

Predicting Humanitarian Crises



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Onome Akpogheneta

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Project 3

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Introduction

Project 1

Project 2

Project 3

-
- Dashed arrows point from Project 1, Project 2, and Project 3 down to a list of three items:
1. Data cleaning & Exploratory Data Analysis
 2. Machine Learning Methods
 3. Machine Learning Results

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- 1. Data cleaning & Exploratory Data Analysis
- 2. Machine Learning Methods
- 3. Machine Learning Results

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Introduction

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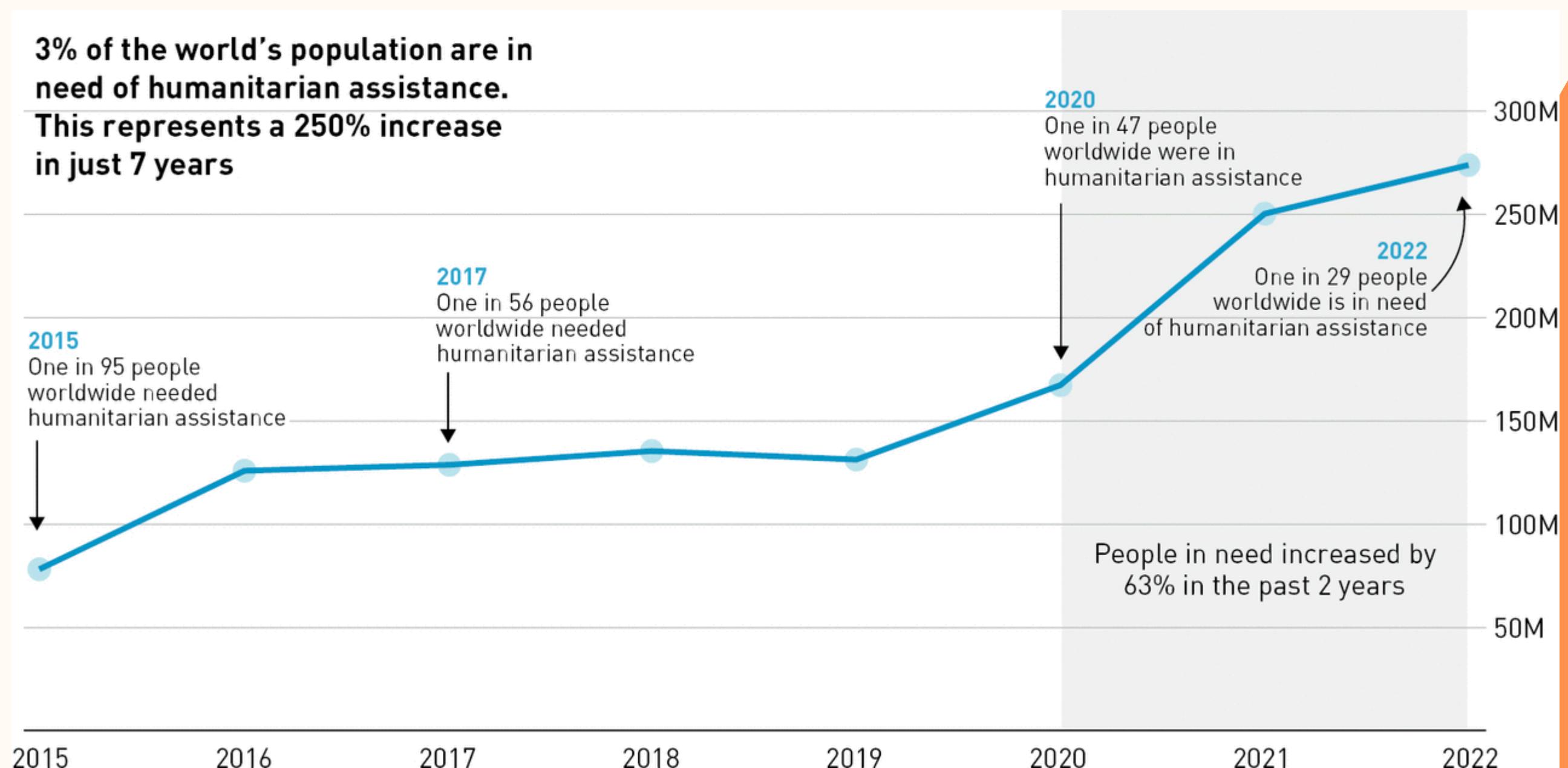
What is a humanitarian crisis?

*A situation or event where there is a significant threat to the health, safety, and well-being of a large number of people, often resulting from factors such as natural disasters, armed conflict, or socio-political instability. This can lead to widespread **displacement, loss of life, and critical shortages** of basic necessities such as food, water, shelter, and medical care*

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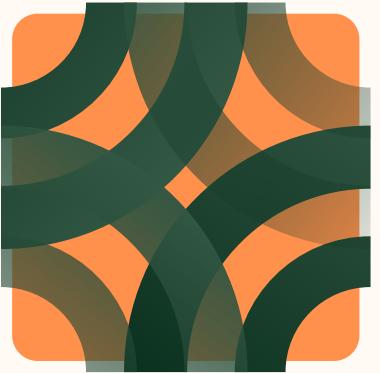
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Humanitarian crises can be prevented

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The humanitarian sector is primarily focused on **response**



If our approach was more **proactive** and **anticipatory** than countless lives could be saved

EXAMPLES

Early Action

African Union Insurance

Intro to the Dataset

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INFORM

SHARING CRISIS ANALYSIS



INFORM is a multi-stakeholder forum for developing **shared, quantitative analysis relevant to humanitarian crises and disasters**

INFORM is developing a suite of products to **support decision-making** on humanitarian crises and disasters

These products help make decisions at different stages of the disaster management cycle, specifically **climate adaptation and disaster prevention, preparedness and response**

1. **INFORM RISK**
2. **INFORM CLIMATE CHANGE**
3. **INFORM SEVERITY**

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Can humanitarian crises be predicted?

Project 1



Explore whether the INFORM data products can be used to predict whether or not there is an ongoing humanitarian crisis

Can humanitarian crises be predicted?

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Project 1

Explore whether the INFORM data products can be used to predict whether or not there is an ongoing humanitarian crisis

Project 2

Explore whether the INFORM data products can be used to predict the **severity of** humanitarian crises

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Can humanitarian crises be predicted?

Project 1

Explore whether the INFORM data products can be used to predict whether or not there is an ongoing humanitarian crisis

Project 2

Explore whether the INFORM data products can be used to predict the **severity** of humanitarian crises

Project 3

Predict & forecast how INFORM risk data changes over time

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Project 1

Explore whether
the INFORM data
products can be
used to predict
whether or not
there is an ongoing
humanitarian
crisis

Data Cleaning & EDA

INFORM Risk Dataset

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COUNTRY (a-z)	ISO3 (a-z)	INFORM RISK (0-10)	RISK CLASS (Very Low-Very High)
Afghanistan	AFG	8.1	Very High
Albania	ALB	3.1	Low
Algeria	DZA	3.6	Medium
Angola	AGO	5.2	High
Antigua and Barbuda	ATG	2.3	Low
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Bangladesh	BGD	5.7	High

INFORM Risk Dataset

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INFORM

Hazard & Exposure

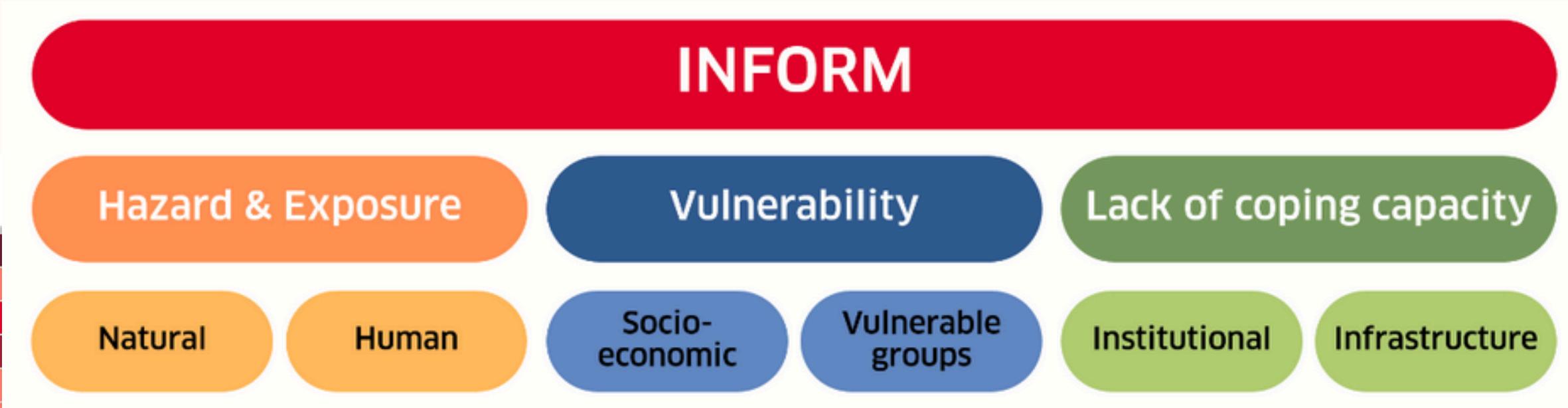
Vulnerability

Lack of coping capacity

INFORM Risk Dataset

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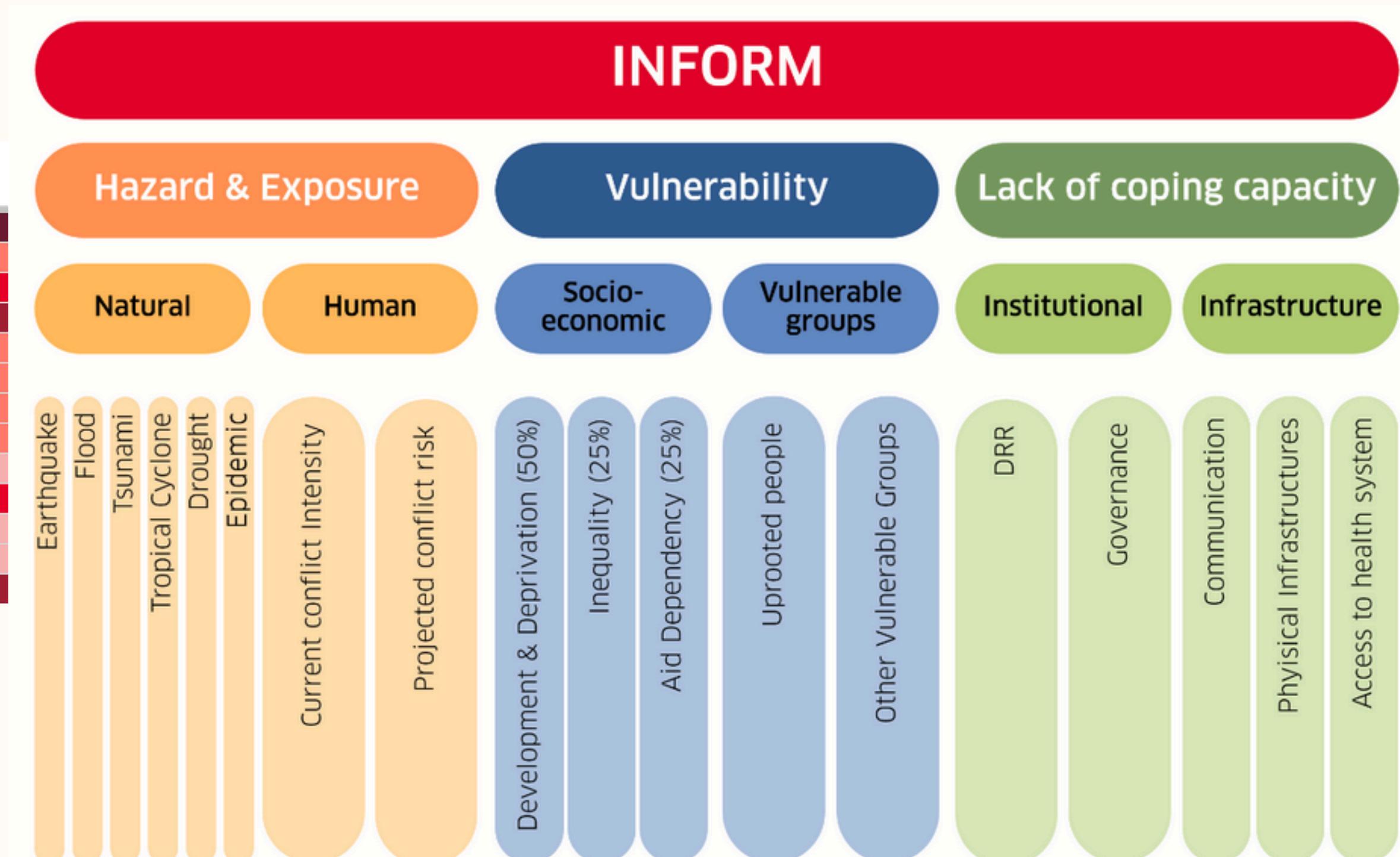
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INFORM Severity Dataset

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Burundi	Complex in Burundi	3.3	High
Cameroon	Multiple crises in Cameroon	4.1	Very High
CAR	Complex crisis in CAR	4.2	Very High
Chad	Complex crisis in Chad	4.3	Very High

INFORM Severity Index

Dimensions

Impact
of the crisis

Conditions
of people
affected

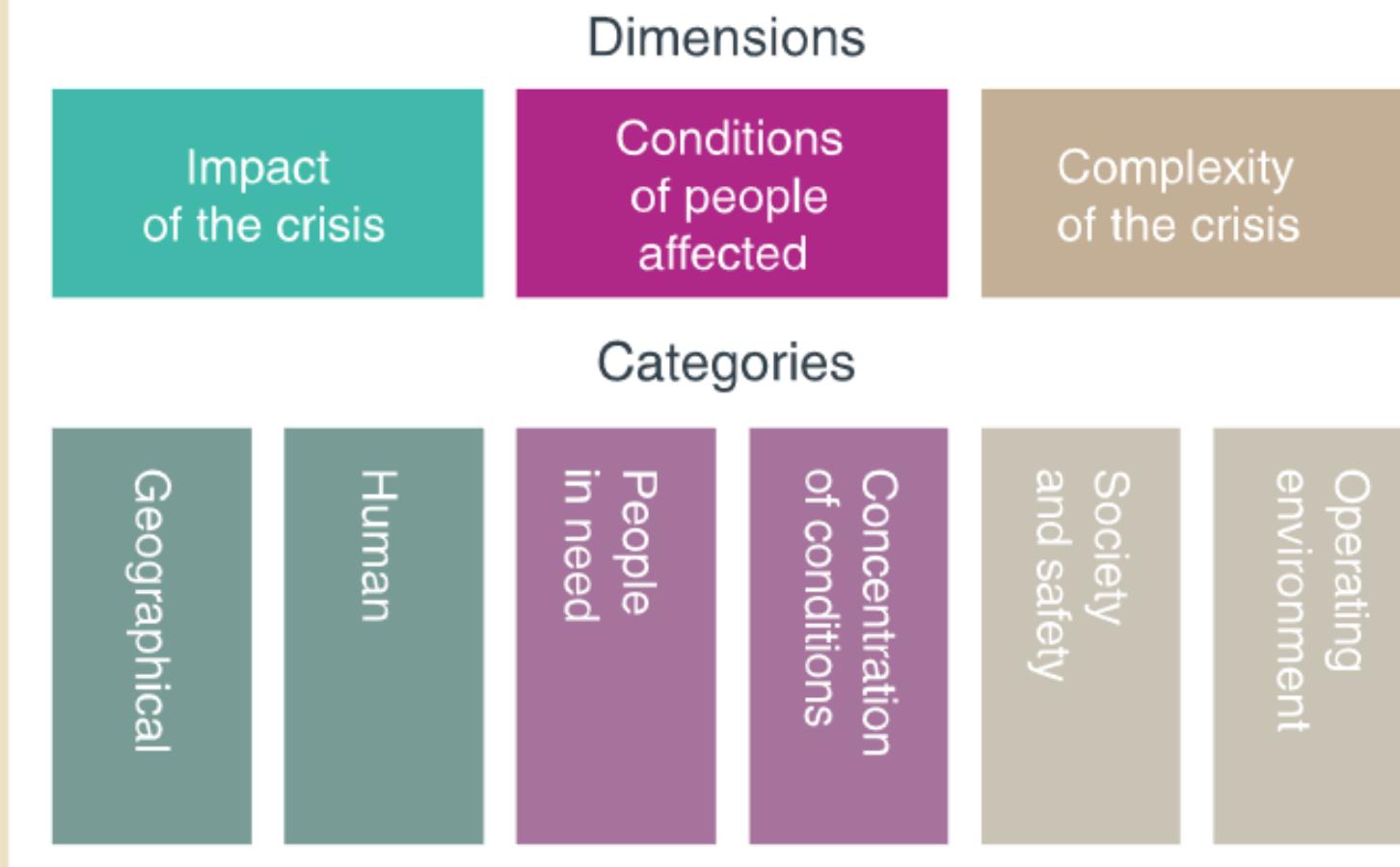
Complexity
of the crisis

INFORM Severity Dataset

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INFORM Severity Index

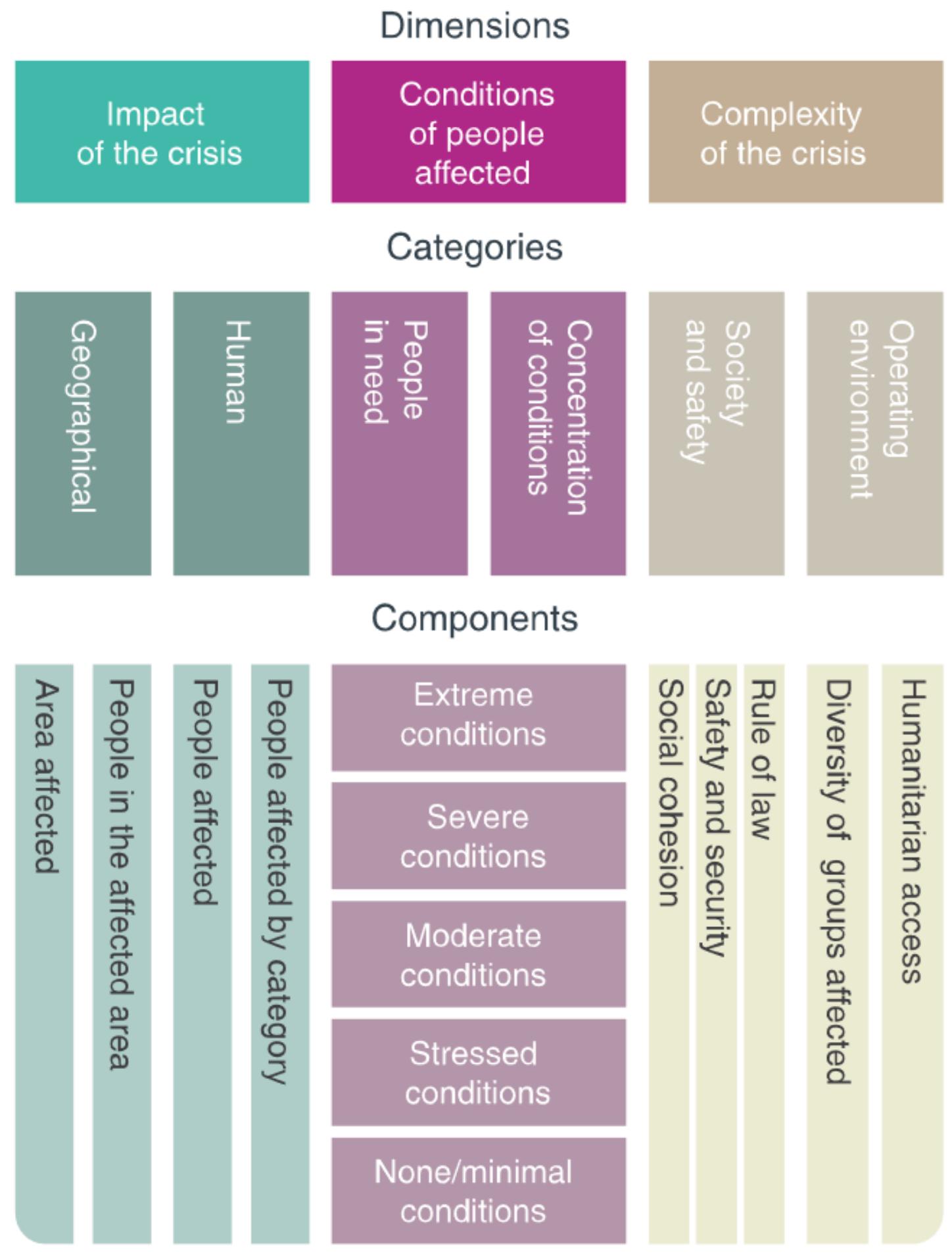


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INFORM Severity Index



INFORM Severity Dataset

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Merged Risk & Severity

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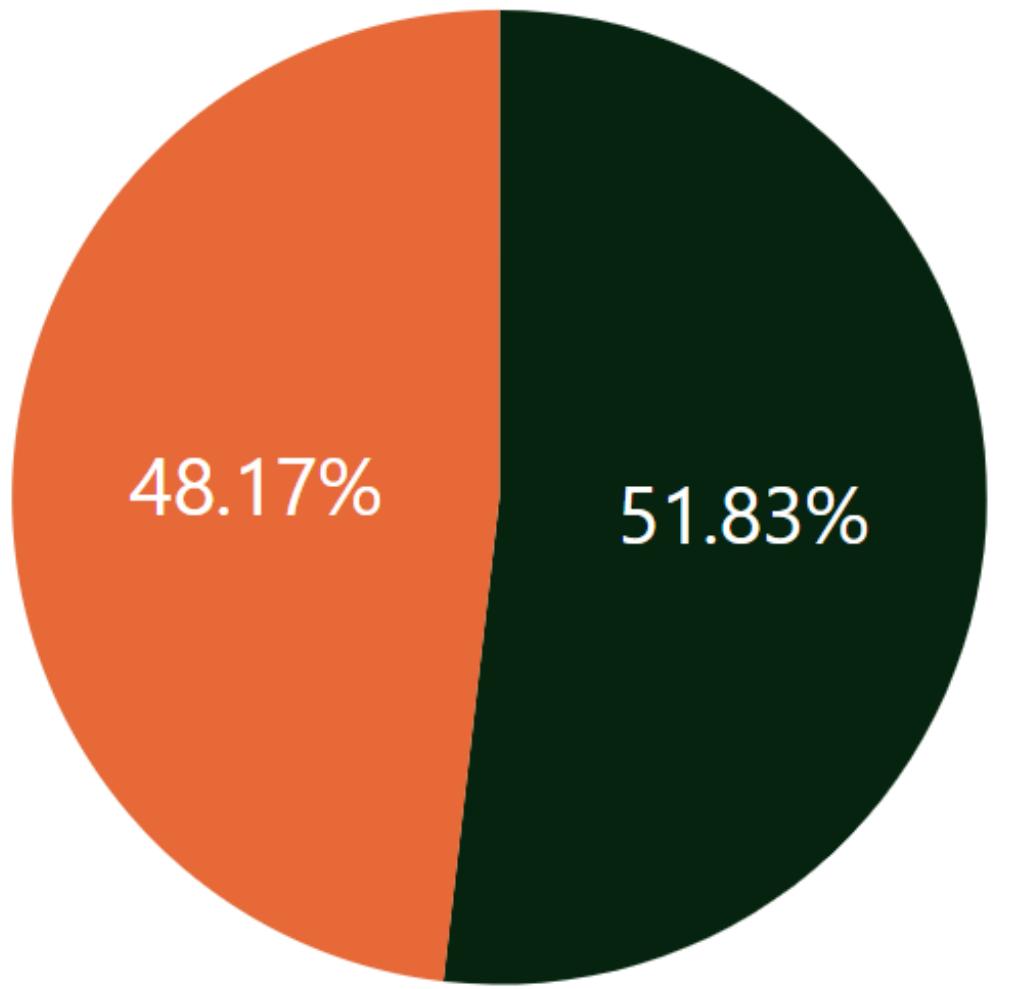
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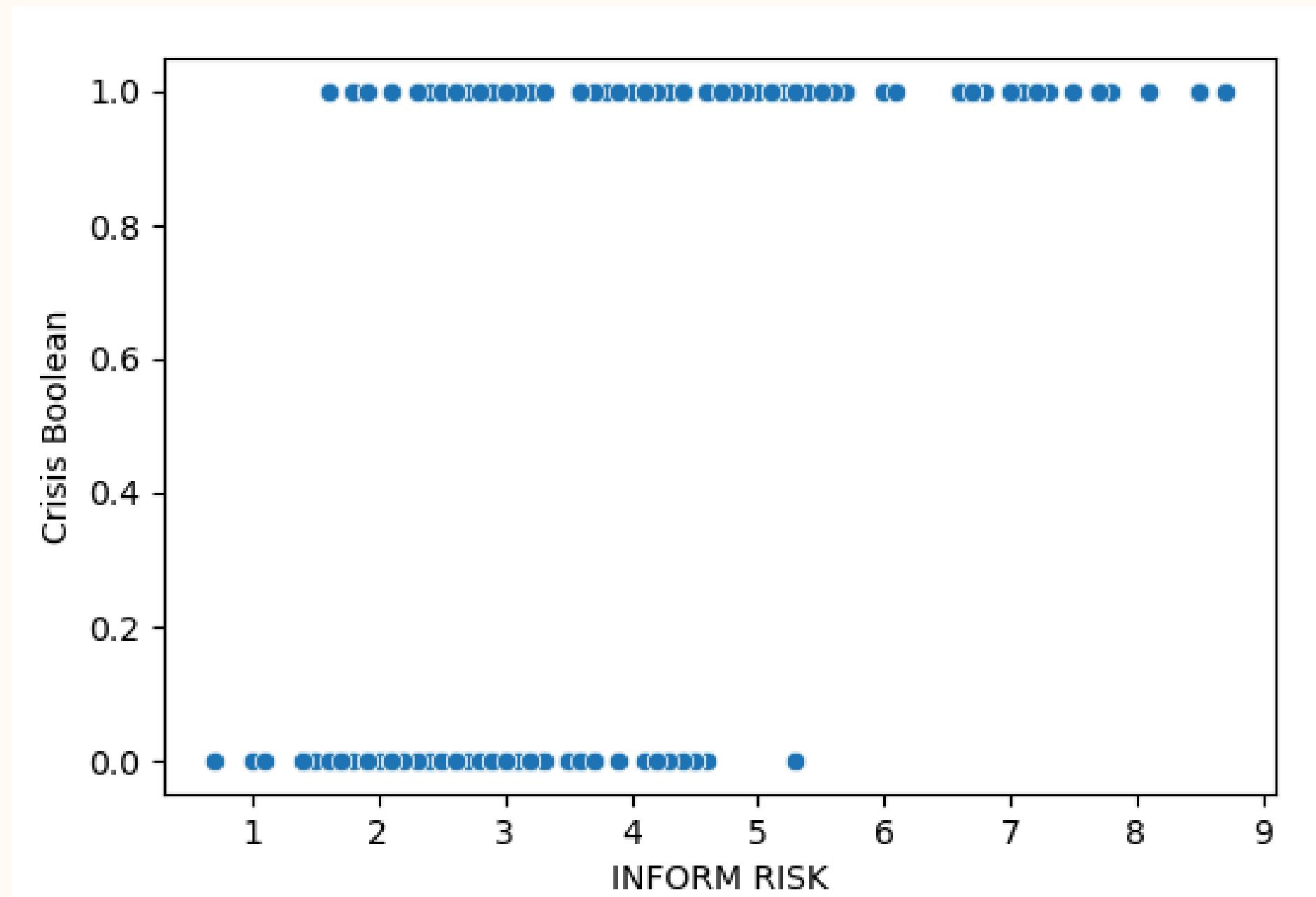
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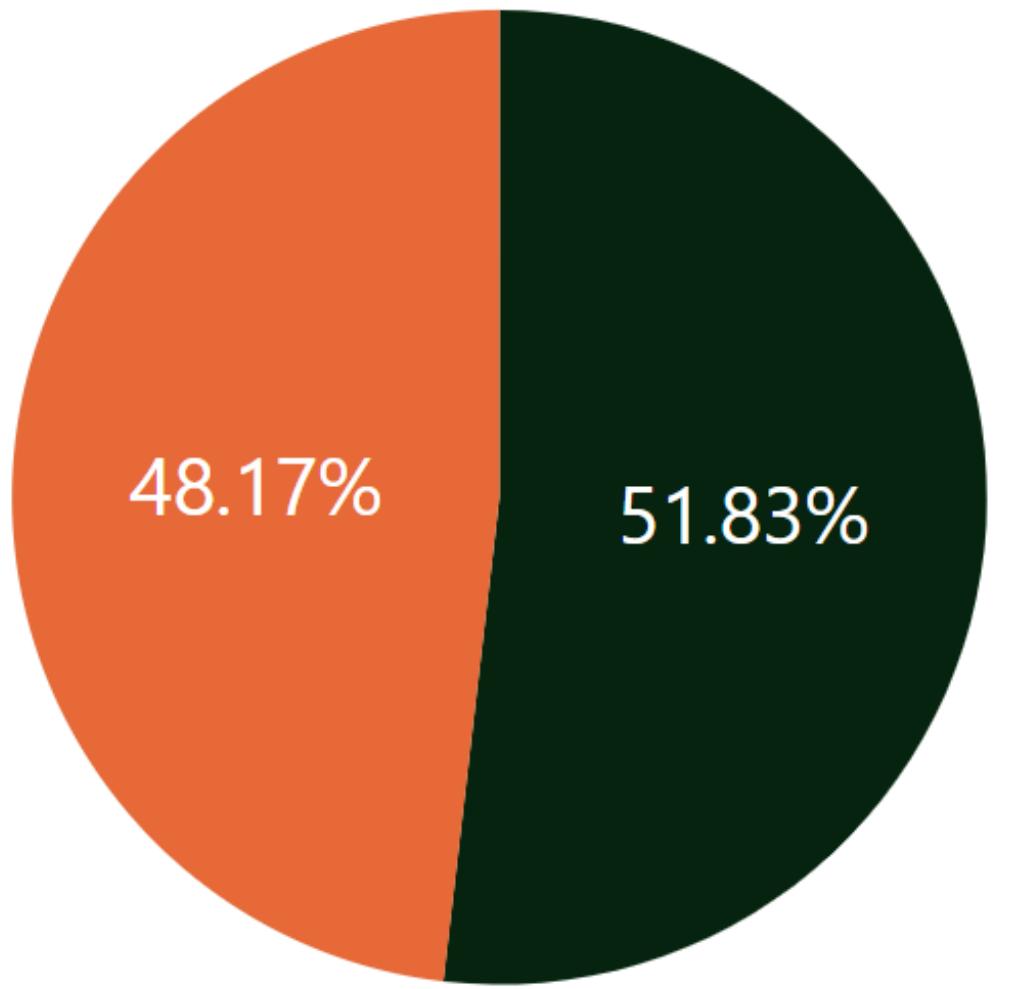
● No crisis ● Has a crisis



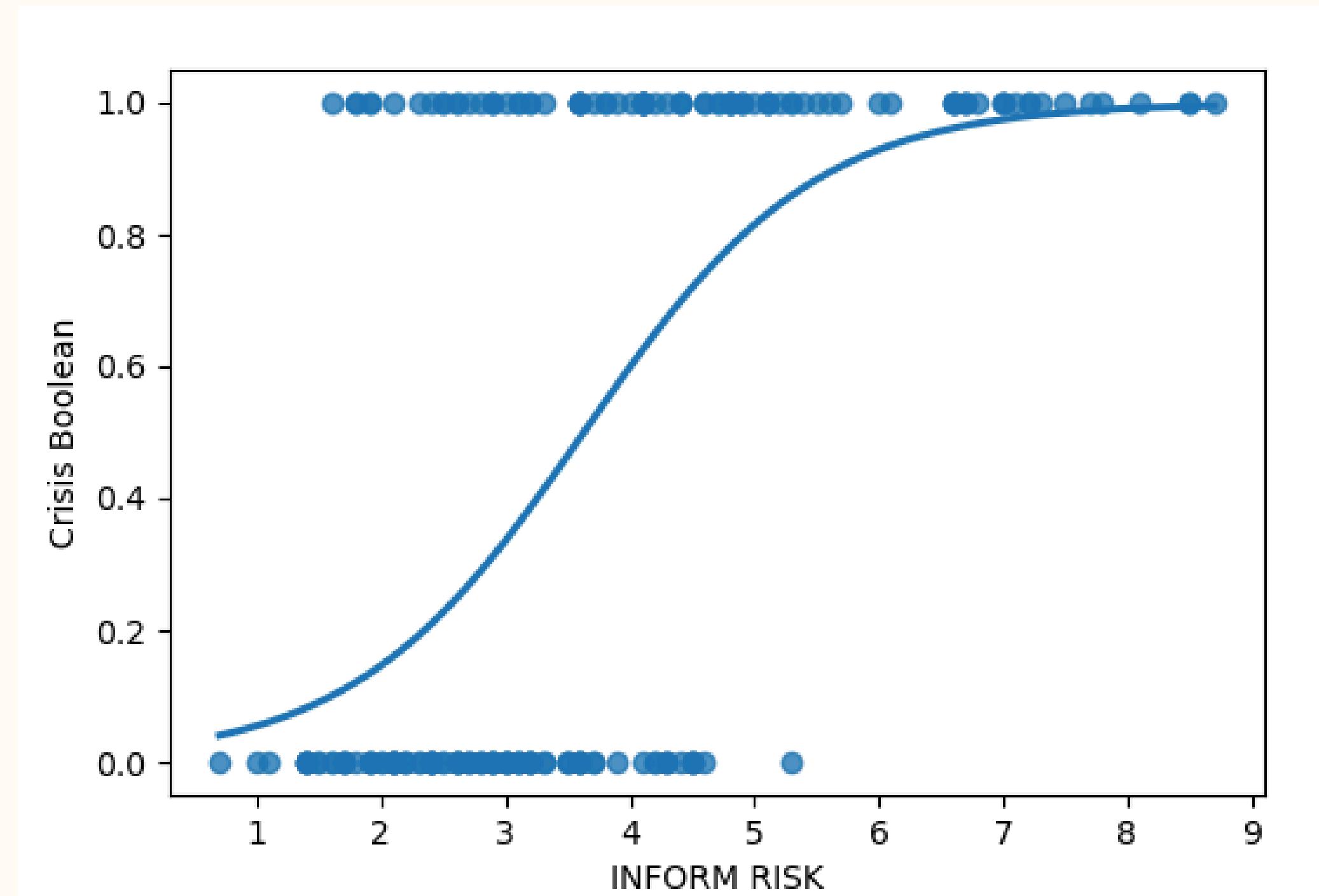
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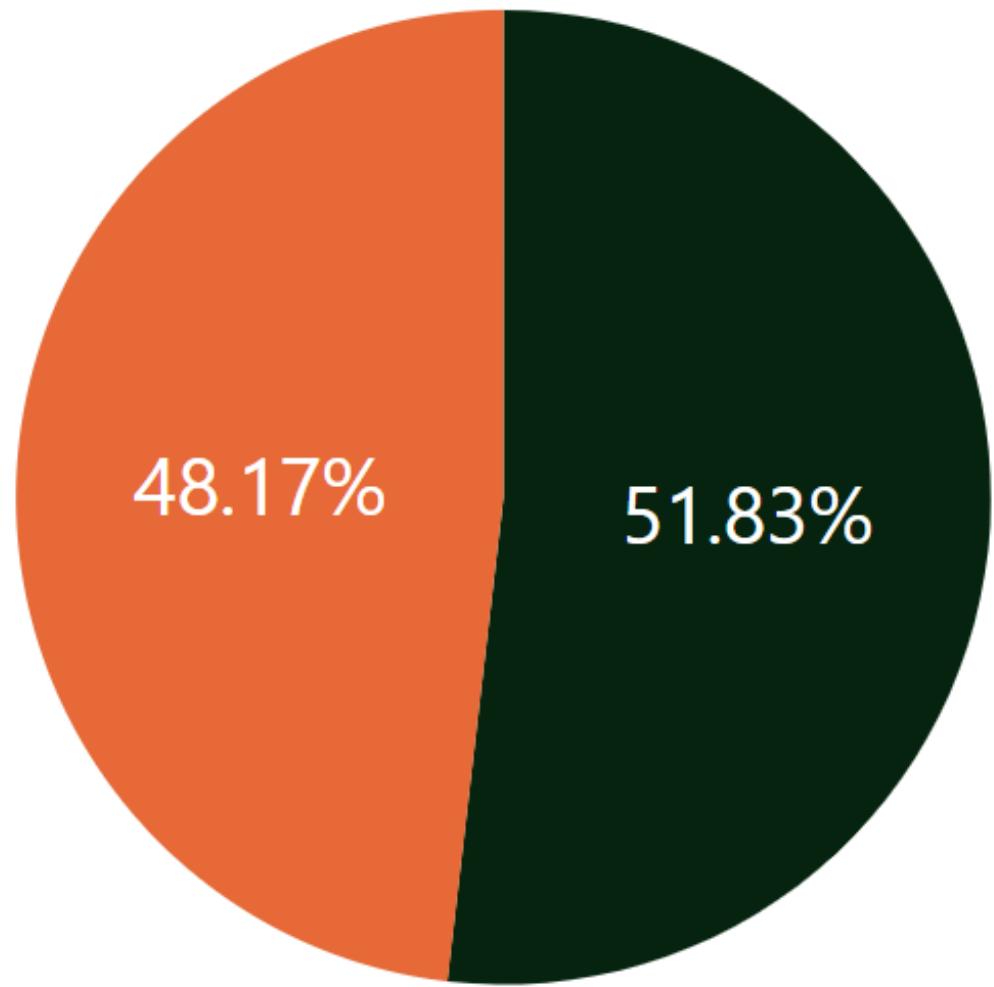
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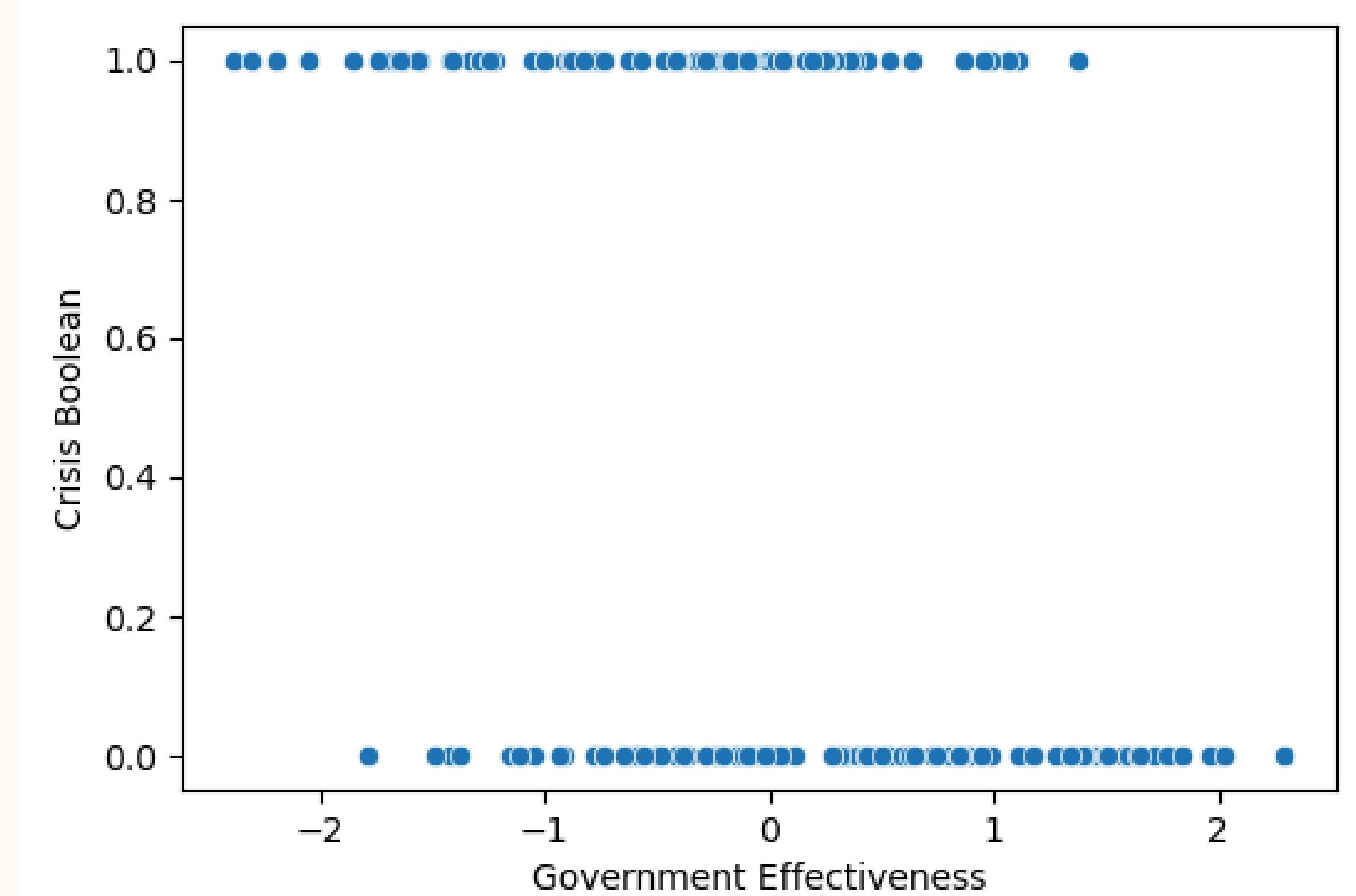
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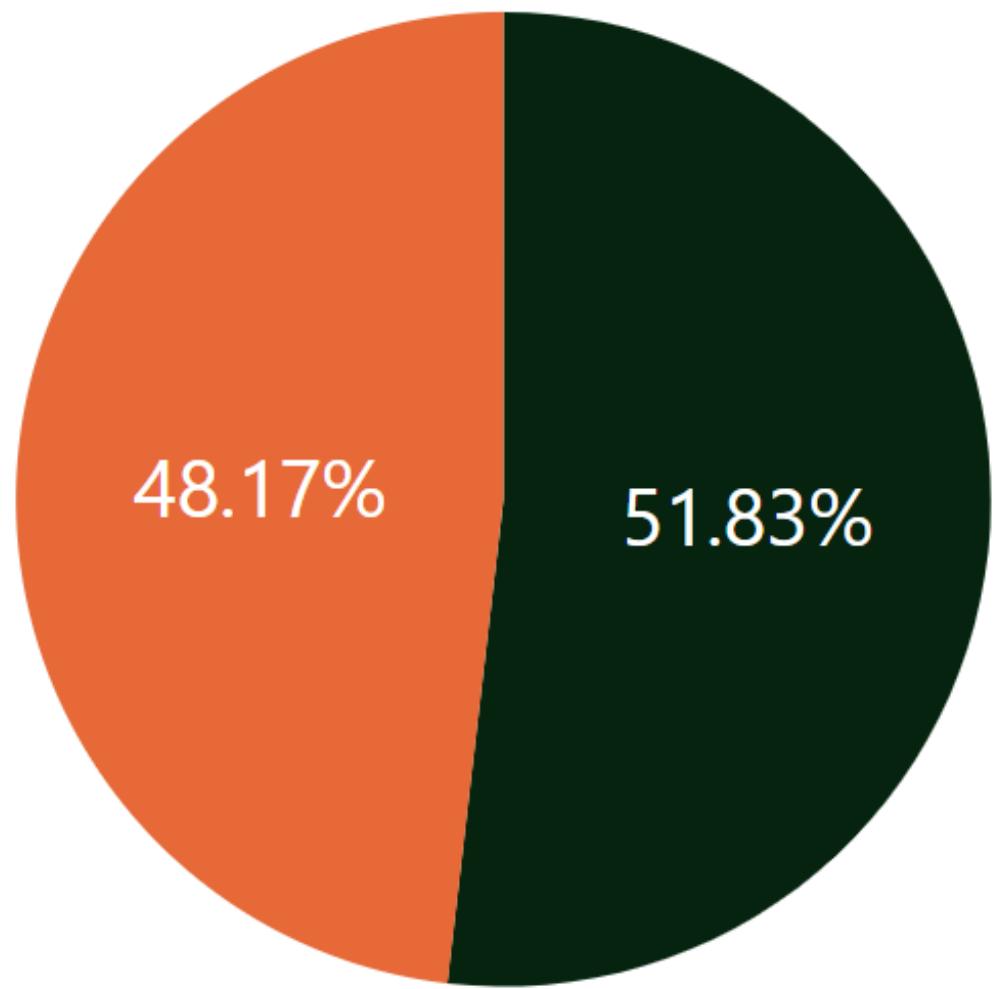
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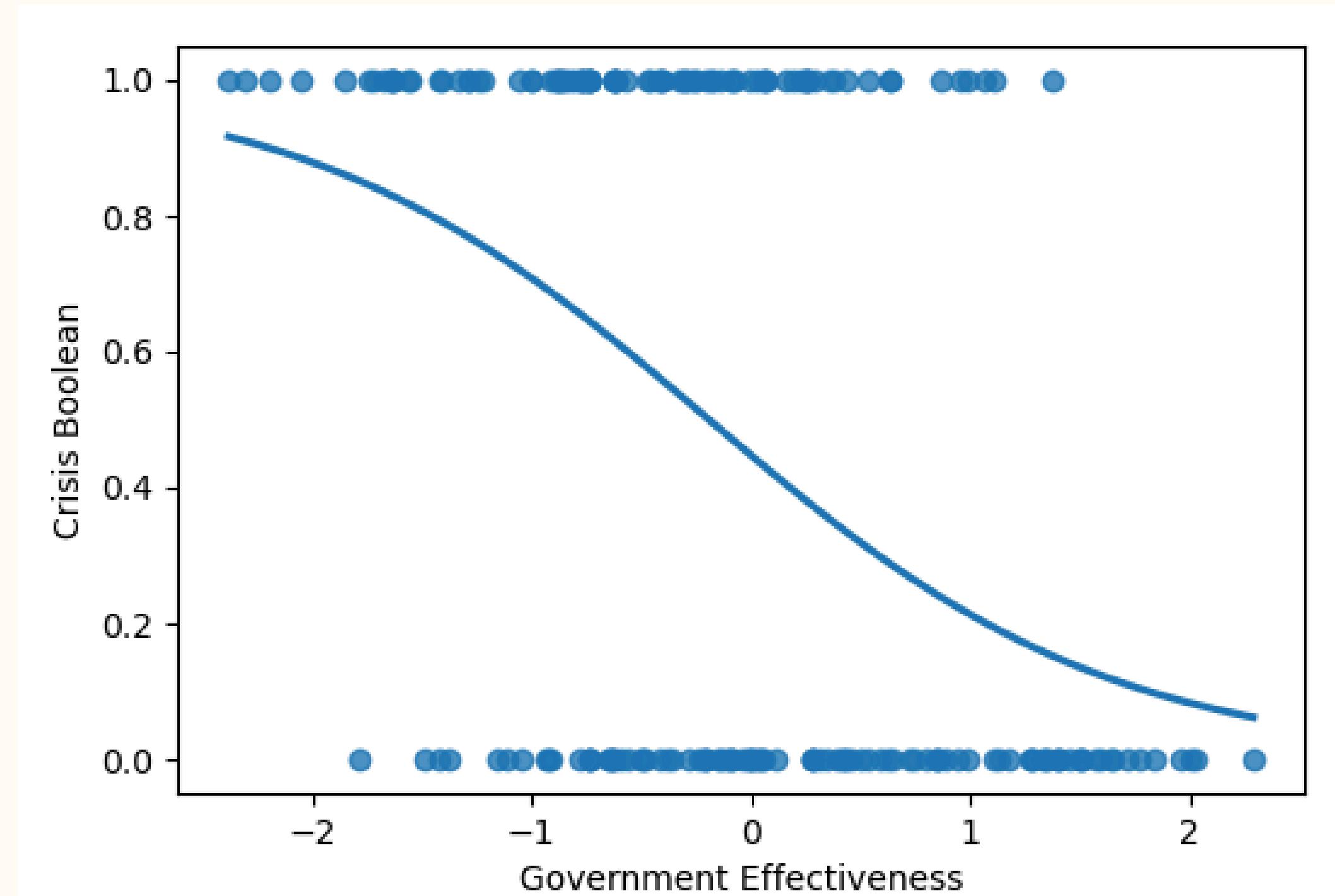
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● No crisis ● Has a crisis

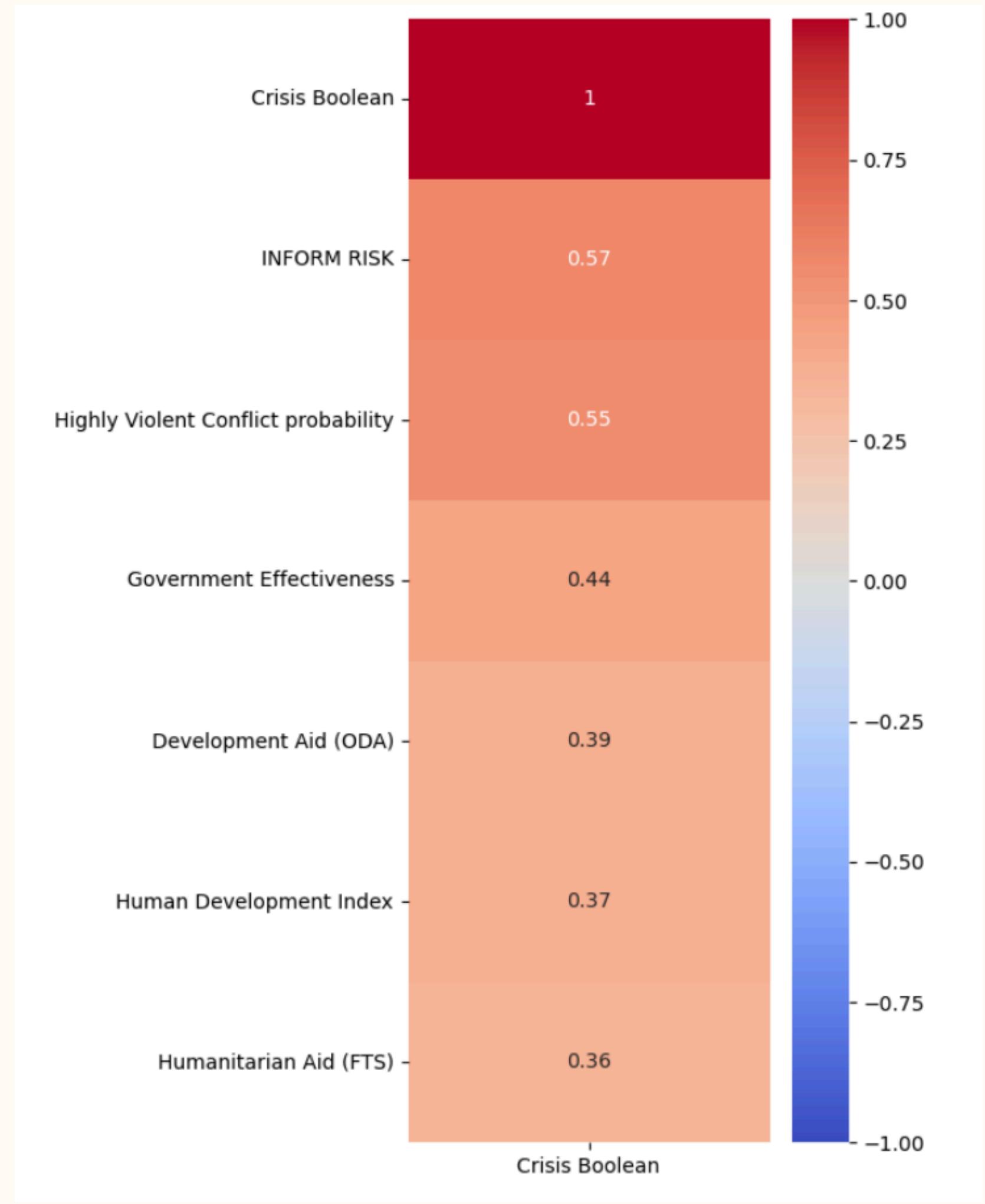


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Correlations

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Project 1

**Explore whether
the INFORM data
products can be
used to predict
whether or not
there is an ongoing
humanitarian
crisis**

Machine Learning

ML Models

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1. Logistic Regression
2. Decision Tree

Problem #1: Logistic Regression

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What is logistic regression?

- Used to predict a categorical outcome, usually binary
- Fits a sigmoid curve using maximum likelihood
- Categorizes data by predicting probability of each point occurring above or below .5

Step 1: Decide what features to use in model

```
x = data[['INFORM RISK']]  
y = data['Crisis Boolean']
```

```
x = data[['INFORM RISK', 'Highly Violent Conflict probability', 'Government Effectiveness',  
          'Humanitarian Aid (FTS)', 'Development Aid (ODA)', 'Human Development Index']]  
y = data['Crisis Boolean']
```

Step 2: Split data into training and test sets

```
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=.2, random_state=42, stratify=y)
```

Problem #1: Logistic Regression

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Step 3: Initiate the model using default parameters

```
lg = LogisticRegression()  
lg.fit(X_train, y_train)
```

Step 4: Perform cross validation using KFold

What is cross validation?

- Splits data into k groups
- One group is test set, rest is training set
- Switch groups till all groups have been test set

```
k_folds = KFold(n_splits=10, random_state=1, shuffle=True)  
scores = cross_val_score(lg, X, y, scoring='accuracy', cv=k_folds)
```

Problem #1: Decision Tree

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What is a decision tree?

- Typically used to predict a categorical outcome
- Starts with a root node, the feature with the most importance
- Using entropy or Gini index to make decisions

Step 1: Decide what features to use in model

```
x = data[['INFORM RISK', 'Highly Violent Conflict probability', 'Government Effectiveness',  
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Step 2: Split data into training and test sets

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x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=.2, random_state=42)
```

Problem #1: Decision Tree

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Step 3: Initiate the model using default parameters

```
dt = DecisionTreeClassifier()  
dt.fit(X_train, y_train)
```

Step 4: Find the best hyperparameters using GridSearchCV hyperparameter tuning

What is GridSearchCV?

- Loops through all hyperparamers
- Output is best performing decision tree

Problem #1: Decision Tree

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Step 4: Find the best hyperparameters using GridSearchCV hyperparameter tuning

```
from sklearn.model_selection import GridSearchCV  
  
params = {  
    'max_depth': [2, 3, 5, 10, 20],  
    'min_samples_leaf': [5, 10, 20, 50, 100],  
    'criterion': ["gini", "entropy"]  
}
```

```
grid_search = GridSearchCV(estimator=dt,  
                           param_grid=params,  
                           cv=4, n_jobs=-1, verbose=1, scoring = "accuracy")
```

```
grid = grid_search.fit(X_train, y_train)
```

Best hyperparameters: max_depth=2, min_samples_leaf=10

Problem #1: Results

Is there an
ongoing crisis?

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YES

NO

Logistic Regression

Logisitic Regression with Cross Validation

With just the INFORM Risk

	precision	recall	f1-score	support
training accuracy score:				
False	0.82	0.70	0.76	20
True	0.73	0.84	0.78	19
accuracy			0.77	39
macro avg	0.78	0.77	0.77	39
weighted avg	0.78	0.77	0.77	39

Accuracy: 0.83

Multivariate

	precision	recall	f1-score	support
training accuracy score:				
False	0.88	0.81	0.84	26
True	0.67	0.77	0.71	13
accuracy			0.79	39
macro avg	0.77	0.79	0.78	39
weighted avg	0.81	0.79	0.80	39

Problem #1: Results

Is there an
ongoing crisis?

YES

NO

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Decision Tree

training accuracy score: 1.0

	precision	recall	f1-score	support
False	0.81	0.65	0.72	26
True	0.50	0.69	0.58	13
accuracy			0.67	39
macro avg	0.65	0.67	0.65	39
weighted avg	0.71	0.67	0.68	39

Decision Tree with Hyperparameter Tuning

training accuracy score: 0.89

	precision	recall	f1-score	support
False	0.86	0.73	0.79	26
True	0.59	0.77	0.67	13
accuracy			0.74	39
macro avg	0.73	0.75	0.73	39
weighted avg	0.77	0.74	0.75	39

Decision Tree with Cross Validation

Accuracy score: 0.81

Problem #1: Results

Is there an
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YES

NO

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Logistic Regression with Cross Validation

Accuracy: 0.83

Decision Tree with Cross Validation

Accuracy score: 0.81

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Project 2

Explore whether
the INFORM data
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severity of
humanitarian
crises

Data cleaning & EDA

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Merged Risk & Severity

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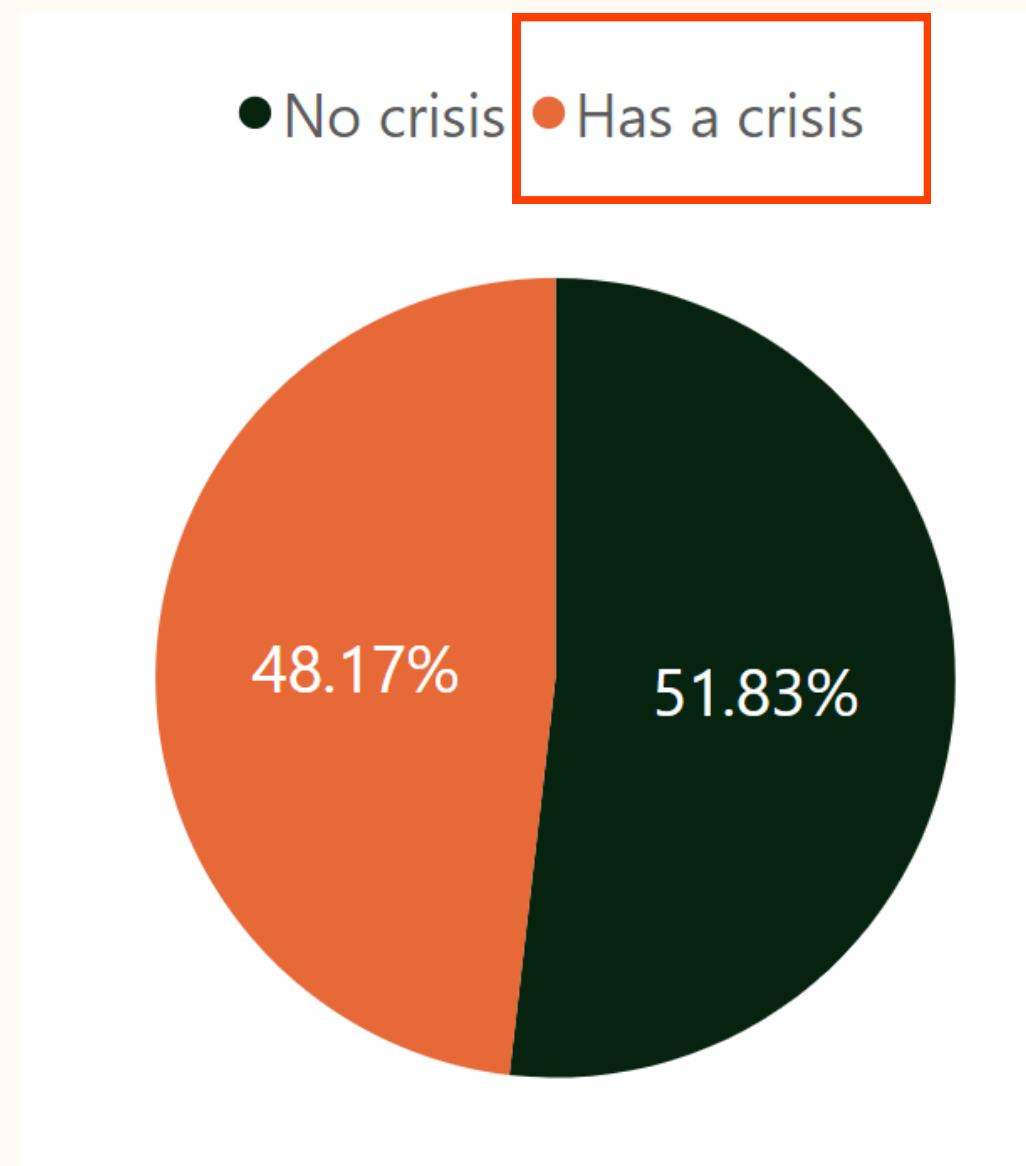


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Average Crisis Severity Index

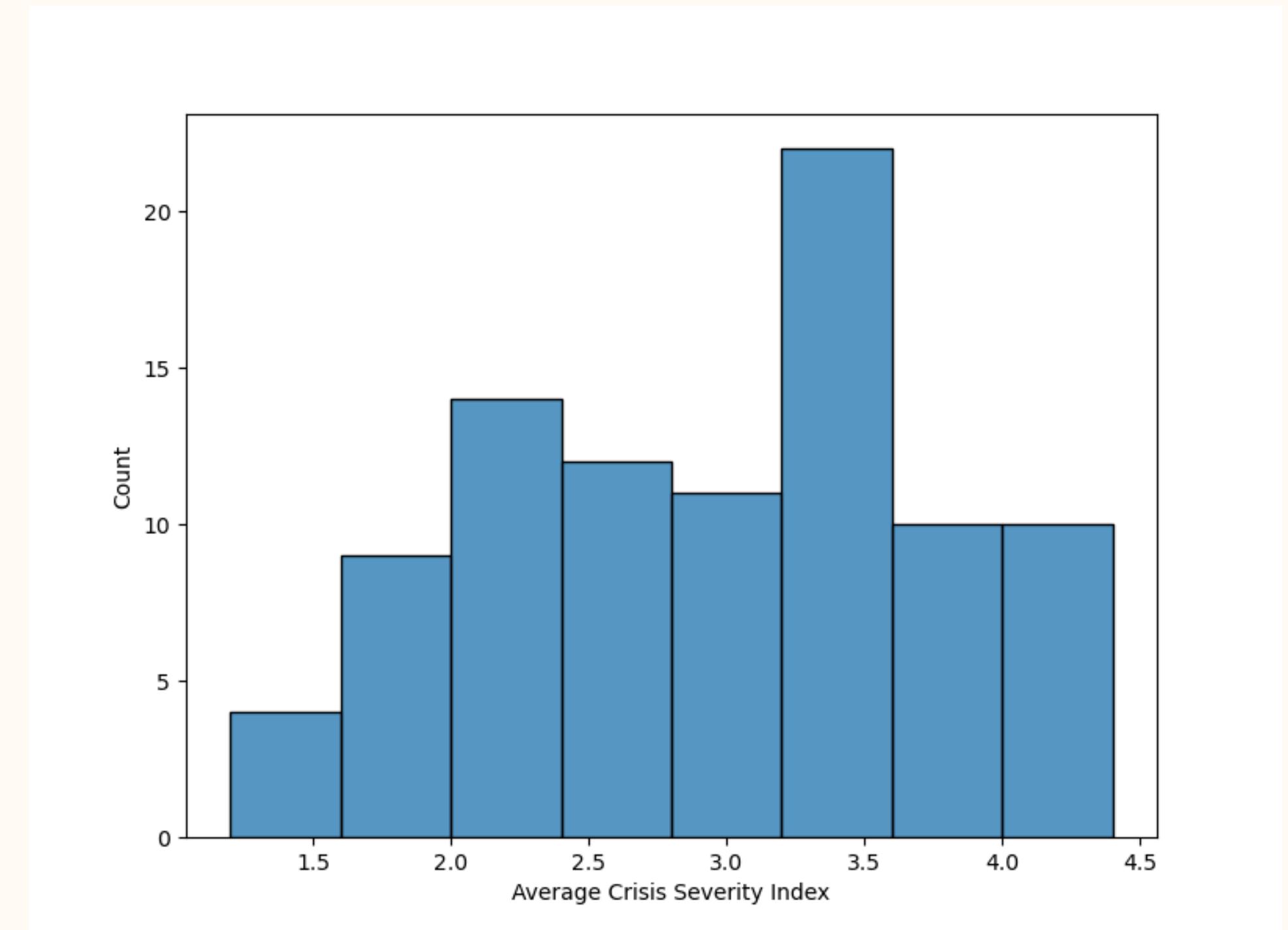
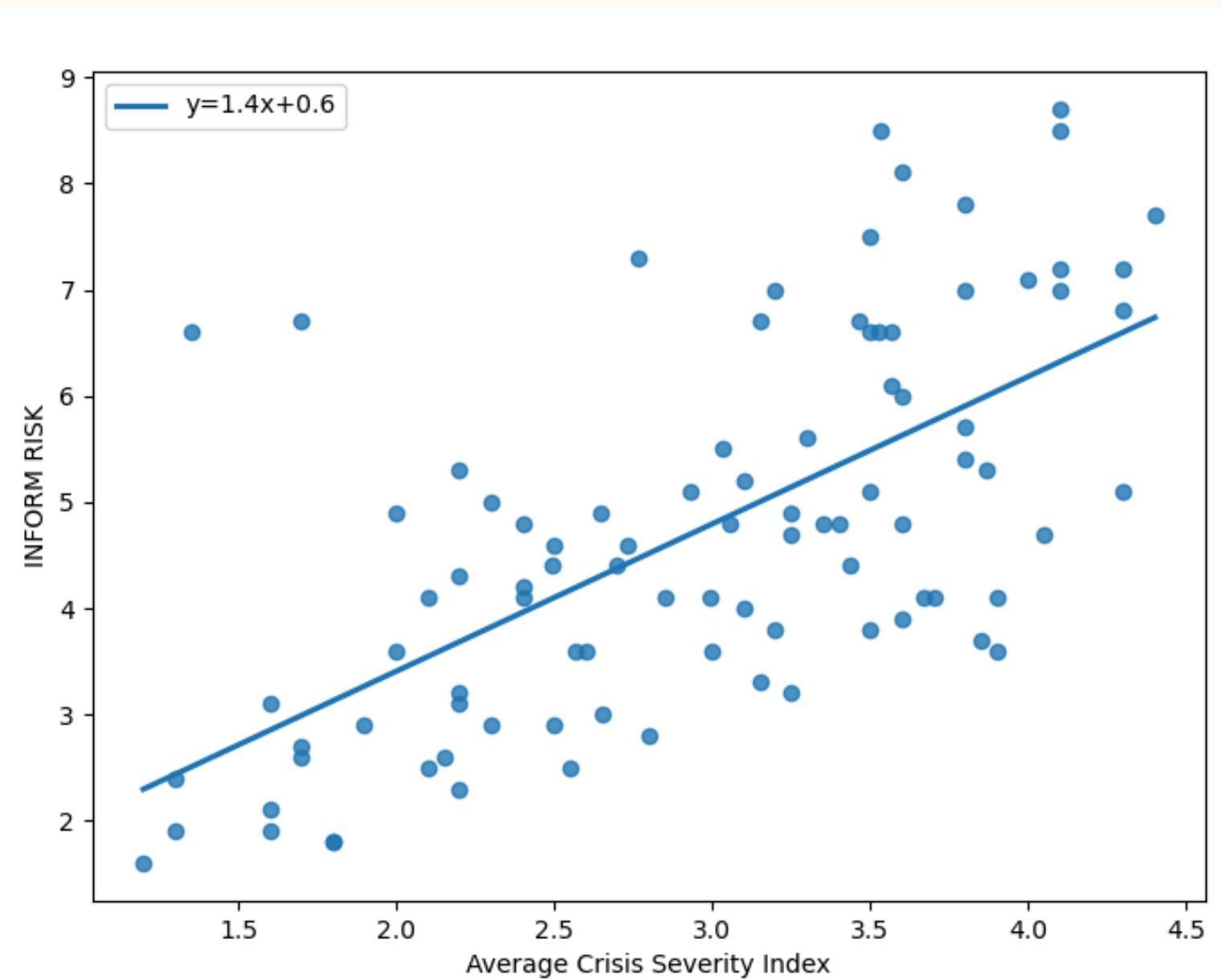


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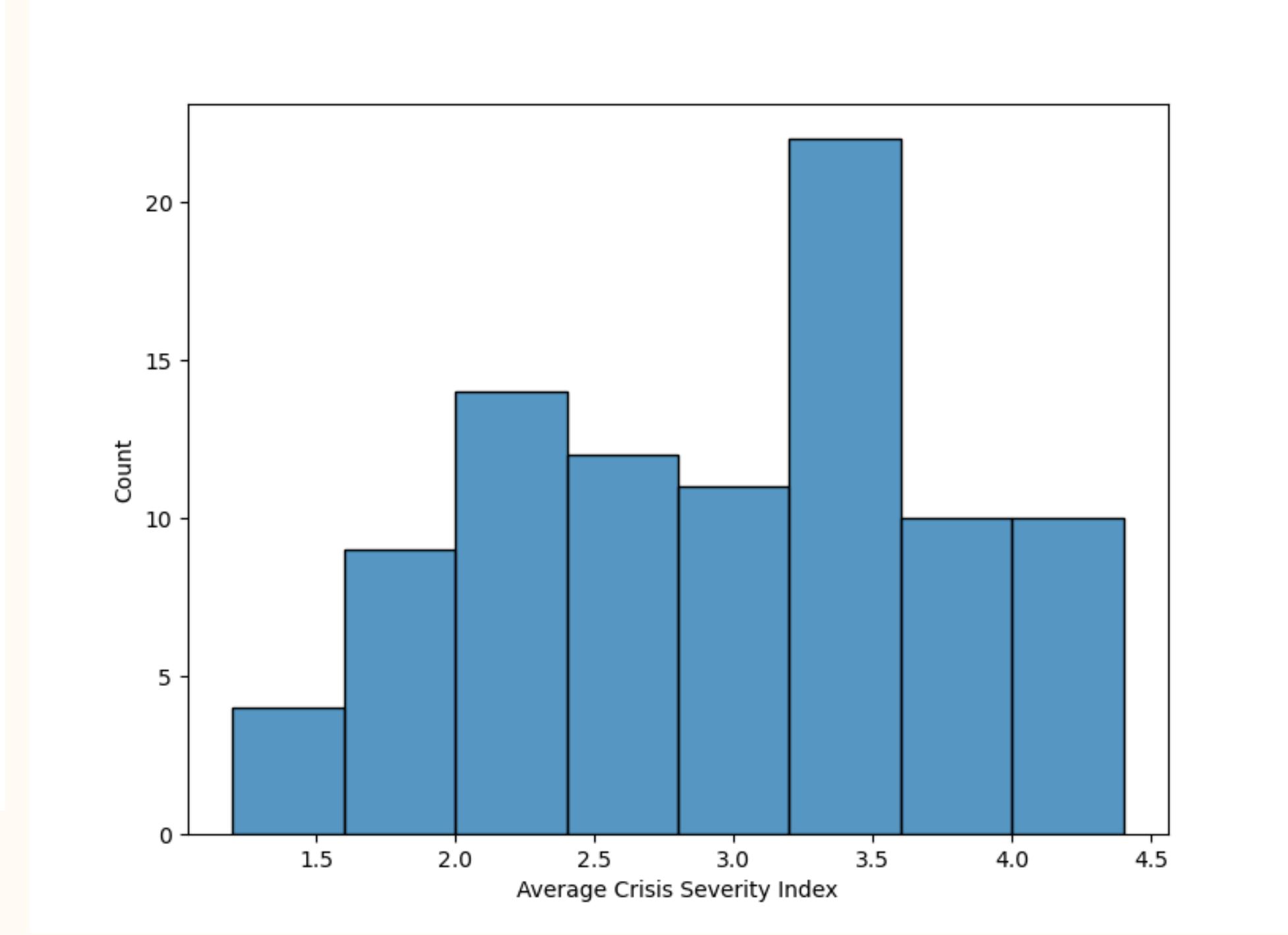
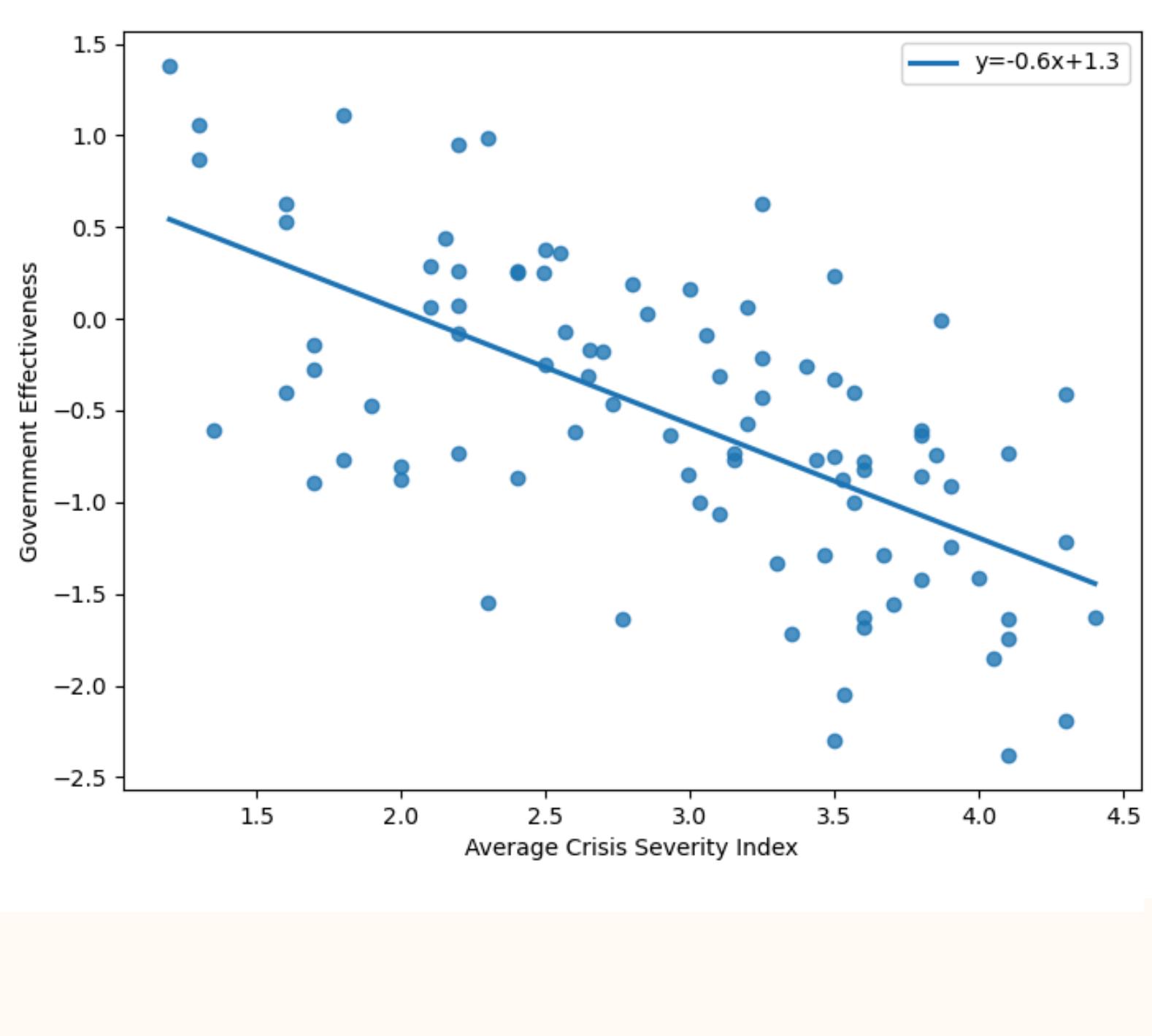


	COUNTRY	ISO3	INFORM RISK	RISK CLASS	Crisis Count	Crisis Boolean	Average Crisis Severity Index	Average Crisis Severity Category
0	Afghanistan	AFG	8.1	Very High	2.0	True	3.600000	High
1	Algeria	DZA	3.6	Medium	4.0	True	2.600000	Medium
2	Angola	AGO	5.2	High	1.0	True	3.100000	High
3	Armenia	ARM	2.9	Low	2.0	True	2.500000	Medium
4	Azerbaijan	AZE	4.8	Medium	2.0	True	2.400000	Medium
5	Bangladesh	BGD	5.7	High	3.0	True	3.800000	High
6	Belarus	BLR	1.8	Very Low	1.0	True	1.800000	Low
7	Brazil	BRA	4.6	Medium	3.0	True	2.733333	Medium

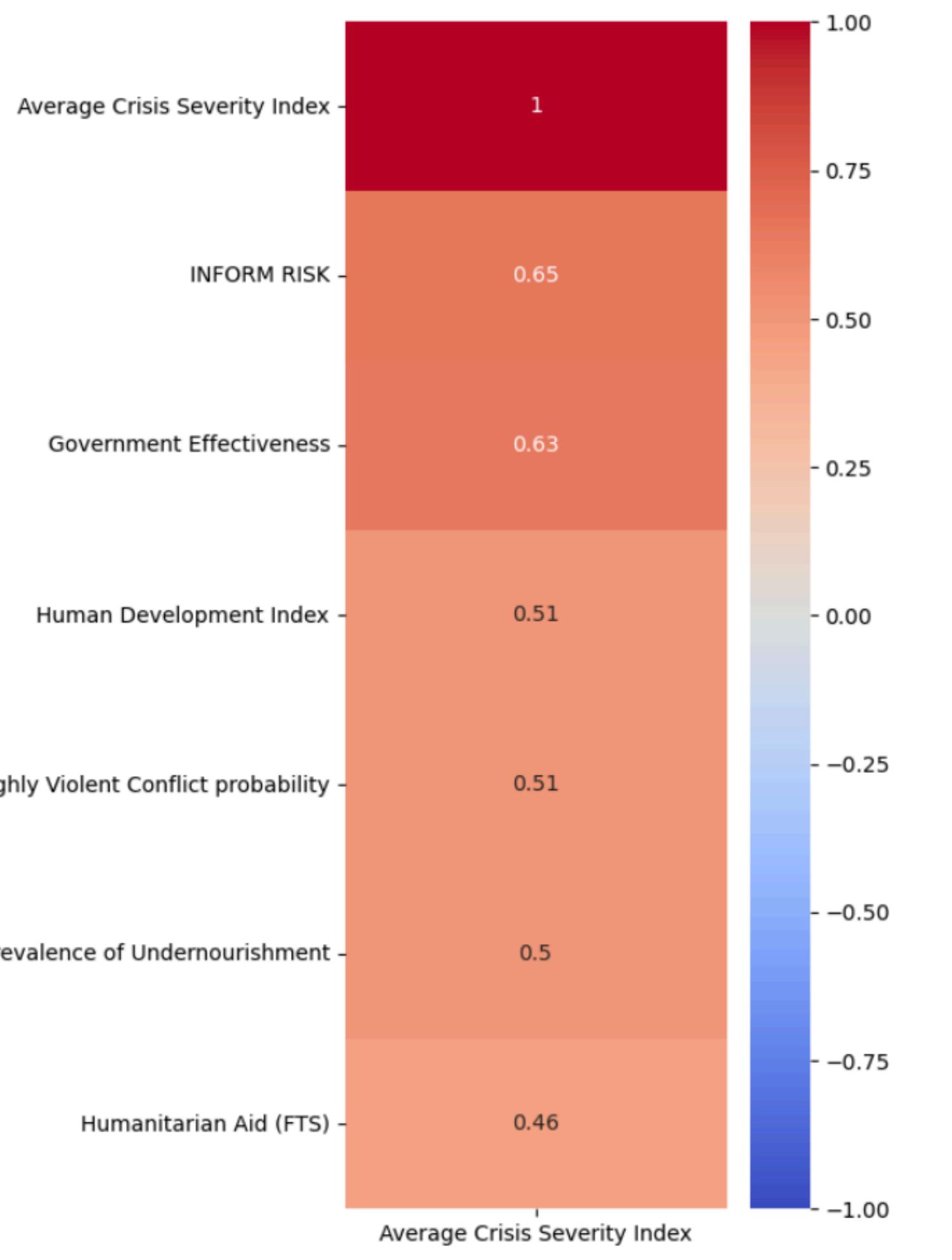
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Correlations



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Project 2

Explore whether
the INFORM data
products can be
used to predict the
severity of
humanitarian
crises

Machine Learning

ML Models

Among the countries
with crises, what is the
average crisis severity?

Index between 1 - 5
(least sever - most
severe)

1. Linear Regression
2. XGBoost Regression

Problem #2: Linear Regression

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Among the countries
with crises, what is
the average crisis
severity?



Index between 1 - 5
(least sever - most
severe)

What is linear regression?

- Used to predict a continuous outcome
- Univariate or multivariate
- Line of best fit = least sum of squared errors

Step 1: Decide what features to use in model

```
x = crisis[['INFORM RISK', 'Government Effectiveness', 'Human Development Index', 'Highly Violent Conflict probability',  
           'Prevalence of Undernourishment', 'Humanitarian Aid (FTS)', 'Development Aid (ODA)', 'Children under 5 (% of population)',  
           'Internally displaced persons (IDPs)', 'Mortality rate, under-5', 'Mobile cellular subscriptions']]  
y = crisis['Average Crisis Severity Index']
```

Step 2: Split data into training and test sets

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=.1, random_state=42)
```

Step 3: Initiate the model

```
lr = LinearRegression()  
lr.fit(X_train, y_train)
```

Problem #2: XGBoost Regression

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Among the countries
with crises, what is
the average crisis
severity?

Index between 1 - 5
(least sever - most
severe)

What is XGBoost regression?

- Can be used to predict continuous or categorical data
- Tree where root node is data average
- Calculates *residual* = the difference between observed value and predicted value
- Predict the residuals and scale them by a learning rate to reduce overfitting
- Learning rate ensures it moves with baby steps (ex: .1)
- Prediction = initial node + learning rate*residual
- Get new residual, keep adding a residual to get new predictions

```
boostR = XGBRegressor()  
boostR.fit(X_train, y_train)
```

Problem #2: Results

Among the countries
with crises, what is the
average crisis
severity?

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Index between 1 - 5
(least severe - most
severe)

Linear Regression

Training R²: **0.51**

Testing R²: **0.52**

MAE: **0.47**

RMSE: **0.54**

XGBoost Regression

Training R²: **0.99**

Testing R²: **0.81**

MAE: **0.29**

RMSE: **0.34**

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Project 3



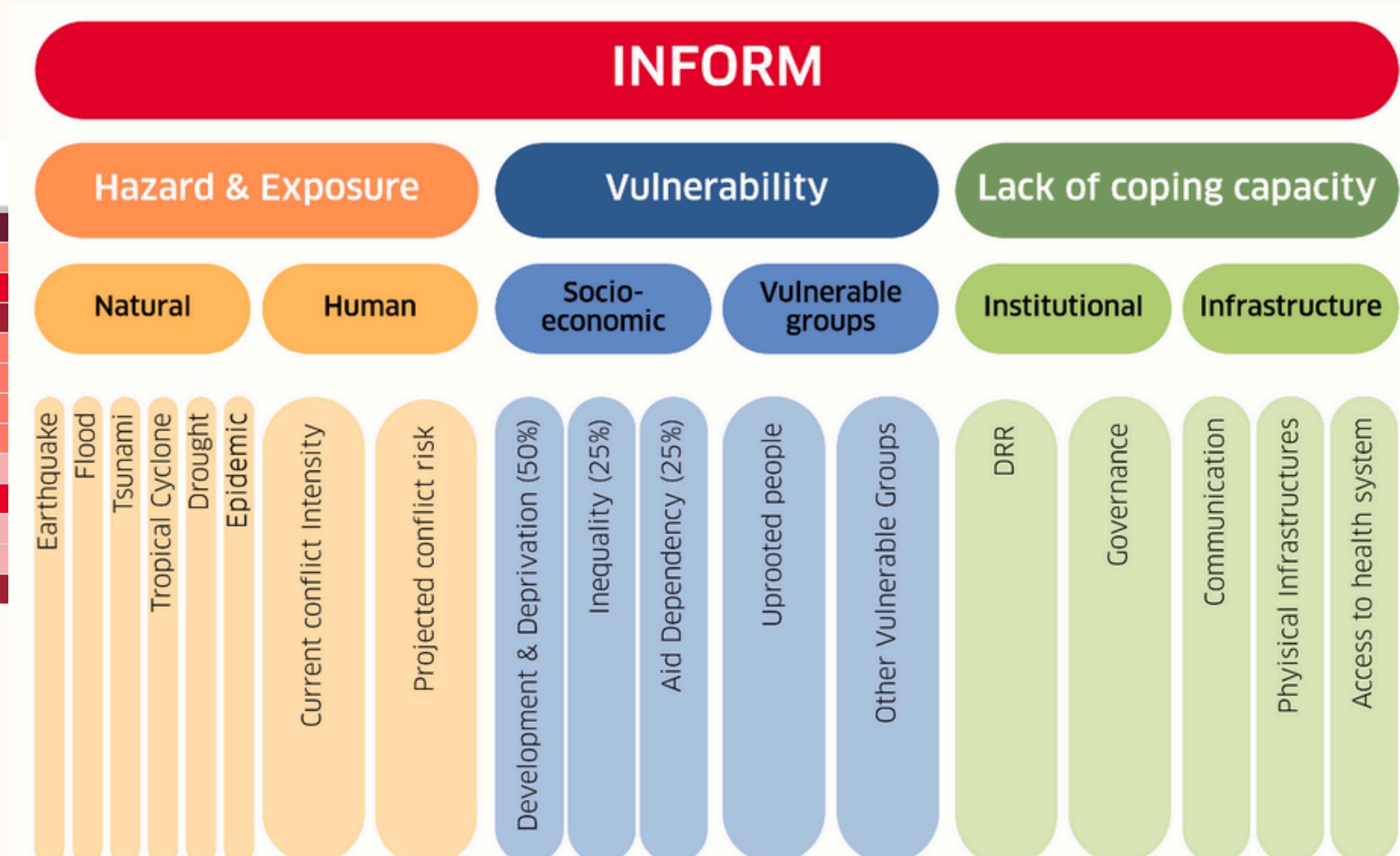
**Predict & forecast
how INFORM risk
data changes over
time**

Data Cleaning & EDA

INFORM Risk Dataset

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COUNTRY (a-z)	ISO3 (a-z)	INFORM RISK (0-10)	RISK CLASS (Very Low-Very High)
Afghanistan	AFG	8.1	Very High
Albania	ALB	3.1	Low
Algeria	DZA	3.6	Medium
Angola	AGO	5.2	High
Antigua and Barbuda	ATG	2.3	Low
Argentina	ARG	2.9	Low
Armenia	ARM	2.9	Low
Australia	AUS	2.4	Low
Austria	AUT	1.9	Very Low
Azerbaijan	AZE	4.8	Medium
Bahamas	BHS	2.1	Very Low
Bahrain	BHR	1.4	Very Low
Bangladesh	BGD	5.7	High



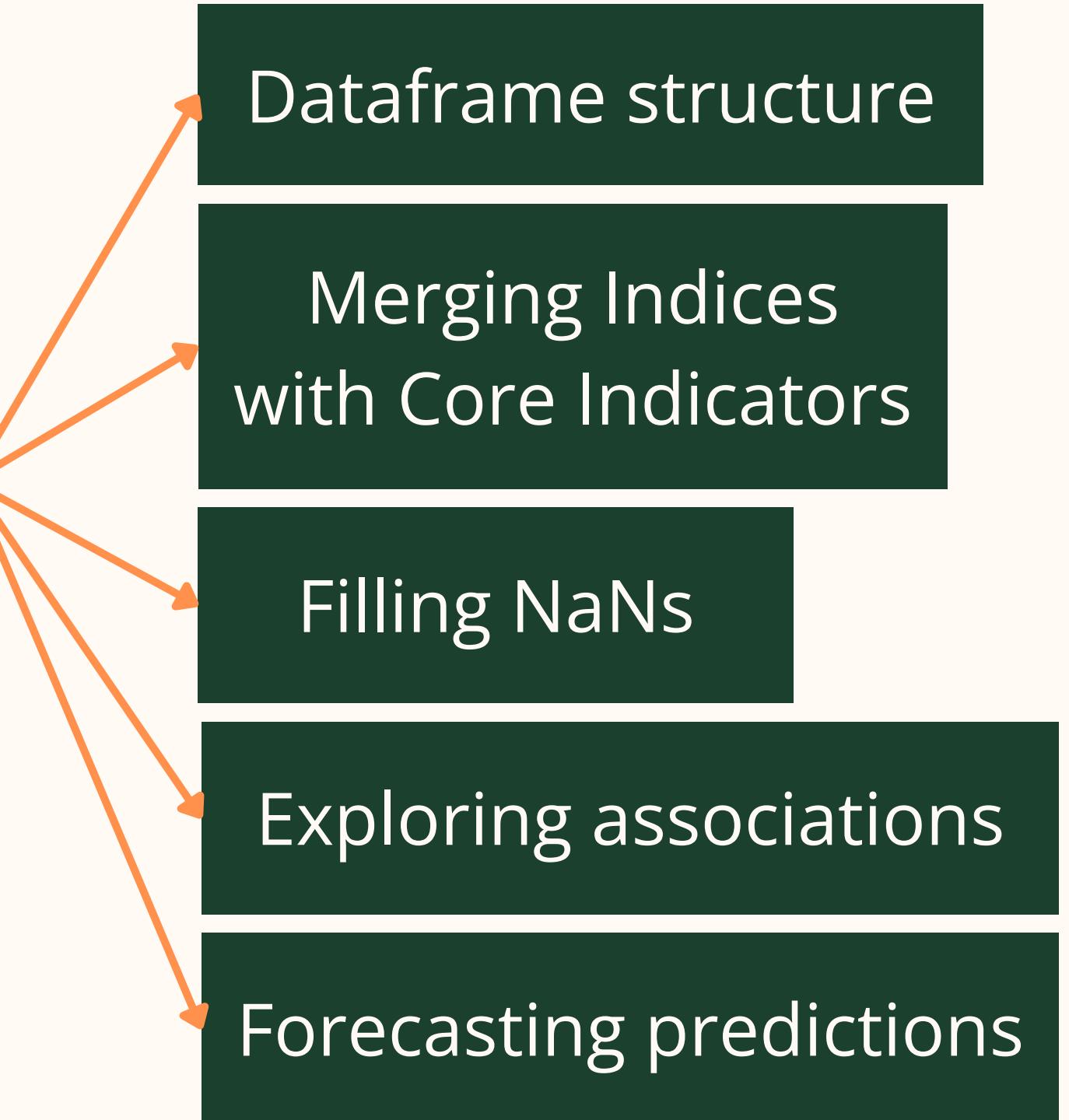
Problem #3

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Can we
forecast the
INFORM Risk
index?



Database of INFORM
Risk Indices Over Time



INFORM Risk Dataset Trend 2015-2024

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Iso3	IndicatorId	IndicatorName	IndicatorScore	SurveyYear	Indicator Type	INFORMYear
AFG	AFF_DR	People affected by disaster	886000	2022	Core Indicators	2024
AGO	AFF_DR	People affected by disaster	197920.4571	2022	Core Indicators	2024
ALB	AFF_DR	People affected by disaster	91428.57143	2022	Core Indicators	2024
ARE	AFF_DR	People affected by disaster	0	2022	Core Indicators	2024
ARG	AFF_DR	People affected by disaster	1000.914286	2022	Core Indicators	2024
ARM	AFF_DR	People affected by disaster	8485.714286	2022	Core Indicators	2024
ATG	AFF_DR	People affected by disaster	0	2022	Core Indicators	2024
AUS	AFF_DR	People affected by disaster	200000	2022	Core Indicators	2024
AUT	AFF_DR	People affected by disaster	0	2022	Core Indicators	2024
AZE	AFF_DR	People affected by disaster	0	2022	Core Indicators	2024
BDI	AFF_DR	People affected by disaster	87500	2022	Core Indicators	2024
BEL	AFF_DR	People affected by disaster	0	2022	Core Indicators	2024
BEN	AFF_DR	People affected by disaster	0	2022	Core Indicators	2024
BFA	AFF_DR	People affected by disaster	461349.0857	2022	Core Indicators	2024
BGD	AFF_DR	People affected by disaster	142857.1429	2022	Core Indicators	2024
BGR	AFF_DR	People affected by disaster	0	2022	Core Indicators	2024
BHR	AFF_DR	People affected by disaster	0	2022	Core Indicators	2024
BHS	AFF_DR	People affected by disaster	0	2022	Core Indicators	2024
BIH	AFF_DR	People affected by disaster	1787.857143	2022	Core Indicators	2024
BLR	AFF_DR	People affected by disaster	0	2022	Core Indicators	2024
BLZ	AFF_DR	People affected by disaster	0	2022	Core Indicators	2024
EST	CC.INF.AHC.HEAL	Health expenditure per capita	0	2021	INORM Index	2024
ETH	CC.INF.AHC.HEAL	Health expenditure per capita	9.9	2020	INORM Index	2024
FIN	CC.INF.AHC.HEAL	Health expenditure per capita	0	2020	INORM Index	2024
FJI	CC.INF.AHC.HEAL	Health expenditure per capita	8.7	2020	INORM Index	2024
FRA	CC.INF.AHC.HEAL	Health expenditure per capita	0	2020	INORM Index	2024
FSM	CC.INF.AHC.HEAL	Health expenditure per capita	8.9	2020	INORM Index	2024

Split
dataframe:
INFORM Risk
Indices &
Core
Indicators

DataFrame for Indicator Types Core Indicators:
<class 'pandas.core.frame.DataFrame'>
Index: 147420 entries, 0 to 473667
Data columns (total 7 columns):
 # Column Non-Null Count Dtype

 0 Iso3 147420 non-null object
 1 IndicatorId 147420 non-null object
 2 IndicatorName 147420 non-null object
 3 IndicatorScore 147420 non-null float64
 4 SurveyYear 147420 non-null int64
 5 Indicator Type 147420 non-null object
 6 INFORMYear 147420 non-null int64
dtypes: float64(1), int64(2), object(4)
memory usage: 9.0+ MB
None

DataFrame for Indicator Types INORM Index:
<class 'pandas.core.frame.DataFrame'>
Index: 326248 entries, 21 to 473143
Data columns (total 7 columns):
 # Column Non-Null Count Dtype

 0 Iso3 326248 non-null object
 1 IndicatorId 326248 non-null object
 2 IndicatorName 325091 non-null object
 3 IndicatorScore 326248 non-null float64
 4 SurveyYear 326248 non-null int64
 5 Indicator Type 326248 non-null object
 6 INFORMYear 326248 non-null int64
dtypes: float64(1), int64(2), object(4)
memory usage: 19.9+ MB
None

Melting & Pivoting 2015-2024 Trend Data

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Iso3	IndicatorName	IndicatorScore	INFORMYYear
0 AFG	People affected by drought (absolute) - raw	886000.000000	2024
1 AGO	People affected by drought (absolute) - raw	197920.457143	2024
2 ALB	People affected by drought (absolute) - raw	91428.571429	2024
3 ARE	People affected by drought (absolute) - raw	0.000000	2024
4 ARG	People affected by drought (absolute) - raw	1000.914286	2024
...
473663 GNB	Population living in slums (% of urban populat...	60.810370	2024
473664 GTM	Population living in slums (% of urban populat...	37.600000	2024
473665 GUY	Population living in slums (% of urban populat...	12.140200	2024
473666 HTI	Population living in slums (% of urban populat...	48.900000	2024
473667 IDN	Population living in slums (% of urban populat...	19.410830	2024

473668 rows × 4 columns

Melt: Unpivot a DataFrame from wide to long format, optionally leaving identifiers set

```
df1 = pd.melt(df,
               id_vars=['INFORMYYear', 'Iso3', 'IndicatorName'],
               var_name='IndicatorScore',
               value_name='Score')
```

```
# Pivot the melted DataFrame to create individual columns for each indicator
df1 = df1.pivot_table(index=['INFORMYYear', 'Iso3'],
                      columns='IndicatorName',
                      values='Score').reset_index()
```

Dataframe Structure
for Time Series
Analysis

INFORMYYear	Iso3	IndicatorName	IndicatorScore	Score
0 2024	AFG	People affected by drought (absolute) - raw	IndicatorScore	886000.000000
1 2024	AGO	People affected by drought (absolute) - raw	IndicatorScore	197920.457143
2 2024	ALB	People affected by drought (absolute) - raw	IndicatorScore	91428.571429
3 2024	ARE	People affected by drought (absolute) - raw	IndicatorScore	0.000000
4 2024	ARG	People affected by drought (absolute) - raw	IndicatorScore	1000.914286
...
473663 2024	GNB	Population living in slums (% of urban populat...	IndicatorScore	60.810370
473664 2024	GTM	Population living in slums (% of urban populat...	IndicatorScore	37.600000
473665 2024	GUY	Population living in slums (% of urban populat...	IndicatorScore	12.140200
473666 2024	HTI	Population living in slums (% of urban populat...	IndicatorScore	48.900000
473667 2024	IDN	Population living in slums (% of urban populat...	IndicatorScore	19.410830

473668 rows × 5 columns

IndicatorName	INFORMYYear	Iso3	% of Populations at risk of Plasmodium falciparum malaria	% of Populations at risk of Plasmodium vivax malaria	Access to Health Care	Access to electricity	Access to improved sanitation facilities	Access to improved water source	Adult literacy rate	Adult prevalence of HIV-AIDS	Urban population growth ...	Urban population growth (annual %)	Vets per capita
0 2015	AFG	0.872426	0.908841	8.9	45.300000	6.5	8.3	9.9	0.15	...	9.1	4.531768	0.008513
1 2015	AGO	0.996012	0.996146	7.7	19.400000	6.0	9.3	6.2	2.85	...	9.7	4.853340	0.000933
2 2015	ALB	0.000000	0.000000	3.7	49.974998	0.3	1.4	0.6	0.15	...	3.3	1.646116	0.043124
3 2015	ARE	0.000000	0.000000	1.5	50.000000	0.2	0.0	2.1	0.15	...	2.6	1.318987	0.003350
4 2015	ARG	0.000000	0.000000	1.3	50.000000	0.6	0.2	0.2	0.60	...	2.5	1.239639	0.024787
...
1905 2024	WSM	0.000000	0.000000	6.3	49.250002	0.4	1.6	0.2	NaN	...	1.9	0.928355	0.004769
1906 2024	YEM	0.685021	0.419070	6.5	38.688599	5.1	7.9	NaN	0.15	...	7.6	3.796455	0.001715
1907 2024	ZAF	0.125373	0.249348	4.5	45.200002	2.4	1.2	1.1	14.15	...	3.1	1.557749	0.003141
1908 2024	ZMB	1.000000	1.000000	5.7	25.992558	7.6	6.9	2.6	10.40	...	8.0	4.009238	0.009208
1909 2024	ZWE	0.000000	0.000000	6.6	27.039964	7.2	7.5	2.1	10.80	...	4.6	2.308437	0.033776

1910 rows × 240 columns

Data Cleaning

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Merge Index & Core Indicator dataframes

Create Mean INFORM Risk Index & INFORM Risk Categories Columns

Manage NaNs for Core Indicators

Access to Health Care' has 10 null values
Adult literacy rate' has 354 null values
Adult prevalence of HIV-AIDS' has 420 null values
Corruption Perception Index' has 137 null values
GDP per capita' has 27 null values
Gender Inequality Index' has 216 null values
Health expenditure per capita' has 44 null values
Inequality' has 103 null values
Internet users' has 8 null values
Literacy rate, adult total' has 354 null values
Maternal Mortality Ratio' has 70 null values
Multidimensional Poverty Index' has 753 null values
Palestinian Refugees' has 1870 null values
Personal remittances, received (% of GDP)' has 93 null values
Physicians density' has 27 null values
Population living in slums (% of urban population)' has 894 null values
Under-five mortality rate' has 10 null values
Vets per capita' has 85 null values
Volume of remittances' has 93 null values

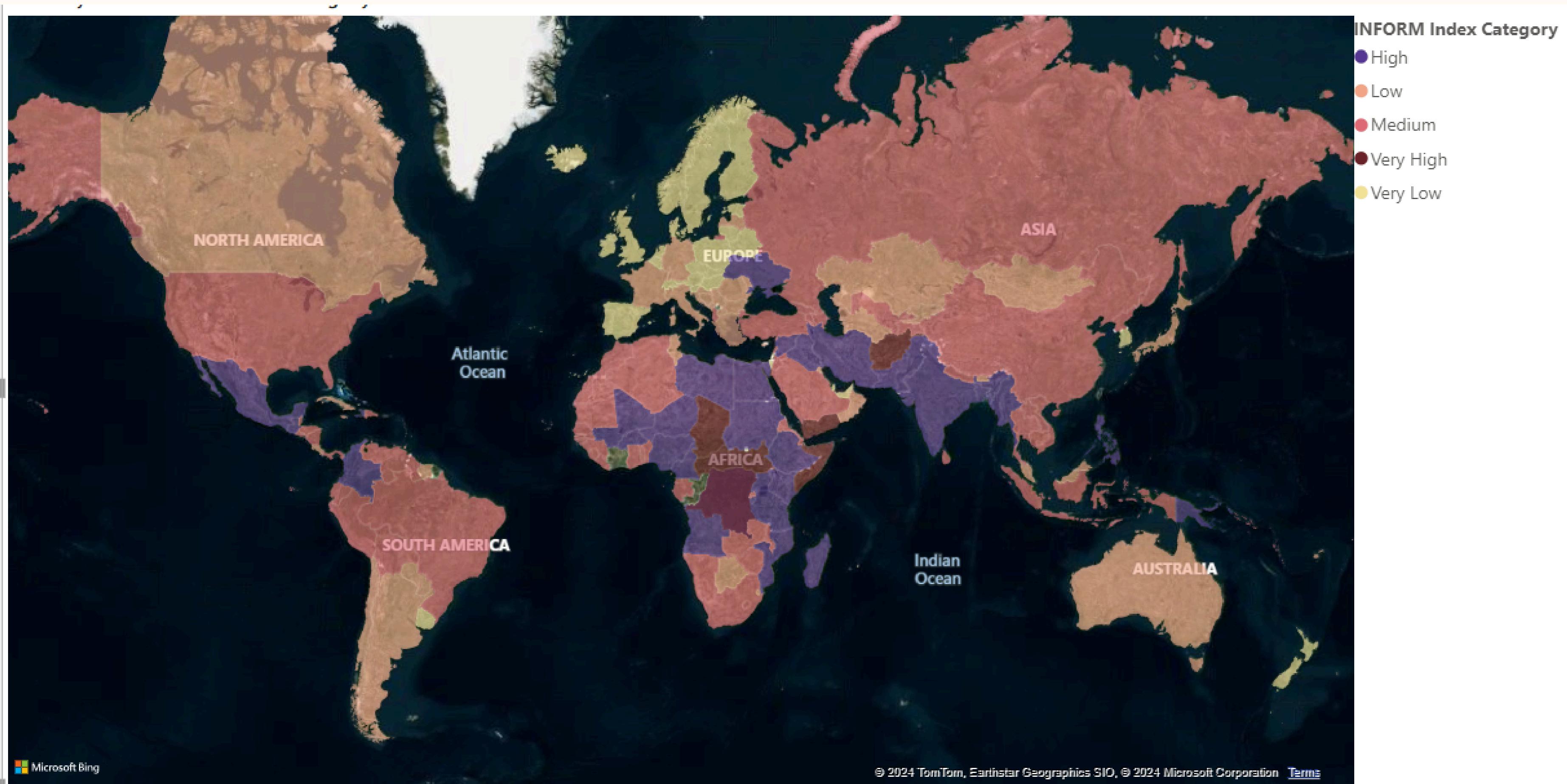
Fill as most recent values per country, or column mean where none available

For Time Series - Set Date as Index for dataframe

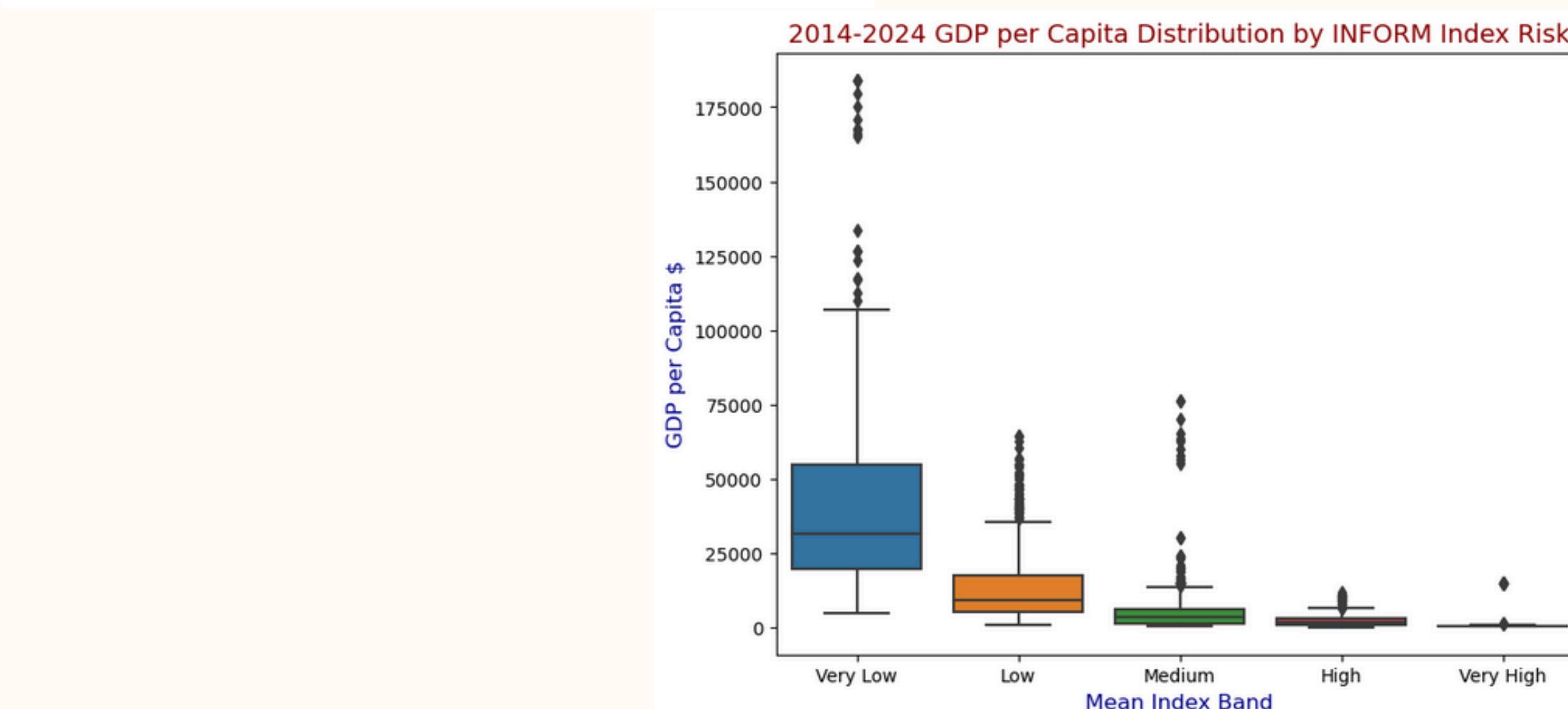
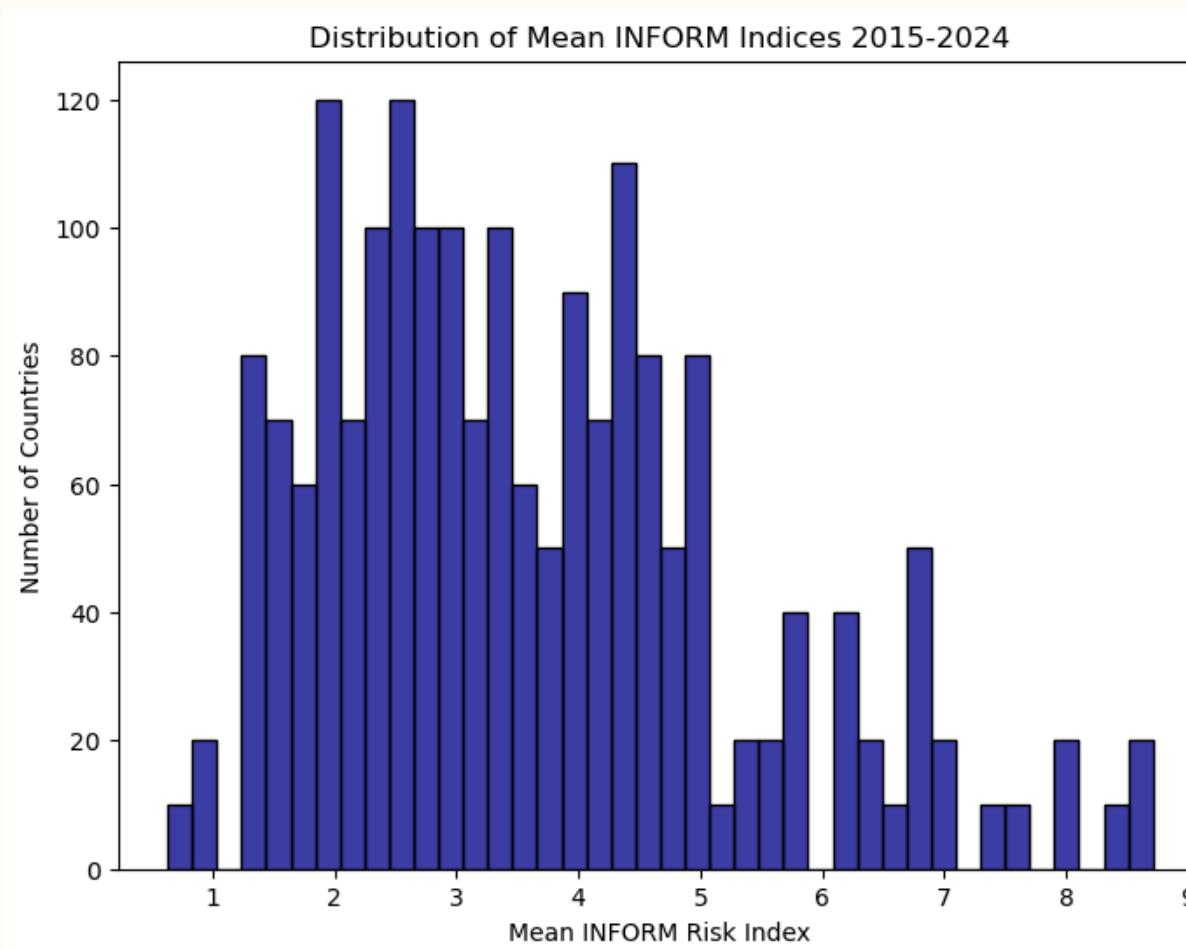
```
df = pd.read_csv("2015-2024_year_df_INFORM_index_core_indicators_mean_index.csv", index_col = 'INFORMYear', parse_dates=True)
```

Duplicate Year column before setting as dataframe Index for easy groupby

EDA: 2015-2024 INFORM Risk Index Categories

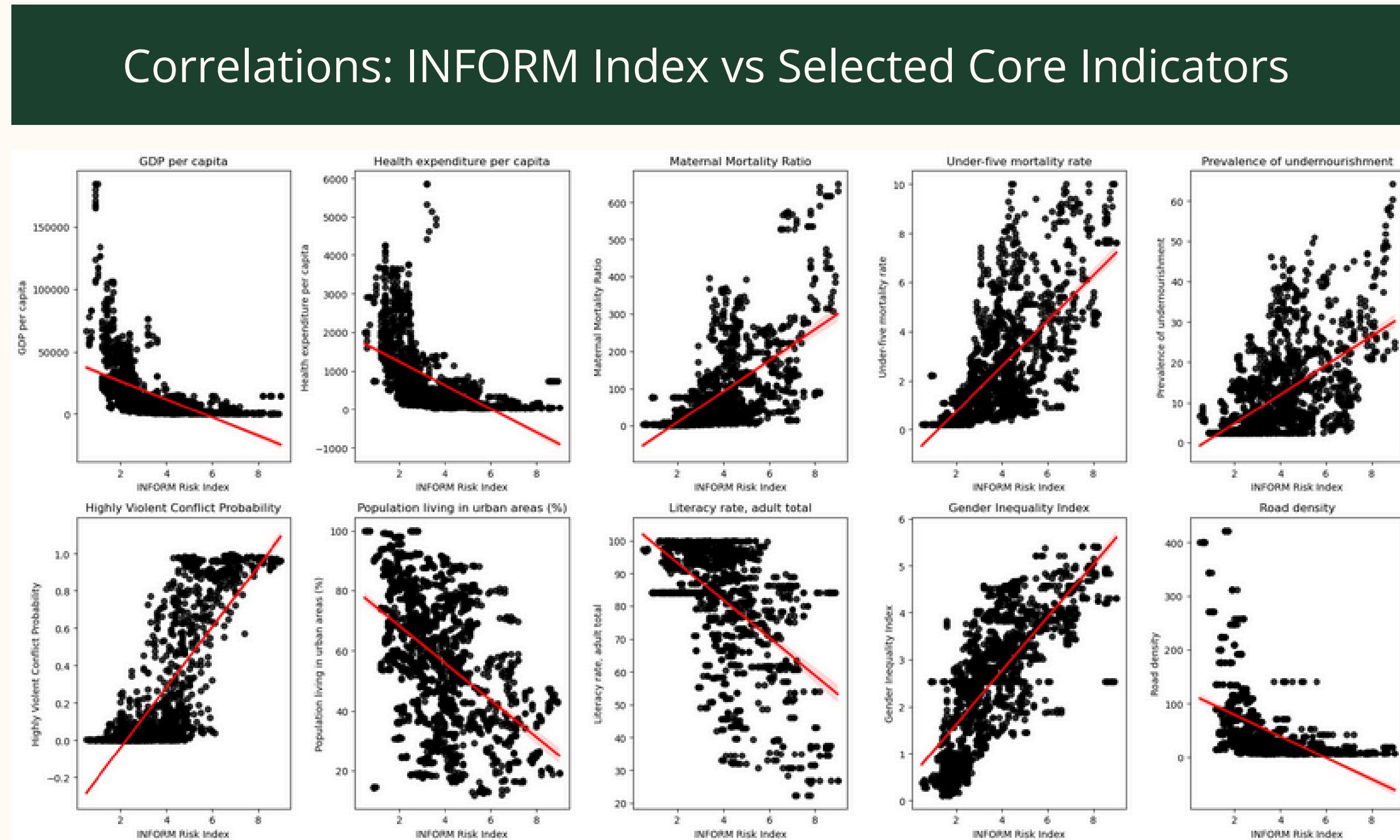


EDA



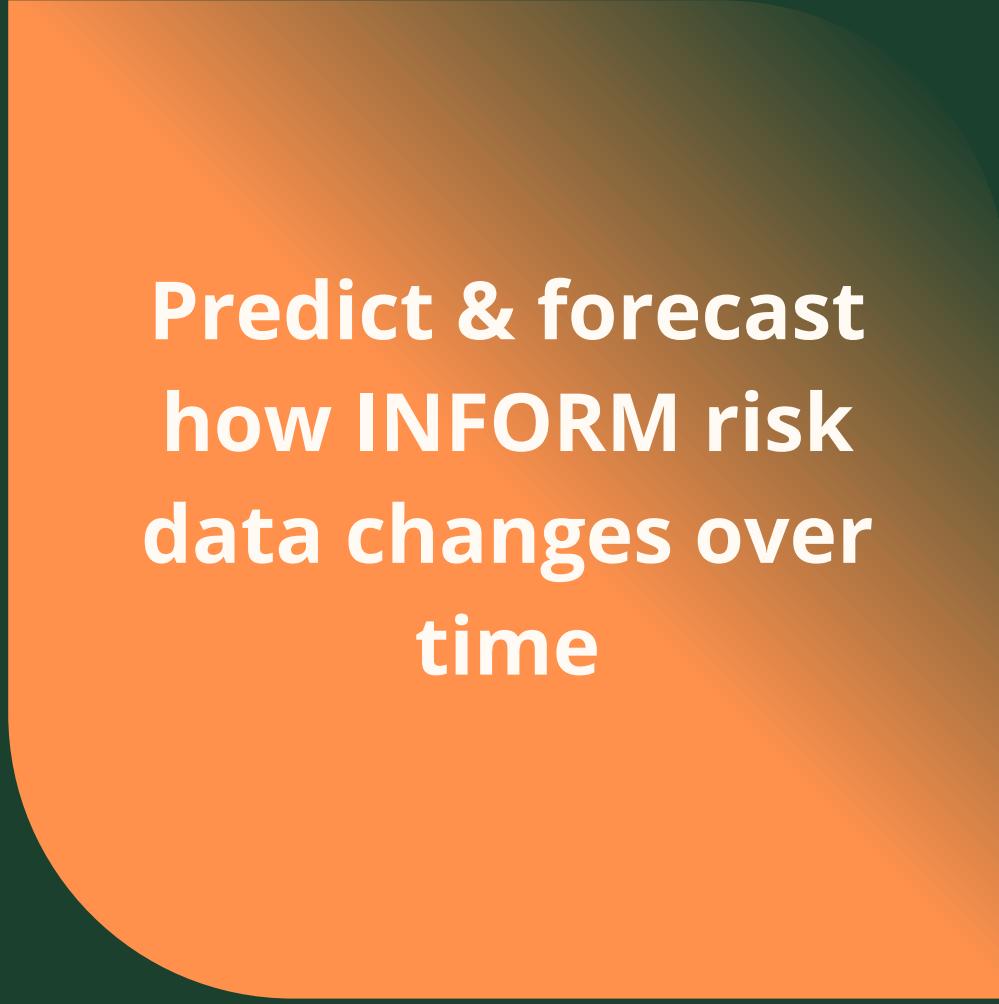
EDA

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Project 3



**Predict & forecast
how INFORM risk
data changes over
time**

Machine Learning

ML Models

Can we
forecast the
INFORM Risk
index?

Time Series Models for
Prediction & Forecasting

1. ARIMA

Problem #3

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Can we forecast
the INFORM Risk
index?

Machine Learning:
Time Series Models

Traditional Models

Univariate

- ARIMA / SARIMA
- Prophet / Neural
Prophet

Multivariate

- Vector
autoregression

Other Models:

- Long Short-Term
Memory (LSTM)
- Other regressor

Problem #3

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AutoRegressive (AR)
Integrated (I)
Moving Average (MA)
(ARIMA)

AR(p) AutoRegression

- Regression model that utilizes the dependent relationship between a current observation & observations over a previous period
- An auto regressive (AR(p)) component refers to the use of past values in the regression equation for the time series)

I(d) Integration

- Uses differencing of observations (subtracting an observation from observation at the previous time step) in order to make the time series stationary.
- Differencing involves the subtraction of the current values of a series with its previous values d number of times.

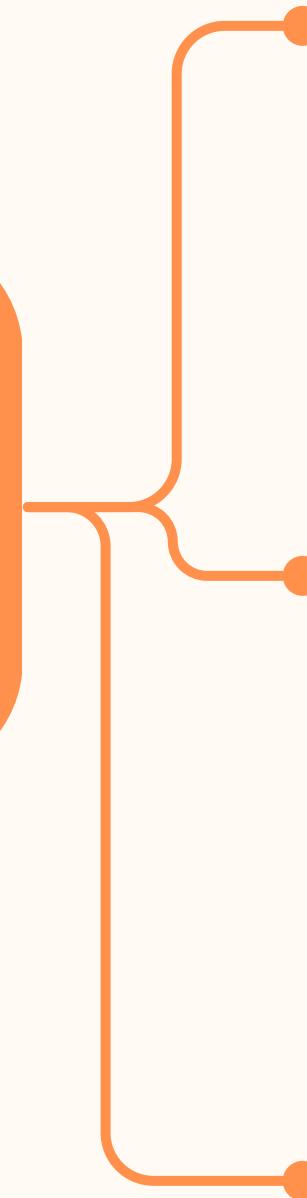
MA(q) Moving Average

- A model that uses the dependency between an observation & a residual error from a moving average model applied to lagged observations. A moving average component depicts the error of the model as a combination of previous error terms. The order q represents the number of terms to be included in the model.

Problem #3

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AutoRegressive (AR)
Integrated (I)
Moving Average (MA)
(ARIMA)



Checking Autocorrelation to determine AR(p)

- Partial Autocorrelation conveys pure correlation of a series & its lag, excluding correlation contributions from intermediate lags.

Test for Stationarity - I(d) Integration

- Uses differencing of observations (subtracting an observation from observation at the previous time step) to make time series stationary
- Subtraction of current values of a series with its previous values d number of times
- Stationary time series has statistical properties or moments (e.g., mean & variance) that do not vary in time. Stationarity is status of a stationary time series. Conversely, nonstationarity - the status of a time series whose statistical properties are changing through time

Checking Autocorrelation to determine MA(q)

- Autocorrelation is the correlation of a series with its own lags.
- If a series is significantly autocorrelated, that means previous values of series (lags) may be helpful in predicting the current value

Problem #3

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AutoRegressive (AR)
Integrated (I)
Moving Average (MA)
(ARIMA)

1. Autocorrelation Function (ACF) Plot:

- ACF plot helps identify "q" parameter (order of moving average component)
- If ACF plot shows a significant spike at lag "q", then cuts off abruptly or decreases gradually, suggests presence of a moving average component of order "q".

2. Partial Autocorrelation Function (PACF) Plot:

- PACF plot helps identify the "p" parameter (order of autoregressive component)
- If PACF plot shows a significant spike at lag "p", then cuts off abruptly or decreases gradually, suggests presence of an autoregressive component of order "p".

Interpretation:

- If both ACF & PACF plots show significant spikes at multiple lags, might suggest more complex ARIMA model with both autoregressive & moving average components (i.e., an ARIMA(p, d, q) model).
- If ACF plot decays exponentially & PACF plot cuts off after a few lags, it may indicate that series can be modeled with a pure moving average process of order "q" (i.e., an MA(q) model).
- Conversely, if PACF plot decays exponentially & ACF plot cuts off after a few lags, may suggest series can be modeled with a pure autoregressive process of order "p" (i.e., an AR(p) model).

Problem #3

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ARIMA Output

- **Mean Squared Error (MSE):** MSE measures average squared difference between the actual & predicted values. It gives more weight to large errors because of the squaring operation. Lower MSE values indicate better model performance.
- **Mean Absolute Error (MAE):** MAE measures average absolute difference between the actual & predicted values. It treats all errors equally regardless of their direction (positive or negative). Where the symbols have the same meaning as in MSE. Like MSE, lower MAE values indicate better model performance.
- **Root Mean Squared Error (RMSE):** RMSE is simply the square root of MSE. It provides an interpretable measure of the average magnitude of the error, in the same units as the response variable. Since RMSE is in the same units as the response variable, it's easier to interpret compared to MSE.

- **ar.L1 & ma.L1** -> estimated coefficients of autoregressive (AR) & moving average (MA)
- **sigma2** -> estimated variance of error term

Problem #3

ARIMA Output

Log Likelihood: Goodness of fit of model to data. Higher log likelihood values indicate better fit of model to data.

AIC (Akaike Information Criterion): Measures relative model quality for data. Penalizes model for complexity, helps select model that most effectively explains data while using fewest parameters. Lower AIC values indicate a better trade-off between goodness of fit & model complexity.

BIC (Bayesian Information Criterion): Penalizes the model for complexity. Puts higher penalty on models with more parameters than AIC. Lower BIC values -> better trade-off between goodness of fit & model complexity.

HQIC (Hannan-Quinn Information Criterion): Another criterion for model selection, similar to AIC & BIC, penalizes model for complexity. Lower HQIC values indicate better trade-off between goodness of fit & model complexity

- Lower AIC, BIC, or HQIC value suggests better-fitting model
- Higher log likelihood values -> better fit
- Compare these values across models to determine better fit model

- **Ljung-Box (L1) (Q):** tests whether any autocorrelation in residuals is different from zero at lag 1. Low p-value suggests evidence of autocorrelation in residuals at lag 1.
- **Jarque-Bera (JB):** tests null hypothesis that data is normally distributed. Low p-value -> residuals not normally distributed
- **Heteroskedasticity (H):** Tests null hypothesis of homoscedasticity (constant variance of errors). Low p-value suggests evidence against null hypothesis -> heteroskedasticity in residuals
- **Skew & Kurtosis:** Measures distribution - skewness & kurtosis/ "tailedness" of residuals

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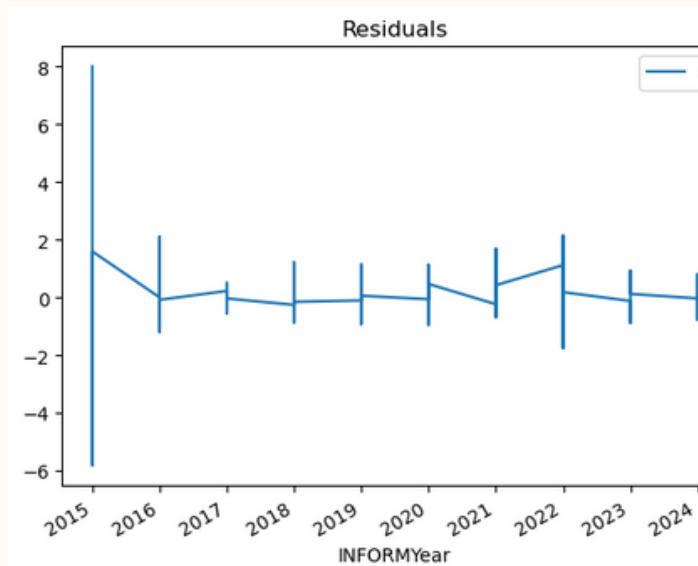
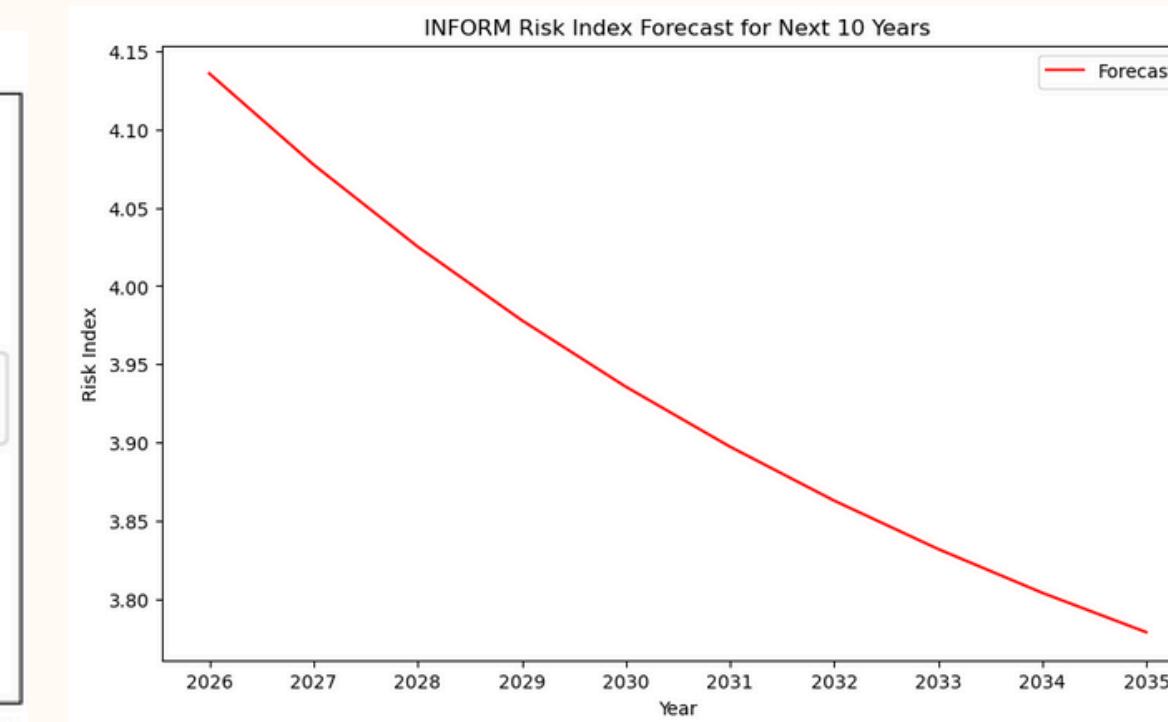
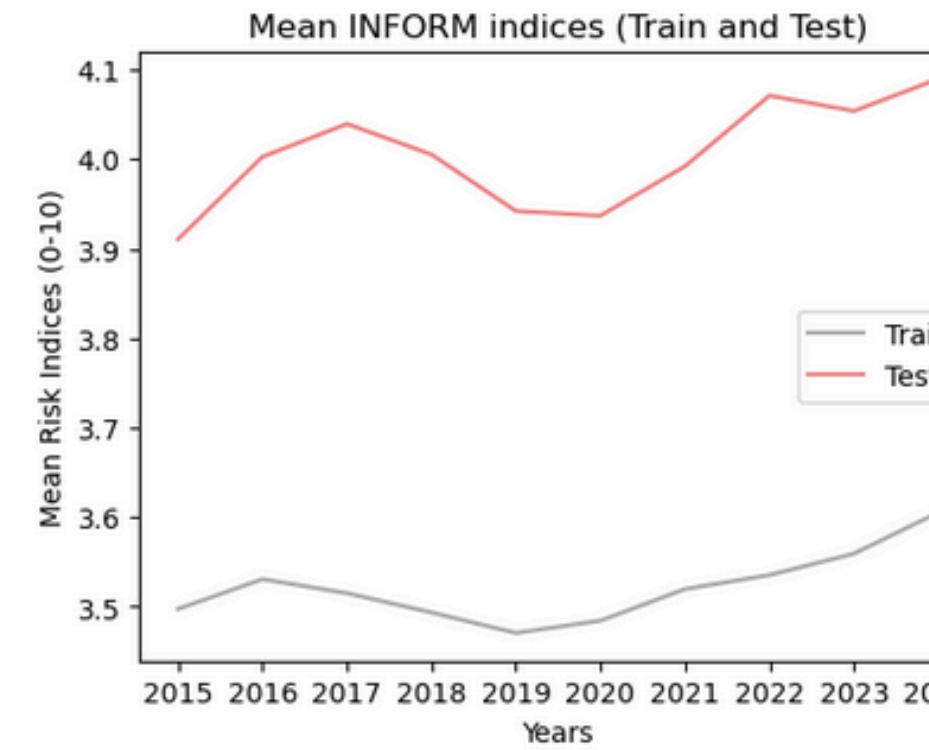
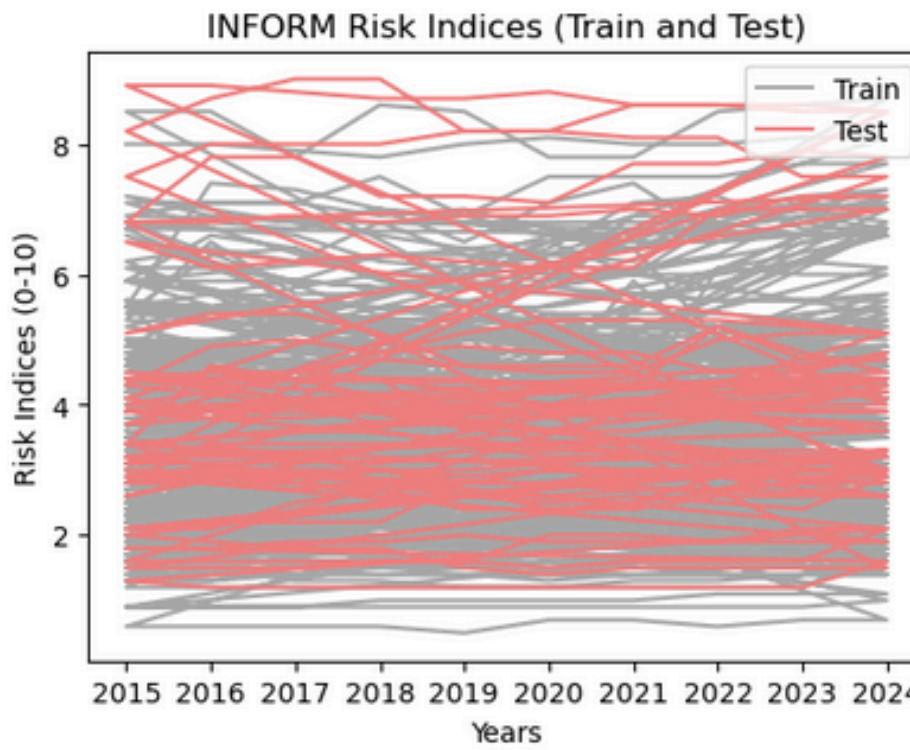
Project 3

**Predict & forecast
how INFORM risk
data changes over
time**

INFORM Risk Index ARIMA Model

ARIMA Train - Test Model to forecast INFORM Risk indices:

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Mean Squared Error (MSE): 3.6829821042967064
 Mean Absolute Error (MAE): 1.377148768592445
 Root Mean Squared Error (RMSE): 1.9191097165864974

SARIMAX Results

```
=====
Dep. Variable: INFORM Risk Index No. Observations: 1528
Model: ARIMA(1, 1, 1) Log Likelihood: -1671.588
Date: Mon, 08 Apr 2024 AIC: 3349.176
Time: 21:39:47 BIC: 3365.169
Sample: 0 HQIC: 3355.129
- 1528
Covariance Type: opg
=====
```

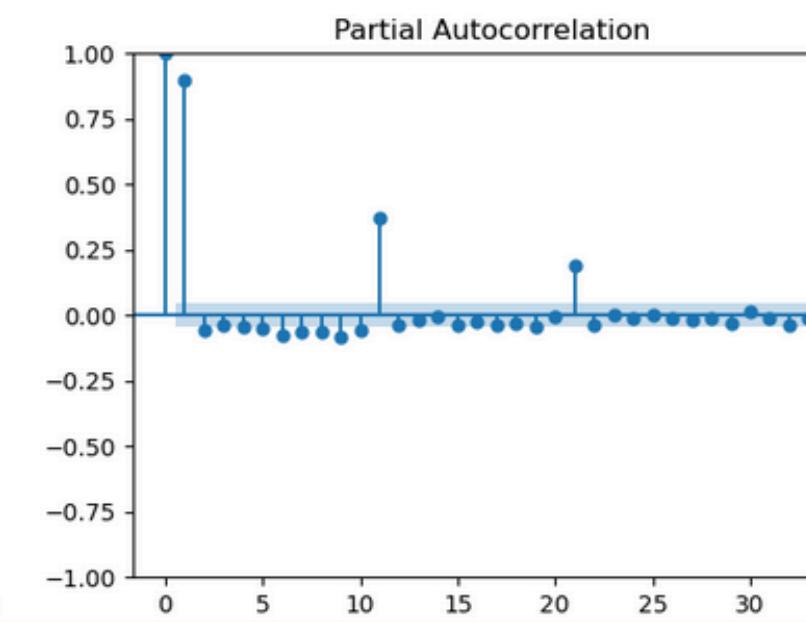
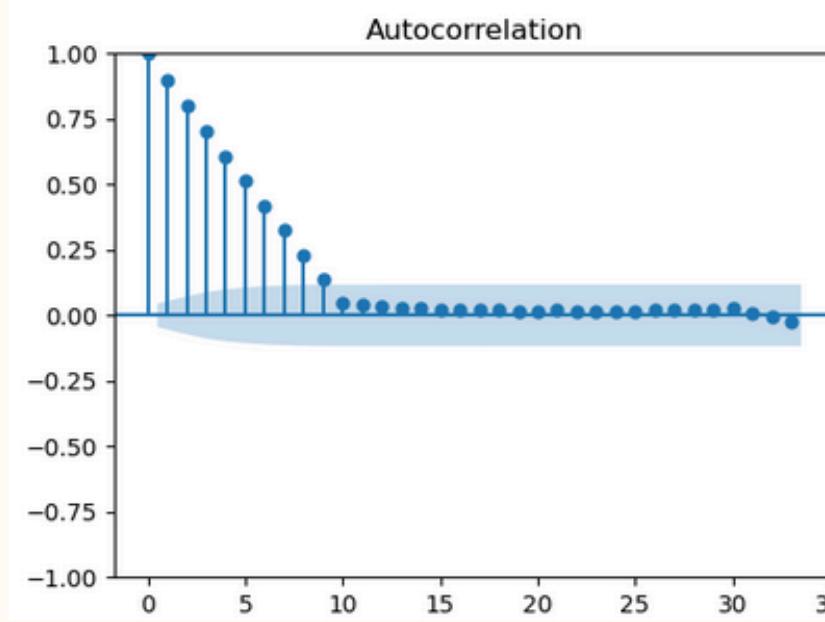
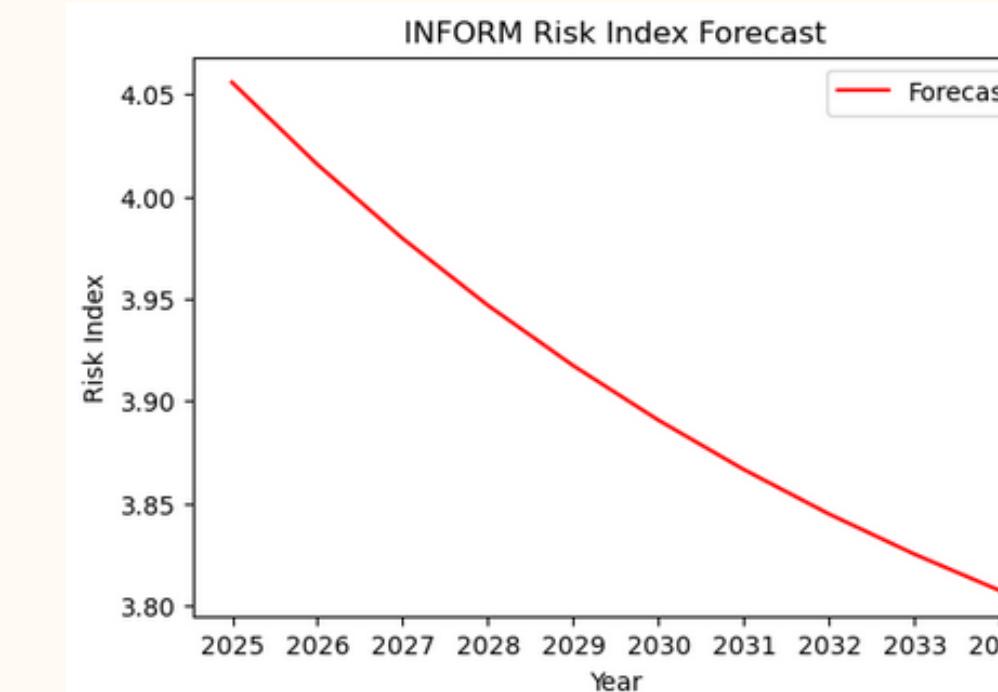
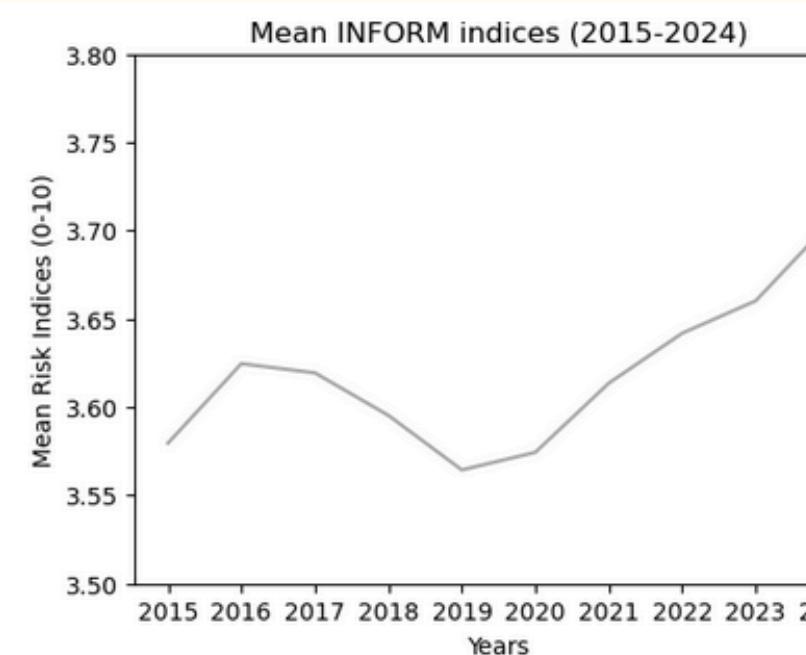
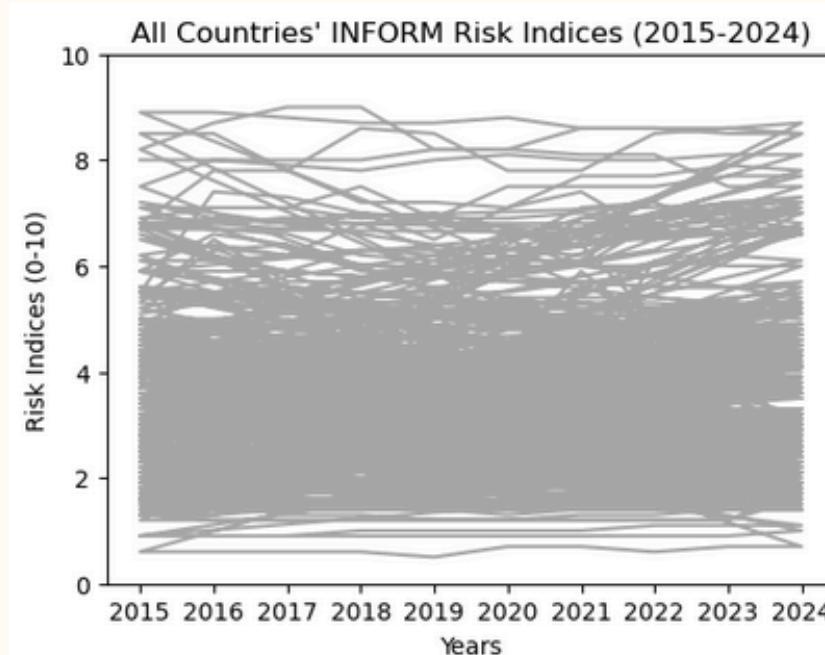
	coef	std err	z	P> z	[0.025	0.975]
ar.L1	0.9007	0.013	66.950	0.000	0.874	0.927
ma.L1	-1.0000	0.245	-4.077	0.000	-1.481	-0.519
sigma2	0.5213	0.129	4.034	0.000	0.268	0.775

```
=====
Ljung-Box (L1) (Q): 3.09 Jarque-Bera (JB): 30368.06
Prob(Q): 0.08 Prob(JB): 0.00
Heteroskedasticity (H): 1.52 Skew: -0.73
Prob(H) (two-sided): 0.00 Kurtosis: 24.80
=====
```

Warnings:
 [1] Covariance matrix calculated using the outer product of gradients (complex-step).

ARIMA Model to forecast INFORM Risk indices:

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Mean Squared Error (MSE): 0.10595662427130725
 Mean Absolute Error (MAE): 0.29619233818658486
 Root Mean Squared Error (RMSE): 0.325509791360117

SARIMAX Results

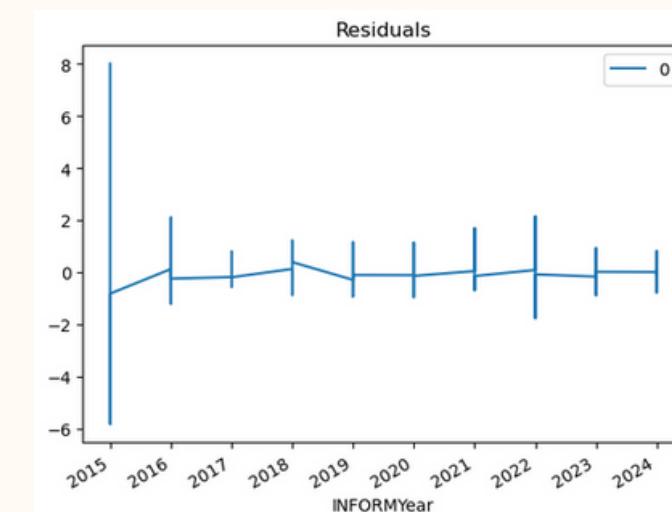
```
=====
Dep. Variable:      INFORM Risk Index   No. Observations:             1910
Model:                  ARIMA(1, 1, 1)   Log Likelihood:          -2128.094
Date: Mon, 08 Apr 2024   AIC:                 4262.187
Time: 02:50:43           BIC:                 4278.850
Sample:                0 - 1910   HQIC:                 4268.320
Covariance Type:        opg
=====
```

	coef	std err	z	P> z	[0.025	0.975]
ar.L1	0.9033	0.012	73.023	0.000	0.879	0.928
ma.L1	-0.9999	0.059	-16.983	0.000	-1.115	-0.885
sigma2	0.5430	0.030	17.965	0.000	0.484	0.602

Ljung-Box (L1) (Q): 4.56 Jarque-Bera (JB): 41753.34
 Prob(Q): 0.03 Prob(JB): 0.00
 Heteroskedasticity (H): 1.35 Skew: -0.44
 Prob(H) (two-sided): 0.00 Kurtosis: 25.89

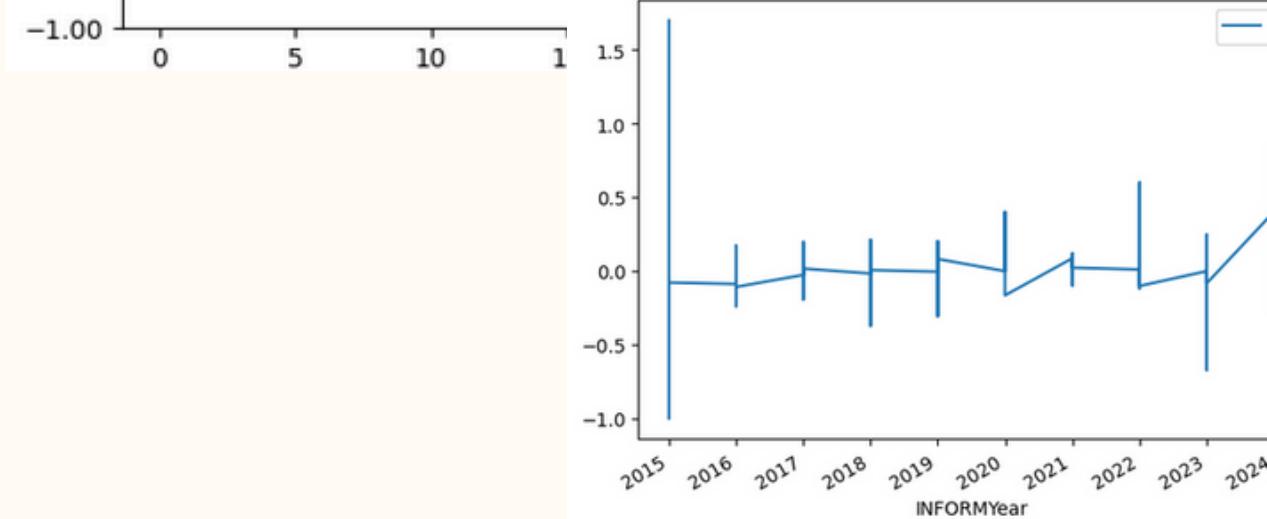
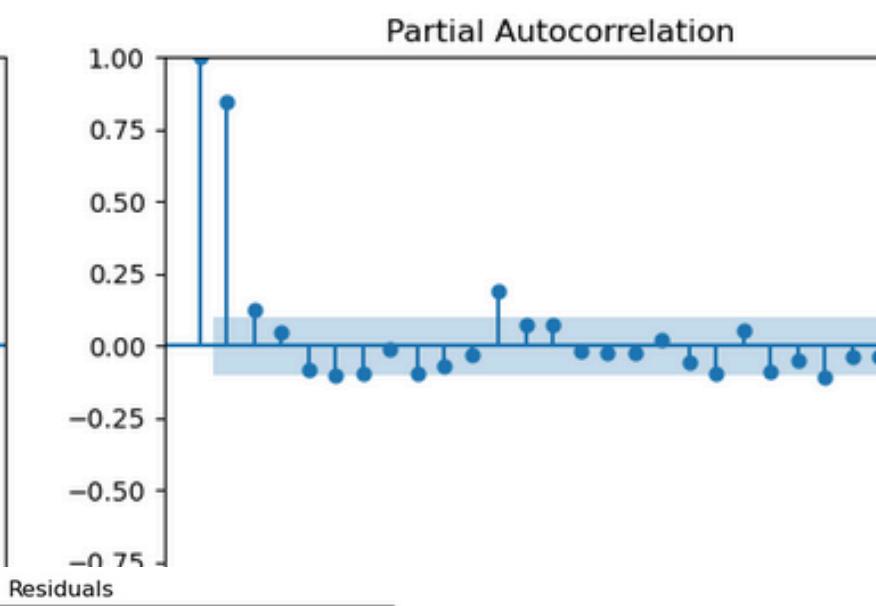
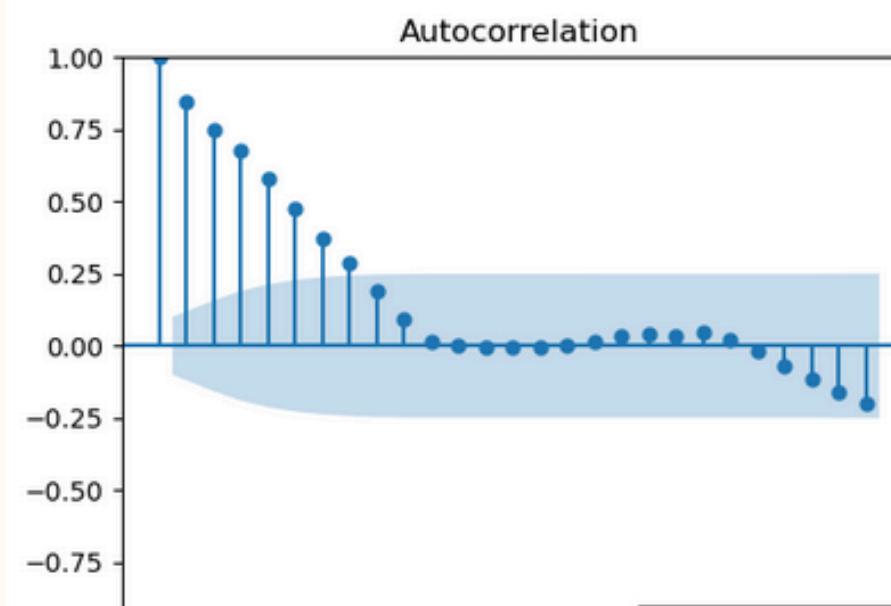
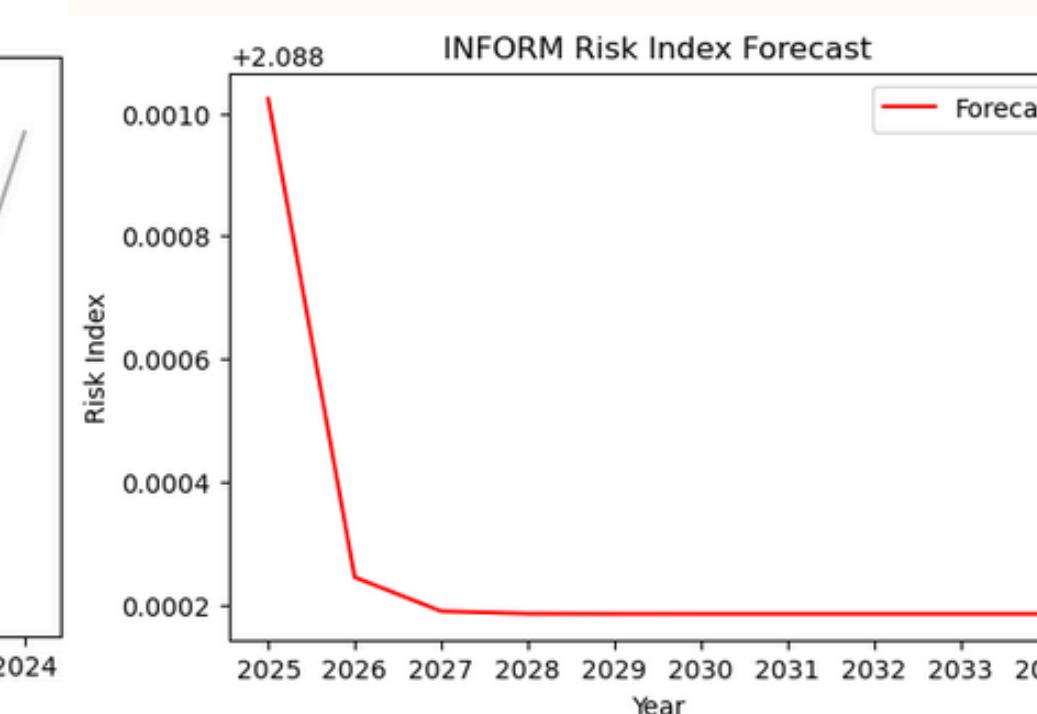
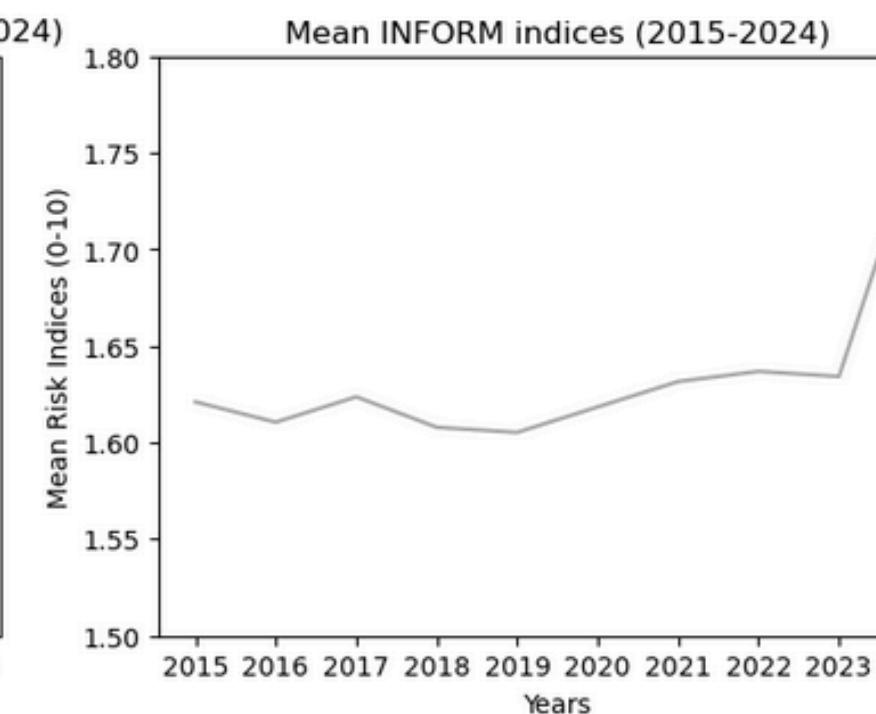
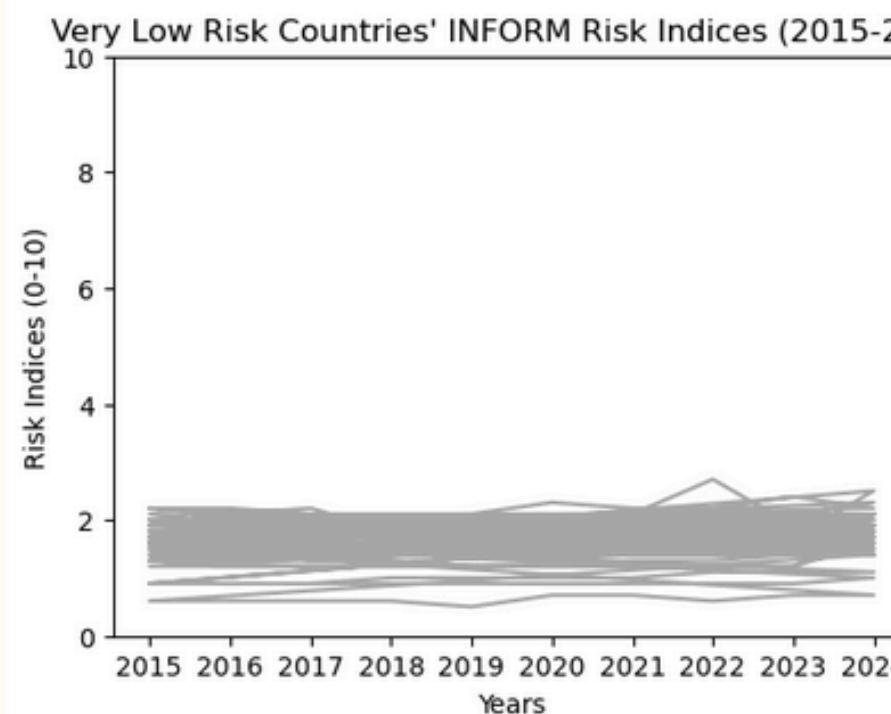
Warnings:

[1] Covariance matrix calculated using the outer product of gradients (complex-step).



ARIMA Model to forecast Very Low Risk Countries' INFORM Risk indices:

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Mean Squared Error (MSE): 0.12437508160867335
 Mean Absolute Error (MAE): 0.2830012484014993
 Root Mean Squared Error (RMSE): 0.35266851519333753

SARIMAX Results						
Dep. Variable:	INFORM Risk Index	No. Observations:	380			
Model:	ARIMA(1, 1, 1)	Log Likelihood:	84.230			
Date:	Mon, 08 Apr 2024	AIC:	-162.460			
Time:	03:19:44	BIC:	-150.648			
Sample:	0 - 380	HQIC:	-157.772			
Covariance Type:	opg					

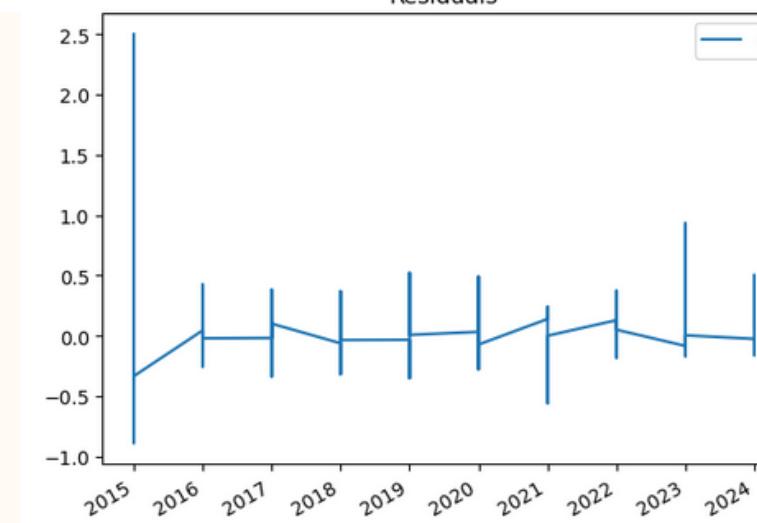
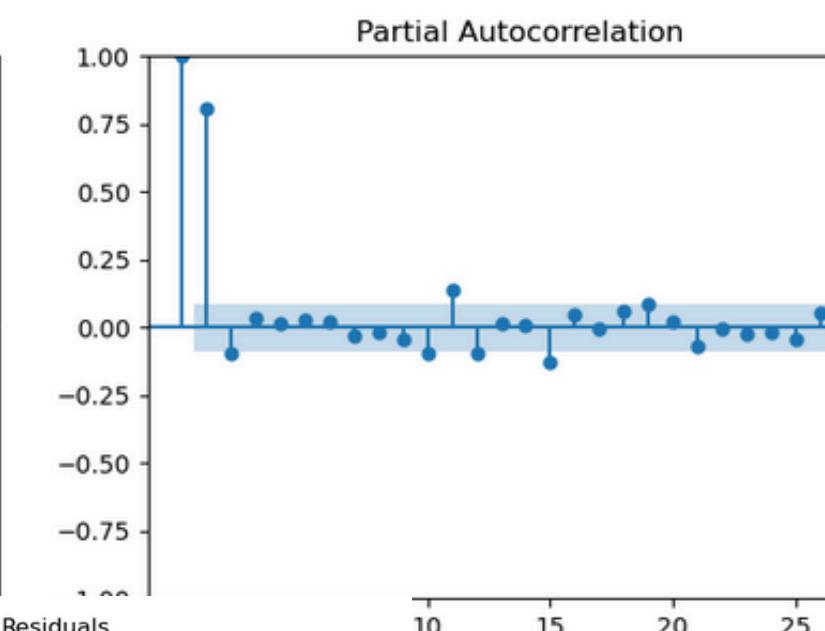
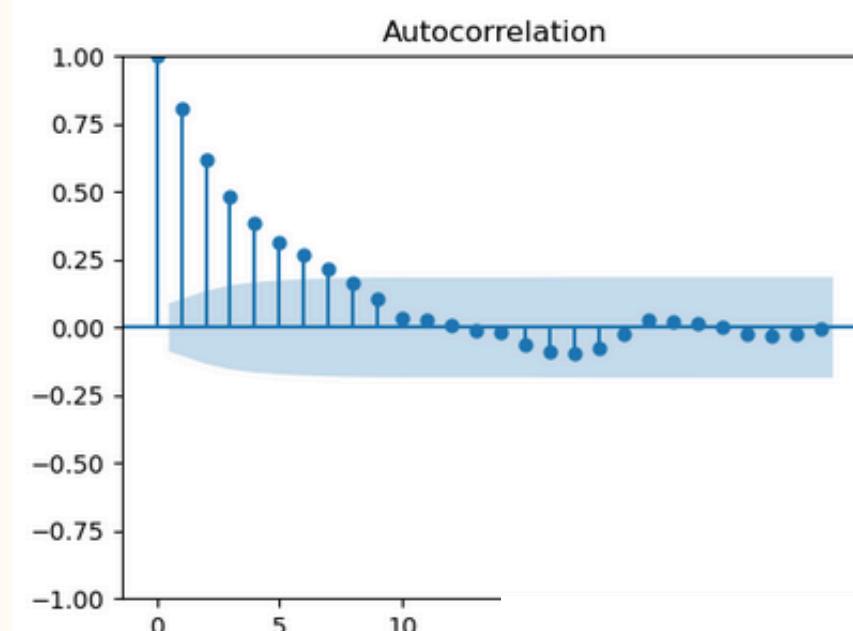
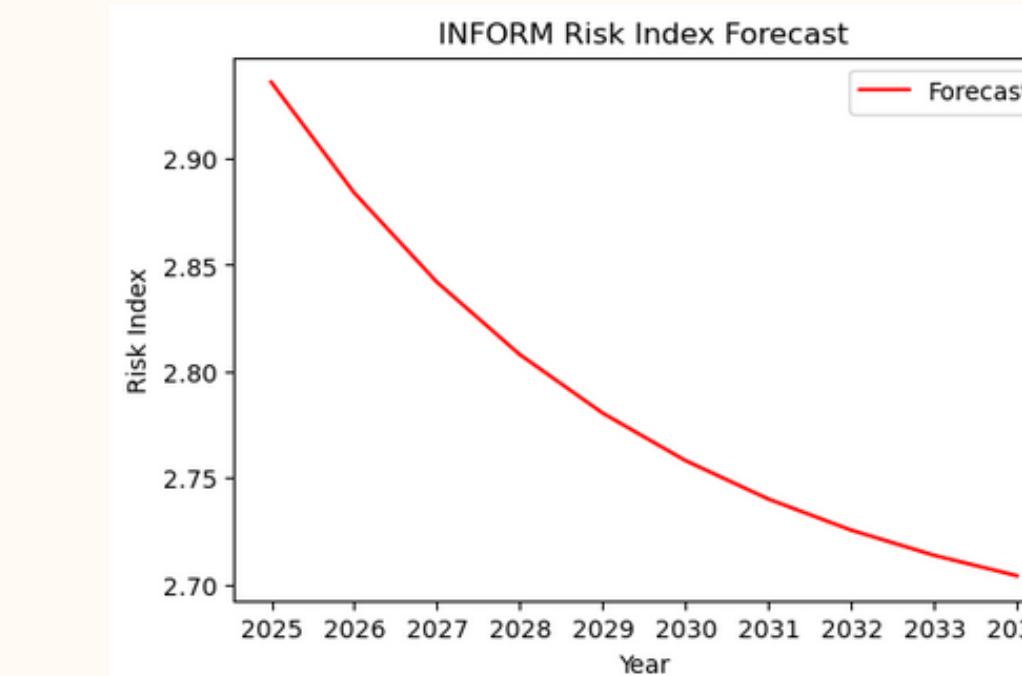
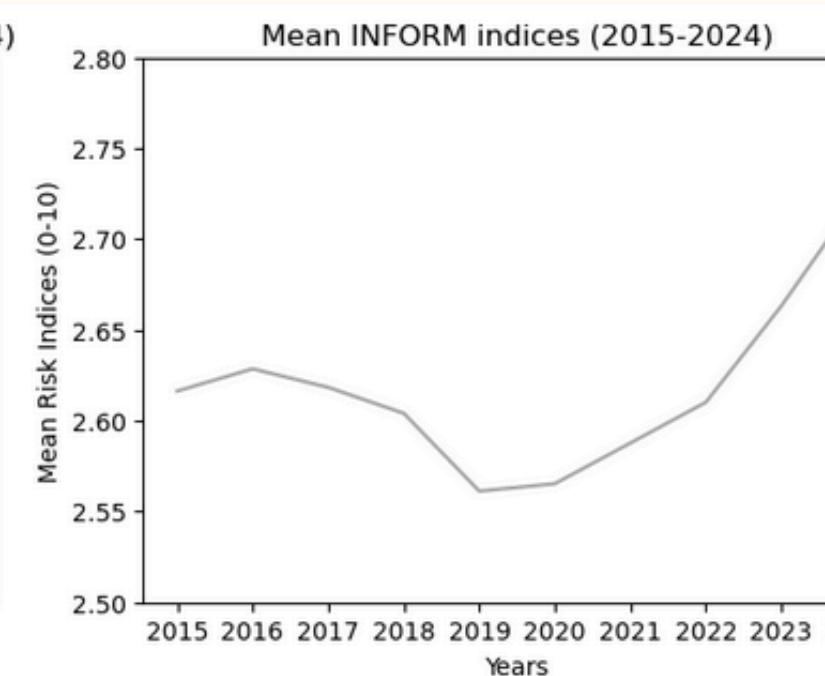
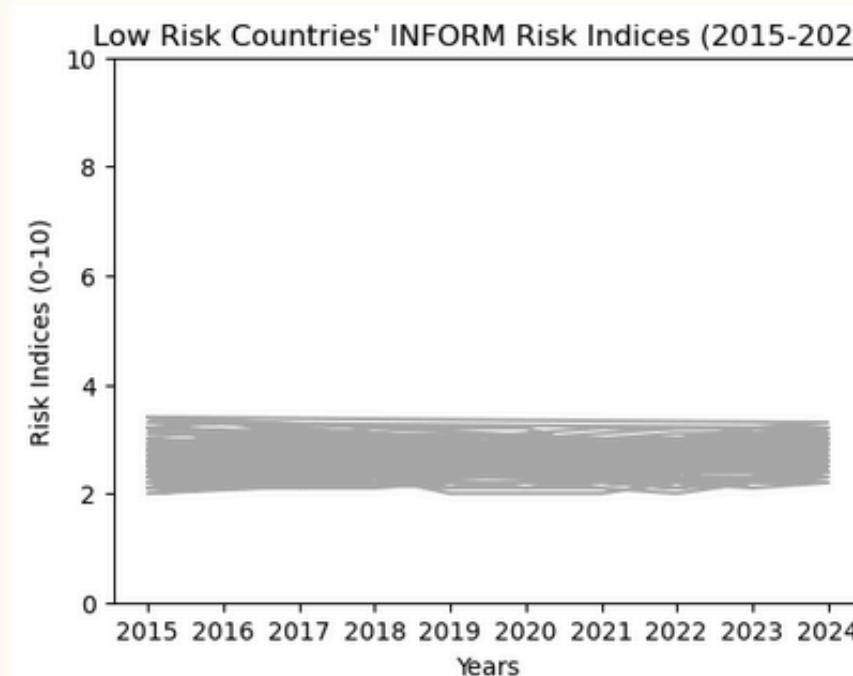
	coef	std err	z	P> z	[0.025	0.975]
ar.L1	0.0710	0.420	0.169	0.866	-0.752	0.894
ma.L1	-0.2844	0.424	-0.670	0.503	-1.116	0.547
sigma2	0.0375	0.001	27.819	0.000	0.035	0.040

Ljung-Box (L1) (Q): 0.00 Jarque-Bera (JB): 997.86
 Prob(Q): 0.98 Prob(JB): 0.00
 Heteroskedasticity (H): 1.58 Skew: -0.49
 Prob(H) (two-sided): 0.01 Kurtosis: 10.89

Warnings:
 [1] Covariance matrix calculated using the outer product of gradients (complex-step).

ARIMA Model to forecast Low Risk Countries' INFORM Risk indices:

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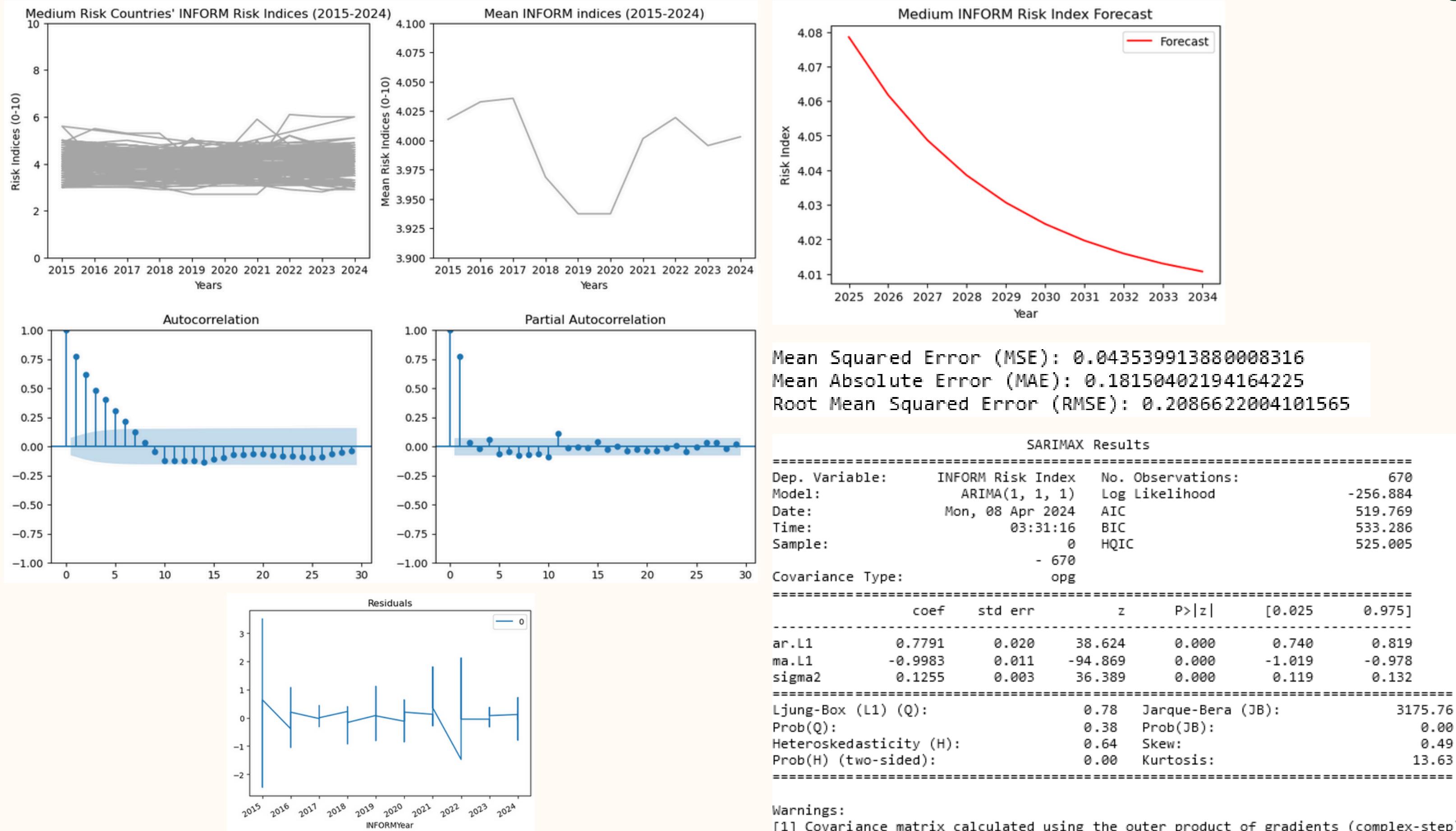
Mean Squared Error (MSE): 0.04001319377486952
 Mean Absolute Error (MAE): 0.16483573517531735
 Root Mean Squared Error (RMSE): 0.20003298171768955

SARIMAX Results						
Dep. Variable:	INFORM Risk Index	No. Observations:	490			
Model:	ARIMA(1, 1, 1)	Log Likelihood	131.461			
Date:	Mon, 08 Apr 2024	AIC	-256.922			
Time:	03:26:37	BIC	-244.344			
Sample:	0 - 490	HQIC	-251.982			
Covariance Type:	opg					
	coef	std err	z	P> z	[0.025	0.975]
ar.L1	0.8097	0.033	24.459	0.000	0.745	0.875
ma.L1	-0.9952	0.011	-94.641	0.000	-1.016	-0.975
sigma2	0.0340	0.001	22.974	0.000	0.031	0.037
Ljung-Box (L1) (Q):			2.81	Jarque-Bera (JB):		727.19
Prob(Q):			0.09	Prob(JB):		0.00
Heteroskedasticity (H):			0.90	Skew:		-0.37
Prob(H) (two-sided):			0.49	Kurtosis:		8.93

Warnings:
 [1] Covariance matrix calculated using the outer product of gradients (complex-step).

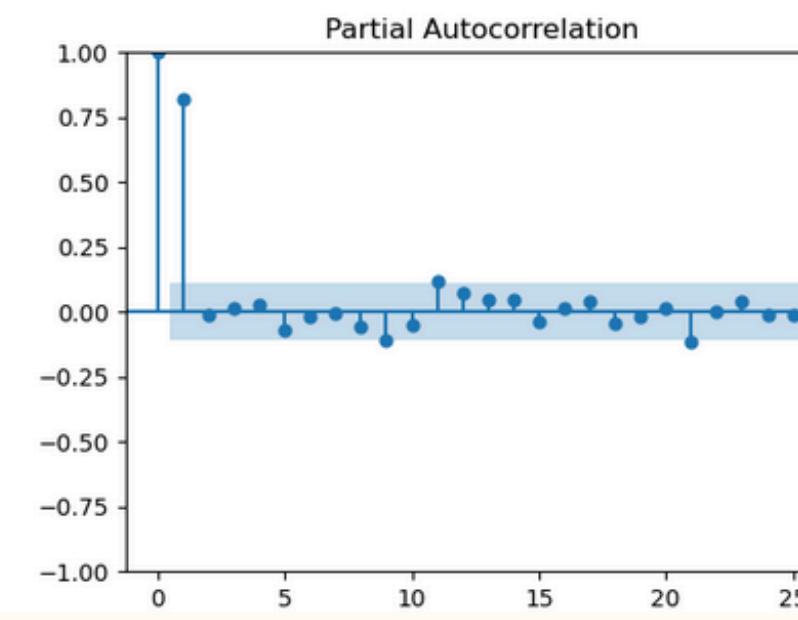
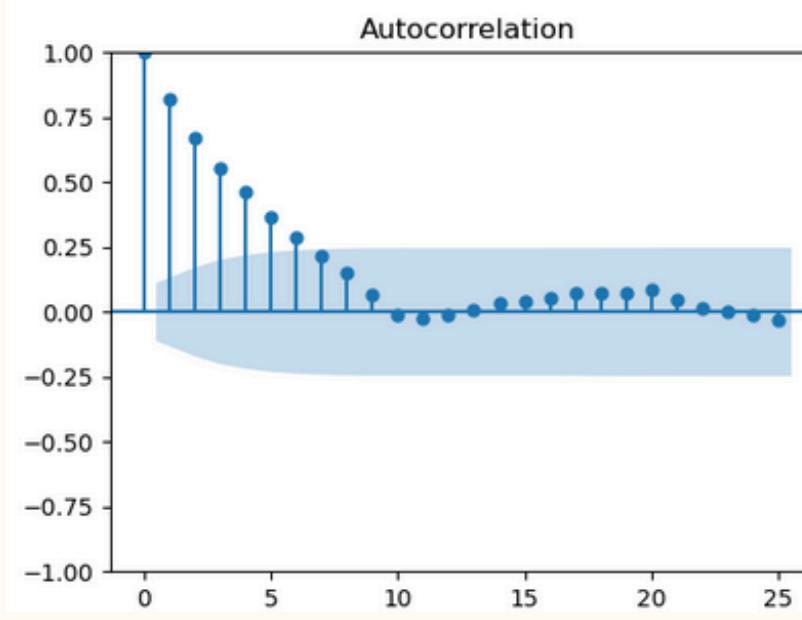
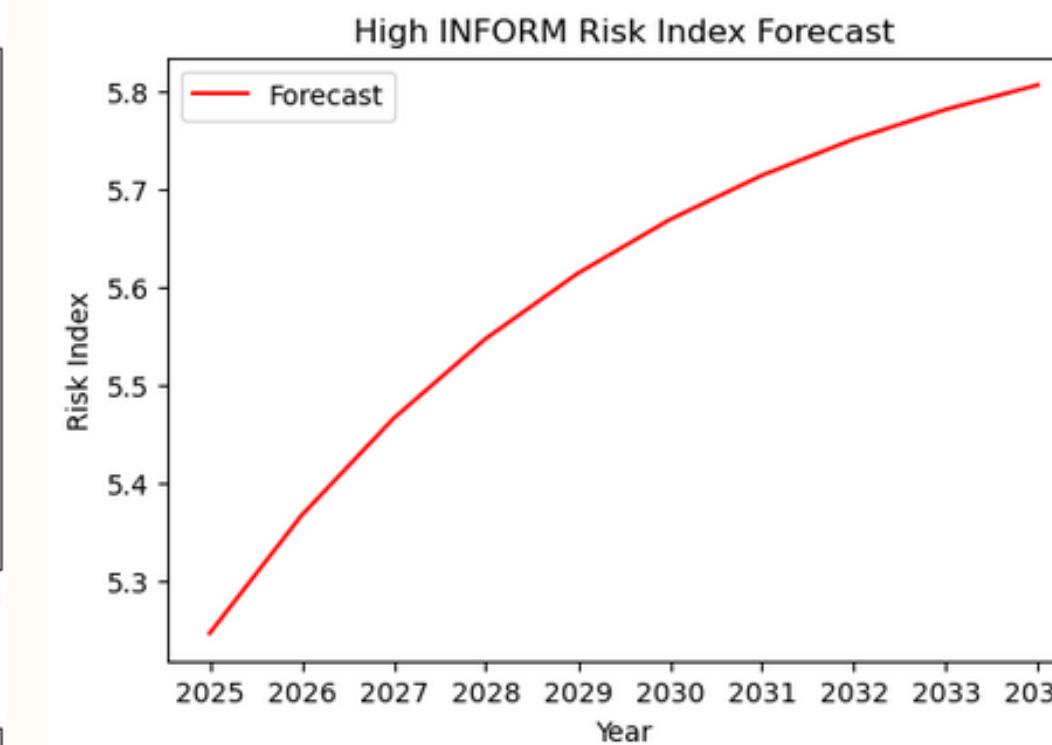
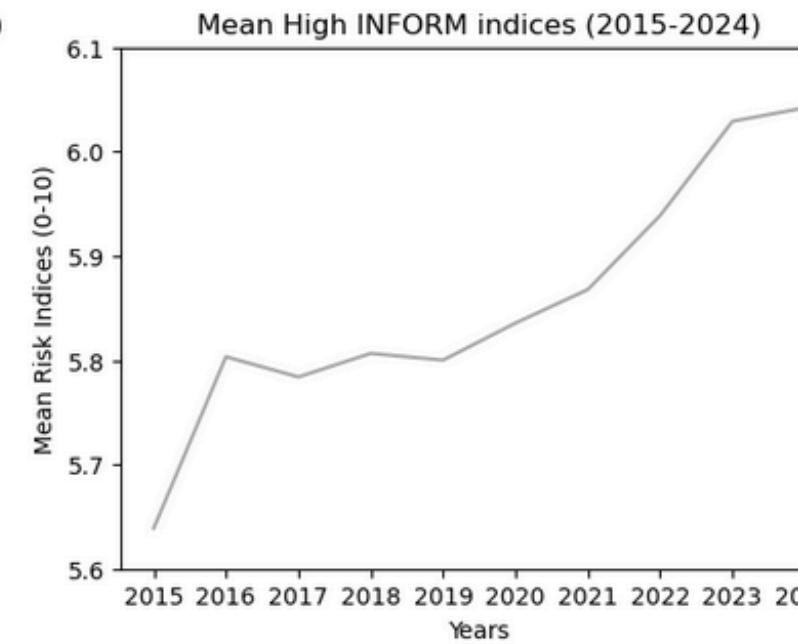
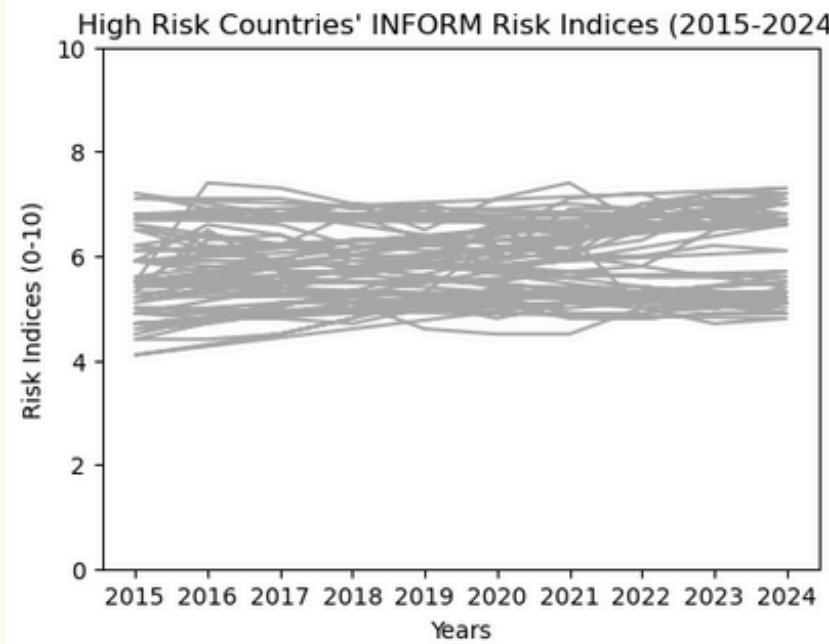
ARIMA Model to forecast Medium Risk Countries' INFORM Risk indices:

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ARIMA Model to forecast High Risk Countries' INFORM Risk indices:

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Mean Squared Error (MSE): 0.5623539349422726
 Mean Absolute Error (MAE): 0.6229084757735233
 Root Mean Squared Error (RMSE): 0.7499026169725457

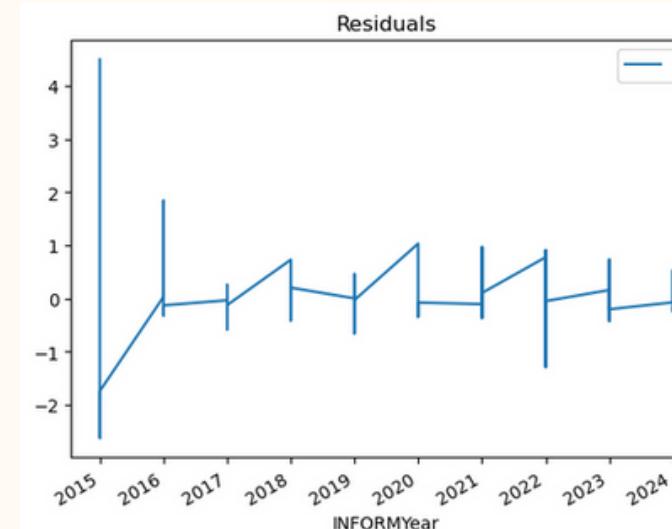
SARIMAX Results

```
=====
Dep. Variable: INFORM Risk Index No. Observations: 310
Model: ARIMA(1, 1, 1) Log Likelihood: -194.659
Date: Mon, 08 Apr 2024 AIC: 395.318
Time: 03:35:23 BIC: 406.518
Sample: 0 HQIC: 399.795
- 310
Covariance Type: opg
=====
```

	coef	std err	z	P> z	[0.025	0.975]
ar.L1	0.8215	0.047	17.302	0.000	0.728	0.915
ma.L1	-0.9888	0.013	-77.361	0.000	-1.014	-0.964
sigma2	0.2053	0.011	19.222	0.000	0.184	0.226

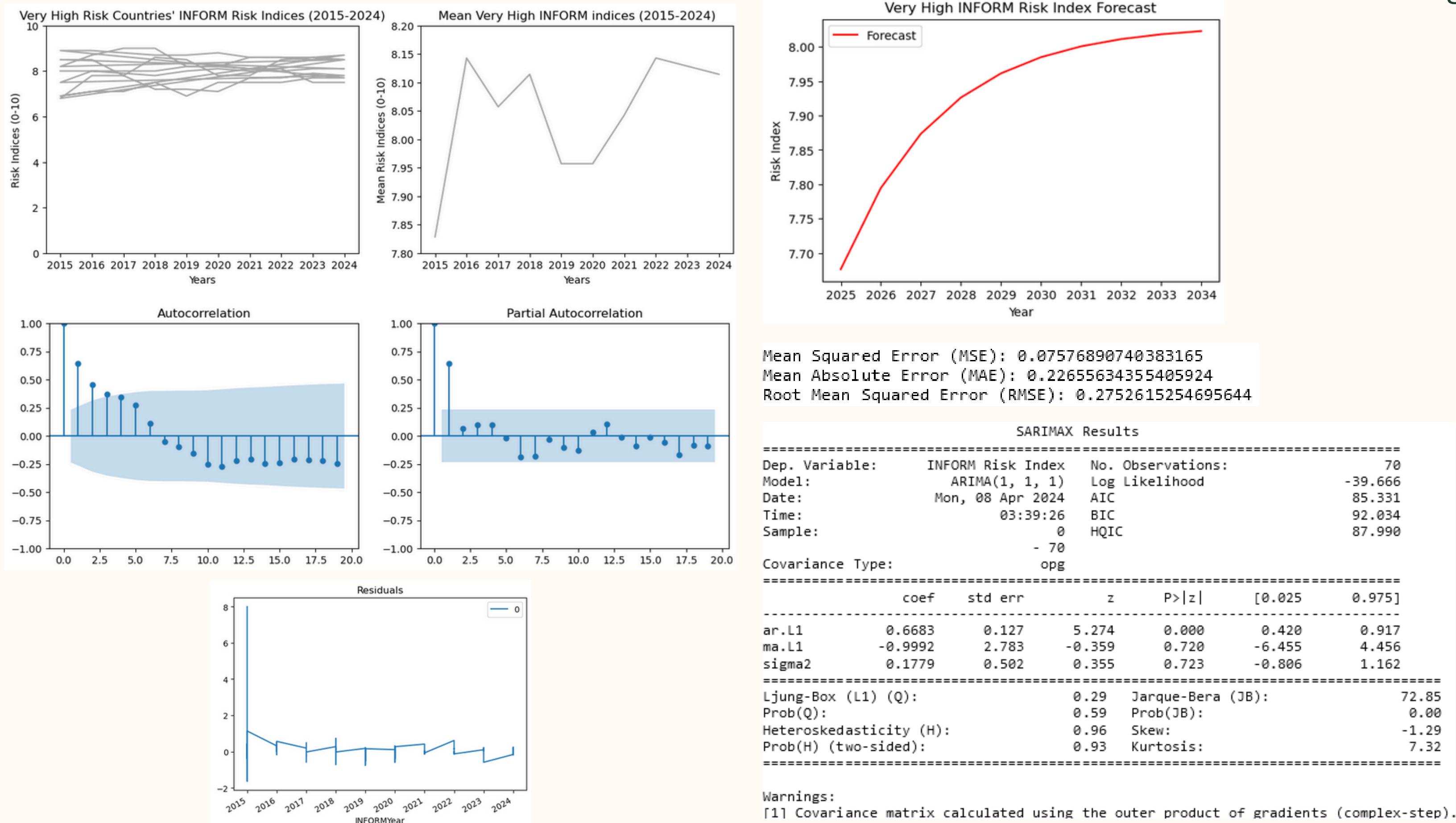
```
=====
Ljung-Box (L1) (Q): 0.01 Jarque-Bera (JB): 872.08
Prob(Q): 0.93 Prob(JB): 0.00
Heteroskedasticity (H): 1.14 Skew: -0.87
Prob(H) (two-sided): 0.49 Kurtosis: 11.05
=====
```

Warnings:
 [1] Covariance matrix calculated using the outer product of gradients (complex-step).



ARIMA Model to forecast Very High Risk Countries' INFORM Risk indices:

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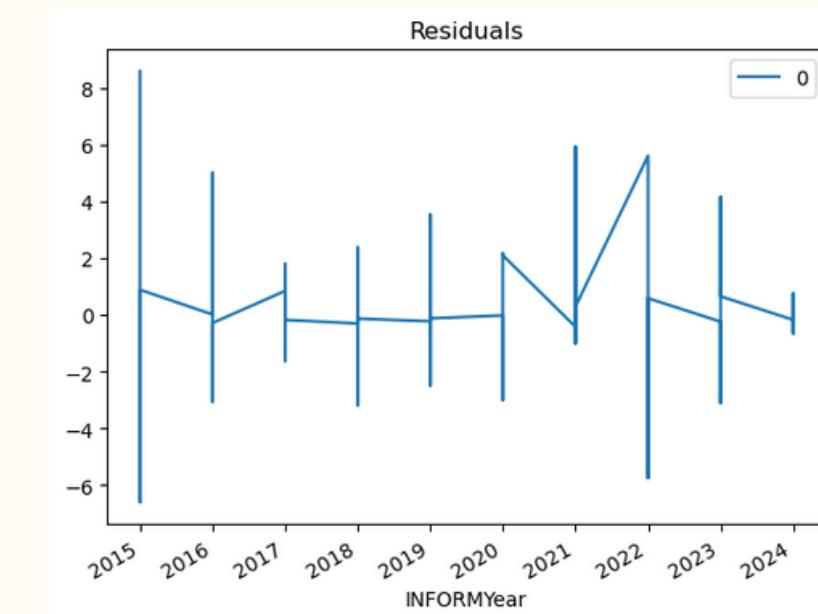
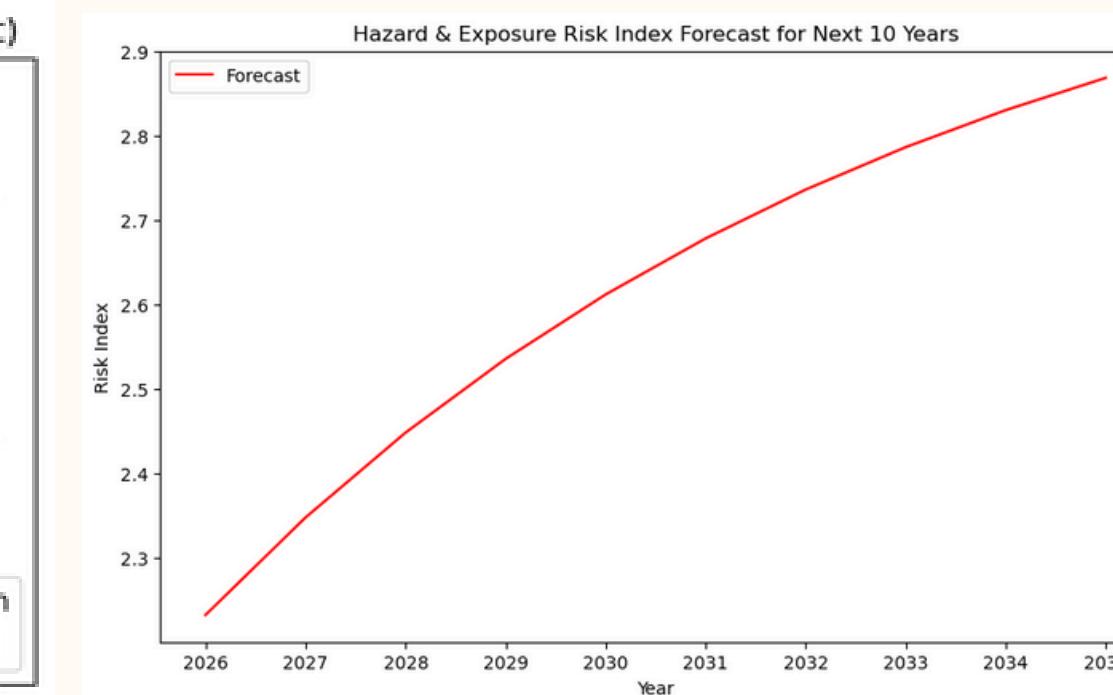
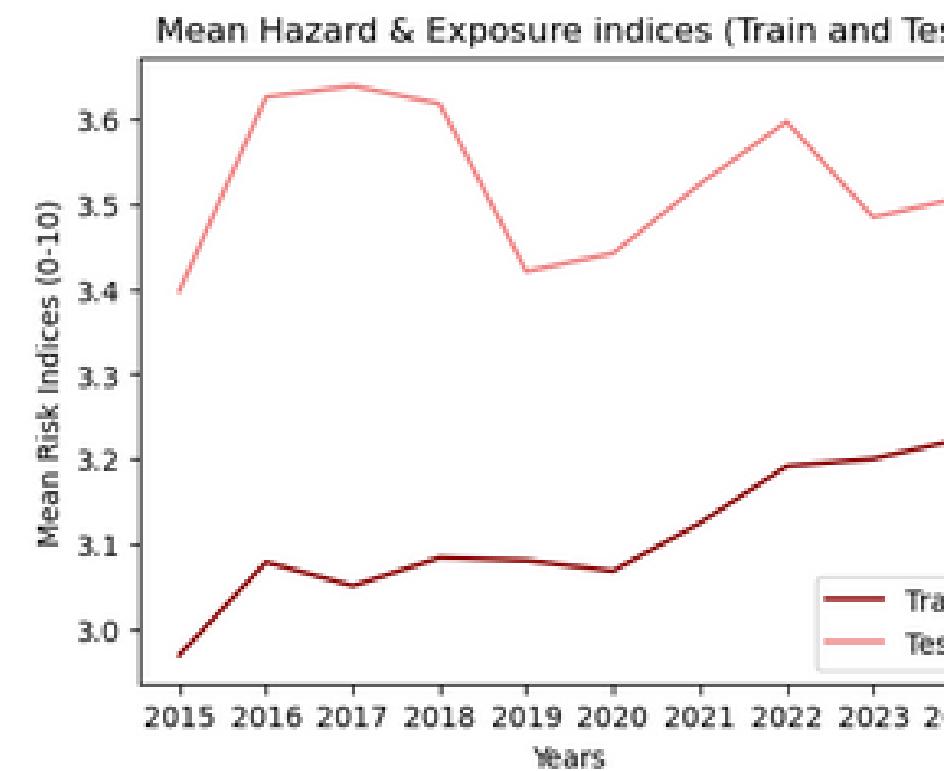
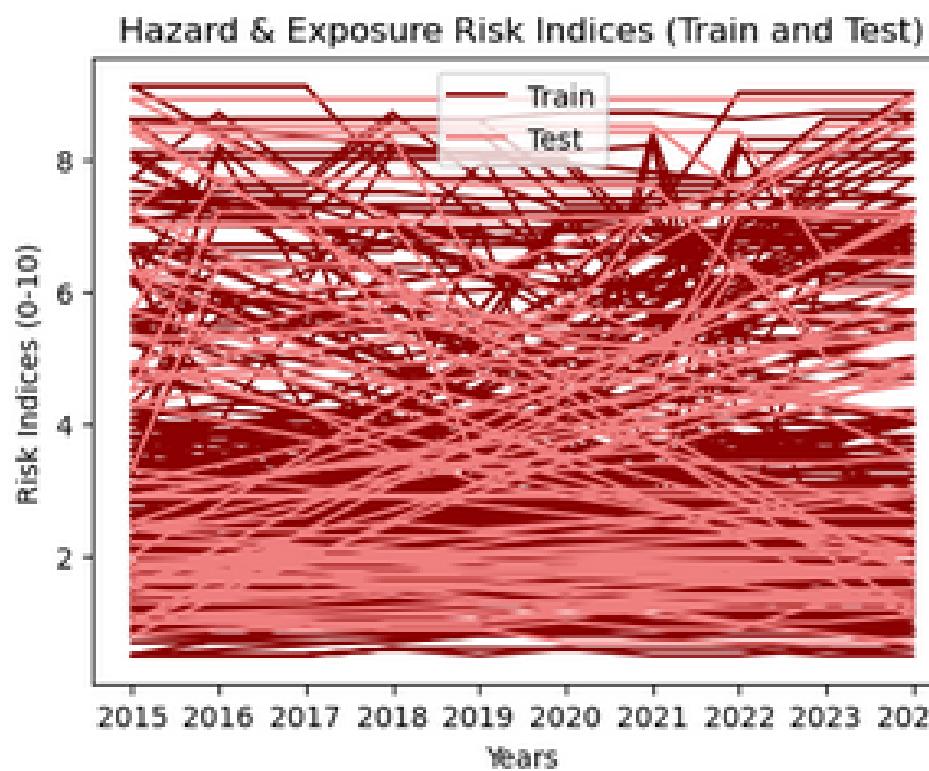
Project 3

**Predict & forecast
how INFORM risk
data changes over
time**

Hazard & Exposure Index

ARIMA Train - Test Model to forecast Hazard & Exposure Risk indices:

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Mean Squared Error (MSE): 5.902127035081362
 Mean Absolute Error (MAE): 1.9747482923871407
 Root Mean Squared Error (RMSE): 2.4294293640855997

SARIMAX Results

```

=====
Dep. Variable: Hazard & Exposure Index No. Observations: 1528
Model: ARIMA(1, 1, 1) Log Likelihood: -2198.746
Date: Mon, 08 Apr 2024 AIC: 4493.493
Time: 22:08:47 BIC: 4419.486
Sample: 0 HQIC: 4409.445
- 1528
Covariance Type: opg
=====
```

	coef	std err	t	P> t	[0.025	0.975]
ar.L1	0.8789	0.013	69.268	0.000	0.846	0.896
ma.L1	-0.9999	0.047	-21.264	0.000	-1.092	-0.908
sigma2	1.0398	0.052	19.822	0.000	0.937	1.143

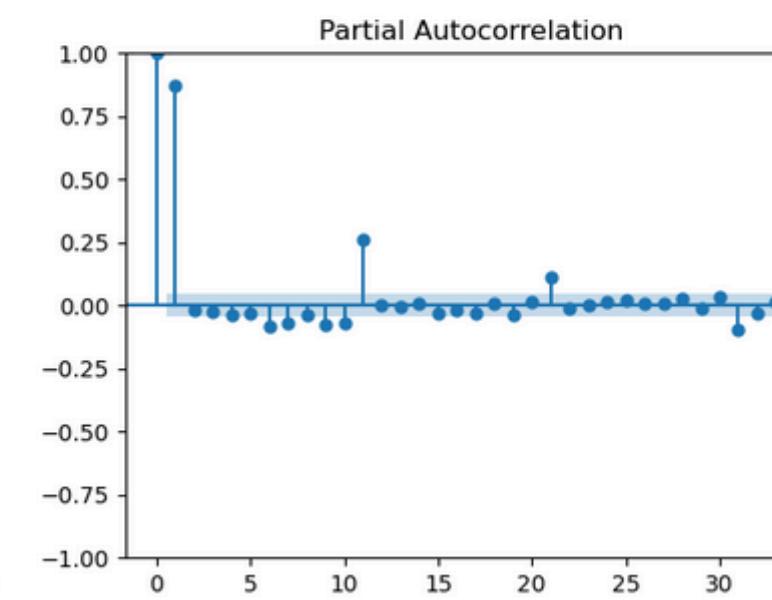
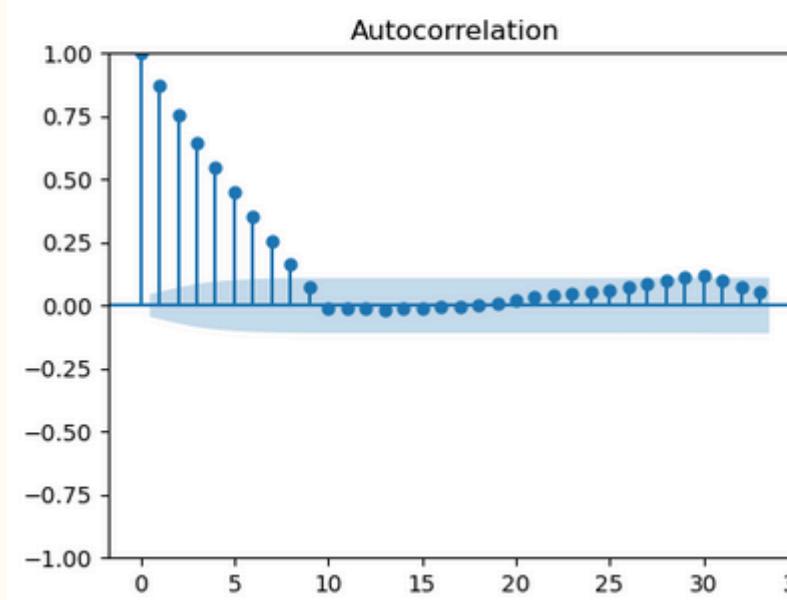
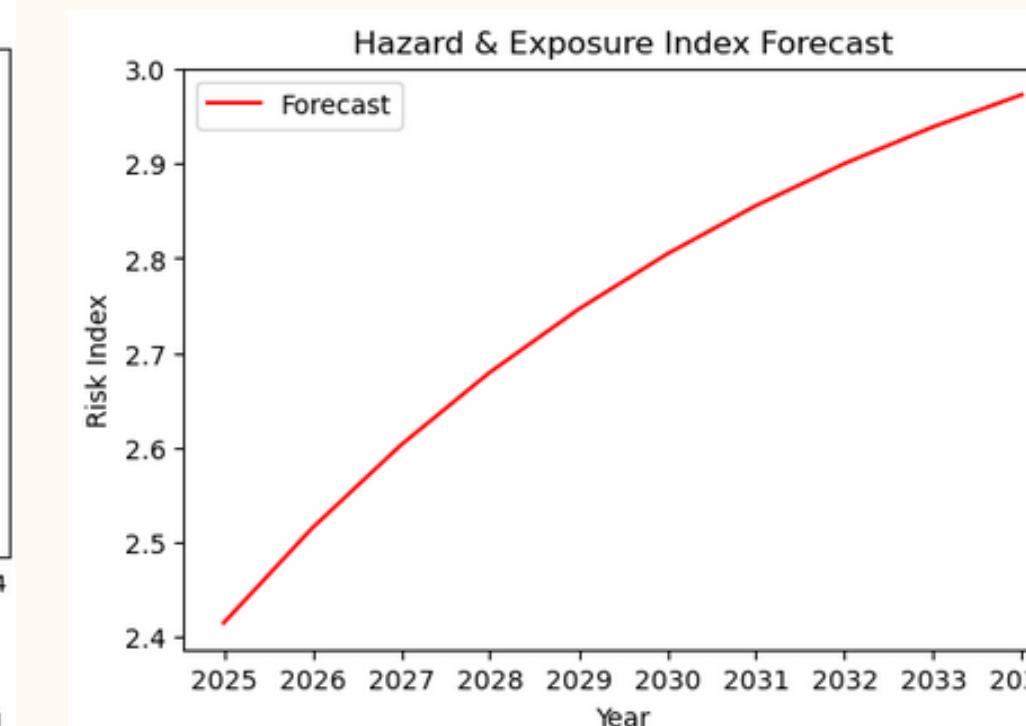
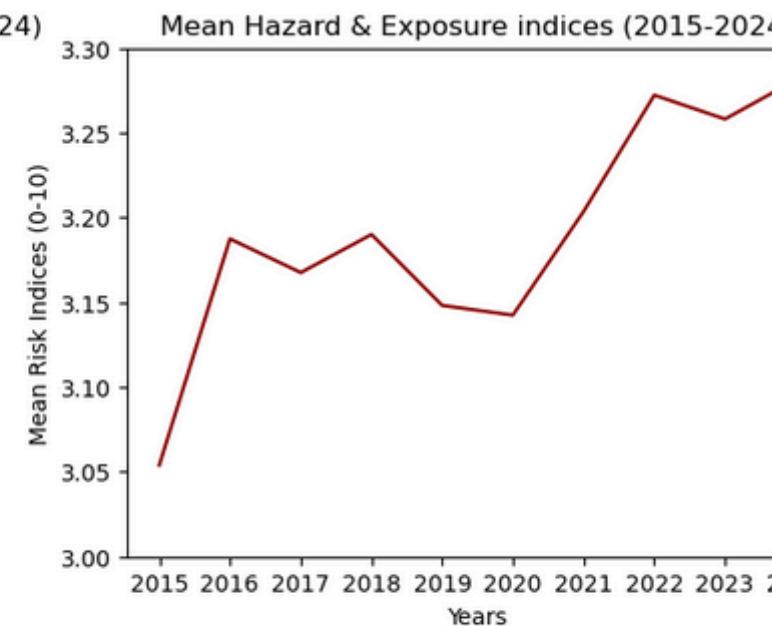
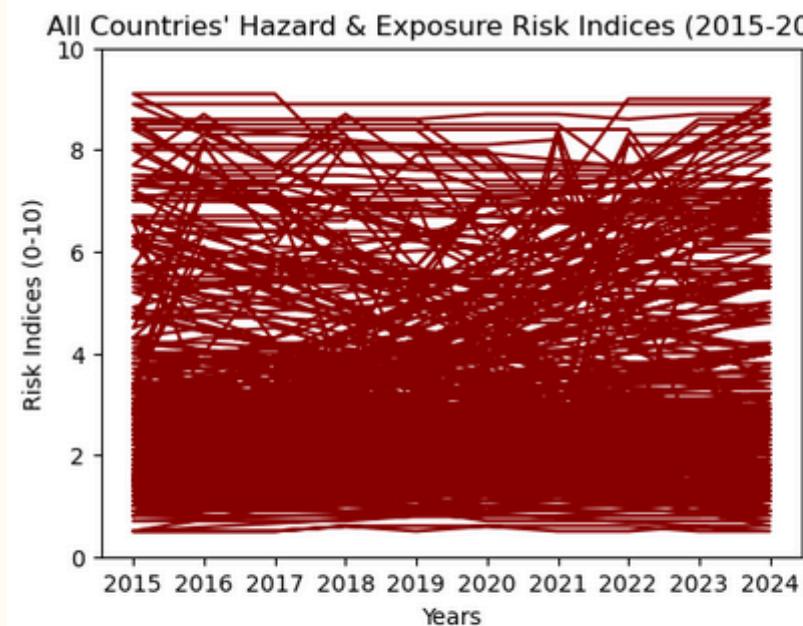
```

Ljung-Box (L1) (Q): 0.02 Jarque-Bera (JB): 17099.64
Prob(Q): 0.88 Prob(JB): 0.00
Heteroskedasticity (H): 1.48 Skew: -0.12
Prob(H) (two-sided): 0.00 Kurtosis: 19.39
=====
```

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).

ARIMA Model to forecast Hazard & Exposure Risk indices:

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Mean Squared Error (MSE): 0.22468855088526024
 Mean Absolute Error (MAE): 0.4530680413699869
 Root Mean Squared Error (RMSE): 0.4740132391455541

SARIMAX Results

```

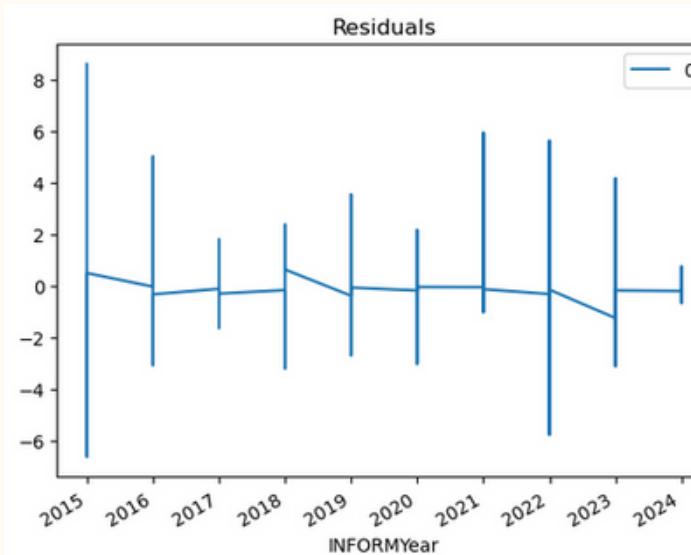
=====
Dep. Variable: Hazard & Exposure Index   No. Observations:      1910
Model: ARIMA(1, 1, 1)           Log Likelihood:       -2797.204
Date: Mon, 08 Apr 2024          AIC:                 5600.407
Time: 02:59:50                  BIC:                 5617.070
Sample: 0 - 1910                HQIC:                 5606.540
Covariance Type: opg
=====
```

	coef	std err	z	P> z	[0.025	0.975]
ar.L1	0.8733	0.012	70.885	0.000	0.849	0.897
ma.L1	-1.0000	0.142	-7.022	0.000	-1.279	-0.721
sigma2	1.0943	0.153	7.160	0.000	0.795	1.394

Ljung-Box (L1) (Q): 0.24 Jarque-Bera (JB): 20759.99
 Prob(Q): 0.63 Prob(JB): 0.00
 Heteroskedasticity (H): 1.42 Skew: 0.05
 Prob(H) (two-sided): 0.00 Kurtosis: 19.16

Warnings:

[[1 Covariance matrix calculated using the outer product of gradients (complex-step).]]



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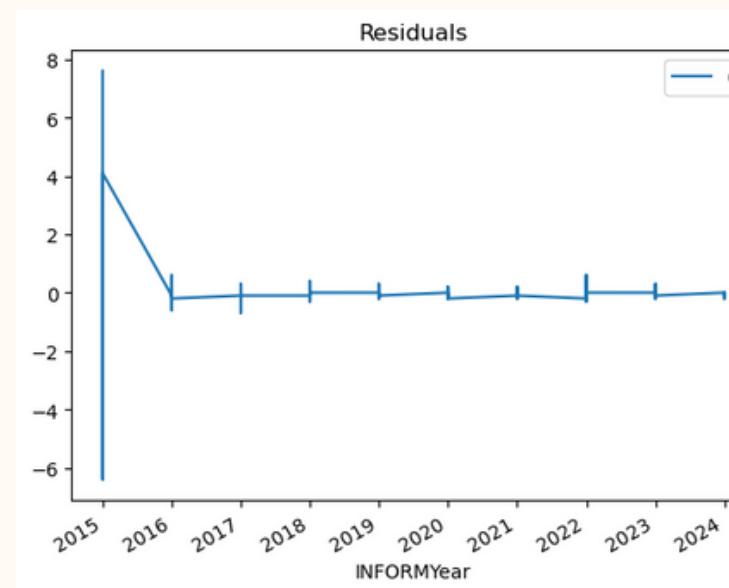
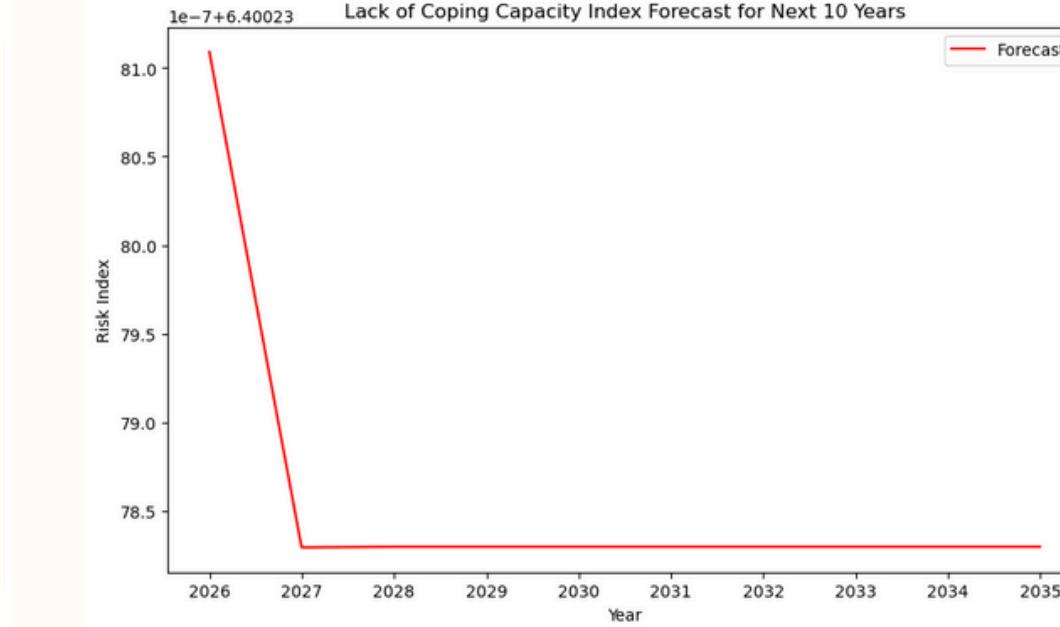
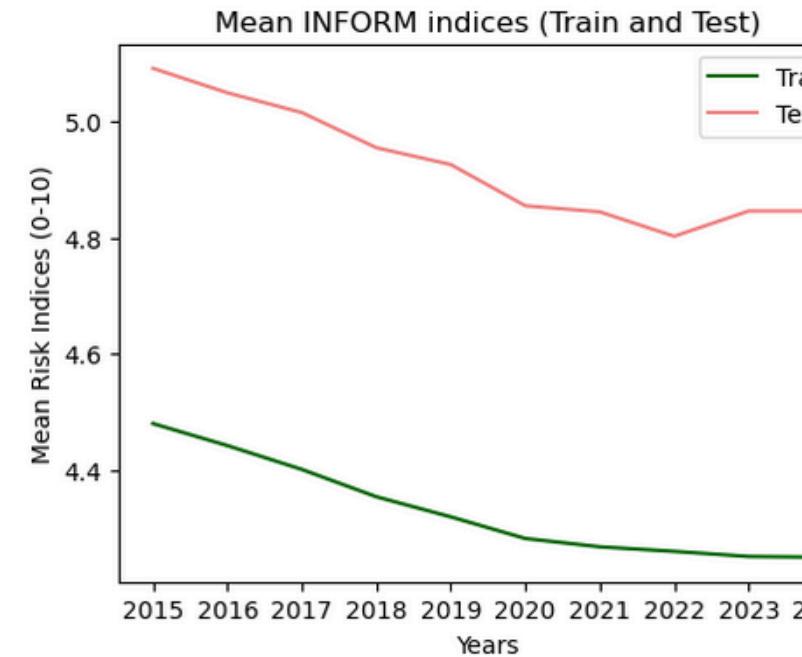
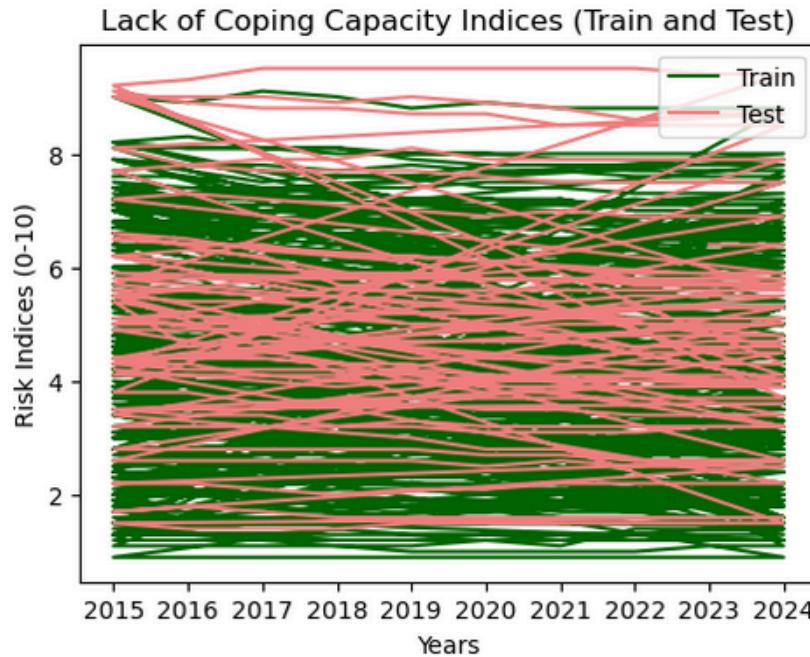
Project 3

**Predict & forecast
how INFORM risk
data changes over
time**

Lack of
Coping
Capacity
Index

ARIMA Train-Test Model to forecast Lack of Coping Capacity Risk indices:

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Mean Squared Error (MSE): 5.79462928977949
 Mean Absolute Error (MAE): 2.064557289776779
 Root Mean Squared Error (RMSE): 2.4072036244945068

SARIMAX Results

```
=====
Dep. Variable:      Lack of Coping Capacity Index   No. Observations:             1528
Model:                  ARIMA(1, 1, 1)            Log Likelihood:          -1902.988
Date:                 Mon, 08 Apr 2024           AIC:                   3811.976
Time:                      22:28:02             BIC:                   3827.969
Sample:                   0 - 1528            HQIC:                   3817.928
Covariance Type:            opg
=====
```

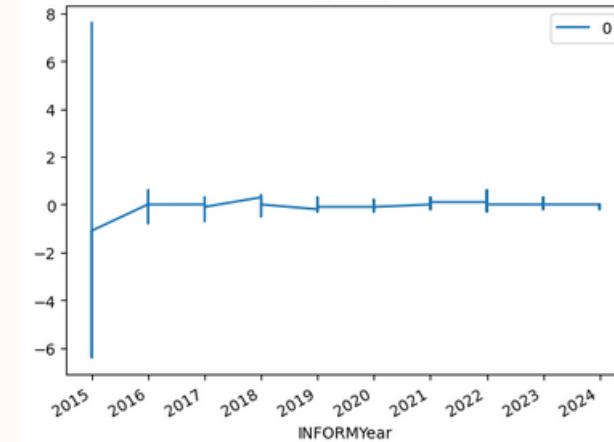
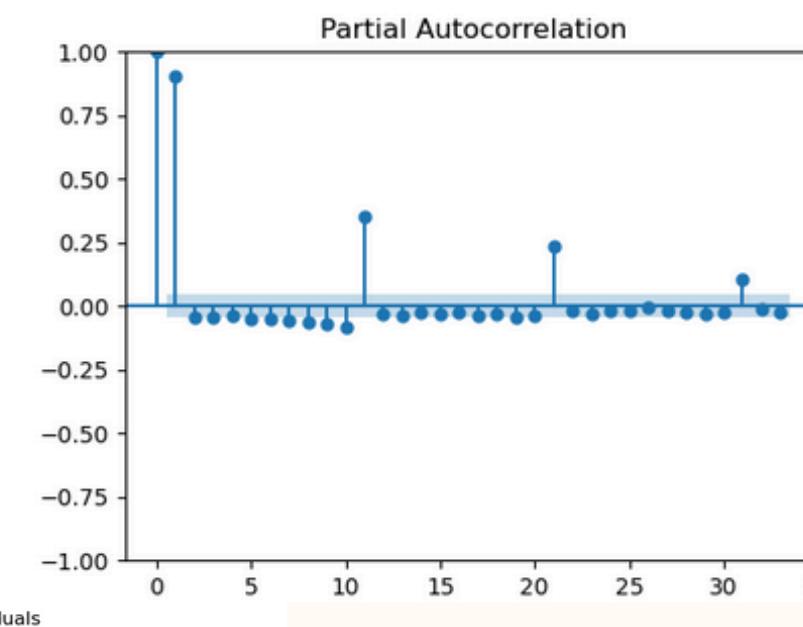
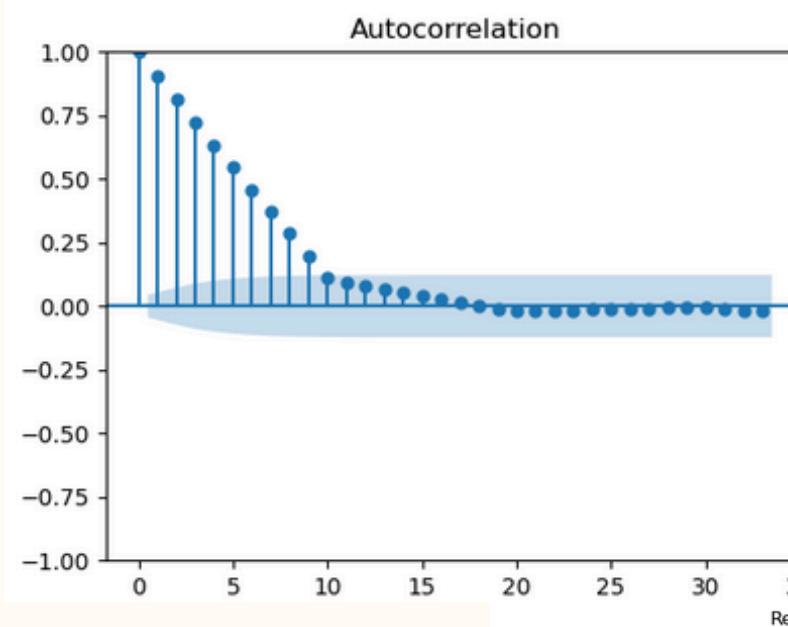
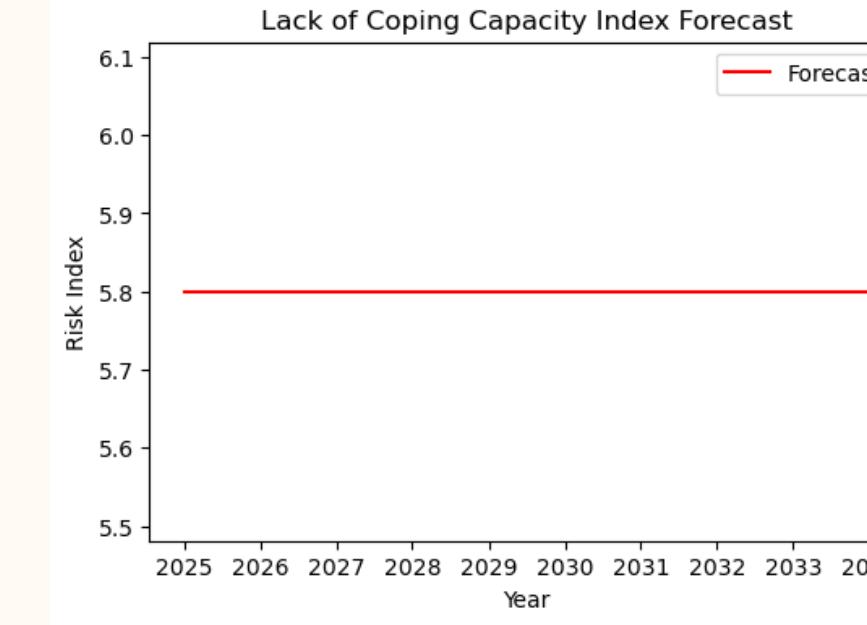
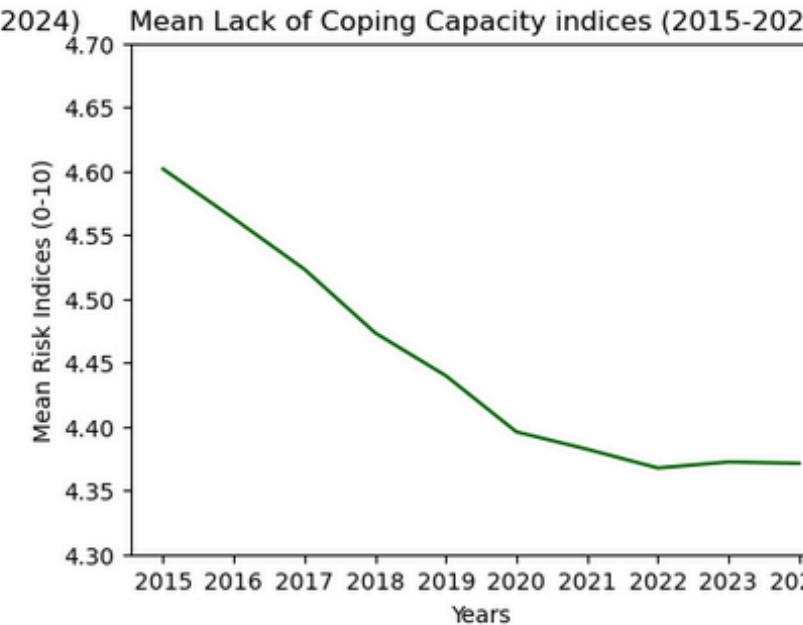
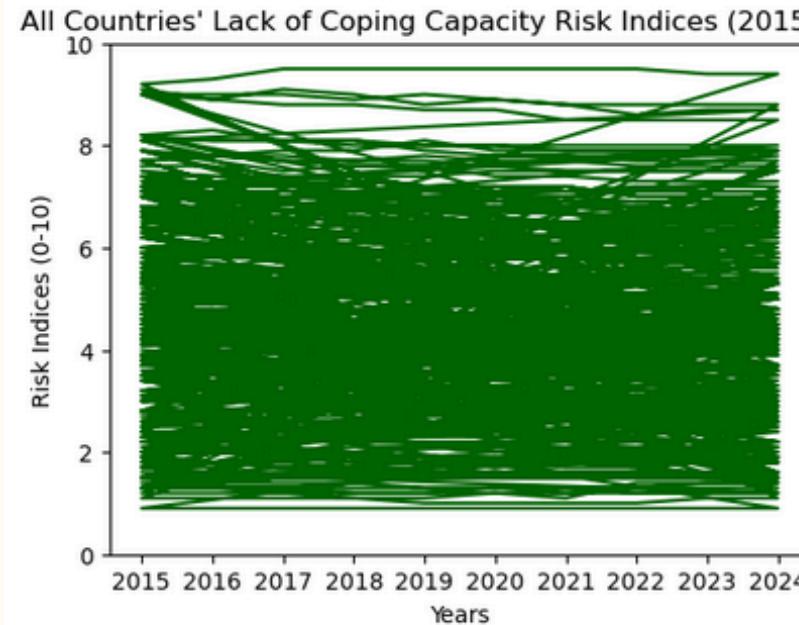
	coef	std err	z	P> z	[0.025	0.975]
ar.L1	-0.0012	50.073	-2.35e-05	1.000	-98.142	98.139
ma.L1	-0.0012	50.072	-2.41e-05	1.000	-98.140	98.138
sigma2	0.7079	0.008	93.769	0.000	0.693	0.723

```
=====
Ljung-Box (L1) (Q):                   0.00   Jarque-Bera (JB):           28310.06
Prob(Q):                           1.00   Prob(JB):                     0.00
Heteroskedasticity (H):               1.33   Skew:                         -0.08
Prob(H) (two-sided):                0.00   Kurtosis:                    24.09
=====
```

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).

ARIMA Model to forecast Lack of Coping Capacity Risk indices:

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Mean Squared Error (MSE): 0.00100000000000106
Mean Absolute Error (MAE): 0.01000000000000054
Root Mean Squared Error (RMSE): 0.031622776601683965

SARIMAX Results						
Dep. Variable:	Lack of Coping Capacity Index	No. Observations:	1910			
Model:	ARIMA(1, 1, 1)	Log Likelihood	-2349.559			
Date:	Mon, 08 Apr 2024	AIC	4705.118			
Time:	03:06:58	BIC	4721.781			
Sample:	- 1910	HQIC	4711.251			
Covariance Type:	opg					
	coef	std err	z	P> z	[0.025	0.975]
ar.L1	-0.0014	37.000	-3.68e-05	1.000	-72.520	72.517
ma.L1	-0.0016	36.999	-4.33e-05	1.000	-72.518	72.515
sigma2	0.6864	0.007	105.031	0.000	0.674	0.699
<hr/>						
Ljung-Box (L1) (Q):	0.00	Jarque-Bera (JB):				
Prob(Q):	1.00	Prob(JB):				
Heteroskedasticity (H):	0.95	Skew:				
Prob(H) (two-sided):	0.49	Kurtosis:				
<hr/>						

Warnings:

[1] Covariance matrix calculated using the outer product of gradients (complex-step).

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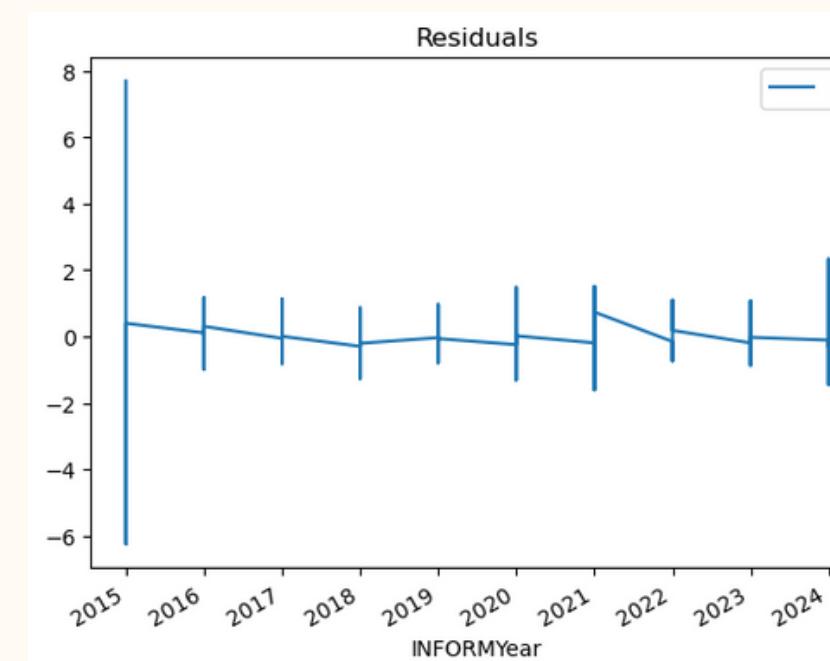
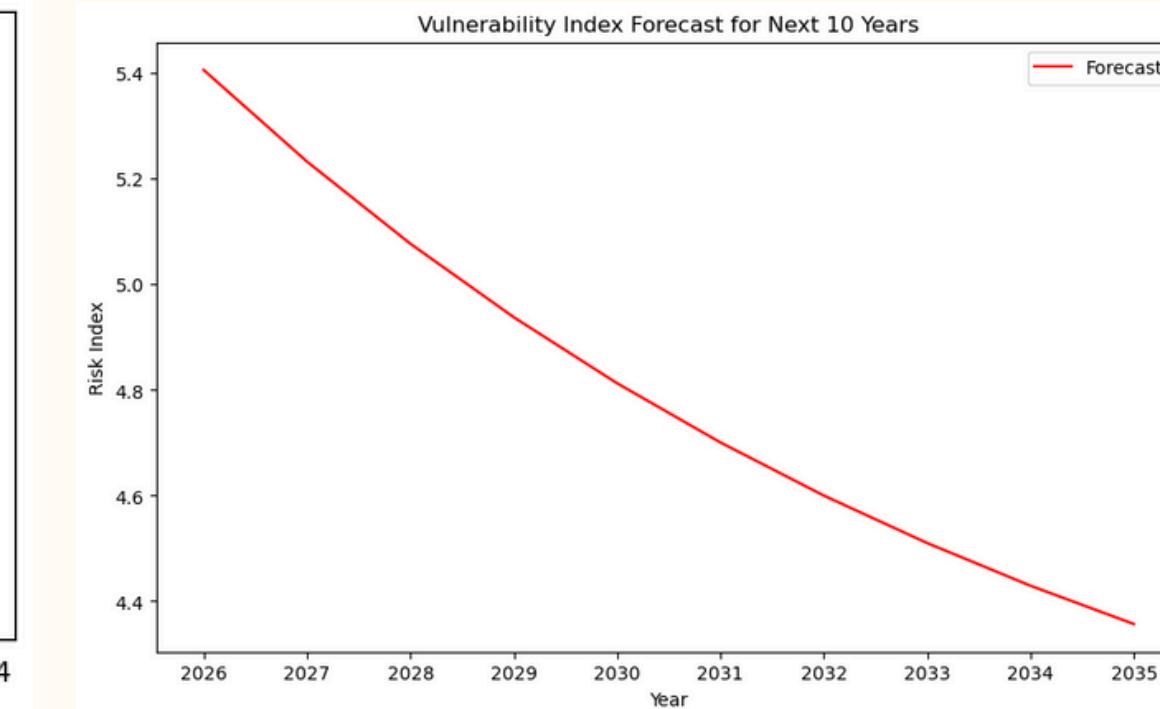
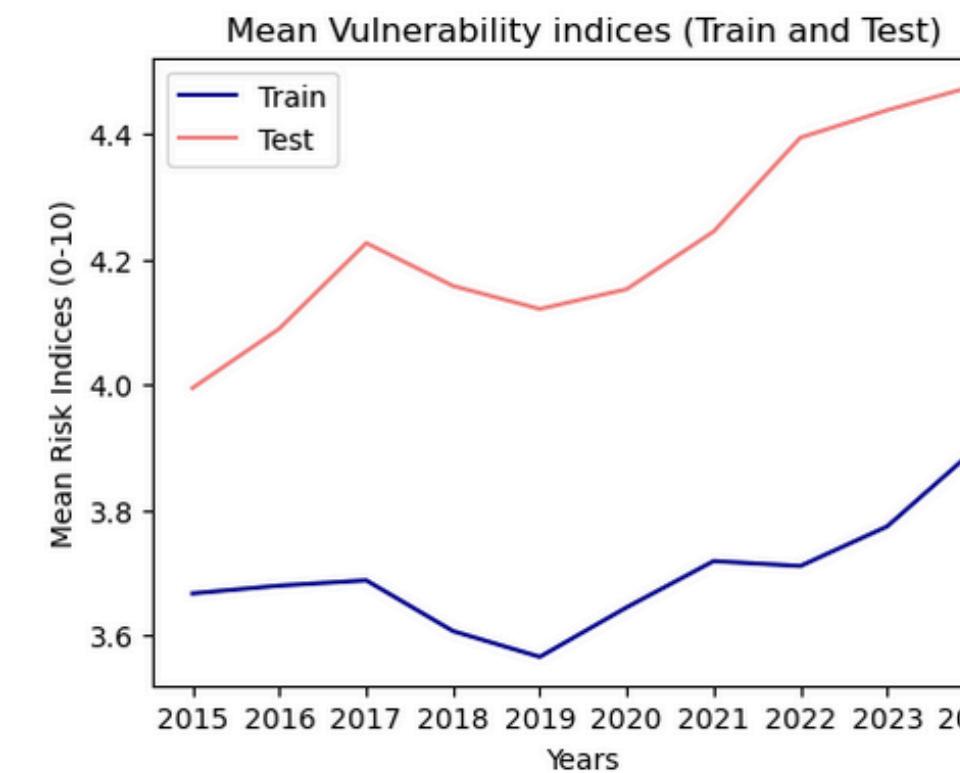
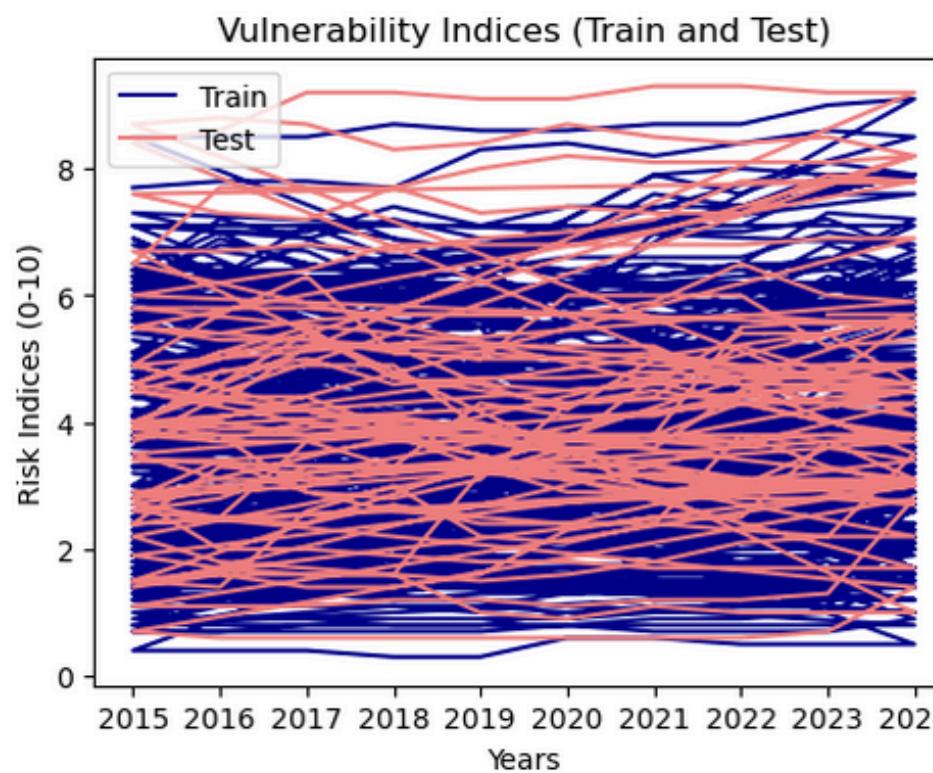
Project 3

**Predict & forecast
how INFORM risk
data changes over
time**

Vulnerability Index

ARIMA Train - Test Model to forecast Vulnerability Risk indices:

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Mean Squared Error (MSE): 4.305888459231918
 Mean Absolute Error (MAE): 1.5919862293228235
 Root Mean Squared Error (RMSE): 2.0750634831811574

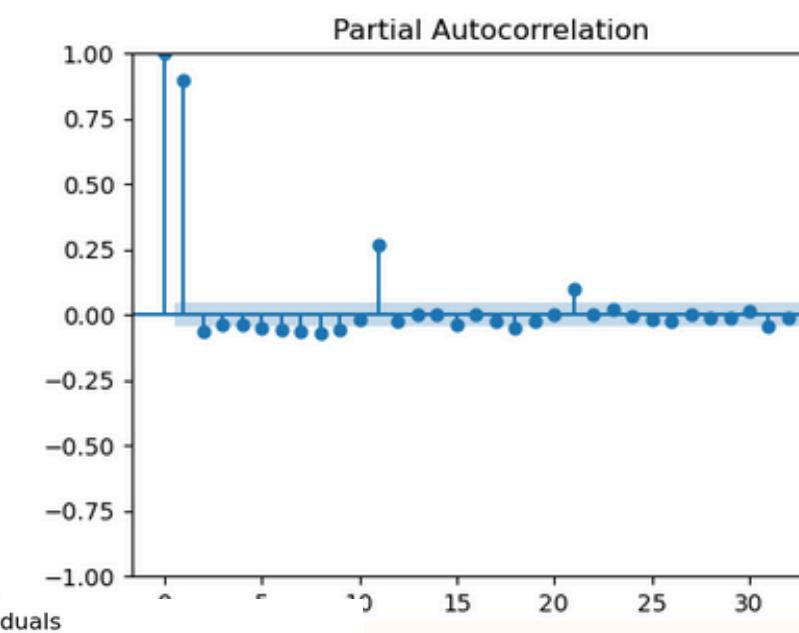
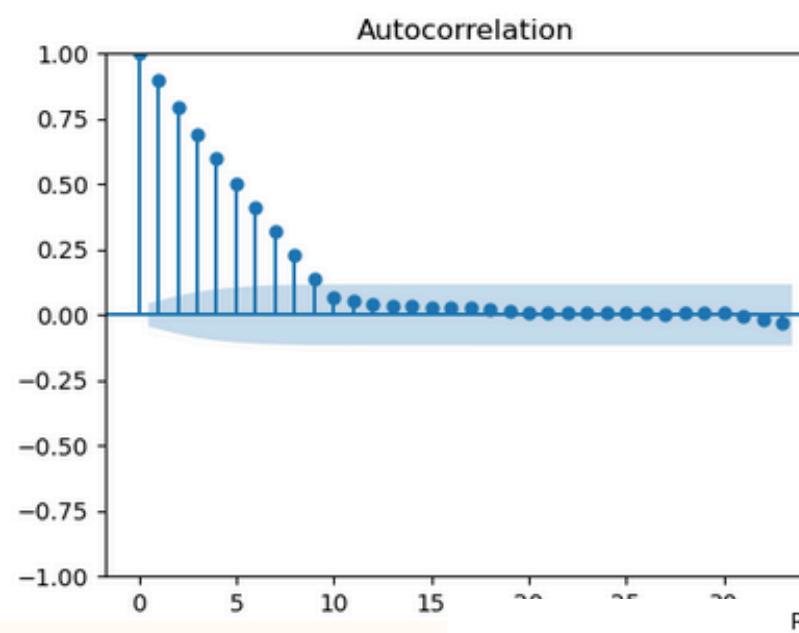
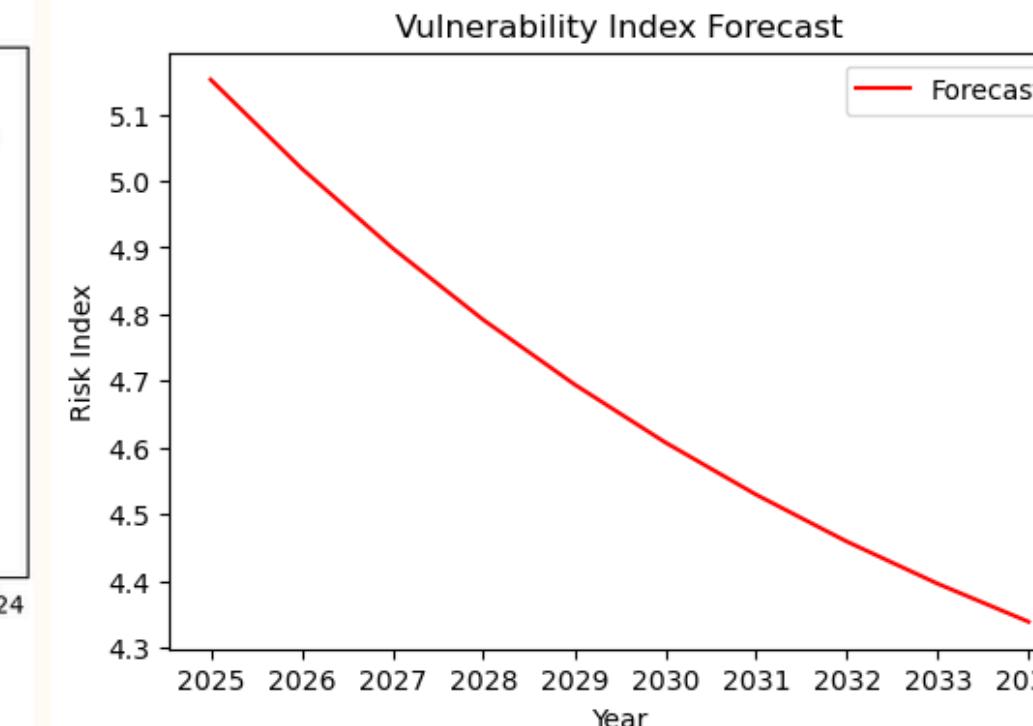
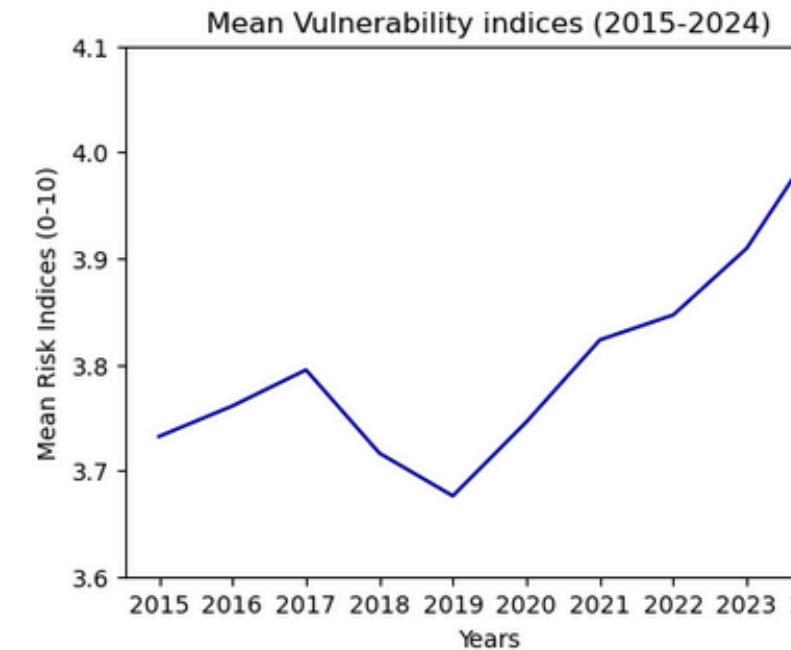
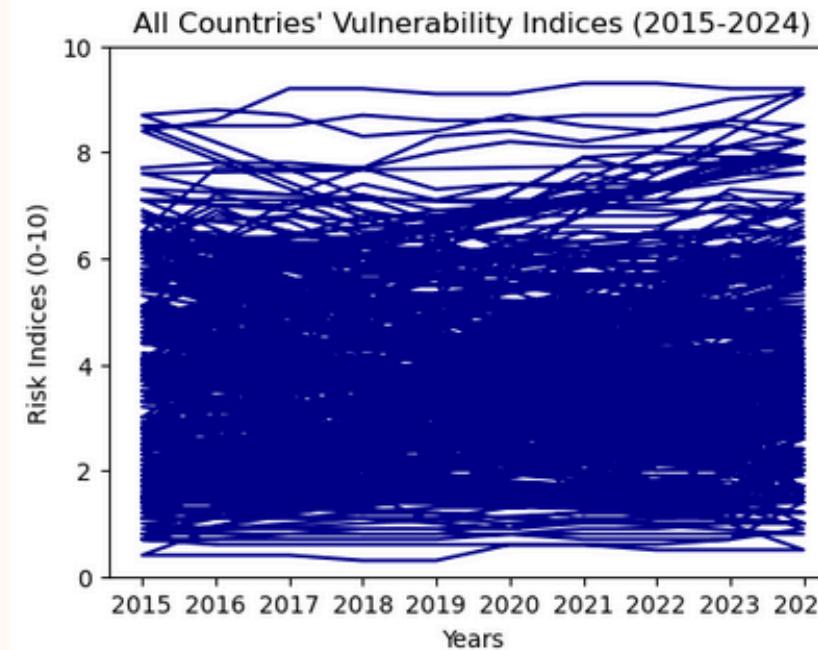
SARIMAX Results

Dep. Variable:	Vulnerability Index	No. Observations:	1528			
Model:	ARIMA(1, 1, 1)	Log Likelihood	-1897.502			
Date:	Mon, 08 Apr 2024	AIC	3801.003			
Time:	22:37:46	BIC	3816.996			
Sample:	0 - 1528	HQIC	3806.956			
Covariance Type:	opg					
<hr/>						
	coef	std err	z	P> z	[0.025	0.975]
ar.L1	0.8967	0.016	54.902	0.000	0.865	0.929
ma.L1	-1.0000	0.186	-5.373	0.000	-1.365	-0.635
sigma2	0.7008	0.133	5.264	0.000	0.440	0.962
<hr/>						
Ljung-Box (L1) (Q):	4.55	Jarque-Bera (JB):	13727.54			
Prob(Q):	0.03	Prob(JB):	0.00			
Heteroskedasticity (H):	1.45	Skew:	-0.42			
Prob(H) (two-sided):	0.00	Kurtosis:	17.66			
<hr/>						

Warnings:
 [1] Covariance matrix calculated using the outer product of gradients (complex-step).

ARIMA Model to forecast Vulnerability Risk indices:

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Mean Squared Error (MSE): 1.072450705808254
 Mean Absolute Error (MAE): 0.9116852017083055
 Root Mean Squared Error (RMSE): 1.035591959126882

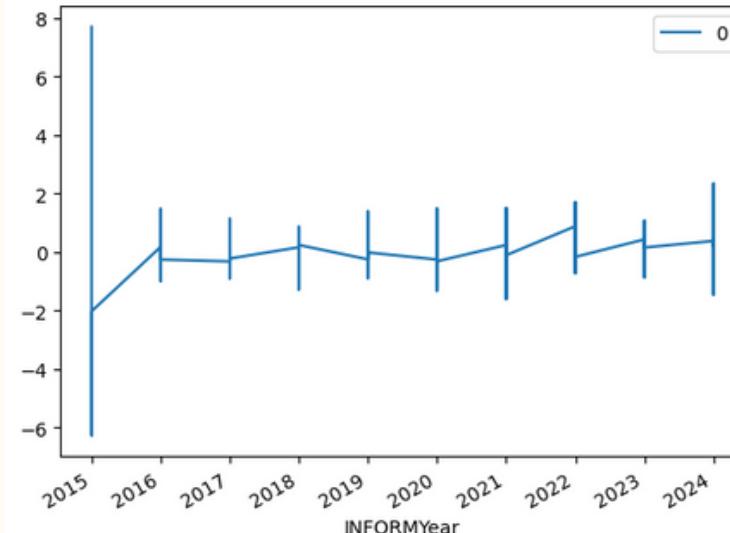
SARIMAX Results

```
=====
Dep. Variable: Vulnerability Index   No. Observations: 1910
Model: ARIMA(1, 1, 1)                 Log Likelihood: -2385.124
Date: Mon, 08 Apr 2024               AIC: 4776.247
Time: 03:11:51                       BIC: 4792.910
Sample: 0 - 1910                      HQIC: 4782.380
Covariance Type: opg
=====
```

	coef	std err	z	P> z	[0.025	0.975]
ar.L1	0.8996	0.014	64.481	0.000	0.872	0.927
ma.L1	-1.0000	0.169	-5.912	0.000	-1.331	-0.668
sigma2	0.7107	0.119	5.969	0.000	0.477	0.944

```
Ljung-Box (L1) (Q): 5.45 Jarque-Bera (JB): 16503.83
Prob(Q): 0.02 Prob(JB): 0.00
Heteroskedasticity (H): 1.41 Skew: -0.27
Prob(H) (two-sided): 0.00 Kurtosis: 17.39
=====
```

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).



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Summary

Summary Project# 3

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All Countries:

- Test-train didn't improve the fit or forecast output
- Using full dataset had better model fit & performance

INFORM Index

- Limited/poor model goodness of fit
- Good model performance

Hazard & Exposure

- Limited/poor model goodness of fit
- Good model performance

Lack of Coping Capacity

- Limited/poor model goodness of fit
- Good model performance

Vulnerability

- Limited/poor model goodness of fit
- Limited/poor model performance

Summary Project# 3

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For Risk Groups:

INFORM Index

- Good model goodness of fit for V.low, Low, Medium Risk Countries
- Good model performance for V.Low, Low & V.High Risk Countries

Hazard & Exposure

- Good model goodness of fit for V.low & Low Risk Countries
- Good model performance for V.High Risk Countries

Lack of Coping Capacity

- Good model goodness of fit for V.low, Low, High & V.High Risk Countries
- Good model performance for V.High Risk Countries

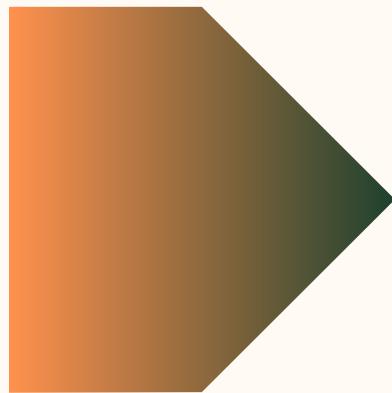
Vulnerability

- Poor model goodness of fit
- Good model performance for V.High Risk Countries

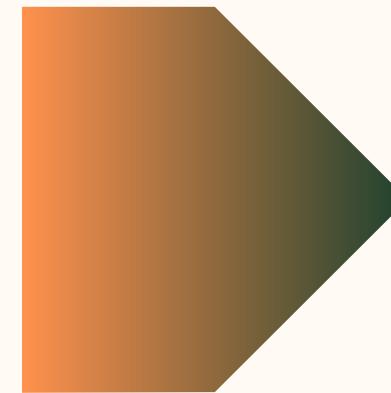
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Conclusions

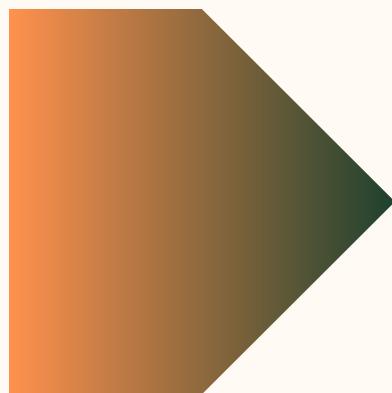
Conclusions Project 1 + 2



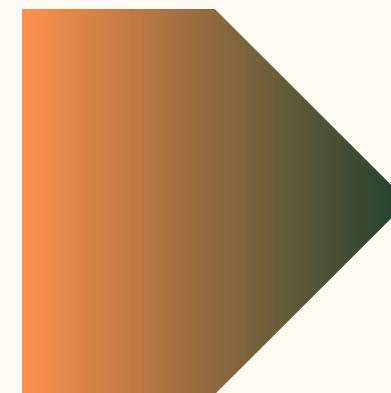
The INFORM Risk index **can** be used to predict humanitarian crises, to a certain extent



Considering the scale of the data, sometimes simplicity is best
For example- logistic model performed better than decision tree



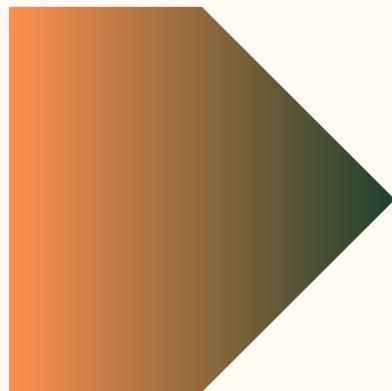
XGBoost was best performing model overall



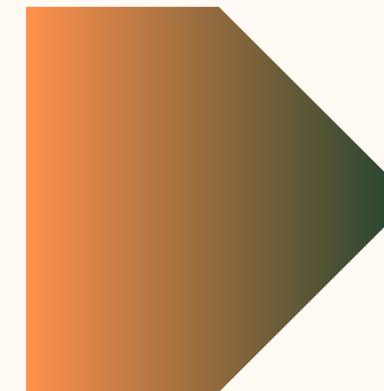
There is a lot of room for improvement

Conclusions Project 3

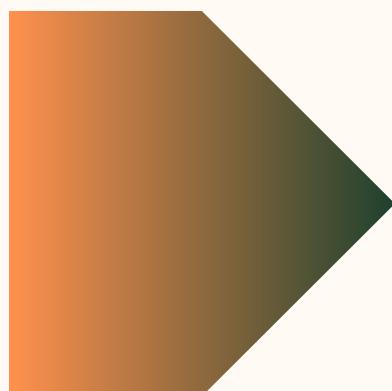
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ARIMA model can provide predictions of future Risk Indices

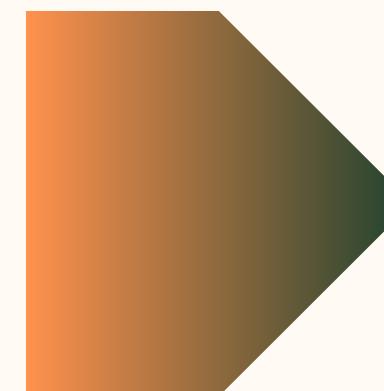


Was ARIMA model most appropriate?
Would simpler **Autoregression** or **Moving Average** be sufficient for prediction? (Autocorrelation & Partial Autocorrelation Plots)



Associations with Core Indicators suggest multivariate model may improve predictions

Useful as indices data on a limited scale & lacks granularity for time series forecasting, ie 10 data points per country over 10 year period



Could more training & testing for risk groups better fit the model improve predictions?

Could **AutoARIMA** be equal or superior to the ARIMA model?

Next Steps Project 1 + 2



Determine why the linear regression performed so badly on Project 2



Take into account the TYPE of crisis



Look more into individual features



Finding the best hyperparameters for XGBoost

Next Steps Project 3

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Further EDA between specific
**INFORM Indices vs Core
Indicators** for use in
multivariate models



Explore whether **simpler models**,
eg **Autoregression or Moving
Average** would improve on ARIMA
forecasting



Explore & identify **more
granular data for time series
forecasting**
Increase data points per month
For specific country/ group of
countries



Determine why the linear
regression performed so
badly on Project 2

Thank you!

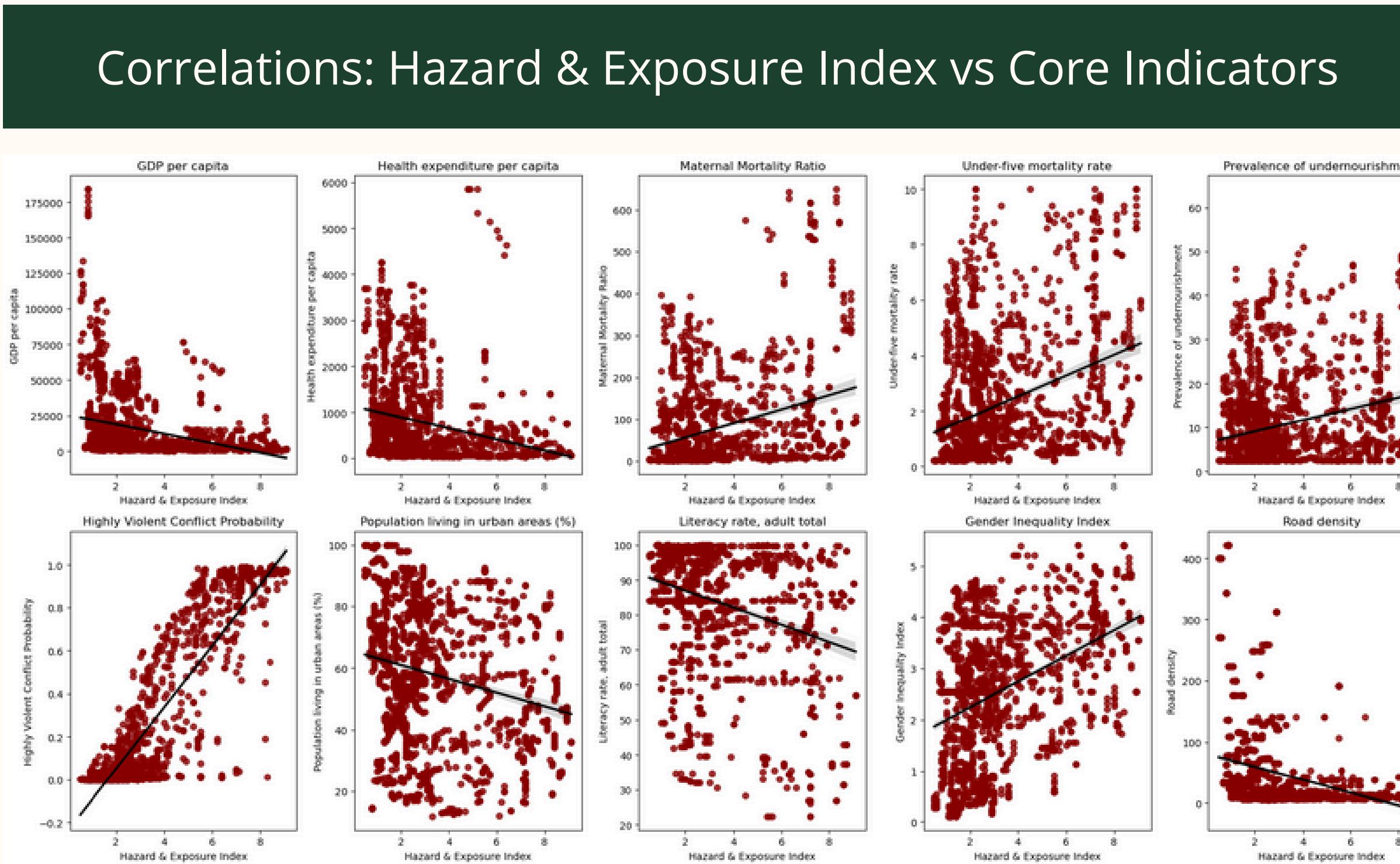
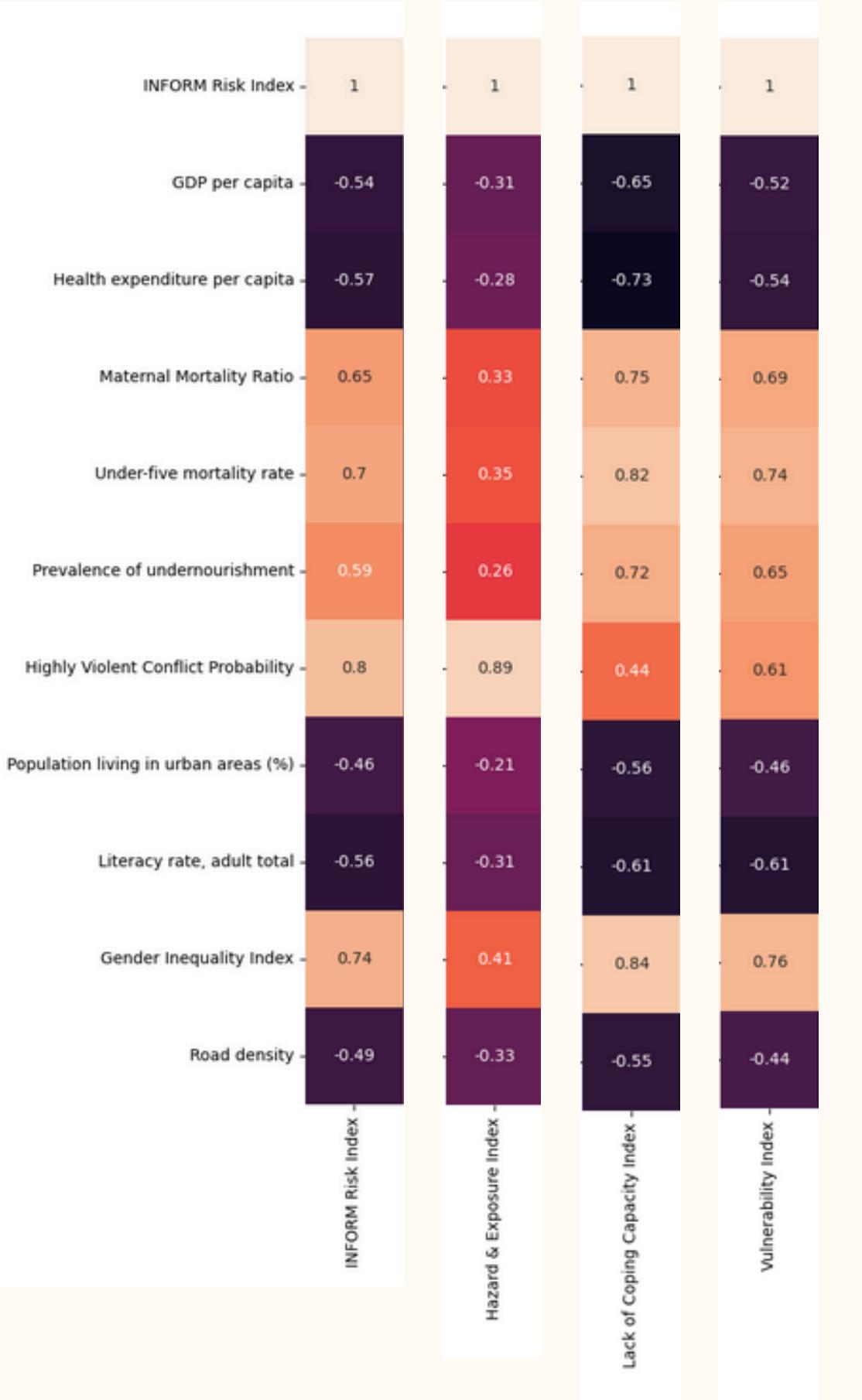


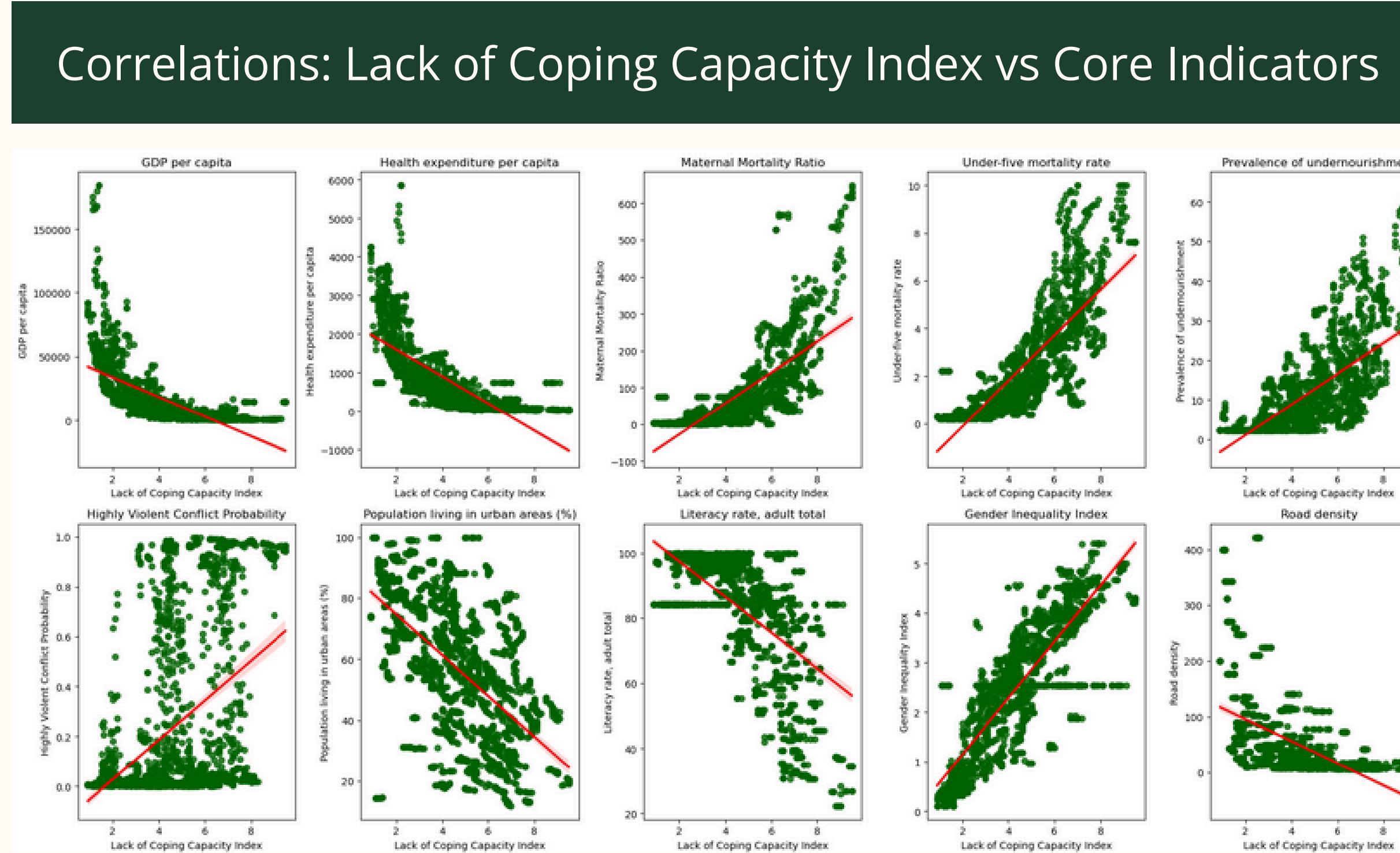
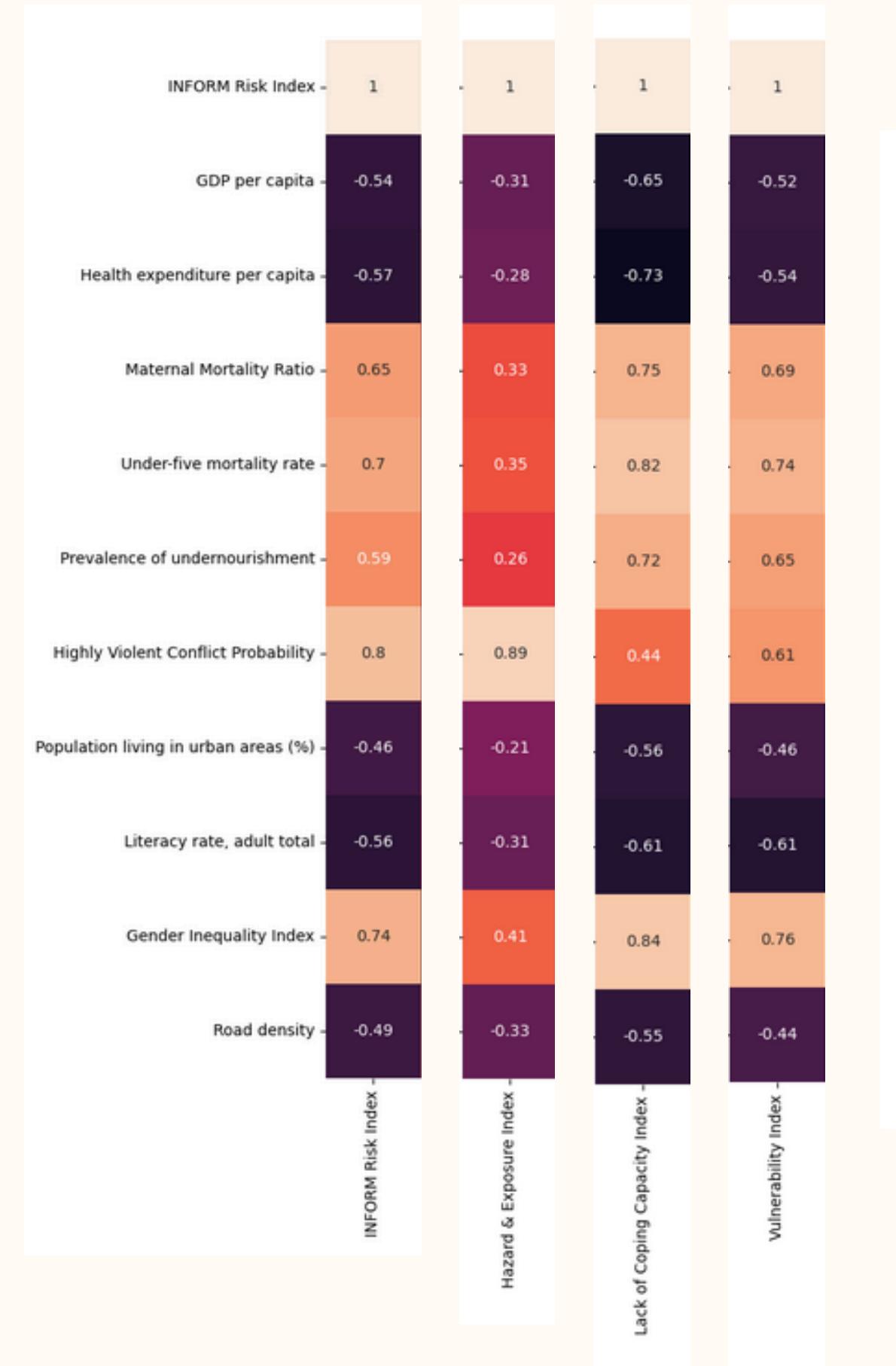
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Additional Slides

EDA

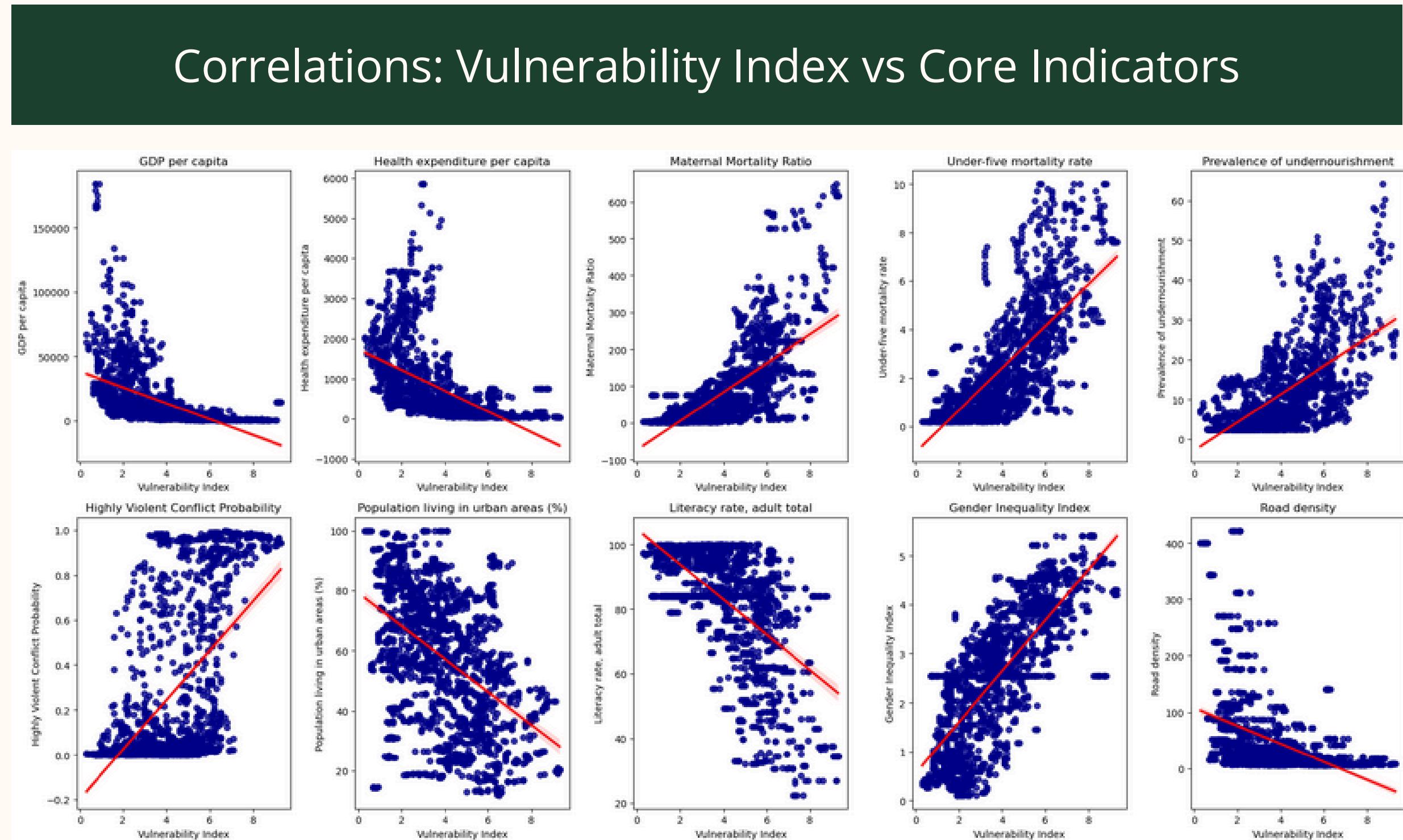
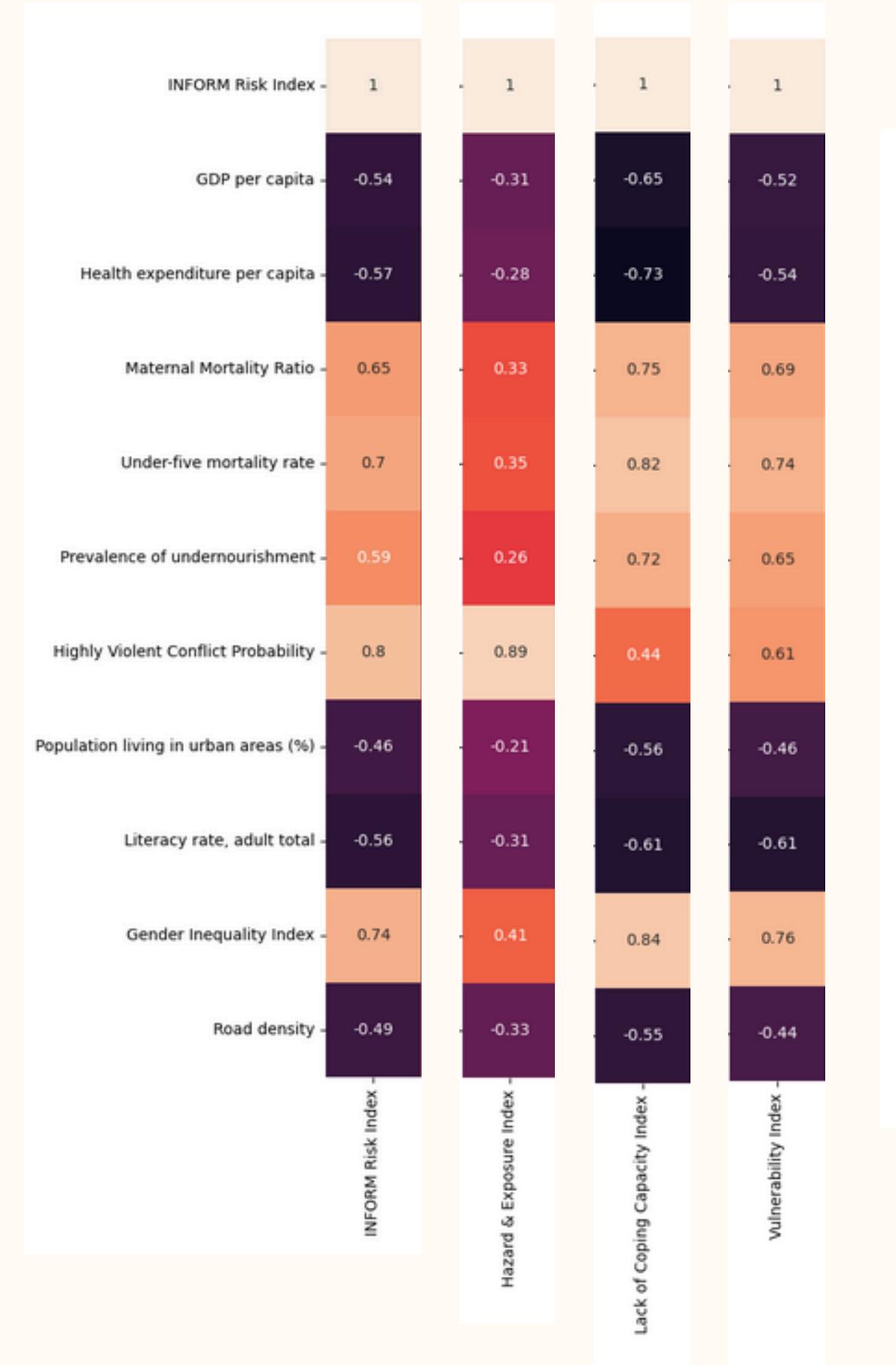
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EDA

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Project 3

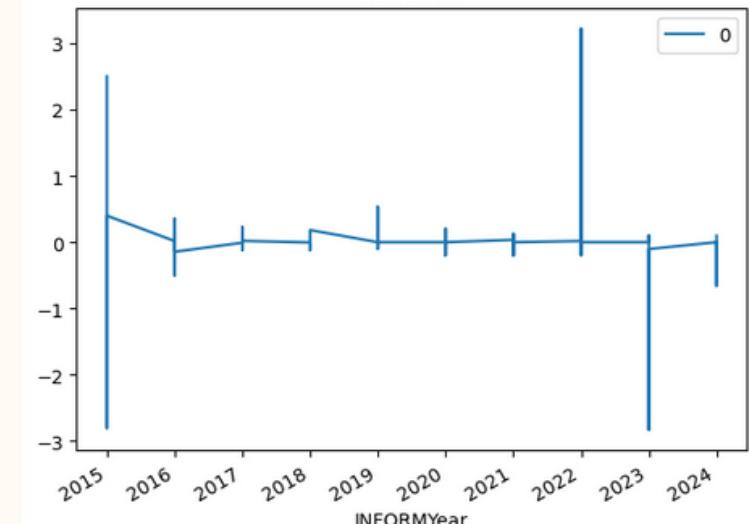
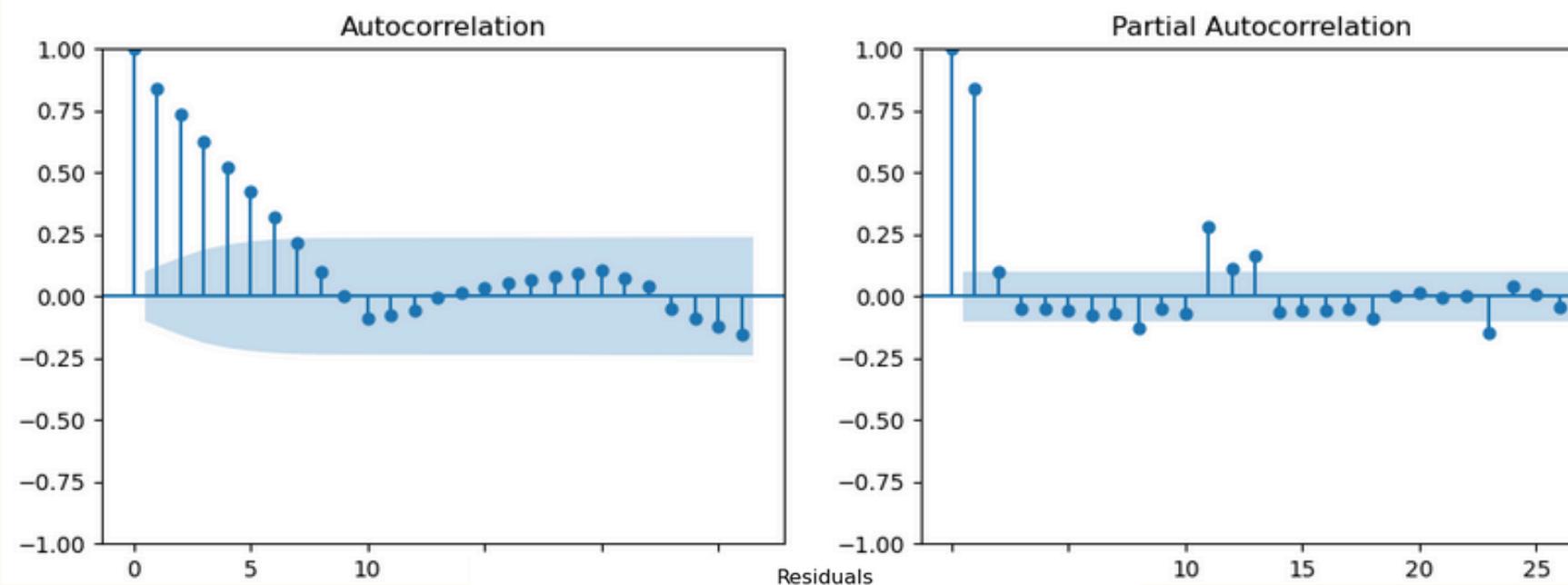
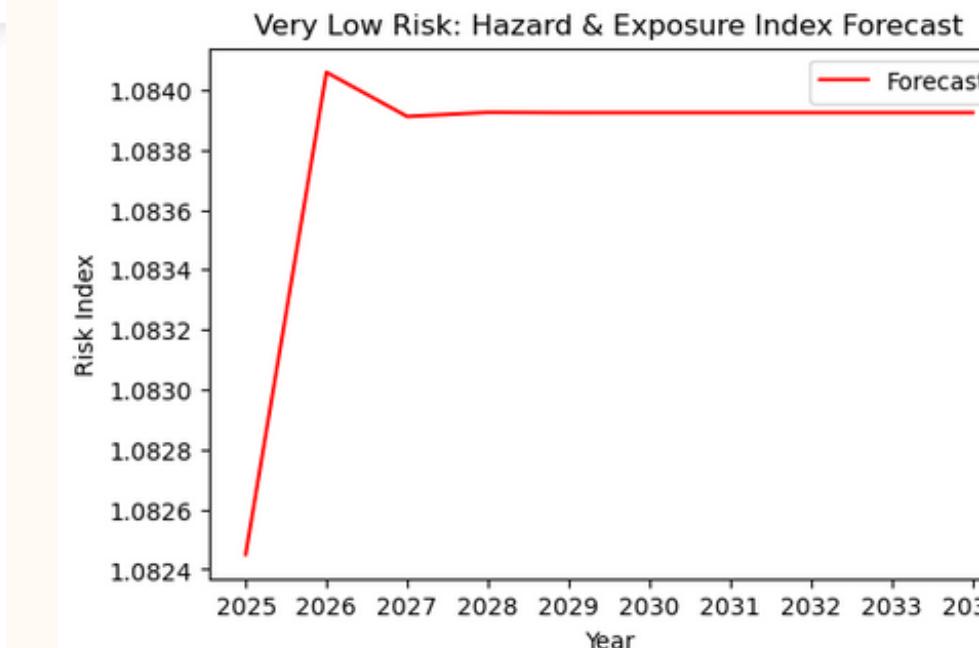
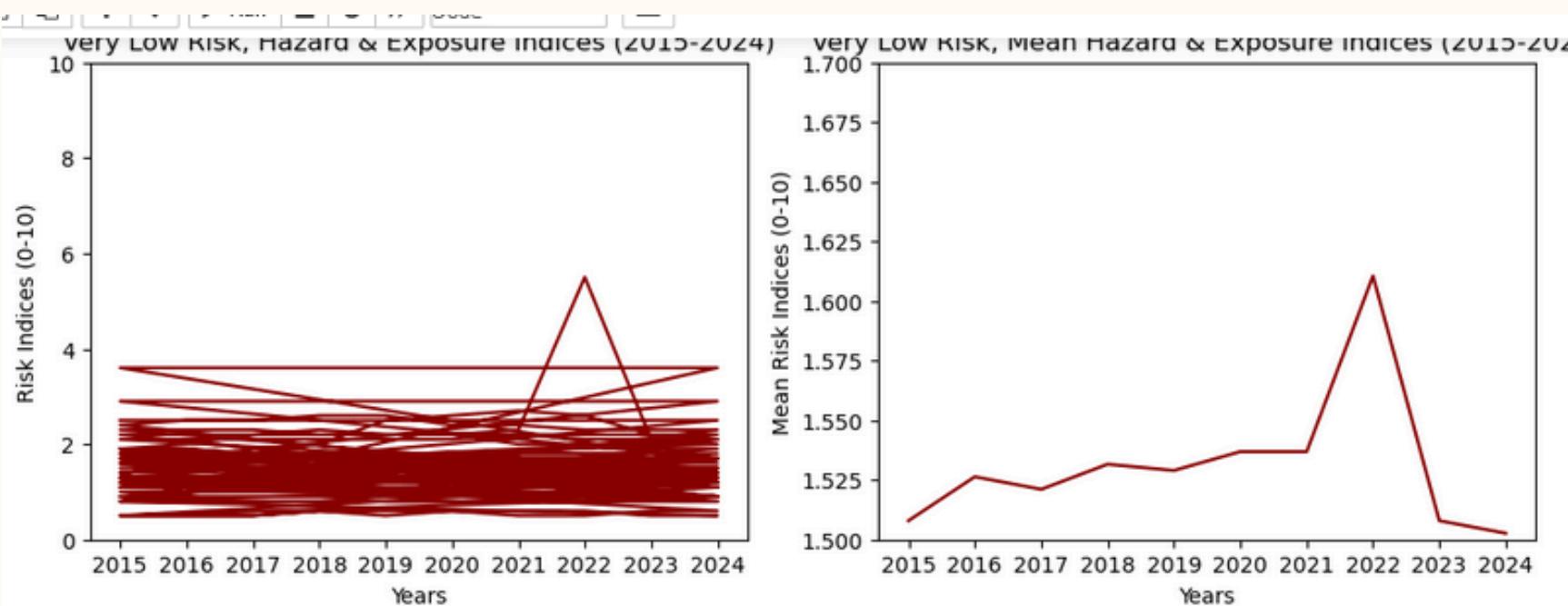


**Predict & forecast
how INFORM risk
data changes over
time**

ARIMA Model

ARIMA Model to forecast Very Low Risk Countries' Hazard & Exposure Risk indices:

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Mean Squared Error (MSE): 0.00762836110749214
 Mean Absolute Error (MAE): 0.08343438748863088
 Root Mean Squared Error (RMSE): 0.08734048950797185

SARIMAX Results

```
=====
Dep. Variable: Hazard & Exposure Index No. Observations: 380
Model: ARIMA(1, 1, 1) Log Likelihood: -168.348
Date: Mon, 08 Apr 2024 AIC: 342.697
Time: 03:50:22 BIC: 354.509
Sample: 0 HQIC: 347.384
- 380
Covariance Type: opg
=====
```

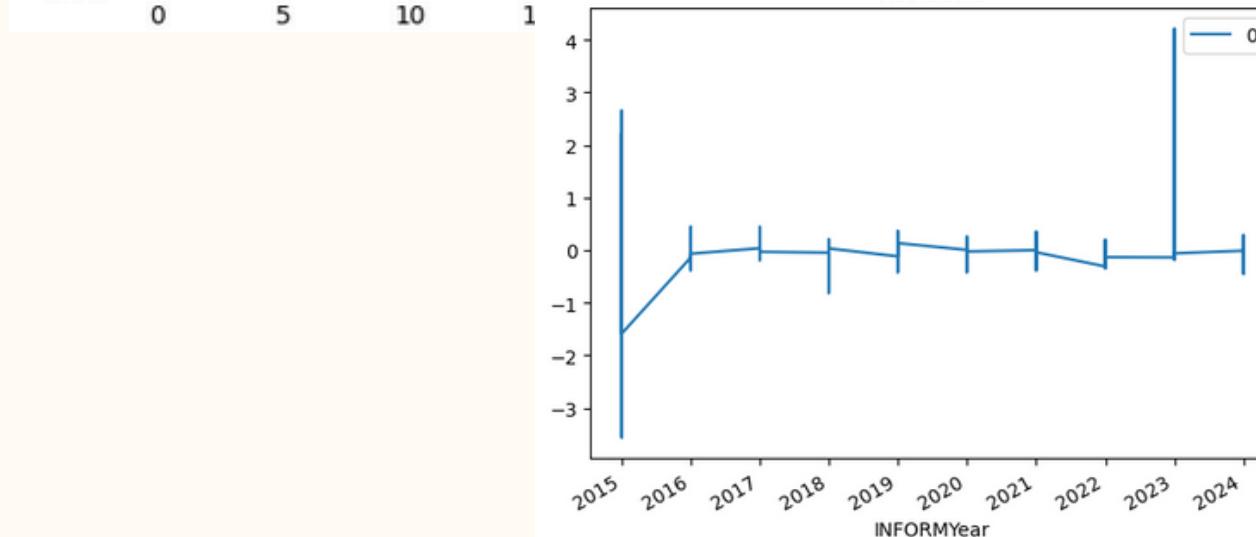
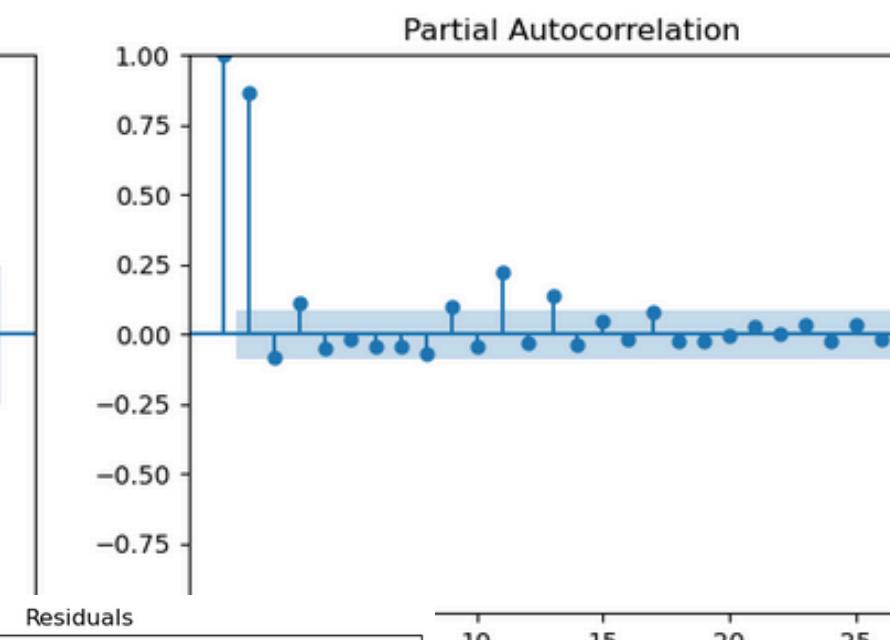
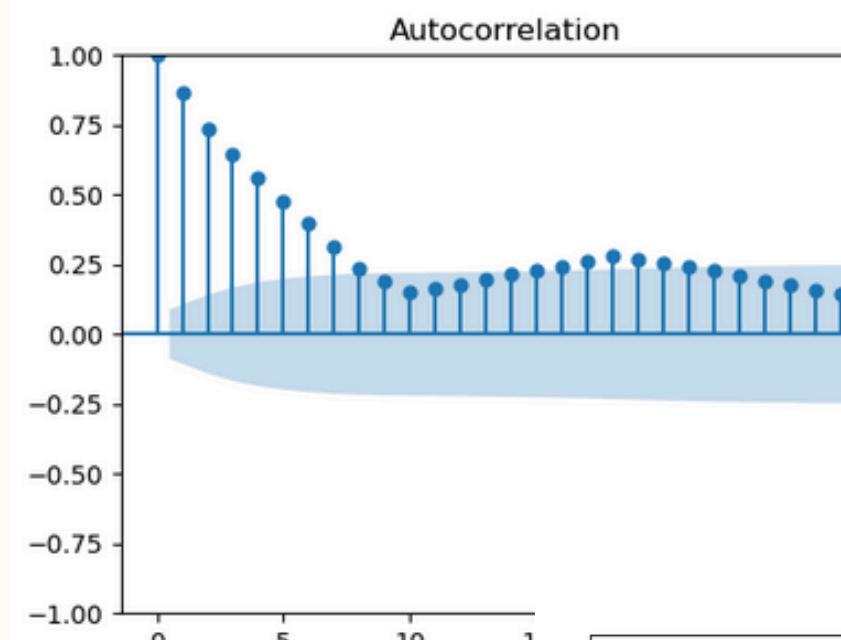
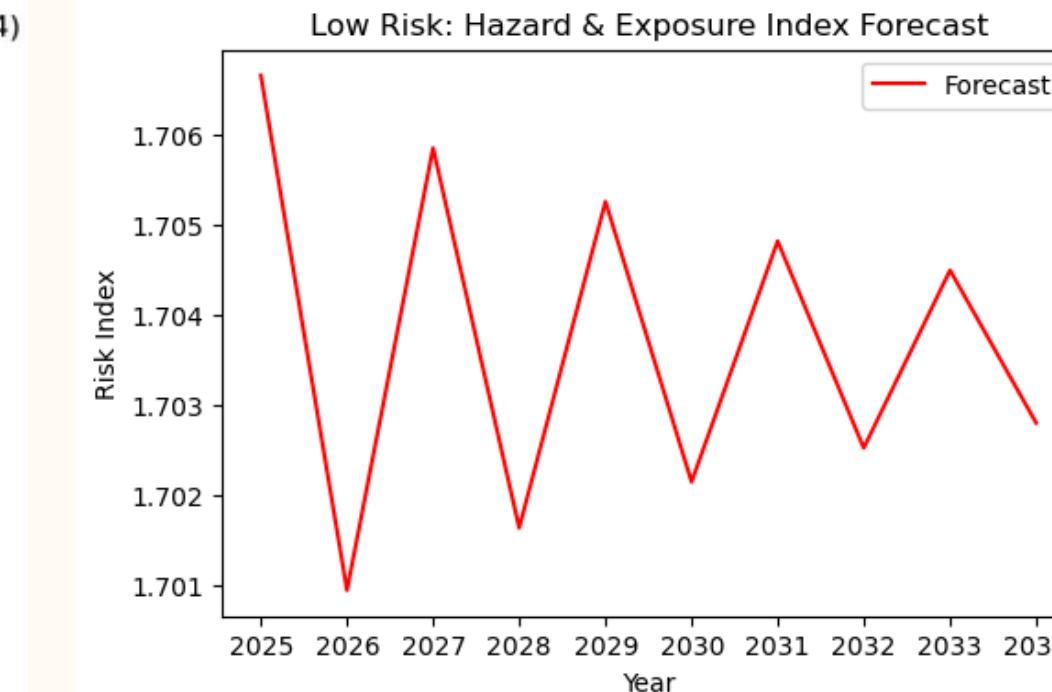
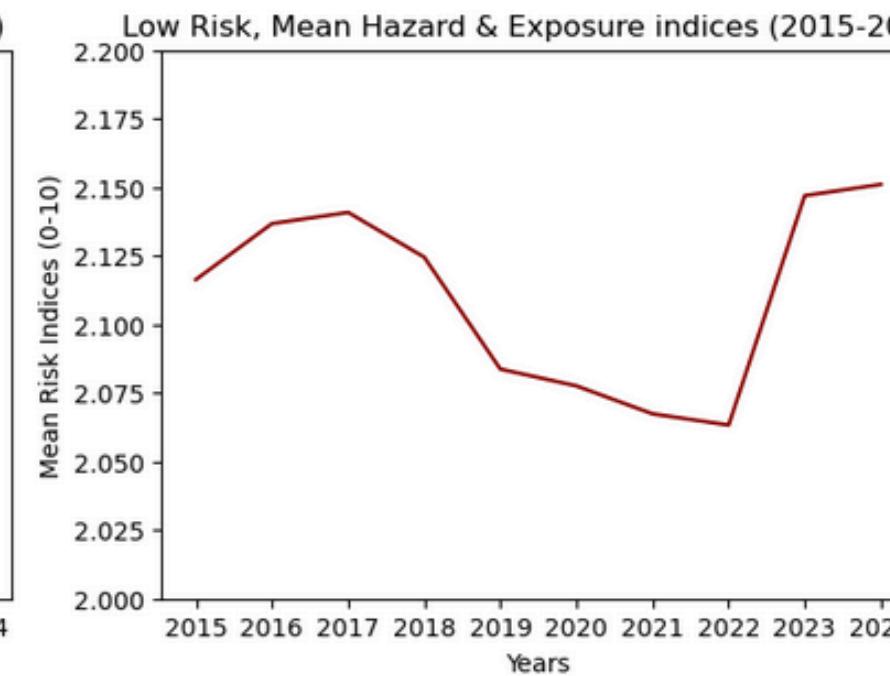
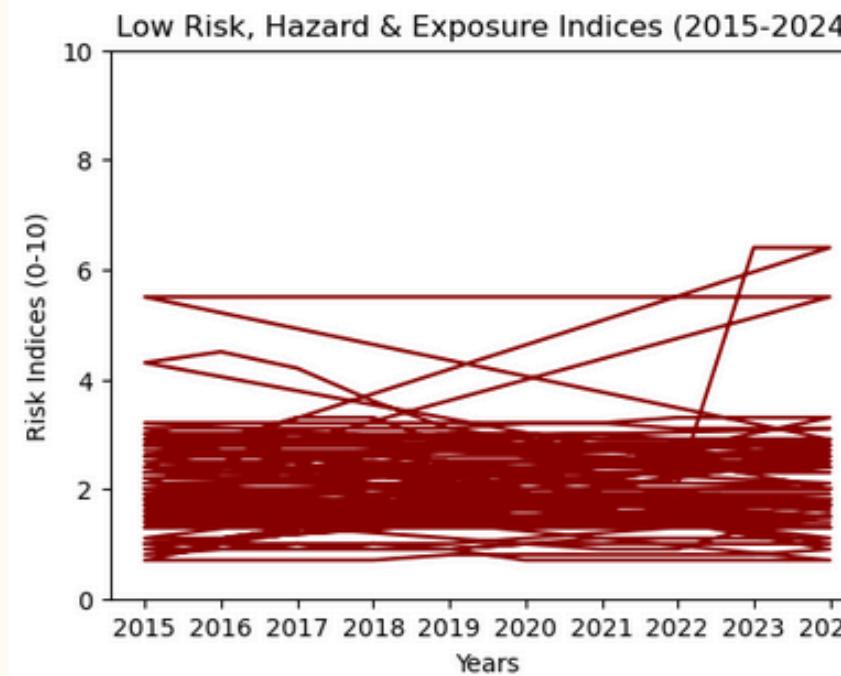
	coef	std err	z	P> z	[0.025	0.975]
ar.L1	-0.0916	0.314	-0.292	0.770	-0.706	0.523
ma.L1	-0.0865	0.315	-0.275	0.783	-0.704	0.531
sigma2	0.1423	0.003	51.268	0.000	0.137	0.148

```
=====
Ljung-Box (L1) (Q): 0.00 Jarque-Bera (JB): 16801.84
Prob(Q): 0.99 Prob(JB): 0.00
Heteroskedasticity (H): 0.54 Skew: -0.21
Prob(H) (two-sided): 0.00 Kurtosis: 35.62
=====
```

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).

ARIMA Model to forecast Low Risk Countries' Hazard & Exposure Risk indices:

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Mean Squared Error (MSE): 0.0054238845169744315
 Mean Absolute Error (MAE): 0.05371051640434208
 Root Mean Squared Error (RMSE): 0.07364702653179171

SARIMAX Results						
Dep. Variable:	Hazard & Exposure Index	No. Observations:	490			
Model:	ARIMA(1, 1, 1)	Log Likelihood	-291.292			
Date:	Mon, 08 Apr 2024	AIC	588.583			
Time:		BIC	601.160			
Sample:		HQIC	593.523			
Covariance Type:		- 490				
		opg				

	coef	std err	z	P> z	[0.025	0.975]
ar.L1	-0.8590	0.034	-25.280	0.000	-0.926	-0.792
ma.L1	0.9842	0.010	96.079	0.000	0.964	1.004
sigma2	0.1923	0.005	38.131	0.000	0.182	0.202

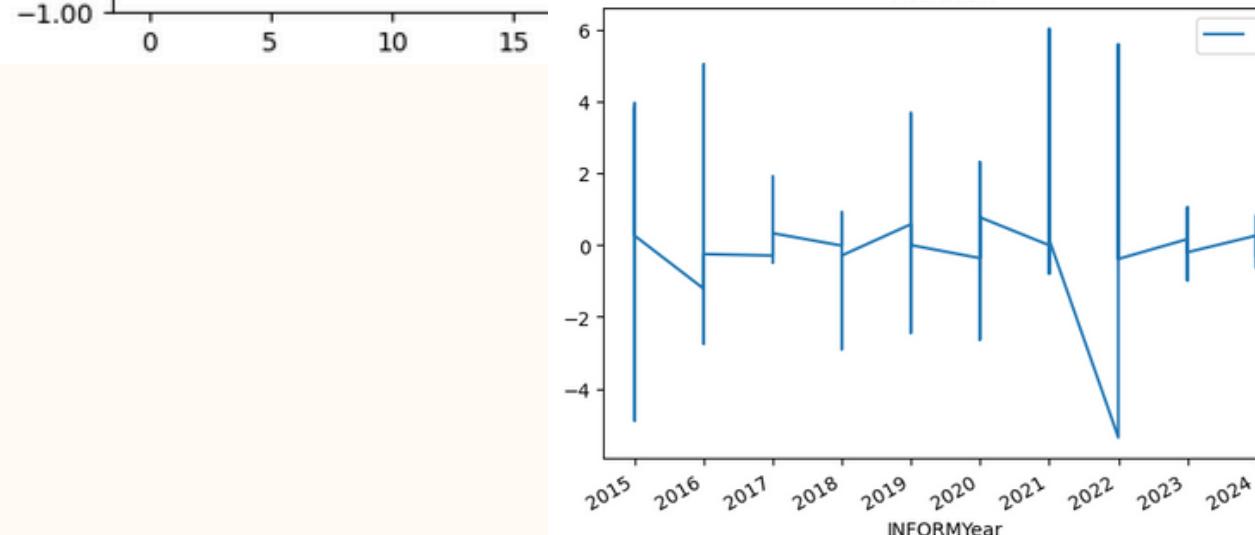
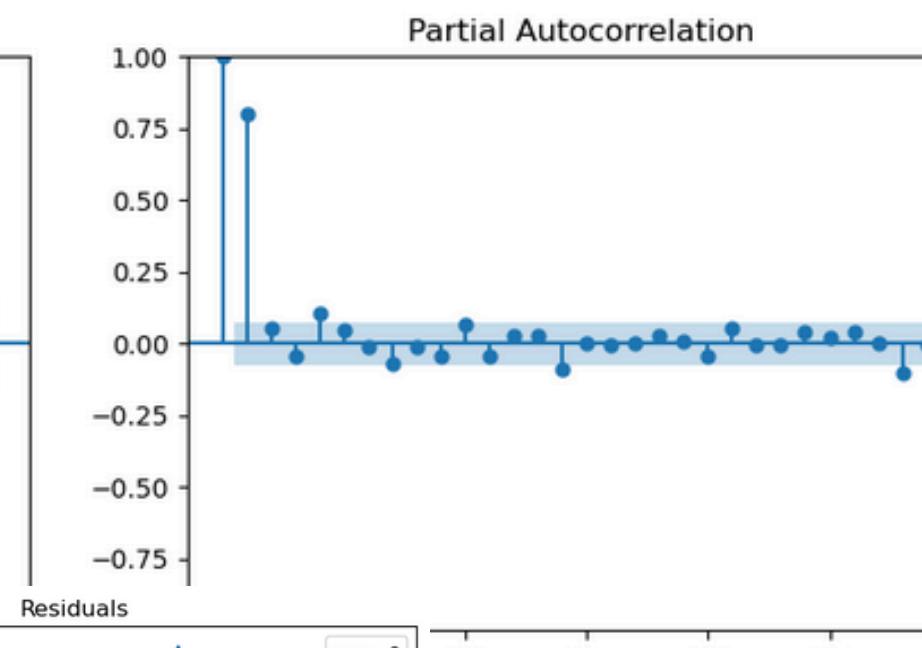
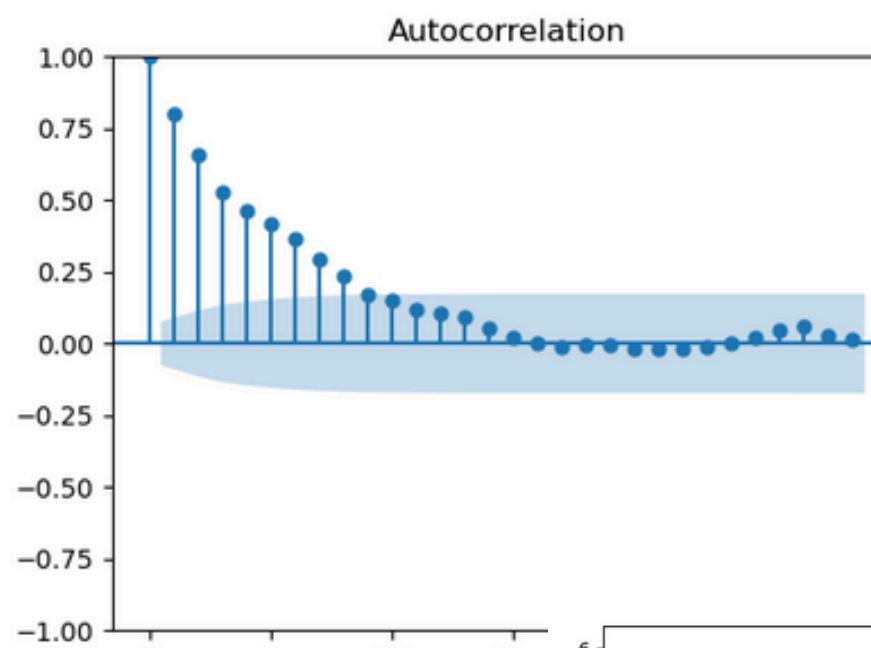
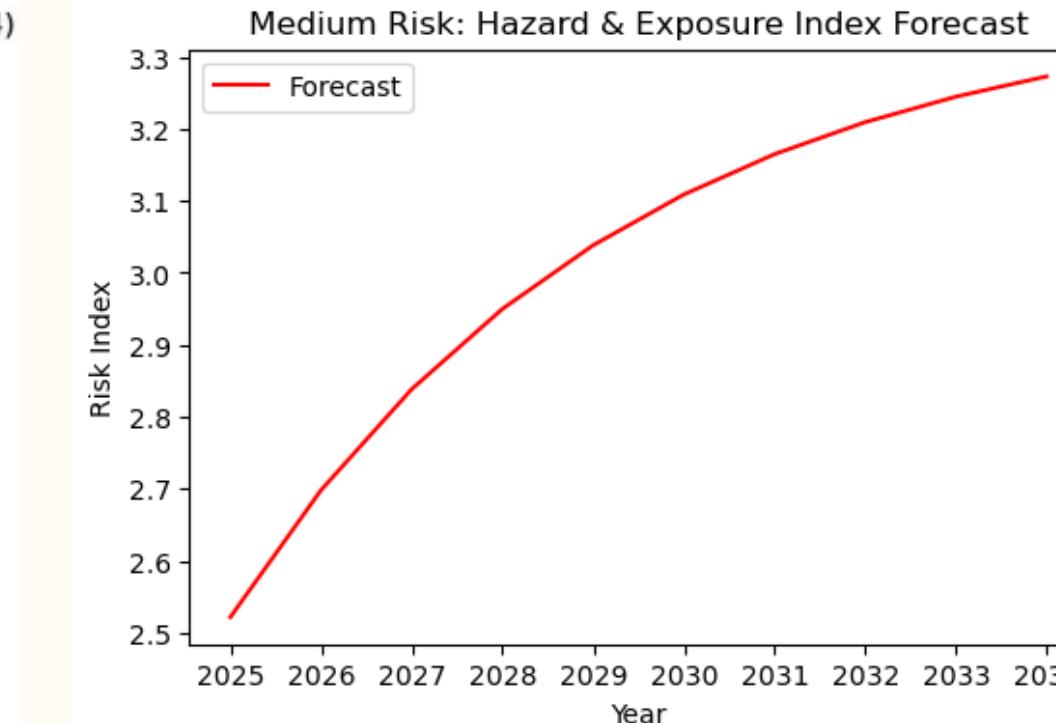
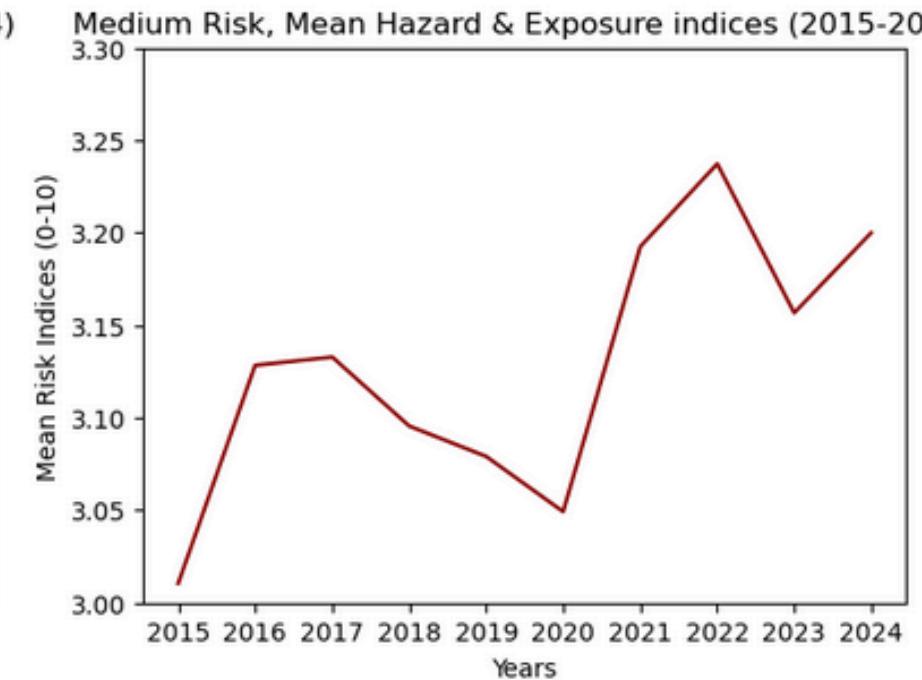
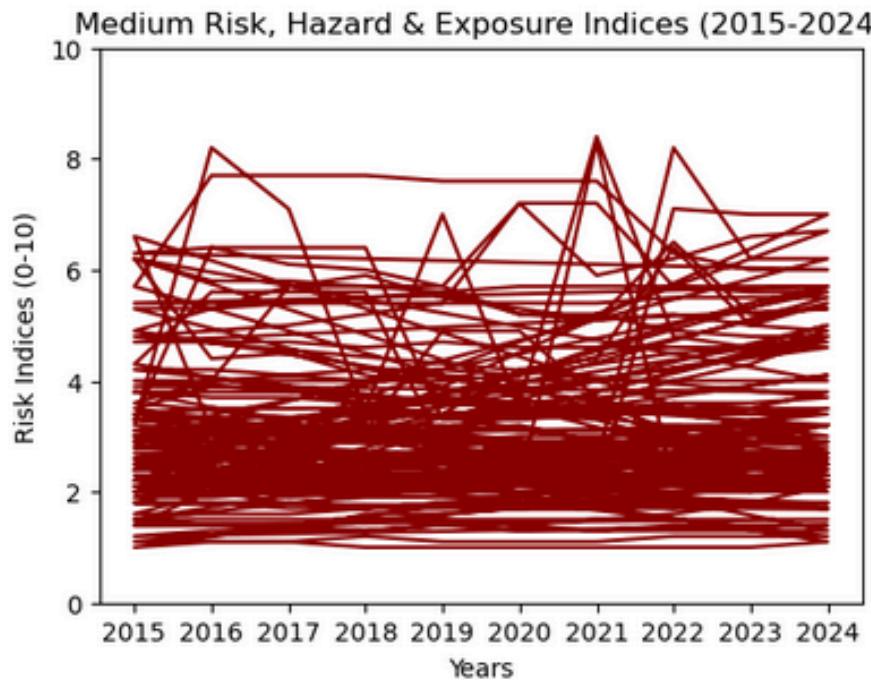
Ljung-Box (L1) (Q):			1.43	Jarque-Bera (JB):		29068.32
Prob(Q):			0.23	Prob(JB):		0.00
Heteroskedasticity (H):			1.36	Skew:		0.54
Prob(H) (two-sided):			0.05	Kurtosis:		40.76

Warnings:

[1] Covariance matrix calculated using the outer product of gradients (complex-step)

ARIMA Model to forecast Medium Risk Countries' Hazard & Exposure Risk indices:

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Mean Squared Error (MSE): 0.5499464852573603
 Mean Absolute Error (MAE): 0.7147981896867188
 Root Mean Squared Error (RMSE): 0.7415837681997633

SARIMAX Results

```
=====
Dep. Variable: Hazard & Exposure Index No. Observations: 670
Model: ARIMA(1, 1, 1) Log Likelihood: -869.607
Date: Mon, 08 Apr 2024 AIC: 1745.213
Time: 04:07:43 BIC: 1758.731
Sample: 0 HQIC: 1750.449
- 670
Covariance Type: opg
=====
```

	coef	std err	z	P> z	[0.025	0.975]
ar.L1	0.7950	0.021	38.299	0.000	0.754	0.836
ma.L1	-0.9936	0.007	-144.158	0.000	-1.007	-0.980
sigma2	0.7854	0.018	43.496	0.000	0.750	0.821

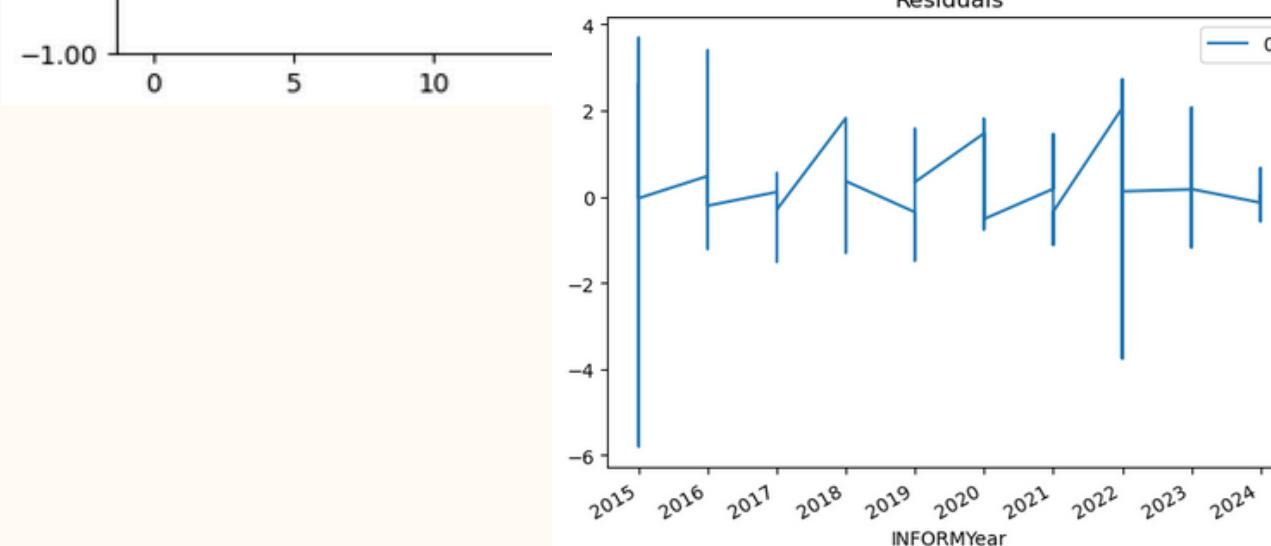
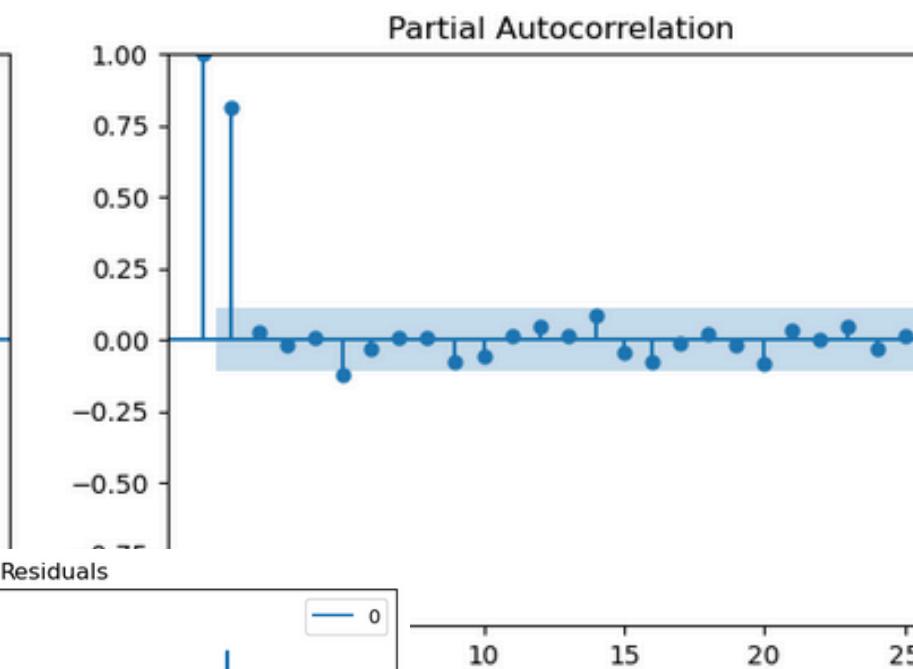
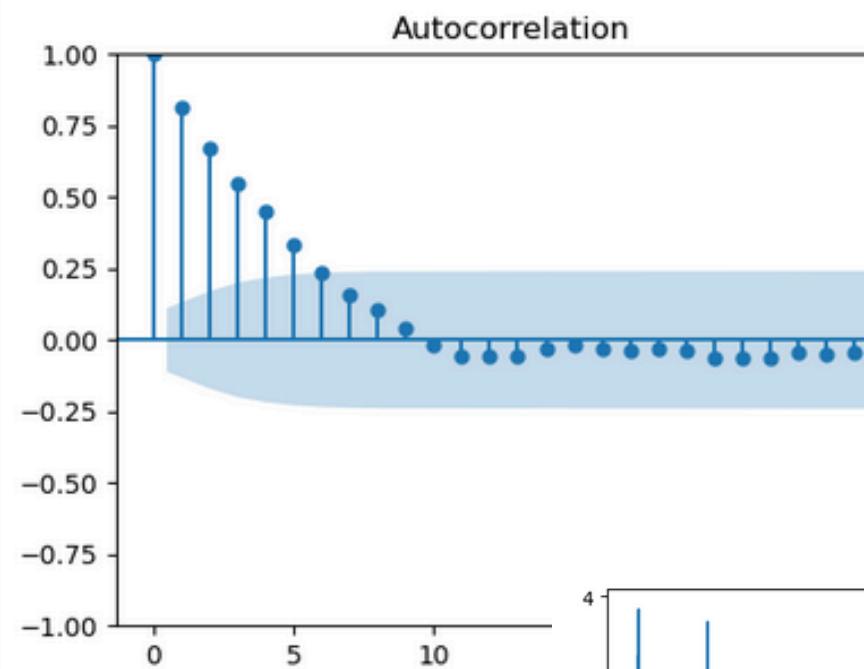
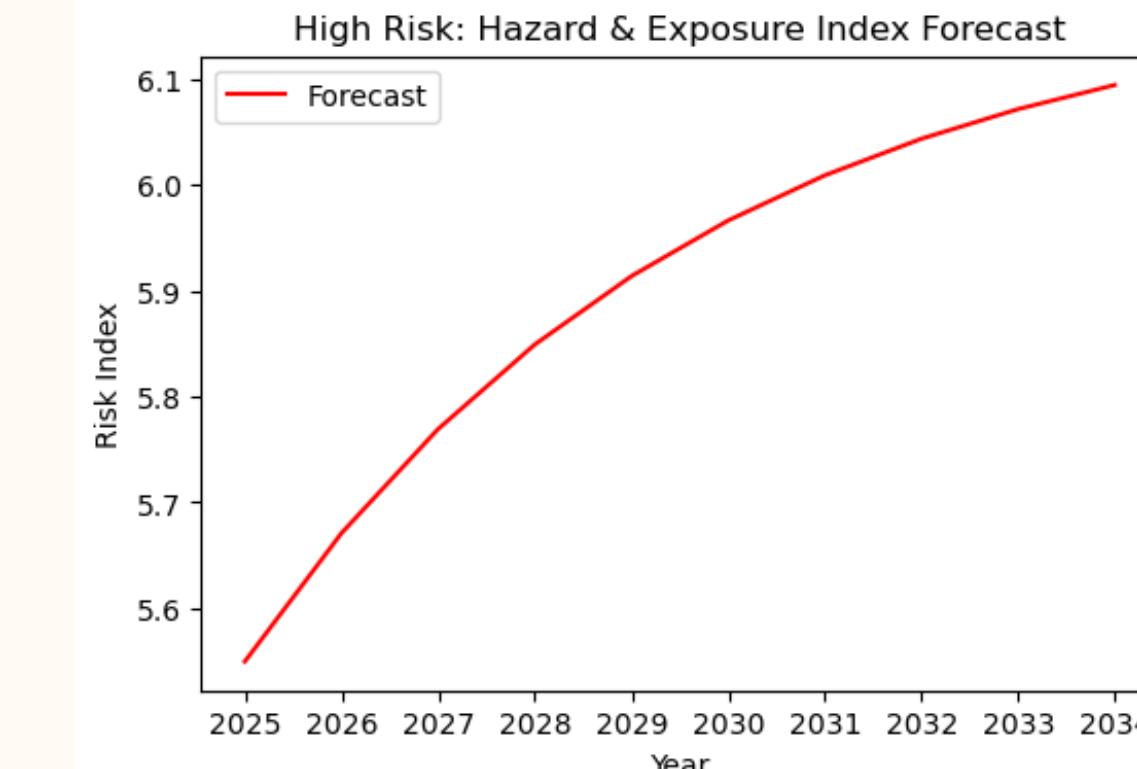
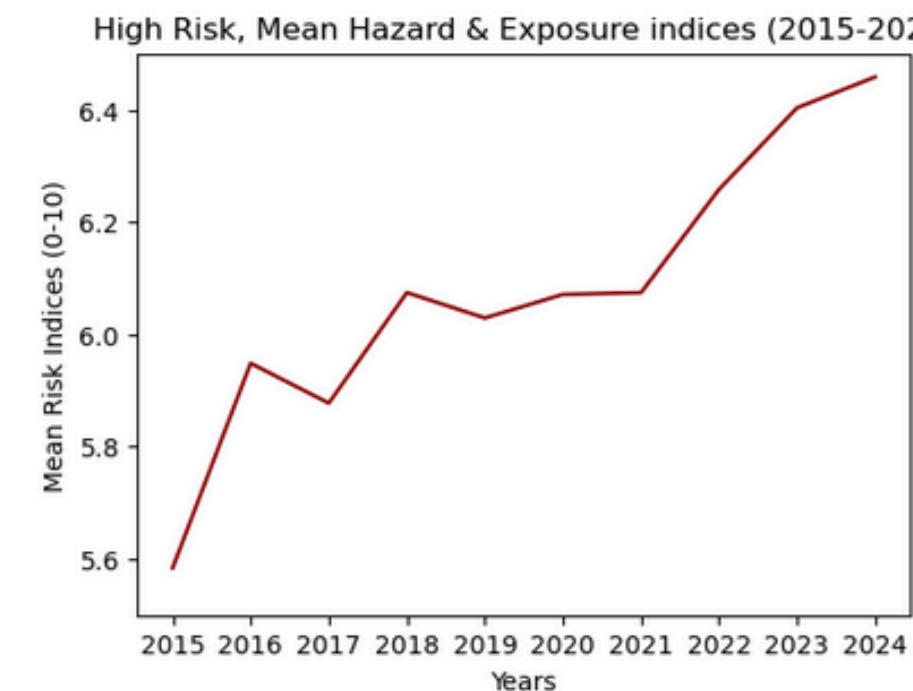
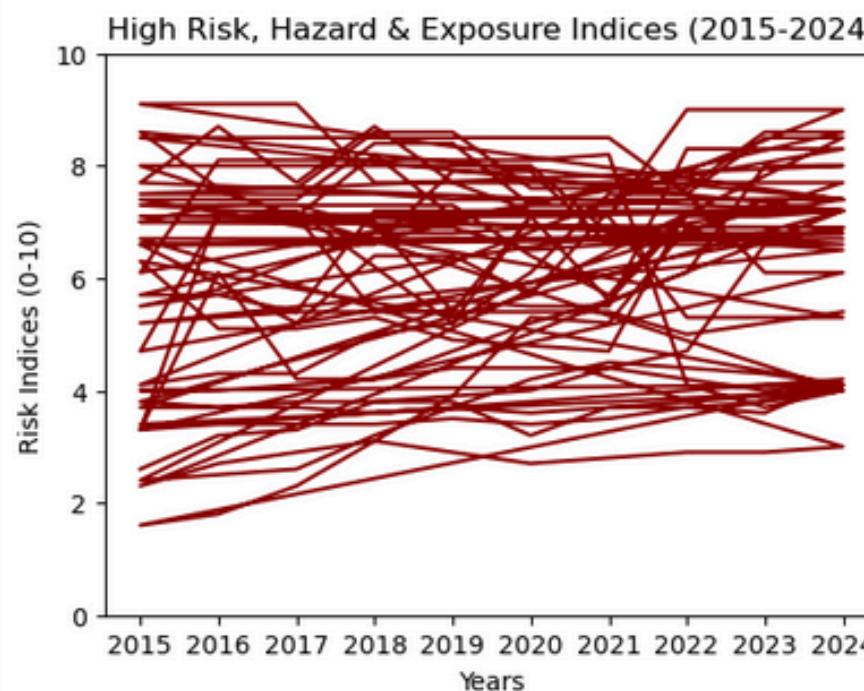
```
=====
Ljung-Box (L1) (Q): 1.15 Jarque-Bera (JB): 6510.32
Prob(Q): 0.28 Prob(JB): 0.00
Heteroskedasticity (H): 1.09 Skew: 1.04
Prob(H) (two-sided): 0.51 Kurtosis: 18.14
=====
```

Warnings:

[1] Covariance matrix calculated using the outer product of gradients (complex-step).

ARIMA Model to forecast High Risk Countries' Hazard & Exposure Risk indices:

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Mean Squared Error (MSE): 0.9997580409036935
 Mean Absolute Error (MAE): 0.9460648697163029
 Root Mean Squared Error (RMSE): 0.9998790131329357

SARIMAX Results

```
=====
Dep. Variable: Hazard & Exposure Index   No. Observations: 310
Model: ARIMA(1, 1, 1)                        Log Likelihood: -445.771
Date: Mon, 08 Apr 2024                       AIC: 897.543
Time: 04:04:27                                BIC: 908.743
Sample: 0 - 310                               HQIC: 902.021
                                                opg
Covariance Type: opg
=====
```

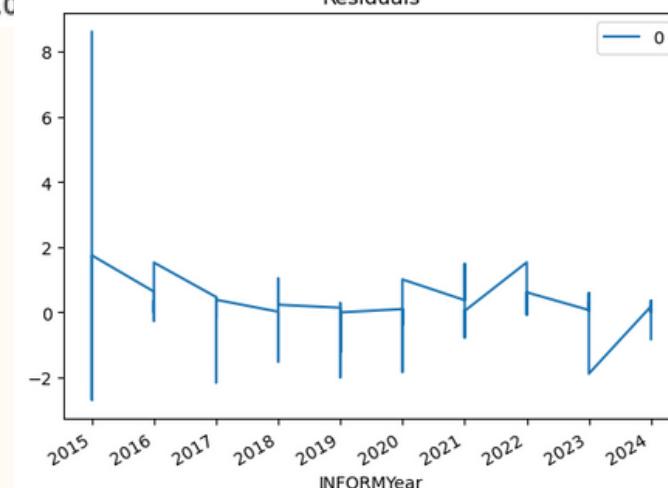
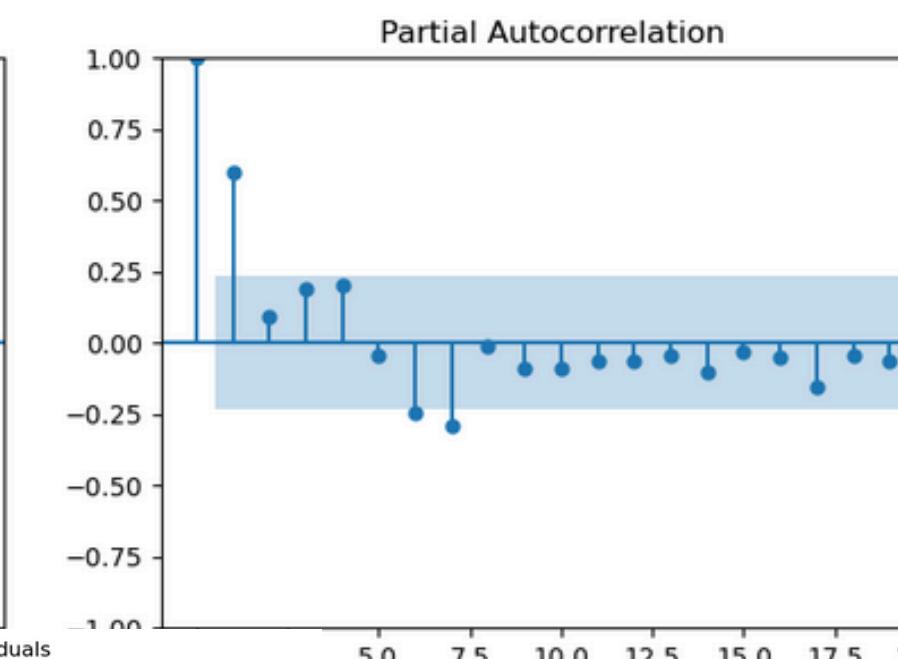
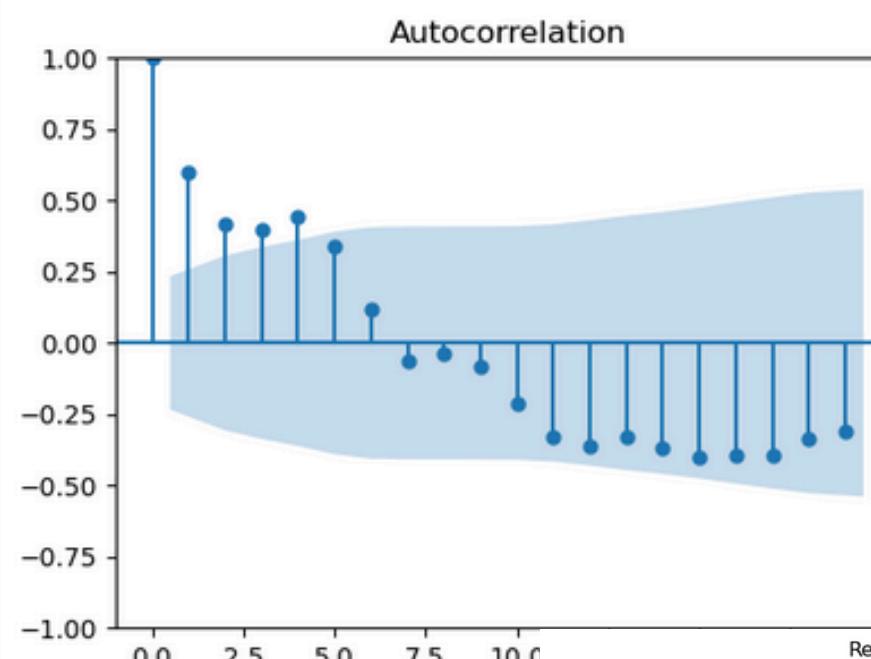
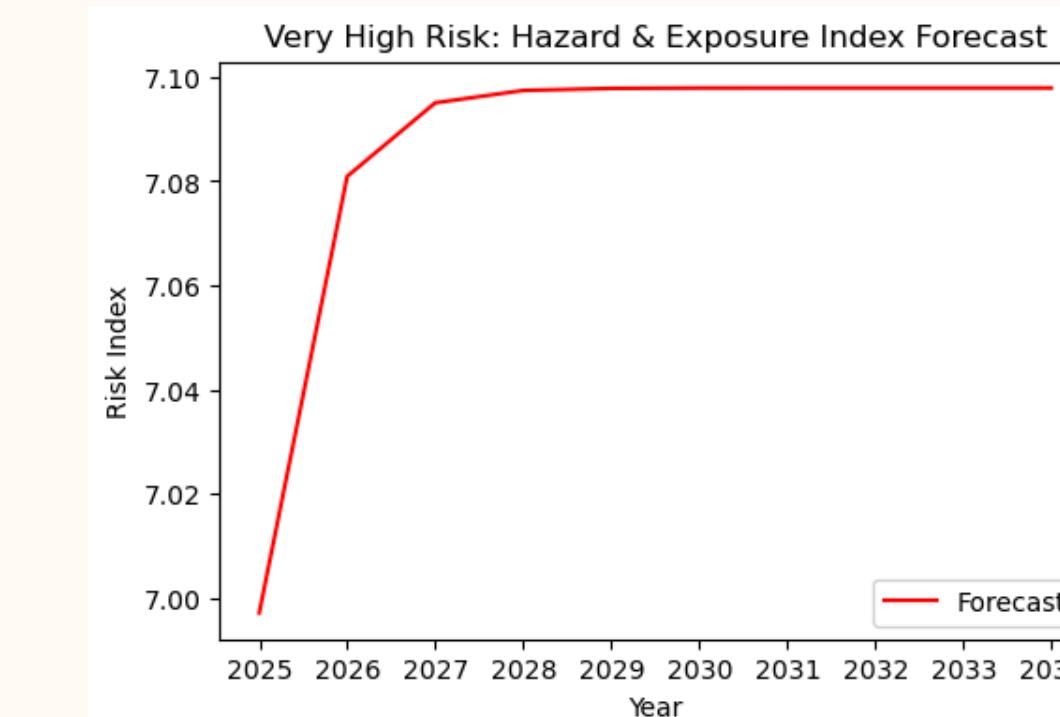
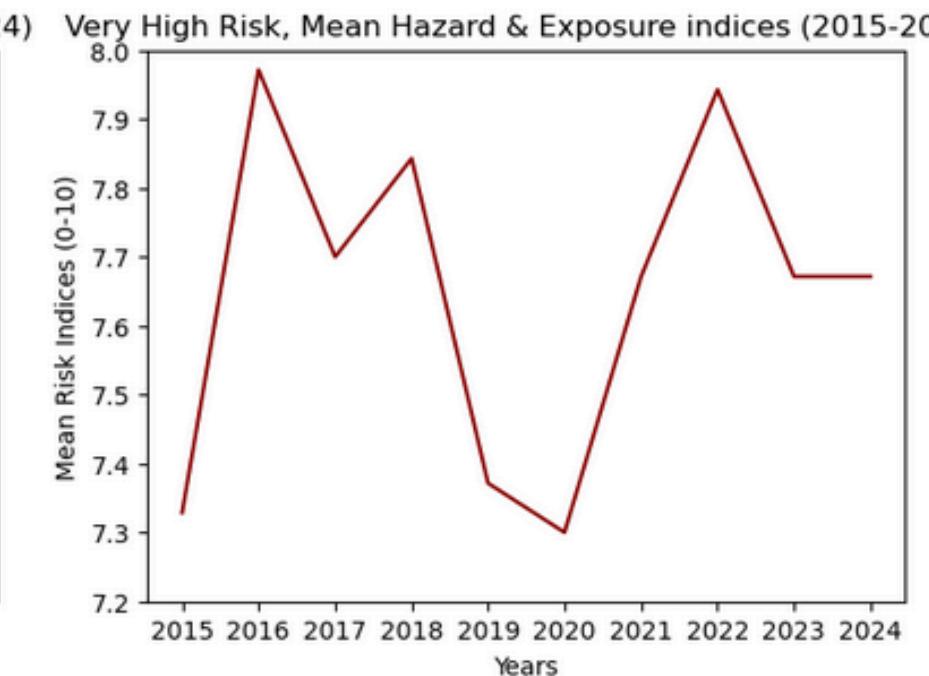
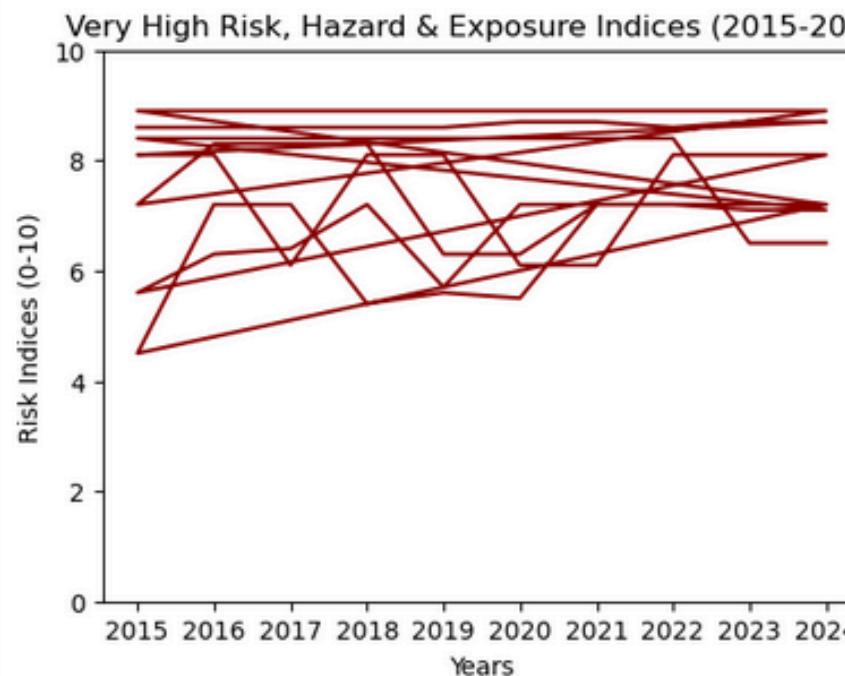
	coef	std err	z	P> z	[0.025	0.975]
ar.L1	0.8114	0.057	14.253	0.000	0.700	0.923
ma.L1	-0.9861	0.014	-72.257	0.000	-1.013	-0.959
sigma2	1.0436	0.064	16.432	0.000	0.919	1.168

```
=====
Ljung-Box (L1) (Q): 0.28 Jarque-Bera (JB): 844.79
Prob(Q): 0.60 Prob(JB): 0.00
Heteroskedasticity (H): 1.19 Skew: -1.16
Prob(H) (two-sided): 0.37 Kurtosis: 10.76
=====
```

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).

ARIMA Model to forecast Very High Risk Countries' Hazard & Exposure Risk indices:

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Mean Squared Error (MSE): 1.460450256613416
 Mean Absolute Error (MAE): 1.1733704281047608
 Root Mean Squared Error (RMSE): 1.20849090050915

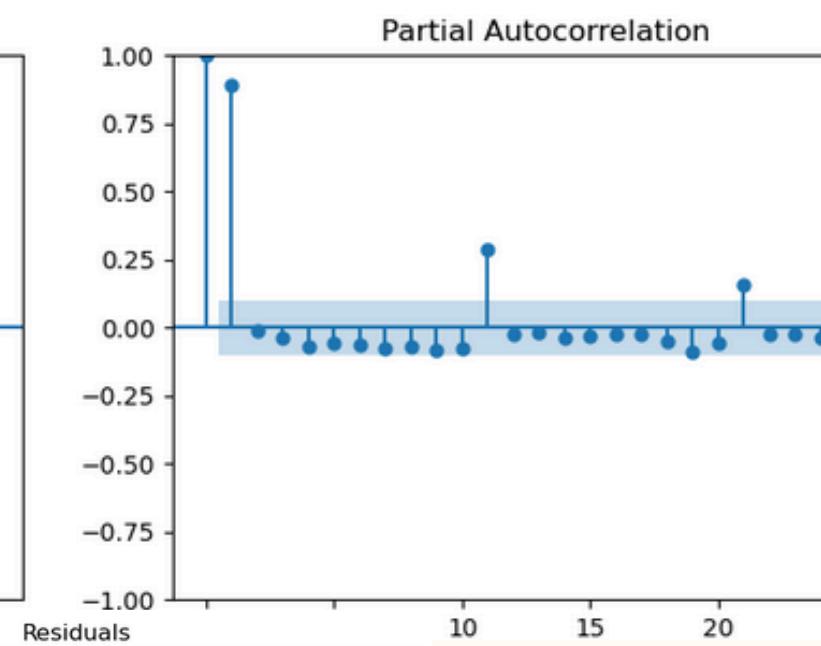
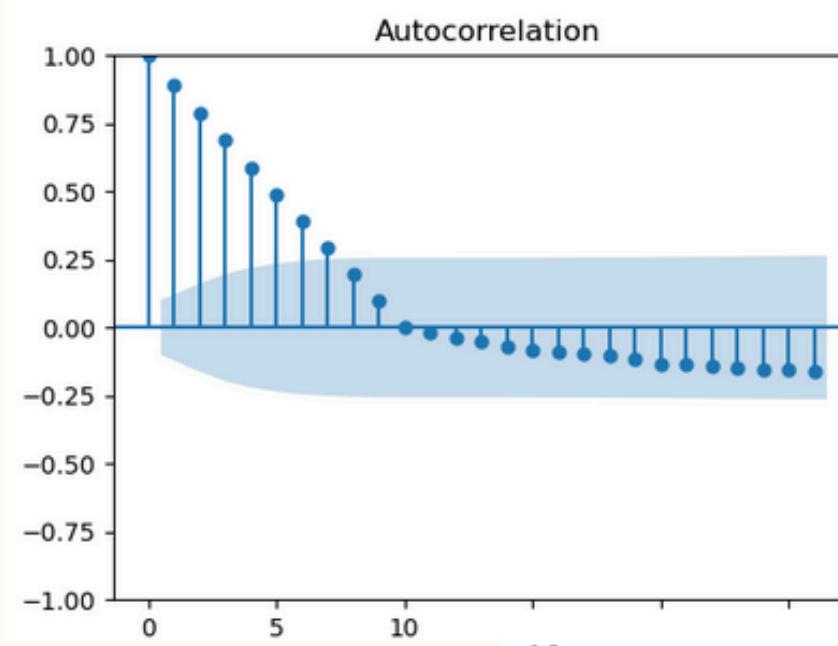
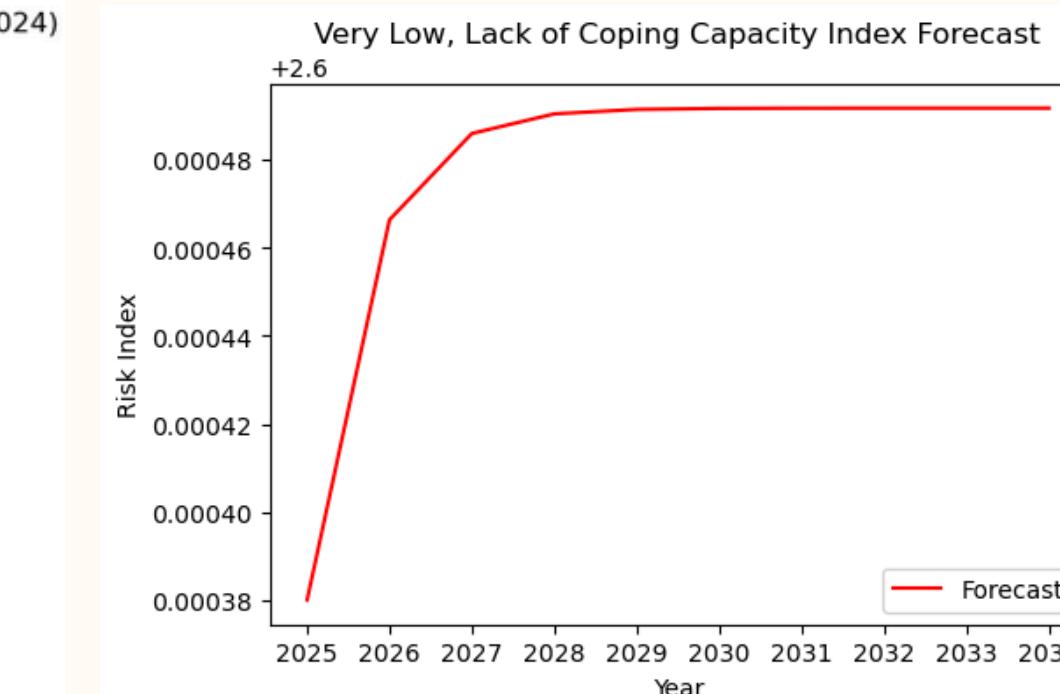
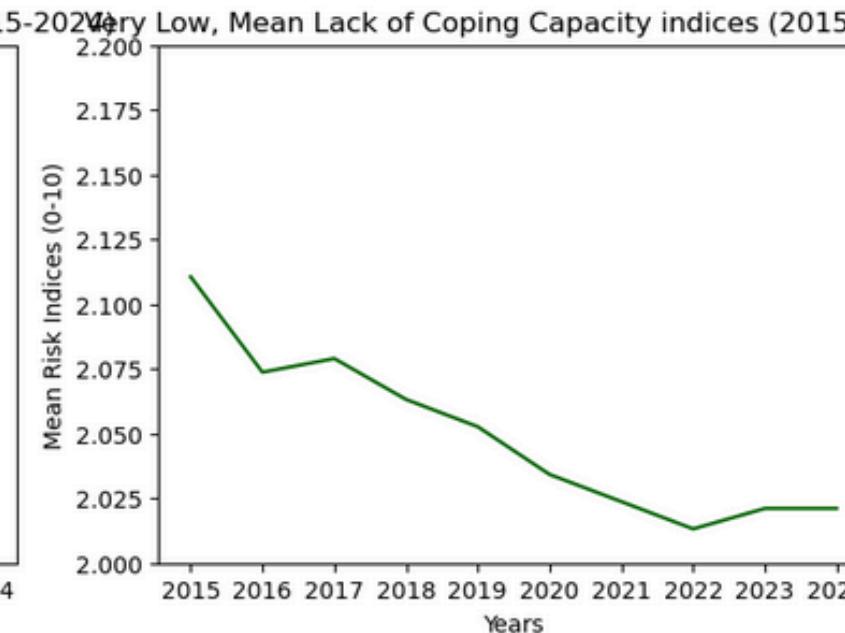
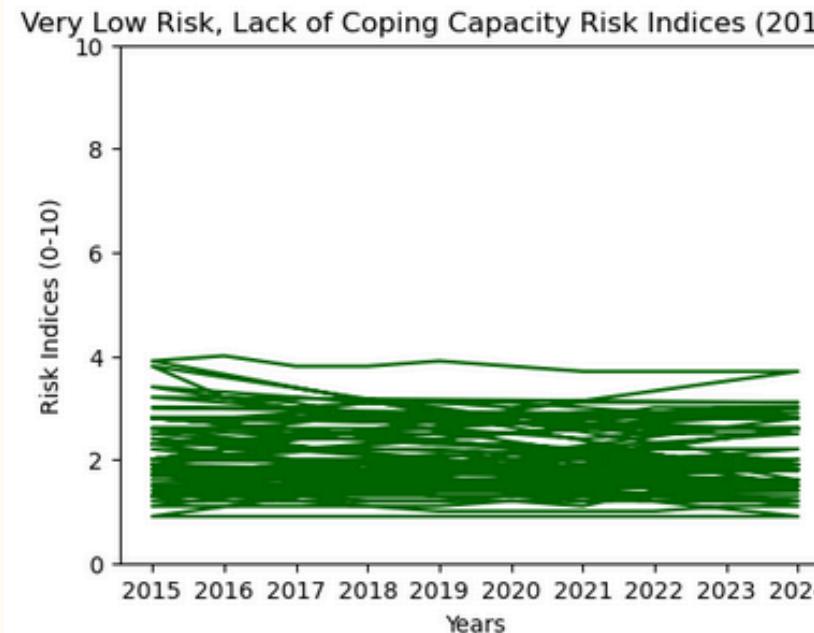
SARIMAX Results						
Dep. Variable:	Hazard & Exposure Index	No. Observations:	70			
Model:	ARIMA(1, 1, 1)	Log Likelihood	-90.340			
Date:	Mon, 08 Apr 2024	AIC	186.679			
Time:		BIC	193.382			
Sample:	0 - 70	HQIC	189.338			
Covariance Type:	opg					
	coef	std err	z	P> z	[0.025	0.975]
ar.L1	0.1684	0.349	0.483	0.629	-0.515	0.852
ma.L1	-0.6062	0.294	-2.060	0.039	-1.183	-0.029
sigma2	0.7999	0.111	7.204	0.000	0.582	1.018
Ljung-Box (L1) (Q):	0.01	Jarque-Bera (JB):	12.62			
Prob(Q):	0.92	Prob(JB):	0.00			
Heteroskedasticity (H):	1.17	Skew:	-0.89			
Prob(H) (two-sided):	0.71	Kurtosis:	4.12			

Warnings:

[1] Covariance matrix calculated using the outer product of gradients (complex-step).

ARIMA Model to forecast Very Low Risk Countries' Lack of Coping Capacity Risk indices:

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Mean Squared Error (MSE): 0.02188798625536835
 Mean Absolute Error (MAE): 0.11981774778535566
 Root Mean Squared Error (RMSE): 0.14794588961971317

SARIMAX Results

```

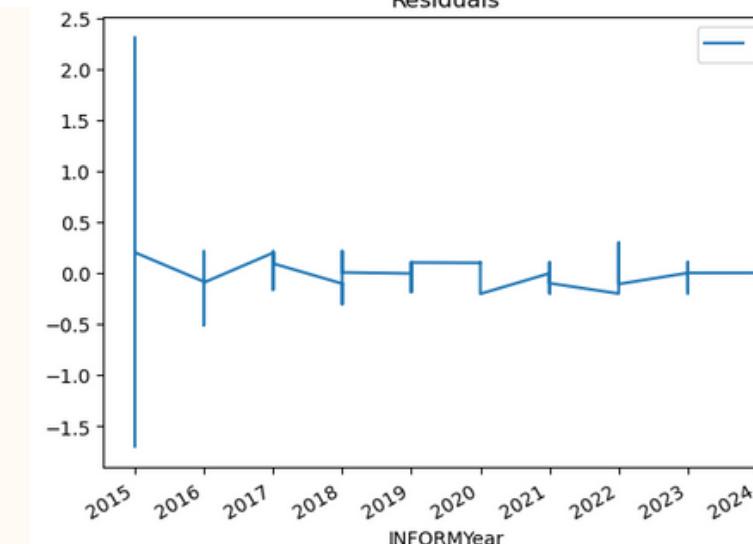
Dep. Variable: Lack of Coping Capacity Index   No. Observations: 380
Model: ARIMA(1, 1, 1)                          Log Likelihood: -109.645
Date: Mon, 08 Apr 2024                         AIC: 225.289
Time: 04:12:57                                     BIC: 237.102
Sample: 0                                     HQIC: 229.977
                                                - 380
                                                opg
Covariance Type: opg

coef      std err      z      P>|z|      [0.025      0.975]
ar.L1      0.2271     2.833     0.080      0.936     -5.326      5.780
ma.L1     -0.2742     2.823    -0.097      0.923     -5.807      5.258
sigma2     0.1044     0.002    46.574      0.000      0.100      0.109

```

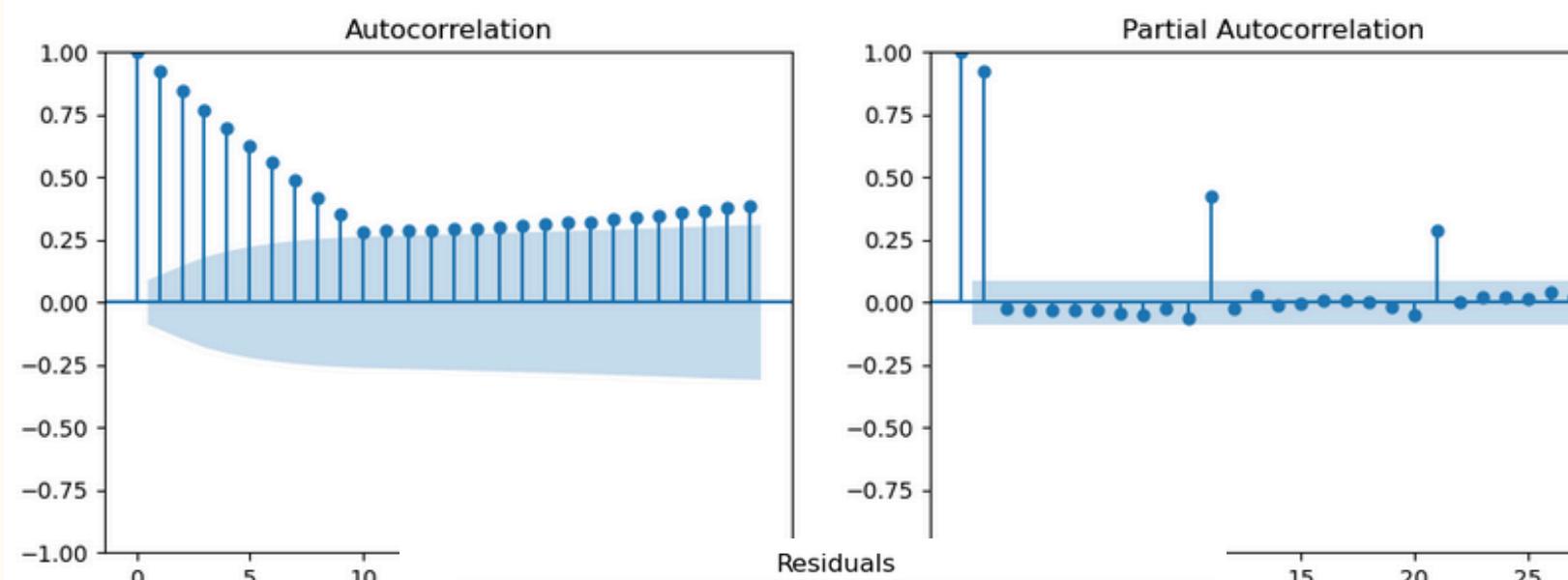
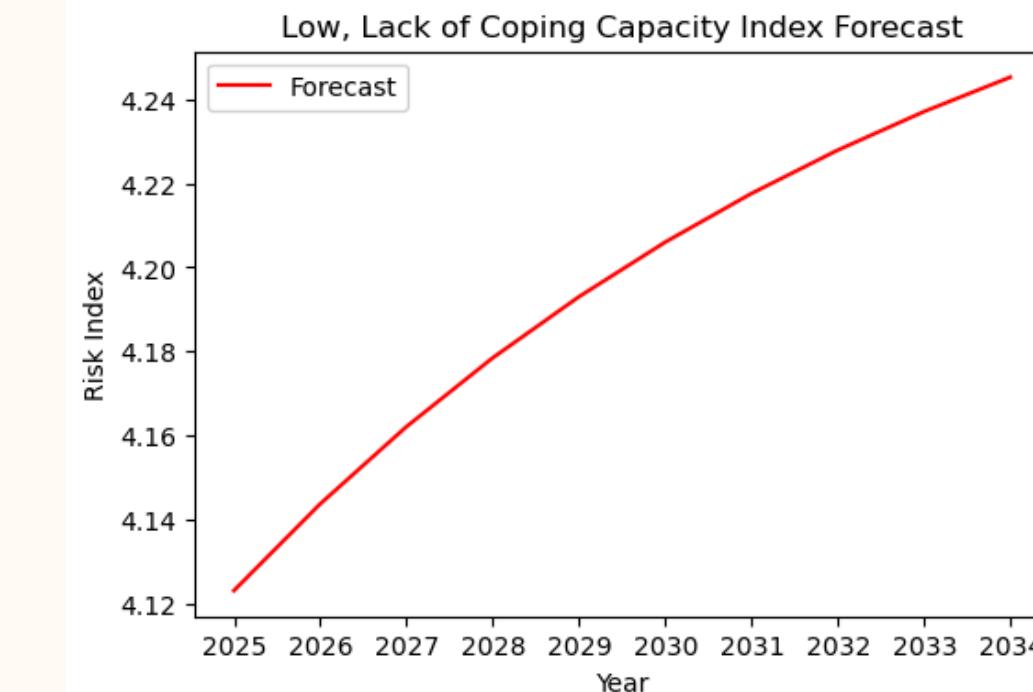
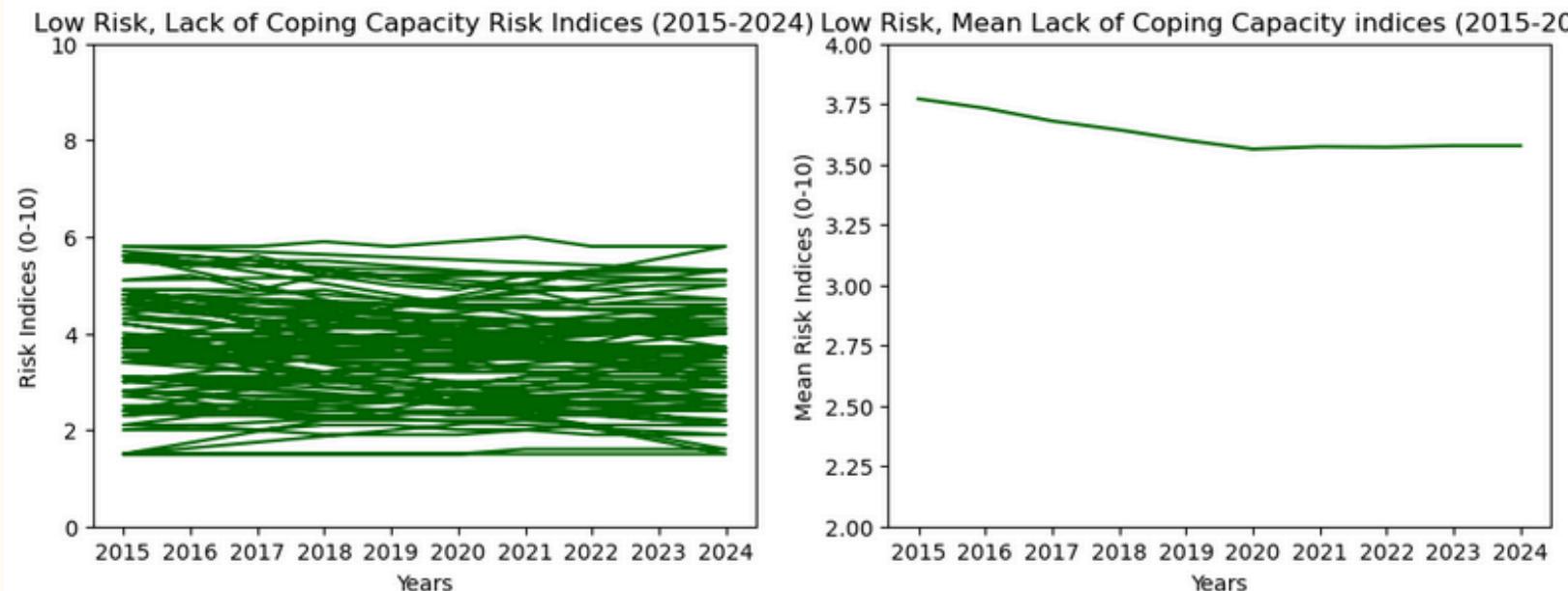
Ljung-Box (L1) (Q): 0.00 Jarque-Bera (JB): 6981.63
 Prob(Q): 0.99 Prob(JB): 0.00
 Heteroskedasticity (H): 1.87 Skew: 1.16
 Prob(H) (two-sided): 0.00 Kurtosis: 23.90

Warnings:
 [1] Covariance matrix calculated using the outer product of gradients (complex-step).



ARIMA Model to forecast Low Risk Countries' Lack of Coping Capacity Risk indices:

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Mean Squared Error (MSE): 0.018059835212866686
 Mean Absolute Error (MAE): 0.12145136003107489
 Root Mean Squared Error (RMSE): 0.1343868863128642

SARIMAX Results

```
=====
Dep. Variable: Lack of Coping Capacity Index No. Observations: 490
Model: ARIMA(1, 1, 1) Log Likelihood: -250.870
Date: Tue, 09 Apr 2024 AIC: 507.741
Time: 00:12:24 BIC: 520.318
Sample: 0 HQIC: 512.681
- 490
Covariance Type: opg
=====
```

	coef	std err	z	P> z	[0.025	0.975]
ar.L1	0.8909	0.044	20.217	0.000	0.805	0.977
ma.L1	-0.9846	0.012	-85.518	0.000	-1.007	-0.962
sigma2	0.1631	0.006	28.778	0.000	0.152	0.174

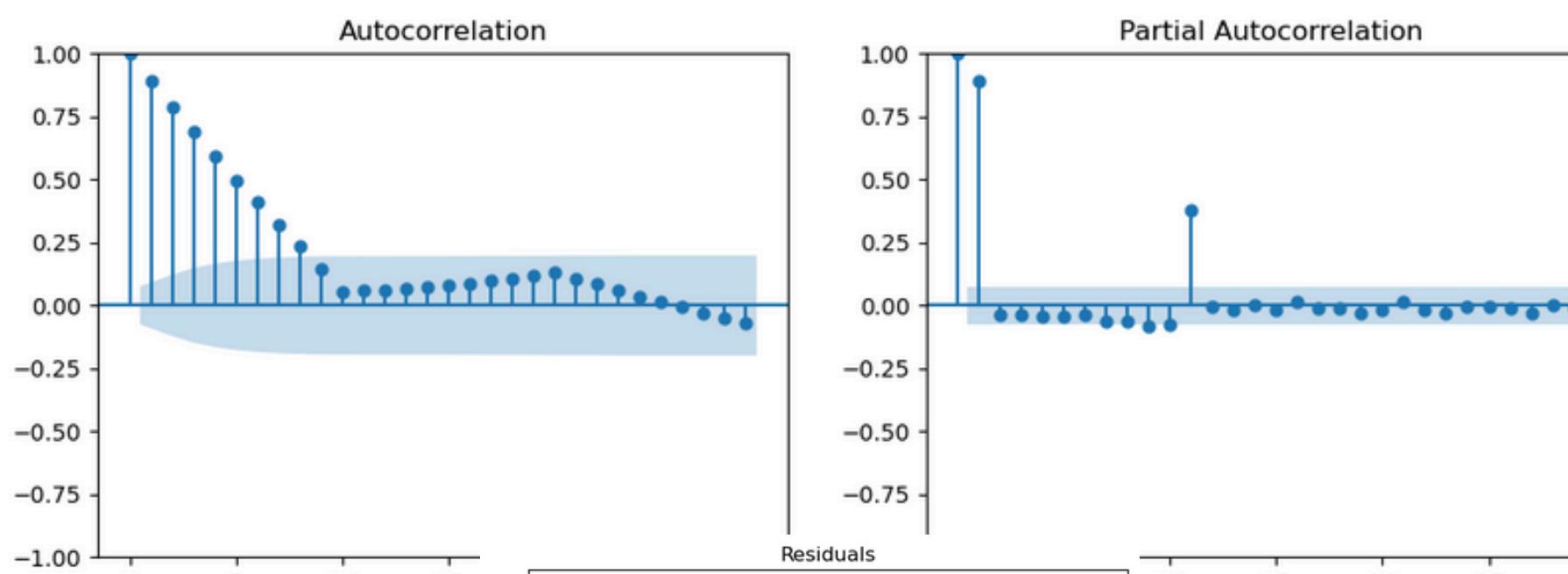
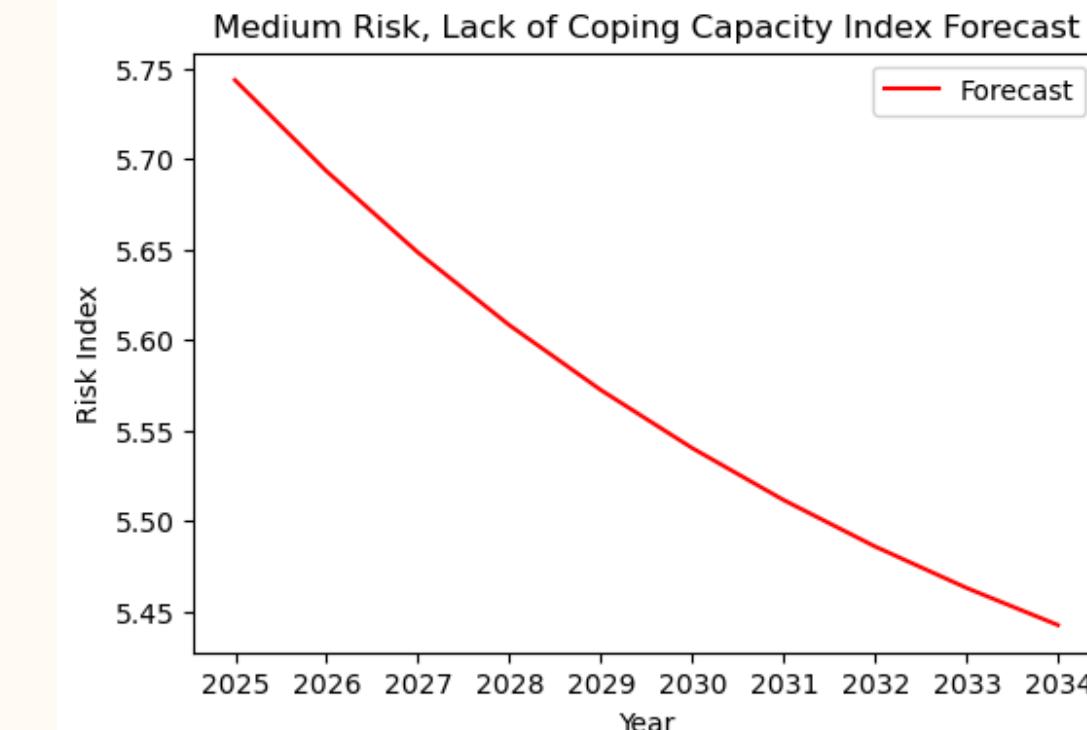
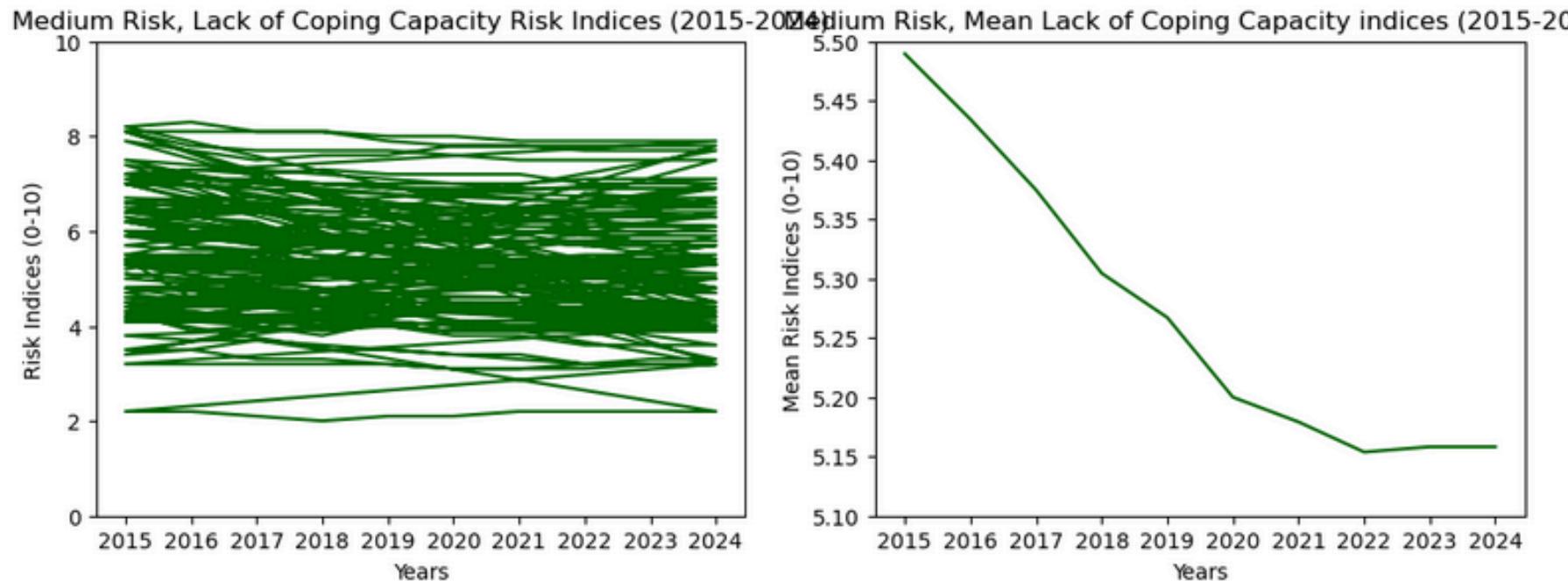
```
=====
Ljung-Box (L1) (Q): 0.64 Jarque-Bera (JB): 5350.98
Prob(Q): 0.42 Prob(JB): 0.00
Heteroskedasticity (H): 1.18 Skew: 1.19
Prob(H) (two-sided): 0.28 Kurtosis: 19.03
=====
```

Warnings:

[1] Covariance matrix calculated using the outer product of gradients (complex-step).

ARIMA Model to forecast Medium Risk Countries' Lack of Coping Capacity Risk indices:

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Mean Squared Error (MSE): 0.06385586356543467
 Mean Absolute Error (MAE): 0.23913521617474282
 Root Mean Squared Error (RMSE): 0.252697177596891

SARIMAX Results

```
=====
Dep. Variable: Lack of Coping Capacity Index No. Observations: 670
Model: ARIMA(1, 1, 1) Log Likelihood: -579.502
Date: Mon, 08 Apr 2024 AIC: 1165.005
Time: 04:25:06 BIC: 1178.522
Sample: 0 - 670 HQIC: 1170.241
Covariance Type: opg
=====
```

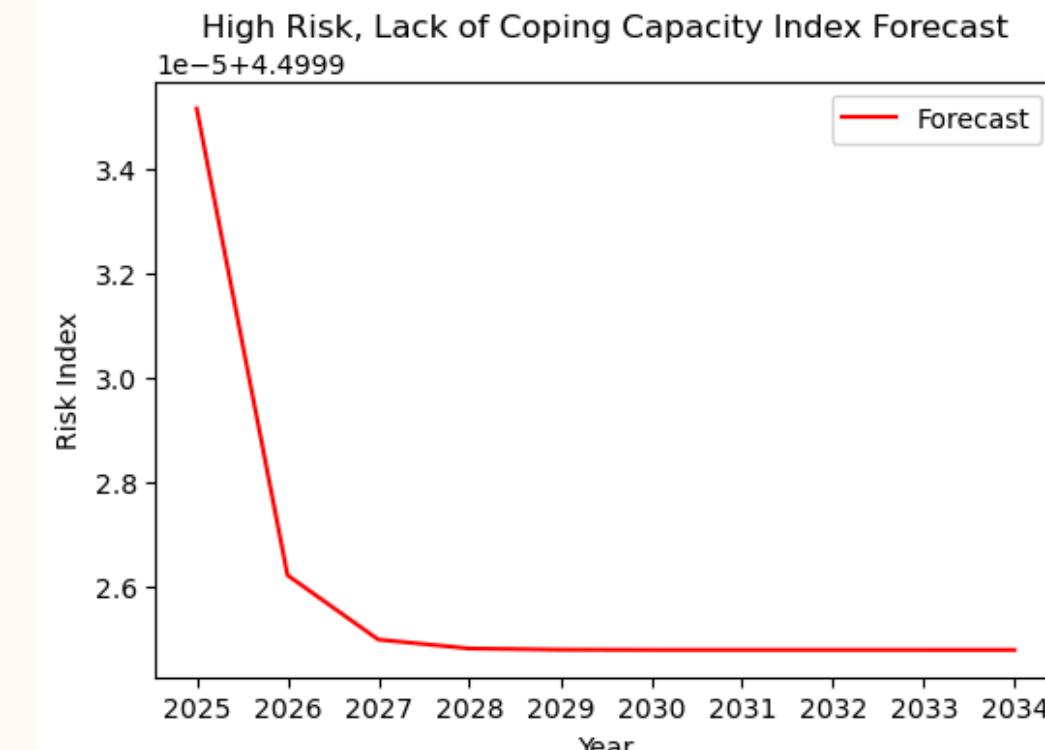
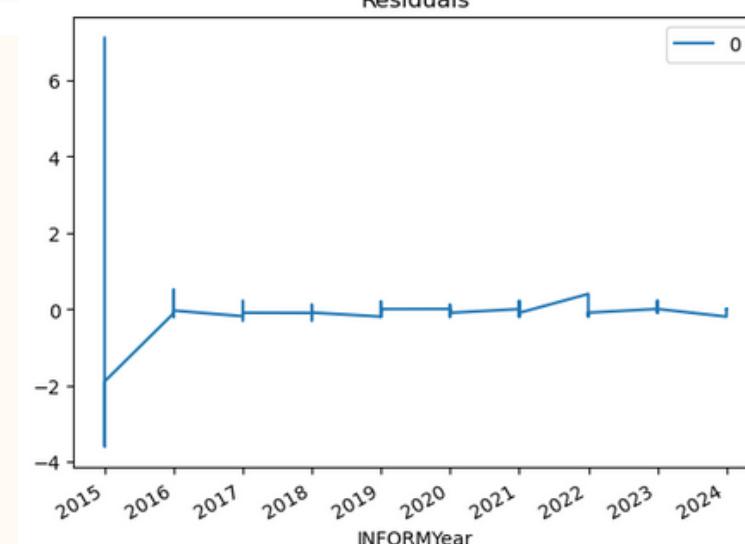
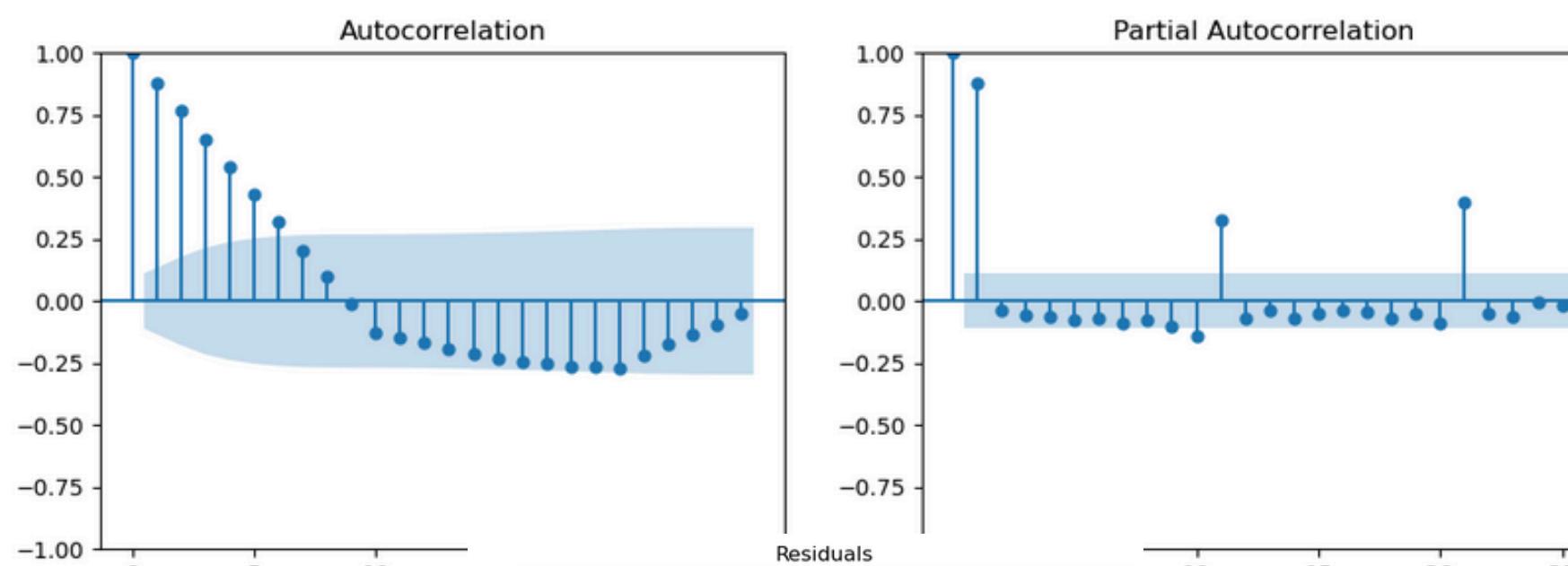
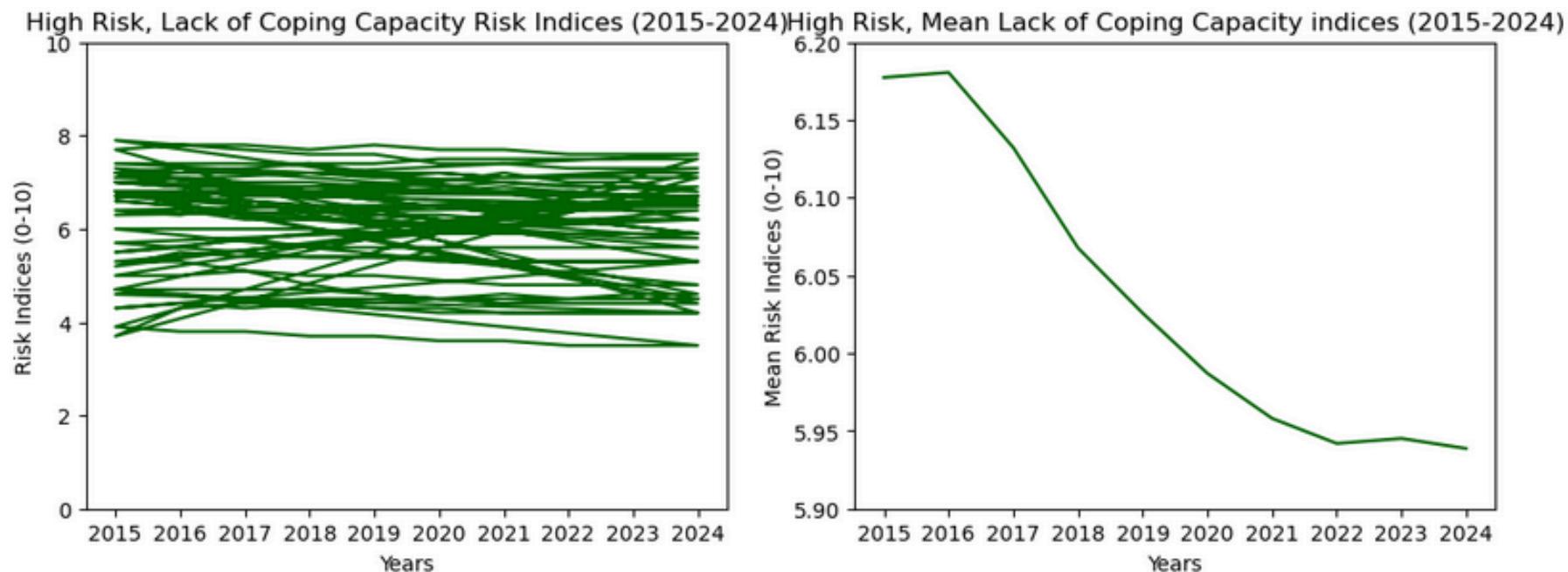
	coef	std err	z	P> z	[0.025	0.975]
ar.L1	0.8941	0.031	29.019	0.000	0.834	0.954
ma.L1	-1.0000	0.462	-2.167	0.030	-1.905	-0.095
sigma2	0.3293	0.149	2.212	0.027	0.038	0.621

```
=====
Ljung-Box (L1) (Q): 0.68 Jarque-Bera (JB): 11232.73
Prob(Q): 0.41 Prob(JB): 0.00
Heteroskedasticity (H): 0.96 Skew: 2.04
Prob(H) (two-sided): 0.74 Kurtosis: 22.66
=====
```

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).

ARIMA Model to forecast High Risk Countries' Lack of Coping Capacity Risk indices:

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Mean Squared Error (MSE): 0.09702738443573523
 Mean Absolute Error (MAE): 0.21005897588719077
 Root Mean Squared Error (RMSE): 0.31149219000760714

SARIMAX Results

```
=====
Dep. Variable: Lack of Coping Capacity Index No. Observations: 310
Model: ARIMA(1, 1, 1) Log Likelihood: -247.462
Date: Mon, 08 Apr 2024 AIC: 500.924
Time: 04:28:24 BIC: 512.124
Sample: 0 HQIC: 505.401
- 310
Covariance Type: opg
=====
```

	coef	std err	z	P> z	[0.025	0.975]
ar.L1	0.1380	8.637	0.016	0.987	-16.790	17.066
ma.L1	-0.1672	8.626	-0.019	0.985	-17.074	16.740
sigma2	0.2905	0.007	43.221	0.000	0.277	0.304

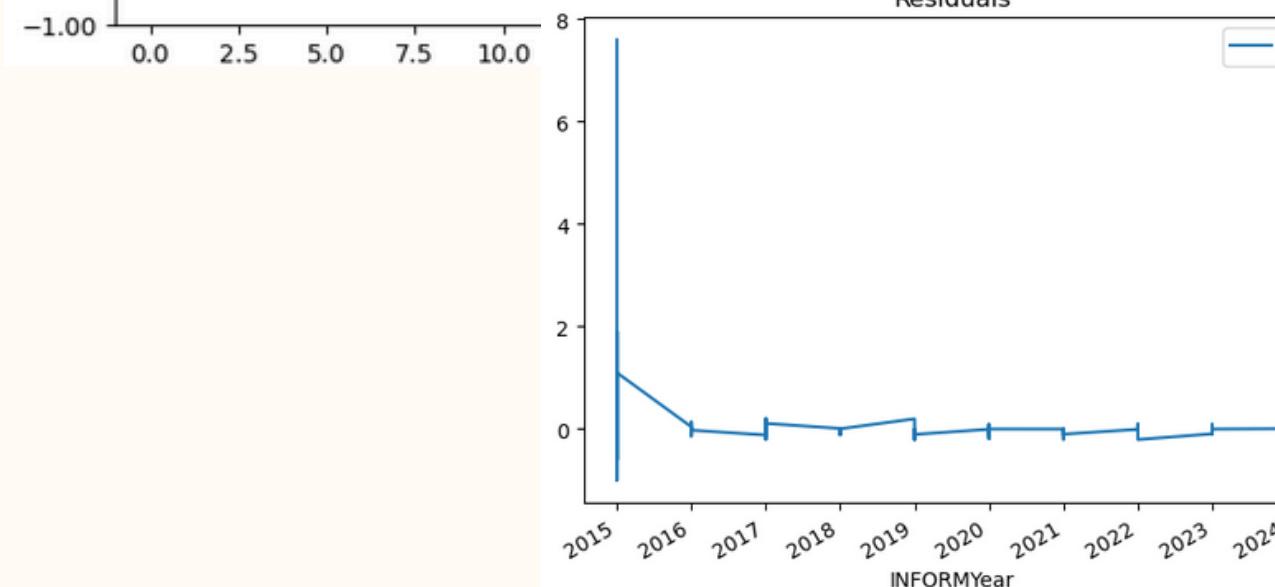
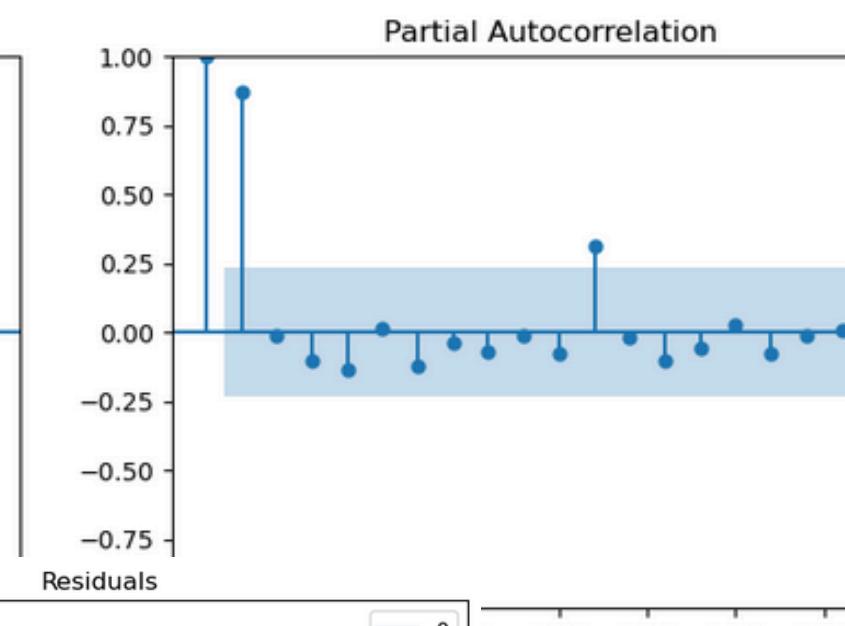
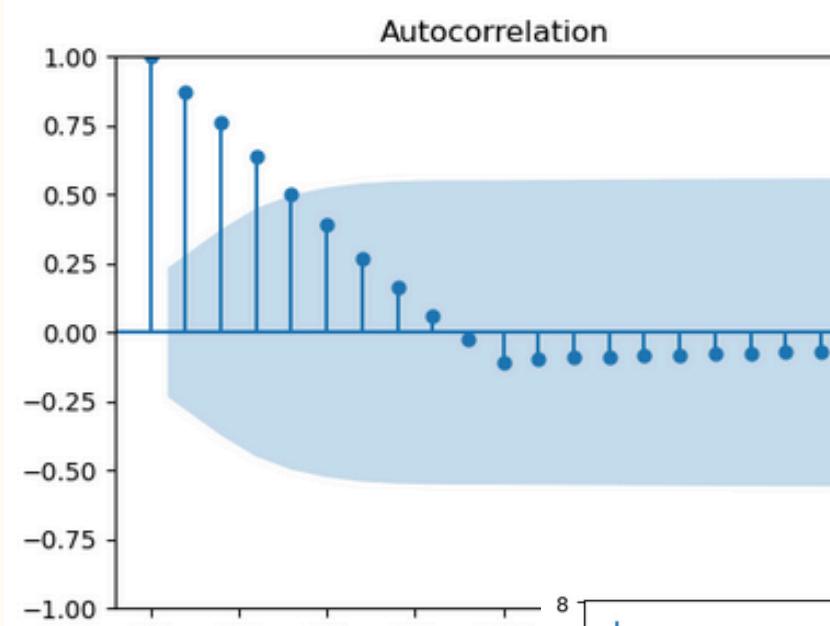
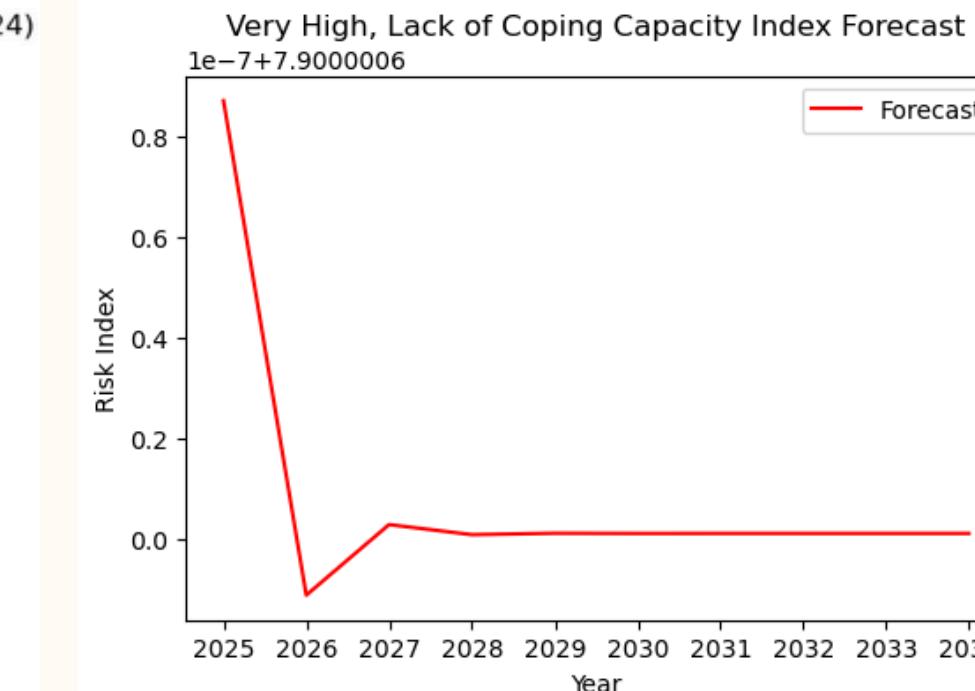
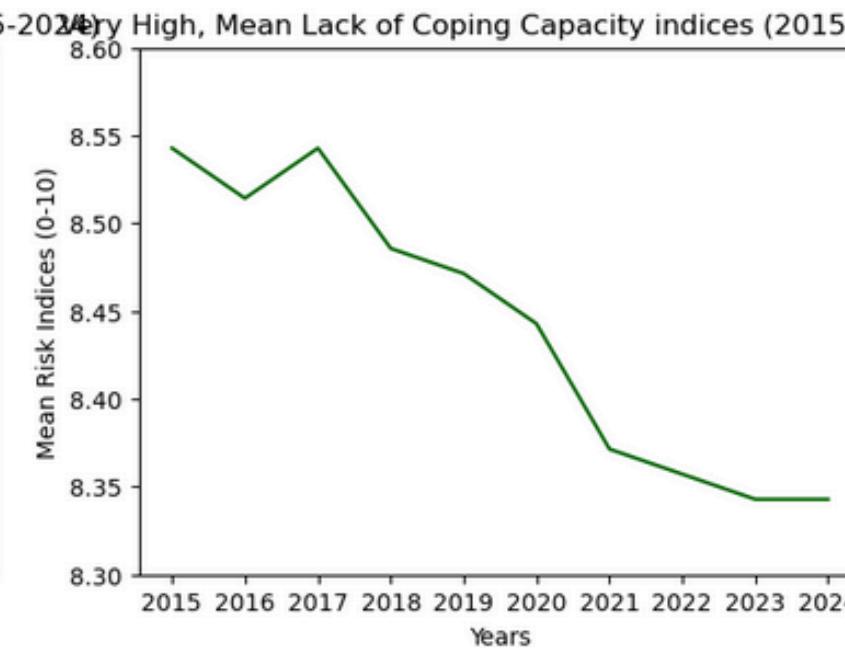
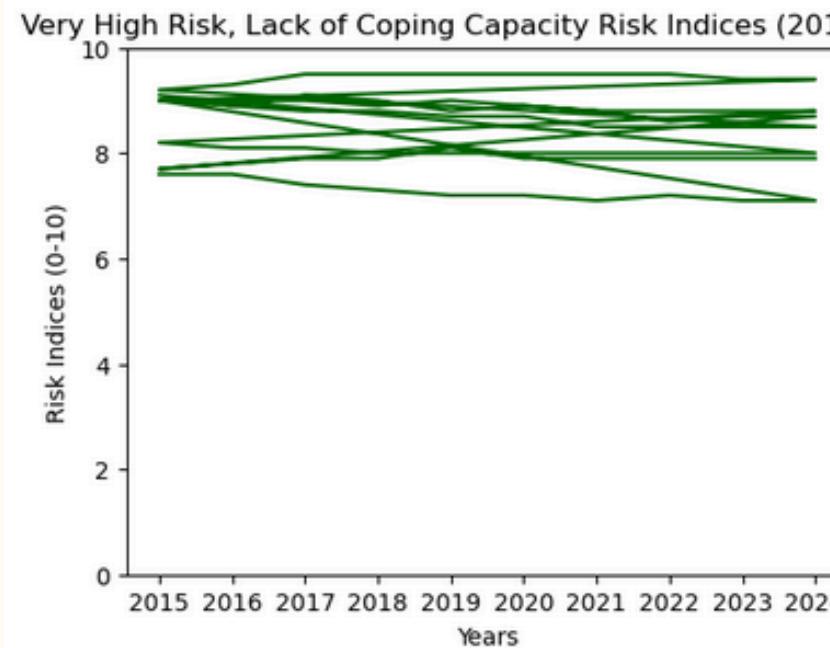
Ljung-Box (L1) (Q): 0.00 Jarque-Bera (JB): 6341.06
 Prob(Q): 1.00 Prob(JB): 0.00
 Heteroskedasticity (H): 0.79 Skew: -0.10
 Prob(H) (two-sided): 0.24 Kurtosis: 25.19

Warnings:

[1] Covariance matrix calculated using the outer product of gradients (complex-step).

ARIMA Model to forecast Very High Risk Countries' Lack of Coping Capacity Risk indices:

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Mean Squared Error (MSE): 0.009000015210840626
 Mean Absolute Error (MAE): 0.05000048846028733
 Root Mean Squared Error (RMSE): 0.09486840997318668

SARIMAX Results

Dep. Variable:	Lack of Coping Capacity Index	No. Observations:	70
Model:	ARIMA(1, 1, 1)	Log Likelihood	-20.815
Date:	Mon, 08 Apr 2024	AIC	47.630
Time:	04:31:05	BIC	54.333
Sample:	0 - 70	HQIC	50.290
Covariance Type:	opg		

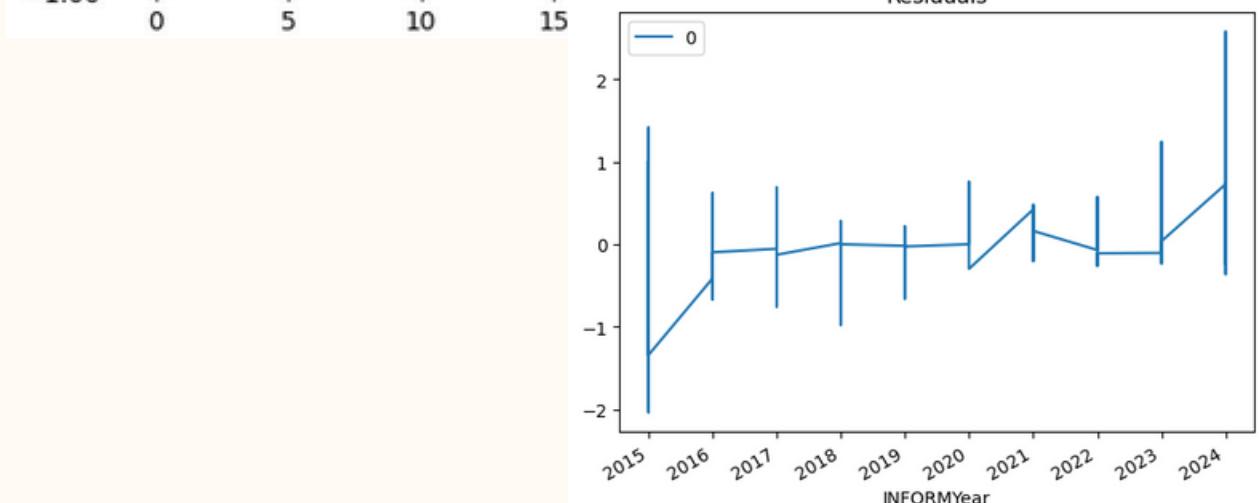
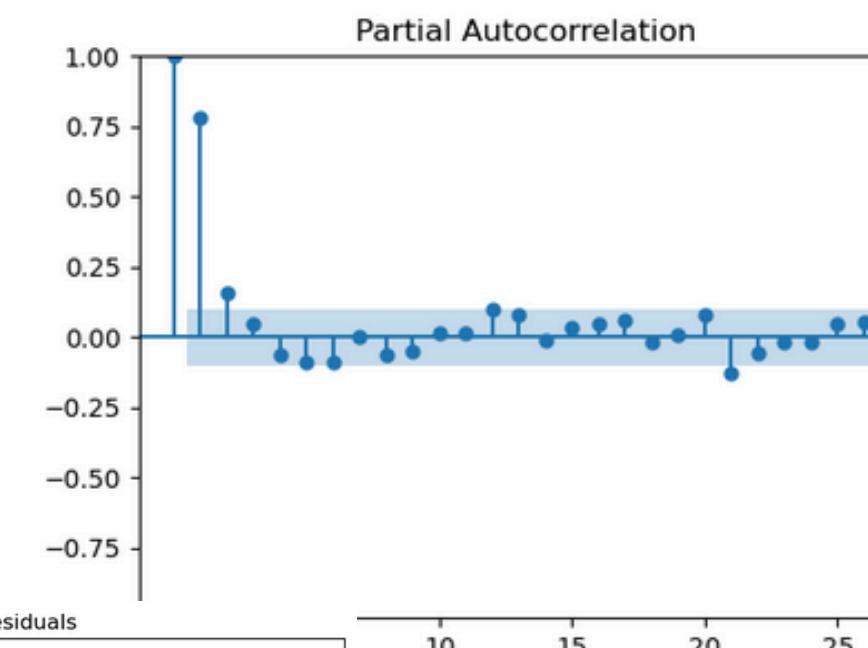
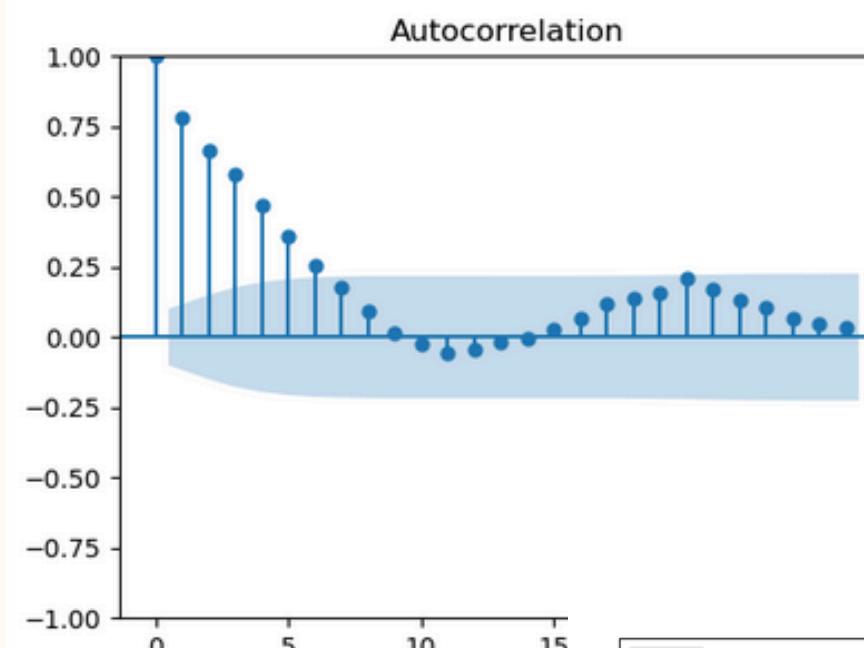
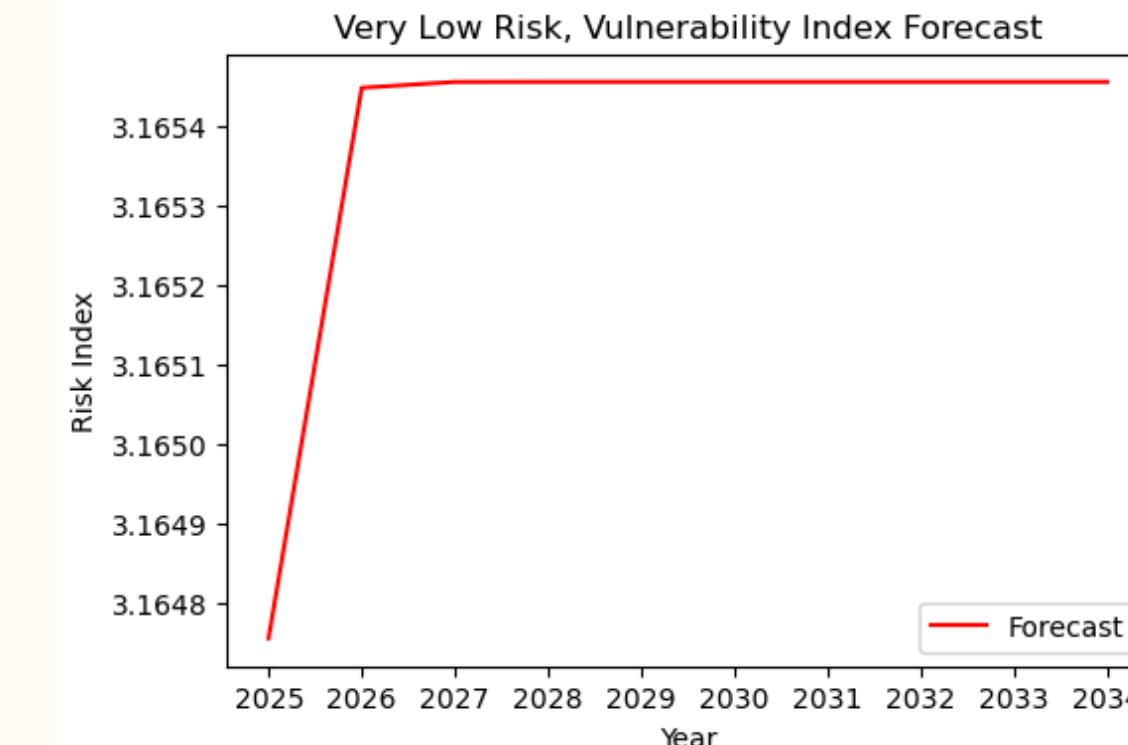
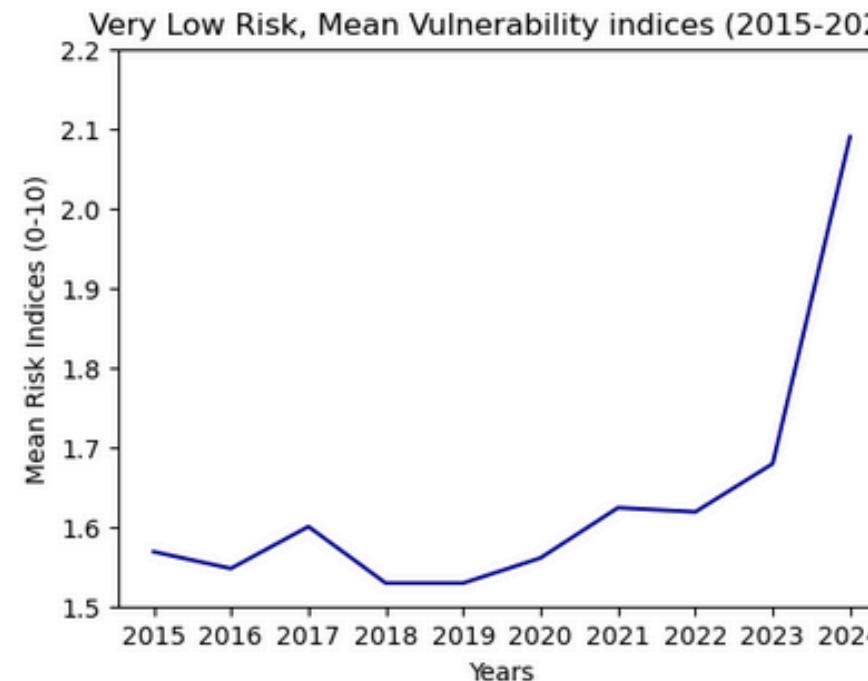
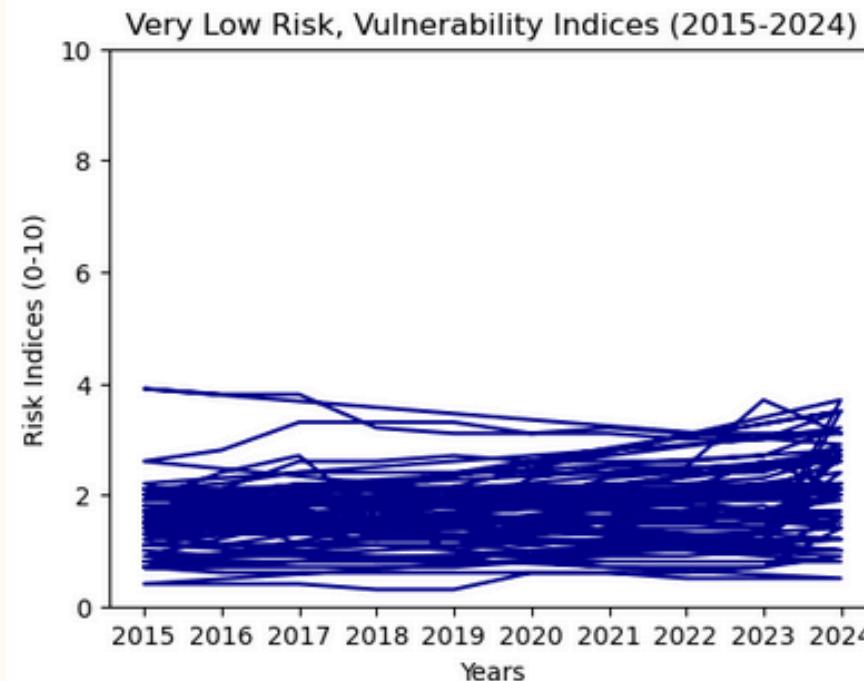
	coef	std err	z	P> z	[0.025	0.975]
ar.L1	-0.1428	4.400	-0.032	0.974	-8.767	8.482
ma.L1	0.0866	4.503	0.019	0.985	-8.739	8.913
sigma2	0.1070	0.007	15.921	0.000	0.094	0.120

Ljung-Box (L1) (Q): 0.00 Jarque-Bera (JB): 929.51
 Prob(Q): 1.00 Prob(JB): 0.00
 Heteroskedasticity (H): 0.32 Skew: 2.95
 Prob(H) (two-sided): 0.01 Kurtosis: 19.98

Warnings:
 [1] Covariance matrix calculated using the outer product of gradients (complex-step).

ARIMA Model to forecast Very Low Risk Countries' Vulnerability Risk indices:

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Mean Squared Error (MSE): 1.583103628619634
 Mean Absolute Error (MAE): 1.1122929107320618
 Root Mean Squared Error (RMSE): 1.2582144605033094

SARIMAX Results

```

=====
Dep. Variable:      Vulnerability Index   No. Observations:             380
Model:                  ARIMA(1, 1, 1)    Log Likelihood:          -223.279
Date: Mon, 08 Apr 2024   AIC:                 452.558
Time: 04:36:06           BIC:                 464.371
Sample:                0 - 380            HQIC:                 457.246
Covariance Type:         opg
=====
```

	coef	std err	z	P> z	[0.025	0.975]
ar.L1	0.0107	0.202	0.053	0.958	-0.385	0.406
ma.L1	-0.3079	0.205	-1.505	0.132	-0.709	0.093
sigma2	0.1902	0.006	29.751	0.000	0.178	0.203

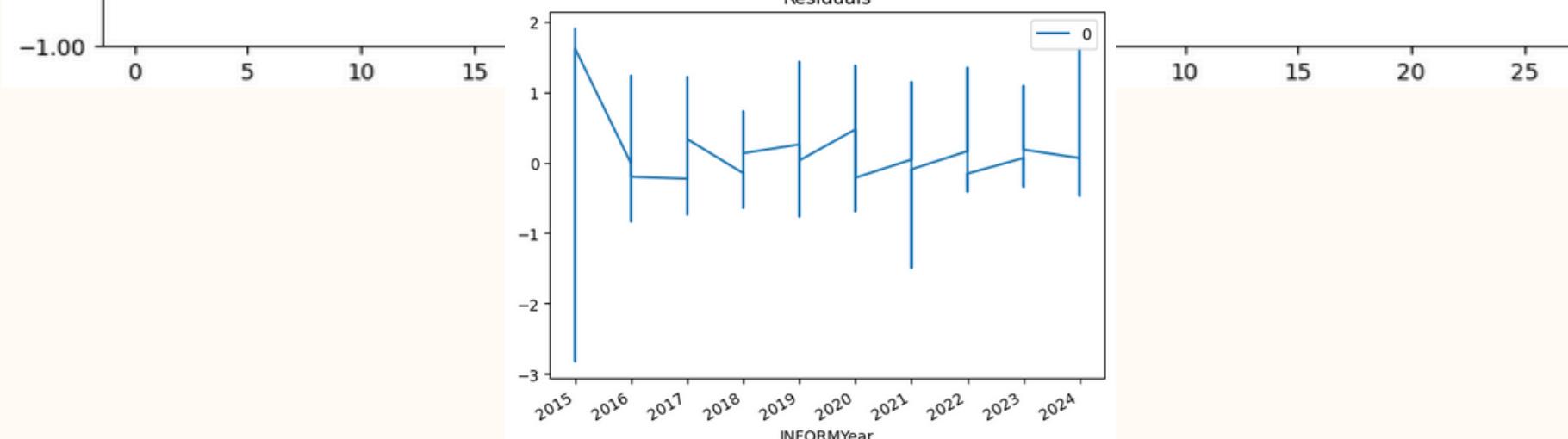
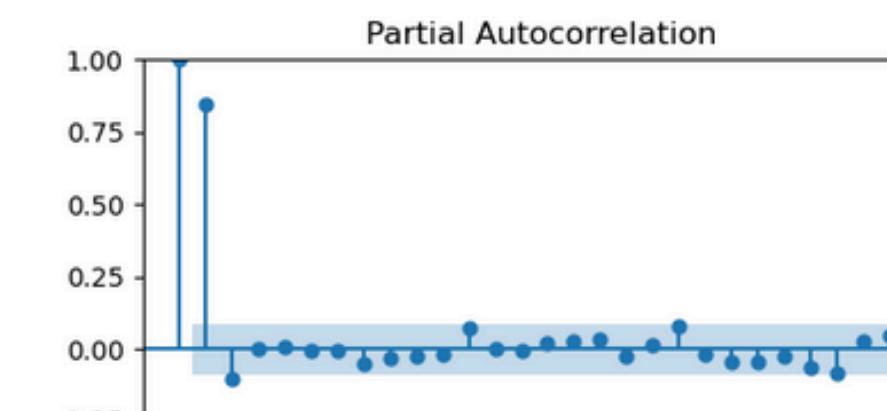
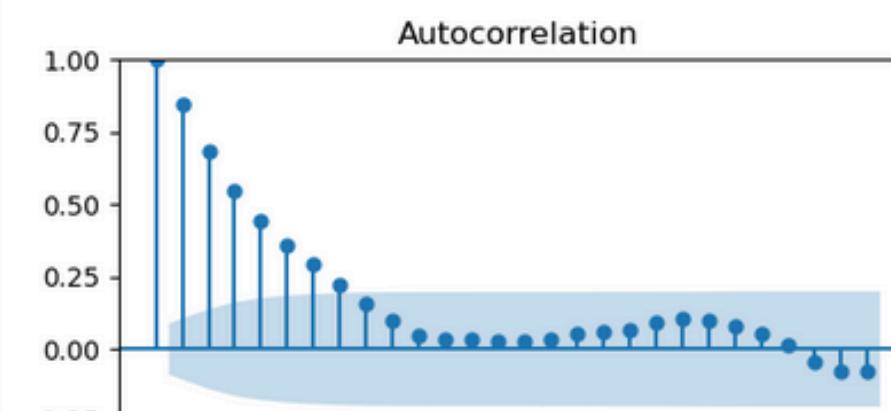
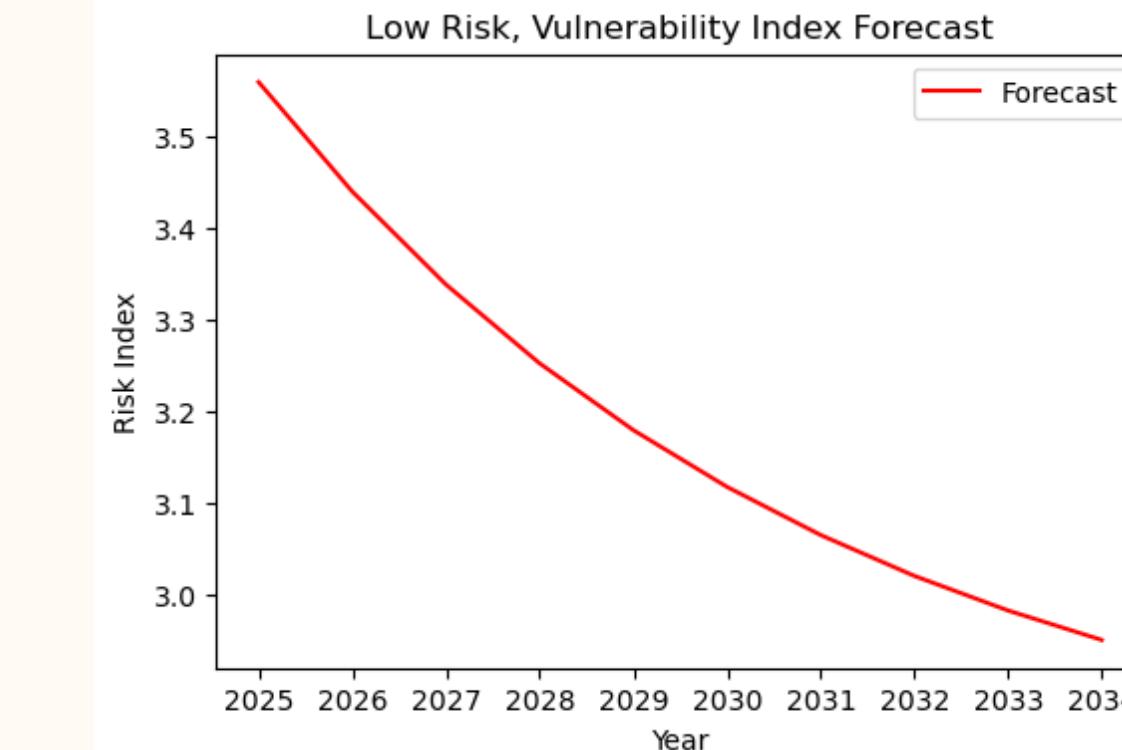
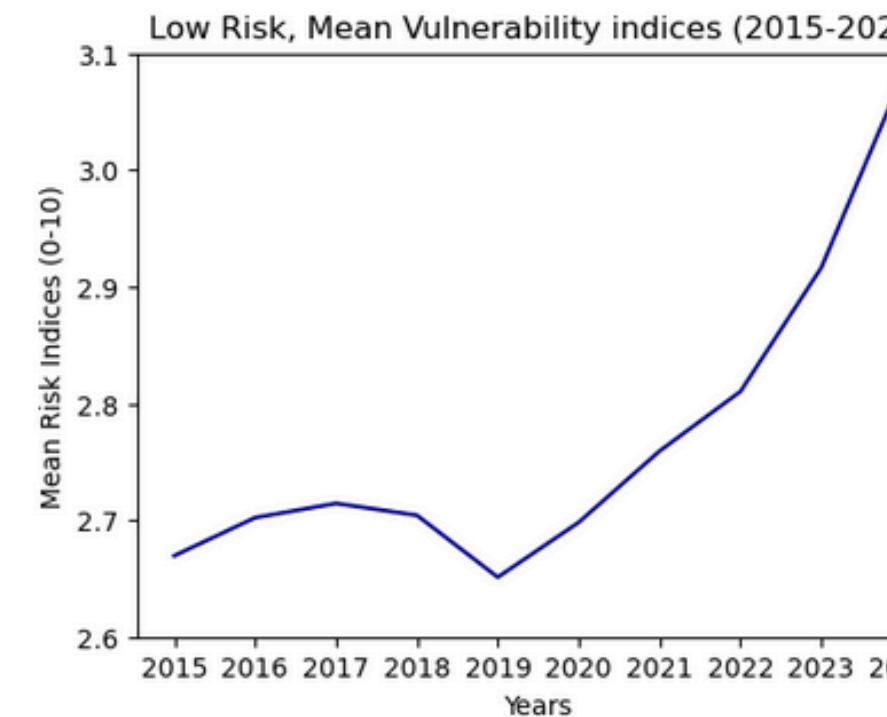
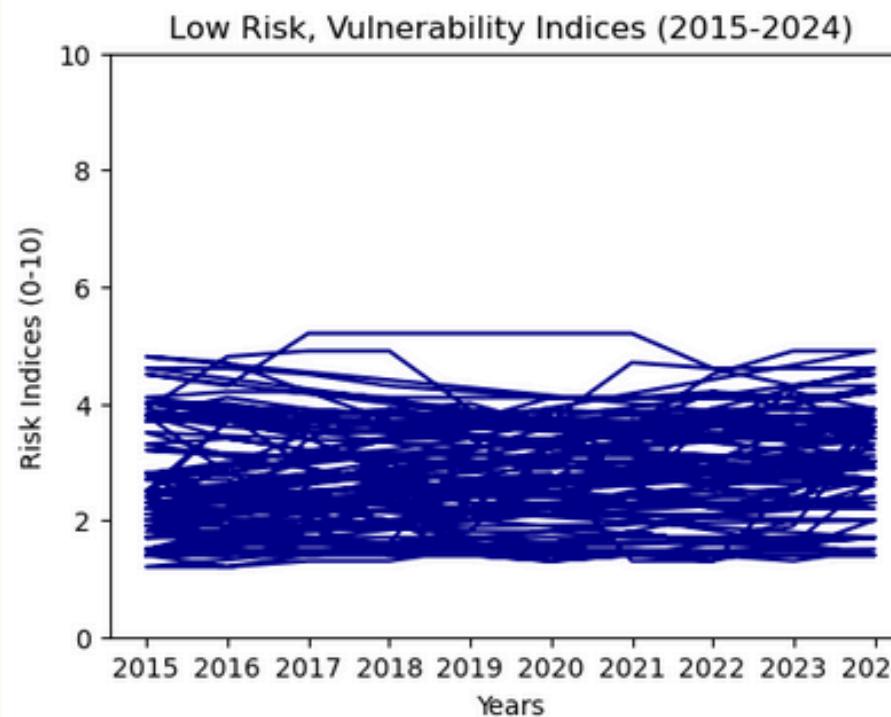
```

=====
Ljung-Box (L1) (Q):                   0.00   Jarque-Bera (JB):       1404.91
Prob(Q):                           0.98   Prob(JB):               0.00
Heteroskedasticity (H):              1.22   Skew:                  0.40
Prob(H) (two-sided):                0.27   Kurtosis:              12.40
=====
```

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).

ARIMA Model to forecast Low Risk Countries' Vulnerability Risk indices:

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Mean Squared Error (MSE): 0.2795727269637688
 Mean Absolute Error (MAE): 0.4472900082770751
 Root Mean Squared Error (RMSE): 0.5287463730029444

SARIMAX Results

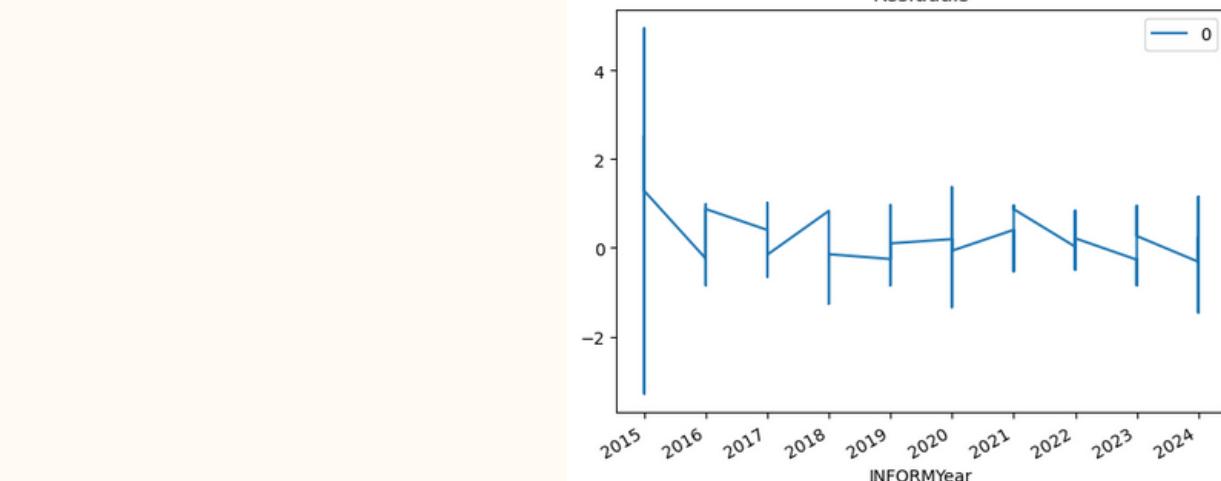
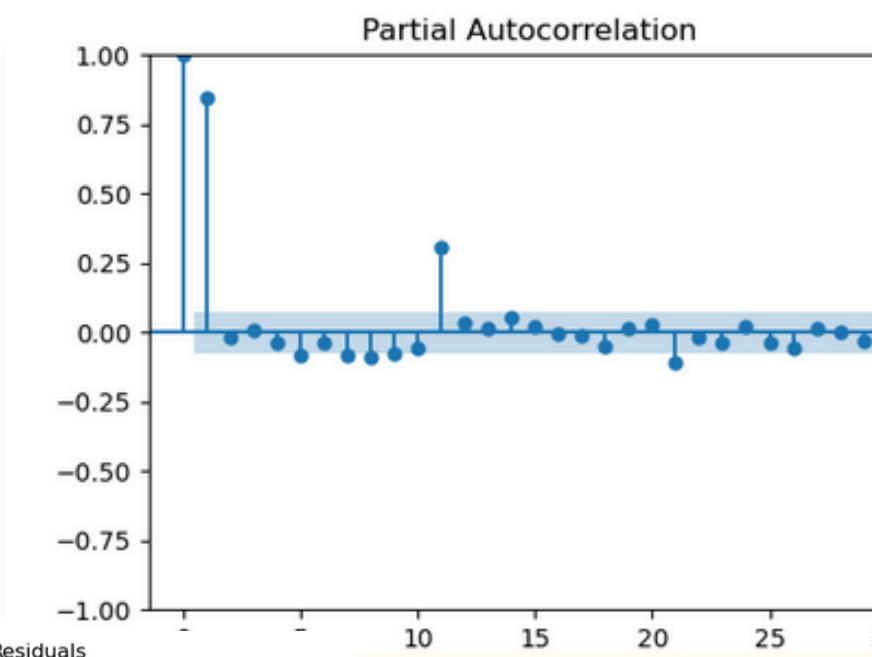
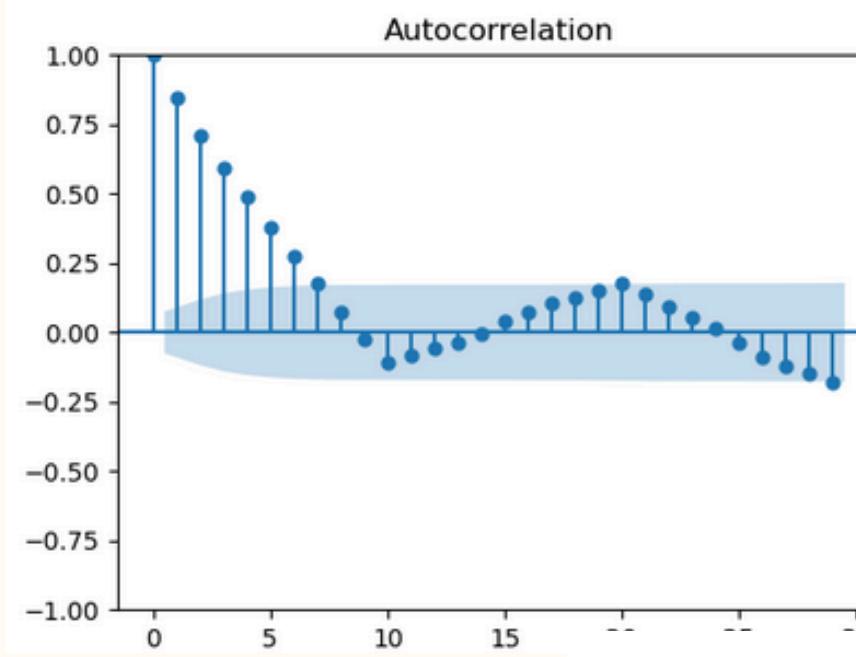
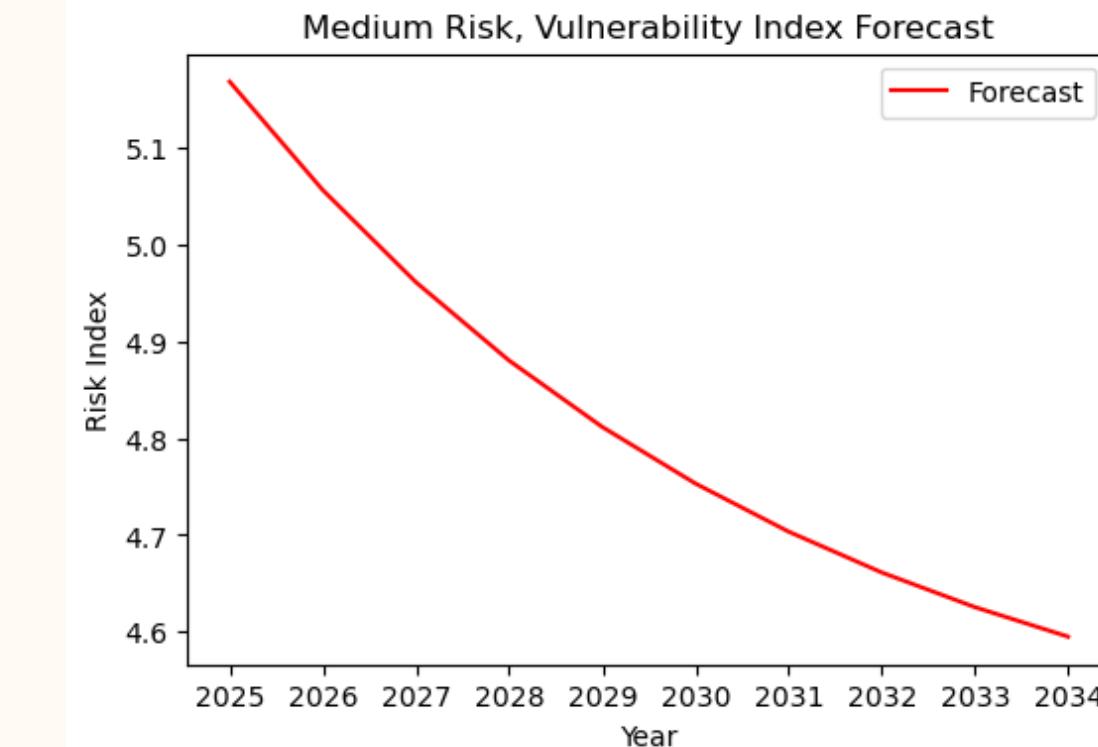
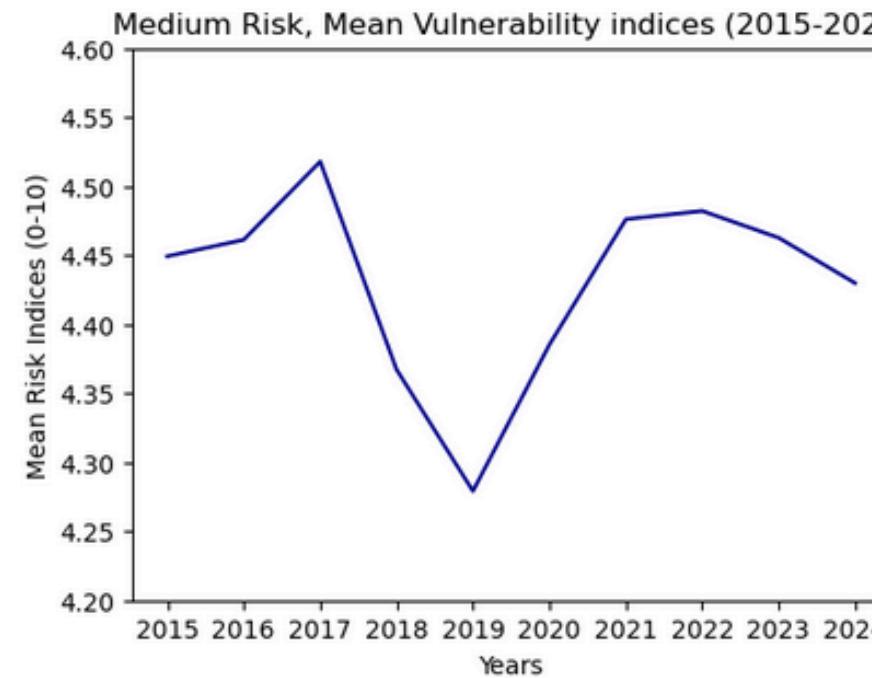
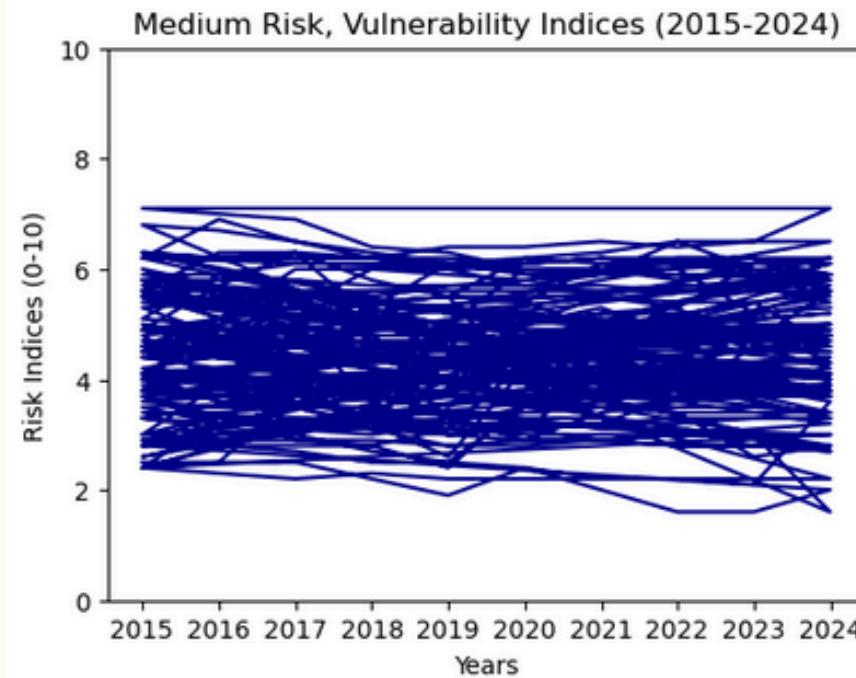
```
=====
Dep. Variable: Vulnerability Index No. Observations: 490
Model: ARIMA(1, 1, 1) Log Likelihood: -366.625
Date: Mon, 08 Apr 2024 AIC: 739.249
Time: 04:39:28 BIC: 751.826
Sample: 0 HQIC: 744.189
- 490
Covariance Type: opg
=====
```

	coef	std err	z	P> z	[0.025	0.975]
ar.L1	0.8486	0.032	26.797	0.000	0.787	0.911
ma.L1	-1.0000	3.983	-0.251	0.802	-8.806	6.806
sigma2	0.2603	1.037	0.251	0.802	-1.773	2.294

```
=====
Ljung-Box (L1) (Q): 3.27 Jarque-Bera (JB): 725.70
Prob(Q): 0.07 Prob(JB): 0.00
Heteroskedasticity (H): 1.39 Skew: -0.58
Prob(H) (two-sided): 0.03 Kurtosis: 8.85
=====
Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).
```

ARIMA Model to forecast Medium Risk Countries' Vulnerability Risk indices:

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Mean Squared Error (MSE): 0.8217599681280845
 Mean Absolute Error (MAE): 0.7820684905056288
 Root Mean Squared Error (RMSE): 0.906509772770313

=====
 Dep. Variable: Vulnerability Index No. Observations: 670
 Model: ARIMA(1, 1, 1) Log Likelihood: -633.906
 Date: Mon, 08 Apr 2024 AIC: 1273.813
 Time: 04:43:45 BIC: 1287.330
 Sample: 0 HQIC: 1279.049
 - 670
 Covariance Type: opg

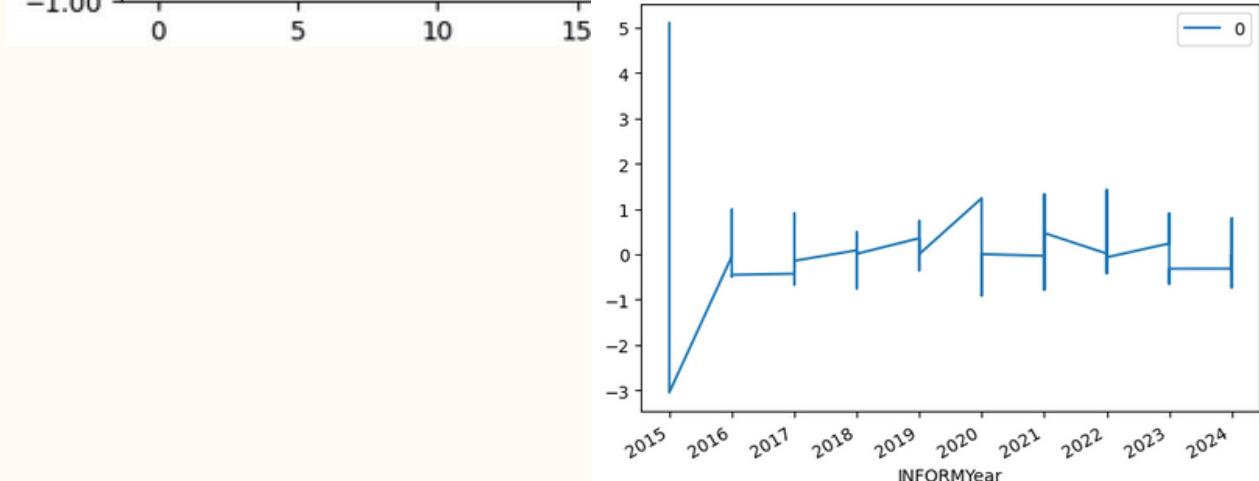
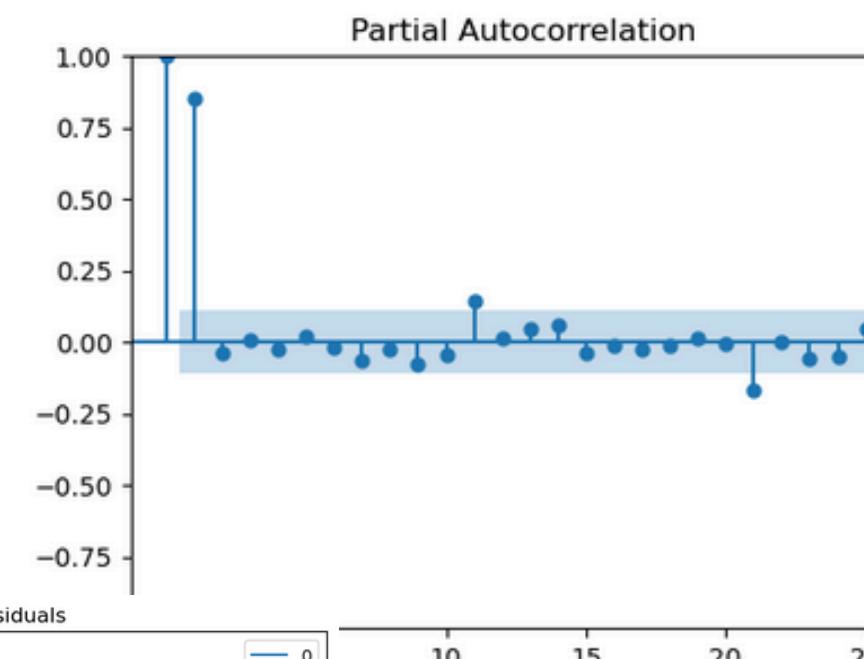
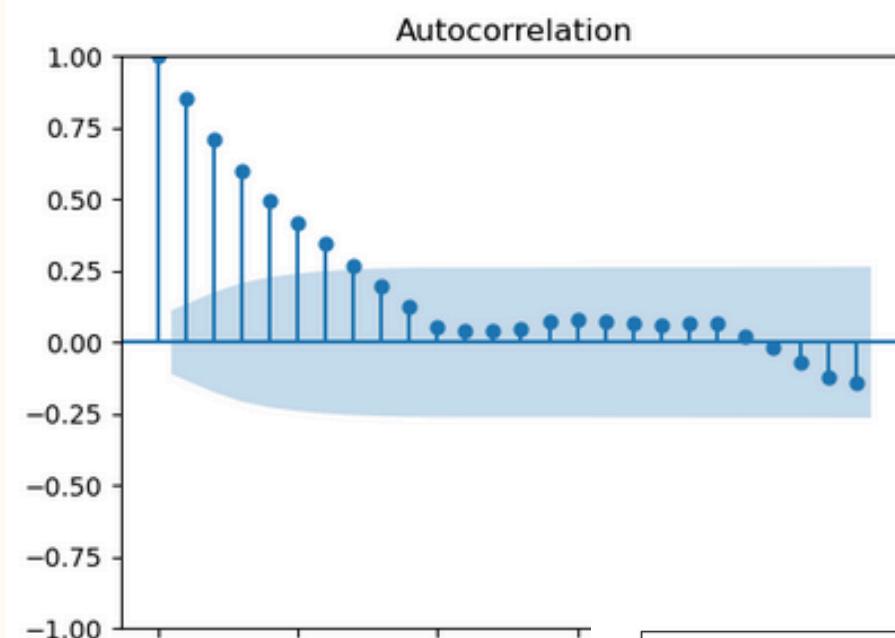
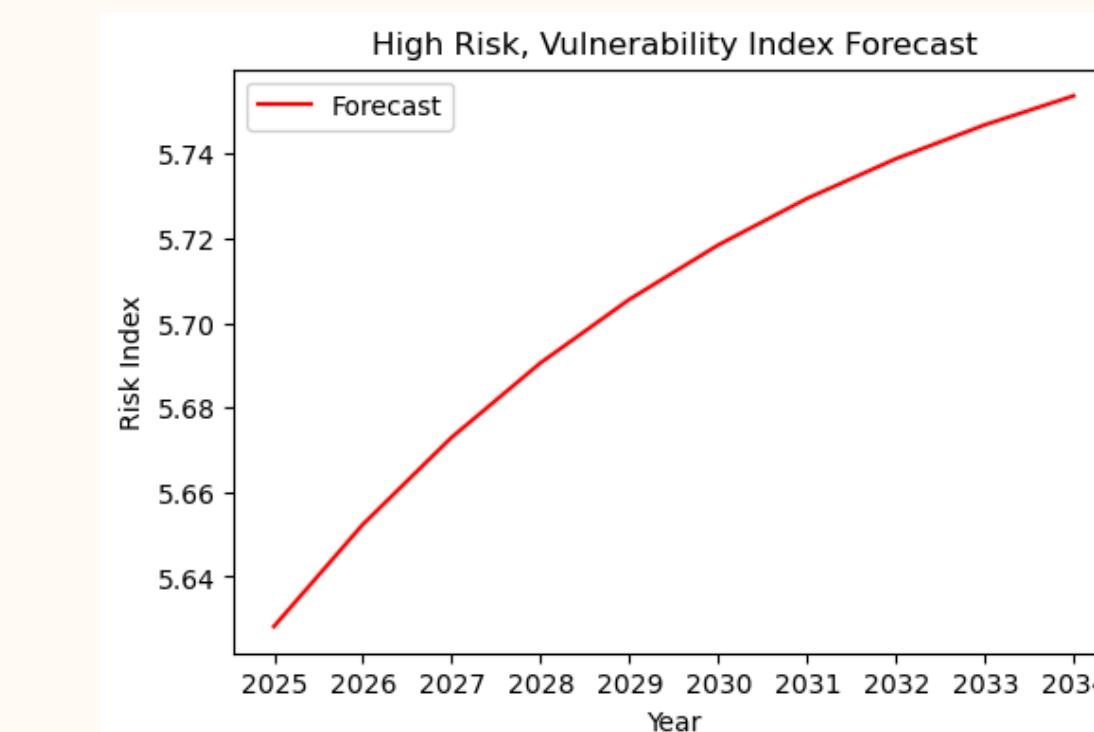
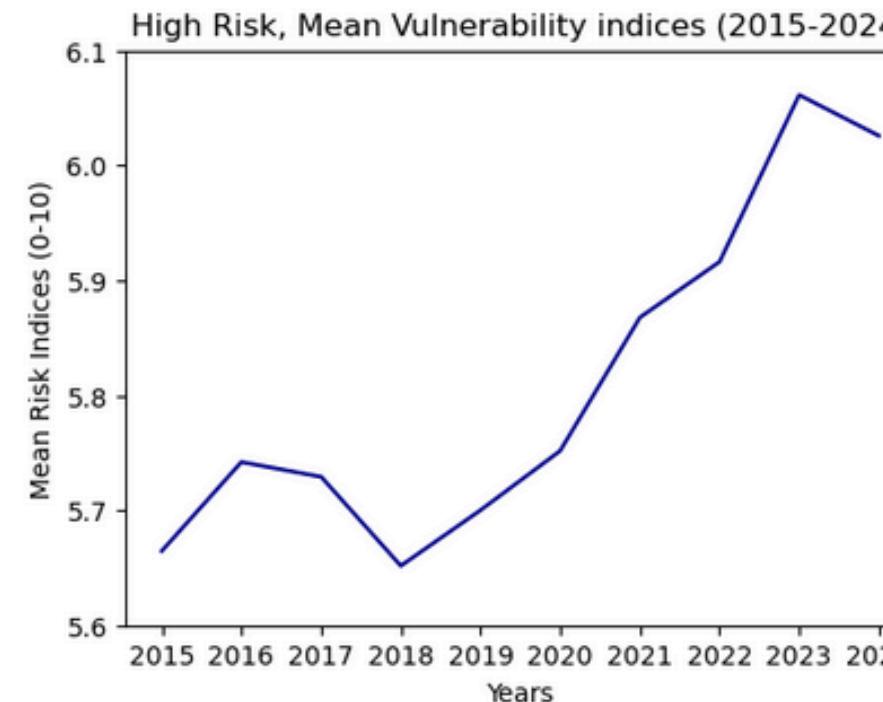
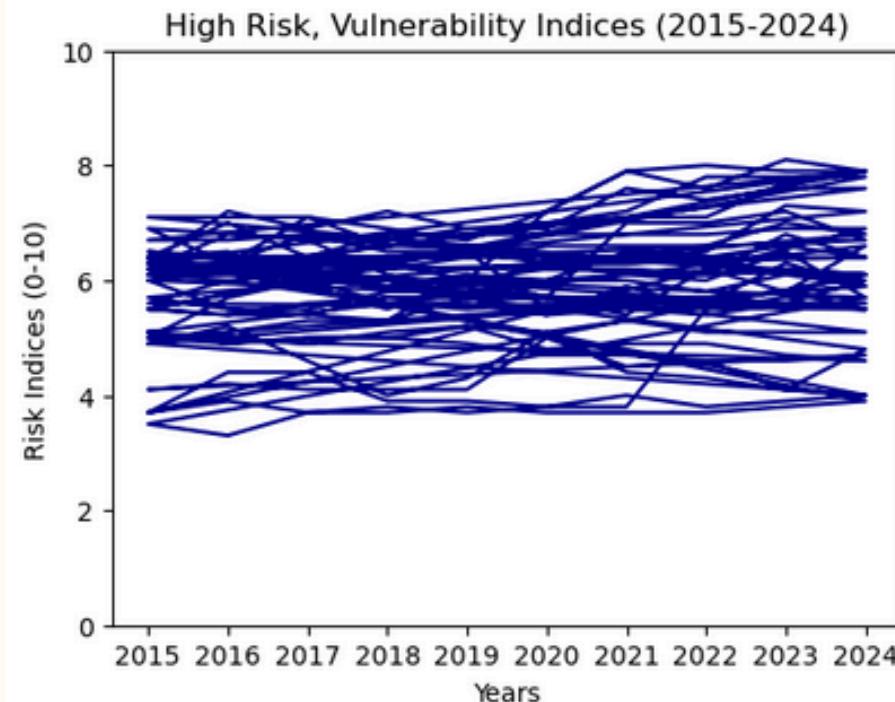
	coef	std err	z	P> z	[0.025	0.975]
ar.L1	0.8499	0.030	28.063	0.000	0.791	0.909
ma.L1	-0.9998	0.073	-13.789	0.000	-1.142	-0.858
sigma2	0.3873	0.030	12.873	0.000	0.328	0.446

Ljung-Box (L1) (Q):	0.05	Jarque-Bera (JB):	4187.41
Prob(Q):	0.82	Prob(JB):	0.00
Heteroskedasticity (H):	1.31	Skew:	0.56
Prob(H) (two-sided):	0.05	Kurtosis:	15.21

Warnings:
 [1] Covariance matrix calculated using the outer product of gradients (complex-step)

ARIMA Model to forecast High Risk Countries' Vulnerability Risk indices:

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Mean Squared Error (MSE): 2.087772772142515
 Mean Absolute Error (MAE): 1.243671031554546
 Root Mean Squared Error (RMSE): 1.444912721288907

SARIMAX Results

```
=====
Dep. Variable: Vulnerability Index No. Observations: 310
Model: ARIMA(1, 1, 1) Log Likelihood: -250.370
Date: Mon, 08 Apr 2024 AIC: 506.741
Time: 04:46:43 BIC: 517.941
Sample: 0 HQIC: 511.218
- 310
Covariance Type: opg
=====
```

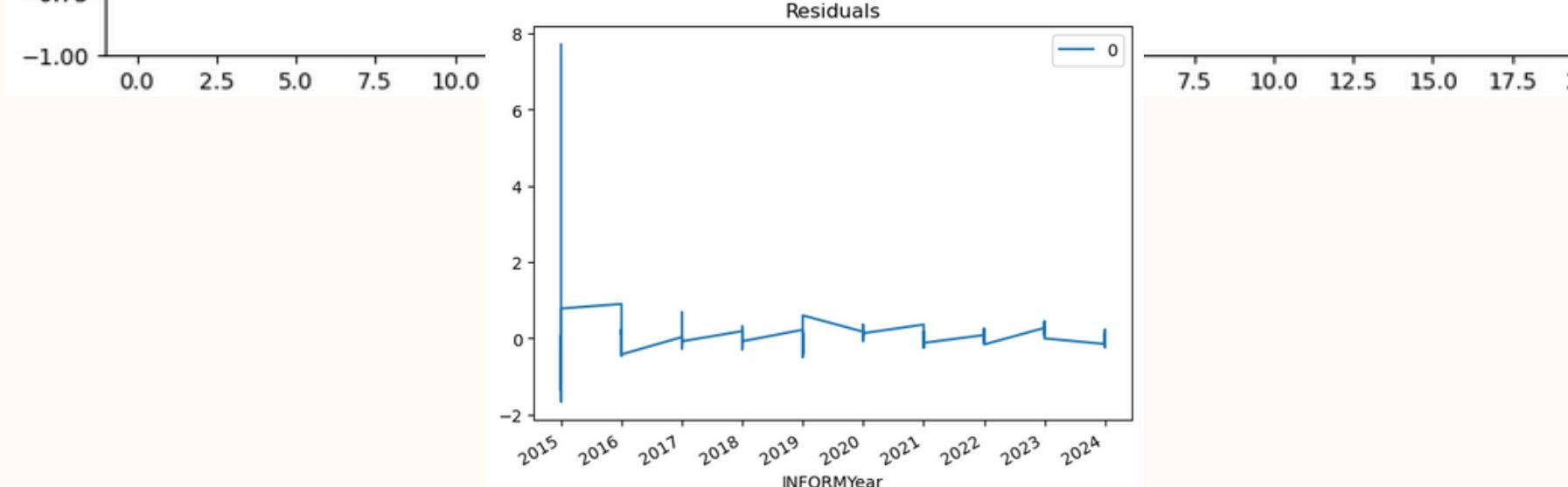
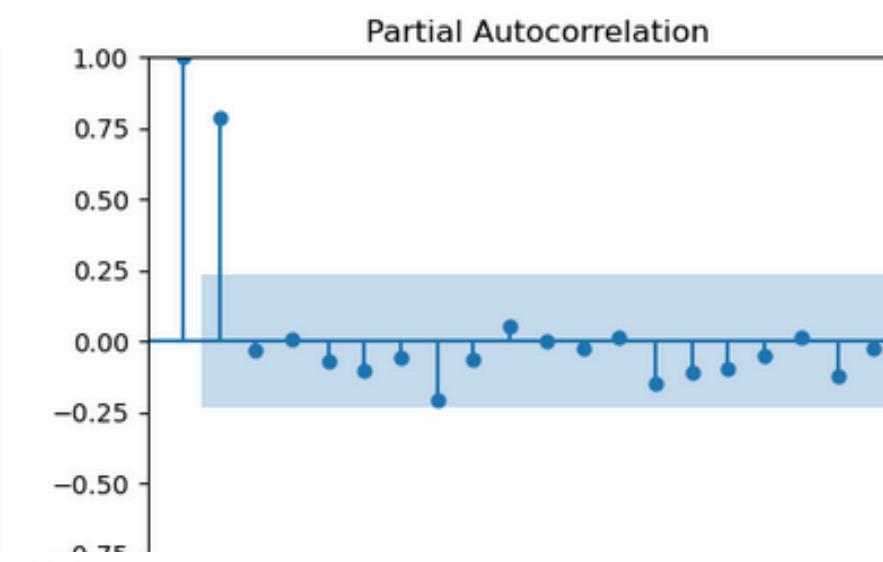
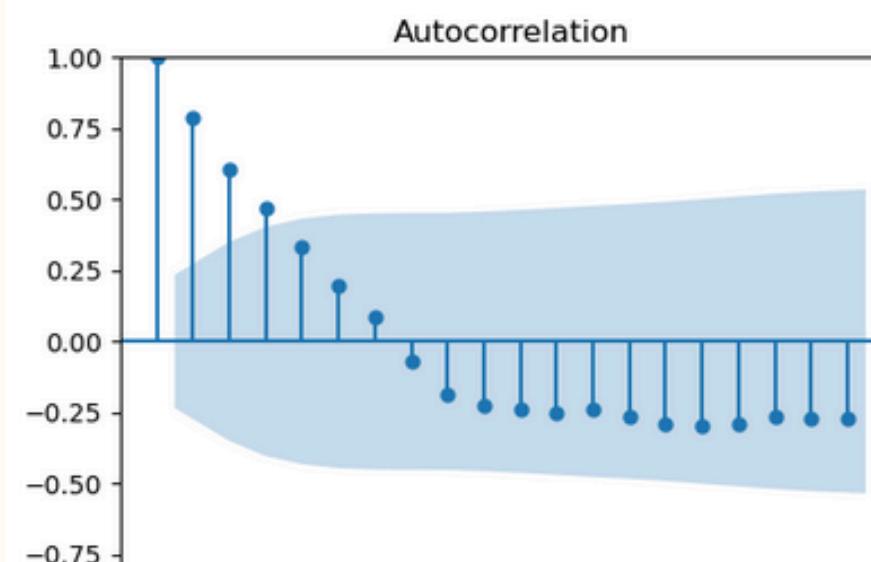
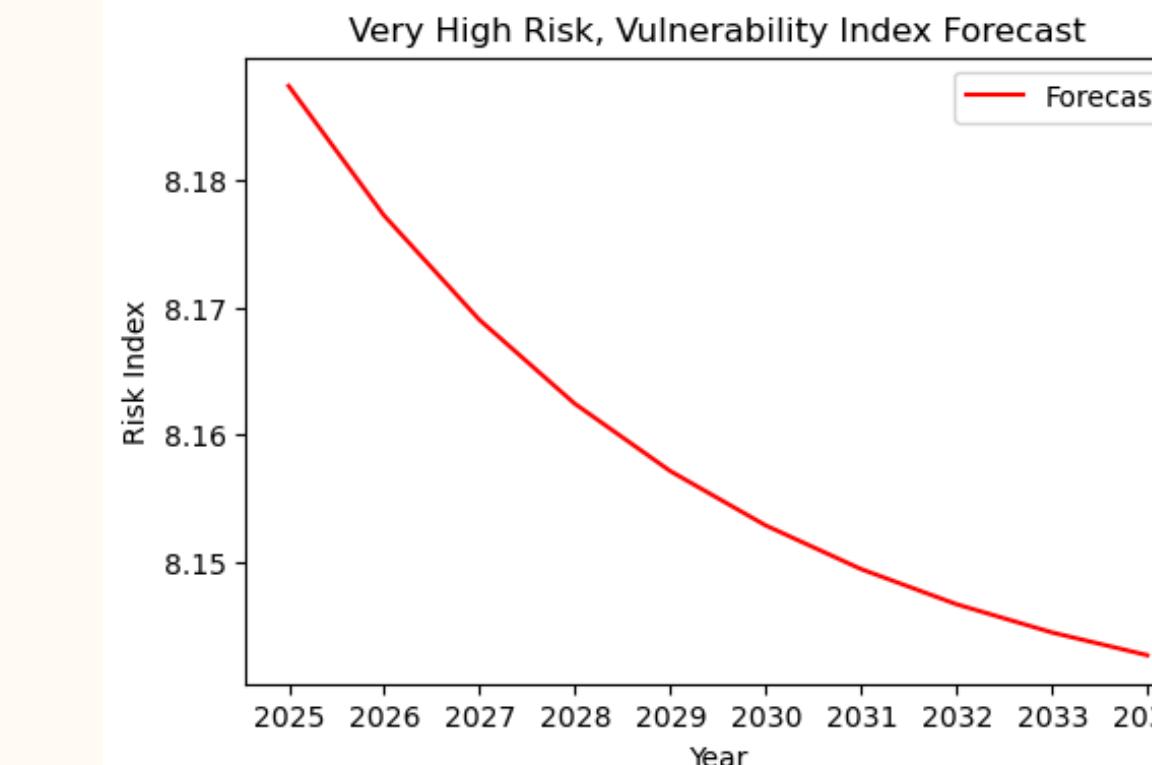
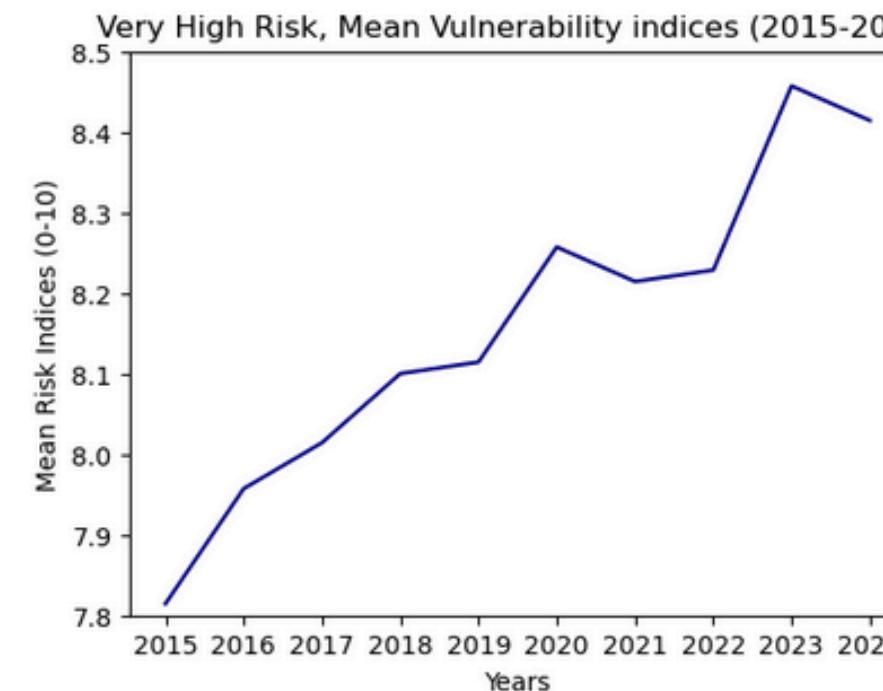
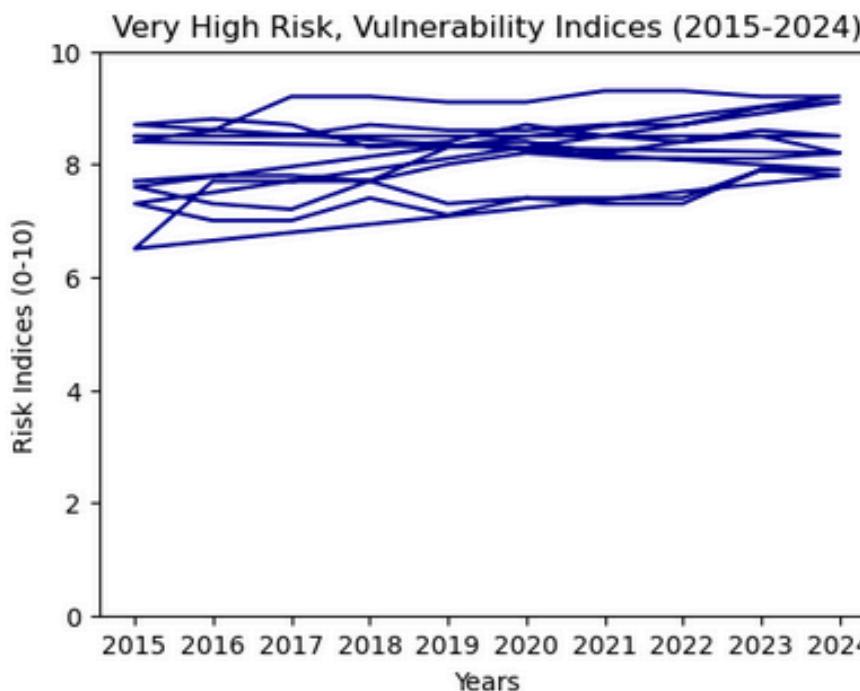
	coef	std err	z	P> z	[0.025	0.975]
ar.L1	0.8547	0.036	24.018	0.000	0.785	0.924
ma.L1	-1.0000	2.451	-0.408	0.683	-5.804	3.804
sigma2	0.2929	0.722	0.406	0.685	-1.121	1.707

```
=====
Ljung-Box (L1) (Q): 0.27 Jarque-Bera (JB): 718.05
Prob(Q): 0.60 Prob(JB): 0.00
Heteroskedasticity (H): 1.06 Skew: -0.83
Prob(H) (two-sided): 0.77 Kurtosis: 10.28
=====
```

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).

ARIMA Model to forecast Very High Risk Countries' Vulnerability Risk indices:

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Mean Squared Error (MSE): 0.3545506871275879
 Mean Absolute Error (MAE): 0.34981788796145186
 Root Mean Squared Error (RMSE): 0.5954415900217148
 SARIMAX Results
 ======
 Dep. Variable: Vulnerability Index No. Observations: 70
 Model: ARIMA(1, 1, 1) Log Likelihood: -37.413
 Date: Mon, 08 Apr 2024 AIC: 80.826
 Time: 04:49:50 BIC: 87.528
 Sample: 0 HQIC: 83.485
 - 70
 Covariance Type: opg
 ======

	coef	std err	z	P> z	[0.025	0.975]
ar.L1	0.8045	0.133	6.039	0.000	0.543	1.066
ma.L1	-1.0000	206.818	-0.005	0.996	-406.356	404.356
sigma2	0.1679	34.716	0.005	0.996	-67.873	68.209

 ======
 Ljung-Box (L1) (Q): 0.01 Jarque-Bera (JB): 128.25
 Prob(Q): 0.92 Prob(JB): 0.00
 Heteroskedasticity (H): 1.52 Skew: -1.80
 Prob(H) (two-sided): 0.32 Kurtosis: 8.62
 ======
 Warnings:
 [1] Covariance matrix calculated using the outer product of gradients (complex-step)