Green Growth in Arab Countries: A Predictive Analysis Based on Economic Complexity and Macroeconomic Indicators Using the XGBoost Machine Learning Algorithm

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Abstract. This study examines how trade and research complexity predict Arab green growth trajectories. A comprehensive framework of institutional, environmental, and macroeconomic indicators frames this analysis. A composite green growth index (GGI) was created using the directional distance function to monitor GDP and undesirable outputs (carbon emissions and energy intensity) from 2000 to 2022. The dataset includes 13 oil-dependent, diversified emerging, and structurally constrained Arab countries. The model uses the Trade Complexity Index (TCI) and Research Complexity Index (RCI) and 12 control variables to assess institutional and governance, development and human capital, market and economic structure, innovation and technological readiness, energy composition and sustainability, environmental pressures, and external influences. XGBoost, optimized via Bayesian hyperparameter tuning, is used in the systematic design to capture nonlinear relationships and interaction effects across multidimensional and heterogeneous data. Gain was used to determine each factor's predictive performance contribution. The RCI predicted green growth best, followed by the Anti-Corruption Index (CC) and TCI. This analysis shows the importance of national innovation capacity, institutional integrity, and trade's technological content. Traditional environmental indicators like carbon dioxide emissions and renewable energy use were less predictive, suggesting that structural and institutional factors drive green growth in Arab economies more than direct environmental interventions. These findings suggest replacing narrow environmental strategies with integrated policy frameworks that link innovation, trade development, and institutional reform to environmental goals.

Keywords: Green Growth, Economic Complexity, Trade Complexity, Research Complexity, XGBoost Machine Learning Algorithm.

1 Introduction

For decades, the pursuit of sustainable economic development has stood at the forefront of national, regional, and global policy agendas. In the context of Arab economies—marked by structural heterogeneity and a predominant reliance on natural resources in shaping production and export profiles—advancing green growth entails more than environmental adjustments. It requires a strategic integration of industrial diversification, innovation, and knowledge with long-term ecological sustainability.

Within this broader framework, economic complexity emerges as a critical, yet underexplored, driver of green transformation. Economic complexity reflects the depth of productive knowledge and the extent of intangible capabilities embedded in an economy's industrial and innovation base. Through its influence on technological progress, export sophistication, and systemic innovation capacity, it can play a pivotal role in steering countries toward more sustainable development trajectories.

The economic complexity paradigm, pioneered by Hidalgo and Hausmann (2009), argues that sustainable growth is contingent upon a country's ability to accumulate, recombine, and deploy productive knowledge across increasingly sophisticated sectors. Nations exhibiting high economic complexity—measured by their capacity to produce and export diverse, knowledge-intensive goods—are also more likely to develop green technologies, adopt cleaner production methods, and transition toward low-carbon economies.

Yet, the empirical relationship between economic complexity and green growth remains insufficiently examined, especially in the Arab region, where economies range from hydrocarbon-dependent rentiers to emerging industrial players and low-income nations. This study seeks to fill this gap by analyzing how economic complexity—captured through both trade-based (TCI) and research-based (RCI) dimensions—alongside key macroeconomic indicators, contributes to shaping green growth outcomes in Arab countries.

1.1 Research Problem

While economic complexity is increasingly recognized as a structural determinant of green growth—associated with more diversified production, stronger innovation systems, and greater institutional adaptability—its specific contribution within the Arab context remains empirically underexplored. In particular, how do different facets of complexity, such as trade sophistication and research capabilities, interact with macroeconomic and environmental factors to influence green growth? This study thus investigates the following core question:

To what extent can economic complexity—measured through trade and research indicators combined with macroeconomic variables, predict green growth trajectories in Arab economies using the XGBoost machine learning algorithm?

1.2 Research Objectives

This research aims to explore the predictive relationship between economic complexity and green growth in Arab economies, leveraging advanced empirical tools suited to capturing structural heterogeneity and non-linear dynamics. The specific objectives are:

- To construct a composite Green Growth Index (GGI) for Arab countries that integrates economic, environmental, and institutional dimensions, while reflecting regional development priorities and data constraints.
- To assess the predictive power of economic complexity—through Trade Complexity Index (TCI) and Research Complexity Index (RCI)—in determining green growth outcomes.
- To investigate the mechanisms through which trade sophistication, innovation capacity, and knowledge systems influence environmentally sustainable development pathways.
- To examine the roles of complementary macro-institutional variables, including corruption control, regulatory quality, renewable energy use, human development, and export concentration, in shaping green growth trajectories.
- To provide evidence-based policy recommendations for advancing an inclusive, innovation-driven, and environmentally responsible growth model across Arab countries.

1.3 Significance of the Study

This study holds both theoretical and applied significance. Theoretically, it bridges a critical gap in the literature by linking economic complexity—in both its technological (RCI) and trade (TCI) forms to green growth performance. It offers a fresh analytical lens by embedding this complexity-growth relationship within a predictive modeling framework based on machine learning, thus moving beyond traditional regression-based approaches.

Practically, the research contributes to the design of context-specific green growth metrics and provides a nuanced understanding of how innovation, governance, and structural diversification can jointly influence environmental performance. By incorporating machine learning techniques—specifically XGBoost with Bayesian optimization—it accounts for cross-country heterogeneity, interaction effects, and non-linearity, producing policy-relevant insights grounded in robust quantitative evidence.

While the findings offer new insights into the strategic role of economic complexity in sustainable development, the study also serves as a foundation for further empirical research, policy experimentation, and interdisciplinary dialogue on green transformation in the Arab region.

2 Review of Empirical Literature

Numerous empirical studies have explored the relationship between economic complexity and green growth, generally framing complexity as a proxy for advanced productive structures and knowledge-based economies. However, the nature and magnitude of its impact are highly context-dependent—shaped by income levels, structural features, and institutional capacity.

Much of the literature has examined the channels through which complexity affects green growth, particularly its interaction with innovation, renewable energy adoption, policy stringency, and trade openness. These studies aim to uncover when and how complexity supports sustainable development.

This review synthesizes key findings while highlighting contextual factors that condition the complexity–green growth nexus, especially in the case of developing regions like the Arab world.

2.1 Economic Complexity: Environmental Impact, Emissions, Renewable Energy, and Sustainable Development Pathways

Empirical studies show that economic complexity tends to support green growth in high-income countries by enabling cleaner production and facilitating renewable energy adoption (Aluko et al., 2024; Neagu & Teodoru, 2024). More complex economies often possess the technological infrastructure and policy frameworks that reduce carbon emissions and ecological footprints.

Stojkoski et al. (2022) highlight the multidimensional nature of complexity—including trade, innovation, and scientific capacity—as a driver of inclusive and low-emission growth. Similarly, Lee et al. (2022) find a significant negative relationship between complexity and per capita CO_2 emissions, particularly when paired with technological advancement and trade diversification.

In emerging economies, the role of complexity is more conditional. Saud et al. (2024) and ElMassah & Hassanein (2023) suggest that environmental gains from complexity only materialize beyond certain thresholds of renewable energy adoption and policy stringency. For example, in GCC countries, positive environmental effects are observed only when economic diversification is accompanied by investments in clean energy.

Conversely, some studies reveal mixed or even negative effects. Nathaniel (2021) finds that in parts of Southeast Asia, increased complexity correlates with higher emissions, indicating that the environmental benefits of complexity depend on how production systems are structured and whether they are aligned with green technologies.

In sum, economic complexity can reduce environmental harm and promote sustainable development, but its effectiveness varies across countries. Technological readiness, energy composition, and environmental policy frameworks all shape the direction and intensity of its impact.

2.2 Economic Complexity, Human Capital, and Green Technological Innovation

Economic complexity fosters green growth not only through cleaner production, but also by enhancing knowledge accumulation, human capital development, and green technological innovation. As economies become more complex, they demand higher-skilled labor and advanced innovation systems, which drive structural transformation toward environmentally sustainable production.

A consistent finding across the literature is that this process strengthens resource efficiency and facilitates low-carbon industrial upgrading. Studies by Sun et al. (2024), Ai-hui et al. (2024), Lin, S. et al. (2022), and Stojkoski et al. (2022) confirm that innovation ecosystems and human capital play a decisive role in shaping the complexity–green growth link.

For example, Lin et al. (2024) show that in China, higher economic complexity increases total factor productivity by boosting green innovation. Similarly, Wang, F. et al. (2023) and Okombi & Lebomoyi (2024) highlight regional differences, finding that areas with stronger innovation capacity reap greater environmental returns from complexity.

Overall, this literature suggests that the full potential of economic complexity to support green growth is conditional on a country's investment in education, research, and institutional support for innovation.

2.3 Economic Complexity, Trade Diversification, and Mechanisms of Influence

Trade diversification and economic complexity are mutually reinforcing: diversified trade fosters innovation and complexity, while complex economies produce high-value, environmentally efficient goods. This synergy is a crucial pathway through which complexity contributes to green growth.

Several studies confirm that the alignment of complex production structures with trade diversification leads to lower emissions and better environmental outcomes. Neagu & Teodoru (2022) and Wang, B. et al. (2022) show that in both high-complexity and BRICS countries, this interaction significantly reduces greenhouse gas emissions. Lee et al. (2022) further demonstrate that in the EU, the complementarity between green trade and complexity strengthens sustainability outcomes.

This evidence highlights that integrating trade policy with complexity strategies can amplify environmental gains. Diversified, knowledge-based exports not only enhance economic resilience but also reduce ecological impact—making this nexus a vital channel for green transformation.

2.4 Economic Complexity, Institutional Quality, and the Conditioning of Impact

Institutional quality shapes how economic complexity translates into environmental outcomes. In strong institutional settings, complexity is more likely to drive sustainable production, eco-innovation, and low-emission technologies. In contrast, weak institutions may divert complexity toward pollution-intensive sectors.

Neagu & Neagu (2024) demonstrate a two-way causality between institutional quality and green growth in Eastern Europe, while the effect of complexity on green development is unidirectional. Similarly, Lin et al. (2024) and Zhang & Zhou (2023) stress that environmental regulation and good governance amplify complexity's contribution to green growth, particularly in China.

The literature thus suggests that complexity alone is insufficient. Without institutional capacity—such as regulatory enforcement, transparency, and public investment—the structural benefits of complexity may fail to produce green outcomes, or worse, exacerbate environmental harm.

2.5 Government Interventions, Economic Policies, and the Amplification of Economic Complexity Effects

Government policies are essential for steering economic complexity toward green outcomes. Especially in early development stages, environmental gains from complexity depend on effective institutions, targeted green investments, and supportive regulatory frameworks.

Studies like Obaid et al. (2024) and Wang, F. et al. (2022) highlight that public green finance, environmental taxation, and investment in education significantly enhance the environmental impact of complexity. Grazini & Guarini (2023) show that strict environmental policies and fiscal tools accelerate clean technology adoption and emissions reduction.

Education spending emerges as a key factor. By strengthening human capital, it enables better absorption of complex technologies and boosts innovation capacity—thus reinforcing the complexity–green growth link, as shown by Okombi & Lebomoyi (2024).

Overall, complexity's positive effects are not automatic—they require strategic government action to convert potential into sustainable transformation.

2.6 Heterogeneous Effects of Economic Complexity across Stages of Development

The relationship between economic complexity and green growth is highly context-dependent, varying significantly across income levels and stages of development.

In high-income countries, complexity tends to yield strong environmental benefits, due to advanced technologies, robust institutions, and clean energy investments. For instance, Lian (2024) and Grazini & Guarini (2023) show that clean energy finance and strong regulations amplify complexity's green effects in G7 economies.

Middle-income countries face a dual outcome. Complexity can support innovation and green growth, but if fossil fuels dominate the energy mix, emissions may rise. Evidence from the GCC indicates that only after achieving thresholds in renewable adoption and policy enforcement does complexity reduce degradation (ElMassah & Hassanein, 2023; Wang, A. et al., 2024).

Low-income countries, with less sophisticated production and weak institutions, risk amplifying environmental harm through complexity unless it's paired with investments in clean energy and knowledge sectors. Emmanuel et al. (2024) and Arslan et al. (2023) stress the need for structural reforms and green capacity building.

Finally, Doğan et al. (2019) reveal that complexity increased environmental pressure in low- and upper-middle-income countries, but reduced emissions in high-income economies—confirming the uneven nature of complexity's environmental impact.

In sum, the green dividends of complexity are not guaranteed—they hinge on development level, energy structure, and institutional quality, calling for differentiated, context-aware policy responses.

2.7 Research Gap

While the relationship between economic complexity and green growth has received increasing attention in recent empirical research, significant gaps remain—especially in the context of developing economies, and Arab countries in particular. Much of the existing literature has centered on advanced or emerging economies, where high-quality environmental data and established green growth metrics are more readily available. Arab economies, by contrast, have been largely excluded from comparative studies due to persistent data limitations and the absence of context-specific indices capable of capturing the multi-dimensional nature of green growth. This study addresses this gap by constructing a tailored Green Growth Index that integrates economic, environmental, and institutional indicators aligned with both international standards and regional development realities.

Beyond the data gap, Arab economies possess unique structural and institutional characteristics that limit the applicability of findings derived from other regions. The region exhibits substantial variation in economic complexity, spanning resource-dependent rentier states to relatively diversified economies. Moreover, challenges such as weak environmental innovation systems, institutional fragilities, and mounting development pressures complicate the green transition. These factors underscore the need for localized, data-driven investigations into how economic complexity and macroeconomic structures jointly shape green growth outcomes.

On the methodological front, a critical limitation of prior studies lies in their reliance on traditional linear econometric models, which often assume homogeneous relationships across countries and fail to capture complex, non-linear, or interactive dynamics. Such approaches risk oversimplifying the influence of economic complexity on green growth. To overcome this, the present study introduces a novel predictive framework based on the Random Forest algorithm—a machine learning technique well-suited for capturing heterogeneity, nonlinearities, and interaction effects across diverse national settings. Unlike linear models, Random Forest allows for flexible modeling of complex structures without imposing rigid parametric assumptions.

By combining a regional focus with a cutting-edge methodological approach, this study makes a dual contribution: first, by empirically incorporating Arab economies into a literature where they have been historically underrepresented; and second, by offering a predictive lens that better accounts for the structural diversity and environmental challenges shaping green growth trajectories in the Arab world.

3 Methodology

Building on the empirical literature examining the relationship between economic complexity and green growth—literature which highlights the variability in both the direction and magnitude of this relationship depending on income levels, economic structure, knowledge accumulation, innovation capacity, the nature of government interventions, environmental and economic policies, institutional quality, and the degree of renewable energy adoption—this study requires a careful selection of explanatory variables and an appropriate econometric approach. The diversity of the Arab economies, characterized by structural and institutional asymmetries, varied development trajectories, and heterogeneous levels of economic complexity, necessitates a methodological framework capable of capturing these differences effectively and disentangling the potential effects across different levels of green growth performance.

3.1 Scope of the Study

The sample of this study comprises a group of Arab countries, namely: Algeria, Tunisia, Morocco, Egypt, Kuwait, Saudi Arabia, the United Arab Emirates, Qatar, Iraq, Jordan, Lebanon, Oman, and Yemen, covering the period from 2000 to 2022. These countries can be categorized into three main groups, which allows for a more nuanced understanding of the internal heterogeneities in the impact of economic complexity on green growth.

3.2 Study Variables

Given the structural heterogeneity across Arab economies included in the sample, and in line with previous empirical literature, the relationship between economic complexity and green growth is expected to exhibit regional disparities. This necessitates the incorporation of additional economic variables that contribute to explaining the phenomenon. Accordingly, the analysis is framed within a model that accounts for interaction effects based on income levels, the nature of economic structures, innovation capacities, degrees of economic openness, levels of human development, the composition of energy production and consumption (both conventional and renewable), as well as the nature of government interventions and economic policies.

Dependent Variable: Green Growth Index for Arab Countries

Green growth is a development approach that aims to balance economic growth with environmental protection by improving the efficiency of resource use—namely labor, capital, and energy—while promoting GDP growth with a concurrent reduction in the environmental impact of economic activities (Kuzior, 2022; Dźwigoł & Dźwigoł-Barosz, 2020). Accordingly, the Green Growth Index is adopted as a composite measure that reflects the extent to which an economy achieves inclusive, low-emission growth, and serves as the main dependent variable in this study.

This index is based on a framework that links economic output (GDP) on the one hand, with environmental outcomes (emissions and energy use) on the other, in a manner that captures both environmental and economic efficiency. In the context of Arab countries, resource use efficiency is expressed in the form of a sustainable GDP output ratio, as illustrated in Equation (1).

$$P^G = \left[\left(\frac{y,x,b}{x\ can\ produce(y,b)}\right)\right] \tag{1}$$

Where:

- x denotes the vector of inputs (available resources in the country),
- y represents the desirable output (e.g., real GDP or economic output),
- b denotes the undesirable output (e.g., carbon emissions, energy intensity).

This formulation allows for comparing the growth performance of countries relative to the production possibility frontier, which defines the most efficient combination of inputs and outputs. The index measures the productivity change over time by computing the gap between actual production and the maximum attainable output, as discussed in Ojaleye & Narayanan (2022). Changes in this gap reflect variations in national productivity and efficiency levels. Thus, Equation (1) encapsulates the efficiency-driven nature of green growth, accounting for both economic and environmental performance.

The Green Economic Development Index (Ged) between period t and t+1 is calculated using the following formula:

$$Ged_t^{t+1} = \frac{1+\vec{D}_0^G(x^t,y^t,b^t;y^t,b^t)}{1+\vec{D}_0^G(x^{t+1},y^{t+1},b^{t+1};y^{t+1},b^{t+1})} \tag{2}$$

Where:

- Ged_t^{t+1} denotes the green growth index of a country between time t and t+1,
- x represents the vector of available inputs (including labor force and gross fixed capital formation),
- y is the desirable output (gross domestic product of the country),
- b is the undesirable output (greenhouse gas emissions),
- $\vec{D}_0^G$ is the directional distance function in the green productivity framework, evaluating the gap between current production and the efficient frontier, taking into account both desirable and undesirable outputs.

This dynamic index captures changes in green productivity over time, providing a more comprehensive measure of sustainable economic performance by considering the dual objectives of economic growth and environmental protection.

$$\vec{D}_0^G(x^s, y^s, b^s; y^s, b^s) = max\{\beta: (y^s + \beta y^s, b - \beta b^s \in P^G(x^s))\}, \quad (3)$$

s=t;t+1 It is the sum of global technology.

The integration of environmental factors into equation (2) reflects the negative externalities of production on the environment. The value of the Green Economic Growth Index ranges from 0 to infinity, where (Kwilinski et al., 2023a):

- A value of 1 indicates no change in productivity over time;
- A value greater than 1 reflects an improvement in green productivity over time;
- A value less than 1 suggests a decline in green productivity.

This index thus provides a coherent framework to assess green economic growth, capturing not only increases in desirable output but also reductions in undesirable environmental outcomes. It enables the evaluation of countries' efficiency in transforming available inputs into economic value while minimizing environmental harm.

- Considering the qualitative and quantitative characteristics of input data, the model enables a granular estimation of the environmental impact of production (Kwilinski et al., 2023b, p. 511).
- It also allows for a cross-country comparison of productivity growth, thereby facilitating the identification of best practices along the path toward green growth (J. Li et al., 2022).

Key Explanatory Variable: Economic Complexity

The central explanatory construct in this study is Economic Complexity, operationalized through two interrelated dimensions: Trade Complexity (TCI) and Research Complexity (RCI). Both indicators are derived from the Observatory of Economic Complexity (OEC) and are designed to capture the structural and cognitive depth of national economies. Together, they reflect the extent to which a country is capable of producing, exchanging, and embedding knowledge within its economic and technological systems.

Trade Complexity Index (TCI)

TCI captures the diversity and sophistication of a country's export basket and the embedded knowledge content of traded goods and services. A higher TCI value reflects a broader and more technologically advanced export portfolio, often associated with stronger integration into global value chains and a higher capacity to produce complex products. It serves as a proxy for the productive capabilities and technological maturity of the economy.

Research Complexity Index (RCI)

RCI measures a country's scientific and technological advancement by assessing the systemic capacity to generate, absorb, and apply knowledge. It incorporates key indicators such as gross R&D expenditure, patenting activity, institutional infrastructure for innovation, and the linkage between research and industrial output. A high RCI score reflects a dynamic innovation ecosystem capable of supporting transformative, green technologies and accelerating structural change toward sustainability.

These two dimensions of economic complexity offer complementary perspectives: while TCI emphasizes the external productive sophistication, RCI focuses on internal knowledge generation and innovation potential—both of which are critical for enabling green growth transitions.

Control Variables: Macroeconomic, Institutional, and Environmental Factors

To account for structural heterogeneity among Arab economies, the model integrates a comprehensive set of control variables grounded in the empirical literature. These variables are grouped into thematic clusters to reflect their conceptual relevance:

Institutional and Governance Indicators

- Control of Corruption (CC): Measures the extent to which public power is exercised for private gain, reflecting institutional transparency and integrity (Kaufmann et al., 2011).
- Regulatory Quality (RQ): Captures the ability of governments to formulate and implement sound policies and regulations that permit and promote private sector development.

Development and Human Capital

Human Development Index (HDI): Synthesizes information on life expectancy, education, and per capita income to assess overall human capability (UNDP).

Market and Economic Structure

- Economic Freedom Index (EFI): Assesses the degree of market openness, property rights, and rule of law, based on data from the Heritage Foundation.
- Export Concentration Index (ECI): Measures the diversification of exports, with higher values indicating stronger dependence on a narrow range of products or markets (UNCTAD).

Innovation and Technological Readiness

Patent Applications by Residents (INOV): Reflects national innovation output in terms of the number of patent applications filed domestically, based on World Bank data.

Energy Composition and Sustainability

- Clean and Nuclear Energy (REP): The share of low-carbon energy sources (hydropower, nuclear, solar, geothermal) in total national energy use.

- Electricity Production from Renewables Excl. Hydropower (ELCP): Indicates the proportion of electricity generated from modern renewables—such as wind, solar, and biomass excluding traditional hydropower.
- Combustible Renewables and Waste (EG-USE): Represents energy derived from biomass, biogas, and municipal or industrial waste combustion.
- Energy Depletion (% of GNI) (DNGY): Expresses the monetary value of fossil fuel depletion as a share of Gross National Income, signaling long-term resource sustainability.

Environmental Pressure and Externalities

- CO_2 Emissions (excl. LULUCF) (CO2): Measures carbon dioxide emissions from economic activity, excluding land-use change and forestry, in megatons of CO_2-equivalent.
- Air Pollution (PM2.5) (AIRP): Population-weighted exposure to fine particulate matter (PM2.5), indicating environmental stress and public health risks.

3.3 Method and Econometric Tools

In this study, we adopt the Extreme Gradient Boosting (XGBoost) algorithm—an advanced and efficient ensemble learning method within supervised machine learning—to model and predict green growth in Arab economies. The model is implemented in the R programming environment, with a focus on regression tasks. XGBoost is particularly suitable for capturing non-linear relationships, handling high-dimensional data, and achieving high predictive accuracy, which makes it a powerful tool for analyzing complex economic-environmental interactions in the context of green growth.

To ensure robust estimation and minimize overfitting, the dataset is partitioned into a training set (80%) and a testing set (20%), a commonly used ratio that allows the model to learn from a substantial portion of the data while preserving an independent subset for evaluating predictive accuracy. Additionally, we apply 10-fold cross-validation during the training process to assess the model's stability and generalization capacity across different data subsets.

Model performance is evaluated using two key statistical indicators: the Root Mean Squared Error (RMSE) and the Mean Absolute Error (MAE). RMSE provides a measure of how much predicted values deviate from actual observations by penalizing larger errors more heavily. The formula used is as follows (Lassouad et al., 2025):

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{4}$$

- y_i Represents the actual values, while y^_i represents the expected values
- yi-yˆi Calculate the error: For each data point, calculate the difference between the actual value and the predicted value.
- Squaring errors: This makes all values positive and gives more weight to large errors.

- n: The total number of data points, which is the number of pairs (actual value, predicted value) used to calculate the error.
- (y_i-y^_i)^2: The squared difference between the actual value and the predicted value: It is used to measure the size of the error for each observation with more weight given to larger errors.

RMSE is calculated by first computing the squared errors for all observations, taking their mean (Mean Squared Error), and then extracting the square root:

$$RMSE = \sqrt{MSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad (5)$$

In parallel, we use Mean Absolute Error (MAE) as a complementary indicator. Unlike RMSE, MAE treats all errors equally by taking the absolute value of the prediction errors:

$$MAE = \sqrt{MSE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \quad (6)$$

MAE provides an intuitive interpretation of the average error size in the original units of the dependent variable, offering a straightforward assessment of prediction accuracy.

XGBoost is a powerful machine learning algorithm that integrates the strengths of boosting and regularization to produce highly accurate and robust predictive models. The boosting mechanism constructs an ensemble of decision trees in a sequential manner, where each new tree is trained to correct the errors of the previous ones. Regularization, introduced through shrinkage (i.e., learning rate) and feature importance penalties, plays a critical role in preventing overfitting and enhancing the model's generalization ability (Suhendra et al., 2023).

A key factor in the success of XGBoost lies in its capacity to capture complex nonlinear relationships in the data while offering interpretable feature importance scores. However, to fully exploit its predictive capabilities, careful tuning of hyperparameters is essential. This process is inherently challenging, particularly in high-dimensional parameter spaces or when computational resources are limited. To address this, we employ Bayesian Optimization, a method that systematically explores the hyperparameter space using probabilistic models. It offers significant advantages over traditional approaches such as grid search or random search, especially when the evaluation of the objective function (e.g., a performance metric) is costly or time-intensive (Maulana et al., 2023).

Bayesian Optimization operates as a global optimization strategy that leverages probabilistic surrogate models to approximate the behavior of the objective function. This approach unfolds through an iterative, sequential process in which the surrogate model is continually refined based on newly acquired data. The central idea is to strategically select the next set of hyperparameters to evaluate, balancing the exploration of uncertain regions and the exploitation of known promising areas. This is achieved by combining the model's predictive mean with its uncertainty estimates, thereby guiding the search toward high-performing configurations with fewer evaluations.

The process begins with the specification of a prior distribution over the objective function ff, reflecting initial beliefs before any data is observed. In practice, this prior is commonly modeled using a Gaussian Process (GP), which not only predicts the expected value of ff at a given point but also quantifies the uncertainty of that prediction (Wu et al., 2019). As more data points are gathered through successive evaluations, the surrogate model is updated, and the prior evolves into a posterior distribution that more accurately reflects the true behavior of the function.

At each iteration, this posterior is refined by applying Bayes' theorem, which formally integrates the likelihood of the observed data with the prior distribution. According to Bayes' rule, the posterior probability of a parameter, given observed data, is proportional to the product of the likelihood of the data under that parameter and the prior belief about it. In Bayesian Optimization, this updating process enables the surrogate model to continuously improve its predictions and uncertainty estimates as new observations are incorporated (Snoek et al., 2012).

Over time, as the posterior distribution becomes increasingly informed by the data, the optimizer is able to focus its evaluations more effectively. This iterative refinement of the posterior lies at the heart of Bayesian Optimization's efficiency, allowing it to converge rapidly and reliably toward the global optimum of the hyperparameter space (Wang et al., 2023).

This approach is particularly well-suited for uncovering the potentially complex and nonlinear relationships between economic complexity, macroeconomic conditions, and green growth outcomes across structurally diverse Arab economies.

Given the heterogeneity of the region—ranging from resource-rich rentier states to emerging and transition economies—traditional linear models may fail to fully capture the underlying interactions. In contrast, the use of advanced machine learning techniques such as XGBoost allows for greater flexibility in modeling interactions, nonlinear effects, and higher-order dependencies among variables, thereby offering more nuanced insights into how structural and economic characteristics shape green development trajectories in different national contexts.

4 Results and Discussion

The results obtained from tuning the XGBoost model using Bayesian optimization (via the ParBayesianOptimization package in R) indicate a solid predictive performance, reflecting both the robustness and balance of the final model. The optimized hyperparameter values—most notably a low learning rate (eta = 0.0248) and shallow tree depth (max_depth = 3)—suggest that the model adopted a conservative learning strategy. This configuration effectively reduces the risk of overfitting while enhancing generalization capacity. The model's predictive accuracy is further supported by error metrics, with a Mean Absolute Error (MAE) of 0.1153 and a Root Mean Square Error (RMSE) of 0.1565.

In addition, the selection of subsample = 0.5 and colsample_bytree = 0.672 reflects the model's use of selective randomness in both sample and feature selection, which increases structural diversity across trees within the gradient boosting ensemble. This diversity is essential for improving model stability and reducing bias, especially in complex, high-dimensional data settings.

Table 1. Optimal Hyperparameter Configuration and Associated Performance Metrics

Hyperparameter	Optimal Value
Learning rate (eta)	0.0248
Maximum tree depth	3
Subsample ratio	0.5
Minimum child weight	9.86
Column sample by tree	0.672
Performance Metric	Value
Mean Absolute Error (MAE)	0.1153
Root Mean Square Error (RMSE)	0.1565

In addition, the relatively high value of min_child_weight (9.86) indicates the model's preference for avoiding weak or unstable splits that are based on insufficient data points. This constraint contributes to the structural stability of the decision trees by ensuring that nodes are only split when a substantial amount of information is present, thereby enhancing overall model reliability.

Taken together, these results reflect a carefully balanced trade-off between accuracy and simplicity. The model achieves strong predictive performance without resorting to overly deep or complex tree structures. As such, the selected hyperparameter configuration serves as a robust foundation for developing a final model with greater generalization capacity and practical applicability in real-world policy analysis.

The results of the XGBoost algorithm, employed to assess variable importance in explaining the Green Growth Index (GGI) across Arab countries, reveal a notable differentiation in the predictive weights assigned to the explanatory variables. The model relies on the Gain metric, which quantifies each variable's contribution to reducing the loss function and enhancing predictive performance. These findings highlight that green growth is not driven by a single dominant factor, but rather emerges from a complex interplay between innovation, governance quality, trade structure, and environmental pressures. Such multidimensionality underscores the need for integrated policy frameworks that account for these diverse and interacting drivers.

The following figure presents the ranking of variables based on their relative importance as determined by the model:

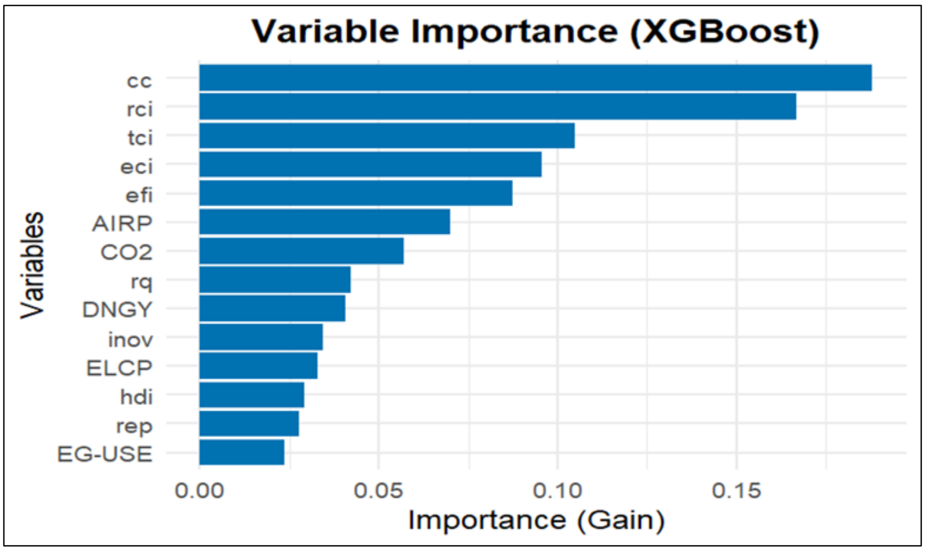


Figure 1. Key Variables Contributing to the Predictive Performance of Green Growth in Arab Countries

The study's results indicate that the Research Complexity Index (RCI) is the most influential predictor of green growth performance across Arab countries. It is followed by control of corruption (CC) and Trade Complexity Index (TCI). Variables with moderate importance include carbon emissions (CO_2), export concentration (ECI), air pollution (AIRP), electricity production from renewables (ELCP), and energy depletion (DNGY). The variables found to have lower predictive impact include economic freedom (EFI), regulatory quality (RQ), use of renewable and combustible waste (EG_USE), human development index (HDI), nuclear energy use (REP), and lastly, the number of patent applications (Inov).

The prominent role of RCI reflects the central importance of national capacities in research and technological innovation in steering the transition toward a low-emission economy. This aligns with Acemoglu et al. (2012), who argue in their theory of Directed Technical Change that green growth requires more than market-based instruments—it demands robust innovation incentives and technology-oriented policies that actively reshape production structures.

The strong impact of corruption control—ranked as the second most influential variable underscores the critical importance of an effective and transparent institutional environment for successful environmental policies. Corruption consistently undermines environmental governance by distorting resource allocation, weakening the enforcement of environmental standards, and discouraging investment in clean technologies. Conversely, strong governance bolsters accountability and facilitates the transition toward sustainable production patterns.

Similarly, the significance of the Trade Complexity Index suggests that countries engaged in the export of more sophisticated products—often embedded within local, regional, or global value chains—are better positioned to adopt cleaner and more efficient production methods. This reflects the role of productive and trade diversification in reducing environmental pressure and enhancing economic resilience in the face of climate challenges. In essence, the composition and complexity of a country's economic output significantly influence its ability to achieve sustainable green growth.

Notably, the results indicate that environmental variables—while essential—emerged more as moderating factors rather than primary drivers of green growth trajectories in Arab countries. Although carbon emissions (CO_2) and air pollution (AIRP) are among the most widely used environmental indicators, their predictive power in the model was comparatively lower than that of institutional and technological variables. This suggests that environmental policies alone are insufficient to generate meaningful green outcomes unless they are supported by knowledge-based reforms, institutional strengthening, and structural transformation. In this regard, the role of environmental pressure appears to be mediated through broader systems of innovation and governance.

The Export Concentration Index (ECI) also showed moderate predictive importance, indicating that economies reliant on a narrow export base—either in terms of products or trade partners—are less capable of adapting to environmental shifts. Such countries are more vulnerable to disruptions caused by global changes in demand for environmentally harmful goods. This finding reinforces the argument that primary commodity dependence constrains green adaptability and undermines resilience to climate-driven economic shocks.

Energy-related variables, despite their environmental relevance, demonstrated limited predictive influence. Variables such as electricity production from renewable sources (ELCP), energy depletion (DNGY), and use of renewable and combustible waste (EG-USE) ranked relatively low. This may reflect the limited availability of green energy infrastructure in many Arab countries or the absence of coherent strategies for integrating clean energy into national energy mixes. As a result, their current contribution to green growth remains marginal, despite their potential relevance in long-term transitions.

Finally, indicators such as economic freedom (EFI), regulatory quality (RQ), and the Human Development Index (HDI) exhibited non-central, complementary roles. While their standalone impact on green growth may be modest, their interactive effects with core variables (e.g., RCI, CC, TCI) may become more pronounced in causal or interaction-based modeling frameworks. Their contribution should not be overlooked, particularly when considering policy synergies and institutional readiness for sustainability transitions.

The predictive model based on XGBoost reveals a significant divergence in the relative importance of explanatory variables: the Research Complexity Index (RCI) emerges as the most influential factor in explaining variations in green growth across Arab economies, while the number of patent applications ranks last.

Although both indicators belong to the broader domain of scientific and technological innovation, this disparity highlights a crucial distinction between innovation efficiency—as captured by RCI—and the mere quantitative output of patents, which does not necessarily reflect either the quality of innovation or its direct environmental impact.

Indeed, countries with high patenting activity that fail to integrate these innovations into productive sectors often fall short of generating the expected value added from research (Dziallas & Blind, 2019). This issue is exacerbated by the limited environmental orientation of R&D policies in many Arab countries, revealing deeper structural challenges in how innovation is conceived and implemented.

From a methodological perspective, the divergence between the two indicators underscores a fundamental distinction:

The RCI functions as a composite index that reflects the overall efficiency of a national innovation system, capturing its ability to convert scientific research into economic and environmental value through active integration with production and technology ecosystems.

In contrast, the number of patent applications (Inov) represents a quantitative metric that may fail to capture the effectiveness of innovation, especially when patents are filed for academic or symbolic purposes without contributing to productivity or emission reduction (OECD, 2021).

The RCI encapsulates a country's capacity to generate and internalize complex knowledge, taking into account factors such as institutional structures, R&D expenditure levels and orientation, the coherence of innovation governance, and the degree of integration between research outputs and national or global value chains. In this sense, RCI measures not only what is produced, but how effectively knowledge is translated into green technologies that enhance resource efficiency and reduce environmental footprints.

On the other hand, innovation measured purely by patent counts often reflects symbolic or fragmented outputs, especially in contexts where patents are disconnected from industrial applications. In several Arab countries, patenting is driven by academic incentives or administrative procedures, without follow-up mechanisms to support commercialization, industrial scaling, or alignment with green priorities.

Consequently, a high volume of patents does not necessarily indicate a vibrant knowledge economy—unless accompanied by proactive policies that facilitate technology transfer, support innovation incubators, and direct research toward green national priorities. Moreover, without industrial strategies that embed patented innovations into productive structures, the patent system can become a costly and inefficient exercise.

This finding reinforces the explanatory power of RCI as a qualitative indicator that reflects the dynamic functionality of innovation systems, rather than their superficial outputs. It aligns with the perspective of Transformative Innovation (Schot & Steinmueller, 2018), which emphasizes that green growth is not driven by the number of innovations per se, but by a country's ability to absorb, finance, test, and scale innovation within its economic system.

The absence of institutional linkages between research centers and industry, as well as the disconnect between scientific knowledge and public policy, are major barriers limiting the real impact of innovation on green outcomes. Therefore, advancing green growth in the Arab world requires a functional integration between knowledge, production, and market systems—not merely the generation of isolated scientific outputs.

5 Conclusion and Policy Implications

This study provides a empirical contribution to the understanding of green growth determinants in Arab economies by integrating the dual dimensions of economic complexity—Trade Complexity (TCI) and Research Complexity (RCI)—into a predictive analytical framework. Through the application of the XGBoost machine learning algorithm, the research identifies key macro-structural and institutional variables that shape the green growth trajectories of structurally diverse Arab countries over the period 2000–2022.

The findings highlight that research complexity (RCI) emerged as the most influential predictor of green growth performance. This underscores the pivotal role of national innovation systems and the capacity to generate, absorb, and deploy knowledge in accelerating the transition toward low-carbon, resource-efficient economies. In contrast, the number of patent applications, often used as a proxy for innovation, showed minimal predictive significance reflecting the limitations of purely quantitative innovation metrics in contexts where institutional integration between research and production remains weak.

Furthermore, the study reveals that governance quality, particularly control of corruption, ranks as a key enabler of effective environmental policy implementation. It significantly outperforms conventional environmental indicators—such as CO_2 emissions or air pollution—in predictive importance. This suggests that green growth in Arab countries is fundamentally rooted in the structural interplay between institutional integrity, productive capabilities, and knowledge-based innovation rather than in environmental regulation alone.

Notably, environmental and energy-related variables—while conceptually central to green growth—played a secondary role in the model's predictive power. This reflects the region's structural challenges, including limited renewable energy infrastructure and weak integration of clean technologies into national energy systems. It also points to the need for coordinated policy efforts that simultaneously address technological readiness, institutional frameworks, and sectoral transformation.

Based on these findings, several strategic policy recommendations can be drawn:

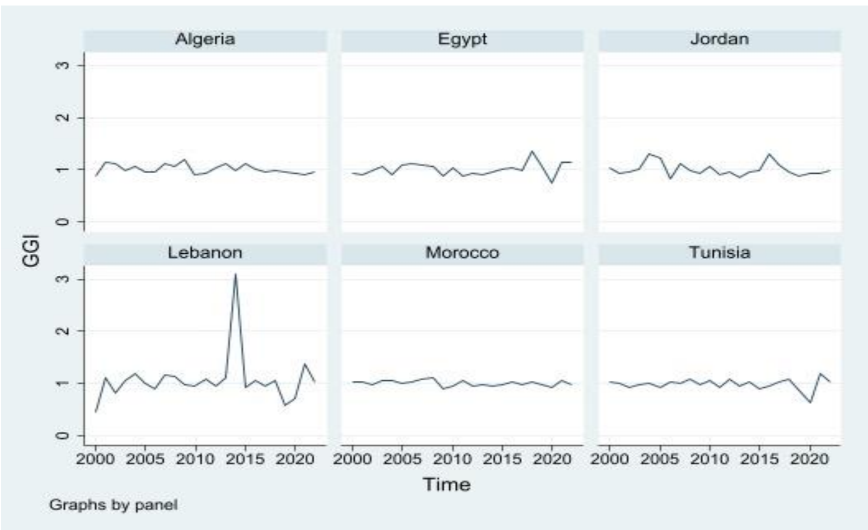
- **Strengthen National Innovation Systems (NIS)**: Governments should invest in enhancing the coherence, funding, and industrial linkages of research institutions. Policies should go beyond promoting patenting activity and focus on the effective translation of research into green technologies and industrial applications.
- **Institutional Reform for Environmental Governance**: Tackling corruption and strengthening the regulatory environment are preconditions for successful green policy implementation. Transparent governance enhances investor confidence, reduces policy leakage, and promotes accountability in environmental programs.
- **Embed Complexity in Trade and Industrial Policy**: Economic diversification strategies should prioritize the development of complex and green-intensive export

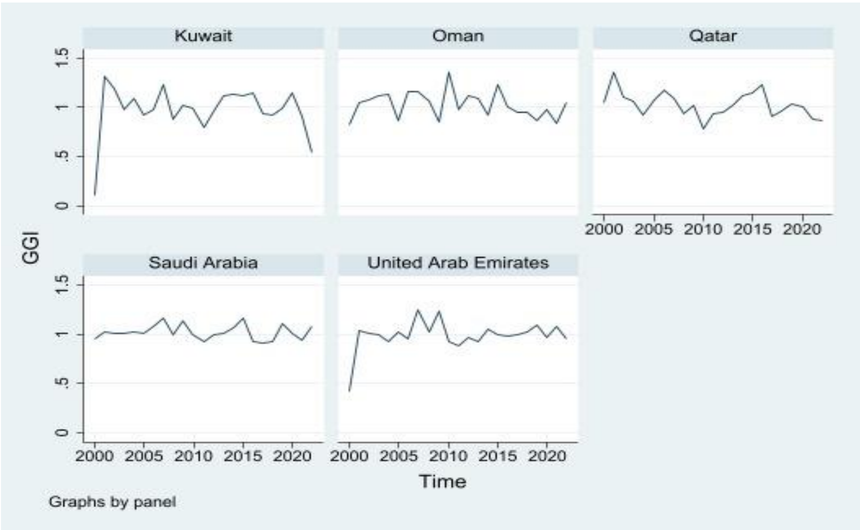
sectors. This includes supporting the transition of traditional industries toward low-carbon technologies and integrating local firms into regional and global green value chains.

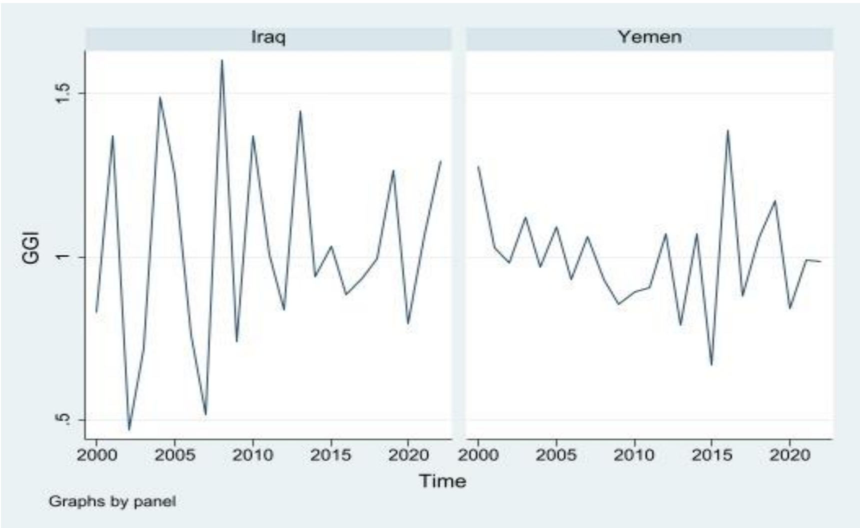
- **Reframe Environmental Policy through Innovation and Structural Reform**: Rather than relying solely on environmental regulation, policy design should integrate environmental goals into broader innovation, trade, and industrial strategies—ensuring that green growth is treated as a cross-cutting priority.
- **Targeted Support for Clean Energy Infrastructure**: While energy-related variables currently show weak predictive impact, their long-term significance cannot be ignored. Expanding renewable energy capacity and embedding clean energy transitions into national development plans are crucial for future resilience.
- **Tailor Green Growth Strategies to Structural Realities**: Given the heterogeneity of Arab economies, green growth policies should be context-specific, accounting for differences in resource endowments, income levels, innovation capacities, and institutional maturity. Regional cooperation and knowledge sharing can amplify national efforts and facilitate collective progress.

In conclusion, the study affirms that economic complexity—when rooted in institutional depth and innovation efficiency—can serve as a catalyst for green transformation. Green growth in Arab countries is not a linear or uniform process; it is shaped by the nuanced interaction of knowledge, governance, trade structure, and environmental context. Therefore, future strategies must adopt a systemic, multidimensional approach that aligns innovation, institutional capacity, and environmental priorities within coherent development frameworks. This not only enhances the prospects for sustainable growth but also strengthens the region's resilience in the face of global environmental and economic transitions.

Appendix







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