P-ISSN 2586-9000
E-ISSN 2586-9027
Homepage : https://tci-thaijo.org/index.php/SciTechAsia
Science & Technology Asia
Vol. 29 No.4 October - December 2024
Page: [39-50]
*Original research article*

# Assessing Non-Linearity and Stationarity in the Time Series of Albania's Annual Emissions of CO2 from Land-Use Change

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Received 28 July 2024; Received in revised form 23 November 2024
Accepted 3 December 2024; Available online 27 December 2024

**ABSTRACT**

The annual emissions of CO2 from land-use change in Albania are the main focus of this research. The aim is to analyze the presence of non-linearity and stationarity. A mixed-methods strategy is used, which combines descriptive, inferential, and exploratory data analysis in time series data. A data sample was obtained from the Our World in Data website, spanning from 1850 through 2022. After the Isolation Forest technique was employed to identify outliers in the time series, the Long-Short-Term Memory model was used to impute them. Exploratory data analysis was applied to the original and imputed time series to ensure that the basic characteristics of the initial data distribution were preserved. Non-linearity and stationarity were checked in the imputed time series before and after applying the first differences. Non-linearity was assessed using the BDS test and the Teräsvirta Neural Network test. In the presence of non-linearity, stationarity was analyzed using the KPSS test, the Zivot-Andrews Unit Root test, and the Breitung test. The first differencing application transformed the non-stationary series into a stationary one, but it was insufficient to eliminate non-linearity. This highlights the complex nature of CO2 emissions data and the need for sophisticated modeling techniques.

**Keywords:** Carbon emissions; Land-use impacts; LSTM imputation; Non-linearity; Stationarity tests

## 1. Introduction

Agriculture, forestry, and other land-use sectors are some of the contributors to the total greenhouse gas (GHG) emissions in Albania. The main emitters are the 'livestock' with 41% of the total and the 'land' with 38% of the total GHG emissions. Although forests are believed to be a sink of GHG emissions, under the category 'land', they represent one of the key sources of emissions, mostly due to their

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**doi:** 10.14456/scitechasia.2024.69

neglected management in recent years. Furthermore, negative impacts in this direction have arisen from uncontrolled deforestation, massive forest fires, a lack of effective investment in forest improvement and afforestation, informality, and an absence of development reforms [1].

In an empirical investigation [2] with data from Malaysia (1990-2019), it was shown that agricultural land expansion by 1% is associated with an increase of 0.84% in carbon dioxide (CO2) emissions in the long run. Meanwhile, a 1% reduction in the wooded area, has resulted in a 5.41% long-term impact on higher CO2 emissions.

Carbon dioxide emissions from land-use change (CO2-E-LUC) are considered a summation of various activities that emit carbon stored in vegetation or soil [3, 4]. This includes emissions from: deforestation ($CO2\text{-}E_{def.}$), forest degradation ($CO2\text{-}E_{deg.}$), conversion of forest land to agriculture ($CO2\text{-}E_{conv.agric.}$), conversion of natural land to urban areas ($CO2\text{-}E_{urb.conv.}$), soil degradation, and wetland drainage ($CO2\text{-}E_{soil\ deg.\ and\ wetland\ drain.}$). As expressed in a formula we have,

$$\begin{aligned} CO2\text{-}E\text{-}LUC = {} & CO2\text{-}E_{def.} + CO2\text{-}E_{deg.} \\ & + CO2\text{-}E_{conv.agric.} + CO2\text{-}E_{urb.conv.} \\ & + CO2\text{-}E_{soil\ deg.\ and\ wetland\ drain.}, \end{aligned} \tag{1.1}$$

Trajectories of land-use change indicate positive and negative relationships between man and the environment. Land-use change analyses are necessary to assist the government in appropriate zoning to minimize or eliminate negative environmental impacts. With the beginning of land trading in the absence of regulatory legislation from 1996 to 2003 in Albania, land-use changes were more dynamic [5]. According to [6], land-use change caused 215 and 142 Pg C of global emissions and removals, respectively, between 1961 and 2020, resulting in an average net emissions of 1.21 Pg C per year.

The state of climate change in six Western Balkan countries (Albania included) was studied in [7]. The development of sustainable forestry, the improvement of forest management practices, and the rehabilitation of degraded forest land are integral parts of the strategies that have to do with land-use change and forestry.

The annual emissions of CO2 from land-use change in Albania, as measured in tonnes per person (CO2-E-LUC per capita), are the primary focus of analysis in this research, seen from a statistical perspective. CO2-E-LUC per capita is expressed by,

$$CO2\text{-}E\text{-}LUC \text{ per capita} = \frac{CO2\text{-}E\text{-}LUC}{\text{population}}. \tag{1.2}$$

There are several reasons, such as climate change [8, 9], health [10], economic development [11, 12], carbon budgets [13], etc., why it is important to conduct research on the CO2-E-LUC per capita time series data in Albania as well as abroad. Further, to our knowledge, in Albania, there is a lack of studies in the area of CO2 emissions data, divided by their categories.

Albania is committed to implementing policies to lower GHG emissions from various economic sectors. By December 2022, the country had partially aligned with the Regulation on the Governance of the Energy Union and Climate Action. The level of emission reductions planned for 2021-2030 in the National Energy and Climate Plan adopted in 2021 is 18.7%. The plan relies significantly on the reduction of CO2 by forests, but in contrast with this, there are very limited financial means and capacity allocated to protecting and managing forests, including measures to promote reforestation and manage forest fire risks. In February 2023, a ministerial decision approved the National Strategy for Development and European Integration 2022-2030, which sets out a series of priority measures like adopting climate secondary legislation, climate budgeting, and nature-based solutions. Furthermore, Albania needs to address strategic investment planning, and the implementation and monitoring capacity of infrastructure projects [14].

The main objective of this research is to analyze the presence of non-linearity and stationarity in the time series data of annual CO2-E-LUC per capita. To further study this objective, we raise the following research questions:

- RQ1: Is there non-linearity in the time series data?
- RQ2: Is the time series data stationary?

Non-linearity and non-stationarity are processes that are often encountered in time series, and they can be the result of complex underlying dynamics. If these issues are not addressed before building specific predictive models, it would compromise the reliability of the results. In the context of CO2 emissions, since many decision-making policies are based on predictive models of time series of emissions, they are directly influenced by the accuracy of these models.

## 2. Materials and Methods

The present research implemented a mixed-methods approach to investigate the presence of non-linearity and stationarity in the annual CO2-E-LUC per capita series data. It is a combination of inferential, descriptive, and exploratory methods. Data sampling related to Albania's annual CO2-E-LUC per capita was gathered from Our World in Data, available for download at [15]. Ritchie in [16] provides sources and methods used to produce CO2 emissions dataset. The data timeframe that is analyzed herein spans from 1850 to 2022. The variables under study are "annual CO2-E-LUC per capita" and "year", analyzed as a time series.

**Table 1.** The non-linearity and stationarity tests applied.

| Purpose | Test | Function utilized in R for the test implementation | Null hypothesis | Alternative hypothesis | Rejection of Null hypothesis |
|---|---|---|---|---|---|
| Non-linearity testing RQ1 | The Brock-Dechert-Scheinkman (BDS) Test [17, 18] | bds.tst() [19] with embedding dimensions values (2, 3) and four epsilon values (0.5SD, 1SD, 1.5SD, 2SD). | The time series is independently and identically distributed (i.i.d.). | The time series is not i.i.d. (exhibits nonlinearity or chaotic behavior). | $p<0.05$ |
| | The Teräsvirta Neural Network Test [20, 21] | terasvirta.test() [22] | The time series follows a linear model. | The time series follows a nonlinear model. | $p<0.05$ |
| Stationarity testing RQ2 | The Kwiatkowski-Phillips-Schmidt-Shin (KPSS) Test [23] | ur.kpss() [24] type= c("mu", "tau") lags=c("short", "long")[1] | The time series has stationarity around a mean / deterministic trend. | The time series is not level / trend-stationary. | The test statistic exceeds the critical values (1%, 2.5%, 5%, 10%). |
| | Zivot-Andrews Unit Root Test [25] | ur.za() [24] model =c("intercept", "trend", "both") Optimal lag value[2] | The time series has a unit root and is non-stationary, with no structural break. | The time series is stationary with a structural break at some unknown point in the time series. | The test statistic is less than the critical value values (1%, 5%, 10%) |
| | Breitung Test (Elliot, Rothenberg, and Stock Unit Root Test) [26, 27] | ur.ers() [24] type= "P-test" model= c("constant", "trend") | The time series has a unit root, it is non-stationary around a constant mean/deterministic trend. | The time series is stationary around a constant mean/deterministic trend. | The test statistic is less than the critical values (1%, 5%, 10%) |

**Note 1**: lags= "short" sets the number of lags to $4\left(\frac{n}{100}\right)$, whereas lags= "long" sets the number of lags to $12\left(\frac{n}{100}\right)$.

**Note 2:** The Akaike Information Criterion (AIC) [28] was used to select the optimal lag length, rotating from 1 to 40, minimizing the AIC value. This ensures that the model includes enough lags to capture autocorrelation without overfitting.

The statistical procedure started with the identification of time series outliers. Their presence and mishandling can affect the accuracy of predictive models. The Isolation Forest technique [29, 30] was used to detect them. This technique effectively identifies anomalies without assuming distributional properties, making it well-suited for non-linear, non-stationary time series data. Random binary trees from subsets of the data are constructed to isolate individual points based on their anomaly scores. A range of trees (50, 100, 150, and 200) were evaluated, and the optimal number was selected using cross-validation. Outliers were identified as points that exceeded the 95th percentile threshold of the anomaly scores.

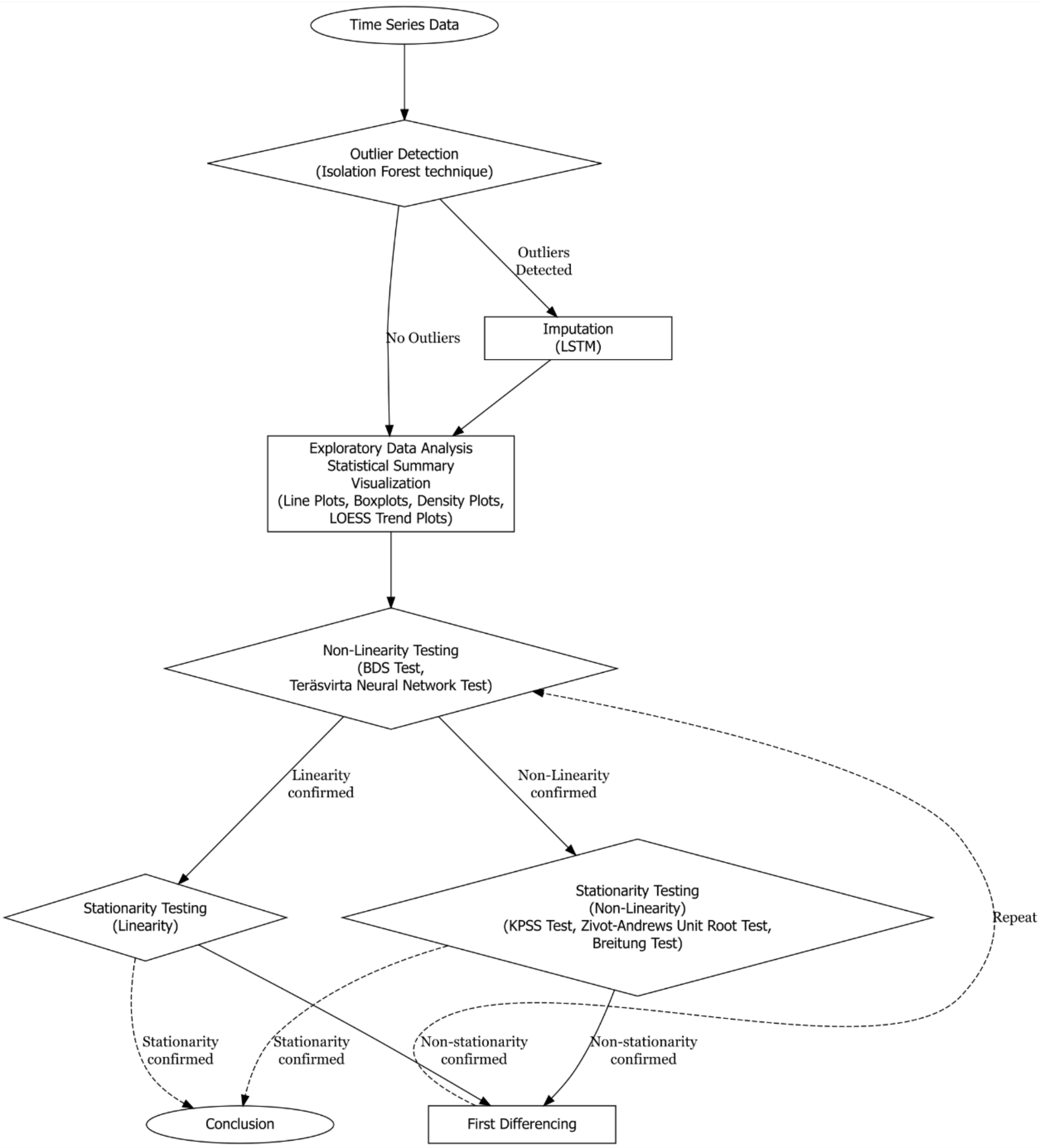


**Fig. 1.** Flowchart of statistical procedure steps.

After that, the outliers were replaced with NA values. The Long Short-Term Memory (LSTM) model [31-34] was chosen for the imputation, due to its ability to capture complex temporal dependencies in non-linear and non-stationary data. The model architecture details were as follows: two layers, each containing 30 units; a specified timestep of 5; 100 epochs; and a batch size 16. Model performance [35, 36] was evaluated using metrics: Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), Symmetric Mean Absolute Percentage Error (sMAPE), Mean Absolute Scaled Error (MASE), and R-squared ($R^2$).

Furthermore, it was continued with an exploratory data analysis of both original and imputed time series data to verify if the basic characteristics of the initial data distribution were preserved. The summary statistics used were: minimum (Min), first quartile (Q1), median (Q2), mean, third quartile (Q3), maximum (Max), standard deviation (SD), skewness, and kurtosis. The data was tested for normality using the Anderson-Darling normality test [37]. Locally estimated scatterplot smoothing (LOESS) was obtained through the function loess() with span=0.3 [38] [39].

Graphical representations such as boxplots, line plots, density plots, and LOESS trend plots, were used to visually see the approximation made by the imputation method. Before checking for the stationarity of a series, it is necessary to analyze its linearity, because some tests that assess stationarity assume that the series is linear. Conversely, if the non-linearity of the series is confirmed, then the tests for stationarity should be chosen under this circumstance.

The applied tests to check on the two research questions are described with implementation details in Table 1. All the procedure steps in analyzing the time series data are outlined in the flowchart in Fig. 1. The statistical computations are gathered using R software [40].

## 3. Results and Discussion

### 3.1 Exploratory Data Analysis

The optimal number of trees chosen by cross-validation was 50, while applying the Isolation Forest technique. Nine outliers' values were identified in the time series data of annual CO2-E-LUC per capita, using the threshold 0.6237087. These values represent only 5% of the sample. Together with the corresponding years and the imputed values, they are presented in Table 2.

**Table 2.** Outliers, corresponding imputed values, and the respective years.

| Year | Outlier | Imputed |
|---|---|---|
| 1951 | 3.536 | 3.171 |
| 1954 | 4.071 | 3.650 |
| 1955 | 4.163 | 3.569 |
| 1956 | 4.238 | 3.446 |
| 1957 | 4.348 | 3.302 |
| 1959 | 4.401 | 3.671 |
| 1960 | 3.755 | 3.632 |
| 2002 | -0.113 | 0.048 |
| 2004 | -0.312 | 0.048 |

**Table 3.** Summary statistics of time series data before and after imputation.

| Statistic | Before | After |
|---|---|---|
| **Min** | -0.312 | -0.071 |
| **Q1** | 1.060 | 1.060 |
| **Q2** | 2.56 | 2.56 |
| **Mean** | 2.08 | 2.06 |
| **Q3** | 2.891 | 2.891 |
| **Max** | 4.40 | 4.37 |
| **SD** | 1.17 | 1.12 |
| **Skewness** | -0.499 | -0.628 |
| **Kurtosis** | -0.811 | -0.93 |
| **Anderson-Darling Test** | Test Statistic (A): 8.3608 | Test Statistic (A): 9.7374 |
| | *p*-value: < 2.2e-16 | *p*-value: < 2.2e-16 |

The LSTM model imputation achieved an RMSE of 0.1336, indicating a minimal average error, and MAPE of 2.06%, emphasizing a low percentage of error. The sMAPE of 2.93%, further supported the consistency of the imputation. Additionally, the MASE of 0.279 showed scaled accuracy, while the $R^2$ of 0.988 confirmed a near-perfect fit between imputed and outliers' values.

Future analysis could be conducted to investigate what might have occurred in these years to result in these extreme values for annual CO2-E-LUC per capita, but this is not the focus of the current study.

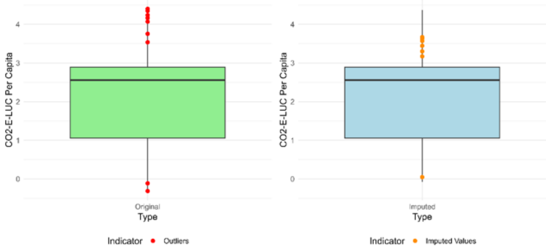


**Fig. 2.** Box plots of annual CO2-E-LUC-per capita before and after imputation.

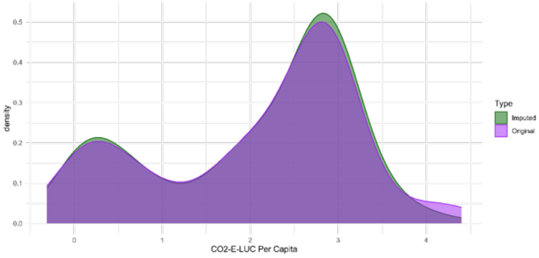


**Fig. 3.** Density plots of annual CO2-E-LUC-per capita before and after imputation.

In the following, the imputed time series is obtained from the original time series, where outlier values have been replaced by the imputed values. The summary statistics are presented in Table 3. The visual representations are given by box plots in Fig. 2 and density plots in Fig. 3. When comparing the two series, very small changes are observed. The central tendency of the data is preserved. A reduction in the extreme values and less variability is seen after imputation. Although a shift in the values of skewness and kurtosis is seen, the distribution remains moderately left skewed and flat. The results from both the original and imputed time series indicate that neither of them follows a normal distribution according to the Anderson-Darling test. Fig. 4 shows the line plots of the time series, highlighting the outliers and imputed points, and also provides the LOESS trend plots.

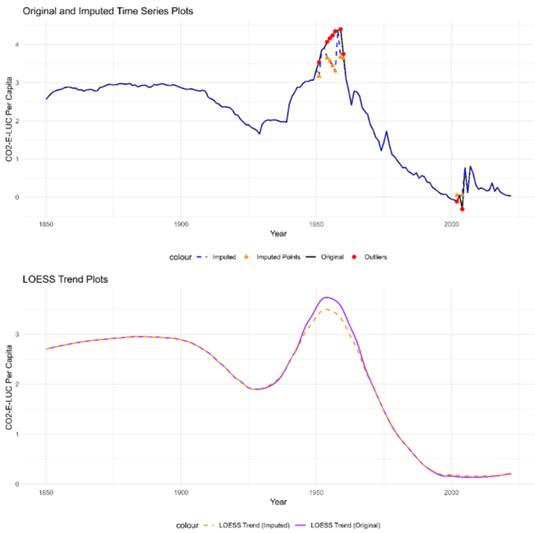


**Fig. 4.** Annual CO2-E-LUC per capita time series plots with outliers and imputed points. LOESS trend of the original and imputed time series.

## 3.2 Non-linearity and Stationarity

### *3.2.1 Before First Differencing*

Based on the results obtained from the BDS test (Tables 4-5) applied to the imputed time series of CO2-E-LUC per capita, the standard normal statistics values are high and the *p*-values are less than 0.001. This occurs for all values of epsilon and embedding dimensions considered. Therefore, the initial hypothesis of the test is rejected. This fact indicates the presence of non-linearity or dependence in the time series data.

**Table 4.** BDS results for embedding dimension = 2, before and after first differencing.

| First Differencing | Epsilon | Standard Normal | *p*-value |
|---|---|---|---|
| Before | 0.5622 | 47.256 | <0.001 |
| | 1.1244 | 44.122 | <0.001 |
| | 1.6866 | 39.828 | <0.001 |
| | 2.2489 | 34.212 | <0.001 |
| After | 0.0932 | 8.0449 | <0.001 |
| | 0.1864 | 6.269 | <0.001 |
| | 0.2795 | 5.9787 | <0.001 |
| | 0.3727 | 4.9951 | <0.001 |

**Table 5.** BDS results for embedding dimension = 3, before and after first differencing.

| First Differencing | Epsilon | Standard Normal (2) | Standard Normal (3) | *p*-value (2) | *p*-value (3) |
|---|---|---|---|---|---|
| Before | 0.5622 | 46.125 | 72.716 | <0.001 | <0.001 |
| | 1.1244 | 42.704 | 51.523 | <0.001 | <0.001 |
| | 1.6866 | 38.775 | 42.586 | <0.001 | <0.001 |
| | 2.2489 | 33.572 | 34.694 | <0.001 | <0.001 |
| After | 0.0932 | 8.0288 | 10.3137 | <0.001 | <0.001 |
| | 0.1864 | 6.2542 | 7.5684 | <0.001 | <0.001 |
| | 0.2795 | 5.9498 | 6.9286 | <0.001 | <0.001 |
| | 0.3727 | 4.9703 | 5.6501 | <0.001 | <0.001 |

As can be seen in Table 6, non-linearity is confirmed also by the Teräsvirta Neural Network test, where the *p*-value is 4.961e-06 (<0.05). To further continue testing stationarity, we use tests that can handle non-linearity.

**Table 6.** Teräsvirta Neural Network test result, before and after first differencing.

| First Differencing | Statistic | | |
|---|---|---|---|
| | X-squared | Df | *p*-value |
| **Before** | 24.428 | 2 | 4.961e-06 |
| **After** | 12.538 | 2 | 0.001894 |

The results of the KPSS test are displayed in Table 7. Across both short (4 lags) and long (13 lags) configurations for the KPSS test, the test statistics exceed the critical values at 5%, for stationarity around the mean ("mu") and trend ("tau"). For the "mu" test, the short lag test statistic is 2.25, and the long lag test statistic is 0.8653. In the "tau" test, the short lag test statistic is 0.4681, and the long lag test statistic is 0.1873. This means that the null hypothesis of the test is rejected, and the imputed time series of CO2-E-LUC per capita is neither level nor trend-stationary.

Table 8 provides the results of Zivot-Andrews's test applied for varying lag values, from 1 to 40. Before first differencing, the Zivot-Andrew's test provides the following results. In the "intercept" model, the test statistic -4.4048 is greater than all the critical values considered. This suggests that the series is non-stationary, even considering potential structural breaks. A break is identified at observation 141, and the optimal lag based on AIC is 18, indicating that the model explains a significant amount of autocorrelation in the data.

In the "trend" model, the test statistic -4.6469 is greater than the critical value at 1% but less than the critical value at 5% and 10%. According to this, there is weak evidence that the series remains non-stationary to a trend, and the potential structural break is detected at observation 126. The optimal lag is again 18, signifying similar autocorrelation patterns as in the "intercept" model.

In the "both" (intercept and trend) model, the test statistic of -6.0411 is less than all critical values (10%, 5%, and 1%). This suggests that the series is stationary when accounting for structural breaks in intercept and the trend. The structural break is identified at observation 90, and the optimal lag remains at 18, emphasizing once more long-term dependencies.

The data in Table 9 provides the results of the Breitung test. In both the models considered, we see that the value of the test statistic before differencing is greater than the critical values at all significance levels. This means that the null hypothesis of the test cannot be rejected.

In summary, after applying the three tests to check the stationarity of the imputed time series for CO2-E-LUC per capita, we come to the same conclusion: the series is non-stationary.

**Table 7.** KPSS test results on the imputed time series before and after first differencing.

| Test Type | Lag | First Differencing | Test Statistic | Critical Values (10%) | (5%) | (2.5%) | (1%) |
|---|---|---|---|---|---|---|---|
| **KPSS (mu)** | Short (4) | Before | 2.25 | 0.347 | 0.463 | 0.574 | 0.739 |
| | | After | 0.2407 | | | | |
| | Long (13) | Before | 0.8653 | | | | |
| | | After | 0.1635 | | | | |
| **KPSS (tau)** | Short (4) | Before | 0.4681 | 0.119 | 0.146 | 0.176 | 0.216 |
| | | After | 0.0792 | | | | |
| | Long (13) | Before | 0.1873 | | | | |
| | | After | 0.0556 | | | | |

### *3.2.2 After First Differencing*

To make the series stationary, we take the first differences. Then, we re-check if the series is non-linear. It turns out from the BDS test (Table 4 and Table 5) that the p-values remain less than 0.001, thus rejecting the null hypothesis of the test. It is noted that the values of standard normal statistics have decreased significantly compared to those before taking the first differences. However, based on this test, the series remains non-linear.

The same phenomenon is observed in the Teräsvirta Neural Network test's output (Table 6). Although the value of the test statistic has decreased, the p-value (0.001894) provides statistical evidence at the 0.05 significant level that the time series exhibits non-linearity.

**Table 8.** Zivot-Andrews Unit root test results before and after first differencing, with optimal lag based on AIC

| Model Type | First Differencing | Test Statistic | Critical Values 10% | 5% | 1% | Potential Break Point | Optimal Lag (AIC) |
|---|---|---|---|---|---|---|---|
| **Intercept** | Before | -4.4048 | -4.58 | -4.80 | -5.34 | 141 | 18 |
| | After | -10.4096 | | | | 108 | 1 |
| **Trend** | Before | -4.6469 | -4.11 | -4.42 | -4.93 | 126 | 18 |
| | After | -9.214 | | | | 130 | 1 |
| **Both** | Before | -6.0411 | -4.82 | -5.08 | -5.57 | 90 | 18 |
| | After | -10.842 | | | | 108 | 1 |

The first differencing has some effect on reducing non-linearity, but it is insufficient to fully eliminate it. Regarding the stationarity of the differenced time series, we continue testing with the same group of tests as before the first differencing due to the same conditions related to non-linearity.

Based on the results of the tests, we see that the first differencing has shifted the non-stationary series into a stationary one. The KPSS test statistics (see Table 7) for both short and long lags are found to be less than the critical values. For the "mu" test, the short lag test statistic dropped to 0.2407, and the long lag test statistic fell to 0.1635, both less than the critical thresholds, indicating stationary around the mean. For the "tau" test, the short lag test statistic is 0.0792, and the long lag test statistic is 0.0556, providing evidence for trend stationarity after differencing.

**Table 9.** Breitung test results on the imputed time series before and after first differencing.

| Test Type | Model | Lag | Test Statistic | Critical Values | | |
|---|---|---|---|---|---|---|
| | | | | (10%) | (5%) | (1%) |
| **P-test** | constant | 1 | Before: 29.112<br>After: 0.4701 | 4.33 | 3.17 | 1.91 |
| **P-test** | trend | 1 | Before: 36.8543<br>After: 1.4403 | 6.86 | 5.66 | 4.05 |

After first differencing, the Zivot-Andrews's test results (Table 8), present statistical evidence that the series becomes stationary across all model types. As a result, the null hypothesis of a unit root is rejected. In the "intercept" model, the test statistic value (-10.4096) is less than all critical values. The structural break shifts to observation 108, and the optimal lag based on AIC reduces to 1. In the "trend" model, the test statistic is -9.214, again less than all critical values, indicating that the series is now trend-stationary. The structural break occurs at observation 130, and the optimal lag is reduced to 1. In the "both" (intercept and trend) model, the test statistic of -10.842, less than all the critical values considered, confirms stationarity in both the intercept and trend after differencing. The structural break remains at 108, and the optimal lag is 1.

We see that after the first differencing, the autocorrelation is largely resolved, reducing the optimal lag to 1 in all three models, based on the Zivot-Andrews's test results. Structural breaks still exist but occur at different points. While differencing eliminates non-stationarity, it does not entirely remove the impact of key structural changes in the series.

Results of the Breitung test after first differencing (Table 9) prove that the test statistic's value becomes less than the critical values, in both models. In this case, the time series is stationary around a constant mean and also in a deterministic trend.

Taking first differences has successfully removed the unit root from the time series, making it suitable for further time series analysis or modeling. Our results related to non-linearity and stationarity of CO2 emissions data are consistent with other studies [41-43].

## 4. Conclusion

The statistical analysis of Albania's annual CO2 emissions from land-use change per capita was the main focus of this research. The Isolation Forest technique was employed to identify the outliers in the time series data and the LSTM model for imputation. The exploratory data analysis preserved the basic characteristics of the initial data distribution after imputation.

The BDS test and the Teräsvirta Neural Network test confirm the presence of non-linearity in the time series data, both before and after applying the first differences. The findings from the KPSS, Zivot-Andrews Unit Root, and Breitung tests indicate that the original time series was non-stationary, but first differencing transformed it into a stationary series, although non-linearity persisted.

The significance of this research lies in its detailed investigation of CO2-E-LUC per capita time series data in Albania, focusing on assessing the presence of non-linearity and stationarity. Furthermore, our study sheds light on the dynamic behavior of CO2 emissions from land-use changes. This is crucial for policymakers and researchers aiming to develop accurate predictive models and implement effective GHG emission reduction strategies. The study's limitations are rooted in the non-primary nature of the data we analyze, potentially affecting our conclusions. Future research on this dataset will employ advanced modeling techniques that account for non-linearity and stationarity, aiming for improved accuracy and reliability.

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