sustainability

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Is the Load Capacity Curve Hypothesis Valid for the Top Ten Tourism Destinations?

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Abstract: Environmental deformations and changes put countries under socioeconomic stress at the global level and are, therefore, an essential topic of discussion. In this context, this paper analyzes the impact of financial development, tourism, and economic growth on three different environmental indicators using second-generation panel data techniques for the top ten tourism destinations. This study tests whether there is a U-shaped relationship between income and the load capacity factor and an inverse U-shaped link between carbon emissions, ecological footprint and income for the period 2004–2018. Despite the environmental Kuznets curve (EKC) hypothesis, which is often analyzed in this context, this empirical analysis investigates a new one—that of the load capacity curve (LCC) hypothesis. The results of the study show that the LCC and EKC hypotheses are not valid. The long-run panel estimators also indicate that international tourist arrivals are a factor that improves environmental quality, while financial development reduces the load capacity factor. Based on the results, it is recommended to support eco-friendly tourism for sustainable development.

Keywords: economic growth; EKC hypothesis; financial development; load capacity factor; LCC hypothesis; tourism

Citation: Pata, U.K.; Tanriover, B. Is the Load Capacity Curve Hypothesis Valid for the Top Ten Tourism Destinations? *Sustainability* **2023**, *15*, 960. https://doi.org/10.3390/su15020960

Academic Editors: Marc A. Rosen and Colin Michael Hall

Received: 10 October 2022
Revised: 29 December 2022
Accepted: 3 January 2023
Published: 4 January 2023

1. Introduction

Humanity is feeling the effects of various difficulties and responsibilities, such as increasing environmental pressure, pollution of air, water, and soil, and the inability to absorb waste. The problem of global warming, caused by increasing emissions of carbon dioxide (CO_2), is unfortunately negatively affecting humanity in many economic, social, and cultural aspects, and various international organizations, such as the United Nations Environmental Program are working to minimize these negative effects. The United Nations COP26 also specifically targets adaptation to protect natural habitats and communities affected by climate change.

Increasing ecological problems, externalities at the micro level, and the sustainability of economic growth (EG) at the macro level have put this issue on the agenda. In this context, countries have begun to develop strategies that address environmental factors for sustainable development. Researchers have generally focused on the amount of CO_2 to measure environmental pollution and, thus, sustainability. However, CO_2 emissions indicate the amount of gases emitted into the atmosphere, which is only related to air pollution. Global ecological degradation includes not only air pollution but also water and soil pollution. Solarin and Bello [1] and Wu et al. [2] state that CO_2 may not be sufficient to capture and analyze the full spectrum of global ecological degradation. To address this shortcoming, Wackernagel and Rees [3] developed a natural resource calculation tool, the ecological footprint (EF), to measure environmental sustainability. EF shows how much biologically productive environ is required to produce all demanded resources and repair environmental damage. EF measures the biological area required to meet all needs in global hectares. This indicator is a more comprehensive measure than CO_2 emissions because it consists of a combination of footprints.

However, both CO_2 and EF reflect only ecological degradation on the demand side. Nature's ability to satisfy human needs should also be considered in environmental analyzes. The capacity of nature to produce available fertile land and marine areas or needed biological space can be measured by biocapacity. Accordingly, EF is the demand for biologically productive land; biocapacity refers to the supply of productive land [4]. To analyze ecological sustainability more accurately, it is necessary to consider biocapacity and EF simultaneously. In this context, Siche et al. [5] proposed an indicator calculated as the ratio of biocapacity to EF, called the load capacity factor (LCF). The LCF shows ecological sustainability, that is, the ability of the ecological system to cope with environmental degradation, while taking into account the supply and demand aspects of nature. If the LCF value is equal to or greater than "1", the environmental conditions are sustainable because nature's supply is greater than its demand.

Researchers study the link between EG and environmental pollutant indicators such as CO_2 emissions and EF in general using the environmental Kuznets curve (EKC) developed by Grossman and Krueger [6]. According to the EKC hypothesis, EG initially increases pollution due to scale effect, and later decreases pollution with composition and technique effects. With the transition from the agricultural to the industrial sector, production increases due to increasing economies of scale, which is accompanied by higher consumption of natural resources. This increase in production, natural resource consumption, and consumption due to economies of scale lead to higher environmental pollution. In the later stages of the EG process, the structure of the economy changes with the transition from the industrial to the service sector. Thus, the economy undergoes a structural change from the industrial sector, where energy is used more intensively, to the service sector, where technology and human capital are used more intensively. This structural effect may mean that EG based on the service sector reduces environmental pressure. CO_2 and EF are indicators of environmental pollutants, but LCF is an environmental quality indicator that simultaneously incorporates EF and biocapacity. In this context, the relationship between LCF and EG can be "U-shaped", unlike the other two common indicators. We refer to this relationship as the "load capacity curve" hypothesis. According to this hypothesis, LCF decreases in the early stages of EG due to increasing economies of scale (the demand side of nature increases), while the LCF improves in later stages due to structural and technological changes (biocapacity increases and EF decreases). Figure 1 graphically compares the EKC and LCC hypotheses.

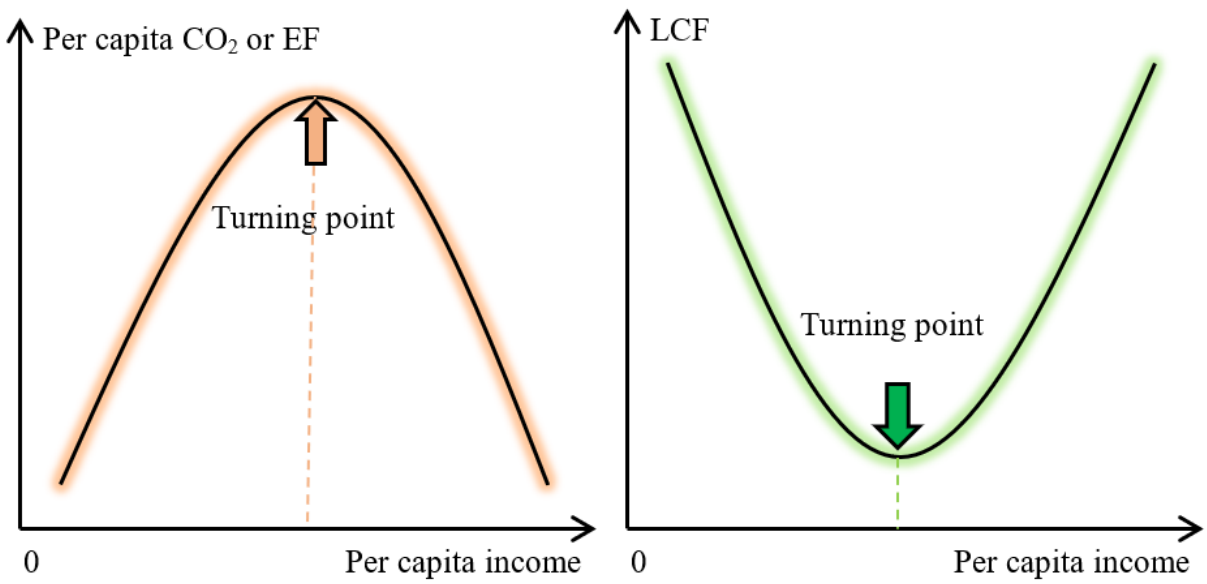

Figure 1. Graphical representation of the EKC and LCC hypotheses.

In Figure 1, the red inverted U-shaped curve and the green U-shaped curve represent EKC and LCC, respectively. The red curve implies an increasing relationship between income levels and environmental pollutants in the early stages of EG. In contrast, the green curve indicates that there is an inverse decreasing relationship between environment and income level since LCF is an indicator of environmental quality, and after reaching a certain level of prosperity, an increase in income may play a role in improving LCF.

This study tests the LCC hypothesis by incorporating the effects of financial development (FD) and tourism into the analysis. Researchers show that FD is an important factor for environmental sustainability, along with EG [7,8]. FD can contribute to the growth of world trade and EG of countries by increasing capital flows in the global market. The extent of environmental degradation can vary depending on which sectors provide the funds for investment in the capital growth that follows FD. If the increase in funds resulting from the FD leads to the creation of resources for fossil fuel-based sectors, environmental degradation increases, while it decreases when the FD leads to the creation of resources for renewable energy sectors.

Another important factor affecting environmental sustainability is tourism. In recent years, countries have attached great importance to tourism investments as they transition from industrial to the service sector. For this reason, the literature discusses how the increasing share of the tourism sector affects global environmental degradation. The expansion of the tourism sector can affect environmental conditions through the construction of roads, facilities, infrastructure, seaports, airports, and other means [9]. Fossil fuel-based travel, which is the most important component of the tourism sector, and excessive GHG emissions from accommodations and food services can lead to increasing environmental degradation [10]. Since the tourism sector requires large infrastructure investments such as roads, airports, resorts, hotels, stores, golf courses, and marinas, it can create various environmental problems such as air pollution, marine pollution, soil erosion, and habitat loss [11]. However, a sustainable tourism model that includes the use of environmentally friendly energy sources and offers energy-saving accommodations can help reduce environmental pressure [12]. The LCF is closely related to tourism as it reflects the demand for water and land resources and the supply of these resources together. How do the impacts of tourism development on the LCF affect the ecosystem's water and land resources? The role of tourism in assessing the LCF provides the answer to this question.

According to Katircioglu et al. [13], tourism can increase environmental pollution until income reaches a certain level, then the tourism sector reduces environmental degradation with the help of the tourism-induced EKC hypothesis. In other words, it is possible that high-income countries implement activities that improve environmental quality thanks to more employment, higher income, economic expansion, and fund flow through the tourism sector. In an economy, tourism can enhance GDP, and its impact on the environment depends on the direction in which economic growth is going. Increasing GDP can increase the favorable environmental impact of tourism development if high-income countries adopt friendly regulations. In light of this information, it can be said that the environmental impact of tourism depends on the level of development of countries. In countries with high tourist numbers and incomes, as well as a high GDP, the interaction between the environment and tourism can be better and more accurately reflected. Therefore, the study focuses on the top ten tourism destinations shown in Figure 2.

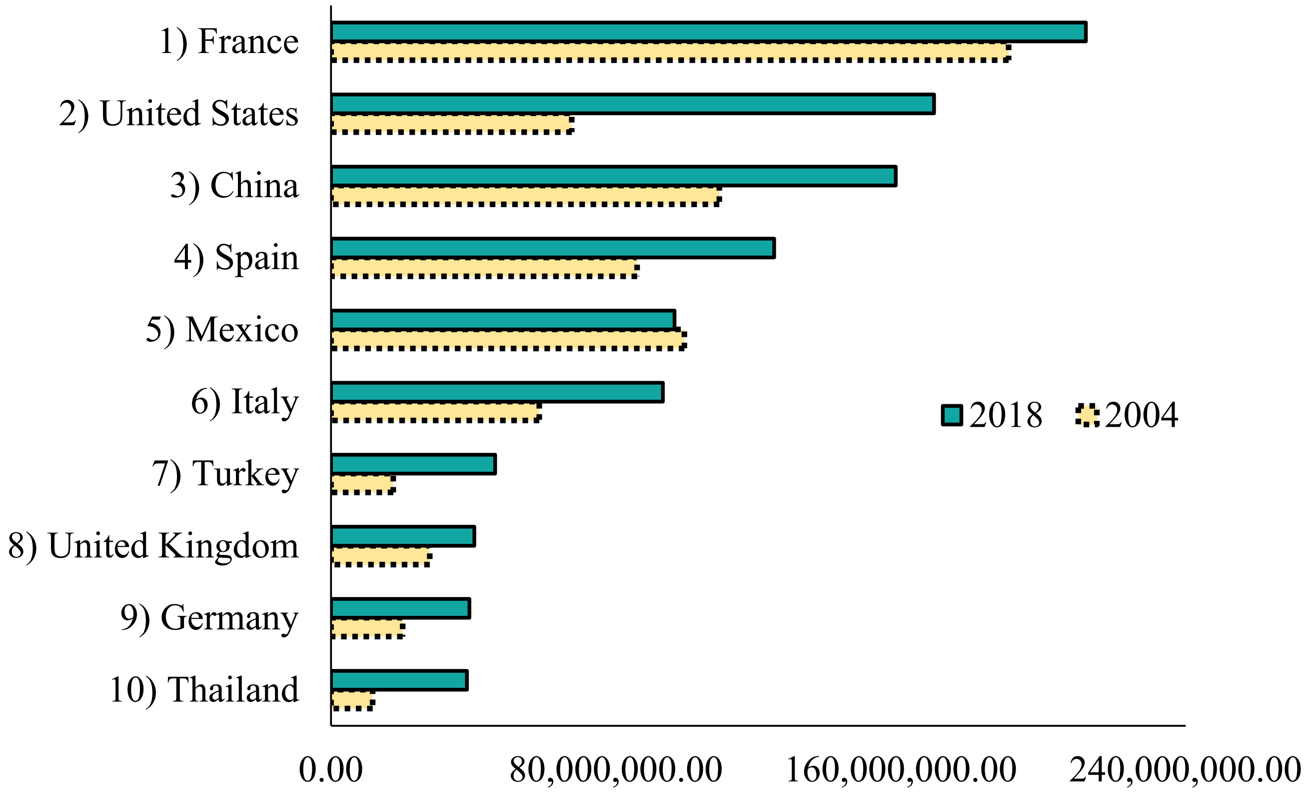

Figure 2. International tourist arrivals of the top 10 destinations (billions of people). Source: Based on data collected by the authors from the World Bank [14].

In Figure 2, the green bars represent international inbound tourists (overnight visitors) in 2018, and the yellow bars represent international inbound tourists in 2004, in billions of people in the top 10 destinations. The selection of the top 10 destinations is based on the UNWTO [15] report. According to the data in Figure 2, France, the United States, and China are the three countries with the most tourists worldwide. Turkey and the United States have managed to increase the number of tourists coming to their countries by 165% and 150%, respectively, over a 15-year period. However, increasing international tourist arrivals in Turkey are also related to the devaluation of the national currency. Since the goods and services offered to tourists in Turkey remain relatively cheap, it is likely that the number of tourists will increase greatly. At the same time, these 10 countries generate about 60% of the world's GDP. In such large economies, it is important to analyze the impact of tourism and income on environmental quality. Can higher incomes and improvements in the tourism sector helps reduce environmental pollutants such as EF and CO_2 emissions? What is the influence of tourism and income on the LCF, which is a new environmental indicator? The study aims to find answers to these two new research questions. The absence of a study in the literature regarding the application of the LCC hypothesis to tourism represents a research gap. In this context, the study aims to contribute to the current literature by investigating whether there is a U-shaped relationship between income and LCF, while testing the impact of tourism on environmental quality in terms of biocapacity and EF simultaneously. This study represents an important novelty to the literature, as it is the first to examine the determinants of the LCF for the top 10 tourism destinations in the context of the LCC hypothesis.

This study consists of five parts. The second part presents studies from the literature on tourism and LCF. The third part introduces the data set, model, and methodology. The fourth part discusses the empirical results, and the last part contains the findings and policy recommendations.

2. Literature Review

In recent years, scholars, researchers, and policymakers have focused on the impact of tourism on environmental sustainability in growing economies. The environmental impacts of tourism have become more important as the industrial sector has transitioned into the service sector.

The tourism–environment nexus is based on the fact that tourism includes infrastructure investments such as ports, airplanes, roads, and railroads, and that tourism is linked to climate-sensitive sectors such as energy and agriculture. Because of these linkages, tourism is known to have environmental and ecological impacts. As the tourism sector increases demand for accommodation and transportation, it leads to an increase in energy consumption. The increase in energy demand leads to higher consumption of fossil fuels and thus to environmental degradation. In this context, Zaman et al. [16], Eyuboglu and Uzar [17], Ehigiamusoe [18], and Kocak et al. [19] found that tourism increases CO_2 emissions because it is associated with environmentally sensitive sectors such as transport, energy, agriculture, and marine. Although carbon emissions are an important indicator of environmental degradation, they represent environmental problems only in terms of air pollution. Recently, researchers have also used the EF to study soil and water pollution. Godil et al. [20], Alola et al. [9], and Nathaniel et al. [21] found that tourism increases EF. However, other researchers have expressed the opinion in the literature that tourism investments made in the context of environmentally friendly policies reduce the use of natural resources and thus environmental degradation. Studies using both carbon emissions and EF show that tourism development improves environmental quality [12,13,19,22–24]. Depending on the tourism variable used, the environmental effects of tourism sector may also change. According to Kocak et al. [19], international tourist arrivals lead to environmental degradation, while tourism revenues reduce pollution.

Some studies examining the impact of EG and tourism on environmental degradation have included FD in the analysis. As capital flows into countries through FD, it is assumed that environmental degradation depends on the technologies used to deploy this increased capital in productive sectors. According to Godil et al. [20], environmental degradation may increase if the increased supply of capital creates resources for sectors that produce with fossil fuels. In contrast, Akadiri et al. [22] and Xu et al. [23] assume that pollution can decrease if financial resources are directed to sectors that use renewable energy.

The EG–pollution nexus is often examined using the EKC hypothesis. While some studies defend the validity of EKC [16,24–26], others take the opposite view (see, for example, [18,27]). Since EKC studies usually focus on CO_2 emissions and EF, they are only interested in the demand side of nature. However, the ability of nature to satisfy human needs, i.e., the supply side of nature, should also be considered to conduct a robust environmental assessment. In this context, the number of studies that empirically analyze the determinants of the LCF, thus examining the supply and demand sides of nature together, is increasing day by day. Since the seminal study by Pata [28], which was the first to examine the effects of indicators such as renewable energy, income, and health spending on the LCF in the United States and Japan, new literature has emerged. This new LCF literature and studies analyzing the relationship between tourism and environmental quality, which is the focus of this study, are listed in Table 1.

Table 1. Summary of the relevant literature.

Work	Time Interval	Sample	Method	Related Findings
Panel (a) Tourism-environment nexus				
Lee and Brahmasrene [29]	1988–2009	27 EU countries	Fisher-type cointegration	The increase in TR reduces CO_2
Katircioglu [24]	1971–2010	Singapore	Maki cointegration, DOLS	The increase in TOUR reduces CO_2,
Zaman et al. [16]	2005–2013	34 developed countries	Panel data estimators	A rise in TOUR, TR, and TE increase CO_2. Existence of the EKC.
Danish and Wang [25]	1995–2014	BRICS	Westerlund panel cointegration	The increase in TR increases CO_2. Existence of the EKC.
Katircioglu et al. [13]	1995–2014	Top 10 tourist countries	Panel random effects	The increase in TOUR reduces EF. Existence of the EKC.
Eyuboglu and Uzar [17]	1960–2014	Turkey	Fourier ADL and ARDL	The increase in TOUR increases CO_2
Ehigiamusoe [18]	1995–2016	31 African countries	Fisher-type Johansen cointegration	The increase in TR and TOUR increase CO_2; non-existence of the EKC.
Godil et al. [20]	1986–2018	Turkey	QARDL	TOUR increases EF; existence of the EKC.
Isik et al. [27]	1995–2015	G7 countries	AMG	The increase in TOUR reduces CO_2 in Canada; non-existence of the EKC.
Kocak et al. [19]	1995–2014	Top 10 tourist countries	CUP-FM, CUP-BC	The increase in TOUR increases CO_2;the increase in TR reduces CO_2
Kongbuamai et al. [26]	1995–2016	ASEAN countries	Driscoll–Kraay estimator	The increase in TOUR reduces EF, Existence of the EKC.
Alola et al. [9]	1995–2016	Top 10 tourist countries	Kao panel cointegration	The increase in TOUR increases EF
Khan and Hou [12]	1995–2018	38 IEA countries	FMOLS	A rise in TOUR, TR, and TE reduce EF
Nathaniel et al. [21]	1995–2016	Top 10 tourist countries	CUP-FM, CUP-BC	A rise in TR and TOUR increases EF
Panel (b) Studies on the determinants of the LCF.				
Pata [28]	1982–2016	United States and Japan	Augmented ARDL	The increase in GDP reduces LCF
Fareed et al. [30]	1965–2014	Indonesia	Fourier quantile causality	The increase in GDP reduces LCF
Pata and Isik [31]	1981–2016	China	Dynamic ARDL	Existence of the EKC.
Awosusi et al. [32]	1980–2017	South Africa	ARDL	The increase in GDP reduces LCF; existence of the EKC.
Pata and Balsalobre-Lorente [33]	1965–2017	Turkey	Dynamic ARDL	The increase in TOUR reduces LCF; existence of the EKC.
Pata and Samour [34]	1977–2017	France	Fourier ARDL	Existence of the EKC.
Shang et al. [35]	1980–2018	10 ASEAN countries	CS-ARDL	The increase in GDP reduces LCF
Xu et al. [23]	1970–2017	Brazil	ARDL	The increase in GDP reduces LCF
Akadiri et al. [22]	1970–2017	India	HP filter, ARDL	The increase in GDP reduces LCF
Agila et al. [36]	1970–2018	South Korea	Quantile cointegration	The increase in GDP reduces LCF

DOLS: dynamic ordinary least squares. TOUR: international tourist arrivals. TR: tourism receipts. EU: European Union. FMOLS: fully modified ordinary least squares. IEA: International Energy Agency. ASEAN: Association of Southeast Asian Nations. TE: tourism-related expenditure.

As shown in Table 1, there is no consensus among researchers on the impact of tourism on environmental quality. Pata and Balsalobre-Lorente [33] is the first and only study to examine the impact of tourism on LCF. Moreover, the studies that investigated the determinants of LCF used exclusively linear models. On the one hand, Pata [28], Fareed et al. [30], Awosusi et al. [32], Shang et al. [35], and Xu et al. [23] found that EG reduces LCF. Pata and Isik [31] and Pata and Samour [34], on the other hand, based on the approach of Narayan and Narayan [37] and using linear models, concluded that the EKC hypothesis is valid for LCF. However, none of these studies analyzed whether there is a U-shaped relationship between income and LCF. In addition, since the analysis of Pata and Balsalobre-Lorente [33] refers only to Turkey, there is a regional limitation. In this context, the lack of a study in the literature that tests the validity of the LCC hypothesis and analyzes the impact of tourism on LCF globally is a research gap. Our study aims to contribute to the literature by filling this research gap.

3. Data, Model, and Methodology

3.1. Data and Model

This study uses annual data from 2004–2018 to examine the impact of tourism, FD, and economic growth on environmental quality in the top ten tourism destinations under the LCC and EKC hypotheses. As LCF and EF data are available through 2018 and France's international tourist arrivals data have been available since 2004, the data range is limited to 15 years for each country. Thus, the study works with a panel data of 150 years. Following Destek and Sarkodie [38] and Lee and Chen [39] financial and tourism developments are selected as important environmental determinants and modeled in the following way to examine the LCC hypothesis:

$$lnLCF_{it} = \delta_0 + \delta_1 lnGDP_{it} + \delta_2 lnGDP^2_{it} + \delta_3 lnTOUR_{it} + \delta_4 lnFD_{it} + e_{it} \quad (1)$$

$$lnEF_{it} = \sigma_0 + \sigma_1 lnGDP_{it} + \sigma_2 lnGDP^2_{it} + \sigma_3 lnTOUR_{it} + \sigma_4 lnFD_{it} + v_{it} \quad (2)$$

$$lnCO_{2,it} = \gamma_0 + \gamma_1 lnGDP_{it} + \gamma_2 lnGDP^2_{it} + \gamma_3 lnTOUR_{it} + \gamma_4 lnFD_{it} + u_{it} \quad (3)$$

where *ln* is the logarithm; *i* is cross-sections; *t* is the time period; δ_0, σ_0, and γ_0 are the constant terms; $\delta_{1\ldots4}$, $\sigma_{1\ldots.4}$ and $\gamma_{1\ldots4}$ are the long-term coefficients; and e_{it}, v_{it} and u_{it} are i.i.d. error terms. As can be seen in Equations (1)–(3), all variables are transformed logarithmically before being included in the analysis to calculate elasticities. The symbols, calculation methods, and sources of the data are listed in Table 2.

The LCF data for the 10 countries are calculated using biocapacity/ecological footprint data from the Global Footprint Network [39]. Ecological footprint symbolizes anthropogenic environmental degradation in nature, while biocapacity measures nature's ability to compensate for human-caused environmental degradation in global hectares. A higher LCF indicates a better environment because the LCF contains biocapacity in the denominator and EF in the denominator [40]. By comparing biocapacity and ecological footprint, the LCF provides a more comprehensive environmental assessment [41].

Table 2. Details of the data.

Variables	Symbol	Method of Calculation	Sources
Load capacity factor	LCF	Biocapacity/ecological footprint.	Global Footprint Network [42]
Ecological footprint	EF	Ecological footprint refers to the negative impact of human activities on biologically productive land and water areas (global hectares).	Global Footprint Network [42]
Carbon dioxide emissions	CO_2	Carbon emissions refer to carbon dioxide from cement production, fossil fuel combustion, and solid, gaseous, and gaseous fuel consumption (metric tons per capita).	World Bank [14]
Gross domestic product	GDP	Gross domestic product is calculated by subtracting subsidies not included in the production process from the sum of gross value added and all product taxes of all producers located in a country (per capita, constant 2015 USD).	World Bank [14]
International tourist arrivals	TOUR	International inbound tourists refer to the number of people who have traveled to a country other than their country of residence for a period not exceeding 12 months (billion people)	World Bank [14]
Financial development	FD	Financial development index, which integrates financial institutions and financial markets in terms of depth, access, and efficiency. (Takes a value between 0 and 1)	IMF [43]

As a prerequisite for the EKC, $\delta_1(\sigma_1)$ must be positive, while the coefficient $\delta_2(\sigma_2)$ must be negative, and all must be statistically significant. Since EF and CO_2 are environmental pollutants, the existence of an inverted U-shaped relationship between income and these variables can be discussed. However, since biocapacity is included in the numerator part of the LCF, this indicator represents environmental quality, and therefore the LCC hypothesis is valid if the coefficient γ_1 is negative and γ_2 is positive and both are statistically significant.

This section is divided by subheadings. It should provide a concise and precise description of the experimental results, their interpretation, as well as the experimental conclusions that can be drawn.

3.2. Methodology

Researchers analyze the earth, its layers, and environmental conditions using various statistical methods (e.g., [44–48]). The study follows the econometric framework shown in Figure 3. We first examine whether cross-sectional dependence (CSD) exists in the panel data using the LM test of Breusch and Pagan [49], the CD_{LM} test of Pesaran [50], the LM_{adj} test of Pesaran et al. [51], and the CD test of Pesaran [52]. Then, we investigate whether the slope coefficient is heterogeneous by using the $\hat{\Delta}$ and $\hat{\Delta}_{adj}$ tests of Pesaran and Yamagata [53]. In the next step, we apply the Dickey–Fuller tests (CADF) and cross-sectional tests IPS (CIPS) proposed by Pesaran [54], since the analysis of second-generation panel data provides more effective results in the case of CSD and heterogeneity.

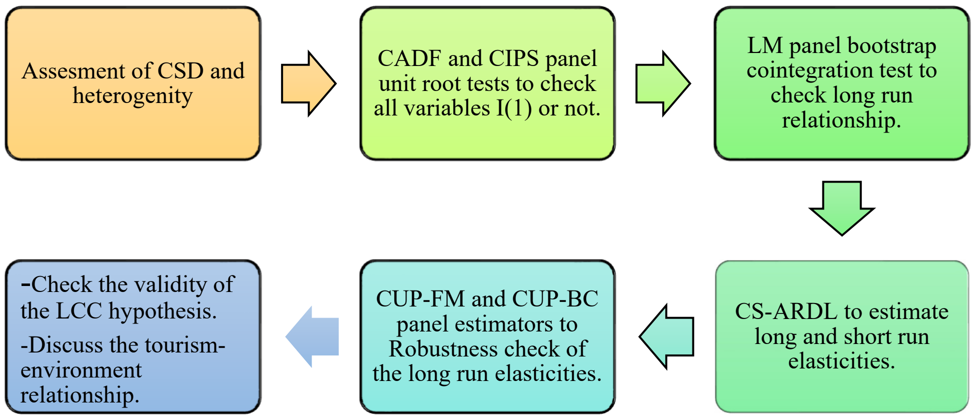

Figure 3. Econometric framework.

In the third step, the study tests the long-run relationships among variables using the LM panel cointegration test and then produces short- and long-run coefficient estimates using the cross-sectionally augmented ARDL (CS-ARDL) method. In the fifth step, continuously updated fully modified (CUP-FM) and continuously updated bias-corrected (CUP-BC) estimators of Bai et al. [55] are used for robustness check, and finally, the validity of the LCC hypothesis and the findings on the relationship between tourism and the environment are discussed.

3.2.1. LM Bootstrap Panel Cointegration Test

Westerlund and Edgerton [56] developed the LM panel bootstrap cointegration test that takes CSD and heterogeneity into account. This test statistic can be estimated by the following equation:

$$LM_N^+ = \frac{1}{NT^2}\sum_{i=1}^{N}\sum_{t=1}^{T}\hat{w}_i^{-2}s_{it}^2 \quad (4)$$

In Equation (4), N denotes sample size, T illustrates time period, $\hat{w}_i$ is the long-run variance of the error terms, and s_{it} shows the partial sum of the residuals. The null hypothesis of the LM panel bootstrap test indicates the presence of cointegration.

3.2.2. Cross-Sectionally Augmented ARDL (CS-ARDL)

The CS-ARDL method proposed by Chudik et al. [57] allows simultaneous estimation of short- and long-term elasticities by considering CSD in panel data. In addition, this method prevents serial correlations by filtering out unobservable common effects and removing bias due to misspecification. The CS-ARDL method can be applied with Equation (5).

$$\Delta Y_{i,t} = \vartheta_0 + \vartheta_1 \sum\nolimits_{i=1}^{a} \Delta Y_{i,t-1} + \vartheta_2 \sum\nolimits_{i=0}^{b} \Delta X_{i,t-1} + \vartheta_3 \sum\nolimits_{i=0}^{c} \Delta \overline{Z}_{i,t-1} + e_{i,t} \quad (5)$$

where ϑ_0 is the intercept; Δ is the difference operator; a, b, and c are the optimal lags; $Y_{i,t}$ represents the dependent variables such as CO_2, EF and the LCF; $X_{i,t}$ includes a set of independent variables such as GDP, TOUR and FD; and $\overline{Z}_{i,t}$ denotes cross sectional averages ($\overline{Z}_{i,t} = \Delta\overline{Y}_{i,t}, \overline{X}_{i,t}$).

This section is divided by subheadings. It should provide a concise and precise description of the experimental results, their interpretation, as well as the experimental conclusions that can be drawn.

4. Empirical Results

Before conducting the analysis, the study first examines the descriptive statistics of the variables in Table 3. GDP and TOUR have the highest volatility, while FD and LCF have the lowest. TOUR and GDP are the variables with the highest average values. LCF has the highest minimum, while TOUR has the highest maximum. For each dataset, 150 observations are analyzed, and balanced panel data analysis methods are used.

Table 3. Descriptive statistics.

Variables	Observation	Mean	Std. Dev.	Min	Max
lnLCF	150	−1.050	0.354	−1.763	−0.517
lnEF	150	1.430	0.392	0.741	2.324
$\ln CO_2$	150	1.829	0.453	1.173	2.975
lnGDP($\ln GDP^2$)	150	9.872	0.861	8.026	10.995
lnTOUR	150	18.009	0.791	16.263	16.263
lnFD	150	−0.401	0.294	−1.143	−1.143

After examining the descriptive statistics, the study tests for the CSD between the cross sections for each series and the heterogeneity of the slope coefficients in each model for Equations (1) to (3). The results of LM, CDLM, CD, and LM_{adj} in Table 4 show that the null hypothesis of no CSD in each series is rejected. In this case, a tourism, financial, or economic shock in one country may spill over to the other country through the spillover effect. The first-generation panel data methods cannot provide effective results when CSD is valid. Moreover, the findings of the $\hat{\Delta}$ and $\hat{\Delta}_{adj}$ tests indicate that the slope coefficients are heterogeneous for all three models. For this reason, the study makes use of second-generation panel unit root tests, cointegration tests, and long-run estimators.

Table 4. CSD and heterogeneity check.

	lnLCF	lnEF	$\ln CO_2$	lnGDP	lnTOUR	lnFD
LM	99.990 *	227.654 *	201.247 *	191.525 *	63.450 **	168.998 *
CD_{LM}	5.796 *	19.253 *	16.470 *	15.445 *	1.945 **	13.071 *
CD	25.760 *	25.817 *	25.853 *	25.976 *	25.979 *	25.435 *
LM_{adj}	14.444 *	33.593 *	29.876 *	26.170 *	23.528 *	22.454 *
Models	lnLCF		lnEF		$\ln CO_2$	
$\hat{\Delta}$	5.483 *		7.452 *		7.157 *	
$\hat{\Delta}_{adj}$	6.715 *		9.127 *		8.766 *	

* and ** denote the significance at 1% and 5% levels, respectively.

Table 5 shows the results of the CADF and CIPS panel unit root tests. It is found that all series are stationary I(1) at the first difference with a significance level of at least 5%. This allows for testing the cointegration relationship between the variables [58].

Table 5. Panel unit root test results.

Tests	**CADF**		**CIPS**	
Variables	I(0)	I(1)	I(0)	I(1)
lnLCF	−1.698	−3.759 *	−2.257	−4.000 *
lnEF	−1.301	−2.452 **	−1.770	−3.452 *
$\ln CO_2$	−0.823	−3.104 *	−1.255	−2.913 *
lnGDP($\ln GDP^2$)	−1.884	−2.637 **	−0.842	−2.867 *
lnTOUR	−2.034	−3.249 *	−1.526	−3.120 *
lnFD	−1.575	−3.051 *	−2.987 *	—

* and ** denote the significance at 1% and 5% levels, respectively.

As the study identifies CSD and heterogeneity, it applies the LM panel bootstrap cointegration test, which accounts for these two characteristics of the panel data. The null hypothesis of the LM cointegration test states that there is a long-run relationship between the series. The results of the cointegration test are shown in Table 6. The test statistics of models 1 and 2 and the corresponding bootstrap p-values for the LCF and EF variables show that the null hypothesis cannot be rejected, so there is a cointegration relationship between environmental quality, GDP, TOUR, and FD. For CO_2, there is no cointegration according to model 1. However, the test statistic of model 2 and the probability value imply that there can be a long-run relationship between CO_2, GDP, TOUR, and FD.

Table 6. LM panel bootstrap cointegration test results.

Model	**Model I Constant**		**Model II Constant + Trend**	
Dependent variable	Statistic	Bootstrapped *p*-value	Statistic	Bootstrapped *p*-value
lnLCF	18.699	0.156	20.618	0.997
lnEF	18.314	0.206	19.747	0.995
$\ln CO_2$	20.547 **	0.038	17.298	0.992

** denote the significance at 5% level.

As shown in Figure 3, after checking the cointegration relationships, the study performs elasticity calculations using the CS-ARDL and CUP estimators, respectively. Table 7 presents the findings of CS-ARDL. According to the estimation results, a short-term 1% change in TOUR increases LCF by 0.47%, while a 1% increase in FD decreases environmental quality by 0.54%, and these coefficients are statistically significant. In the models constructed for EF and CO_2, the independent variables are not statistically significant.

Table 7. The results for CS-ARDL.

Dependent Variable		**lnLCF**		**lnEF**		**lnCO_2**
Long run	coefficient	Prob.	coefficient	Prob.	coefficient	Prob.
lnGDP	−33.994	0.415	16.808	0.497	45.259	0.781
lnGDP^2	1.686	0.394	−0.681	0.497	−2.359	0.761
lnTOUR	0.210 **	0.029	0.048	0.586	−1.048	0.211
lnFD	−0.247	0.114	−0.259 **	0.010	−0.010	0.967
Short run	coefficient	Prob.	coefficient	Prob.	coefficient	Prob.
ΔlnGDP	−68.031	0.457	55.043	0.326	5.458	0.971
ΔlnGDP^2	3.364	0.438	−2.374	0.393	−0.467	0.949
ΔlnTOUR	0.467 **	0.040	−0.050	0.899	−1.133	0.105
ΔlnFD	−0.540 ***	0.089	−0.513 *	0.006	0.138	0.623
ECT_{t-1}	−1.130 *	0.000	−1.143 *	0.000	−0.333 ***	0.076

*, **, and *** represent the significance at 1%, 5%, and 10% levels, respectively.

The long run coefficient of GDP and its square are not statistically significant for LCF, CO_2, and EF. Although the signs of the coefficients are within expectations, the EKC and LCC hypotheses are not valid because they are not significant. More specifically, this means that income level cannot act as a factor that improves environmental conditions per se. FD has a negative impact on environmental quality. However, a 1% increase in tourism increases the LCF by 0.21% in the long-run. In both the short and long term, tourism has a positive effect on environmental quality. According to Katircioglu et al. [13], the tourism sector can be environmentally beneficial for the top 10 tourism destinations, and the results of our study confirm this. The governments of the top 10 destinations are able to manage tourism efficiently and cleanly, and the expansion of this sector supports environmental sustainability.

Finally, Table 8 presents the results of the CUP-FM and CUP-BC estimators of Bai et al. used for the robustness check. The elasticities of GDP and the squares of GDP estimated for the LCF model alone are not statistically significant, so the LCC hypothesis is not valid. FD reduces environmental quality with its negative impact on LCF. The positive coefficient of TOUR highlights the environmental role of tourism, which is also determined by CS-ARDL.

Table 8. Robustness check for long run estimation of LCF.

Estimators	**CUP-FM**		**CUP-BC**	
Variables	coefficient	t-stat.	coefficient	t-stat.
lnGDP	−1.039	−1.108	−0.208	−0.257
lnGDP^2	0.918	0.946	0.025	1.236
lnTOUR	0.321 *	6.262	0.471 *	7.277
lnFD	−0.196 *	−5.986	−0.108 *	−6.403

* denote the significance at 1% level.

Figure 4 graphically summarizes the results of this study. As can be seen in the figure, the LCC hypothesis is not valid according to the results of CS-ARDL and CUP. All three estimators show that international tourist arrivals have an environmental quality-enhancing effect. However, the results of the estimators for FD differ. According to CS-ARDL, FD has no effect on LCF in the long run, while the CUP estimators prove that FD reduces environmental quality in the long run.

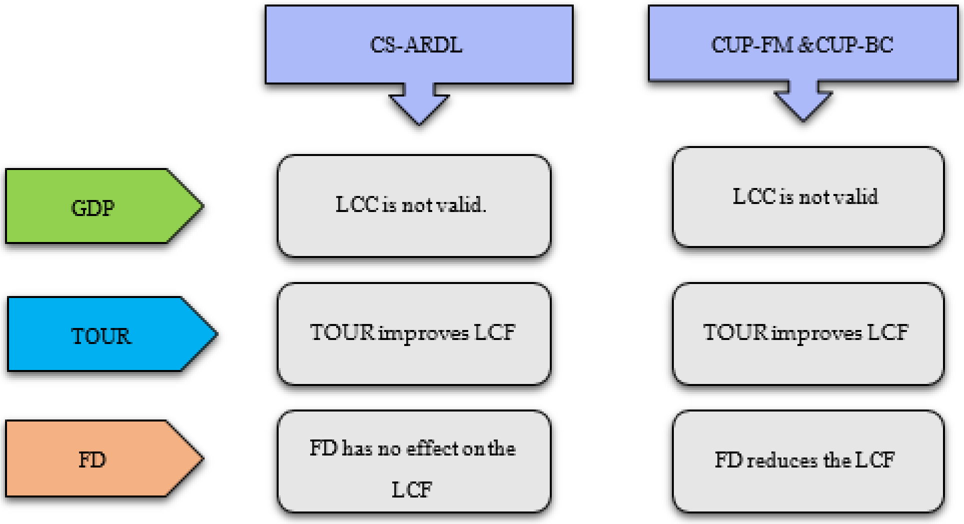

Figure 4. Summary of the long run results.

Overall, the results from three separate panel data estimators suggest that tourism is a factor that improves LCF and promotes environmental quality in the long run. The eco-friendly role of tourism is consistent with the findings of Lee and Brahmasrene [29], Katircioglu [24], Katircioglu et al. [13], Kongbuamai et al. [26], and Khan and Hou [12]. One reason why tourism is an environmentally friendly factor could be the growing environmental awareness that comes from the demand of international tourists for environmentally friendly services and green nature. The invalidity of EKC for the top 10 tourist destinations contrasts with the findings of Katircioglu et al. [13]. Finally, the view that FD is a harmful element for the environment is consistent with Godil et al. [20] and Saud et al. [8].

5. Conclusions and Policy Recommendation

This study empirically examined the validity of the EKC and LCC hypotheses for the top ten tourism destinations simultaneously using second-generation panel data approaches. To this end, the study applied the LM bootstrap cointegration test, CS-ARDL, CUP-FM, and CUP-BC, and examined the impact of FD, tourism, and GDP on three different environmental indicators such as CO_2 emissions, EF, and LCF. The results of the study emphasize that (i) the EKC and LCC hypotheses are not valid, (ii) tourism improves environmental quality, and (iii) FD harms the environment.

Overall policy recommendations urge government officials and environmentalists to emphasize the promotion of tourism development to preserve the natural order. Empirical evidence on tourism shows that this service sector can simultaneously meet economic and environmental goals. The top 10 destinations can increase their income through the increase of international tourist arrivals and tourism development policies, while making tourism regions environmentally friendly facilities. Thus, tourism can contribute to the development of LCF by leveraging both its economic and environmental benefits. The environmental role of tourism shows that these 10 countries are managing the tourism sector in an environmentally friendly and good manner. Policymakers in these countries need to help raise environmental awareness by expanding sustainable tourism concepts. In this regard, the top 10 tourism destinations can provide greener and cleaner areas for tourists, monitor pollution, tax emission-intensive facilities in hotels and camps, and penalize tourism facilities that generate large amounts of waste in land and marine areas. All of these measures can help increase the environmental benefits and LCF of sustainable tourism.

The fact that the LCC hypothesis is not valid shows that these ten countries cannot solve their environmental problems by relying only on economic development. There is no U-shaped relationship between income and environmental quality. In this context, the governments of the top 10 tourism destinations can make their EG strategies more environmentally friendly by, for example, imposing carbon taxes that encourage the use of renewable energy sources in production processes and penalize the use of fossil fuels. In this way, income growth in the future could improve LCF and environmental quality.

FD is environmentally harmful. FD expands the fossil fuel consumption and production scale in the countries studied. Companies do not use the funds acquired through FD for environmentally friendly and clean production technologies. The companies channel these funds into a cheap and cost-efficient production process that leads to increased pollution, destruction of water and land areas, and more waste. To prevent this, governments must redirect financial resources to environmental awareness programs and to companies that invest in renewable energy with proactive policies.

The study has some research limitations. First, the data from EF and LCF are only available through 2018. When the data are updated for 2021–2022, the tourism–environment relationship can be analyzed with a more current data set. Another limitation is that the study focuses on only 10 countries. Future studies could provide more comprehensive results by examining the tourism–LCF relationship in larger groups of countries such as the OECD. In addition, researchers can study the impact of tourism revenue and investment on LCF in the future so that the relationship between the tourism sector and the LCF can be evaluated from different perspectives.

Author Contributions: Conceptualization, U.K.P.; methodology, U.K.P.; investigation, U.K.P. and B.T.; writing—original draft preparation, U.K.P. and B.T.; writing—review and editing, U.K.P. and B.T.; supervision, U.K.P.; project administration, U.K.P. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Data will be available upon request.

Acknowledgments: This article is devoted to the remembrance of Harun Terzi, who passed away on 19 September 2017. UKP and BT are proud to have been Terzi's students at Karadeniz Technical University. Our sincere thanks to the anonymous reviewers for their valuable contributions and constructive feedback.

Conflicts of Interest: The authors declare no conflict of interest.

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