Using Machine Learning to Predict Countries' Climate Readiness*

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January 2026

Abstract

Climate readiness indices like the Notre Dame Global Adaptation Initiative (ND-GAIN) can provide critical guidance for adaptation resource allocation but require extensive data collection across numerous specialized indicators. This study investigates whether machine learning methods can accurately classify national climate readiness using a lean set of publicly available macro-indicators. Through comparison of logistic regression, Random Forests, Support Vector Machines, and XGBoost on 3,912 country-year observations (182 countries, 2000-2023), results show XGBoost achieves 93.3% macro-averaged F1-score in replicating ND-GAIN's readiness-vulnerability matrix classifications using just 12 World Bank indicators, reducing data requirements from 45 indicators across 74 sources while maintaining classification accuracy. Temporal validation demonstrates robust generalization: trained on 2000-2018 data, the model achieves 86.2% F1-score predicting 2019-2023 classifications, with particularly strong performance in identifying highly vulnerable (94% F1) and well-prepared (94% F1) nations. The findings demonstrate that machine learning can substantially simplify climate readiness assessment while enabling more timely monitoring as annual macroeconomic data becomes available, offering a practical complement to comprehensive indices for policymakers and investors in decision making and resource allocation.

1 Introduction

Climate change represents one of the most urgent and complex challenges of our time, with global temperatures projected to rise between 1.5°C and 4.5°C by 2100 under various emission scenarios (IPCC, 2023). Mitigation efforts alone cannot further avoid climate change impacts (Klein et al., 2007), and although adaptation planning and implementation have progressed across all sectors and regions, adaptation gaps still exist and will continue to grow at current rates of implementation (IPCC, 2023). This highlights the need for policymakers and investors to accurately identify which nations are most vulnerable and least prepared for climate change to facilitate allocation of resources where urgent or where it yields greatest reductions in risks.

Several indices have been developed to evaluate the ability of nations to adjust their economic and social systems to climate-related challenges, their 'climate readiness', quantifying their vulnerability and preparedness. Among the most widely adopted is the Notre Dame Global Adaptation Initiative (ND-GAIN) Country Index. It is a composite index that assigns a score from 0 to 1 for each of 182 UN countries based on two dimensions: (1) vulnerability and (2) readiness. These two scores also allow countries to be mapped into a readiness-vulnerability matrix, where those with lower readiness and higher vulnerability are considered to face the greater challenges and with urgency to act (ND-GAIN, 2024).

These climate readiness indices are complex. Their multidimensional structure of climate-related risks means composite measures require extensive data collection and processing. The ND-GAIN, for example, incorporates 45 indicators from 74 data sources across its vulnerability and readiness components, each selected, weighted, and scaled by experts (ND-GAIN, 2024). The reliance on numerous indicators, some of which exhibit temporal lags, limited coverage, while some datasets are stagnant (ND-GAIN, 2024), may hinder real-time assessment and further complicate

*Disclaimer: This paper was submitted as a final project for the course "Introduction to Machine Learning for Economists" at the University of Bologna (Fall 2025). It is intended for portfolio demonstration and has not been peer-reviewed.

computation. This raises the question: can simpler, more accessible approaches achieve comparable predictive accuracy while maintaining operational feasibility?

Machine learning (ML) has increasingly been applied to climate-related prediction tasks, including forecasting climate impacts and climate-induced disasters (Reichstein et al., 2019; Haggag et al., 2021), and assessing climate risk in sectors such as agriculture (Jha et al., 2023) and finance (Ferrara et al., 2024). However, existing applications focus primarily on biophysical climate modeling or sector-specific impact prediction. While recent advancements in climate readiness indices are focusing on granular-level or sector-specific readiness rather than national-level readiness classification (Neder et al., 2021; Damba et al., 2024; Epule et al., 2025).

To the author's knowledge, machine learning has not yet been applied to simplify or predict composite climate readiness indices like ND-GAIN using sets of publicly available macro-indicators. This represents an important methodological gap, if ML can accurately approximate complex multi-indicator frameworks with fewer, more accessible predictors, it could enable more timely monitoring of climate adaptation capacity, this is particularly valuable as annual macroeconomic data becomes available well before specialized climate indicators are updated.

This study addresses this gap by investigating whether machine learning classifiers can accurately replicate ND-GAIN's readiness-vulnerability matrix classifications using a "lean" set of 12 publicly available macroeconomic and governance indicators from the World Bank's World Development Indicators (WDI) and Worldwide Governance Indicators (WGI). I compare four classification approaches; logistic regression, Random Forests, Support Vector Machines, and XGBoost to evaluate whether the superior pattern recognition capacity of ensemble methods can compensate for reduced indicator complexity. By demonstrating that a ML model can achieve predictive performance comparable to ND-GAIN's 45-indicator framework, this research aims to lower the barrier to real-time climate readiness monitoring while maintaining classification accuracy sufficient for policy guidance on adaptation resource allocation.

2 Data

2.1 Target

The target variable for this classification model is the ND-GAIN Matrix Category of a country in a given year. The data is sourced from the Notre Dame Global Adaptation Initiative (ND-GAIN) Country Index, a composite index developed by the University of Notre Dame to quantify the gap between climate urgency and adaptation capacity.

The ND-GAIN Index covers 182 United Nations countries from 1995 to the present (2023 is the latest data point available to date). While the index itself produces a continuous score (0-100), this study treats the problem as a classification task by using the ND-GAIN Matrix. This matrix visualizes the relationship between the two primary dimensions of the index:

- Vulnerability: Measures a country's propensity to be negatively impacted by climate risks. It aggregates 36 indicators across six life-supporting sectors: food, water, health, ecosystem services, human habitat, and infrastructure.
- Readiness: Measures a country's ability to leverage investments for adaptation actions. It aggregates 9 indicators across three components: economic readiness, governance readiness, and social readiness.

To generate the target labels for our machine learning model, I follow the method by ND-GAIN (2024) and classify each country-year observation into one of four quadrants represent by different colors, each separated by the median score of vulnerability and the median score of readiness across all countries and years, resulting in four distinct classes as shown in Figure 1. I will use label encoding and convert these quadrant categories into numeric labels for multiclass classification.

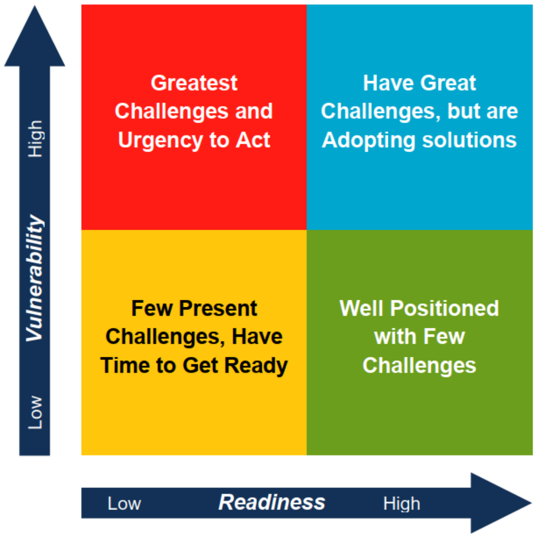

Figure 1: ND-GAIN Matrix

Source: ND-GAIN Technical Report (2024)

- Red, encoded as 0 : Countries with the greatest challenges and urgency to act.
- Yellow, encoded as 1 : Countries with few present challenges but needing time to get ready.
- Blue, encoded as 2 : Countries with great challenges but are actively adopting solutions.
- Green, encoded as 3: Well-positioned countries with few challenges.

2.2 Predictors

To construct an alternative set of indicators to ND-GAIN's specialised 45-indicator framework, 12 macro-indicators were strategically selected from the World Bank's World Development Indicators (WDI) and Worldwide Governance Indicators (WGI). These databases were chosen for its comprehensive country coverage, consistent annual updates, standardized methodology across nations, and free public accessibility. These 12 indicators are selected to proxy major sectors across two primary dimensions of the original index. The details are shown in Table 1.

While the indicators from the original index are available from 1995, many modern indicators have only been consistently available since year 2000. I have discovered that some ND-GAIN indicators use interpolation to fill the multi-year gaps back to 1995. However, relying on such extensive artificial trends data for our inputs may introduce artificial noise and may reduce the validity of our machine learning model. Therefore I have restricted the training and testing data to the period from 2000 to the present. We will apply interpolation for minor, incidental missing values to maintain continuity without compromising data integrity during data preprocessing.

Table 1: Selected Predictor Variables from World Bank's WDI and WGI

Category	Variable Name	Series Code	Description & Rationale
Vulnerability	Agriculture, value added (% of GDP)	`NV.AGR.TOTL.ZS`	**Sector: Food.** Measures economic reliance on climate-sensitive sectors.
Vulnerability	Access to basic drinking water services (% of pop)	`SH.H2O.BASW.ZS`	**Sector: Water.** A direct measure of the capacity to deliver reliable water.
Vulnerability	Mortality rate, under-5 (per 1,000)	`SH.DYN.MORT`	**Sector: Health.** Proxies for the overall strength of the healthcare system and its ability to protect sensitive populations.
Vulnerability	Agricultural land (% of land area)	`AG.LND.AGRI.ZS`	**Sector: Ecosystem.** Proxies pressure on natural capital. High agricultural land use may indicate biome stress and reduced ecosystem's complexity.
Vulnerability	Urban population (% of total)	`SP.URB.TOTL.IN.ZS`	**Sector: Human Habitat.** Captures "density risk." High urban concentration increases sensitivity to extreme weather events and communicable diseases.
Vulnerability	Access to electricity (% of population)	`EG.ELC.ACCS.ZS`	**Sector: Infrastructure.** The fundamental proxy for physical resilience.
Vulnerability	Mobile cellular subscriptions (per 100 people)	`IT.CEL.SETS.P2`	**Sector: Infrastructure/Social.** Proxies soft infrastructure and preparedness. Mobile networks are critical for early warning systems.
Readiness	GDP per capita (US $)	`NY.GDP.PCAP.CD`	**Component: Economic.** The primary indicator of a country's economy and financial capabilities
Readiness	FDI, net inflows (% of GDP)	`BX.KLT.DINV .WD.GD.ZS`	**Component: Economic.** Measures connectedness to global economy, closely mirroring the ND-GAIN "Doing Business" indicators.
Readiness	Government Effectiveness	`GE.EST`	**Component: Governance.** Measures the quality of public services and policy formulation. Proxies the institutional stability. (source: WGI)
Readiness	School enrollment, secondary (% gross)	`SE.SEC.ENRR`	**Component: Social.** Measures human capital development essential for adaptive capacity.
Readiness	Unemployment, total (% of total labor force)	`SL.UEM.TOTL.ZS`	**Component: Social.** Indicates social fragility and the ability to absorb economic shocks.

Note: Economic and social variables sourced from World Bank WDI. Governance data sourced from WGI.

3 Methodology

3.1 Problem Formulation

The objective is to approximate the unknown function $f : X \to Y$, where X represents the vector of 12 macro-indicators and Y represents the categorical ND-GAIN matrix quadrant.

Let $y_{it} \in 0, 1, 2, 3$ denote the categorical label (Red, Yellow, Blue, Green) for country i at time t, derived from the ND-GAIN matrix quadrants.

Let X_{it} be the vector of $K = 12$ macro-economic and social predictors described in Table 1.

This study will use the naive pooling approach by treating each country-year observation (y_{it}, X_{it}) as independent, disregarding the panel time-series structure. I chose this approach to simplify computation and to leverage a larger effective sample size. This will come with some limitations and will be addressed with robustness check and discussed later on.

3.2 Data Preprocessing

Prior to training, I apply the following transformations:

- Imputation: Minor missing values in the continuous predictors (WDI and WGI data) are handled via linear interpolation, consistent with the ND-GAIN methodology.
- Standardization: As our predictors vary in magnitude. (e.g., GDP per capita vs. percentages), we will apply standard scaling (Z-Score Normalization) to all features to have zero mean and unit variance.

This is to ensure numerical stability and model validity, it is also a common practice in constructing readiness index in context of climate change as seen in Epule et al. (2021)

3.3 Model Selection

This analysis employs a tournament-style comparative assessment of classification algorithms from a simple baseline to more flexible machine learning models. Models are evaluated on the same resampling scheme and ranked primarily by macro-average F1 score (discuss in section 3.4)

3.3.1 Baseline Model: Multinomial Logistic Regression

I will use multinomial logistic regression as the baseline due to its interpretability, computational efficiency, and established use in multi-class classification tasks. For the four-quadrant classification problem in this study, the model estimates the probability that a country-year observation belongs to quadrant $j \in \{Red, Yellow, Blue, Green\}$ as:

$$P\left(y_{it} = j \mid X_{it}\right) = \frac{\exp\left(\beta_j^T X_{it}\right)}{\sum_{k=0}^{3} \exp\left(\beta_k^T X_{it}\right)}$$

Where β_j represents the coefficient vector for quadrant j and X_{it} is the vector of 12 standardized predictors.

Logistic regression assumes that the relationship between predictors and readiness follows a smooth, monotonic pattern through linearity in the log-odds. In practice, this can be restrictive for climate readiness, where effects may exhibit thresholds, diminishing returns, or interactions across drivers. Prior work examining the Climate Readiness Index alongside predictors such as GDP per capita reports evidence consistent with nonlinear relationships (Ul Mustafa et al., 2025). Therefore, this baseline model is expected to face limitations in capturing complex functional forms and cross-variable dependencies. Machine learning methods can potentially address these shortcomings.

3.3.2 Random Forests

Random Forests is a machine learning method that operates by combining the predictions of many individual decision trees to reach a single classification. Rather than fitting a single global parametric function, decision trees recursively partition the feature space using data-driven splits. At each node, the algorithm selects the predictor and threshold that maximize class separation, typically by reducing an impurity measure such as Gini index or entropy.

Each tree in the ensemble is trained on a bootstrap sample of the data and considers only a random subset of predictors at each split. By averaging across weakly correlated predictors, they substantially reduce variance relative to individual decision trees (Breiman, 2001). This variance reduction comes with minimal increase in bias, as each tree in the group remains flexible allowing it to capture nonlinearity. This approach makes Random forests robust to the noise inherent in developing-nation data. Random Forests also have been proven highly effective in social science applications with modest sample sizes and complex predictor relationships (Muchlinski et al., 2016). However, the ensemble's flexibility means it can still overfit if trees grow excessively deep without constraints, particularly when the number of observations is limited relative to feature space dimensionality.

3.3.3 Extreme Gradient Boosting (XGBoost)

XGBoost is a highly effective and widely used machine learning method (Chen and Guestrin, 2016). It is an ensemble technique that builds decision trees sequentially rather than in parallel.

The model is trained in an additive, stage-wise manner where new tree is added at each iteration to reduce the current training loss rather than building all trees independently and averaging them as in Random Forests.

The sequential error correction mechanism allows XGBoost to achieve very low bias. The primary risk is therefore high variance and overfitting. XGBoost addresses this through explicit regularization by optimizing an objective function that combines training loss with penalties on tree complexity. This helps control model complexity and reduce overfitting in flexible tree ensembles, particularly when the data set is not large (XGBoost Developers, 2026; Pandit and Ahlawat, 2025). This is well aligned with the setting of this study, making it a suitable candidate for the multi-class classification task.

3.3.4 Support Vector Machines (SVM)

Support Vector Machines (SVM) is another popular machine learning method which has been used in development economics classification tasks, such as predicting poverty status using household survey data (Hassan et al., 2024). The main goal of the SVM algorithm is to find a hyperplane in an N-dimensional feature space that maximizes the margin between classes (Pandit and Ahlawat, 2025). The maximum margin principle provides theoretical regularization and controls variance, while kernel functions and its parameter control bias.

The bias-variance trade off in SVMs is governed by the choice of kernel and the regularization parameter. Here we employ the Radial Basis Function (RBF) kernel, which allows for highly flexible, non-linear boundaries. The regularization parameter C, which controls the penalty for misclassified points, are tuned to modulate the margin width and maintain generalisability.

I chose one-vs-one (OvO) strategy for this four-class classification problem, training binary classifiers for each pair of classes and assigning each country-year to the class receiving the most votes. This is the default multiclass setting in Python's scikit-learn.

3.4 Evaluation Strategy

ND-GAIN consultation page mentioned that ND-GAIN score is highly correlated to a country's economic development. We can expect poorer countries to be among the more vulnerable group and less prepared for the lack of resources. Indeed, we can observe a negative relationship between readiness and vulnerability when looking at the visualisation as shown in appendix A.

In anticipation of the imbalanced distribution of quadrants, Macro-Averaged F1-Score is preferred over simple accuracy for classification model evaluation. This ensures that the model is penalized for misclassifying minority instances, as opposed to using simple accuracy which weights performance by class frequency, so the model effectively learns the characteristics of all four class profiles.

When express in term of True Positive (TP), False Positive (FP), and False Negative (FN), we can express F1 score as:

$$\text{F1 Score} = \frac{\text{TP}}{\text{TP} + \frac{1}{2}(\text{FP}+\text{FN})}$$

and Macro-Averaged F1-Score is the arithmetic mean of our 4 classes' F1 scores :

$$\text{Macro-Averaged F1-Score} = \frac{\text{F1}_{red} + \text{F1}_{blue} + \text{F1}_{yellow} + \text{F1}_{green}}{4}$$

I will also be using a Stratified Train-Test Split to ensure that the proportionality of class structure is maintained for the Train-Test data. For hyperparameter optimization, I utilize k-fold Cross-Validation (k=5) within the training set to reduce the variance of performance estimates by rotating the validation fold across the training set.

Model with the best performance will be subjected to robustness check via Time-Series Split test.

3.5 Robustness Check

While the primary analysis employs a naive pooling approach for computational efficiency, I acknowledge that panel data inherently violates the independent and identically distributed (i.i.d.) assumption due to serial correlation (Wooldridge, 2010). The presence of strong temporal autocorrelation implies that a model might memorise a country's status throughout the years rather than learning the underlying relationship, leading to biases.

In an attempt to address this limitation and assess the model's forecasting utility, I will conduct a robustness check using a Time-Series Split. Even though it is not the focus of this study, this remains a useful test of temporal out-of-sample performance under a realistic forward-looking setting. In this procedure, the best classifier identified in the cross-validation stage is retrained exclusively on historical data (2000-2018) and evaluated on a hold-out set of the 5 most recent available years (2019-2023).

3.6 Workflow Diagram

Figure 2 shows the workflow of the project:

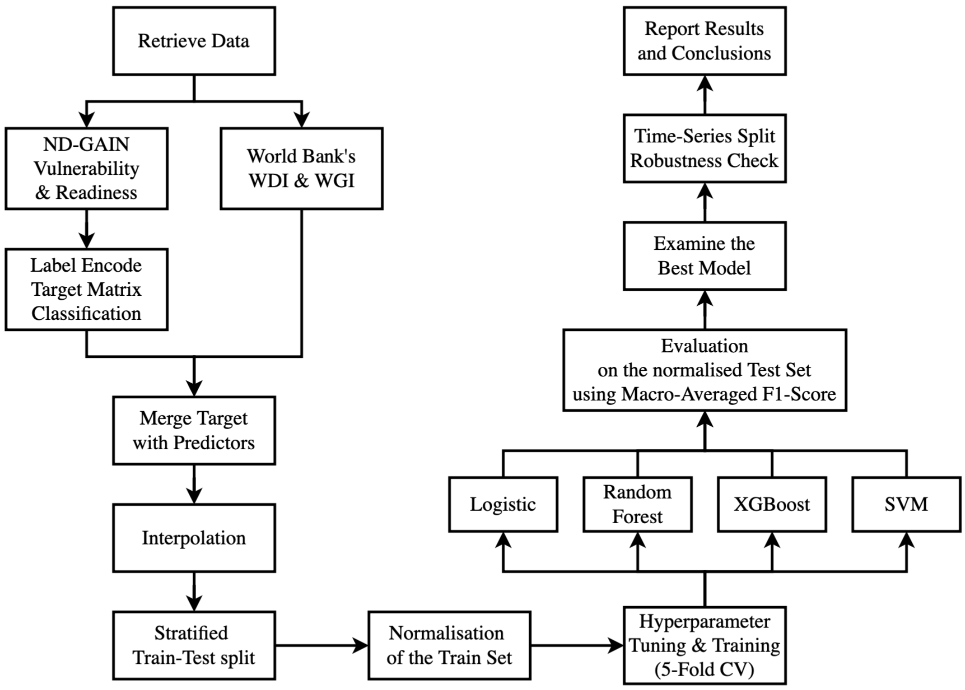

Figure 2: Project Workflow

4 Findings

4.1 Primary Analysis

Table 2 presents performance metrics from the model tournament, evaluated on a held-out test set of 782 country-year observations (20% of the full dataset). All models were trained on the remaining 80% and assessed using Macro-Averaged F1-Score as the primary metric.

Table 2: Model performance on training and test sets

Model	Test F1	Train F1	Test Acc	Best Params
XGBoost	0.9326	0.9989	0.9540	`{'learning_rate': 0.1, 'n_estimators': 100}`
Random Forest	0.9142	1.0000	0.9425	`{'max_depth': None, 'n_estimators': 100}`
SVM	0.8539	0.9038	0.9041	`{'C': 10, 'kernel': 'rbf'}`
Logistic Regression	0.6394	0.6599	0.7545	`{'C': 10}`

The result shows XGBoost as the winner with a test Macro-F1 of 0.9326 (95.4% accuracy), substantially outperforming Random Forest (0.9142), SVM (0.8539), and Logistic Regression (0.6394). This indicates XGBoost correctly classifies countries into ND-GAIN readiness quadrants with high precision and recall across all four categories, achieving this with only 12 readily-available macro-indicators.

XGBoost's training F1 of 0.9989 versus test F1 of 0.9326 indicates a 6.6 percentage point gap, suggesting some overfitting. However, the test performance remains strong. XGBoost's 93.26% test

F1 substantially exceeding all competitors and demonstrates that the model appear to has learned genuine predictive structure sufficient to maintain generalization despite high training accuracy.

Random Forest exhibits a larger train-test gap (8.6 percentage points: 100% training vs. 91.4% test), consistent with unrestricted tree depth (`max_depth = None`) allowing complete memorization of training data. While bagging across 100 trees provides regularization, it remained less effective than XGBoost's.

SVM shows the smallest train-test gap, suggesting underfitting rather than overfitting. The model lacks capacity to fully capture the complex nonlinear boundaries separating readiness quadrants, possibly due to suboptimal RBF kernel tuning or the limitations of one-vs-one decomposition for multi-class problems with 12-dimensional feature space, SVM may lack sufficient sample density to learn the intricate nonlinear boundaries from only 3,128 observations.

The baseline logistic regression achieves only 63.9% test F1 (75.5% accuracy). The train and test performance (65.9% and 63.9% respectively) are very similar, this suggest underfitting. Logistic regression cannot adequately address the relationship between the predictors and readiness quadrants even in training data. This is not a regularization issue (multiple values of C were tested, finding optimal performance at $C = 10$), but rather reflects the fundamental limitation of linear decision boundaries.

The tournament results provide evidence that machine learning method, particularly XGBoost, dramatically outperform traditional logistic regression for climate readiness classification. XGBoost's demonstrated the capacity to capture nonlinear thresholds, interaction effects, and complex decision boundaries that characterize the relationship between macro-indicators and climate readiness. For practical application, this translates to approximately 229 fewer misclassified country-years in the test set (29% of 782 observations).

4.2 Permutation Importance Analysis of the XGBoost

Permutation Importance analysis was performed to rank predictors based on their contribution to the model's predictive power measured by the degradation in Macro-F1 score when the feature is randomized. This isolates the predictive utility of each variable (without inferring causal mechanisms).

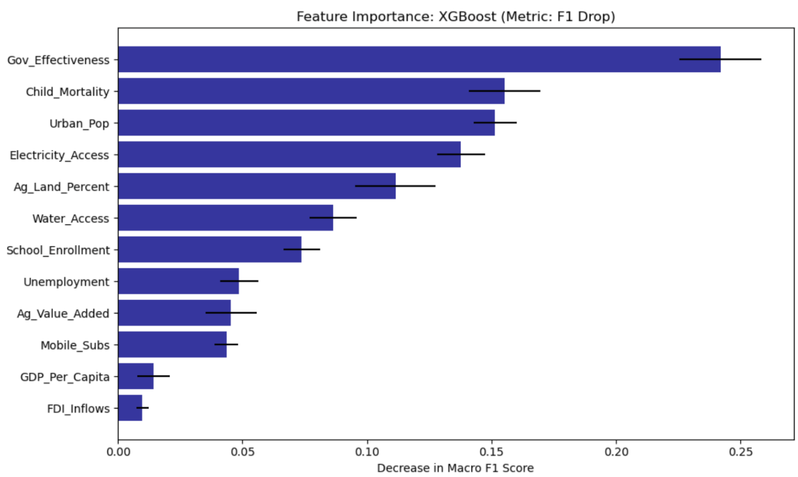

Figure 3: Permutation Importance of the XGBoost model

The permutation importance analysis suggests that Government Effectiveness is the dominant predictor, with a mean importance of 0.2419. (see appendix B.) This indicates that neutralizing governance data results in 24% drop in the model's F1 score, suggesting that institutional capacity is the primary statistical signal distinguishing readiness groups.

Following governance, the model relies heavily on social and infrastructure indicators such as Child Mortality (0.1553), Urban Population (0.1514), and Electricity Access (0.1377). Notably, GDP Per Capita (0.0143) ranked unexpectedly low. This suggests that while wealth is correlated with readiness, specific developmental outcomes (health, infrastructure, governance) provide a clearer signal for classification.

4.3 Robustness Check

The XGBoost model was put to the temporal split analysis. Using training data from 2000–2018 (3,230 observations) and testing data 2019–2023 (680 observations). This is to address the temporal generalisability and to simulate the scenario where policymakers may use past data to monitor current readiness trends. The results are presented below:

Table 3: Classification report (Future data)

Class	Precision	Recall	F1-score	Support
0	0.99	0.89	0.94	255
1	0.74	0.90	0.81	96
2	0.83	0.70	0.76	57
3	0.91	0.96	0.94	272
Accuracy		0.90		680
Macro avg	0.87	0.86	0.86	680
Weighted avg	0.91	0.90	0.91	680

The model achieved a Macro-F1 score of 0.8622 on the unseen future data. While this represents a moderate performance decline of approximately 7% compared to the randomized cross-validation baseline (0.9326). While this gap indicates some degradation when predicting future observations, the absolute performance level remains impressive. This demonstrates that patterns learned from 2000-2018 generalize well to subsequent years despite potential structural changes in the global economy, climate impacts, or adaptation policy over this period.

The model maintained high predictive ability for the primary quadrants of interest. Both the red (0) and green (3) classes achieved F1-scores of 0.94, indicating that the economic and governance signatures of the most and least vulnerable nations remain stable and identifiable across different time periods. The performance drop was concentrated in the transitional quadrants, suggesting that nations with mixed readiness and vulnerability development profiles are more volatile than those at the developmental extremes.

5 Conclusions

5.1 Conclusion of Findings

This study demonstrates that machine learning methods, particularly XGBoost, can accurately replicate ND-GAIN's climate readiness classifications using a drastically simplified set of predictors. The lean framework of 12 publicly available macroeconomic and governance indicators from the World Bank achieves 93.3% macro-averaged F1-score in classifying countries into readiness-vulnerability quadrants, reducing data requirements from ND-GAIN's 45 indicators across 74 sources.

The tournament-style model selection process provides a clear evidence of machine learning's superiority over traditional parametric approaches for this task. All machine learning methods, particularly the XGBoost, outperformed logistic regression. Temporal validation of the the XGBoost confirms this advantage persists under realistic forecasting conditions, maintaining an impressive 86.2% macro-F1 on 2019-2023 observations, demonstrating that learned patterns generalize across time periods despite potential structural changes in the global economy and adaptation.

The model's strongest performance on extreme quadrants (Red and Green both achieving 94% F1-scores in temporal validation) indicates reliable identification of the highly vulnerable nations requiring urgent adaptation investment, and well-prepared countries with capacity to absorb climate shocks. Lower performance on intermediate quadrants reflects ambiguity in transitional categories where countries exhibit mixed readiness profiles.

5.2 Limitations

The findings of this study poses some limitations:

1. The naive pooling approach ignores temporal dependencies and panel structure in the data. While temporal split robustness check addresses this concern to some extent, the approach may still inflate performance estimates by allowing the model to exploit slow year-to-year changes in country status.

2. This model approximates rather than improves upon the ND-GAIN index. The primary contribution of this study is demonstrating the feasibility of simplified prediction rather than proposing superior measures of climate readiness. Consequently, this approach may inherit existing biases or limitations from the original index. Furthermore, national-level readiness classification using macro-level data is limited in its ability to identify specific regions or cities that may be more vulnerable or resilient than others within a nation.

3. While XGBoost identifies which macro-indicators best predict readiness classifications, we cannot infer that improving these indicators will causally shift countries between classes. Unlike the original ND-GAIN indicators that are specifically designed to measure actionable items, the permutation analysis results should be interpreted as diagnostic signals rather than intervention targets.

4. This study's reliance on WDI and WGI data constrains the model to the quality and coverage of these databases. Missing values for certain country-years (handled through linear interpolation following ND-GAIN's methodology) may introduce measurement error, and systematic missingness in fragile or conflict-affected states. Additionally, governance indicators from WGI rely on expert assessments and perception surveys, which carry their own measurement challenges (Kaufmann et al., 2010).

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APPENDIX

A ND-GAIN Matrix

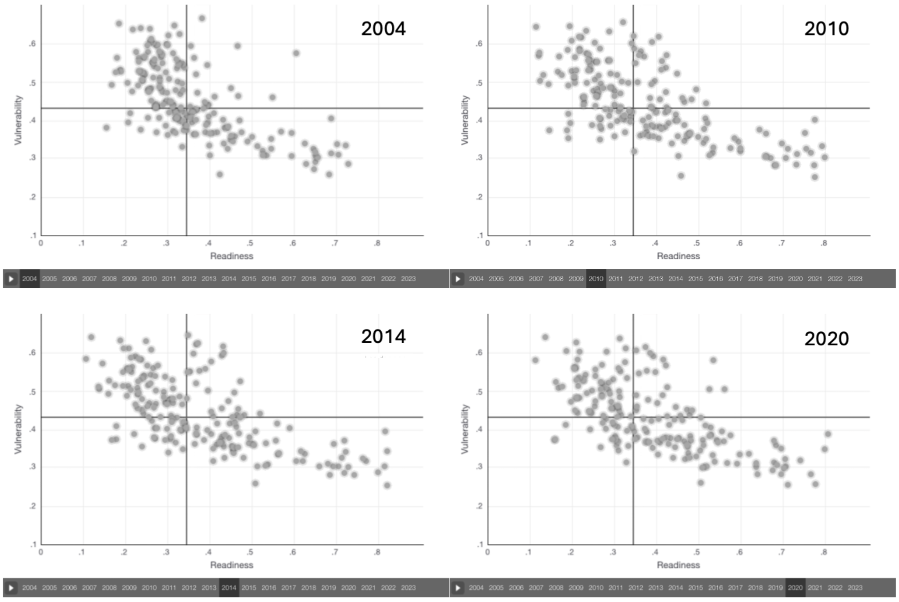

Figure 4: ND-GAIN Matrix of 4 sample years, showing negative relationship between Readiness and Vulnerability

Source: https://gain.nd.edu/our-work/country-index/matrix/

B Permutation Importance

Table 4: Most influential predictors (Permutation Importance) of XGBoost

Feature	Importance	Std Dev
Gov_Effectiveness	0.2419	0.0166
Child_Mortality	0.1553	0.0143
Urban_Pop	0.1514	0.0087
Electricity_Access	0.1377	0.0097
Ag_Land_Percent	0.1114	0.0161
Water_Access	0.0864	0.0096
School_Enrollment	0.0737	0.0073
Unemployment	0.0486	0.0077
Ag_Value_Added	0.0454	0.0103
Mobile_Subs	0.0435	0.0046
GDP_Per_Capita	0.0143	0.0065
FDI_Inflows	0.0098	0.0025