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.

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1 Introduction

For decades, the pursuit of sustainable economic development has been 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 that shape production and export profiles—advancing green growth entails more than environmental adjustments. It requires the 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. By shaping 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), holds that sustainable growth depends on a country's ability to accumulate, recombine, and deploy productive knowledge across increasingly sophisticated sectors. Nations with 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 to low-carbon economies.

Yet the empirical relationship between economic complexity and green growth remains underexplored, especially in the Arab region, where economies range from hydrocarbon-dependent rentier states 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, shapes green growth outcomes in Arab countries.

1.1 Research Problem

While economic complexity is increasingly recognized as a structural determinant of green growth—linked to more diversified production, stronger innovation systems, and greater institutional adaptability—its specific contribution in the Arab context remains empirically underexplored. How do 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 questions:

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

1.2 Research Objectives

This research aims to examine the predictive relationship between economic complexity and green growth in Arab economies, using advanced empirical methods to capture structural heterogeneity and nonlinear dynamics. The specific objectives are:

- To construct a composite Green Growth Index (GGI) for Arab countries that integrates economic, environmental, and institutional dimensions and reflects regional development priorities and data constraints.
- To assess the predictive power of economic complexity—measured by the Trade Complexity Index (TCI) and Research Complexity Index (RCI)—in determining green growth outcomes.
- To investigate the mechanisms by which trade sophistication, innovation capacity, and knowledge systems influence environmentally sustainable development pathways.
- To examine complementary macro-institutional variables, including corruption control, regulatory quality, renewable energy use, human development, and export concentration, and how these variables shape green growth trajectories.
- To provide evidence-based policy recommendations to advance 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 machine-learning-based predictive modeling framework, thus moving beyond traditional regression-based approaches.

In practice, the research contributes to the design of context-specific green growth metrics and offers 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 nonlinearity, yielding 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 lays 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 examined the relationship between economic complexity and green growth, typically treating 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 interactions with innovation, renewable energy adoption, policy stringency, and trade openness. These studies aim to identify when and how complexity supports sustainable development.

This review synthesizes key findings and highlights contextual factors that shape the complexity of the green growth nexus, especially in developing regions such as 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 the adoption of renewable energy (Aluko et al., 2024; Neagu & Teodoru, 2024). More complex economies often have 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, low-emission growth. Similarly, Lee et al. (2022) find a significant negative relationship between complexity and per capita CO_2 emissions, particularly when complexity is 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 materialize only 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 clean energy investments.

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

In sum, economic complexity can reduce environmental harm and promote sustainable development, but its effectiveness varies across countries. Technological readiness, energy mix, and environmental policy frameworks 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 higherskilled labor and advanced innovation systems, driving structural transformation toward environmentally sustainable production.

A consistent finding across the literature is that this process improves resource efficiency and supports low-carbon industrial upgrading. Studies by Sun et al. (2024), Aihui 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 achieve greater environmental returns from complexity.

Overall, this literature suggests that the full potential of economic complexity to support green growth depends 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 supports green growth.

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

This evidence shows 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 channel complexity toward pollution-intensive sectors.

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

The literature 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 yield 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. In the early stages of development, environmental gains from complexity depend on effective institutions, targeted green investments, and supportive regulatory frameworks.

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

Education spending emerges as a key factor. Strengthening human capital improves the absorption of complex technologies and boosts innovation capacity—thereby reinforcing the complexity–green growth link, as shown by Okombi & Lebomoyi (2024).

Overall, the positive effects of complexity are not automatic; they require strategic government action to turn 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 development stages.

In high-income countries, complexity tends to yield strong environmental benefits, thanks 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 the green effects of complexity 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 reaching 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 paired with investments in clean energy and knowledge sectors. Emmanuel et al. (2024) and Arslan et al. (2023) emphasize the need for structural reforms and green capacity building.

Finally, Doğan et al. (2019) show 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 depend on the level of development, energy structure, and institutional quality, necessitating differentiated, context-aware policy responses.

2.7 Research Gap

While the relationship between economic complexity and green growth has attracted increasing attention in recent empirical research, significant gaps remain—especially in developing economies and Arab countries. Much of the existing literature focuses 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 that capture the multidimensional 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 have unique structural and institutional characteristics that limit the applicability of findings from other regions. The region exhibits substantial variation in economic complexity, ranging from 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 is their reliance on traditional linear econometric models, which often assume homogeneous relationships across countries and fail to capture complex, nonlinear, or interactive dynamics. Such approaches risk oversimplifying the influence of economic complexity on green growth. To address this, the present study introduces a novel predictive framework based on the Random Forest algorithm—a machine learning technique well suited to 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 integrating Arab economies into a literature in which 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 that highlights variability in both the direction and magnitude of this relationship across 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 careful selection of explanatory variables and an appropriate econometric approach. The diversity of Arab economies, characterized by structural and institutional asymmetries, varied development trajectories, and heterogeneous levels of economic complexity, necessitates a methodological framework that effectively captures these differences and disentangles potential effects across levels of green growth performance.

3.1 Scope of the Study

The sample for this study comprises 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 grouped into three main categories, allowing for a more nuanced understanding of the internal heterogeneity in the impact of economic complexity on green growth.

3.2 Study Variables

Given the structural heterogeneity across Arab economies in the sample, and consistent with prior empirical literature, the relationship between economic complexity and green growth is expected to vary across regions. This necessitates incorporating additional economic variables to explain 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), and the nature of government interventions and economic policies.

Dependent Variable: Green Growth Index for Arab Countries

Green growth is a development approach that seeks to balance economic growth with environmental protection by improving the efficiency of resource use—namely, labor, capital, and energy—while promoting GDP growth alongside a reduction in the environmental impact of economic activities (Kuzior, 2022; Dźwigoł & Dźwigoł-Barosz, 2020). Accordingly, the Green Growth Index is used 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) to environmental outcomes (emissions and energy use), thereby capturing both environmental and economic efficiency. In the context of Arab countries, resource-use efficiency is expressed as the sustainable GDP-to-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 enables comparison of countries' growth performance relative to the production possibility frontier, which defines the most efficient combination of inputs and outputs. The index measures 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. Thus, Equation (1) captures 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:

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

Where:

- Ged_t^{t+1} denotes the green growth index of a country between 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, measuring the gap between current production and the efficient frontier, accounting for 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.

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

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

The integration of environmental factors into equation (2) reflects the negative environmental externalities of production. 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 for assessing 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 converting available inputs into economic value while minimizing environmental harm.

- Considering the qualitative and quantitative characteristics of the input data, the model enables granular estimation of the environmental impact of production (Kwilinski et al., 2023b, p. 511).
- It also enables cross-country comparisons 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 capture the structural and cognitive depth of national economies. Together, they reflect the extent to which a country can produce, exchange, and embed knowledge within its economic and technological systems.

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

Research Complexity Index (RCI)
RCI measures a country's scientific and technological advancement by assessing its 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 that supports transformative, green technologies and accelerates structural change toward sustainability.

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

Control Variables: Macroeconomic, Institutional, and Environmental Factors
To account for structural heterogeneity across Arab economies, the model incorporates 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 used 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 enable and promote private-sector development.

Development and Human Capital
Human Development Index (HDI): Synthesizes data 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 the rule of law, using data from the Heritage Foundation.
- Export Concentration Index (ECI): Measures export diversification, with higher values indicating greater dependence on a narrow range of products or markets (UNCTAD).

Innovation and Technological Readiness
Patent Applications by Residents (INOV): Reflects national innovation output, measured by 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, and geothermal) in total national energy use.
- Electricity Production from Renewables Excl. Hydropower (ELCP): Indicates the share of electricity generated from modern renewables—such as wind, solar, and biomass—excluding traditional hydropower.
- Combustible Renewables and Waste (EG-USE): Energy derived from biomass, biogas, and the combustion of municipal or industrial waste.
- 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), reflecting 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, efficient ensemble learning method in 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. XGBoost is particularly well suited to capturing nonlinear relationships, handling high-dimensional data, and achieving high predictive accuracy, making 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 split into a training set (80%) and a test set (20%), a commonly used split 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 training to assess the model's stability and generalization 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 quantifies how much predicted values deviate from actual observations, with larger errors penalized more heavily. The formula 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
- $y_i - \hat{y}_i$ Calculate the error: For each data point, compute the difference between the actual and predicted values.
- Squaring errors: This makes all values positive and gives greater weight to large errors.
- n: The total number of data points, i.e., the number of (actual value, predicted value) pairs used to calculate the error.
- $(y_i - \hat{y}_i)^2$: 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 taking the square root:

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

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

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

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

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

A key factor in XGBoost's success is its ability to capture complex nonlinear relationships in the data while providing interpretable feature importance scores. However, to fully exploit its predictive capabilities, careful hyperparameter tuning 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, which systematically explores the hyperparameter space using probabilistic models. It offers significant advantages over traditional approaches such as grid search or random search, especially when evaluating the objective function (e.g., a performance metric) is costly or time-intensive (Maulana et al., 2023).

Bayesian Optimization is a global optimization strategy that uses probabilistic surrogate models to approximate the objective function. It proceeds iteratively, continually refining the surrogate model as new data is acquired. The central idea is to select the next set of hyperparameters to evaluate, balancing exploration of uncertain regions with exploitation of promising known 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 by specifying a prior distribution over the objective function f, reflecting initial beliefs before any data is observed. In practice, this prior is often modeled with a Gaussian Process (GP), which not only predicts the expected value of f 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 function's true behavior.

At each iteration, this posterior is refined using Bayes' theorem, which formally combines the likelihood of the observed data with the prior distribution. According to Bayes' rule, the posterior probability of a parameter, given the 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).

As the posterior distribution becomes increasingly informed by the data, the optimizer can focus its evaluations more effectively. This iterative refinement of the posterior is central to Bayesian Optimization's efficiency, enabling rapid and reliable convergence to 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 region's heterogeneity—ranging from resource-rich rentier states to emerging and transition economies—traditional linear models may not fully capture the underlying interactions. In contrast, advanced machine learning techniques such as XGBoost offer greater flexibility to model interactions, nonlinear effects, and higher-order dependencies among variables, thereby providing more nuanced insights into how structural and economic characteristics shape green development trajectories across national contexts.

4 Results and Discussion

The results from tuning the XGBoost model using Bayesian optimization (via the Par Bayesian Optimization package in R) indicate strong predictive performance, reflecting 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: Mean Absolute Error (MAE) of 0.1153 and 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

Source: Author's calculations.

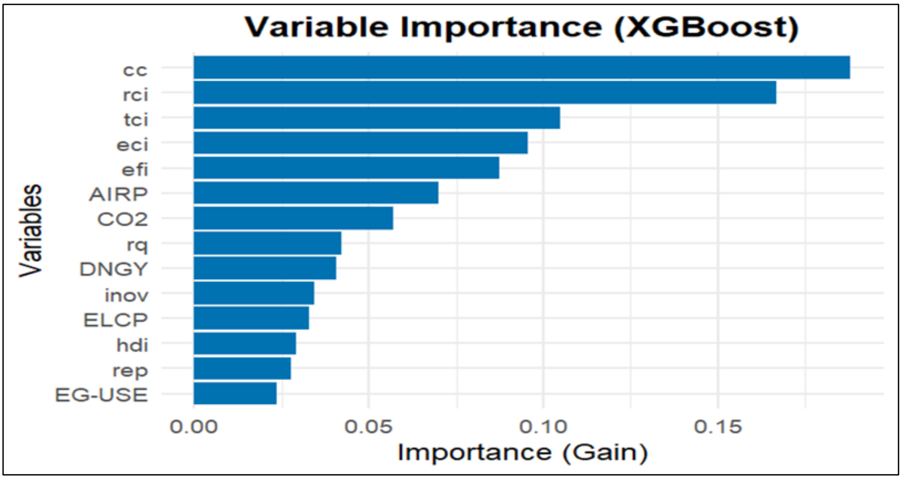
In addition, the relatively high value of min_child_weight (9.86) indicates the model's preference for avoiding weak or unstable splits that are based on insufficient data points. This constraint contributes to the structural stability of decision trees by ensuring that nodes are split only when sufficient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



Source: Authors calculations.

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 the 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 exporting more sophisticated products—often embedded in 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—served more as moderating factors than as 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 able to adapt 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).

RCI encapsulates a country's capacity to generate and internalize complex knowledge, considering 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 of the dynamic functioning 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 an empirical contribution to understanding the determinants of green growth in Arab economies by integrating the dual dimensions of economic complexity—Trade Complexity (TCI) and Research Complexity (RCI)—into a predictive analytical framework. Using 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 the control of corruption, is 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 interplay among knowledge, governance, trade structures, and environmental contexts. 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 prospects for sustainable growth but also strengthens the region's resilience amid global environmental and economic transitions.

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51. https://data.albankaldawli.org/indicator/EN.ATM.PM25.MC.M3
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53. https://data.albankaldawli.org/indicator/IP.PAT.RESD
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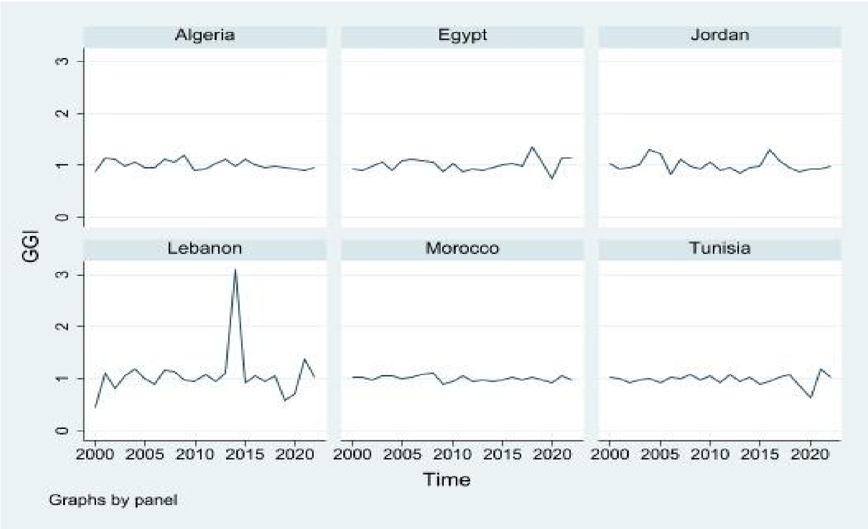
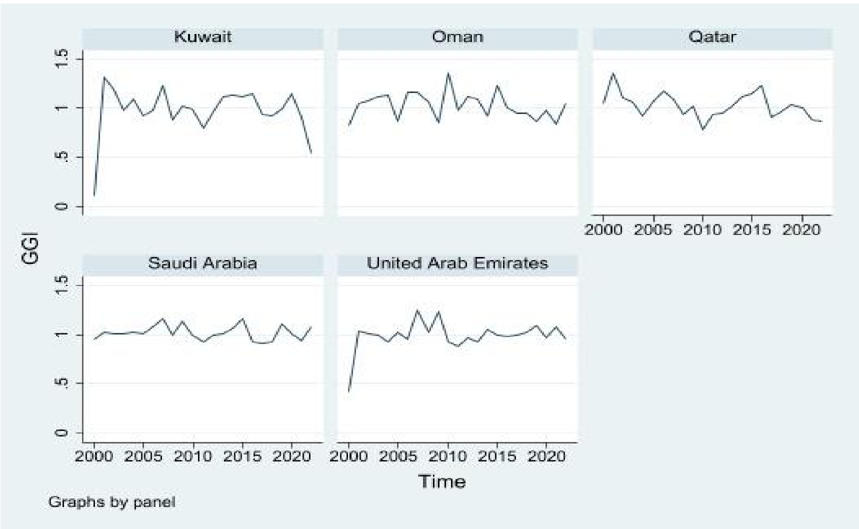
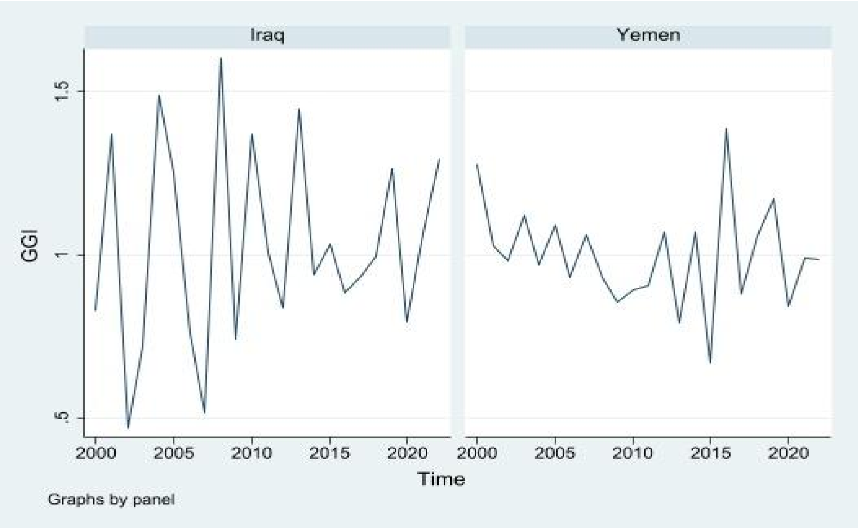
60. https://unctadstat.unctad.org
61. https://www.heritage.org/index
62. https://www.irena.org/Data

Appendix A: GGI over 2000-2022






Iraq
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Graphs by panel