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RESEARCH ARTICLE

Green Growth Index for India: Drivers, Disparities, and Ramifications

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Abstract: This article introduces a novel green growth index (GGI), offering a new benchmark for assessing the performance of Indian states in sustainable development. Departing from traditional indices like the Human Development Index and Sustainable Development Goal Index, our approach integrates economic, environmental, and social factors, providing a comprehensive perspective on sustainable development. The study emphasizes the critical role of energy use and input utilization efficiency as major drivers of green growth disparities, alongside conventional economic growth. The findings suggest that robust governance institutions are also key contributors to green growth. The research reveals that states with higher gross domestic product generally exhibit better performance on the GGI but also underscores the importance of addressing the uneven development across different pillars of green growth. The insights and methodologies presented here are poised to inform targeted policy interventions and contribute to ongoing efforts in promoting inclusive and sustainable green growth, taking into consideration the complex trade-offs between environmental protection and socioeconomic inequalities.

Keywords: green growth, sustainable development, inequality, Indian economy

1. Introduction

Gross domestic product (GDP) is frequently used as a measure of the overall health of an economy. This implies that if a country's GDP rises, so will its people's well-being, because an increase in GDP means an increase in per capita real income, leading to an increase in per capita availability of final goods and services. As a result, a country's greater GDP level might be seen as a measurable index of economic welfare. But this raises three main issues.

First is the nature of who is benefiting from this growth or quality of growth. One seminal work in this domain, "The Quality of Growth" by Thomas et al. [1], concentrates on all assets: physical, human, and natural capital while looking at the distribution of the same across time and highlights the importance of the institutional framework for good governance. Second, this implies an economy can grow forever. Many believe that an ever-growing economy is essential to increase the standards of living of people since if the latter stops growing, there would be ever-increasing competition for access to limited resources. This has raised the question of whether such an assumption of growth is even possible [2]. Third, environmental factors are often not considered in the costs of economic growth and are treated as externalities. This means the environmental costs of running an economy remain unaccounted for and it increases the risk of catastrophes that could undo years of growth altogether. Many still follow the "pollute first; clean up later" principle when it comes to development based on the flawed idea that levels of environmental degradation would fall as countries become richer [3]. Hence the explicit identification of trade-offs between economic benefit and social/ecological impact becomes important.

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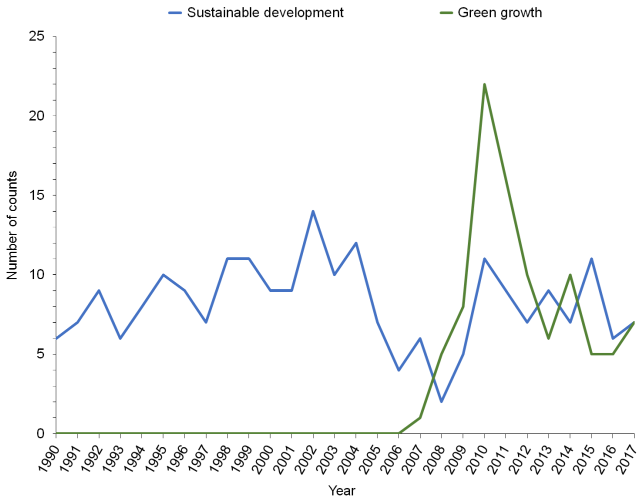
Green Growth entails promoting economic growth and development while ensuring that natural assets continue to supply the resources and environmental services that humanity relies on for their well-being [4]. As such, it is closely related to sustainable development as it looks for a future where current economic growth is not at the cost of exploitative resource consumption and negative environmental externalities. There are differences in the definition of what constitutes green growth. If the World Bank definition focuses on efficiency in its use of natural resources while minimizing environmental impact, the United Nations Environment Programme (UNEP) definition gives equal importance to social equity and ecological scarcity [5, 6].

The term "green growth" was first used in 2005 at the Fifth Ministerial Conference on Environment and Development in Seoul, South Korea, where the *Seoul Initiative Network on Green Growth* was founded. An analysis of reports from major international organizations portrays a major change in global environmental policy over the last 30 years with the emergence of green growth over sustainable development. This shift in policy, as observed in Figure 1 [7], is primarily driven by the recognition of the urgent need to address climate change and its impacts, which pose significant threats to human well-being and economic growth [7]. While sustainable development seeks to reconcile environmental protection and economic prosperity, the discourse of green growth seeks to redefine environmental protection as a positive factor for development rather than as a barrier to it [8].

Our proposed green growth index (GGI) provides a baseline measurement of economic growth that leads to the enhancement of social equity and environmental sustainability. This definition is particularly relevant in the Indian context, where rapid economic development has often come at the expense of environmental degradation and social disparities. In its design, this

Figure 1
The rise of green growth in global environmental discourse



index primarily emulates Global Green Growth Institute's approach of constituting green growth into separate indicator pillars while the selection of relevant indicators comes from the Asian Development Bank's inclusive GGI. The latter includes diverse variables, which provide comprehensive insights into the interplay between the indicator pillars. The index also provides a significant improvement over other India-specific indices like the NITI Aayog's Sustainable Development Goals (SDG) Index, which primarily focuses on achieving specific SDG, while the GGI provides a holistic view that aligns with long-term ecological and societal well-being, making it a more robust measure of progress toward equitable development.

Green growth was one of the seven top priorities of India's Union Budget for 2023–2024, given the reality that real growth is needed to lift millions out of poverty and provide an improved quality of life to people within the ecological space and constraints of carbon emissions. Thinking about green growth is especially relevant in the Indian context, given the increasing environmental degradation and the disproportionate impact of climate change on the poor. Further, biodiversity loss, land degradation, and pollution in India are exacerbated by climate change, threatening ecosystems and livelihoods. As rising temperatures and erratic weather patterns intensify, these environmental challenges undermine efforts to achieve sustainable development [9].

In a country where nearly 50% of the population depends on agriculture, on average, one standard deviation rise in temperature causes a 1.7% fall in consumption in agriculture households across both rural and urban areas [10]. These dynamics underscore the critical need for policies that simultaneously address environmental concerns and socioeconomic inequalities, aligning with the developmental goals aimed at uplifting the disadvantaged while also fostering environmental sustainability. The proposed GGI will help in holistically measuring the progress of achieving development goals with economic growth at the subnational level in India.

2. Literature Review

The comprehensive literature review throws light on the key pillars for the proposed GGI, as given below:

1) Relationship between the environment and the economy

The interplay between income and environmental quality is synonymous with literature on the Environmental Kuznets Curve (EKC), which hypothesizes an inverted U-shaped relationship between various environmental degradation indicators and per capita income. However, there is no clear evidence as to whether such a relationship exists at all. Only a few air quality measures display a strong (but not convincing) indication of an EKC. There is, however, no consensus on the income level at which environmental degradation starts to decline, even when an EKC is actually established. Further, studies that focus on a single nation and look at the environment–income link for a given period find no proof of an EKC [11].

There is also a disparity in the studies focusing on developed economies vis-à-vis developing economies. Ravallion et al. [12] note that the income–emissions relationship depends on the marginal propensity to emit (MPE). Hence, if the poor have a higher MPE, increased inequality will improve aggregate environmental quality, conditional on average income implying that a trade-off exists between promoting inequality/economic growth and carbon emissions at least in the short run. However, Dorn et al. [13] provide a more mixed picture noting that the trade-off between inequality and carbon emissions depends on the level of income. Hence, reductions in income inequality are linked to reduced per capita emissions for nations with high income inequality. Income inequality reductions in less unequal economies are linked to higher per capita carbon emissions.

Another crucial aspect that relates to environmental outcomes is the debt levels in the economy. For developing countries, constrained budgets limit nations' ability to invest in economic development, social protection, emissions reductions, and building resilience to the mounting costs of climate change [14].

2) Impact of institutional factors on environment

One also needs to think that the level of pollution is also directly affected by political choices and social realities. Using greener energy sources often comes at the cost of loss of jobs from traditional energy industries and costlier energy bills in the short term, which makes the transition extremely unpopular. Experience from the Eastern bloc shows that authoritarian regimes often face a trade-off between higher levels of pollution and economic prosperity when compared with the democratic ones in Western Europe. Boyce [15] argues that the distribution of income and societal power can have an impact on a society's decision regarding the level of environmental quality. The hypothesis looks at environmental damage as having winners and losers whereby one could determine the socially optimum levels of pollution. Since social choices governing environmental degradation will consistently favor some people over others, the extent and social costs of environmental deterioration increase with higher power inequality. The inequality–pollution relationship within a nation was examined by Torras and Boyce [16] using the Gini index for economic inequality, adult literacy rates, and a summation of political rights and civil liberties. The results show a strong association between literacy and rights with lower levels of pollution in low-income countries. Similarly, Scruggs [17] analyzed the impact of democracy among other variables on our different pollutants (sulfur dioxide, particulate matter, fecal coliform, and dissolved oxygen), although the results showed a weak association. Evidence from China shows that authoritarian governments are selective in responsive behavior toward environmental governance [18].

3) Relationship between environment and energy consumption

It is widely accepted that utilizing non-fossil fuel energy sources, such as renewable options like solar and wind power, can lead to a reduction in air pollution. However, it is important to note that the use of these alternatives may also result in other forms of pollution, particularly the long-term environmental liabilities. Generally, the adoption of renewable energy contributes to safeguarding the environment. In the context of developing economies, Maji and Adamu [19] examined the effects of renewable energy on environmental quality in Nigeria, and they come to the conclusion that renewable energy has a positive impact on the quality of the environment. But, in developed economies, renewables often don't contribute to emission reduction and showed mixed results owing to issues with storage technology [20]. Ghosh [21] notes that in the context of BRICS economies, policies to reduce inequality and policies to execute infrastructure development for renewable energy are closely related. Further, renewable energy accounts for emission reduction in resource-dependent economies as well with the same having a greater impact on reducing CO_2 emissions in nations with a propensity toward the rule of law [22]. The primary cause of increasing emissions in all South Asian countries is the growth in per capita income. As individuals and households earn more, not only does total energy consumption increase, but the consumption becomes more energy-intensive as well [23]. South Asian countries are highly reliant on coal-based power and need to shift to low-carbon energy like renewables to reduce emissions and secure future energy supply. However, high start-up costs and slow financial returns make this transition difficult, leading to low investments. Nevertheless, pollution was not conceptualized as a major driver of this study; however, the reason for the exclusion of certain data was the lack of state-level information regarding major pollutants or emissions from various activities. To address this gap, we utilized proxy data through the air pollution mortality variable, which examines the percentage of total deaths attributable to air pollution in each state, as reported by the Global Burden of Disease Study [24]. This approach allowed us to infer the impact of air quality on public health, despite the absence of direct emission data.

Combining (1), (2), and (3), we can construct a general function for GGI as

$$GGI = f(economic\ growth,\ social\ equity,\ \ environmental\ sustainability)$$

Hence this paper primarily attempts to answer the following question:

> *How do cross-regional differences in growth, social equity, and environmental performance affect green growth?*

We answer this question with the aid of a GGI that allows us to measure these differences as a baseline and assess the performance of Indian states.

3. Constructing a Green Growth Index: Theoretical Framework

Daly et al. [25] proposed the ISEW (Index of Sustainable Economic Welfare), the first index of sustainable economic welfare, in 1989, which attempted to integrate the economic aspects of an economy, as depicted by conventional national accounting, with social (income inequality) and environmental (pollution) aspects. In the 1990s, the triple bottom line (TBL) framework came to be in parlance, which expanded on traditional profit, return on investment, and shareholder value criteria to incorporate environmental and social elements. TBL reporting hence was used as a significant instrument to support sustainability goals by focusing on total investment results along the interrelated dimensions of profits, people, and the planet [26].

A composite index (indicator) variable is a scale measurement that represents a certain hypothetical construct that cannot be quantified by a single question or category. Hence, by using multiple indicators to construct an index, one can capture complex trends and patterns that might not be apparent through simple measures. This helps in having a nuanced understanding of a socioeconomic phenomenon rather than relying on a single metric. Higher index values would imply "more of," while lower values may indicate "less of," with neither being "right" nor "wrong" [27]. These indicators can be broadly classified into two categories: macroeconomic indicators and structural indicators. While the former explains short-term economic development (e.g., productivity, competitiveness, etc.), the latter focuses on situations that involve a permanent change (innovation, reforms, environment, etc.) [28]. Our proposed index would largely come under the list of structural indicators.

As per the Organisation for Economic Co-operation and Development et al. [29], the standard approach in an index construction consists of selecting suitable, multivariate data to examine the relationship between the individual indicators, normalizing the indicators into a comparable scale to offset the use of different measurements, which is then followed by weighting and aggregation. A composite index is often designed in such a way that its values range from 0 to 1. This simplifies the meaningful interpretation of the results obtained. It is also anticipated that the outcome will be more positive as the value of the composite index increases. Hence, we can assume each indicator to directly influence the index value toward its maximum bound.

Conflicts about the best way to allocate weights are also difficult to resolve. There are numerous common problems encountered when proposing weights to integrate various indicators into a unified measure. Many published weighing procedures are either arbitrary, relying on unnecessarily complicated multivariate approaches, or erroneous and devoid of social value. The optimal selection of differentiated weights is complex and can be misused, leading to skewed results. For instance, a country's index score would be biased when it ranks high on dimensions with the highest weight while being a lower performer on others with lower weights, undermining comparability, and the idea of a multidimensional index. On the other hand, equal weighting of all subcomponents avoids trading off one dimension for another [30].

We construct the GGI using data from widely accepted data sources for 30 Indian states, for 19 variables that are broadly classified into three pillars: *economic growth*, *social equity*, and *environmental sustainability* (Table 1). The summary statistics of the same is provided in Table 2. We have included data from the latest available period and have imputed data from other sources wherever the current data was unavailable. This means a specific base year cannot be retained for the index. However, since the index is constructed using the same underlying principle of other important indices used for comparison at the national level – such as the Human Development Index and SDG Index – it permits cross-analysis and inclusion of socioeconomic and environmental factors that were otherwise not fully captured by these indices. Further, it provides a baseline measurement for green growth across Indian states on the basis of which future monitoring can be maintained. The indicators primarily relate to several aspects of growth, such as growth rate and public debt and policy interventions in sectors where increased investment would result in a greater standard of living, such as gender disparities in education, and environmentally friendly resource usage.

Table 1
List of indicators used in construction of green growth

SI no.	Variable name	Description	Nature of effect	Source
Economic Growth Pillar				
1	GDP capita PPP ($)	The per capita gross domestic product of a given state minus deprecation of capital goods, adjusted to purchasing power parity	+	RBI Handbook of Statistics
2	CV of GDP growth	The coefficient of variation (CV) measures the ratio of the standard deviation to the mean of a state between 2012 and 2019	–	Ministry of Statistics and Programme Implementation
3	Old age dependency ratio	The number the population aged 65-plus per 100 of the population ages 16–64 for a given state	–	Census of India and Indiastat.com
4	Debt-to-GDP ratio	The ratio of government debt to the total GDP of the state in percent	–	RBI and Indiastat.com
5	Worker-to-population ratio	The ratio of the total number of workers in a state and the population in the same, multiplied by 100	+	Periodic Labour Force Survey
Social Equity Pillar				
6	Labor force participation gender gap	The difference in labor force participation rates of females and males in a state	–	Periodic Labour Force Survey
7	Life Expectancy at birth	The average number of years that a new-born could expect to live at current death rates for a specific state	+	National Family and Health Survey 5
8	Infant mortality rate	The number of infant deaths for every 1,000 live births for a state	–	Sample Registration System
9	Primary enrollment gap	The difference in primary enrollment rate between female and male children for a given state	–	Ministry of Education and Indiastat.com
10	Gini coefficient	Measure of inequality of household assets and amenities based on NFHS 4	–	Joe and Mishra [31]
11	Poverty head count (MPI)	Measure of poverty by equally weighted dimensions of health, education, and standard of living based on NFHS 4 data, for a state	–	NITI Aayog
12	Average years of formal education	Number of academic years a person completed in a formal program for a state	+	NSS 75th Round
13	Access to tap water	Percentage of households having access to safe and adequate drinking water in a state	+	Department of Drinking Water and Sanitation and Delhi Socioeconomic Survey
14	No access to electricity	Percentage of households not having access to grid-based electricity in a state	–	India Residential Energy Survey and Council on Energy, Environment and Water (CEEW)
15	Gender participation gap in politics	The difference in the percentage of female and male legislators for a given state	–	Association for Democratic Reforms
Environmental Sustainability Pillar				
16	Renewable fresh water per capita	Availability of total groundwater recharge per person expressed in liters, for a given state	+	Central Ground Water Board
17	Use of renewable energy	Energy consumed from renewable sources as a percentage of total energy consumed for a given state	+	National Power Portal
18	Air pollution mortality	Percentage of total deaths attributable to air pollution in the state	–	Global Burden of Disease Study
19	Energy intensity	State-wise total energy consumption by ultimate consumers divided by GDP expressed in KJ	–	Ministry of Power and Indiastat.com

Table 2
Summary statistics for 19 indicators of green growth index

Variables	(1) N	(2) Mean	(3) SD	(4) min	(5) max
GDP capita PPP	30	7,670	4,322	1,976	19,559
CV of GDP growth	30	0.295	0.104	0.100	0.530
Old age dependency ratio	30	46.69	10.20	32.60	79.80
Debt/GDP	30	32.80	10.15	1.800	55.70
Worker population ratio	30	53.29	7.759	39.90	71.30
Labor force participation gender gap (%)	30	40.19	11.63	19.10	60.30
Life expectancy at birth	30	71.29	2.484	65.70	77
Infant mortality rate	30	22.77	11.94	3	46
Primary enrollment gap	30	5.273	2.845	1.560	13.90
Gini coefficient	30	0.272	0.0685	0.160	0.400
Poverty head count MPI (%)	30	19.43	13.11	0.710	52.91
Average years of formal education	30	8.613	0.792	7.200	10.30
Access to tap water (%)	30	68.65	23.00	31.85	100
No access to electricity (%)	30	1.077	1.715	0	6.800
Women political participation gap (%)	30	85.40	9.839	60	100
Renewable freshwater per capita (L)	30	490,117	466,597	19,061	2.305e + 06
Use of renewable energy (%)	30	48.60	34.49	2.820	100
Air pollution percent of death (%)	30	16.41	2.968	11	21.20
Energy intensity in KJ	30	1,414	622.5	439.4	3,017

4. Data and Methodology

We build a composite indicator using data from various sources that can broadly capture the dimensions of economic growth, social equity, and environmental sustainability.

We normalize each of the 19 variables mentioned above using the min-max normalization approach as follows to achieve an index score range of 1–6. This range makes it compatible with other similar indices like the World Bank's Worldwide Governance Indicators, as shown in Equations (1)–(7).

Given that a = lower bound and b = upper bound:

$$a + \left(\frac{X_i - X_{min}}{X_{max} - X_{min}}\right)(b - a) \tag{1}$$

For indicators where a larger value indicates a worse outcome or when the impact direction is negative (such as air pollution or inequality), the transformation formula is as follows:

$$b + \left(\frac{X_i - X_{min}}{X_{max} - X_{min}}\right)(-1)(b - a) \tag{2}$$

This inverted transformation algorithm assures that ratings of 1 and 6 continue to represent the worst and best conceivable outcomes.

Weight coefficients should meet the condition for equal weighting:

$$\sum_{j=1}^{n} w_j = 1 \tag{3}$$

A given state's scores in the economic growth, social equity, and environmental sustainability pillars are different, which means that it is not performing equally well on all the pillars. To account for this gap, we include an additional pillar "Z" to denote the absolute gap between the three pillars.

$$\begin{aligned} \mathrm{Z} = &|\text{economicpillar} - \text{equitypillar}| \\ &+ |\text{equitypillar} - \text{environmentalpillar}| \\ &+ |\text{environmentalpillar} - \text{economicpillar}| \end{aligned} \tag{4}$$

This value "Z" is further normalized as:

$$Z' = \left(\frac{Z_i - Z_{min}}{Z_{max} - Z_{min}}\right) . (-1) \tag{5}$$

Hence the generalized form of the final balanced GGI would come as:

$$Index_i = \frac{1}{n}\sum_{1}^{n} I_n \tag{6}$$

where n denotes the total number of separate indicator pillars.

Furthermore, an index variable of univariate distribution v with observed min_{old} and max_{old} values (which could be predetermined potential bounds for values) can be rescaled to a new range min_{new} and max_{new} by the following algorithm:

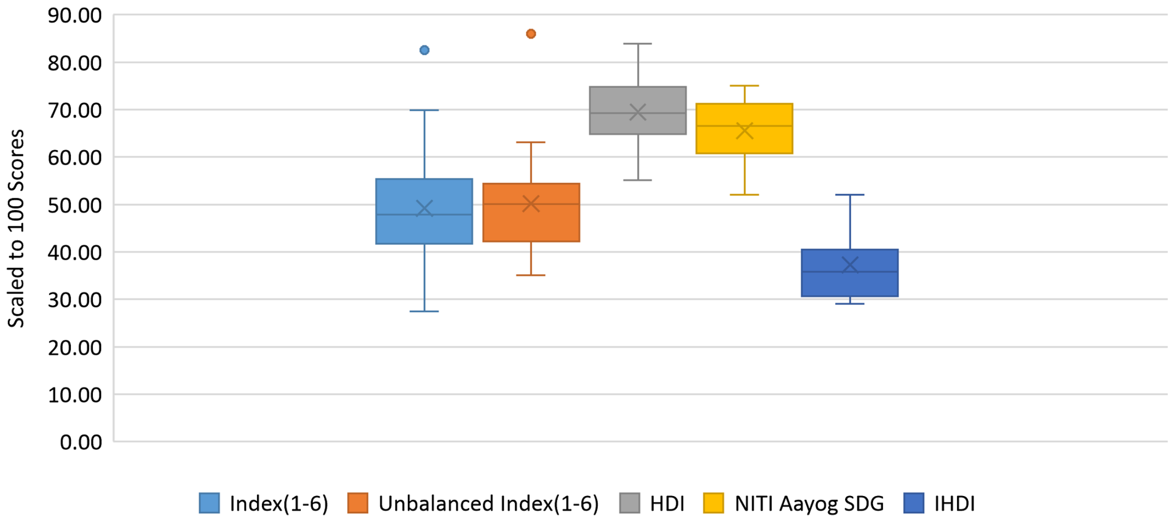
$$\frac{max_{new} - min_{new}}{max_{old} - min_{old}} \times (v - max_{old}) + max_{new} \tag{7}$$

It has to be noted that by using this methodology, we arrive at an unbalanced index, which is the mean score of the three pillars (economic growth, social equity, and environmental sustainability) and a balanced index, which accounts for the gap between these pillars. The balanced index is basically the mean score of the three pillars and the fourth pillar "Z." This balanced index would naturally penalize states that have unequal performance across the three different pillars.

5. Observations

The state-level GGI scores are compared against three other popular development indices that are available for Indian states:

Figure 2
Comparison of green growth index with other indicators



(i) the Human Development Index (HDI), (ii) HDI's inequality-adjusted counterpart, and (iii) NITI Aayog's SDG Index. As given in Figure 2, the range of values of the GGI is at a lower bound than HDI and SDG Indices but on a higher scale than inequality-adjusted HDI. The HDI measures just three broad measures: income, life expectancy, and education, which essentially link measures more prevalent in developed economies. A higher level of health, for example, is a result of a larger income per capita [32]. Critics have questioned the value of including such indicators when one alone might be a better indicator of a country's well-being. The GGI instead includes various environmental and social equity indicators that lead to a lower score. Further, only the economic growth pillar and social equity pillar show a significant correlation that adjusts for some of the pressing criticisms raised against HDI (Table 3).

In the case of NITI Aayog's SDG Index, the difference can be accounted for due to two reasons. First, it leaves out SDG 12, 13, 14, and 17 from its construction. However, these SDGs, that is, 12, 13, and 14 (Sustainable Consumption and Production, Climate Action, and Life Below Water), are roughly included in the GGI via the indicators of renewable freshwater per capita (L), use of renewable energy, and energy intensity in KJ by our index. Second, the SDG Index uses a "National Target" as the upper bound in the normalization method instead of the min-max method followed here.

The inequality-adjusted HDI (IHDI) values are only reported for 18 states as smaller states are missing [33]. These are also the states that typically tend to have higher values of HDI with lesser inequality not to mention the values are over a decade old, which negates the purpose of further investigation. Further, the IHDI uses a geometric mean for the final score, which is fundamentally different from the other three measures that use a simple arithmetic mean. A summary of the methodological differences in the construction of GGI with other aforementioned indicators is given in Table 4.

The salient observations from our index, which is summarized in Table 5, are as follows:

1) The unbalanced index follows a typical pattern, as seen in Figure 3, which is prevalent among other indicators with smaller states coming at the top. This changes dramatically once we account for the absolute gap that exists among the pillars. The top performers in the unbalanced index are Sikkim (5.10), Arunachal Pradesh (4.54), and Goa (4.06). However, for the balanced index, the same becomes Sikkim (5.32), Karnataka (4.18), and Maharashtra (4.06).
2) The loss due to the gap between pillars was the starkest in Arunachal Pradesh (23%), Punjab (21%), and Delhi (17%). While Punjab and Delhi perform well in the economic and social equity pillars they are among the lowest ones in the environmental sustainability pillar. In the case of Arunachal, while it is the frontrunner in environmental sustainability, it performs badly in the other two pillars. It must also be noted that, on average, the loss in the index score is very low since gains are also taken into account.
3) Uttar Pradesh and Jammu and Kashmir have some of the lowest balanced index scores, 2.99 and 2.72 respectively, indicating

Table 3
Correlation matrix between different pillars of green growth index

Variables	(Economic growth pillar)	(Social equity pillar)	(Environmental sustainability pillar)	(Absolute gap)
Economic growth pillar	1.000			
Social equity pillar	0.511*	1.000		
Environmental sustainability pillar	0.227	0.302	1.000	
Absolute gap	−0.015	−0.439*	−0.012	1.000

Note: *Significant at $p < 0.05$

Table 4
Comparison of green growth index with other indices

	Green growth index	Human development index	NITI Aayog SDG index	Inequality human development index
Score	1–6	1–100	1–100	1–100
Normalization method	Min-max normalization	Min-max normalization	Min-max normalization with a target upper bound	Min-max normalization
Total variables	18	3	62	3
Composite score aggregation	Arithmetic mean	Arithmetic mean	Arithmetic mean	Geometric mean

Table 5
State-wise performance on green growth index scores

State	Unbalanced index score	Balanced index score	Change	Unbalanced index rank	Balanced index rank	Difference between rank
Andhra Pradesh	3.67	3.74	1.95%	13	6	7
Arunachal Pradesh	4.54	3.69	−22.79%	2	9	−7
Assam	3.27	3.65	10.39%	21	12	9
Bihar	2.42	3.27	26.01%	30	21	9
Chhattisgarh	2.89	3.04	4.93%	26	24	2
Delhi	3.46	2.95	−17.28%	15	28	−13
Goa	4.06	3.66	−10.85%	3	11	−8
Gujarat	3.30	3.32	0.75%	20	20	0
Haryana	3.36	2.99	−12.26%	18	26	−8
Himachal Pradesh	4.02	3.68	−9.36%	4	10	−6
Jammu and Kashmir	3.11	2.72	−14.37%	23	30	−7
Jharkhand	2.68	3.38	20.66%	27	18	9
Karnataka	3.65	4.18	12.78%	14	2	12
Kerala	3.78	3.50	−7.80%	10	15	−5
Madhya Pradesh	2.94	3.01	2.57%	25	25	0
Maharashtra	3.83	4.06	5.73%	7	3	4
Manipur	3.86	3.61	−7.11%	6	14	−8
Meghalaya	3.68	3.35	−9.85%	12	19	−7
Mizoram	3.95	3.45	−14.60%	5	17	−12
Nagaland	3.75	3.70	−1.37%	11	8	3
Odisha	3.41	3.72	8.28%	17	7	10
Punjab	3.30	2.72	−21.10%	19	29	−10
Rajasthan	2.64	3.23	18.10%	28	22	6
Sikkim	5.10	5.32	4.16%	1	1	0
Tamil Nadu	3.79	3.86	1.76%	8	5	3
Telangana	3.78	3.65	−3.67%	9	13	−4
Tripura	3.17	3.50	9.29%	22	16	6
Uttar Pradesh	2.50	2.99	16.36%	29	27	2
Uttarakhand	3.41	4.06	15.92%	16	4	12
West Bengal	3.05	3.12	1.99%	24	23	1

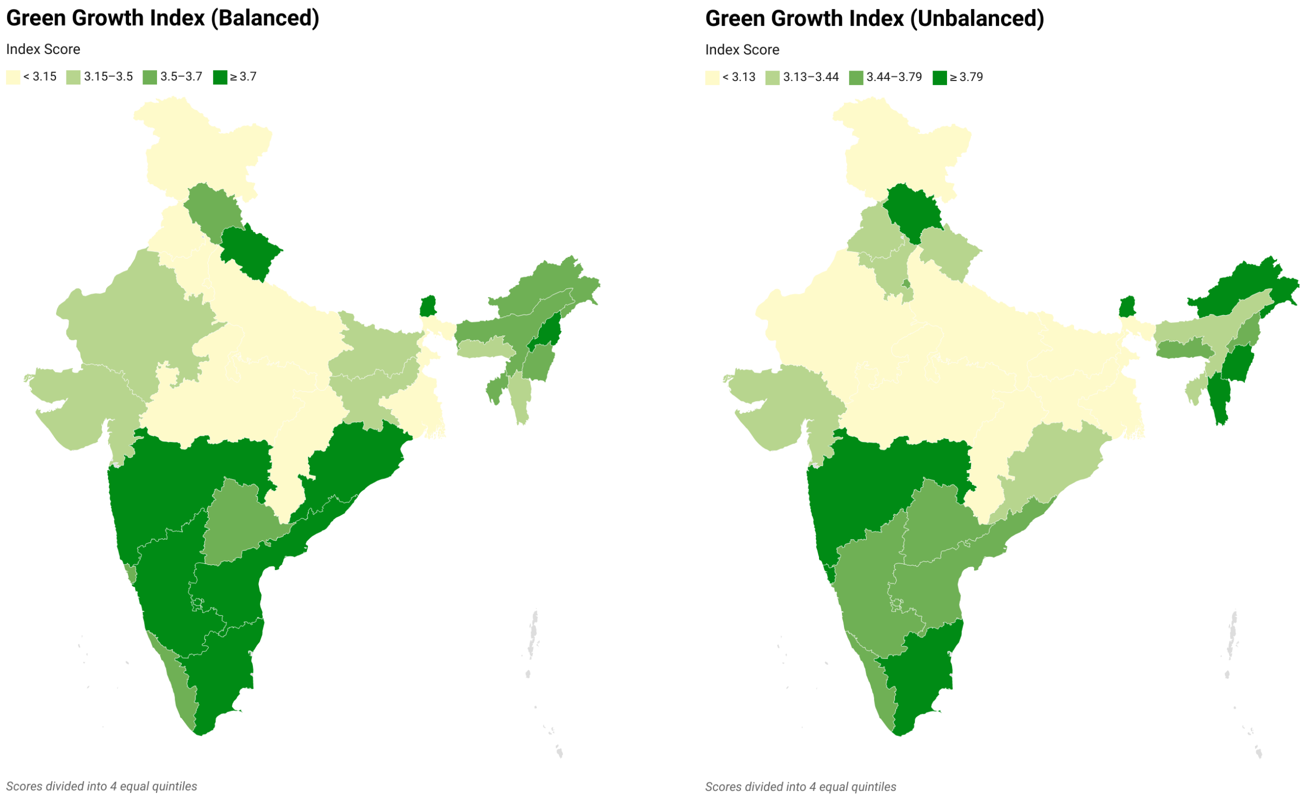
potential disparities in development indicators or challenges in achieving balanced growth.

4) Certain regional patterns also emerge as northeastern states like Arunachal Pradesh (4.54 unbalanced, 3.69 balanced) and Mizoram (3.95 unbalanced, 3.45 balanced) show relatively high unbalanced scores, while their balanced index numbers drop. This could indicate that despite pockets of high development, there are regions within these states lagging in critical areas. At the same time, southern states like Karnataka and Tamil Nadu show strong balanced scores, reinforcing the trend of well-rounded development in South India.
5) One prominent issue with adjusting for the absolute gap is that states that have somewhat equal but lower scores in all three pillars tend to perform better than those that are better off in economic and social measures. But nevertheless, green growth by its definition is to objectively measure economic growth while balancing the trade-offs caused by environmental degradation and social inequities. It is important to note that the balanced index score still maintains a positive and significant correlation ($\rho = 0.638$) with the unbalanced counterpart.

6. Empirical Analysis: Results and Discussion

Understanding the factors that contribute to green growth is of paramount importance in sustainable development. However, accurately pinpointing the underlying determinants can be challenging, particularly when variations in green growth

Figure 3
Panel images of unbalanced and balanced index scores for Indian states



outcomes are observed between distinct groups. To address this challenge, we use the Oaxaca–Blinder decomposition to shed light on the drivers of green growth and the potential sources of differences between groups.

6.1. Oaxaca–Blinder decomposition

We look at the GGI of the Indian states and analyze the factors that explain the variation in green growth performance across them. Specifically, we use the Kitagawa–Oaxaca–Blinder[1] decomposition technique, which is a statistical method that decomposes the difference in the means of a dependent variable between two groups into two components: a portion that arises because of differences in the mean levels of explanatory variables (explained component) and a portion that arises because of differences in the coefficients of explanatory variables (unexplained component) [34]. Although this method has been frequently utilized to investigate gender and race discrimination in the labor market, it can be used to explain disparities in any continuous outcome across two groups. We choose the Oaxaca–Blinder decomposition over more complex decomposition methods like Brown decomposition [35] due to its relative simplicity in incorporating group variables, facilitating easier regression analysis.

As we see in Equations (8)-(11), we split the states into two groups based on their mean GDP and compare their GGI values (balanced) as the dependent variable. The choice for explanatory variables comes from the framework of environmental degradation that was indicative in our literature review. In addition to GDP, population, and energy, we have included variables such as industrial value added (IVA) and agricultural value added that may affect green growth outcomes. Measuring the value added of these sectors can help assess the extent to which they contribute to green growth outcomes, such as resource efficiency. Further, the two variables also account for the relatively high share of both sectors held in the Indian economy. All the data comes from the Centre for Monitoring Indian Economy's States of India database for the year 2019 as a baseline. Our main objective is to identify the sources of green growth disparities among Indian states and provide policy recommendations to improve green growth performance.

In our context, we take the two groups of states as $Index_A$ *and* $Index_B$.

The mean difference can be expressed as:

$$\Delta\,\overline{Index} = \overline{Index_A} - \overline{Index_B}. \tag{8}$$

In the context of linear regression, the mean outcome for Group G ∈ {A, B} can be expressed generally as:

$$\overline{Y}_G = \overline{X}'\,\hat{\beta}_G \tag{9}$$

where $\overline{X}'$ contains the mean values of explanatory variables and $\hat{\beta}_G$ are the estimated regression coefficients.

Hence, $\Delta\overline{Index}$ can be rewritten as $\Delta\overline{Y}$, where:

$$\Delta\overline{Y} = \overline{X}'_A\,\hat{\beta}_A - \overline{X}'_B\,\hat{\beta}_B. \tag{10}$$

The twofold approach decomposes this mean difference in outcome with respect to a vector of reference coefficients $\hat{\beta}_R$, where $\hat{\beta}_R$ is the coefficient estimates from a regression that pools observations from both groups A and B. The twofold decomposition thus divides the

[1]The method was introduced by sociologist and demographer Evelyn M. Kitagawa in 1955.

Table 6
Results from Oaxaca–Blinder decomposition on green growth index

Variables	(1) Overall	(2) Explained	(3) Unexplained
group_1	46.29***		
	(1.435)		
group_2	55.46***		
	(2.916)		
difference	−9.166***		
	(3.250)		
explained	−1.213		
	(4.545)		
unexplained	−7.953*		
	(4.315)		
lgdp		−1.788	−6.416
		(3.032)	(86.34)
lpop		0.746	105.6***
		(0.889)	(36.65)
lenergy		6.733	147.9*
		(7.290)	(81.53)
lIVA		−6.990	−113.1*
		(5.378)	(59.56)
lAGVA		0.0865	−49.83**
		(0.569)	(21.92)
Constant			−92.12
			(99.54)
Observations	29	29	29

Note: Robust standard errors in parentheses (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$)

difference in mean outcomes into a part that is explained by cross-group differences in the explanatory variables and a part that remains unexplained by these differences.

$$\Delta\overline{Y} = \underbrace{\left(\overline{X}_A - \overline{X}_B\right)' \hat{\beta}_R}_{explained} + \underbrace{\overline{X}_A'\left(\hat{\beta}_A - \hat{\beta}_R\right) + \overline{X}_B'\left(\hat{\beta}_R - \hat{\beta}_B\right)}_{unexplained} \quad (11)$$

Our analysis, as seen in Table 6, shows that states with above-average GDP, on average, have an approximately 9-point increase in GGI score. Only the unexplained component shows statistical significance at conventional levels, meaning that the difference in the two groups occurs mainly due to differences in coefficients or that the difference in green growth outcomes of different states cannot be due to aggregate levels of explanatory variables in this context and hence need further decomposition. The impact of population and energy on the dependent variable, GGI, is lower in Group_2 (with above-average GDP) compared to Group_1, while the opposite is applicable for industrial value added and agricultural value added.

The significance of population in the unexplained component suggests that population-related factors, such as demographic traits, population density, or population distribution, have relevance in explaining the residual differences between the groups. In the domain of energy, this could indicate energy composition at the state level, in terms of renewable and nonrenewable sources, plays a meaningful role in contributing to the differences. The same is applicable for industrial value added, as the value addition has a differential impact on green growth within small-scale, medium-scale, and large-scale industries. Similarly, the significance of agriculture value added (AGVA) in the unexplained component suggests that factors related to agricultural value added, such as agricultural productivity, agricultural policies, and state-specific dynamics, have an important influence on the unexplained variation between the groups.

6.2. Findings from regression analysis

The ordinary least squares (OLS) regression analysis allows us to investigate the statistical relationships between green growth and these independent variables, quantifying their individual contributions. Furthermore, hypothesis testing and model evaluation are conducted to examine the statistical significance and validity of multiple hypotheses within the regression model. We can thus create a cross-sectional data of Indian states with the computed GGI (balanced and scaled to 100) for a single baseline year 2019. Due to heteroskedasticity in models 1, 2, 3, and 4, we employed OLS with robust standard errors to address the issue, while for the other models, the same specification was dropped. Further, robustness checks have been reported in Table A1.

For all empirical purposes, we estimate the base equation as follows (Equation (12)) whose results are provided in Table 7:

$$Index_i = \beta_0 + \beta_1 LGDP_i + \beta_2 LPOP_i + \beta_3 LENERGY_i + \beta_4 LIVA_i + \beta_5 LAVA_i + \delta X_i + \varepsilon_i \quad (12)$$

where X is a set of exogenous variables[2] related to environment and governance

Specifically,

$$X = \begin{cases} LForest\ Area - log\ of\ Forest\ Area\ in\ sq.km \\ Corruption\ Case - number\ of\ corruption\ cases\ as\ per\ NCRB \\ Coastal - dummy\ variable\ for\ state\ is\ coastal\ or\ not \end{cases} \quad (12a)$$

As expected, the results of Model 1 (Table 7) show that an increase in per capita income would mean a positive impact on the GGI[3].

Population is a factor that exerts an enormous influence on the environment and rapid population growth exacerbates other conditions such as bad governance, civil conflict, wars, polluting technologies, or distortionary policies – all directly linked to green growth [36]. Nevertheless, we fail to find any significant relation for population with GGI from this specification.

An increase in agriculture value addition is beneficial to the poor and is compatible with the SDG 2 goal since the majority of them are engaged in small-holder agriculture, and an increase would translate to better material conditions. Agriculture-related greenhouse gas emissions has been found to be on a rising trend in many economies [37]. Larger input on agriculture corresponds to fertilizers, pesticides, and equipment that encourage the use of fossil fuels and overall put increasing stress on the environment. Although, theoretically, there is a trade-off between environmental measures and agricultural output in the short due to green growth

[2] We also looked at heterogeneity between different states by using dummy variables for regions (North, South, East, West, and Central) as well for industrial states (=1 if industrial sector contributed most to NSDP). The results were inconclusive.

[3] Given that the green growth index includes measures of environmental indicators as well, we tested a Kuznets type of relation by adding GDP^2 and GDP^3 to the equation. The results were inconclusive and are summarized in Table A2.

Table 7
Regression results for Equation (12) with robust standard errors

	Index (1)	(2)	(3)	(4)
lgdp	7.711**	8.403**	5.781*	6.049*
	(3.134)	(3.201)	(3.251)	(3.152)
lpop	0.760	0.545	0.398	0.551
	(0.788)	(0.600)	(0.649)	(0.636)
lenergy	−10.322***	−6.972*	−10.350***	−9.358**
	(3.082)	(3.369)	(3.052)	(3.376)
lIVA	8.506***	6.751**	8.539***	7.307**
	(3.003)	(3.082)	(3.017)	(3.296)
lAGVA	1.108	−1.724	−0.158	0.383
	(1.832)	(1.676)	(2.024)	(1.813)
lforest		2.795**		
		(1.165)		
‘Corruption Case‘			0.019***	
			(0.006)	
corruptXcoastal				0.017***
				(0.005)
Constant	67.446*	18.034	98.371**	83.702**
	(38.496)	(42.211)	(41.919)	(37.654)
Observations	29	29	29	29
R^2	0.566	0.651	0.648	0.653
Adjusted R^2	0.472	0.555	0.551	0.559
Residual std. error	7.023 ($df = 23$)	6.445 ($df = 22$)	6.474 ($df = 22$)	6.420 ($df = 22$)
F statistic	6.009*** ($df = 5; 23$)	6.832*** ($df = 6; 22$)	6.736*** ($df = 6; 22$)	6.914*** ($df = 6; 22$)

Notes: ***Significant at the 1% level. **Significant at the 5% level. *Significant at the 10% level.

policies as per Stevens [38], our models rule off such a relation between green growth and agricultural value added.

The positive relation in terms of green growth and industrial value added can be explained in terms of greater resource efficiency on inputs, which leads to the overall “greening” of the sector. Li et al. [39] note that technical innovation is the driving force behind industrial green transformation, with regions having the largest investments in R&D funds being the front-runner in the transition. Similarly, the negative impact of energy use on green growth shows the need for fostering energy efficiency policies and low-carbon energy technologies.

Now, turning to our three sets of exogenous variables, the positive coefficient of LForestArea points to the important role forests play in terms of environmental sustainability through carbon sequestration. Arguably, regions with large forest areas are most likely to have access to a large pool of greener resources and increase green growth [40]. The positive impact of corruption cases looks counterintuitive given its negative impact on economic growth and social equity components. But the same can be explained using the “greasing the wheel” hypothesis that corruption to an extent can alleviate the distortions caused by ill-functioning institutions [41]. Another straightforward explanation, which is particularly relevant to the Indian context, is that states that tend to report such cases often have stronger institutional systems present, which points to a higher GGI score. This is further validated by coastalXcorruption variable, which points out that coastal states tend to report higher corruption cases that could be associated with higher economic activities of these states owing to maritime resources and trade opportunities.

In a modification to the initial model, we use the following testable model that includes a nonlinearity and inequality (Equation (13)), which is summarized in Table 8:

Table 8
Regression results for Equations (13) and (14)

	Index (5)	(6)
lgdp	30.640***	30.536***
	(7.114)	(7.318)
lpop	−44.931***	−43.667***
	(14.315)	(14.455)
lpop2	1.619***	1.550***
	(0.499)	(0.503)
GINI	0.808**	
	(0.365)	
GINIxlpop		0.045*
		(0.021)
lenergy	−11.321***	−11.327***
	(3.200)	(3.260)
TFP	1.099*	1.077*
	(0.599)	(0.608)
Constant	252.989**	253.891**
	(109.442)	(111.104)
Observations	21	21
R^2	0.613	0.601
Adjusted R^2	0.447	0.431
Residual std. error ($df = 14$)	6.239	6.332
F statistic ($df = 6; 14$)	3.697**	3.520**

Notes: ***Significant at the 1% level. **Significant at the 5% level. *Significant at the 10% level.

$$Index_i = \beta_0 + \beta_1 LGDP_i + \beta_2 LPOP_i + \beta_3 LPOP_i^2 + \beta_4 GINI_i + \beta_5 LENERGY_i + \beta_6 TFP + \varepsilon_i \quad (13)$$

Total factor productivity (TFP) measures residual growth in the total output of an economy that cannot be explained by the accumulation of traditional inputs such as labor and capital. Recent growth literature suggests that TFP, not factor accumulation, accelerates the growth of an economy. While some studies show that for an average country, TFP accounts for as much as 60% of the growth of output per worker others point to a much lower figure [42]. Data for factor productivity performance at the state level comes from Roy [43], which is the annual average for 2008–2017. Further, the positively significant coefficient agrees with historical data that points out that TFP is positively correlated with energy efficiency, which raises the question of to what extent can consumption of energy be reduced for a given level of growth to minimize other types of environmental damage [44].

The square term of the population being positive and significant shows the existence of a "U" shaped relation between green growth and population rise. It shows that, initially, population rise would have a negative impact up to a threshold and doesn't provide any useful conclusions other than that higher human capital is largely beneficial. It also shows that with increasing population, inequality will also increase and has a positive impact on green growth. Inequality can worsen as the population rises, resulting in discrepancies in resource availability. However, this can also stimulate innovation and encourage sustainable practices, resulting in positive impacts on green growth.

Including interaction terms of inequality to the model, we have Equation (14), which is also summarized in Table 8:

$$Index_i = \beta_0 + \beta_1 LGDP_i + \beta_2 LPOP_i + \beta_3 LPOP_i^2 + \beta_4 GINI_i * LPOP_i + \beta_5 LENERGY_i + \beta_6 TFP + \varepsilon_i \quad (14)$$

The observation that GINI × lpop interaction has a positive and significant coefficient implies that the combined effect of population and inequality has an upward influence on the GGI. In other words, the level of inequality in the model influences the relationship between population and green growth performance. To interpret the coefficient further, it means that the impact of population on green growth is stronger when inequality is higher, as measured by GINI. This implies that reducing inequality may be critical for benefiting from the favorable effects of population rise on green growth.

7. Conclusion

The paper introduces a novel GGI that presents a baseline ranking of Indian States based on their performance in green growth – a pioneering endeavor that sets the stage for future research and policy innovation in sustainable development within India. Distinguished from existing indices such as HDI and the SDG Index, our index aims to rectify methodological shortcomings while encompassing a comprehensive array of indicators. By incorporating economic, environmental, social, and governance dimensions, our index provides a holistic depiction of a country's journey toward sustainable development, minimizing the issue of endogeneity through low correlation among its pillars and thereby enhancing the reliability of our findings. Moreover, future iterations of the index could be enriched by integrating additional data on research and development (R&D) spending and state-level emission policies. The disparity between balanced and unbalanced index scores underscores the importance of equitable distribution in green growth constituents and the necessity of reconciling trade-offs between environmental degradation and social inequities.

In order to understand the unexplained disparities between states and identify the impact of various factors in the index, we employed Oaxaca–Blinder decomposition on the data. We find that energy use and input utilization efficiency are the major drivers of green growth along with the conventional economic growth. Moreover, our analysis shows that the impact of income inequality is more pronounced on economic growth in states with smaller populations. This is in conjunction with the important observation that states with larger populations tend to have lower scores in the GGI. This nuanced understanding of factors can dictate targeted policy interventions and monitor the effectiveness of such interventions in promoting inclusive and sustainable green growth.

Robust governance institutions serve as another significant contributor to green growth, carrying various implications. The recent upsurge in extremist and populist movements exhibits that trust in and quality of democracy is deteriorating worldwide. It is imperative to regain this loss of faith in governance institutions as electoral democracies produce ambitious climate policies and people can actively shape the direction of these policies by active participation. Such institutions allow space for grassroot campaigning, lobbying, and advocacy for a greener future. By creating a groundswell of public pressure and leveraging their collective demand-side influence, people can drive industries, especially upcoming ones, toward more sustainable and environmentally responsible practices. Finally, our GGI puts forward an argument for national government and state ministries to measure development in a more comprehensive manner, in conjunction with the already existing indices such as NITI Aayog SDG Index and HDI.

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Ethical Statement

This study does not contain any studies with human or animal subjects performed by any of the authors.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

Data are available from the corresponding author upon reasonable request.

Author Contribution Statement

Navaneeth M S: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Writing – original draft, Writing – review & editing, Visualization. **Ismail Siddiqui:**

Validation, Formal analysis, Writing – review & editing. **Santosh Kumar Sahu:** Validation, Formal analysis, Writing – review & editing, Supervision, Project administration.

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Appendix

Table A1
Diagnostics test results (OLS)

	M1	*P*-value	M2	*P*-value	M3	*P*-value	M4	*P*-value
Multicollinearity[1]	7.408	–	8.031	–	6.602	–	6.611	–
Heteroskedasticity[2]	14.51	0.01267	8.8327	0.1832	12.898	0.04468	15.728	0.01529
Normality[3]	0.94769	0.1594	0.98878	0.9853	0.9567	0.2719	0.96513	0.4362
1 Variance inflation factor								
2 Breusch–Pagan test								
3 Shapiro–Wilk test								
	M5	*P*-value	M6	*P*-value				
Multicollinearity[1]	2.479	–	3.073	–				
Heteroskedasticity[2]	5.0824	0.5333	5.642	0.4645				
Normality[3]	0.94233	0.2422	0.93981	0.216				
1 Variance inflation factor								
2 Breusch–Pagan test								
3 Shapiro–Wilk test								

Models 1 and 2 explore the Kuznets type of relation between GDP and green growth index score.

Models 3, 4, and 5 look at whether heterogeneity influences the green growth performance. The heterogeneity in question refers to dummy indicators of whether a state is industrial, located on the coast, or shares the same ruling party as in a union.

Table A2
Additional regression results

	Index				
	(1)	(2)	(3)	(4)	(5)
lgdp	−46.792	−1,052.843	7.786**	6.697*	7.723**
	(76.722)	(1,449.108)	(3.226)	(3.417)	(3.239)
lgdp2	3.130	119.167			
	(4.403)	(166.958)			
lgdp3		−4.447			
		(6.396)			
lpop	0.517	0.840	0.828	0.725	0.768
	(1.074)	(1.182)	(1.053)	(1.016)	(1.054)
lenergy	−10.203***	−10.604***	−10.732***	−9.915***	−10.370***
	(2.663)	(2.756)	(3.022)	(2.697)	(3.051)
lIVA	7.853**	8.371**	9.065**	7.998**	8.538**
	(3.018)	(3.144)	(3.467)	(2.935)	(3.068)
lAGVA	2.012	1.305	0.923	0.764	1.117
	(2.292)	(2.533)	(2.025)	(1.949)	(1.946)
‘Industrial State‘			−1.266		
			(4.290)		
Coastal				2.893	
				(3.594)	
NDA					−0.105
					(3.153)
Constant	304.024	3,205.062	69.721	76.256*	67.769
	(335.110)	(4,186.388)	(40.936)	(41.184)	(41.433)
Observations	29	29	29	29	29
R^2	0.576	0.586	0.568	0.579	0.566
Adjusted R^2	0.461	0.448	0.450	0.464	0.448
Residual std. error	7.100 ($df = 22$)	7.185 ($df = 21$)	7.167 ($df = 22$)	7.078 ($df = 22$)	7.181 ($df = 22$)
F statistic	4.984*** ($df = 6; 22$)	4.241*** ($df = 7; 21$)	4.823*** ($df = 6; 22$)	5.039*** ($df = 6; 22$)	4.790*** ($df = 6; 22$)

Notes: ***Significant at the 1% level. **Significant at the 5% level. *Significant at the 10% level.