothesis
Fail to reject the null hypothesis
Data has a unit root and is non-stationary
```

Fig 2b: Ozone

```
Augmented Dickey-Fuller test :
ADF test statistic      -4.494005
p-value                  0.000202
#lag-value               7.000000
#nobs                   12.000000
critical value (1%)     -4.137829
critical value (5%)     -3.154972
critical value (10%)    -2.714477
dtype: float64
Strong evidence against the null hypothesis
Reject the null hypothesis
Data has no unit root and is stationary
```

Fig 2c : Lead

```
Augmented Dickey-Fuller test :
ADF test statistic       2.281099
p-value                  0.998943
#lag-value               8.000000
#nobs                   11.000000
critical value (1%)     -4.223238
critical value (5%)     -3.189369
critical value (10%)    -2.729839
dtype: float64
Weak evidence against the null hypothesis
Fail to reject the null hypothesis
Data has a unit root and is non-stationary
```

Fig 2d: Radon

Since data is recorded on an annual basis, seasonality cannot be found in our data values but an upward trend is observed in all four graphs. Though a significant drop was seen in the death rate due to lead in 2004 and due to Ozone in the year 2010, However, India's living quality deteriorated faster than ever after 2010.

The result shows that many Indians die from the effects of pollution every year and this number is increasing year after year. To forecast these numbers, we have used the ACF PACF plot along with Python's auto_arima function to find the best parameters. After hyperparameter tuning we found the ARIMA (0, 2, 1) model performing best for

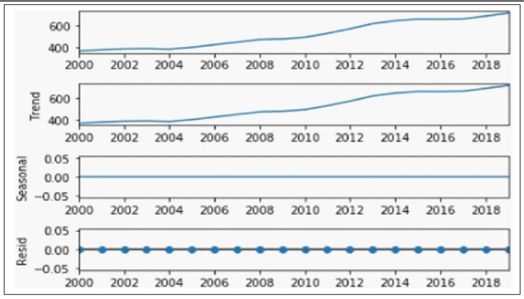


Fig 3a: PM2.5

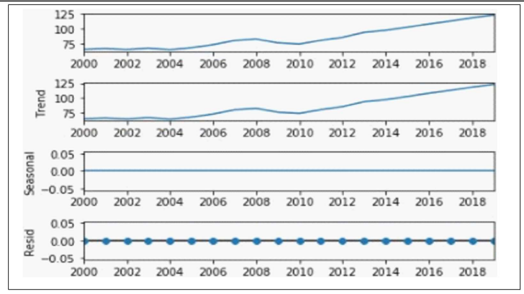


Fig 3b: Ozone

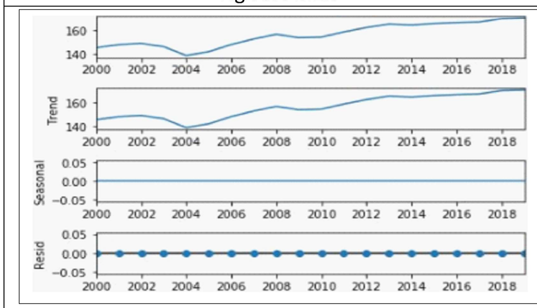


Fig 3c: Lead

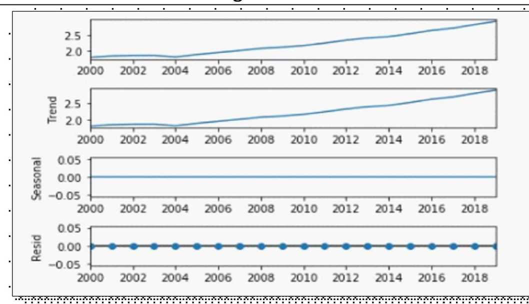


Fig 3d: Radon

Fig 3: Trend, Seasonality and Randomness in the data

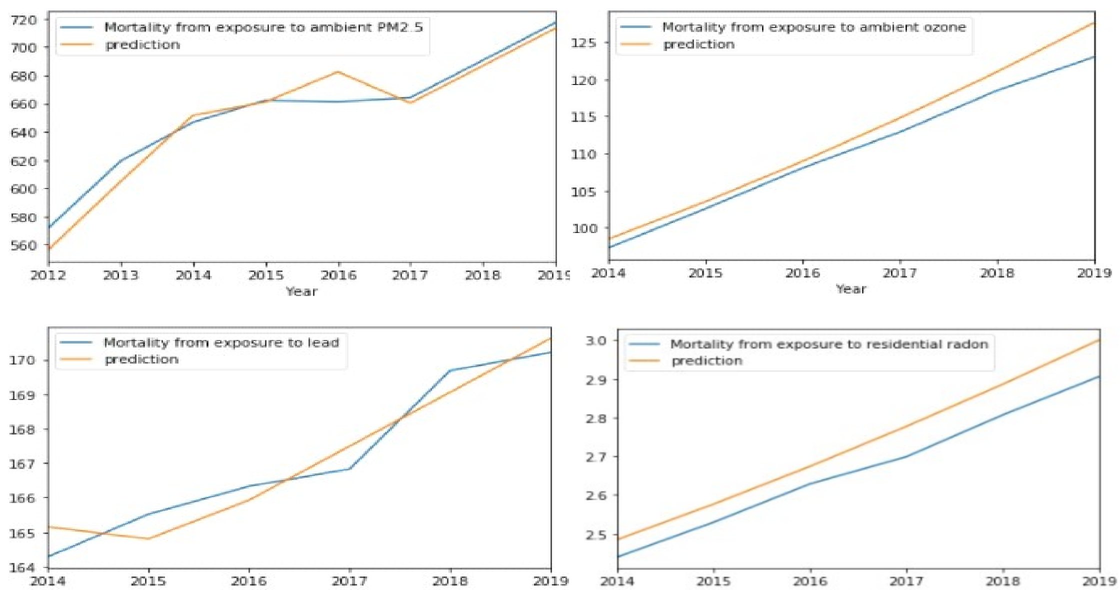


Fig 4 : Fitted model performance over test set

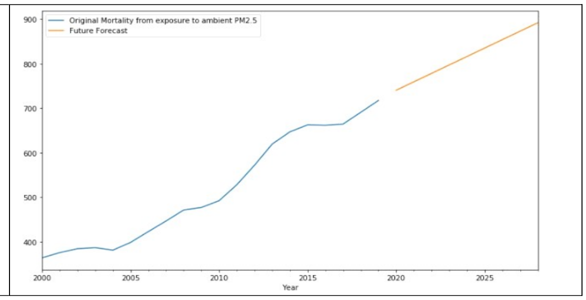
Radon exposure mortality, with 0.06 root mean square error (rmse), for ozone ARIMA (0, 2, 1) is suggested as the best model with relatively higher rmse, i.e. 2.38. For Lead, ARIMA (0, 1, 3) turns out to be the best model with 0.63 rmse, and though an ideal model cannot be found for PM 2.5 but tuning the parameters we achieved the least rmse as 10.98 with ARIMA (0, 1, 1) model (Fig. 4).

Further, we used above mentioned model to forecast the future values which can be checked through the tables given in Fig. 5.

We have further Aggregated the economic losses across different categories to derive a comprehensive estimate of the total impact utilizing the GDP of India from 2000 to 2020 and derived resultant Fig. 6, 7 and 8.

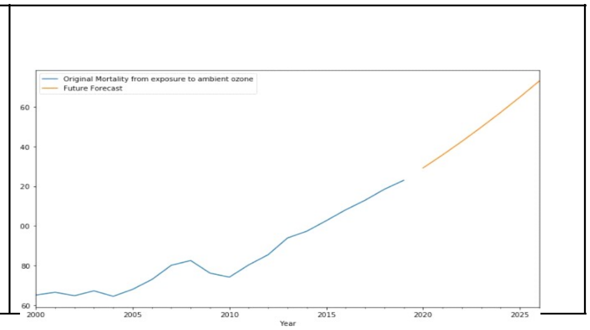
PM2.5

	Forecasted Value
2020-01-01	740.126229
2021-01-01	759.079824
2022-01-01	778.033419
2023-01-01	796.987014
2024-01-01	815.940609
2025-01-01	834.894204
2026-01-01	853.847800
2027-01-01	872.801395
2028-01-01	891.754990

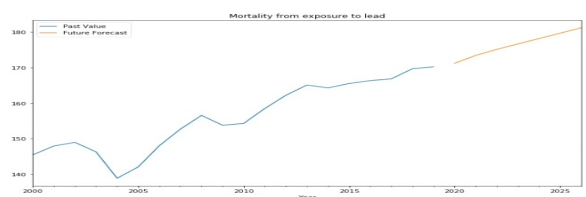


Ozone

	Forecasted value
2020-01-01	129.195675
2021-01-01	135.726540
2022-01-01	142.567597
2023-01-01	149.718845
2024-01-01	157.180285
2025-01-01	164.951915
2026-01-01	173.033737



	Forecasted Value
2020-01-01	171.224223
2021-01-01	173.422411
2022-01-01	175.130027
2023-01-01	176.647438
2024-01-01	178.164849
2025-01-01	179.682260
2026-01-01	181.199671



	forecasted Value
2020-01-01	3.011476
2021-01-01	3.121712
2022-01-01	3.236707
2023-01-01	3.356462
2024-01-01	3.480977
2025-01-01	3.610251

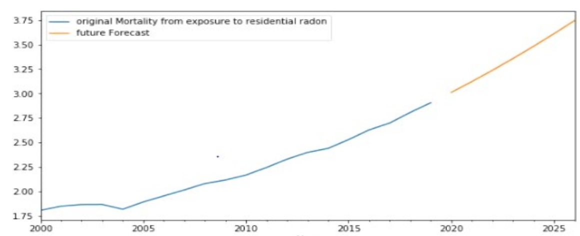


Fig 5 : Future Forecast

The last columns of the above table represent GDP LOSS PERCENT (GPL) concerning GDP

- In the year 2000, out of every 100 USD earned 0.057 is lost due to death due to a few environmental risks. In 2019 this number goes up to 0.1 per 100 USD.

The data revealed a disconcerting trend where the rate of loss in GDP due to environmental hazards outpaced the GDP growth rate. This implies that the economic costs incurred from environmental disasters and degradation are significantly higher than the gains achieved through economic growth. Such a revelation underscores the urgency of addressing environmental risks as a critical impediment to sustainable economic development.

Conclusion

In light of pressing economic and environmental challenges, there has been a noticeable surge in national and international efforts to advocate for green growth as a new avenue for economic development. This momentum offers a promising pathway towards sustainable progress and poverty alleviation. By prioritizing more sustainable utilization of natural resources, enhancing energy efficiency, and recognizing the value of ecosystem services, we can mitigate the adverse effects of detrimental economic practices.

Our analysis underscores a critical point: the pursuit of economic growth, often measured by GDP, has inadvertently led to environmental

Year	Mortality from env risks	GDP loss	GDP Loss, index 2000 = 100	GDP loss percent
2000-01-01	608.606506	2.698039e+08	100.000000	0.057602
2001-01-01	636.019524	2.904924e+08	107.667990	0.059165
2002-01-01	655.691799	3.056611e+08	113.290096	0.059973
2003-01-01	669.078011	3.309076e+08	122.647467	0.060195
2004-01-01	661.968408	3.476689e+08	128.859844	0.058601
2005-01-01	700.260070	3.956283e+08	146.635516	0.061019
2006-01-01	752.256107	4.572543e+08	169.476532	0.064544
2007-01-01	805.934868	5.298407e+08	196.379925	0.068114
2008-01-01	855.145812	5.755740e+08	213.330512	0.071222
2009-01-01	863.153591	6.214010e+08	230.315809	0.070882
2010-01-01	891.785393	6.983894e+08	258.850740	0.072251
2011-01-01	961.290180	7.925180e+08	293.738548	0.076886
2012-01-01	1040.035937	8.931569e+08	331.039280	0.082166
2013-01-01	1127.945439	1.018392e+09	377.456554	0.088063
2014-01-01	1179.989113	1.131293e+09	419.301982	0.091077
2015-01-01	1222.359064	1.253399e+09	464.559430	0.093299
2016-01-01	1242.864735	1.350267e+09	500.462427	0.093835
2017-01-01	1267.131171	1.453072e+09	538.566063	0.094655
2018-01-01	1327.610253	1.596201e+09	591.615190	0.098149
2019-01-01	1384.540549	1.715358e+09	635.779444	0.101326

Fig 6 : GDP loss due to Mortality from environamnetal risks

Year	GDP LOSS RATE	GDP GROWTH RATE
2000-01-01	0.000000	0.0000
2001-01-01	7.667990	4.8240
2002-01-01	13.290096	8.8114
2003-01-01	22.647467	17.3644
2004-01-01	28.859844	26.6631
2005-01-01	46.635516	38.4236
2006-01-01	69.476532	51.2471
2007-01-01	96.379925	66.0714
2008-01-01	113.330512	72.5331
2009-01-01	130.315809	87.1636
2010-01-01	158.850740	106.3665
2011-01-01	193.738548	120.0658
2012-01-01	231.039280	132.0735
2013-01-01	277.456554	146.8940
2014-01-01	319.301982	165.1894
2015-01-01	364.559430	186.8140
2016-01-01	400.462427	207.2142
2017-01-01	438.566063	227.7398
2018-01-01	491.615190	247.2064
2019-01-01	535.779444	261.4268

Fig 7 : GDP growth rate V/s Loss rate table

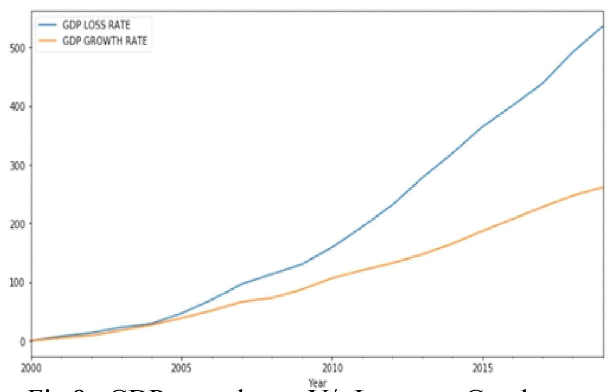


Fig 8 : GDP growth rate V/s Loss rate Graph

degradation that outweighs the economic gains. It's evident from the data presented in the graphs and tables that unsustainable economic practices yield losses far greater than any perceived benefits in economic growth.

The need of the hour is a holistic approach that reconciles economic growth with environmental preservation. Green growth is not merely an economic policy; it's a crucial component of sustainable development policy. It addresses the dual imperatives of fostering inclusive economic growth to alleviate poverty and enhancing environmental stewardship to combat resource depletion and climate change.

Initially, green growth was approached diversely by different governments. Some viewed it through the lens of short-term economic expansion, focusing on the potential for job creation and income generation via investments in green technologies. Others saw it primarily as an environmental imperative, aiming to internalize environmental costs into economic decisionmaking processes.

In many developing countries, the substantial presence of the informal economy underscores the importance of considering its dynamics in any transition towards green growth. Such a transition should aim at not only creating new green opportunities but also ensuring more equitable distribution of costs and benefits, along with resilient livelihoods for marginalized populations.

Ultimately, transitioning to green growth requires a systemic overhaul. It entails better alignment of economic, environmental, and social policies and institutions, identifying synergies while acknowledging trade-offs and uncertainties. Moreover, it demands a nuanced understanding of the political economy underlying the changes needed across diverse contexts.

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