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The Environmental Impact of Tourism, Economy and Natural Resource Rent in South Asia

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Abstract:
South Asia comprises eight emerging countries with rich biodiversity and is home to more than 1.7 billion people. With a cultural heritage spanning over 2000 years, it is also known as one of the world's premier tourist destinations. The study aimed to investigate the relationship between international tourist arrivals, economic growth, and natural resource rents and their effects on the ecological footprints of four South Asian countries from 1995 to 2019. Various statistical tests were used to analyze the data, including slope homogeneity tests, cross-sectional dependency tests, second-generation unit root tests, and Westerlund co-integration tests. The Driscoll-Kraay regression model was used to test the long-run relationship between the series. In addition, the Dumitrescu-Hurlin panel causality test was used to determine the paths of causal interactions. These tests help overcome heterogeneity and cross-dependency issues in panel data analysis. The study found an inverted U-shaped Environmental Kuznets Curve (EKC) behavior in the selected South Asian countries, indicating a negative relationship between natural resources and ecological footprint, while tourism exhibited a positive relationship with the ecological footprint. The estimates imply that natural resource rents improve environmental quality in the selected South Asian countries.

Keywords: South Asian countries, Ecological footprint, Tourism, Natural resources, Panel data analysis.

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1. Introduction

Climate change is a pressing global issue that requires urgent action. Human activity has contributed to this problem, and we must act to minimize the damage. Environmental degradation is measured by various indicators such as biochemical oxygen demand, coal consumption, ecological pressure, SO_2, PM10, and CO_2. Mathis Wackernagel and William Rees (1996) state that ecological footprint has been presented as a comprehensive measure of environmental degradation caused by human activities, but its application to tourism impacts is limited. Compared with the rich literature on the effects of tourism on CO_2 emissions (Ulucak & Bilgili, 2018). In addition, the ecological footprint of the total measure (Solarin & Bello, 2018) and the percentage of CO_2 emissions are used to study environmental degradation (Destek & Sarkodie, 2019). Recently, ecological footprints have become a popular indicator of environmental damage (Ulucak & Bilgili, 2018; Bello et al., 2018; Zafar et al., 2019). The literature on the ecological footprint of tourism is limited (Ozturk et al., 2016; Katircioğlu & Katircioğlu, 2018), while studies on the CO_2 impact of tourism have multiplied (Katircioglu, 2014; Zaman et al., 2016; Zhang & Liu, 2019). Several studies have explored the relationship between natural resources and ecological footprints, with a positive relationship observed in Pakistan (Hassan et al., 2019) and a negative relationship in the United States (Zafar et al., 2019).

Tourism is predicted to become one of the world's largest industries, with a high growth rate in the 21st century, and the number of international tourist arrivals is expected to reach 1.8 billion by 2030, according to UNWTO. This growth in tourism activity will lead to an increase in the consumption of natural resources (Robaina-Alves et al., 2016) and investments in facilities (Ozturk et al., 2016), which will have an impact on environmental quality through resource use and waste generation (Xuchao et al., 2010).

While natural resources are essential for economic growth and social development, their consumption can lead to environmental degradation. In the early stages of economic development, natural resources are heavily relied upon, often neglecting their ecological effects. However, as economies develop, the protection of natural resources becomes increasingly important (Balsalobre-Lorente et al., 2018; Hassan et al., 2019; Zafar et al., 2019). Natural resources are crucial for providing goods and services for human and tourism activities, and materials for facility development such as hotels, restaurants, transportation, and destinations (Robaina-Alves et al., 2016). These activities can negatively impact the environment through processing, human consumption, and waste. Nevertheless, natural resources can also act as emission sinks that help recycle emissions and waste from human and tourism activities.

South Asia includes several countries with unique cultures and histories, including India, Pakistan, Bangladesh, Sri Lanka, Nepal, Bhutan, the Maldives, and Afghanistan. Despite challenges like poverty, political conflict, and natural disasters, South Asia remains a hub of economic growth, technology, and cultural diversity with a rich heritage. South Asia has nearly 1.9 billion people, more than 25% of the world's population, with a population density of 362.3 people per km2. Its area is 5,134,641 square kilometers, or 10.3% of the world's total. Despite this, the area has a low percentage of international tourists, making it a unique destination. According to the World Travel and Tourism Council (2023) (WTTC), the tourism industry has significantly contributed to global GDP, totaling 10 trillion USD in 2019. In South Asia, the sector contributed 257.9 billion USD to GDP in the same year. By 2033, tourism's contribution to global GDP is expected to reach 15.5 trillion USD, of which South Asia contributes 553.9 billion USD. According to the World Bank, in 2023, South Asian countries will have an average total natural resource rent of 2.6% of GDP, equal to 3.0% of global natural resource rents.

This study investigates the relationship between GDP indicators, tourism, natural resources, and ecological footprints in South Asian countries. The study uses techniques such as slope homogeneity, cross-dependence, unit roots, co-integration, panel regression, and panel causality testing to examine the impact of tourism and resources. Natural resources to ecological footprints: Previous studies show that environmental quality initially deteriorates in the early stages of economic growth until a certain level of wealth is reached. It improves under the EKC hypothesis, creating an inverted U-shaped curve. Furthermore, the results indicate that economic growth, tourism, and natural resources can contribute to reducing environmental degradation. The remainder of the study is divided into four parts: The "Literature review" section provides an overview of the current research, while the "Methodology" section describes the data sources and methods used and used in the study. The "Experimental Results" section presents the research results, and the "Conclusions and Policy Implications" section provides conclusions and recommendations for future research.

2. Literature review

Rees first introduced the idea of Ecological Footprints in 1992. Ecological Footprints, regardless of location on earth, were defined by Mathis Wackernagel and William Rees (1996) as the sum of productive land areas and aquatic ecosystems necessary to produce the resources used and assimilated and waste generated by a defined population at a certain material standard of living. The ecological footprint has also been defined by other scholars, such as the Global Footprint Network (2023), as a measure of the amount of biologically productive land and water a person, population, or activity needs to generate all the resources, it uses and absorbs and the waste it generates using current resource management technology and techniques. Since both direct and indirect production and consumption are considered, the ecological footprint is a more comprehensive indicator of environmental damage (Mrabet & Alsamara, 2017a; Ulucak & Bilgili, 2018). Many studies over the past 20 years have used the Ecological Footprint as an environmental indicator to look at its relationship to things like economic development, energy consumption, tourism, and natural resource use (Ulucak & Bilgili 2018; Solarin

& Bello 2018; Zafar et al., 2019). These studies have only focused on one or several countries and have been limited to the data available from 1961 to 2017. Multinational studies included 141 countries (Bagliani et al., 2008), 146 countries (Caviglia-Harris et al., 2009), 150 countries (Y. Wang et al., 2013), and 93 countries (Al-Mulali et al., 2015). Many studies have been performed on specific country groups, including 15 Middle East and North Africa (MENA) (Charfeddine & Mrabet, 2017), 27 highest emitting countries (Uddin et al., 2017), ten major tourist destinations (S. Katircioglu et al., 2018), 17countries in Africa (Sarkodie, 2018), and 11newly industrialized countries (Destek & Sarkodie, 2019). In addition, some specific countries have been studied in depth, such as Qatar, Turkey, Malaysia, Pakistan, and the United States, by Mrabet & Alsamara (2017), Charfeddine (2017), Imamoglu (2018), Solarin & Bello (2018), Destek & Sarkodie (2019), Hassan et al., (2019), and Zafar et al. (2019), respectively. Initially, ecological footprints were studied in terms of scale, but subsequent research focused on exploring their relationship with other variables. Kuznets (1995) proposed the EKC hypothesis, which states that environmental quality deteriorates in the early stages of economic development as per capita income increases but eventually improves when a certain level of wealth is reached. This assumption has been widely used in many different studies. In 2002, Balaguer & Cantavella-Jordá developed TLGH to study the relationship between economic growth and tourism. These two hypotheses were then combined to form the travel-induced EKC hypothesis, which is still used in research conducted in different countries and regions (S. T. Katircioglu, 2014; S. Katircioglu et al., 2018).

2.1 The EKC approach and the ecological footprint

The correlation between economic growth and ecological footprint has been explored using the EKC method, but the study shows no relationship between GDP and ecological footprint when using all research methods. Ordinary least squares (OLS) and weighted least squares (WLS) analysis (Bagliani et al., 2008); OLS and two-stage least squares (2SLS) (Caviglia-Harris et al., 2009); and OLS and spatial econometric models (Y. Wang et al., 2013). The inverted U-shaped EKC pattern was observed only in Chile and Uruguay (Hervieux and Darné 2013), and the autoregressive distributional latency (ARDL) approach was found to be invalid in Qatar (Mrabet et al. 2017). Although real GDP per capita exhibits a favorable long-term association, it has not yet reached the inflection point of the EKC curve based on data from 1980 to 2011. Various studies have been conducted to test the hypothesis of the Environmental Kuznets curve (EKC), whereby economic growth initially leads to an increase in pollution, but ultimately leads to a decrease in pollution as countries develop. Aşıcı & Acar (2018), in their study of 87 countries using fixed and random effects models, found that income has no EKC relationship with non-carbon-based production LCA in the importing country. Similarly, Sarkodie (2018) finds that the EKC assumption of ecological footprint indicators is not valid in 17 African countries. However, other studies have confirmed the existence of an inverted U-shaped EKC relationship, such as that of Al Mulla et al. (2015), which covers 93 countries using the fixed effects model and the general moment method. This relationship is found in middle- and high-income countries but not in low- and middle-income countries. Aşici & Acar (2015) also found an inverted U-shaped EKC relationship in their study of a panel of 116 countries from 2004 to 2008 using a fixed effects model. Mrabet and Alsamara (2016) found a similar relationship in Qatar from 1980–2011 using the ARDL method. Charfeddine (2017) used a Markov transitional equilibrium correction model to analyze data from 1970 to 2015 and found a U-shaped relationship between ecological footprint and real GDP per capita in Qatar. Finally, Charfeddine and Mrabet et al. (2017) analyzed 15 MENA countries from 1975 to 2007 using dynamic ordinary least squares, fully modified ordinary least squares, and causal testing methods (VECM-Granger). For the entire sample, oil-exporting and non-oil-exporting countries, the study shows a U-shaped EKC relationship and a U-shaped EKC relationship. For high-income, middle-income, and low-income countries between 1961 and 2013, Ulucak and Bilgili (2018) used fully revised models (CUP-FM) and bias-corrected models (CUP-BC), updated continuously. They discovered the inverted U-shaped EKC hypothesis for all revenue-generating countries. Sarkodie & Strezov (2018) used data from 1971 to 2013 in Australia, China, Ghana, and the United States to run the U-test algorithm and test the Dumitrescu-Hurlin table causality. The results show that Ghana and the US do not support the U-shaped inverted EKC theory; Australia and China do. Destek et al. (2018) data from EU countries from 1980 to 2013 shows that Austria, Denmark, Germany, Italy, the Netherlands, Portugal, Spain, and the UK all have a U-shaped relationship between real GDP and ecological footprint. Only the inverted U-shaped EKC hypothesis for Portugal has been discovered. Similarly, Austria, Denmark, Finland, Germany, Italy, the Netherlands, Spain, and the United Kingdom confirm the dynamic OLS estimates of U-shaped ECK behaviour, but France and Portugal still have results. inverted U-shaped ECK connector. Bello et al. (2018) conducted a Malaysian study using the ADRL technique and Granger VECM causality; the first period, from 1971 to 1990, revealed a break with the EKC hypothesis. The argument mean group estimation method (AMG) and heterogeneous panel causality were used by Destek and Sarkodie (2019) for data from 1977 to 2013 in 11 newly industrialised countries. Mexico, the Philippines, Singapore, and South Africa have been shown to have valid U-shaped inverted EKC assumptions, while China, India, Korea, Thailand, and Turkey have inverted EKC assumptions. valid U-shape.

2.2 Tourism and the ecological footprint nexus

The tourist sector contributes significantly to human consumption and expenditure by consuming natural and artificial resources and investing in facilities. Ozturk et al. (2016) investigated the connection between the ecological footprint and the GDP from tourism in 144 nations. They discovered an inverted U-shaped behavior, more common in upper-middle and high-income nations, using the GMM and system panel GMM with the EKC hypothesis. The ecological footprint of the top 10 tourist attractions globally was the topic of a different study by Katircioğlu et al. (2018). They found an inverted U-shaped behavior in these nations using the panel RE technique and the tourism-induced EKC theory. Research suggests that the tourist industry, particularly in high-income nations, is essential to improving environmental quality.

2.3 Natural resources and the ecological footprint nexus

Natural resources are crucial for human consumption, activity, and environmental betterment. According to a recent study by Hassan et al. (2019) employing ARDL and VECM Granger causality, natural resources have a long-term beneficial effect on Pakistan's ecological footprint. The ARDL technique was used in a study by Zafar et al. (2019), which discovered a long-term negative correlation between natural resources and the ecological footprint in the United States. GDP, tourism, and natural resource use all impact the ecological footprint. There is, however, a dearth of studies on how tourism and natural resources affect the ecological footprint. This investigation intends to close this gap and examine how it affects the ecological footprint of South Asian nations. Furthermore, this study tackles the slope heterogeneity and cross-sectional dependence issues to contribute to the existing literature.

3. Methodology

3.1 Data sources

The study could only include four of the eight South Asian nations due to data availability. We examined yearly panel data for several South Asian nations, namely Bangladesh, India, Nepal, and Sri Lanka, from 1995 to 2019. We used ecological footprint (EF) data, expressed in gha per person, to assess environmental quality. As proxies for economic growth, GDP per capita (calculated in constant 2017 US dollars) and GDP per capita squared (GDP^2) were utilized. Also, we substituted the number of international tourist arrivals (ITA) and the proportion of total natural resource rents in GDP (%) for natural resources (NRR). The Global Footprint Network's database (Global Footprint Network (2023) provided the EF data, while the World Development Indicators' databases provided the GDP, GDP^2, ITA, and NRR data (World Bank 2023).

3.2 Model Construction

Three potential variables have been considered for this study, including economic growth, tourism, and natural resources. The relationship function of ecological footprint and potential variables is mentioned in Eq. (1). According to the EKC approach setting, squared GDP^2 is added to Eq. (1) to investigate an inverted U-shaped hypothesis. This function can be represented as follows:

$$EF = f(\mathrm{GDP}, \mathrm{GDP}^2, \mathrm{NRR}, \mathrm{ITA}) \qquad \text{Eq. (1)}$$

where EF is the ecological footprint, GDP is GDP per capita, GDP2 is square GDP per capita, ITA is the number of international tourists, and NRR is natural resources. The double logarithmic regression method was utilized, and both the dependent and independent variables were converted into natural logarithmic form. To capture growth impacts and prevent issues related to the data series' dynamic features, it delivers more effective and consistent findings. Similar circumstances can be found in the literature (Katircioglu, (2014); Zaman et al. (2016); Paramati et al. (2017),; Katircioglu et al., (2018). As a result, the log-linear multivariable model is written as follows:

$LnEF_{it} = \beta_0 + \beta_1 LnGDP_{it} + \beta_2 LnGDP_{it}^2 + \beta_3 LnTNRR_{it} + \beta_4 LnITA_{it} + \varepsilon_{it}$ Eq. (2)

where i is the index of countries (1, 2, 3, 4), t is the study period (1995–2019), β_0 is a constant term, and ε is the error term. Furthermore, β_1, β_2, β_3, and β_4 are the coefficients of GDP, GDP2, NRR, and ITA, respectively.

3.3 Econometric strategies

Initially, we analyzed the research data using descriptive statistics and a correlation matrix. Our panel research involved various econometric techniques such as panel pretests, error-correction-based panel co-integration tests, cross-sectional dependency tests, CADF and CIPS unit root tests, and slope homogeneity tests. We used the Driscoll and Kraay standard errors regression panel estimation technique to evaluate coefficients using pooled OLS. We also employed the Dumitrescu-Hurlin Panel individual causality estimation test while examining panel data to ensure accurate findings. This test helped us to consider heterogeneity, cross-sectional dependency, and autocorrelation.

3.3.1 Slope Homogeneity Tests

The framework to determine if the slope coefficients of the co-integration equation are homogenous was created by Swamy in 1970. Swamy's slope homogeneity test was enhanced by Hashem Pesaran & Yamagata (2008), who created two "delta" test statistics: $\tilde{\Delta}$ and $\tilde{\Delta}_{adj}$.

$$\tilde{\Delta} = \sqrt{N}\left(\frac{N^{-1}\bar{S}-k}{\sqrt{2k}}\right) \sim X_k^2$$

$$\tilde{\Delta}_{adj} = \sqrt{N}\left(\frac{N^{-1}\bar{S}-k}{v\sqrt{Tk}}\right) \sim N(0,1)$$

Where **N** indicates the number of cross-section units, **S** represents the Swamy test statistic, and **k** denotes independent variables. If the **p**-value of the test is more significant than 5%, then the null hypothesis is accepted at a 5% significance level, and the cointegrating coefficients are considered homogenous. $\tilde{\Delta}$ and $\tilde{\Delta}_{adj}$ are appropriate for large and small samples, respectively, where $\tilde{\Delta}_{adj}$ Is the "mean-variance bias adjusted" version of $\tilde{\Delta}$. Therefore, the standard delta test ($\tilde{\Delta}$) requires error not to be autocorrelated. By relaxing the assumptions of homoscedasticity and serial independence of Hashem Pesaran & Yamagata (2008), Blomquist & Westerlund (2013) developed a Heteroscedasticity and Autocorrelation Consistent (HAC) robust version of the slope homogeneity test;

Δ_{HAC} and $(\Delta_{HAC})_{adj}$:

$$\Delta_{HAC} = \sqrt{N}\left(\frac{N^{-1}\bar{S}_{HAC}-k}{\sqrt{2k}}\right) \sim X_k^2$$

$$\tilde{\Delta}_{adj} = \sqrt{N}\left(\frac{N^{-1}\bar{S}_{HAC}-k}{v\sqrt{Tk}}\right) \sim N(0,1)$$

3.3.2 Cross-sectional dependence tests

Due to the nations' interdependence on a regional and international scale, cross-sectional dependency is frequently seen in panel data. Studies that fail to account for cross-sectional dependency will result in inconsistent and skewed estimates (Peter C. Phillips and Donggyu Sul, 2003). Consequently, looking at the cross-sectional dependency in the panel data is crucial. This study employs two tests to find cross-sectional dependencies between the chosen variables. Chudik & Pesaran (2015) and Pesaran (2004) CD tests are calculated to determine if cross-sectional dependency exists in the estimable model's residuals.

3.3.3 Panel unit root tests

In cross-sectional dependency, the first-generation unit root findings are ineffectual (Dogan & Seker, 2016). This study applies the augmented cross-sectional IPS (CIPS) and augmented cross-sectional ADF (CADF) techniques to ascertain the variables' stationarity characteristics. Also, performing appropriate unit root tests when panel data contains cross-sectional dependency improves the trustworthiness of the results. Pesaran (2007) recommended using the following equation to test the unit root in the IPS cross-section:

$$\Delta x_{it} = \alpha_{it} + \beta x_{it-1} + \rho_i T + \sum_{j=1}^{n} \theta_{ij} \Delta x_{i,t-j} + \varepsilon_{it}$$

Where Δ denotes the difference operator, x_{it} Illustrations the analyzed variable, α is a specific intercept, T denotes the time trend in the data, and ε_{it} is the error term. The Schwarz information criterion (SIC) approach determines the lag length. In both tests, the null hypothesis is that none of the people in the time series panel data are stationary, and the alternative hypothesis is that at least one individual in the time series panel data is stationary.

3.3.4 Panel Co-integration Test

The Westerlund co-integration test is used in this work to look for long-run equilibrium between model variables. To investigate the alternative hypothesis of co-integration for the entire panel or at least one cross-sectional unit, Westerlund (2007) proposes four fundamental panel co-integration tests. This method's null hypothesis is "no error correction," and co-integration is demonstrated if proven false. A restricted panel error correction model is used to investigate the importance of the error correction component, and the p-values obtained by bootstrapping are resistant to cross-sectional dependency.

Westerlund contemplates the subsequent error correction model:

$$\Delta Y_{it} = \delta_i' d_t + \alpha_i Y_{i,t-1} + \lambda_i' X_{i,t-1} + \sum_{j=1}^{pi} \alpha_{ij} \Delta Y_{i,t-1} + \sum_{j=-qi}^{pi} \gamma_{i,j} \Delta X_{i,t-1} + \varepsilon_{it}$$

Where *i* denotes the cross-sections, t denotes observations, d_t refers to the deterministic components and computes the convergence speed to the equilibrium state after an unexpected shock.

3.3.5 Panel long-run estimation method

Autocorrelation, heteroscedasticity, and cross-sectional dependency may prevent the typical fixed effect model from producing unbiased and effective results. Therefore, efficient and reliable estimation is required. The occurrence of cross-sectional dependency, according to Wang et al. (2021), renders the estimated findings from traditional approaches like FMOLS and DOLS neither accurate nor dependable. Hence, to estimate long-run coefficients in this work, similar to the investigations of Kongbuamai et al. (2020), Baloch et al. (2019), Hashemizadeh et al. (2021), and Rahman & Alam (2022), we adopt Driscoll & Kraay's (1998) standard error technique.

This comprehensive approach considers the estimated model's autocorrelation, heteroscedasticity, and cross-sectional dependency issues. Driscoll & Kraay's (1998) standard error technique has several advantages over many other approaches, including the ability to be used with unbalanced panel data, the ability to account for missing values in the dataset, the fact that it is a non-parametric procedure with flexible features and a more significant time dimension, and, most importantly, the ability to accurately correct for heteroscedasticity, autocorrelation, and anachronism (Hoechle (2007); Rahman & Alam (2022); Wang et al. (2021); Kongbuamai et al. (2020); Baloch et al. (2019)).

3.3.7 Dumitrescu and Hurlin panel causality test

The correlation between dependent and independent variables can be seen using long-run estimating techniques. To formulate policy, it is crucial to understand the direction of the short-run causal link among the variables. We use the Dumitrescu & Hurlin (2012) causality test to ascertain the causal connection between the examined variables. Using the Vector Autoregressive (VAR) framework on stationarity data, this test considers the unobserved heterogeneity in the data. Moreover, this test performs regression independently for each cross-section to ascertain the causal link between variables.

4. Empirical results

The summary of the descriptive statistics and correlation matrix is presented in Table 1. The central tendency, variability, and shape of the distribution of study variables are present in the table. The correlation matrix shows a positive correlation between gross domestic production and international tourist arrivals and the ecological footprint, while natural resources have a negative correlation with the ecological footprint.

Table 1: Descriptive statistics and correlation matrix of variables

Variable	Ln EF	Ln GDP	Ln NRR	Ln ITA
Mean	-0.106568	3.055429	-0.092435	5.907911
Median	-0.114016	2.997190	0.028363	5.731186
Maximum	0.099033	3.626150	0.851830	7.253193
Minimum	-0.400543	2.692461	-1.188196	5.017033
Std. Dev.	0.136986	0.256598	0.481201	0.565747
Skewness	-0.311185	0.638566	-0.492509	0.678301
Kurtosis	2.162556	2.387699	2.386880	2.586655
Jarque-Bera	4.536072	8.358252	5.609078	8.380103
Probability	0.103515	0.015312	0.060535	0.015146
Sum	-10.65680	305.5429	-9.243471	590.7911
Sum Sq. Dev.	1.857752	6.518400	22.92392	31.68692
Observations	100	100	100	100
Ln EF	1.0000			
Ln GDP	0.816216	1.0000		
Ln NRR	-0.435283	-0.664165	1.0000	
Ln ITA	0.566811	0.317299	0.298636	1.0000

Authors Calculations

Table 2 presents the results of the slope homogeneity tests conducted in this study. The findings indicate that the slope coefficients are not homogenous, with a 99% confidence level.

Table 2: Results of the slope homogeneity tests.

Test Statistic	Estimates
$\bar{\Delta}$	8.467[a]
$\bar{\Delta}\boldsymbol{adj}$	9.466[a]
$\Delta_{\boldsymbol{HAC}}$	6.485[a]
$(\Delta_{\boldsymbol{HAC})\boldsymbol{adj}}$	7.251[a]

H_0: slope coefficients are homogenous. [a] represents statistical significance at 1%.

$\bar{\Delta}$ and $\bar{\Delta}$adj represent the "simple" and "mean-variance bias adjusted" slope homogeneity tests, respectively (Pesaran, Yamagata. 2008. Journal of Econometrics).

Δ_{HAC} and $(\Delta_{HAC)adj}$ represent the "Heteroscedasticity and Autocorrelation Consistent" versions of "simple" and "mean-variance bias adjusted" slope homogeneity tests, respectively (Blomquist, Westerlund. 2013. Economic Letters).

"a "p<.01, "b "p<.05, "c "p<.1

Authors Calculations

The results of the cross-sectional dependency tests are presented in Table 3. It suggests that significant evidence exists to reject the null hypothesis of cross-sectional dependence due to a p-value of less than 0.01. Consequently, the results provide proof of the existence of cross-sectional dependence for Ln EF, Ln GDP, Ln NRR, and Ln ITA.

Table 3: Results of Cross-sectional dependence tests

Variable	Pesaran (2015) test for weak cross-sectional dependence.	P value	Pesaran (2004) CD test	P value
Ln EF	7.582^{a}	0.000	7.580^{a}	0.000
Ln GDP	12.163^{a}	0.000	12.160^{a}	0.000
Ln NRR	4.110^{a}	0.000	4.110^{a}	0.000
Ln ITA	5.283^{a}	0.000	5.280^{a}	0.000

“a “p<.01, “b “p<.05, “c “p<.1

Authors Calculations

Table 4 displays the outcomes of CADF and CIPS panel unit root tests. The null hypothesis of non-stationarity is not rejected at the level, indicating that all variables are integrated at the first difference, I (1).

Table 4: Results of Panel unit root tests

Variable	CADF test statistic				CIPS test statistic				Order of integration
	Level		First difference		Level		First difference		
	Constant	Trend	Constant	Trend	Constant	Trend	Constant	Trend	
Ln EF	-1.264	-1.884	-3.150^{a}	-3.095^{b}	-1.705	-2.443	-5.066^{a}	-5.054^{a}	I (1)
Ln GDP	-0.298	-0.588	-2.705^{b}	-3.511^{a}	-1.182	-1.517	-3.769^{a}	-4.423^{a}	I (1)
Ln GDP^2	-0.256	-0.521	-2.523^{b}	-3.406^{a}	-1.070	-1.318	-3.610^{a}	-4.334^{a}	I (1)
Ln NRR	-1.319	-1.960	-4.149^{a}	-4.269^{a}	-2.126	-2.188	-4.237^{a}	-4.456^{a}	I (1)
Ln ITA	-1.076	-0.975	-3.117^{a}	-3.012^{b}	-0.992	-1.313	-3.288^{a}	-3.238^{a}	I (1)

“a “p<.01, “b “p<.05, “c “p<.1

Authors Calculations

According to the Westerlund co-integration test, the null hypothesis of no co-integration is rejected, indicating co-integration between the variables, as shown in Table 5. This presence of co-integration provides compelling evidence for a long-term relationship between one of the study's underlying variables.

Table 5: Results of Westerlund co-integration test

Statistic	Estimate	Z-value	P-value
Gt	-3.765^{a}	-2.436	0.007
Ga	-3.354	3.030	0.999
Pt	-6.642^{b}	-1.823	0.034
Pa	-3.447	2.290	0.989

“a “p<.01, “b “p<.05, “c “p<.1

Authors Calculations

Table 6 presents the findings of the Driscoll-Kraay regression model, which displays Eq 1 and Eq 2 regression estimates. The positive and statistically significant coefficient of economic growth (Ln GDP) indicates a rise in ecological footprint (Ln EF) in the South Asian countries considered. Furthermore, the negative and statistically significant value of the square of economic growth (Ln GDP2) suggests a nonlinear correlation between economic growth and ecological footprint. This validates the existence of an inverted U-shaped EKC behavior between economic growth and ecological footprint in the selected South Asian countries. Specifically, in these countries, increased economic growth beyond a certain level led to a decreased ecological footprint (EF).

Table 6: Regression with Driscoll-Kraay standard errors

Variable	Model (Eq1)		Model (Eq2)	
	Coefficient	**P value**	**Coefficient**	**P value**
Constant	-4.161[a]	0.000	-7.083[a]	0.000
Ln GDP	2.185[a]	0.000	3.773[a]	0.000
Ln GDP^2	-0.279[a]	0.000	-0.581[a]	0.000
Ln NRR			-0.163[a]	0.000
Ln ITA			0.152[a]	0.000
F-statistic	286.23			412.36
P value	0.000			0.000
R^2	0.6836			0.8345
Observations	100			100
Number of groups	4			4

"a "p<.01, "b "p<.05, "c "p<.1
Authors Calculations

According to research conducted by Ozturk et al. in 2016, there seems to be a correlation between the ecological footprint and GDP from tourism in upper-middle and high-income countries that follows an inverted U-shaped pattern. Also, Katircioglu et al. (2018) found that the top 10 tourist countries also determine an inverted U-shaped approach to the environmental Kuznets curve induced by tourism.

The number of foreign visitors (ITA) correlates positively (0.152, P 0.000) with the ecological footprint in the area; travel and tourism enlarge the ecological footprint in the chosen nations.

In selected countries, there appears to be a negative correlation (-0.063, P < 0.000) between the ecological footprint (EF) and the availability of natural resources (NRR). This suggests natural resources can improve environmental quality and ecological footprint by encouraging equilibrium. Additionally, those close to natural resources have valuable knowledge of the situation and practical management issues, making them crucial to protecting these resources. Zafar et al. (2019) also reported a comparable negative relationship between natural resources and ecological footprint over an extended period, while Hassan et al. (2019) discovered the opposite relationship in Pakistan.

Table 7 presents the Dumitrescu-Hurlin panel causality analysis results, which indicate a bidirectional causal relationship between ecological footprint and economic growth. Similar findings have been reported for 11 newly industrialized countries (Destek and Sarkodie 2019), 14 SSA countries (Wang and Dong 2019), the USA in both the short and long run (Zafar et al. 2019), MENA countries in both the short and long run (Charfeddine and Mrabet 2017), and Qatar in both the short and long run (Charfeddine 2017). There is no indication that ITA and NRR directly impact EF. Nevertheless, EF has a considerable one-way influence on both NRR and ITA.

Table 7: Results of Dumitrescu-Hurlin panel causality test

Variable	**Ln EF**	**Ln GDP**	**Ln NRR**	**Ln ITA**
Ln EF	-	5.54063[a]	8.38735[a]	5.31508[b]
Ln GDP	4.41581[b]	-	9.53401[a]	6.53136[a]
Ln NRR	3.41578	2.42270	-	1.10521
Ln ITA	1.49682	7.75809[a]	15.9361[a]	-

"a "p<.01, "b "p<.05, "c "p<.1
Authors Calculations

5. Conclusion and policy implication

The tourism industry is proliferating and has become one of the largest industries in the world. However, the rise in the number of international tourists has led to a greater need for natural resources to support and manage the emissions and waste produced by human and tourism activities. Overuse and depletion of these resources can result in environmental degradation and an increase in ecological impact. To tackle these concerns, a study was conducted on the effects of economic growth, tourism, and natural resources on the ecological impact in selected South Asian countries, using panel data from 1995 to 2019. The study employed various tests to address slope homogeneity and cross-sectional dependence issues. The findings showed an EKC behavior in the selected South Asian countries, with an inverted U-shape, indicating that tourism has a beneficial impact while natural resources hurt the ecological footprint.

The Dumitrescu-Hurlin panel causality analysis indicates that economic growth and the ecological footprint have a mutual causal relationship. The study's results propose particular policy suggestions, such as the requirement for specific countries to hasten the attainment of the turning point of an EKC that is hypothetically inverted U-shaped. To sustain its desired annual GDP growth, South Asian economic progress must partner with the green economy or green growth initiative.

Second, policymakers can raise environmental awareness among tourists by following the United Nations global agenda on sustainable tourism, green tourism, or alternative tourism. Such as ecotourism and community tourism. In addition, policymakers can also increase the environmental awareness of tourism service providers by addressing specific environmental concerns related to their business and operations, like green hotels and restaurants, green transport, and green destinations.

This will lead to improved environmental quality in South Asian countries. Third, policymakers need to pay attention to increasing reserves of natural resources, monitoring their depletion, and other factors such as forest fires and overexploitation of natural resources. To this end, increasing green space, monitoring pollution and environmental degradation, and reducing reuse-recycling campaigns can help "reduce the rate at which natural resources are depleted.". " Finally, environmental taxes or subsidies may be imposed on tourism and natural resource consumption. On the other hand, subsidies can better serve the purpose of green technology development, as Zhang and Yousaf (2019) observe.

This study focuses on the link between ecological footprint and tourism and is limited to available data from a few South Asian countries. Further research can apply this econometric approach by extending the data range over a longer period and to more countries. In addition, several other tourism-dependent countries can be considered to broaden understanding of the ecological footprint and link tourism to time series and panel data analysis. In addition, future studies may introduce new variables related to the link between environmental degradation and tourism, such as PM 2.5, other pollution indices, tourism revenue, tourism GDP, the index of tourism development, and tourism investment. Finally, other nonlinear regression techniques can also be used to solve this problem in the future.

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