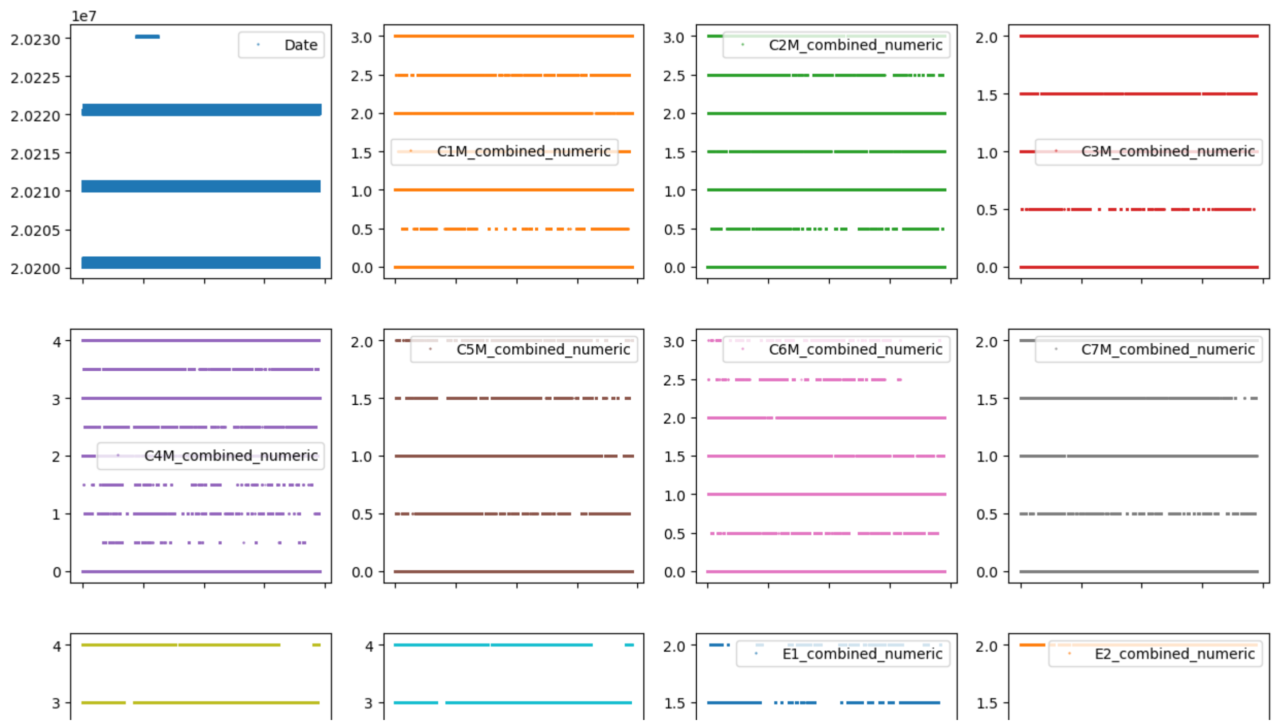
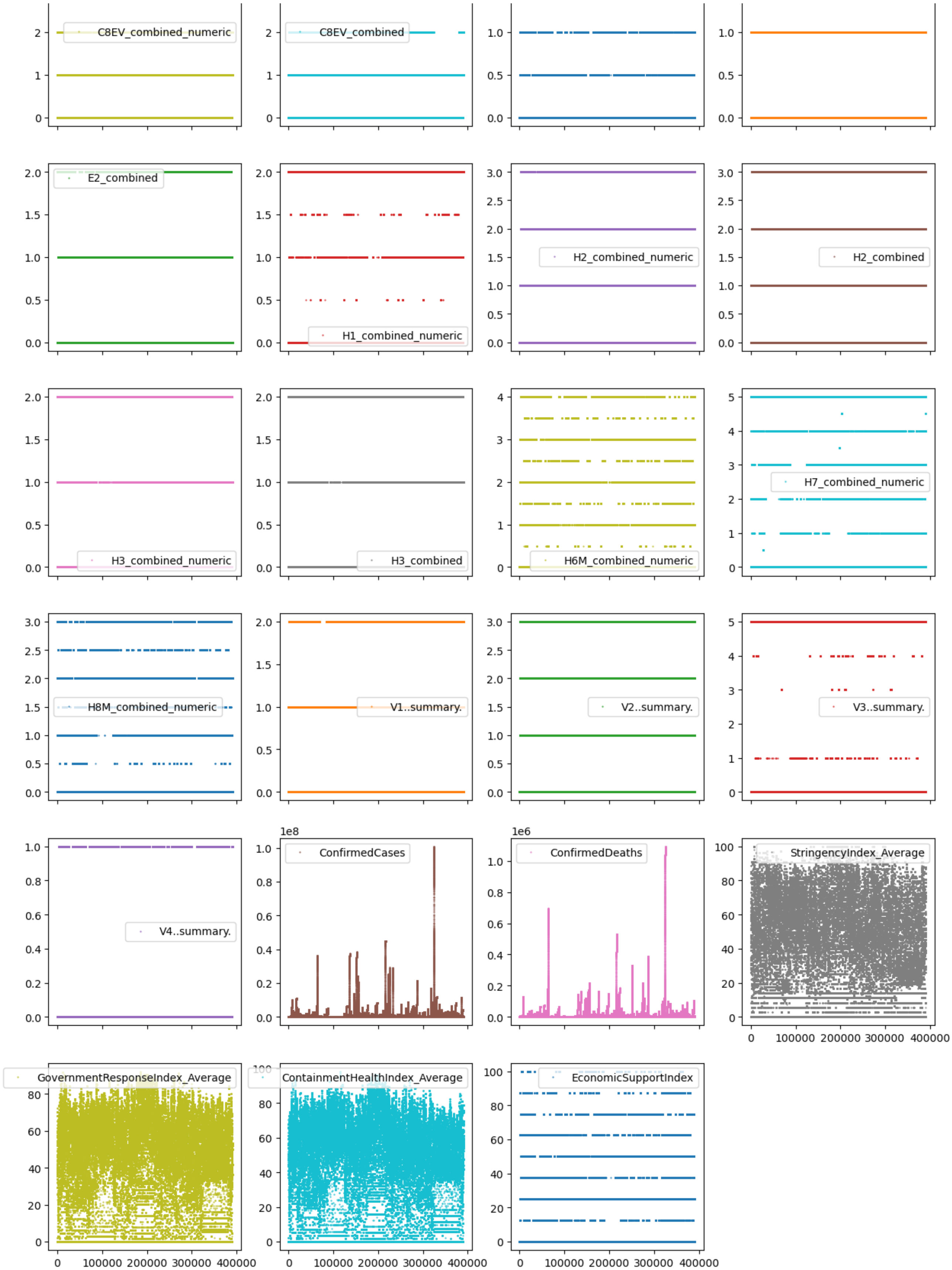
In [1]:
```
# Import the required libraries
import pandas as pd # Used for data manipulation and analysis
from sklearn.model_selection import train_test_split # Used for splitting th
from sklearn.preprocessing import StandardScaler # Used for feature scaling
from sklearn.linear_model import LogisticRegression # Used for logistic regr
import numpy as np # Used for numerical computations
import scipy.stats as stats # Used for statistical analysis
import matplotlib.pyplot as plt # Used for data visualization
import seaborn as sns # Used for data visualization
from sklearn.metrics import classification_report # Used for evaluating the
from sklearn.linear_model import LinearRegression # Used for linear regressi
from sklearn.model_selection import train_test_split # Used for splitting th
from sklearn import metrics # Used for evaluating the performance of the lir
```

In [2]:
```
# Read in the CSV file containing vaccine data and store it in a Pandas Data
# The DataFrame is assigned to the variable "vaccine"
vaccine = pd.read_csv("OxCGRT_simplified_v1.csv")
```

```
/var/folders/r0/jpvr7x216q569bknc6r4kfpm0000gn/T/ipykernel_88242/3320959814.
py:3: DtypeWarning: Columns (2,3,44,45) have mixed types. Specify dtype opti
on on import or set low_memory=False.
  vaccine = pd.read_csv("OxCGRT_simplified_v1.csv")
```

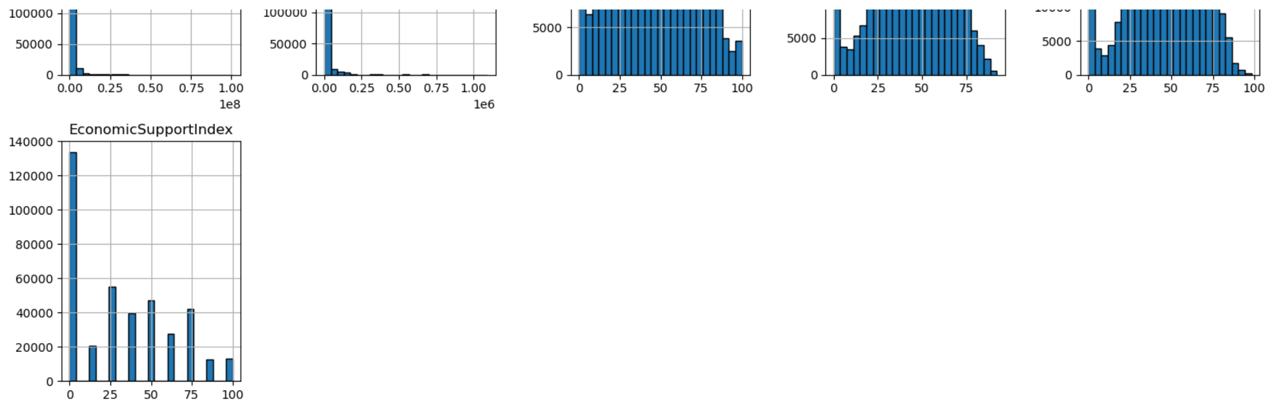
In [3]:
```
# Plot the vaccine data as points with a layout of 1 row and 4 columns.
# Use a marker size of 1 and line width of 0 to only show the points.
# Set the figure size to 15 by 30 to accommodate all 4 plots.
vaccine.plot(lw=0, marker=".", subplots=True, layout=(-1, 4),
             figsize=(15, 30), markersize=1);
```





In [4]:
```
vaccine.hist(bins=25, figsize=(15, 25), layout=(-1, 5),
```

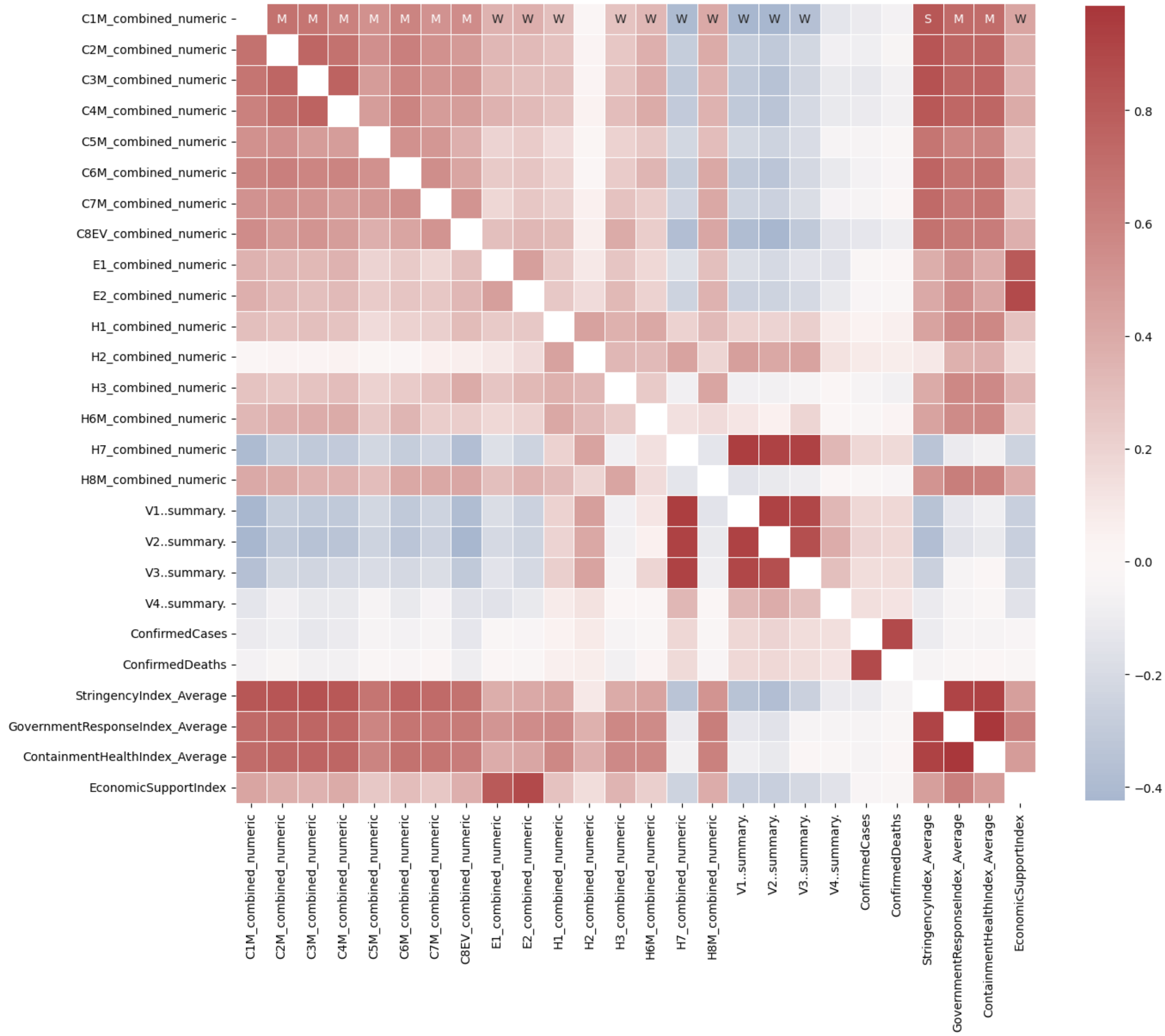
```
edgecolor="black")
plt.tight_layout();
```



In [5]:
```
# Dropping unnecessary columns related to country and region identifiers, co
vaccine.drop(['CountryName', 'CountryCode', 'RegionName', 'RegionCode', 'Jur
              'C1M_combined', 'C2M_combined', 'C3M_combined', 'C4M_combined'
              'C5M_combined', 'C6M_combined', 'C7M_combined', 'C8EV_combined
             axis=1, inplace=True)

# Dropping columns related to specific combined measures and vaccination sta
vaccine.drop(['E1_combined', 'E2_combined', 'H1_combined', 'H2_combined', 'H
              'H6M_combined', 'H7_combined', 'H8M_combined', 'MajorityVaccin
             axis=1, inplace=True)

# Dropping redundant columns for vaccination statistics.
vaccine.drop(['PopulationVaccinated'], axis=1, inplace=True)

# Dropping the column containing date information, as it may not be relevant
vaccine.drop(['Date'], axis=1, inplace=True)
```

In [6]:
```
vaccine_corr = vaccine.corr(method="pearson")
```

In [7]:
```
# Create labels for the correlation matrix
labels = np.where(np.abs(vaccine_corr)>0.75, "S",
np.where(np.abs(vaccine_corr)>0.5, "M",
np.where(np.abs(vaccine_corr)>0.25, "W", "")))
# Plot correlation matrix
plt.figure(figsize=(15, 15))
sns.heatmap(vaccine_corr, mask=np.eye(len(vaccine_corr)), square=True,
center=0, annot=labels, fmt='', linewidths=.5,
cmap="vlag", cbar_kws={"shrink": 0.8});
```



In [8]:

```
#count the null value
count_nan = vaccine.isna().sum()
print(count_nan)
```

```
C1M_combined_numeric                  0
C2M_combined_numeric                  0
C3M_combined_numeric                  0
C4M_combined_numeric                  0
C5M_combined_numeric                  0
C6M_combined_numeric                  0
C7M_combined_numeric                  0
C8EV_combined_numeric                 0
E1_combined_numeric                   0
E2_combined_numeric                   0
H1_combined_numeric                   0
H2_combined_numeric                   0
H3_combined_numeric                   0
H6M_combined_numeric                  0
H7_combined_numeric                   0
H8M_combined_numeric                  0
V1..summary.                          0
V2..summary.                          0
V3..summary.                          0
V4..summary.                     111805
ConfirmedCases                     1321
ConfirmedDeaths                    1611
StringencyIndex_Average               0
GovernmentResponseIndex_Average       0
ContainmentHealthIndex_Average        0
EconomicSupportIndex                  0
dtype: int64
```

In [39]:

```
vaccine_SI_time_series=pd.read_csv("OxCGRT_timeseries_StringencyIndex_v1.csv
```

In [40]:

```
vaccine_SI_time_series
```

Out[40]:

	CountryCode	CountryName	RegionCode	RegionName	CityCode	CityName	Ju
0	ABW	Aruba	NaN	NaN	NaN	NaN	N
1	AFG	Afghanistan	NaN	NaN	NaN	NaN	N
2	AGO	Angola	NaN	NaN	NaN	NaN	N
3	ALB	Albania	NaN	NaN	NaN	NaN	N
4	AND	Andorra	NaN	NaN	NaN	NaN	N
...	...	...	...	...	...	...	
390	VUT	Vanuatu	NaN	NaN	NaN	NaN	N
391	YEM	Yemen	NaN	NaN	NaN	NaN	N
392	ZAF	South Africa	NaN	NaN	NaN	NaN	N
393	ZMB	Zambia	NaN	NaN	NaN	NaN	N
394	ZWE	Zimbabwe	NaN	NaN	NaN	NaN	N

395 rows × 1162 columns

In [41]:

```
selected_row_india = vaccine_SI_time_series[(vaccine_SI_time_series['Country
selected_row_usa = vaccine_SI_time_series[(vaccine_SI_time_series['CountryNa
selected_row_uk = vaccine_SI_time_series[(vaccine_SI_time_series['CountryNam
selected_row_brazil = vaccine_SI_time_series[(vaccine_SI_time_series['Countr
```

In [42]:

```
selected_row_india.drop(selected_row_india.iloc[:, 1:7], inplace=True, axis=
selected_row_usa.drop(selected_row_usa.iloc[:, 1:7], inplace=True, axis=1)
selected_row_brazil.drop(selected_row_brazil.iloc[:, 1:7], inplace=True, axi
selected_row_uk.drop(selected_row_uk.iloc[:, 1:7], inplace=True, axis=1)
```

```
/var/folders/r0/jpvr7x216q569bknc6r4kfpm0000gn/T/ipykernel_88242/2275625999.
py:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/
stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  selected_row_india.drop(selected_row_india.iloc[:, 1:7], inplace=True, axi
s=1)
/var/folders/r0/jpvr7x216q569bknc6r4kfpm0000gn/T/ipykernel_88242/2275625999.
py:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/
stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  selected_row_usa.drop(selected_row_usa.iloc[:, 1:7], inplace=True, axis=1)
/var/folders/r0/jpvr7x216q569bknc6r4kfpm0000gn/T/ipykernel_88242/2275625999.
py:3: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/
stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  selected_row_brazil.drop(selected_row_brazil.iloc[:, 1:7], inplace=True, a
xis=1)
/var/folders/r0/jpvr7x216q569bknc6r4kfpm0000gn/T/ipykernel_88242/2275625999.
py:4: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/
stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  selected_row_uk.drop(selected_row_uk.iloc[:, 1:7], inplace=True, axis=1)
```

In [43]:
```
selected_row_uk
```

Out[43]:

	CountryCode	01Jan2020	02Jan2020	03Jan2020	04Jan2020	05Jan2020	06
183	GBR	0.0	0.0	0.0	0.0	0.0	

1 rows × 1156 columns

In [44]:
```
df1_transposed_india = selected_row_india.T # or df1.transpose()
df1_transposed_usa = selected_row_usa.T # or df1.transpose()
df1_transposed_brazil = selected_row_brazil.T # or df1.transpose()
df1_transposed_uk = selected_row_uk.T # or df1.transpose()
```

In [45]:
```
df1_transposed_uk.isnull()
```

Out[45]:

	183
CountryCode	False
01Jan2020	False
02Jan2020	False
03Jan2020	False
04Jan2020	False
...	...
24Feb2023	True
25Feb2023	True
26Feb2023	True
27Feb2023	True
28Feb2023	True

1156 rows × 1 columns

In [46]:

```
df_melted_india = pd.melt(selected_row_india, id_vars=[], value_vars=selecte
df_melted_usa = pd.melt(selected_row_usa, id_vars=[], value_vars=selected_ro
df_melted_brazil = pd.melt(selected_row_brazil, id_vars=[], value_vars=selec
df_melted_uk = pd.melt(selected_row_uk, id_vars=[], value_vars=selected_row_
```

In [47]:

```
India_SI_clean = df_melted_india.dropna()
USA_SI_clean = df_melted_usa.dropna()
Brazil_SI_clean = df_melted_brazil.dropna()
UK_SI_clean = df_melted_uk.dropna()
```

In [48]:

```
UK_SI_clean
```

Out[48]:

	column	value
0	CountryCode	GBR
1	01Jan2020	0.0
2	02Jan2020	0.0
3	03Jan2020	0.0
4	04Jan2020	0.0
...	...	...
1092	27Dec2022	5.56
1093	28Dec2022	5.56
1094	29Dec2022	5.56
1095	30Dec2022	5.56
1096	31Dec2022	5.56

1097 rows × 2 columns

In [49]:

```
# Delete the first row
India_SI_clean = India_SI_clean.drop(India_SI_clean.index[0])
USA_SI_clean = USA_SI_clean.drop(USA_SI_clean.index[0])
Brazil_SI_clean = Brazil_SI_clean.drop(Brazil_SI_clean.index[0])
UK_SI_clean = UK_SI_clean.drop(UK_SI_clean.index[0])

India_SI_clean
```

Out[49]:

	column	value
1	01Jan2020	0.0
2	02Jan2020	0.0
3	03Jan2020	0.0
4	04Jan2020	0.0
5	05Jan2020	0.0
...	...	...
1092	27Dec2022	28.7
1093	28Dec2022	28.7
1094	29Dec2022	28.7
1095	30Dec2022	28.7
1096	31Dec2022	28.7

1096 rows × 2 columns

In [51]:

```
India_SI_clean.reset_index(drop=True)
USA_SI_clean.reset_index(drop=True)
Brazil_SI_clean.reset_index(drop=True)
UK_SI_clean.reset_index(drop=True)
```

Out[51]:

	column	value
0	01Jan2020	0.0
1	02Jan2020	0.0
2	03Jan2020	0.0
3	04Jan2020	0.0
4	05Jan2020	0.0
...	...	...
1091	27Dec2022	5.56
1092	28Dec2022	5.56
1093	29Dec2022	5.56
1094	30Dec2022	5.56
1095	31Dec2022	5.56

1096 rows × 2 columns

In [52]:

```
# Delete the first row
India_SI_clean = India_SI_clean.drop(India_SI_clean.index[0])
USA_SI_clean = USA_SI_clean.drop(USA_SI_clean.index[0])
Brazil_SI_clean = Brazil_SI_clean.drop(Brazil_SI_clean.index[0])
UK_SI_clean = Brazil_SI_clean.drop(Brazil_SI_clean.index[0])
#India_SI_clean
#Brazil_SI_clean
UK_SI_clean
```

Out[52]:

	column	value
3	03Jan2020	0.0
4	04Jan2020	0.0
5	05Jan2020	0.0
6	06Jan2020	0.0
7	07Jan2020	0.0
...	...	...
1092	27Dec2022	22.22
1093	28Dec2022	22.22
1094	29Dec2022	22.22
1095	30Dec2022	22.22
1096	31Dec2022	22.22

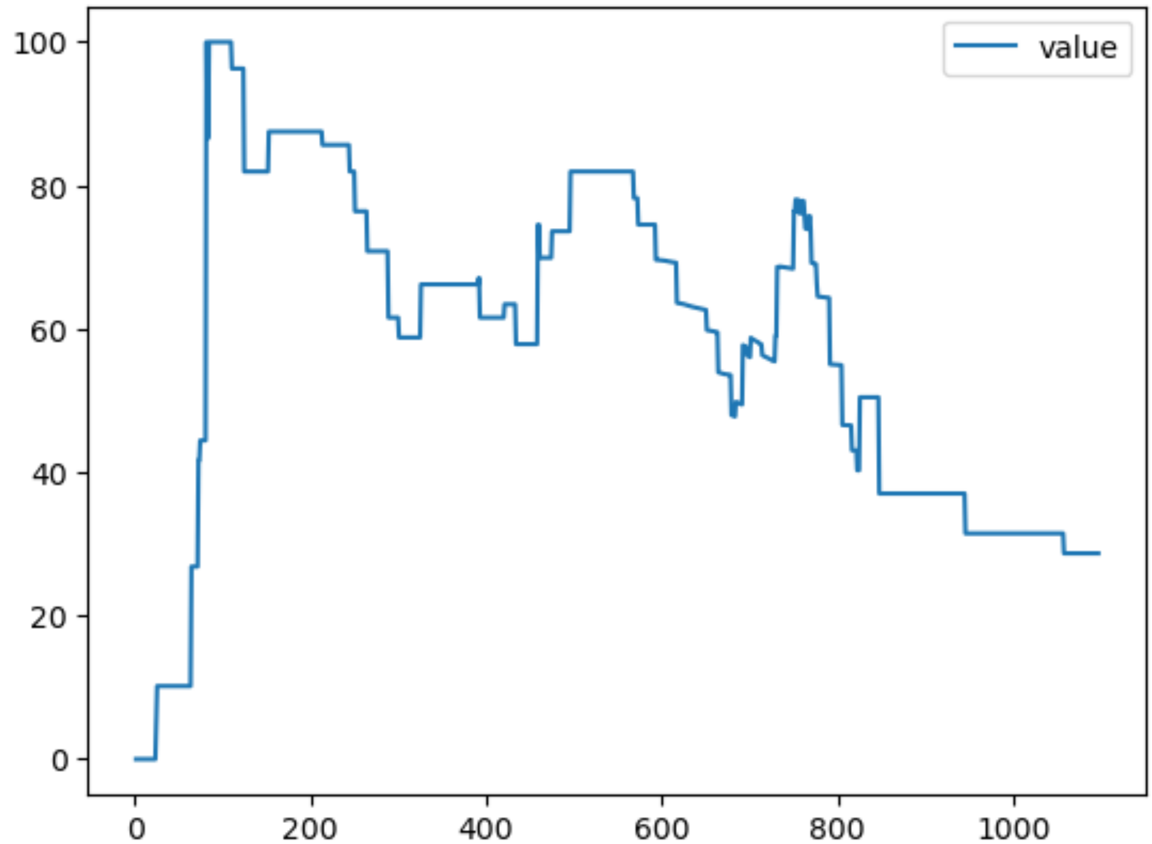
1094 rows × 2 columns

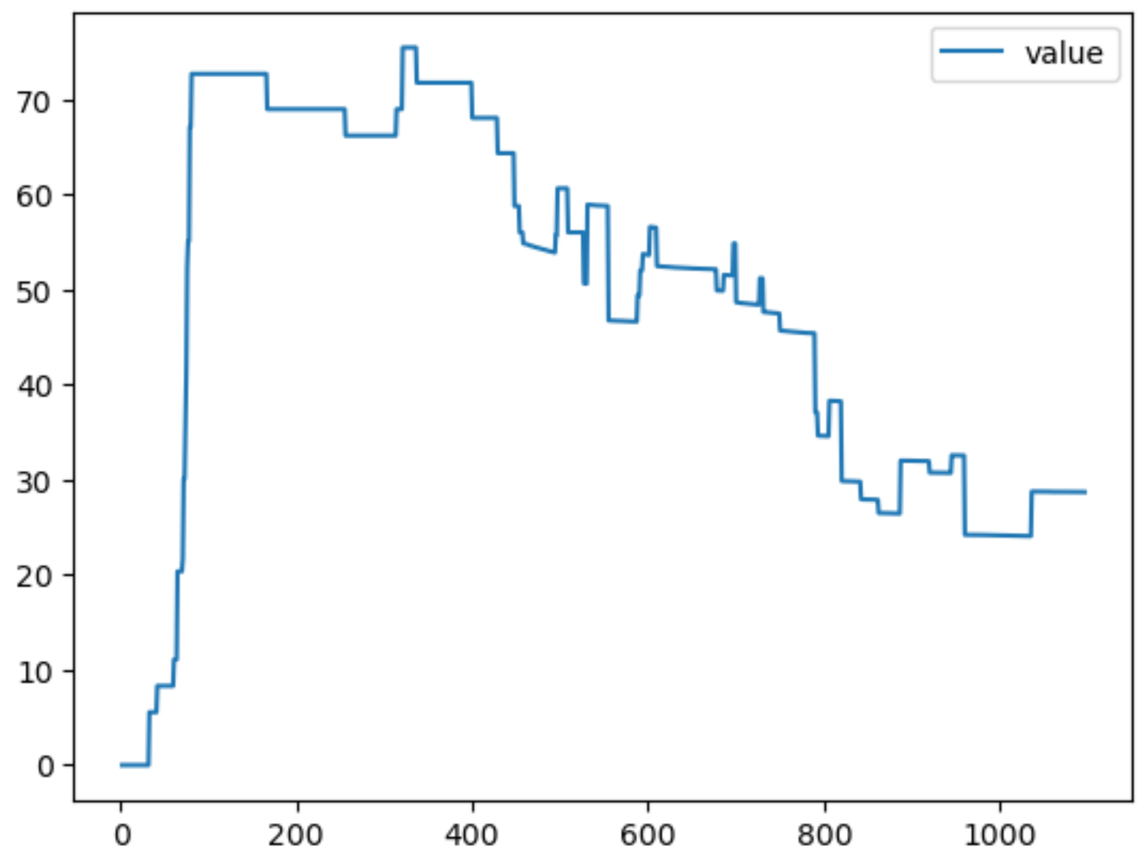
In [130…

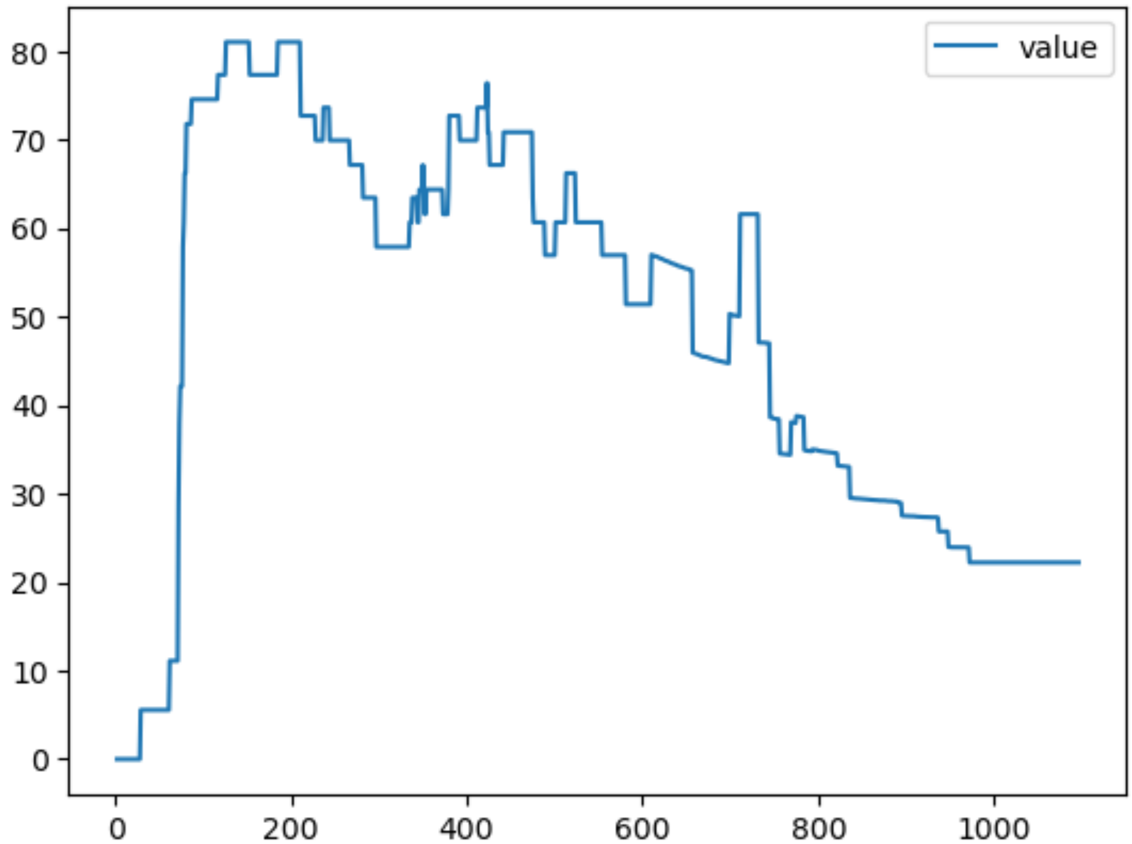
```
#India_SI_clean.set_index('column', inplace=True)
#USA_SI_clean.set_index('column', inplace=True)
#Brazil_SI_clean.set_index('column', inplace=True)
```

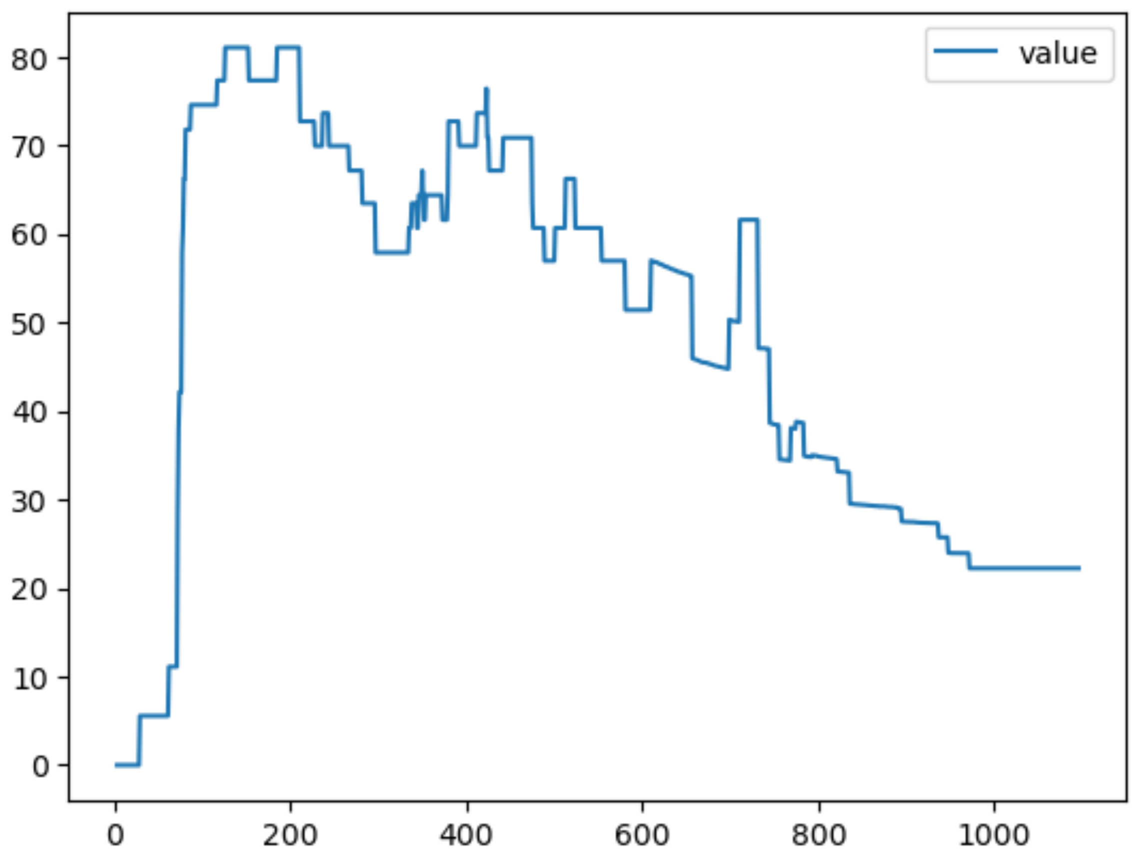
In [53]:

```
India_SI_clean.plot()
USA_SI_clean.plot()
Brazil_SI_clean.plot()
UK_SI_clean.plot()
plt.show()
```


value
0
20
40
60
80
100
0
200
400
600
800
1000


value
0
10
20
30
40
50
60
70
0
200
400
600
800
1000

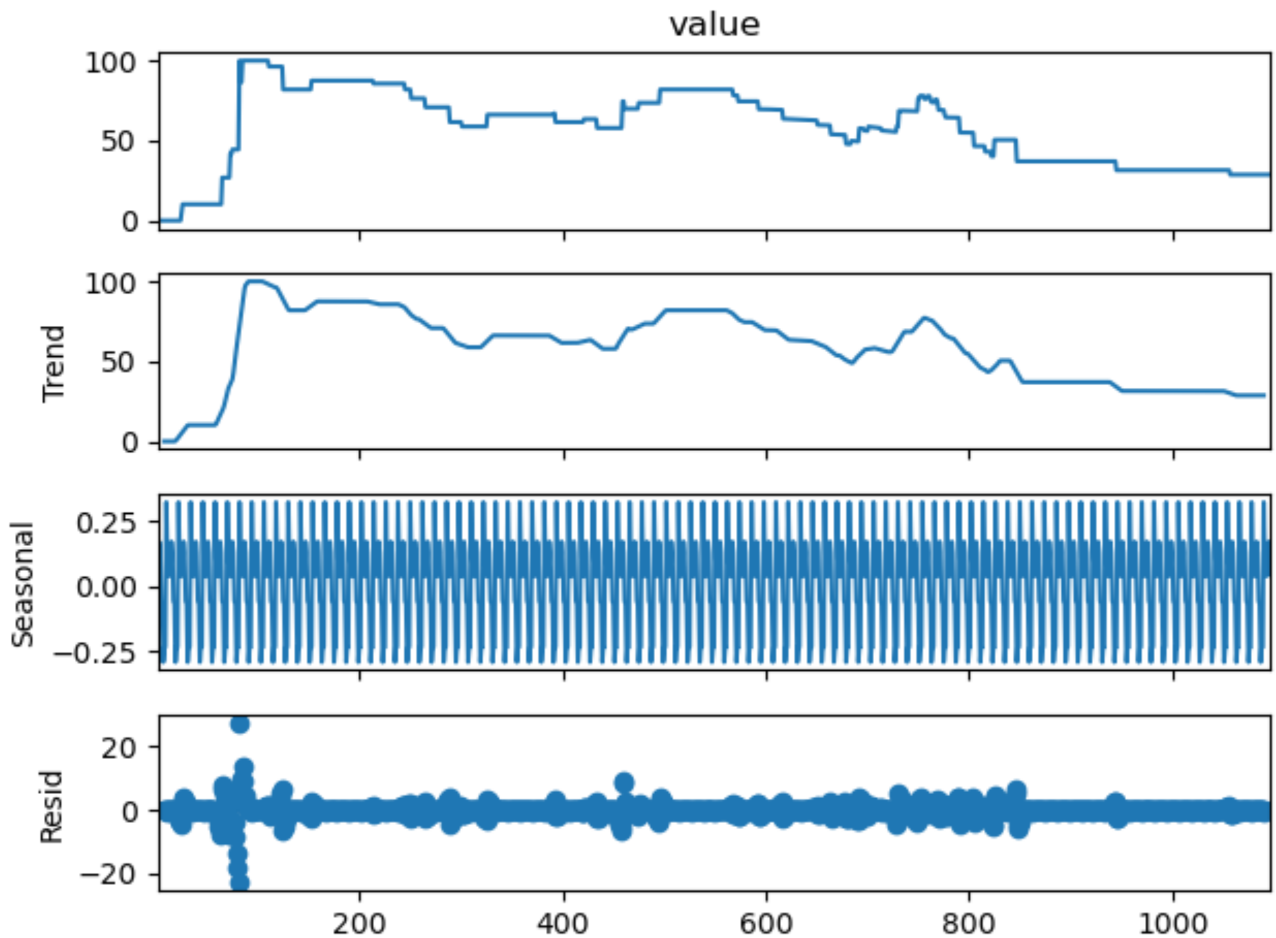

value
0
10
20
30
40
50
60
70
80
0
200
400
600
800
1000

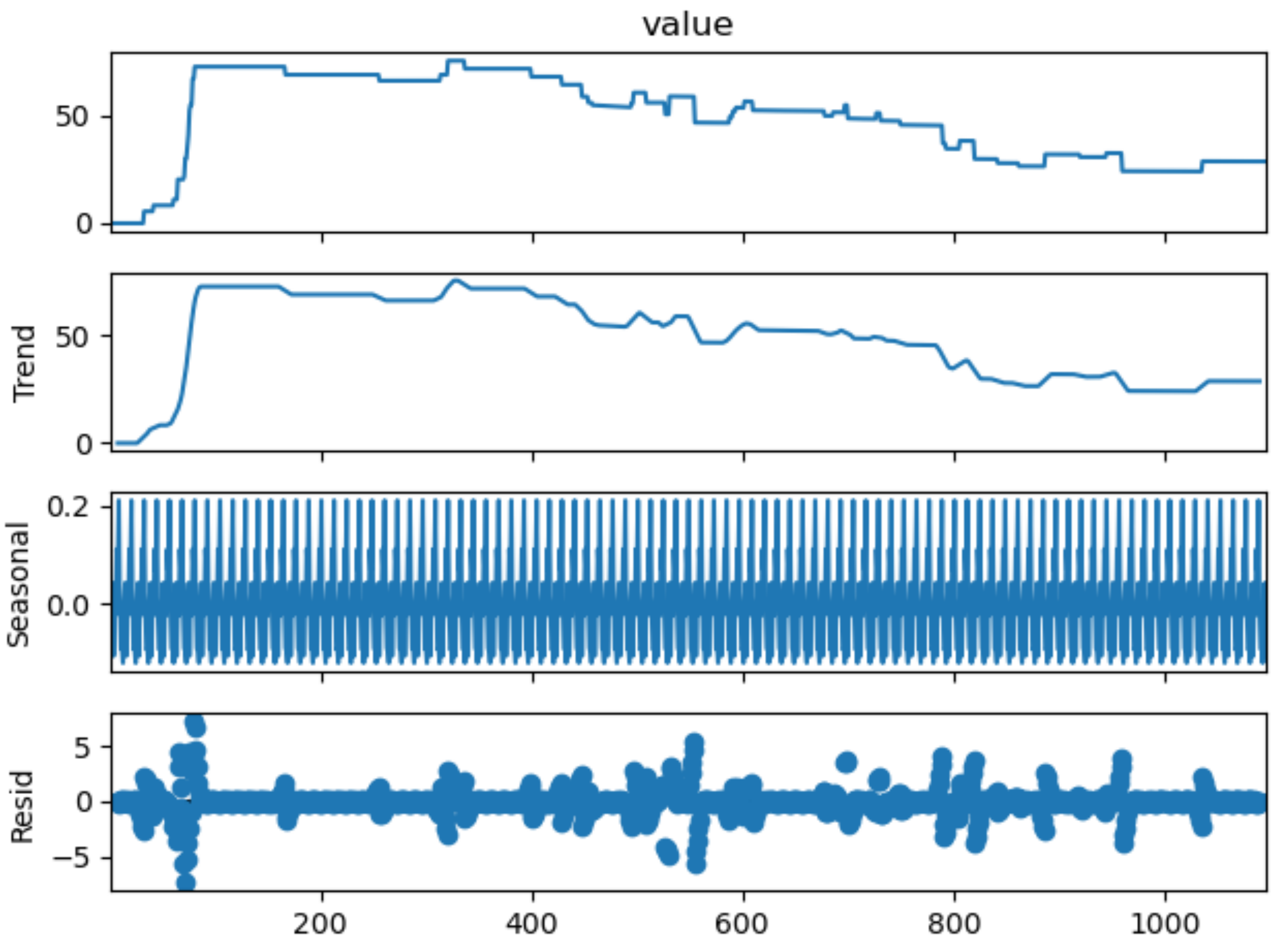

value
0
10
20
30
40
50
60
70
80
0
200
400
600
800
1000

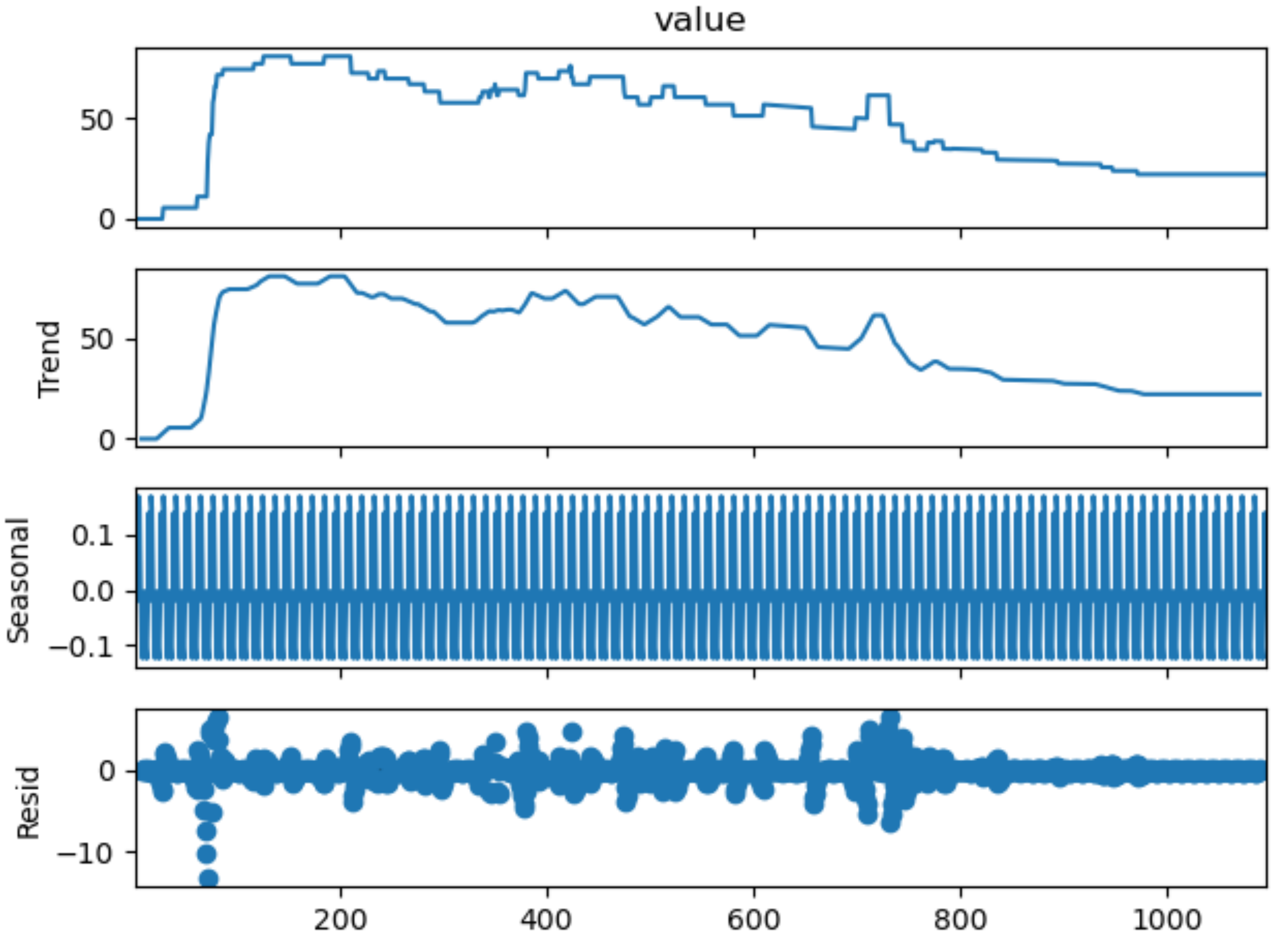
In [54]:
```
stringency_index_India = India_SI_clean.index
stringency_index_USA = USA_SI_clean.index
stringency_index_Brazil = Brazil_SI_clean.index
stringency_index_UK = UK_SI_clean.index
```

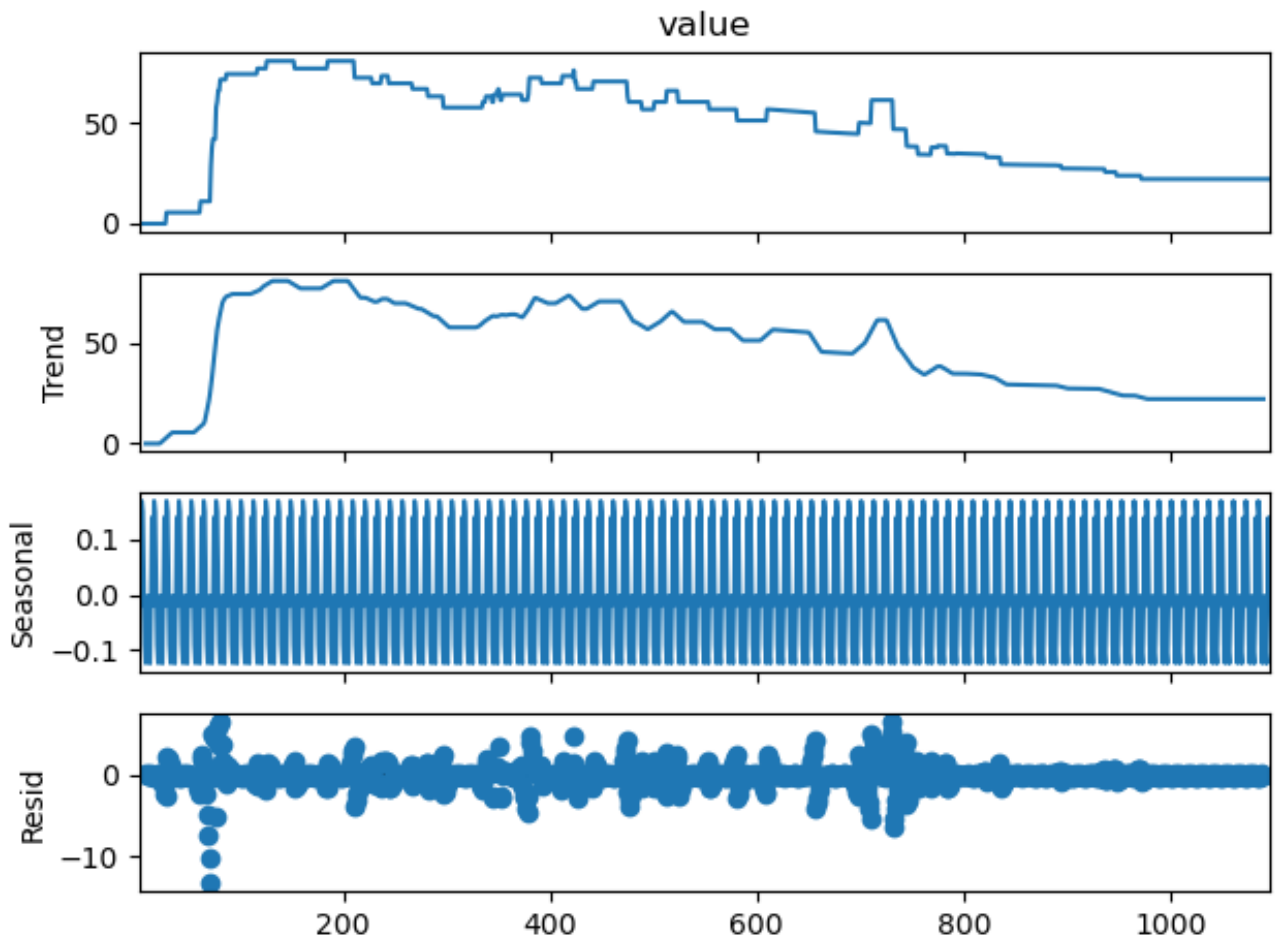
In [57]:
```
stringency_ts_India = pd.Series(India_SI_clean.squeeze().value, index=string
stringency_ts_USA = pd.Series(USA_SI_clean.squeeze().value, index=stringency
stringency_ts_Brazil = pd.Series(Brazil_SI_clean.squeeze().value, index=stri
stringency_ts_UK = pd.Series(UK_SI_clean.squeeze().value, index=stringency_i
```

In [58]:
```
from statsmodels.tsa.seasonal import seasonal_decompose
import numpy as np
result_India = seasonal_decompose(stringency_ts_India, model='additive', per
result_USA = seasonal_decompose(stringency_ts_USA, model='additive', period 
result_Brazil = seasonal_decompose(stringency_ts_Brazil, model='additive', p
result_UK = seasonal_decompose(stringency_ts_UK, model='additive', period = 

result_India.plot()
result_USA.plot()
result_Brazil.plot()
result_UK.plot()

plt.figure().set_figwidth(15)
plt.show()
```


value
100
50
0
Trend
100
50
0
Seasonal
0.25
0.00
−0.25
Resid
20
0
−20
200
400
600
800
1000


value
50
0
Trend
50
0
Seasonal
0.2
0.0
Resid
5
0
−5
200
400
600
800
1000


value
50
0
Trend
50
0
Seasonal
0.1
0.0
−0.1
Resid
0
−10
200
400
600
800
1000



<Figure size 1500x480 with 0 Axes>

In [135…
```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error, r2_score
from matplotlib import pyplot
from sklearn.model_selection import KFold
from sklearn.model_selection import cross_val_score
from sklearn.linear_model import LinearRegression, Ridge, Lasso, ElasticNet
from sklearn.tree import DecisionTreeRegressor
from sklearn.neighbors import KNeighborsRegressor
from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegresso
from sklearn.svm import SVR
from sklearn.neural_network import MLPRegressor
from xgboost import XGBRegressor
```

In [136…
```
vaccine = vaccine.iloc[:, [8, 9,-1]]
```

In [137…
```
vaccine
```

Out [137…

	E1_combined_numeric	E2_combined_numeric	EconomicSupportIndex
0	0.0	0	0.0
1	0.0	0	0.0
2	0.0	0	0.0
3	0.0	0	0.0
4	0.0	0	0.0
...	...	...	...
390904	0.0	0	0.0
390905	0.0	0	0.0
390906	0.0	0	0.0
390907	0.0	0	0.0
390908	0.0	0	0.0

390909 rows × 3 columns

In [138…

```
vaccine.isnull().sum()
```

Out[138…

```
E1_combined_numeric     0
E2_combined_numeric     0
EconomicSupportIndex    0
dtype: int64
```

In [142…

```
X = vaccine.drop(['EconomicSupportIndex'], axis=1)
y = vaccine['EconomicSupportIndex']
```

In [143…

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, rar
```

In [144…

```
models = []
models.append(('LR', LinearRegression()))
models.append(('Ridge', Ridge()))
models.append(('Lasso', Lasso()))
models.append(('ElasticNet', ElasticNet()))
models.append(('KNN', KNeighborsRegressor()))
models.append(('DecisionTree', DecisionTreeRegressor()))
models.append(('SVR', SVR()))
models.append(('RandomForest', RandomForestRegressor()))
models.append(('GradientBoosting', GradientBoostingRegressor()))
models.append(('MLP', MLPRegressor()))
models.append(('XGBoost', XGBRegressor()))
```

In [145…

```
import time
from tqdm import tqdm
from sklearn.metrics import mean_absolute_error, r2_score, explained_varianc
from math import sqrt

results = []
models_stats = []
names = []
scoring = 'neg_mean_absolute_error' # Change to 'r2' for R2, 'neg_mean_squar

for name, model in tqdm(models):
    start = time.time()
    kfold = KFold(n_splits=10, random_state=7, shuffle=True)
    model.fit(X_train, y_train)
    train_time = time.time() - start
    cv_results = -1 * cross_val_score(model, X_train, y_train, cv=kfold, scc
    results.append(cv_results)
    names.append(name)

    # Make predictions
    start = time.time()
    y_pred = model.predict(X_test)
    predict_time = time.time() - start

    # Coefficients are not available for all models
    if hasattr(model, 'coef_'):
        print(f"Coefficients for {name}: ", model.coef_)

    print(model)
    print("\tTraining time: %0.3fs" % train_time)
    print("\tPrediction time: %0.3fs" % predict_time)
    print("\tExplained variance:", explained_variance_score(y_test, y_pred))
    print("\tMean absolute error:", mean_absolute_error(y_test, y_pred))
    print("\tR2 score:", r2_score(y_test, y_pred))
    print("\tMean Squared Error:", mean_squared_error(y_test, y_pred))
    print("\tRoot Mean Squared Error:", sqrt(mean_squared_error(y_test, y_pr
    print()

    model_stats = {
        'name': name,
        'mean_score': cv_results.mean(),
        'std_score': cv_results.std(),
        'explained_variance': explained_variance_score(y_test, y_pred),
        'mean_absolute_error': mean_absolute_error(y_test, y_pred),
        'r2_score': r2_score(y_test, y_pred),
        'mean_squared_error': mean_squared_error(y_test, y_pred),
        'root_mean_squared_error': sqrt(mean_squared_error(y_test, y_pred)),
    }

    models_stats.append(model_stats)
```

```python
# Boxplot to compare algorithms
fig = pyplot.figure(figsize=(15, 10))
fig.suptitle('Algorithm Comparison')
ax = fig.add_subplot(111)
pyplot.boxplot(results)
ax.set_xticklabels(names, rotation = 45)
pyplot.show()

# Sorting the models based on mean absolute error
models_stats.sort(key=lambda x: x['mean_absolute_error'])

print("\nModels performance:")
for model in models_stats:
    print(f"{model['name']} - Mean Absolute Error: {model['mean_absolute_err
```

```
 18%|████████                                   | 2/11 [00:00<00:01,  5.23i
t/s]
Coefficients for LR:  [25. 25.]
LinearRegression()
        Training time: 0.027s
        Prediction time: 0.001s
        Explained variance: 1.0
        Mean absolute error: 6.348357886889212e-11
        R2 score: 1.0
        Mean Squared Error: 5.451858769533616e-21
        Root Mean Squared Error: 7.383670340375182e-11

Coefficients for Ridge:  [24.99983445 24.99993514]
Ridge()
        Training time: 0.024s
        Prediction time: 0.001s
        Explained variance: 0.9999999999802829
        Mean absolute error: 0.00011656979060435019
        R2 score: 0.9999999999802822
        Mean Squared Error: 1.84571947085102e-08
        Root Mean Squared Error: 0.00013585725857866485

 27%|████████████                               | 3/11 [00:00<00:01,  4.23i
t/s]
Coefficients for Lasso:  [22.92935695 24.18859114]
Lasso()
        Training time: 0.046s
        Prediction time: 0.001s
        Explained variance: 0.9969150668959943
        Mean absolute error: 1.4580894202125017
        R2 score: 0.9969149671396089
        Mean Squared Error: 2.887802016623034
        Root Mean Squared Error: 1.6993534113370985
```

```
 36%|████████████████                            | 4/11 [00:00<00:01,  4.10i
t/s]
Coefficients for ElasticNet:  [12.73715174 16.10137629]
ElasticNet()
        Training time: 0.033s
        Prediction time: 0.003s
        Explained variance: 0.8285595659718505
        Mean absolute error: 10.927111979730267
        R2 score: 0.8285543382117605
        Mean Squared Error: 160.48487982412746
        Root Mean Squared Error: 12.668262699523067

 45%|████████████████████                        | 5/11 [01:09<02:28, 24.79
s/it]
KNeighborsRegressor()
        Training time: 0.081s
        Prediction time: 14.776s
        Explained variance: 1.0
        Mean absolute error: 0.0
        R2 score: 1.0
        Mean Squared Error: 0.0
        Root Mean Squared Error: 0.0

 55%|████████████████████████                    | 6/11 [01:09<01:22, 16.48
s/it]
DecisionTreeRegressor()
        Training time: 0.030s
        Prediction time: 0.003s
        Explained variance: 1.0
        Mean absolute error: 0.0
        R2 score: 1.0
        Mean Squared Error: 0.0
        Root Mean Squared Error: 0.0

 64%|████████████████████████████                | 7/11 [02:04<01:55, 28.92
s/it]
SVR()
        Training time: 5.091s
        Prediction time: 0.930s
        Explained variance: 0.9999911434621832
        Mean absolute error: 0.09250309449311922
        R2 score: 0.9999901090289857
        Mean Squared Error: 0.009258626191109563
        Root Mean Squared Error: 0.09622175529010871

 73%|████████████████████████████████            | 8/11 [02:27<01:21, 27.26
s/it]
```

```
RandomForestRegressor()
        Training time: 2.340s
        Prediction time: 0.179s
        Explained variance: 1.0
        Mean absolute error: 0.0
        R2 score: 1.0
        Mean Squared Error: 0.0
        Root Mean Squared Error: 0.0
```

```
 82%|████████████████████████████████████       | 9/11 [02:56<00:55, 27.74
s/it]
```

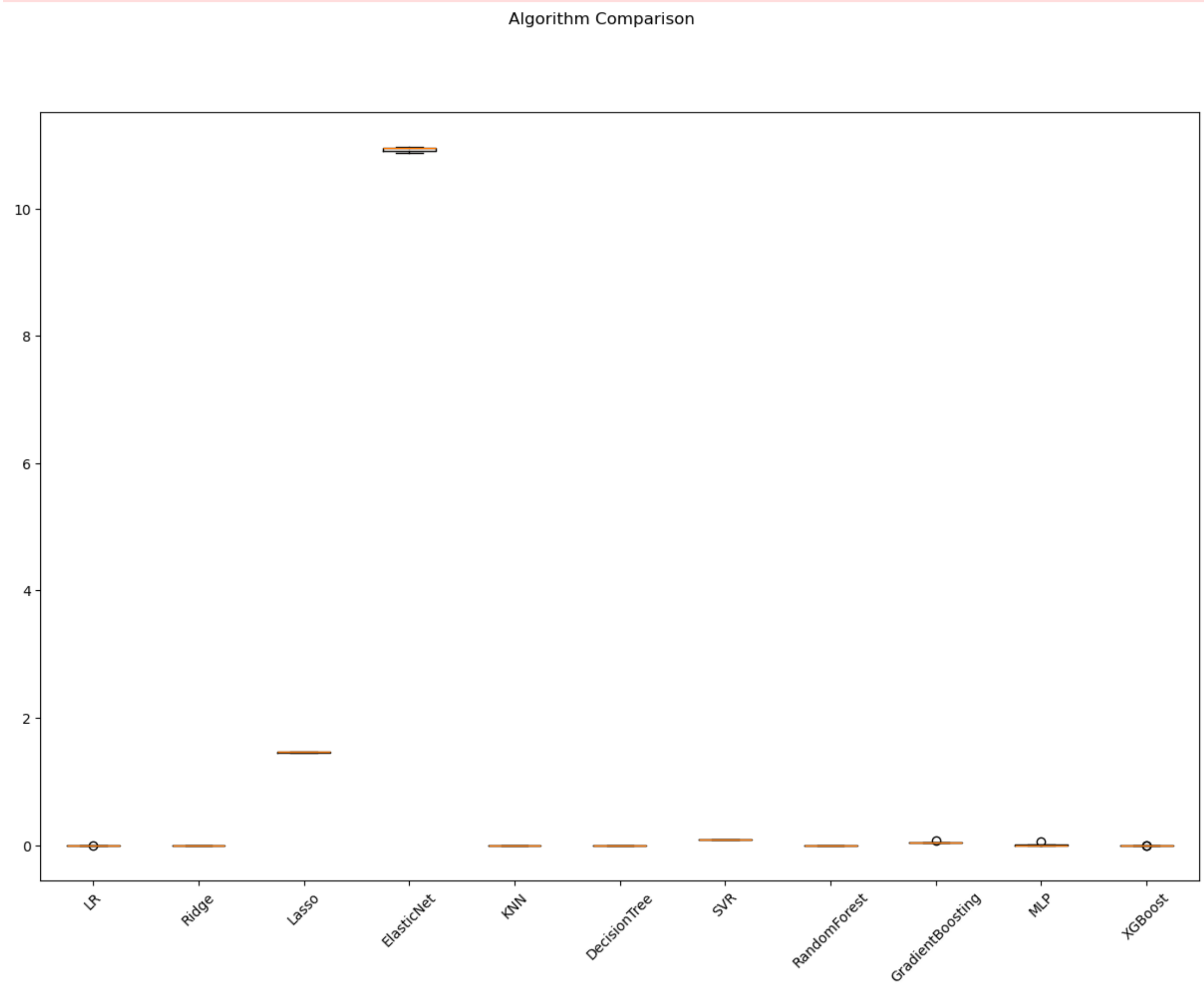
```
GradientBoostingRegressor()
        Training time: 2.843s
        Prediction time: 0.096s
        Explained variance: 0.9999973588707738
        Mean absolute error: 0.03650487193925271
        R2 score: 0.9999973588707346
        Mean Squared Error: 0.0024722778537209743
        Root Mean Squared Error: 0.049722005729063004
```

```
 91%|███████████████████████████████████████    | 10/11 [04:05<00:40, 40.28
s/it]
```

```
MLPRegressor()
        Training time: 8.853s
        Prediction time: 0.032s
        Explained variance: 0.9999999926873896
        Mean absolute error: 0.0033033359751068465
        R2 score: 0.9999999810300922
        Mean Squared Error: 1.77571326702134e-05
        Root Mean Squared Error: 0.004213921293784852
```

```
100%|███████████████████████████████████████████| 11/11 [04:18<00:00, 23.48
s/it]
```

```
XGBRegressor(base_score=None, booster=None, callbacks=None,
             colsample_bylevel=None, colsample_bynode=None,
             colsample_bytree=None, early_stopping_rounds=None,
             enable_categorical=False, eval_metric=None, feature_types=None,
             gamma=None, gpu_id=None, grow_policy=None, importance_type=Non
e,
             interaction_constraints=None, learning_rate=None, max_bin=None,
             max_cat_threshold=None, max_cat_to_onehot=None,
             max_delta_step=None, max_depth=None, max_leaves=None,
             min_child_weight=None, missing=nan, monotone_constraints=None,
             n_estimators=100, n_jobs=None, num_parallel_tree=None,
             predictor=None, random_state=None, ...)
        Training time: 1.510s
        Prediction time: 0.006s
        Explained variance: 0.9999999999999863
        Mean absolute error: 2.896869155057386e-06
        R2 score: 0.9999999999999835
        Mean Squared Error: 1.5476472174271006e-11
        Root Mean Squared Error: 3.934014765385484e-06
```



```
Models performance:
KNN - Mean Absolute Error: 0.0
DecisionTree - Mean Absolute Error: 0.0
RandomForest - Mean Absolute Error: 0.0
LR - Mean Absolute Error: 6.348357886889212e-11
XGBoost - Mean Absolute Error: 2.896869155057386e-06
Ridge - Mean Absolute Error: 0.00011656979060435019
MLP - Mean Absolute Error: 0.0033033359751068465
GradientBoosting - Mean Absolute Error: 0.03650487193925271
SVR - Mean Absolute Error: 0.09250309449311922
Lasso - Mean Absolute Error: 1.4580894202125017
ElasticNet - Mean Absolute Error: 10.927111979730267
```

In [146…

```
# Fit the model
lr = LinearRegression().fit(X_train, y_train)

# Make predictions
y_pred = lr.predict(X_test)

# Evaluate predictions
print('Mean Squared Error:', mean_squared_error(y_test, y_pred))
print('R2 Score:', r2_score(y_test, y_pred))
```

```
Mean Squared Error: 5.451858769533616e-21
R2 Score: 1.0
```

In [147…

```
# Print out the features used in the model
print("Features used in the model: ", X_train.columns.tolist())

# Now let's create new data for prediction
# This should have the same features as the original data
# For illustration, let's assume we have three features: 'Feature1', 'Featur

# new_data = pd.DataFrame({
#     'Feature1': [10, 20, 30],
#     'Feature2': [1, 2, 3],
#     'Feature3': [5, 10, 15],
    # add more features here as needed
# })
```

```
Features used in the model:  ['E1_combined_numeric', 'E2_combined_numeric']
```

In [148…

```
new_data = pd.DataFrame({
    'E1_combined_numeric': [0],
    'E2_combined_numeric': [2],
    # add more features here as needed
})

print("New data: ")
print(new_data)
```

```
New data:
   E1_combined_numeric  E2_combined_numeric
0                    0                    2
```

In [149…

```
# Get current hyperparameters
model = DecisionTreeRegressor()  # Replace with your best model if it's not
print("Current hyperparameters: ", model.get_params())
# Fitting the model with your data
model.fit(X_train, y_train)
```

```
Current hyperparameters:  {'ccp_alpha': 0.0, 'criterion': 'squared_error', '
max_depth': None, 'max_features': None, 'max_leaf_nodes': None, 'min_impurit
y_decrease': 0.0, 'min_samples_leaf': 1, 'min_samples_split': 2, 'min_weight
_fraction_leaf': 0.0, 'random_state': None, 'splitter': 'best'}
```

Out[149…

```
▾ DecisionTreeRegressor
DecisionTreeRegressor()
```

In [150…

```
new_data_preprocessed = pd.get_dummies(new_data)

# Use the existing model to make predictions
y_new_pred = model.predict(new_data_preprocessed)
print("Predictions on new data: ", y_new_pred)
```

```
Predictions on new data:  [50.]
```

In [151…

```
vaccine
```

Out [151…

	E1_combined_numeric	E2_combined_numeric	EconomicSupportIndex
0	0.0	0	0.0
1	0.0	0	0.0
2	0.0	0	0.0
3	0.0	0	0.0
4	0.0	0	0.0
...	...	...	...
390904	0.0	0	0.0
390905	0.0	0	0.0
390906	0.0	0	0.0
390907	0.0	0	0.0
390908	0.0	0	0.0

390909 rows × 3 columns

In [152…

```
vaccine1 = pd.read_csv("OxCGRT_simplified_v1.csv")
```

```
/var/folders/r0/jpvr7x216q569bknc6r4kfpm0000gn/T/ipykernel_3067/2464975989.p
y:1: DtypeWarning: Columns (2,3,44,45) have mixed types. Specify dtype optio
n on import or set low_memory=False.
  vaccine1 = pd.read_csv("OxCGRT_simplified_v1.csv")
```

In [153…

```
# Dropping unnecessary columns related to country and region identifiers, co
vaccine1.drop(['CountryName', 'CountryCode', 'RegionName', 'RegionCode', 'Ju
              'C1M_combined', 'C2M_combined', 'C3M_combined', 'C4M_combined'
              'C5M_combined', 'C6M_combined', 'C7M_combined', 'C8EV_combined
             axis=1, inplace=True)

# Dropping columns related to specific combined measures and vaccination sta
vaccine1.drop(['E1_combined', 'E2_combined', 'H1_combined', 'H2_combined', '
              'H6M_combined', 'H7_combined', 'H8M_combined', 'MajorityVaccin
             axis=1, inplace=True)

# Dropping redundant columns for vaccination statistics.
vaccine1.drop(['PopulationVaccinated'], axis=1, inplace=True)

# Dropping the column containing date information, as it may not be relevant
vaccine1.drop(['Date'], axis=1, inplace=True)
```

In [154…

```
vaccine1
```

Out[154…

	C1M_combined_numeric	C2M_combined_numeric	C3M_combined_numeric
0	0.0	0.0	0.0
1	0.0	0.0	0.0
2	0.0	0.0	0.0
3	0.0	0.0	0.0
4	0.0	0.0	0.0
...	...	...	...
390904	1.0	2.0	1.0
390905	1.0	2.0	1.0
390906	1.0	2.0	1.0
390907	1.0	2.0	1.0
390908	1.0	2.0	1.0

390909 rows × 26 columns

In [155…

```
vaccine1 = vaccine1.iloc[:, [0,1,2,3,4,5,6,7,12,-4]]
```

In [156…

```
vaccine1
```

Out[156…

	C1M_combined_numeric	C2M_combined_numeric	C3M_combined_numeric
0	0.0	0.0	0.0
1	0.0	0.0	0.0
2	0.0	0.0	0.0
3	0.0	0.0	0.0
4	0.0	0.0	0.0
...	...	...	...
390904	1.0	2.0	1.0
390905	1.0	2.0	1.0
390906	1.0	2.0	1.0
390907	1.0	2.0	1.0
390908	1.0	2.0	1.0

390909 rows × 10 columns

In [157…

```
vaccine1.isnull().sum()
```

Out[157…

```
C1M_combined_numeric       0
C2M_combined_numeric       0
C3M_combined_numeric       0
C4M_combined_numeric       0
C5M_combined_numeric       0
C6M_combined_numeric       0
C7M_combined_numeric       0
C8EV_combined_numeric      0
H3_combined_numeric        0
StringencyIndex_Average    0
dtype: int64
```

In [158…

```
X = vaccine1.drop(['StringencyIndex_Average'], axis=1)
y = vaccine1['StringencyIndex_Average']
```

In [159…

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, rar
```

In [160…

```
models = []
models.append(('LR', LinearRegression()))
models.append(('Ridge', Ridge()))
models.append(('Lasso', Lasso()))
models.append(('ElasticNet', ElasticNet()))
```

```
models.append(('KNN', KNeighborsRegressor()))
models.append(('DecisionTree', DecisionTreeRegressor()))
#models.append(('SVR', SVR()))
models.append(('RandomForest', RandomForestRegressor()))
models.append(('GradientBoosting', GradientBoostingRegressor()))
models.append(('MLP', MLPRegressor()))
models.append(('XGBoost', XGBRegressor()))
```

In [162…

```
import time
from tqdm import tqdm
from sklearn.metrics import mean_absolute_error, r2_score, explained_varianc
from math import sqrt

results = []
models_stats = []
names = []
scoring = 'neg_mean_absolute_error' # Change to 'r2' for R2, 'neg_mean_squar

for name, model in tqdm(models):
    start = time.time()
    kfold = KFold(n_splits=10, random_state=7, shuffle=True)
    model.fit(X_train, y_train)
    train_time = time.time() - start
    cv_results = -1 * cross_val_score(model, X_train, y_train, cv=kfold, scc
    results.append(cv_results)
    names.append(name)

    # Make predictions
    start = time.time()
    y_pred = model.predict(X_test)
    predict_time = time.time() - start

    # Coefficients are not available for all models
    if hasattr(model, 'coef_'):
        print(f"Coefficients for {name}: ", model.coef_)

    print(model)
    print("\tTraining time: %0.3fs" % train_time)
    print("\tPrediction time: %0.3fs" % predict_time)
    print("\tExplained variance:", explained_variance_score(y_test, y_pred))
    print("\tMean absolute error:", mean_absolute_error(y_test, y_pred))
    print("\tR2 score:", r2_score(y_test, y_pred))
    print("\tMean Squared Error:", mean_squared_error(y_test, y_pred))
    print("\tRoot Mean Squared Error:", sqrt(mean_squared_error(y_test, y_pr
    print()

    model_stats = {
        'name': name,
        'mean_s core': cv_results.mean(),
        'std_score': cv_results.std(),
```

```python
        'explained_variance': explained_variance_score(y_test, y_pred),
        'mean_absolute_error': mean_absolute_error(y_test, y_pred),
        'r2_score': r2_score(y_test, y_pred),
        'mean_squared_error': mean_squared_error(y_test, y_pred),
        'root_mean_squared_error': sqrt(mean_squared_error(y_test, y_pred)),
    }

    models_stats.append(model_stats)

# Boxplot to compare algorithms
fig = pyplot.figure(figsize=(15, 10))
fig.suptitle('Algorithm Comparison')
ax = fig.add_subplot(111)
pyplot.boxplot(results)
ax.set_xticklabels(names, rotation = 45)
pyplot.show()

# Sorting the models based on mean absolute error
models_stats.sort(key=lambda x: x['mean_absolute_error'])

print("\nModels performance:")
for model in models_stats:
    print(f"{model['name']} - Mean Absolute Error: {model['mean_absolute_err
```

```
 10%|████                                     | 1/10 [00:00<00:04,  1.88i
t/s]
Coefficients for LR:  [4.05198666 3.68667432 5.32018627 2.80771317 5.1830735
8 3.75173731
 5.28247417 2.78159462 1.35887556]
LinearRegression()
        Training time: 0.044s
        Prediction time: 0.004s
        Explained variance: 0.9804061700379557
        Mean absolute error: 2.120541426182424
        R2 score: 0.9804061700077541
        Mean Squared Error: 11.80565154305396
        Root Mean Squared Error: 3.4359353228857437

 20%|█████████                                | 2/10 [00:00<00:03,  2.65i
t/s]
```

```
Coefficients for Ridge:  [4.05199381 3.68668703 5.32013515 2.80773169 5.1830
2579 3.75173543
 5.28245441 2.78160244 1.35887237]
Ridge()
        Training time: 0.013s
        Prediction time: 0.001s
        Explained variance: 0.9804061696470391
        Mean absolute error: 2.12053916368399
        R2 score: 0.9804061696167667
        Mean Squared Error: 11.805651778631173
        Root Mean Squared Error: 3.435935357167124

 30%|█████████████                               | 3/10 [00:04<00:12,  1.81
s/it]
Coefficients for Lasso:  [4.47010928 3.80008781 3.45921299 3.73233252 2.7711
6375 3.10130514
 4.69541207 3.08567865 0.        ]
Lasso()
        Training time: 0.689s
        Prediction time: 0.002s
        Explained variance: 0.9720046075223449
        Mean absolute error: 2.841684440446434
        R2 score: 0.9720045495900986
        Mean Squared Error: 16.867786056168537
        Root Mean Squared Error: 4.107041034147156

 40%|█████████████████                           | 4/10 [00:06<00:11,  1.85
s/it]
Coefficients for ElasticNet:  [3.91742498 3.41605935 2.97468302 4.00183005
2.35472697 2.92806132
 3.32520307 3.16139659 0.82787278]
ElasticNet()
        Training time: 0.196s
        Prediction time: 0.003s
        Explained variance: 0.9589969314610346
        Mean absolute error: 3.766288453390682
        R2 score: 0.9589967111617181
        Mean Squared Error: 24.705253660745004
        Root Mean Squared Error: 4.970437974740758

 50%|██████████████████████                      | 5/10 [00:53<01:31, 18.26
s/it]
```

```
KNeighborsRegressor()
        Training time: 0.142s
        Prediction time: 9.949s
        Explained variance: 0.9894707317621614
        Mean absolute error: 1.1569705558824286
        R2 score: 0.9894457214963067
        Mean Squared Error: 6.359151546801053
        Root Mean Squared Error: 2.521735820184393
```

```
 60%|██████████████████████████                  | 6/10 [00:56<00:51, 12.95
s/it]
```

```
DecisionTreeRegressor()
        Training time: 0.256s
        Prediction time: 0.009s
        Explained variance: 0.9906195045050925
        Mean absolute error: 1.089038639573828
        R2 score: 0.9906195002584497
        Mean Squared Error: 5.651927739103386
        Root Mean Squared Error: 2.37737833318624
```

```
 70%|███████████████████████████████             | 7/10 [03:56<03:22, 67.56
s/it]
```

```
RandomForestRegressor()
        Training time: 17.432s
        Prediction time: 0.816s
        Explained variance: 0.9906425357994203
        Mean absolute error: 1.0942859173533666
        R2 score: 0.9906425336554376
        Mean Squared Error: 5.6380496836747005
        Root Mean Squared Error: 2.3744577662436326
```

```
 80%|███████████████████████████████████         | 8/10 [05:31<02:32, 76.41
s/it]
```

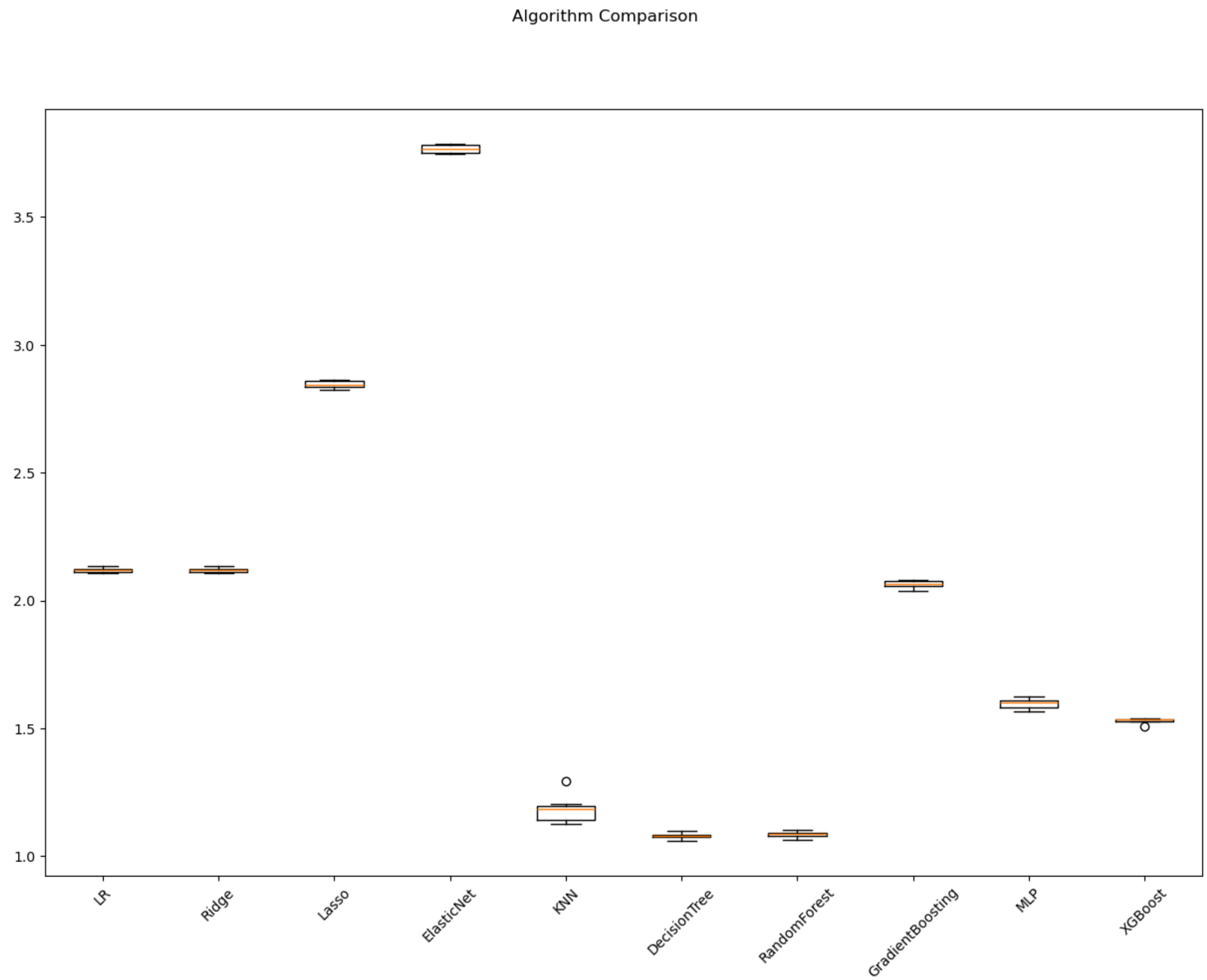
```
GradientBoostingRegressor()
        Training time: 9.564s
        Prediction time: 0.088s
        Explained variance: 0.9842757945427958
        Mean absolute error: 2.065381460749278
        R2 score: 0.9842757652227587
        Mean Squared Error: 9.474147557406777
        Root Mean Squared Error: 3.078010324447723
```

```
/Users/kaushikpatil/anaconda3/lib/python3.10/site-packages/sklearn/neural_ne
twork/_multilayer_perceptron.py:691: ConvergenceWarning: Stochastic Optimize
r: Maximum iterations (200) reached and the optimization hasn't converged ye
t.
  warnings.warn(
/Users/kaushikpatil/anaconda3/lib/python3.10/site-packages/sklearn/neural_ne
twork/_multilayer_perceptron.py:691: ConvergenceWarning: Stochastic Optimize
```

```
r: Maximum iterations (200) reached and the optimization hasn't converged ye
t.
  warnings.warn(
/Users/kaushikpatil/anaconda3/lib/python3.10/site-packages/sklearn/neural_ne
twork/_multilayer_perceptron.py:691: ConvergenceWarning: Stochastic Optimize
r: Maximum iterations (200) reached and the optimization hasn't converged ye
t.
  warnings.warn(
/Users/kaushikpatil/anaconda3/lib/python3.10/site-packages/sklearn/neural_ne
twork/_multilayer_perceptron.py:691: ConvergenceWarning: Stochastic Optimize
r: Maximum iterations (200) reached and the optimization hasn't converged ye
t.
  warnings.warn(
/Users/kaushikpatil/anaconda3/lib/python3.10/site-packages/sklearn/neural_ne
twork/_multilayer_perceptron.py:691: ConvergenceWarning: Stochastic Optimize
r: Maximum iterations (200) reached and the optimization hasn't converged ye
t.
  warnings.warn(
/Users/kaushikpatil/anaconda3/lib/python3.10/site-packages/sklearn/neural_ne
twork/_multilayer_perceptron.py:691: ConvergenceWarning: Stochastic Optimize
r: Maximum iterations (200) reached and the optimization hasn't converged ye
t.
  warnings.warn(
/Users/kaushikpatil/anaconda3/lib/python3.10/site-packages/sklearn/neural_ne
twork/_multilayer_perceptron.py:691: ConvergenceWarning: Stochastic Optimize
r: Maximum iterations (200) reached and the optimization hasn't converged ye
t.
  warnings.warn(
/Users/kaushikpatil/anaconda3/lib/python3.10/site-packages/sklearn/neural_ne
twork/_multilayer_perceptron.py:691: ConvergenceWarning: Stochastic Optimize
r: Maximum iterations (200) reached and the optimization hasn't converged ye
t.
  warnings.warn(
/Users/kaushikpatil/anaconda3/lib/python3.10/site-packages/sklearn/neural_ne
twork/_multilayer_perceptron.py:691: ConvergenceWarning: Stochastic Optimize
r: Maximum iterations (200) reached and the optimization hasn't converged ye
t.
  warnings.warn(
/Users/kaushikpatil/anaconda3/lib/python3.10/site-packages/sklearn/neural_ne
twork/_multilayer_perceptron.py:691: ConvergenceWarning: Stochastic Optimize
r: Maximum iterations (200) reached and the optimization hasn't converged ye
t.
  warnings.warn(
 90%|█████████████████████████████████████▌    | 9/10 [36:15<10:29, 629.02
s/it]
```

```
MLPRegressor()
        Training time: 102.620s
        Prediction time: 0.047s
        Explained variance: 0.9871629190922099
        Mean absolute error: 1.5955165274509167
        R2 score: 0.9871598965808972
        Mean Squared Error: 7.736404102857446
        Root Mean Squared Error: 2.781439214302093
```

```
100%|██████████████████████████████████████████| 10/10 [40:50<00:00, 245.03
s/it]
XGBRegressor(base_score=None, booster=None, callbacks=None,
             colsample_bylevel=None, colsample_bynode=None,
             colsample_bytree=None, early_stopping_rounds=None,
             enable_categorical=False, eval_metric=None, feature_types=None,
             gamma=None, gpu_id=None, grow_policy=None, importance_type=Non
e,
             interaction_constraints=None, learning_rate=None, max_bin=None,
             max_cat_threshold=None, max_cat_to_onehot=None,
             max_delta_step=None, max_depth=None, max_leaves=None,
             min_child_weight=None, missing=nan, monotone_constraints=None,
             n_estimators=100, n_jobs=None, num_parallel_tree=None,
             predictor=None, random_state=None, ...)
        Training time: 242.473s
        Prediction time: 0.018s
        Explained variance: 0.9889407277606327
        Mean absolute error: 1.5495102409824761
        R2 score: 0.9889407265796413
        Mean Squared Error: 6.663420493685079
        Root Mean Squared Error: 2.581360202235457
```




```
Models performance:
DecisionTree - Mean Absolute Error: 1.0890386395738 28
RandomForest - Mean Absolute Error: 1.0942859173533666
KNN - Mean Absolute Error: 1.1569705558824286
XGBoost - Mean Absolute Error: 1.5495102409824761
MLP - Mean Absolute Error: 1.5955165274509167
GradientBoosting - Mean Absolute Error: 2.065381460749278
Ridge - Mean Absolute Error: 2.12053916368399
LR - Mean Absolute Error: 2.120541426182424
Lasso - Mean Absolute Error: 2.841684440446434
ElasticNet - Mean Absolute Error: 3.766288453390682
```

In [163…

```
# Fit the model
lr = DecisionTreeRegressor().fit(X_train, y_train)

# Make predictions
y_pred = lr.predict(X_test)

# Evaluate predictions
print('Mean Squared Error:', mean_squared_error(y_test, y_pred))
```

```
print('R2 Score:', r2_score(y_test, y_pred))
```

```
Mean Squared Error: 5.654733869641528
R2 Score: 0.9906148429259425
```

In [164…

```
# Print out the features used in the model
print("Features used in the model: ", X_train.columns.tolist())
```

```
Features used in the model:  ['C1M_combined_numeric', 'C2M_combined_numeri
c', 'C3M_combined_numeric', 'C4M_combined_numeric', 'C5M_combined_numeric',
'C6M_combined_numeric', 'C7M_combined_numeric', 'C8EV_combined_numeric', 'H3
_combined_numeric']
```

In [165…

```
# Now let's create new data for prediction
# This should have the same features as the original data
# For illustration, let's assume we have three features: 'Feature1', 'Featur

# new_data = pd.DataFrame({
#     'Feature1': [10, 20, 30],
#     'Feature2': [1, 2, 3],
#     'Feature3': [5, 10, 15],
    # add more features here as needed
# })
new_data = pd.DataFrame({
    'C1M_combined_numeric': [1],
    'C2M_combined_numeric': [2],
    'C3M_combined_numeric': [2],
    'C4M_combined_numeric': [4],
    'C5M_combined_numeric': [0],
    'C6M_combined_numeric': [0],
    'C7M_combined_numeric': [2],
    'C8EV_combined_numeric': [1],
    'H3_combined_numeric': [0],
    # add more features here as needed
})

print("New data: ")
print(new_data)
```

```
New data:
   C1M_combined_numeric  C2M_combined_numeric  C3M_combined_numeric  \
0                     1                     2                     2

   C4M_combined_numeric  C5M_combined_numeric  C6M_combined_numeric  \
0                     4                     0                     0

   C7M_combined_numeric  C8EV_combined_numeric  H3_combined_numeric
0                     2                      1                    0
```

In [166…

```
# Get current hyperparameters
model = DecisionTreeRegressor()  # Replace with your best model if it's not
```

```
print("Current hyperparameters: ", model.get_params())
# Fitting the model with your data
model.fit(X_train, y_train)
```

```
Current hyperparameters:  {'ccp_alpha': 0.0, 'criterion': 'squared_error', '
max_depth': None, 'max_features': None, 'max_leaf_nodes': None, 'min_impurit
y_decrease': 0.0, 'min_samples_leaf': 1, 'min_samples_split': 2, 'min_weight
_fraction_leaf': 0.0, 'random_state': None, 'splitter': 'best'}
```

Out[166…

▾ DecisionTreeRegressor

DecisionTreeRegressor()

In [167…

```
# Apply the same preprocessing steps as you did for your training data
# In this case, convert categorical variables to dummy/indicator variables
new_data_preprocessed = pd.get_dummies(new_data)

# Use the existing model to make predictions
y_new_pred = model.predict(new_data_preprocessed)
print("Predictions on new data: ", y_new_pred)
```

```
Predictions on new data:  [59.26]
```

In [ ]:

```

```