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Fractional integration and energy demand: A time series analysis for Latin America

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ABSTRACT

In this paper, we examine energy demand in a group of Latin American regions using a fractional integration approach. Employing annual data from 1965 to 2023 on primary energy consumption in exajoules (EJ) and per capita consumption in gigajoules (GJ), we investigate the persistence and mean-reverting properties of energy demand over time. The application of fractional integration techniques allows us to capture both short- and long-term dependencies, offering a more flexible framework compared to traditional time series models. Our findings indicate that energy demand in Latin America exhibits long-memory characteristics, implying that shocks to consumption may have prolonged effects, with some countries displaying a slow mean-reverting process while others show evidence of permanent shocks. These heterogeneous results suggest that structural factors, such as economic development, energy policies, and technological advancements, play a crucial role in shaping consumption patterns. Additionally, the study highlights the importance of considering long-run dynamics in energy demand forecasting and policymaking, particularly in the context of economic growth and environmental sustainability. The results emphasize the need for adaptive energy strategies that consider the varying degrees of persistence across countries, aiming for a balance between economic development and the transition towards cleaner energy sources.

1. Introduction

Energy fundamentally shapes economies. Economic activity grows when abundant and cheap energy resources are available and falls when such resources are spent or become too expensive to use. Moreover, economic activity itself can be traced to energy-expenditure processes used to rearrange matter in convenient ways, i.e., to produce goods. Yet, the casual path of this relation is not so direct, as economic activity itself affects energy demand. Empirical efforts to establish such a casual path have been empirically difficult to determine despite considerable efforts. For example, Beaudreau [1], Weissenbacher [2], Ostolaza et al. [3], Fernandes and Reddy [4] and Tambini & Vergara [5] have addressed the link between energy demand and economic growth and found mixed results.

Meta-analyses in this field have highlighted several avenues for future research. Drawing on 51 studies, Menegaki [6] suggests that upcoming research should prioritize developing countries, employ more sophisticated econometric techniques, and incorporate multivariate analysis. Similarly, Kalimeris et al. [7], based on 158 studies, advocate for considering energy prices and elasticities, using quality-adjusted energy measures, and categorizing countries with comparable energy consumption patterns. Lastly, Bruns et al. [8], reviewing 72 studies, emphasize the need for extended time series, improved quality-adjusted energy metrics, and stronger theoretical frameworks.

Energy is also closely tied to environmental impact. More energy demand implies more material change, which usually (although not necessarily) involves the extraction of valuable materials from nature or the dumping of waste into nature. This relationship can be modified in specific cases, such as the CO_2 emissions associated with electricity production when switching from coal to renewable sources, yet even renewables carry environmental impacts associated with the extraction of metals and the eventual disposition of solar panels and wind turbines. Formally, there is evidence of relative decoupling between energy demand and environmental impact (e.g., by switching to renewables as traditional energy industries have been a major contributor to pollution and environmental impact [9], but absolute decoupling is conceptually

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more challenging and has no empirical evidence to date.

The Statistical Review of Energy Institute [10] notes that total energy consumption increased by 2 % in 2023, 0.6 % above the 10-year average and 5 % above pre-pandemic levels in 2019. Renewable energies reached 14.6 % of primary energy consumption (+0.4 % compared to 2022) and, together with nuclear energy, accounted for 18 % of the total. On the other hand, fossil fuels decreased by only 0.4 %, although they still account for 81.5 % of total consumption.

Worryingly, however, greenhouse gas (GHG) emissions from energy use, industrial processes, flaring and methane rose by 2.1 %, reaching a new record high. Carbon dioxide emissions from flaring rose by 7 %, while emissions from industrial processes and methane increased by more than 5 %.

These relationships make the study of energy demand itself relevant to determine the opportunities for economic growth and the environmental challenges faced by countries. Studies on energy demand dynamics abound, for example in the work of Peng et al. [11], Philips and Jayakumar [12], Al-Haija et al. [13], Nikseresht and Amindavar [14]. Yet, specific work on Latin America is thin. Leiva and Rubio-Varas [15] used advanced methodologies such as super-exogeneity, Granger employed causality tests and structural breaks to study the long-run relationship between GDP and energy demand in 20 Latin American countries between 1900 and 2010, and found heterogeneous causal relationships between energy and economic growth.

In this context, the main contribution of this research is the application of fractional integration methods to identify significant trends in the time series of energy demand in Latin America, using historical data from 1965 to 2023. This methodology enables the modeling of short- and long-term persistence and the analysis of mean-reverting behavior and patterns of change. Fractional integration offers advantages over traditional methods, such as the Auto Regressive Integrated Moving Average (ARIMA) models, by capturing long-term patterns and classifying shocks as transitory (if the order of integration is less than one) or permanent (if equal to or greater than one) (see, e.g., Jiang et al. [16]; Franzke et al. [17]; Lenti and Gil-Alana [18]; Yuan et al. [19]; Imeri and Gil-Alana [20]).

The analysis of energy dynamics given its relation to economic activity and environmental impact underlines the urgency of moving towards models that increase energy supply with renewable sources while reducing the absolute use of fossil fuels in the energy mix. The fractional (ARFIMA) model offers advantages in the study of energy consumption by capturing long-term dependencies and persistent effects. This allows the identification of short- and long-term patterns, facilitating the design of more effective strategies to deal with both positive and negative consequences of fluctuations. The analysis can also highlight consumption dynamics that may be unsustainable, highlighting the urgency to transform the region's economies towards low-carbon, more resilient and sustainable models of energy provision.

In summary, the main objectives of the paper are as follows: first, we investigate the issue of energy demand in Latin America, a not much investigated issue in the economic literature; second, we use an updated time series technique named fractional integration, which outperforms standard methodologies that only consider integer degrees of differentiation, basically, zero for the stationary series and one for nonstationary ones; moreover, within this context of fractional integration, we use a procedure, based on Robinson [21], that has numerous advantages with respect to other methods of fractional integration; in particular, it is the most efficient method against local departures, which is important in our fractional context; it is also characterized by a standard null limit distribution (unlike for instance what happens with most unit root methods) and more importantly, it is valid for any real order of integration, and thus, includes values outside the stationary region. Note that most procedures require preliminary differentiation of the data if they are believed to be nonstationary; finally, the last contribution of the article deals with the policy implications of the results obtained, which are reported at the end of the manuscript.

2. Literature review

The rapidly increasing use of energy worldwide has raised concerns about depleting energy resources, exceeding supply capacities, and causing severe environmental impacts such as global warming, ozone layer depletion, and climate change, Pérez-Lombard et al. [22]. Energy consumption's role in economic growth has been extensively studied in the energy economics literature, e.g., Arora et al. [23]; Shahbaz et al. [24]. While much research focuses on Western countries, some also examines Middle Eastern contexts.

The findings vary: Shahbaz et al. [24] suggest a nexus where increased economic growth necessitates higher energy use, and productive energy usage requires higher growth rates. Using Granger causality tests, studies reveal diverse outcomes across countries and regions. For New Zealand, Bartleet and Gounder [25] found a unidirectional relationship from economic growth to energy consumption using data from 1960 to 2004. For the G7 Countries, Narayan and Smyth [26] identified a bidirectional causal relationship via panel cointegration and FMOLS techniques. In the context of African countries, Wolde-Rufael [27] observed unidirectional causality from energy to output in three countries, the reverse in six countries, and bidirectional causality in three others. No causal link was found in one country. Finally, for Asian countries, Asafu-Adjaye [28] found mixed results, with unidirectional causality from energy to growth in India and Indonesia but bidirectional causality in the Philippines and Thailand. In China, Hou [29] confirmed a bidirectional relationship, while in Pakistan, Siddiqui [30] noted unidirectional causality from energy to output. For a group of 119 countries, Yasar [31] found varying results, with no long-term relationship in low-income countries.

Yu & Choi [32] analyzed the 1954–1981 period, discovering unidirectional causality between energy usage and GDP in Korea and the Philippines, while no causality was found in the USA, UK, or Poland. Similarly, Masih and Masih [33] identified unidirectional causality in Pakistan, India, and Indonesia but none in Malaysia, Singapore, or the Philippines. Filippini and Pachauri [34] emphasized the role of population and industrialization in increasing energy use.

Lee [35] confirmed both short- and long-run causality between energy consumption and GDP in 18 developing countries. Francis et al. [36] employed multivariate Bayesian VAR techniques to explore the relationship between energy and GDP. Jamil [37] studied seven countries from 1955 to 2021, focusing on the impact of exchange rates and prices on energy policies.

2.1. Renewable energy and economic growth

Farhani and Rajeb [38] analyzed 15 MENA countries, finding no causality in the short run but unidirectional causality from energy consumption to economic growth in the long run. Studies on renewable energy consumption have also gained traction: for the US and using wavelet coherence, Bilgili [39] supported the growth hypothesis between renewable energy and industrial production (1981–2013). For Canada, Japan, and the US, Mutascu [40] observed two-way causality between energy consumption and GDP (1970–2012). Finally, for the Sub-Saharan Africa, Adams et al. [41] found evidence supporting the feedback hypothesis for energy consumption and economic growth (1971–2013).

2.2. CO_2 emissions and energy consumption

Fei et al. [42] analyzed data from 30 Chinese provinces (1985–2007) to examine the causal relationship between CO_2 emissions, energy consumption, and GDP. They identified unidirectional causality from GDP to energy consumption and found that a 1 % increase in per capita GDP corresponded to a 0.5 % rise in energy usage. Hye and Riaz [43] noted unidirectional causality in the long run and bidirectional causality in the short run. They concluded that energy consumption affects economic growth, job creation, and social stability.

2.3. Time series forecasting of energy consumption

Precise forecasting of energy consumption aids in resource allocation, energy-saving strategies, and economic development [44–46]. Moreover, various methods have been developed, including statistical models: thus, ARIMA is widely used for linear time series, Kumaresan and Ganeshkumar [47]. Non-linear patterns necessitate advanced methods such as neural networks, Mengesha et al. [48]; Shaeri et al. [49]. Machine Learning Techniques such as LSTM and Bi-LSTM models in modeling complex, non-linear patterns have been employed in Fischer and Krauss [50], Abbasimehr et al. [51] and Kulshrestha et al. [52].

Bi-LSTM models outperform ARIMA and SARIMA models, achieving lower RMSE and MAE values in energy consumption forecasting [53] Hybrid models combining decomposition techniques with Bi-LSTM have also been shown to improve accuracy in predicting solar irradiance, Singla et al. [54]. A comparative study of long short-term memory (LSTM), bidirectional LSTM, and traditional machine learning approaches for energy consumption prediction was examined in Alizadegan et al. [55].

Table 1
Mapping of base studies according to methodology, scope and relevance to our research.

No	Author(s) & Year	Region/ Countries	Methodology	Main Findings	Relation to our study
1	Al-Haija et al. [65]	Worldwide	Shallow Neural Network (R_SNN, 20 neurons); data 2000–2019; forecast 2020–2025	99 % accuracy in forecasting renewable energy additions; linear growth trend 2020–2025.	Highlights an alternative machine learning approach for forecasting; complements the long-term perspective of our research with short-term predictions.
2	Jiajie et al. [66]	China	VMD for denoising; LSTM network for forecasting short-term energy consumption	Accurate short-term forecasting; useful for carbon control planning; adaptive model updated with real values.	Proposes a deep learning-based method for energy demand prediction; contrasts with our fractional integration approach.
3	Subathra et al. [67]	India	Delhi Rajasthan Assam	ARIMA model applied to solar energy generation data (daily/weekly/monthly) ARIMA captures temporal trends; helps in energy planning and grid integration; comparative insight across states and timeframes.	Establishes direct comparison with classical time series models; useful to highlight the strengths of our fractional models.
4	Wu et al. [68]	Zhejiang Province	ECV method (Entropy + CRITIC + Coefficient of Variation) for evaluation; ARIMA + Deep Belief Network (DBN) for prediction; enterprise-level energy consumption data.	Proposed method improves accuracy in evaluating and forecasting energy usage; ARIMA-DBN model captures dynamic trends effectively; validated with real-world enterprise data.	Complements our research by combining classical ARIMA with neural networks; provides comparison points with our macro-regional fractional integration methodology.
5	Ramya et al. [69]	Global (116 countries)	ARIMA model applied to energy data from Our World in Data (1965–2022); 8 energy sources; forecast for low-carbon transition trends.	Forecasts a global decline in fossil fuel use over the next decade; ARIMA provides credible insight for policy and planning; supports renewable energy adoption strategies.	Shares a large-scale time series approach; provides methodological contrast with our long-memory models, relevant for energy transition policies.
6	Al-Haija et al. [65]	Global	ARMA(3,3) modeling on historical CO_2 emissions data from 1975 to 2018	Predicts linear increase in energy-related CO_2 emissions, reaching 35 Gt in 2023. 86.1 % accuracy.	Provides methodological reference for short-term energy emissions prediction, complementing our work.
7	Yan and Ouyang [70]	International	Hybrid model: physical power curve + error correction with data mining algorithms	60–80 % improvement over physical model and 30–70 % over traditional statistical models	Presents a two-phase approach (prediction + correction) applicable to our energy time series analysis.
8	Al-Haija et al. [71]	Middle East	Estimation of energy consumption for DH-EKE encryption with different key sizes and neighbor nodes	Consumption ranges from 4.8 μJ to 1.6 mJ. Supports design of low-consumption cryptography for sensors	Provides perspective on digital system efficiency; useful as contrast with our macro-energy consumption studies.
9	Yoshida et al. [72]	USA	Linear programming using hourly load profiles over one year to size Energy Storage Systems (ESS)	Achieves 10 % and 28 % savings in two cases. Combining loads reduces required capacity by 10 %	Provides basis for hourly analysis and energy decision-making, enriching our models with real data.
10	Al-Haija et al. [73]	International	Review and application of AI in energy simulation and optimization (neural networks, fuzzy logic, etc.)	AI improves efficiency, accuracy and energy system management; includes case studies and ethical/legal analysis	Includes methodological tools directly related to our research in prediction and optimization.
11	Panapongpakorn & Banjerdpongchai [74]	Thailand	ARIMA, SARIMA, ANN, and LSTM applied to short-term electricity demand; enhancement with Average True Range (ATR) indicator; model comparison using RMSE and MAPE.	LSTM with ATR outperforms other models in forecasting short-term electricity load; results applied to a micro Energy Management System (EMS) for real-time planning and operation.	Combines classical and AI models for performance evaluation; contrasts with our fractional integration approach at macro-regional scale and long-term scope.
12	Revathi et al. [75]	International	Dual-model time series forecasting using ARIMA, Prophet, and LSTM; open energy consumption datasets; feature selection via statistical and machine learning techniques	Combining multiple models improves forecasting accuracy for short-term load in VPPs; effective at capturing seasonality, trends, and nonlinear patterns; useful under varying renewable energy penetration and demand conditions; enhances reliability and stability of smart grids	Supports the use of advanced models and open data; relevant for methodological comparison and robustness of our models under complex consumption patterns.

2.4. Fractional integration

Finally, regarding the specific use of fractional integration in the context of energy, there are some studies that have used this methodology. These include the contributions of Elder & Serletis [56] regarding energy future prices, Barros et al. [57] focusing on U.S. renewable energy consumption, Weron [58] and Gil-Alana et al. [59] in the field of electricity prices, as well as Barros et al. [60] on energy prices. Additionally, Gil-Alana et al. [61] analyze the Iberian energy market by addressing the relationship between energy consumption and energy prices.

By leveraging time series analysis and advanced forecasting models, researchers can address the growing complexity of energy systems while supporting policy decisions and sustainable development goals. Furthermore, studies such as those by Da Silva and Meneses [53], Marques Serrano et al. [62], Harikrishnan et al. [63], and Li et al. [64] on renewable energy highlight its critical role in reducing environmental impacts and fostering sustainable economic growth.

As can be seen from Table 1, which compiles the most outstanding studies related to our work, trends relevant to the present study can be detected. The methods studied show an evident predominance of machine learning techniques for short-term projections (items 1, 2, 7), while our research provides an innovative vision by dealing with the problem through fractional integration over broad time scales. This analogy makes it easier for us to place our contribution within the current context of energy forecasting research, highlighting how we complement and expand existing methods.

3. Methodology

This paper employs a fractional integration methodology widely used in the analysis of time series of many different disciplines (including, for example, climatology, Yuan et al. [76]; economics, Abbritti et al. [77]; tourism, Gil-Alana & Huijbens [78]; environmental studies, Bello et al. [79]; urbanism, Martin-Valmayor & Gil-Alana [80]; etc.)

Fractional integration belongs to a broader category of processes called long memory or long range dependent processes, which are characterized because the density function contains at least one singularity or pole at a frequency in the interval $[0, \pi)$. It is well known that this frequency is in many cases the smallest (zero) frequency when dealing aggregated data. Among the many mathematical models which are able to describe this long memory feature, with the singularity or pole at the zero frequency, a common one is the fractionally integrated model as described by equation (1) below. It was the Nobel prized Clive C.W. Granger who proposed this model in the 80s [81] under the observation that the estimation of the spectral density of many aggregated series displayed a very large value at such a zero frequency, and that doing the same on the first differenced series, the values at that zero frequency were close to zero, indicating over-differentiation. See Granger [81], Granger and Joyeux [82] and Hosking [83] for the first representations of these models that have been later widely employed in the analysis of time series data.

What is behind this approach is that a series may require a fractional degree of differentiation to render it stationary or I(0). By I(0) we refer to a process where the infinite sum of its autocovariances is finite, such as white noise or the stationary and invertible ARMA type of processes. Denoting L the lag operator, i.e., $L^k x(t) = x(t-k)$, we can use a Binomial expansion on the polynomial $(1 - L)^d$ such that, for all real d,

$$(1-L)^d = \sum_{j=0}^{\infty} \binom{d}{j} (-1)^j L^j = 1 - dL + \frac{d(d-1)}{2} L^2 - \dots$$

and thus, an I(d) process of the form

$$(1-L)^d x(t) = u(t), t = 1, 2, \dots, \tag{1}$$

may be expressed as

$$x(t) = d\, x(t-1) - \frac{d(d-1)}{2}\, x(t-2) + \dots + u(t),$$

where u(t) is I(0). Note that based on the above expression, d can be taken as an indicator of the degree of persistence of the series, since the higher the value of d is, the higher the level of dependence in the data is, and values of d lower than 1 support the hypothesis of reversion to the mean with a hyperbolic decay in the infinite MA representation of the series [84]. Thus, if d is smaller than 1, shocks will be expected to be transitory, while values of d equal to or above 1 indicate permanency of shocks. A clear advantage of this approach is that it permits us to consider nonstationary processes though with mean reversion if the order of integration of the series d is in the interval (0, 0.5).

In the empirical work, conducted in Section 5, we suppose that x(t) in (1) are the errors in a regression model that includes a constant and a linear time trend. Thus, the model under examination is:

$$y(t) = \beta_0 + \beta_1 t + x(t),$$

$$(1-L)^d x(t) = u(t), t = 1, 2, \dots \tag{2}$$

where y(t) refers to the observed data and β_0 and β_1 are unknown coefficients to be estimated from the data along with d. The estimation is conducted via a likelihood function expressed in the frequency domain, through a simple version of the procedure developed in Robinson [21]. This method displays several features that makes it particularly interesting. First, it has a standard normal limit distribution, which is an unusual feature in the context, for example, of unit roots tests, where critical values have been computed numerically on a case by case simulated basis; moreover, this standard behavior is unaffected by the presence of deterministic terms as those appearing in the first equality in (2); another interesting feature is that being a testing procedure, it allows us to compute confidence bands for non-rejection values of d, choosing as an estimator the value of d that produces the lowest test statistic and being an approximation to the maximum likelihood estimate; in addition, this method is valid for any range of values of d, including those outside the stationary region (i.e., $d \geq 0.5$); a final interesting feature is that it is the most efficient method in the Pitman sense against local departures. (More details of this specific method can be found in Ref. [85]).

4. Data

The present research takes data from the Statistical Review of World Energy belonging to the Energy Institute [10], considering primary energy consumption data for Latin American countries in exajoules (EJ), as well as primary per capita consumption expressed in gigajoules (GJ).

Table 2
Descriptive statistics on primary energy consumption in Latin American countries, expressed in exajoules (EJ), for the years 1965–2023.

Country	Mean	Std. Dev.	Min.	Max.	Range
Mexico	5.1	2.4	1.1	8.5	7.4
Argentina	2.3	0.8	1.2	3.7	2.5
Brazil	7.1	4.0	1.0	13.9	12.9
Chile	0.9	0.5	0.3	1.8	1.6
Colombia	1.1	0.5	0.4	2.3	1.9
Ecuador	0.4	0.2	0.0	0.8	0.8
Peru	0.6	0.3	0.2	1.2	1.0
Trinidad & T	0.4	0.3	0.1	0.8	0.7
Venezuela	2.2	0.9	0.7	3.8	3.1
Central Am.	0.7	0.4	0.2	1.5	1.4
Other Caribbean	1.4	0.3	0.8	1.9	1.1
Other South Am.	0.7	0.4	0.1	1.4	1.2

Source: Own elaboration based on Energy Institute's Statistical Review of World Energy (2024).

Table 3
Descriptive statistics on primary energy consumption per capita in Latin American countries, expressed in gigajoules (GJ), for the years 1965–2023.

Country	Mean	Std. Dev.	Min.	Max.	Range
Mexico	53.9	14.0	24.7	70.7	46.0
Argentina	66.1	9.6	53.4	83.3	30.0
Brazil	41.4	15.2	11.7	64.1	52.5
Chile	56.8	23.4	29.0	92.5	63.5
Colombia	30.2	6.1	19.2	43.3	24.1
Ecuador	26.8	12.2	5.8	46.4	40.5
Peru	23.1	6.0	16.1	36.0	19.9
Trinidad & T	310.2	157.5	130.4	596.1	465.7
Venezuela	101.7	18.6	66.7	128.9	62.2
Central Am.	18.6	6.0	10.2	29.7	19.5
Other Caribbean	41.7	4.6	34.9	49.7	14.8
Other South Am.	38.4	16.3	14.9	59.8	44.9

Source: Own elaboration based on *Energy Institute's Statistical Review of World Energy (2024)*

Both time series cover the period from 1965 to 2023.

Tables 2 and 3 present results on descriptive statistics for Latin American countries,[1] considering primary energy consumption. They include average values, standard deviations, minimum and maximum values, as well as the range of the data, considering the same period of time of the analysis.

The results of Table 2 and Fig. 1 indicate that, in Latin America, the countries with the highest primary energy consumption in average are Brazil (7.1 EJ) and Mexico (5.1 EJ), the latter country with a wide range (1.00–13.9 EJ). It is also observed that these countries have a higher standard deviation, which may reflect their demographic size, their industrialized economy and the weight of their industry. On the other hand, in Figs. 2 and 3, we show that the lowest consumers in the region include countries such as Ecuador (average 0.4 EJ), Trinidad and Tobago (average 0.4 EJ) and Central America as a whole (average 0.7 EJ), which have the lowest total consumption due to their size and limited population, despite being energy producers.

As for the countries with less variability in their consumption, Argentina (average 0.8 EJ), Chile (average 0.5 EJ), Colombia (average 0.5 EJ), Ecuador (average 0.2 EJ), Peru (average 0.3 EJ) and the Caribbean (average 0.3 EJ) stand out, showing more consistent and stable patterns over time.

In the case of per capita consumption presented in Table 3 and in Figs. 4 and 5 it is important to highlight the exceptionally high consumption of Trinidad and Tobago (average 310.2 GJ/person), attributable to its energy industry and small population. This figure reflects an intensive use of energy in proportion to its size, mainly influenced by the export of hydrocarbons. Similarly, Venezuela stands out with a consumption of 101 GJ/person, also reflecting its abundant energy resources.

When analyzing the variability in consumption, Trinidad and Tobago leads with the highest standard deviation (157.5 GJ/person), which is evidence of a highly fluctuating consumption in different periods. Chile follows with a significant standard deviation (23.4 GJ/person), probably due to its energy diversification. As for the lowest average consumption per person, Central America has the lowest average with 18.6 GJ/person, followed by Peru with a low consumption of 23.1 GJ/person. Countries such as Mexico (average 53.9 GJ/person) and Argentina (average 66.1 GJ/person) show intermediate consumption, characterized by their stability and consistency with emerging economies.

In general terms we observe in Fig. 6 that per capita energy consumption varies drastically in the region, from countries with high levels of energy consumption and dependence (Trinidad and Tobago, Venezuela) to regions with lower energy access or use (Central America, Peru).

The comparison that the data allows between total consumption and per capita consumption shows energy inequality in the region. Although Brazil and Mexico lead in total consumption, smaller countries such as Trinidad and Tobago and Venezuela show significantly higher per capita consumption, highlighting an unequal distribution of energy in Latin America. On the other hand, countries with low total consumption but moderate per capita consumption, such as Chile and Argentina, suggest economies that use energy more efficiently in relation to their population.

Finally in this section, to motivate further the use of fractional integration we display in Figs. 7 and 8 the periodograms of the series corresponding to the primary energy consumption (in Fig. 7) and those corresponding to the first differenced series (in Fig. 8). Figs. 9 and 10 are similar but for the primary per capita energy consumption data. We clearly observe that the periodograms of the original series display high values at the smallest (zero) frequency, suggesting the need for some type of differentiation; however, the periodograms of the first differenced data (in Figs. 8 and 10) clearly show values close to zero in some cases or slightly above in others at the same zero frequency, implying that first differentiation might not be appropriate at all, and suggesting the need for fractional differentiation.

5. Empirical results

As a preliminary step in the analysis we tested for the presence of long memory in the data using the modified R/S statistic as proposed in Lo (1991). As expected, the results supported this hypothesis in all series examined. Then, within this class of models, we decided to employ the I (d) approach as explained in Section 3.

Below, in Tables 4 and 5, we report the results in terms of the differencing parameter d, for the total primary energy consumption of different countries and subregions in Latin America, applying the I(d) methodology for three different models (without additional deterministic terms, with an intercept, and with an intercept and a linear time trend).

Considering the results, mean reversion is observed only in three cases: Ecuador $d = 0.78$, Colombia $d = 0.80$, and Central America $d = 0.84$. This suggests that, in response to increases or decreases in energy consumption, the series tend to stabilize in the long run. However, in the case of Colombia, the stabilization process may be slower due to its d value being higher than that of Ecuador. This behavior could be related to specific energy policies or efficiency patterns in consumption. For the rest of the countries, the $d > 1$ values (e.g., Venezuela, Trinidad & Tobago, and the Caribbean) reflect non-stationary processes with permanent effects and a possible persistent growth in energy consumption. This could be associated with structural changes or a sustained increase in demand. Finally, we observe that in most countries and subregions, it is necessary to include a linear time trend component in the model, except for Venezuela, Trinidad & Tobago, and the Caribbean. The most pronounced trends are observed in Mexico (0.127) and Brazil (0.221), indicating sustained growth in energy consumption over time. (See Table 5).

Tables 6 and 7 present the results for per capita primary energy consumption for countries and subregions in Latin America. The results of the per capita analysis demonstrate a marked diversity in energy consumption patterns across the various regions and countries of Latin America and the Caribbean. In terms of mean reversion, this is observed only in two cases: Central America, with a parameter $d = 0.69$, indicating a quick adjustment to average levels after a shock, and Colombia,

[1] Country groupings are made purely for statistical purposes and are not intended to imply any judgment about political or economic standings. Certain countries are grouped together in South America and Central America because their consumption is low. 1. Other Caribbean: Atlantic islands between the US Gulf Coast and South America, including Puerto Rico, US Virgin Islands and Bermuda. 2. Central America: Belize, Costa Rica, El Salvador, Guatemala, Honduras, Nicaragua, Panama. 3. Other South America: Bolivia, Paraguay and Uruguay. https://www.energyinst.org/statistical-review/about.

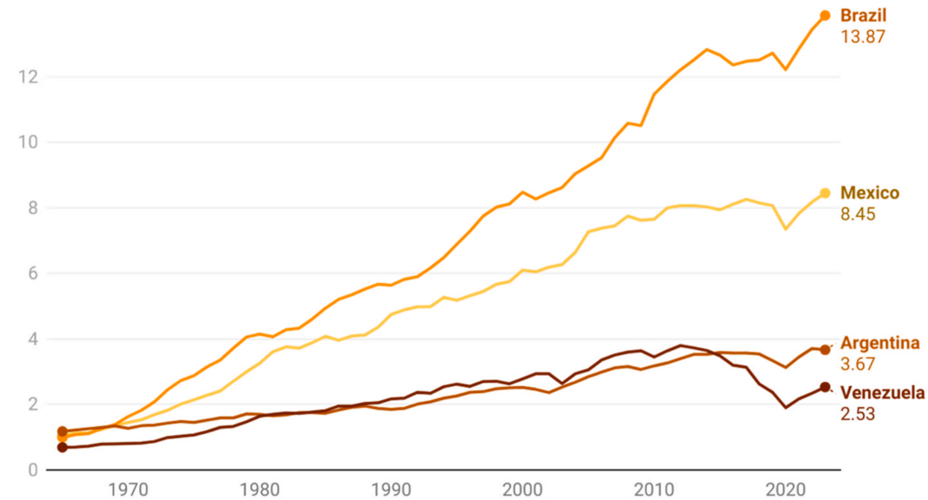

Fig. 1. Most Primary Energy: Consumption. In Exajoules, for the years 1965–2023.
Source: Own elaboration based on Energy Institute's Statistical Review of World Energy (2024).

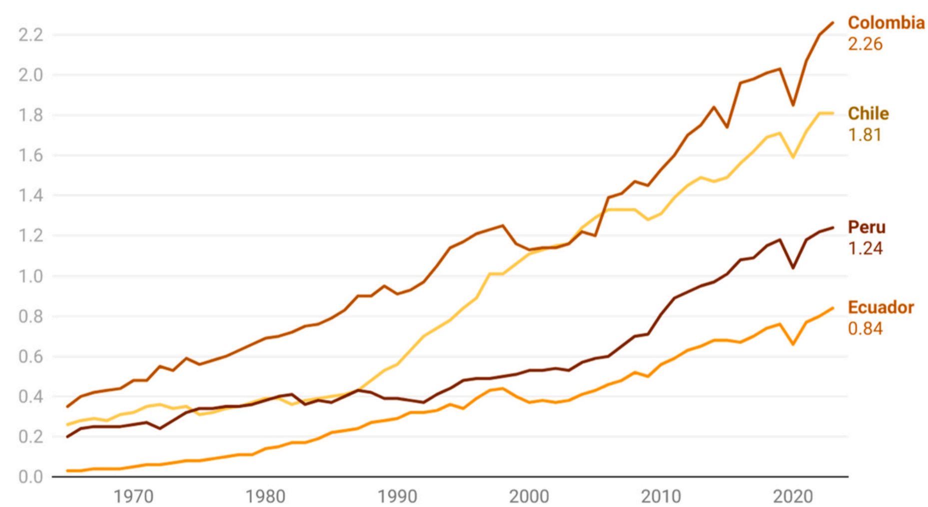

Fig. 2. Min Primary Energy: Consumption. In Exajoules, for the years 1965–2023.
Source: Own elaboration based on Energy Institute's Statistical Review of World Energy (2024).

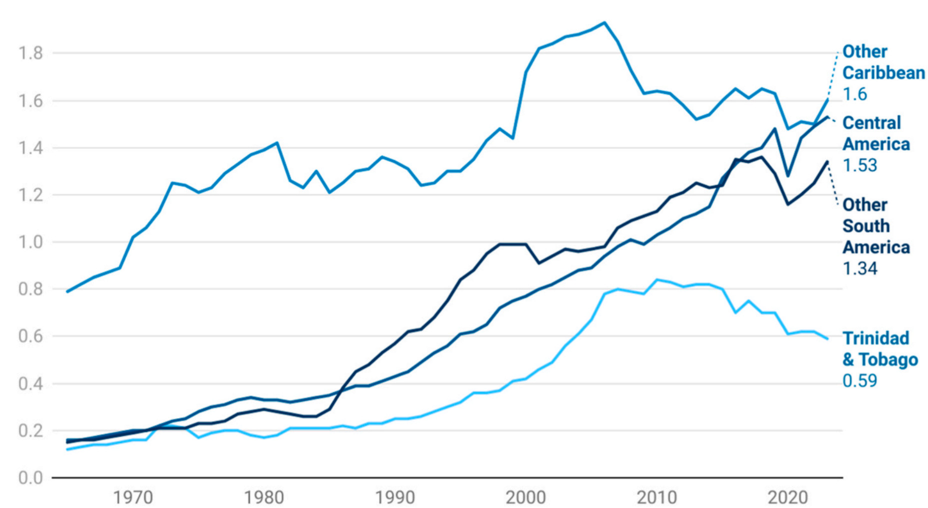

Fig. 3. Min Primary Energy: Consumption. In Exajoules, for the years 1965–2023.
Source: Own elaboration based on Energy Institute's Statistical Review of World Energy (2024).

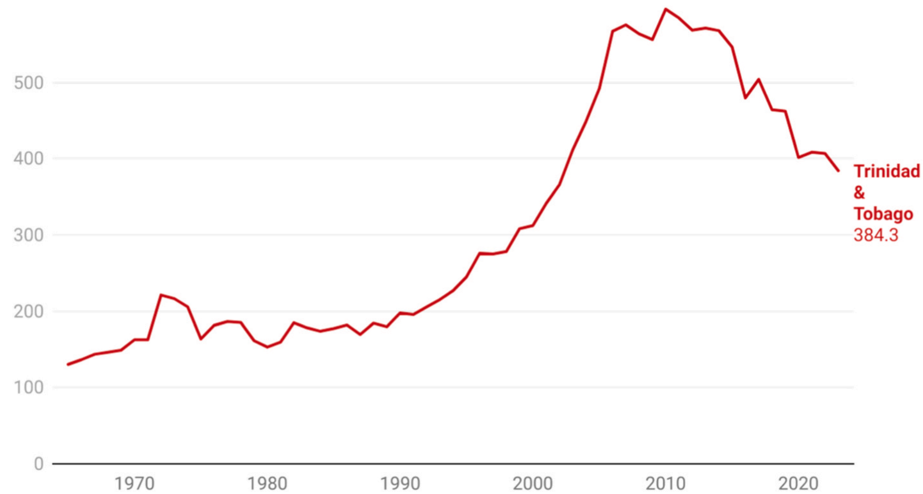

Fig. 4. Trinidad & Tobago Primary energy: Consumption per capita in Gigajoule, for the years 1965–2023.
Source: Own elaboration based on Energy Institute's Statistical Review of World Energy (2024).

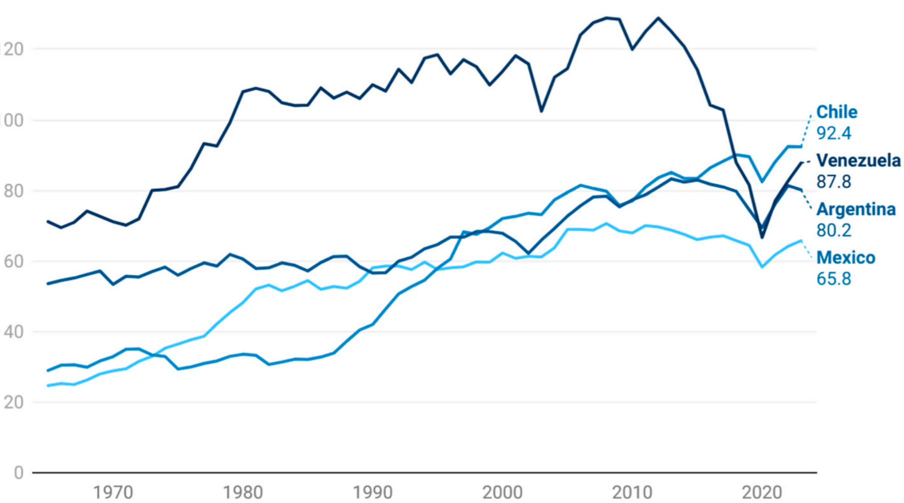

Fig. 5. Most Primary energy: Consumption per capita in Gigajoule, for the years 1965–2023.
Source: Own elaboration based on Energy Institute's Statistical Review of World Energy (2024).

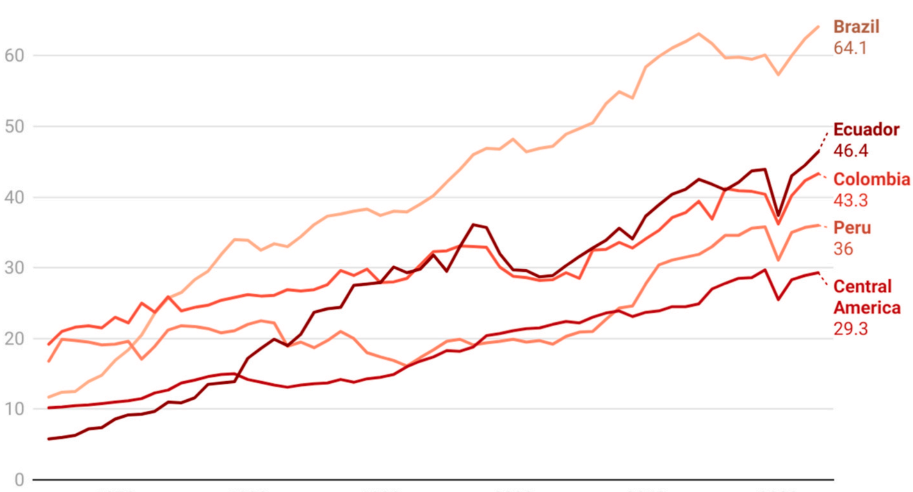

Fig. 6. Min Primary energy: Consumption per capita in Gigajoule, for the years 1965–2023.
Source: Own elaboration based on Energy Institute's Statistical Review of World Energy (2024).

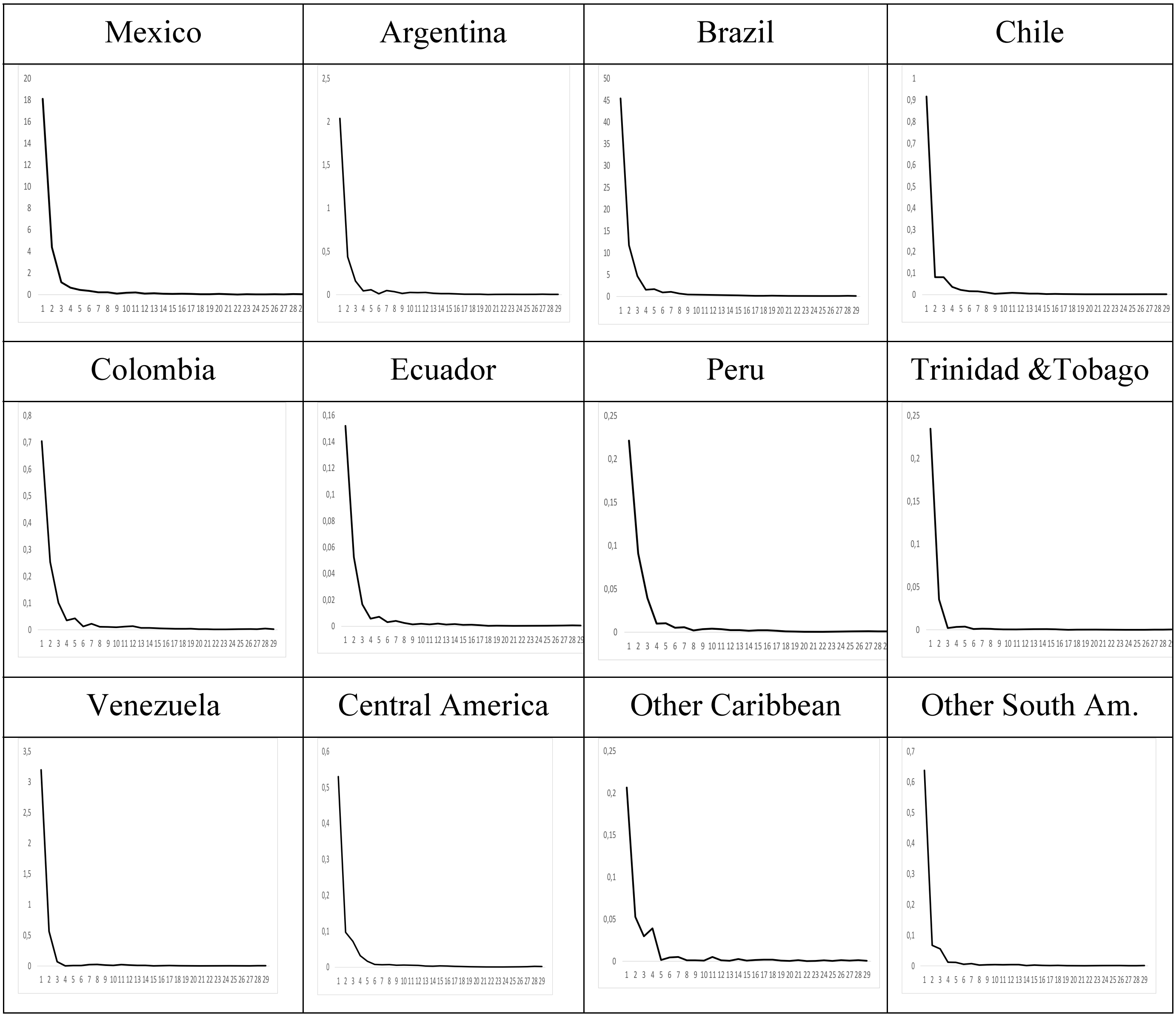

Fig. 7. Periodograms of the original data. Primary energy consumption
Note: The periodograms were computed on the discrete frequencies $\lambda_j = 2\pi j/T$, for j = 1, 2, …, T/2.

with $d = 0.71$, where the reversion is slightly slower, probably due to structural characteristics of the Colombian energy market.

For the rest of the countries and subregions, the d coefficients are equal to or greater than 1, evidencing a permanent pattern in energy consumption where shocks have lasting effects. A noteworthy case is Trinidad & Tobago, with a parameter $d = 1.20$, significantly higher than the rest. This suggests persistent and non-stationary growth in energy consumption, likely related to its limited territorial extent, its energy-dependent economy, and its role as a key regional producer of natural gas.

Regarding linear time trends, most countries and subregions exhibit a significant linear trend in energy consumption. Mexico, with a trend coefficient of 0.711, reflects growth associated with increased industrialization and urbanization. Brazil, with 0.917, shows a more pronounced increase, likely linked to its sustained economic growth. Chile, with 1.064, stands out with the highest trend, which could be attributed to the consolidation of its energy matrix and the growing electrification of its economy. On the other hand, regions such as Other Caribbean, Other South American, Trinidad & Tobago, and Venezuela do not exhibit significant trends. This may be due to the high variability or noise in their energy consumption series, potentially related to economic and political factors that disrupt long-term growth patterns.

As a robustness method, we also employed alternative fractionally integrated methods, in particular, Sowell's (1992) maximum likelihood parametric approach in the time domain, Geweke and Porter-Hudak's (1983) semiparametric log-periodogram approach and the Whittle estimate proposed in Shimotsu and Phillips (2005). The results, though showing some quantitative differences in the values of d, generally produce very similar qualitative results, supporting the hypothesis of mean reversion exclusively in the cases of Central America, Colombia and Ecuador.

Next, following the recommendation of various reviewers, the possibility of nonlinearities and/or structural breaks was considered. This is an interesting point noting that both issues (fractional integration and the presence of breaks) are very much related (see, e.g., Diebold and Inoue, 2001; Granger and Hyung, 2004; Banerjee and Urga, 2005; Gil-Alana, 2008; etc.). However, the modelization of structural breaks produces an abrupt change in the model that can be solved by using non-

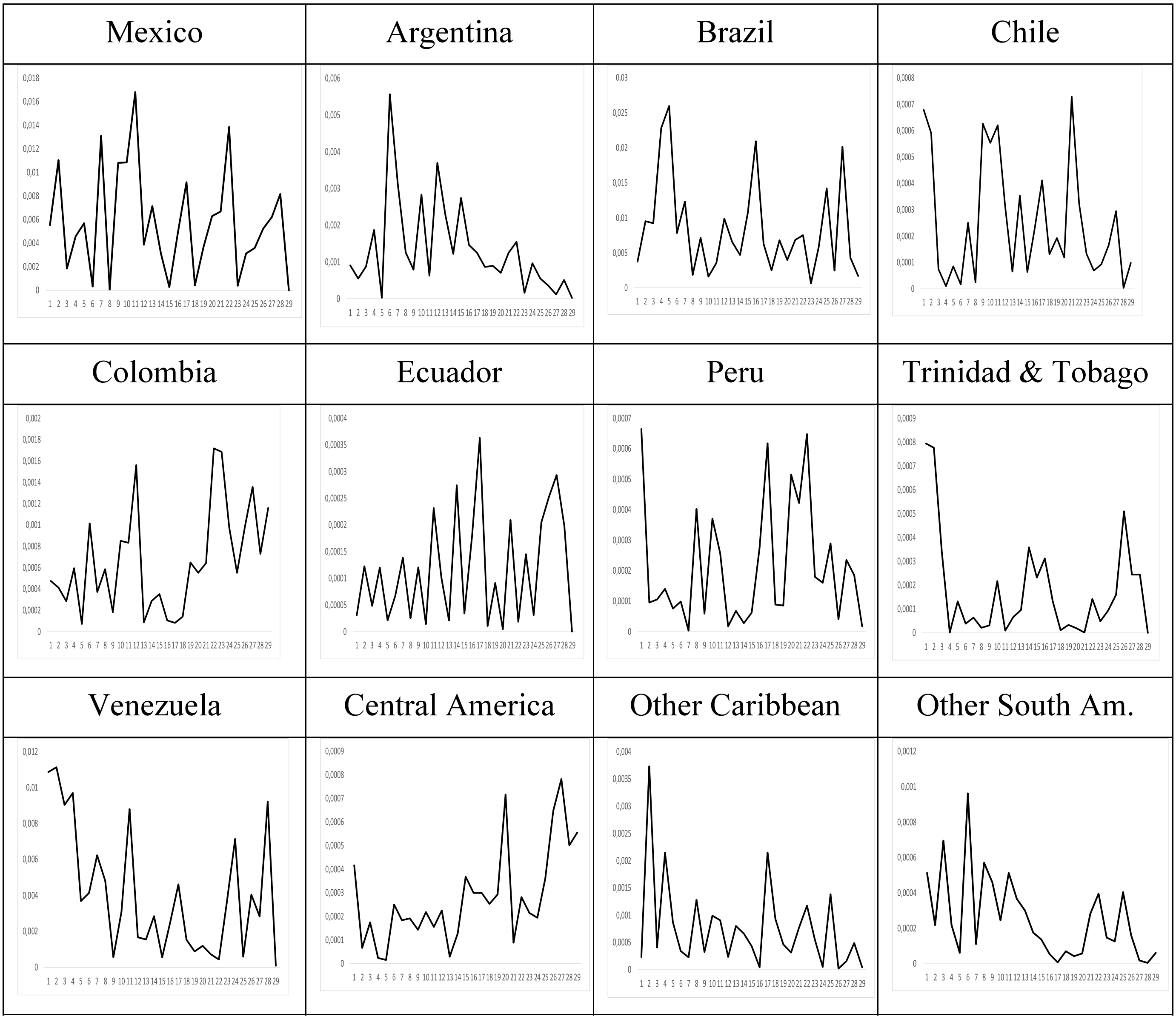

Fig. 8. Periodograms of the first differenced data. Primary energy consumption
Note: The periodograms were computed on the discrete frequencies $\lambda_j = 2\pi j/T$, for j = 1, 2, …, T/2.

linear deterministic trends. Thus, what we did instead was to consider the Chebyshev polynomials in time in replacement of the linear time trend in the first equality in Eq. (2). These polynomials are expressed as:

$$y(t) = \sum_{i=0}^{m} \theta_i P_i(t) + x(t), t = 1, 2, \ldots . \tag{3}$$

where m indicates the number of Chebyshev coefficients, and $P_{i,T}(t)$ refers to the polynomials in time defined as:

$$P_{0,T}(t) = 1,$$

$$P_{i,T}(t) = \sqrt{2} \cos (i\,\pi\,(t - 0.5)\ /\ T), t = 1, 2, \ldots, T; \quad i = 1, 2, \ldots. \tag{4}$$

In this context, if $m = 0$ the model includes only an intercept, and positive integer values of m permit the presence of nonlinearities – the higher m is, the more nonlinear the approximated deterministic component becomes. This model is fully described in Hamming [86], Smyth [87] and Tomasevic et al. [88], proposing it to approximate highly non-linear trends with polynomials of a relatively low order.

Tables 8 and 9 display the estimates of d and the θ-coefficients in the model given by:

$$y(t) = \sum_{i=0}^{m} \theta_i P_i(t) + x(t), t = 1, 2, \ldots$$

$$(1 - L)^d x(t) = u(t), t = 1, 2, \ldots \tag{5}$$

with m = 3, respectively for the total primary energy consumption and the per capita values. Here, we use an extension of Robinson [21] approach developed in Cuestas and Gil-Alana [89] for this specific non-linear model.

Starting with the results in Table 8 we first observe that mean reversion takes place in the cases of Colombia and Ecuador (with an estimated value of d equal to 0.66) along with Central America (0.58) and Peru (0.38). That is, there is one extra country (Peru), compared with the linear model, for which shocks have a transitory effect. For the rest of the countries, the unit root null cannot be rejected. Focusing on the non-linear structure, we notice that the four countries displaying

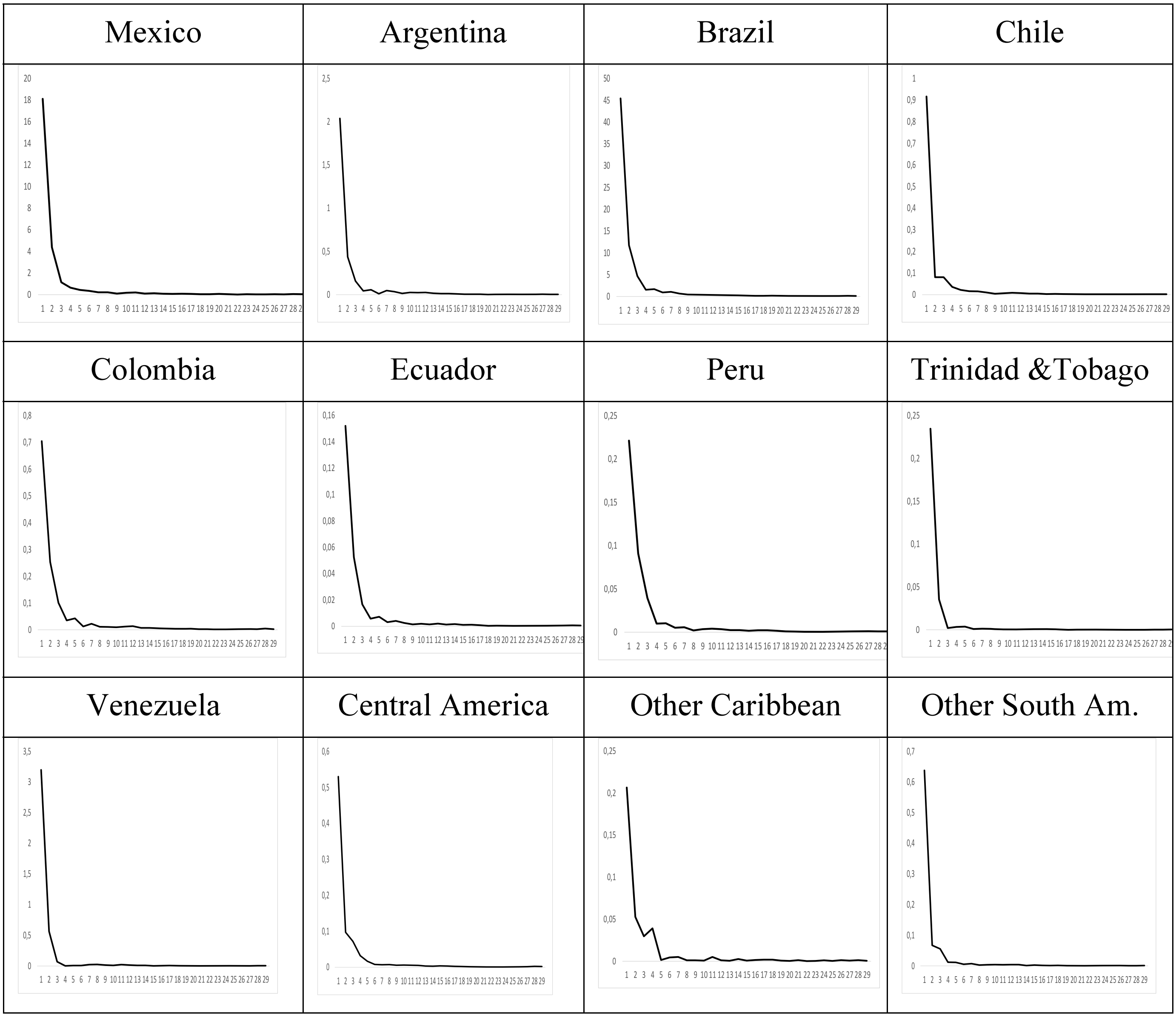

Fig. 9. Periodograms of the original data. Primary per capita energy consumption
Note: The periodograms were computed on the discrete frequencies $\lambda_j = 2\pi j/T$, for $j = 1, 2, \ldots, T/2$.

mean reversion are the four where all the Chebyshev coefficients are statistically significantly different from zero; Venezuela and Other Caribbean are the only two with no evidence of non-linearities, and mixed evidence is found in the rest of the cases.

Looking finally at the per capita values, in Table 9, the results are fairly similar, with Colombia, Ecuador, Peru and Central America showing evidence of mean reversion (i.e., $d < 1$) and with these countries also displaying the highest level of non-linearities, while Other Caribbean and Other South American countries are the two series with no evidence of non-linear structures.

6. Concluding comments

This research used data from the Statistical Review of World Energy by the Energy Institute [10], considering primary energy consumption data for Latin American countries in exajoules (EJ), as well as per capita primary consumption expressed in gigajoules (GJ). Both time series span the period from 1965 to 2023.

The descriptive results of the variables indicate that Brazil (7.1 EJ) and Mexico (5.1 EJ) are the largest consumers of primary energy in Latin America, with Mexico showing a broad range (1.0–13.9 EJ). These countries also have higher standard deviations, reflecting their demographic size, industrialized economies, and the weight of their industries. On the other hand, countries with lower average consumption include Ecuador (0.4 EJ), Trinidad and Tobago (0.4 EJ), and Central America (0.7 EJ), with low total consumption due to their smaller size and populations, despite being energy producers.

Countries with lower variability in consumption, such as Argentina (0.8 EJ), Chile (0.5 EJ), Colombia (0.5 EJ), Ecuador (0.2 EJ), Peru (0.3 EJ), and the Caribbean (0.3 EJ), show more consistent and stable patterns over time.

In terms of per capita consumption, Trinidad and Tobago stands out with an exceptionally high consumption of 310.2 GJ/person, attributable to its energy industry and small population. This reflects intensive energy use, primarily due to hydrocarbon exports. Venezuela also stands out with 101.7 GJ/person, reflecting its abundant energy resources. In relation to variability, Trinidad and Tobago leads with the highest standard deviation (157.5 GJ/person), indicating highly fluctuating

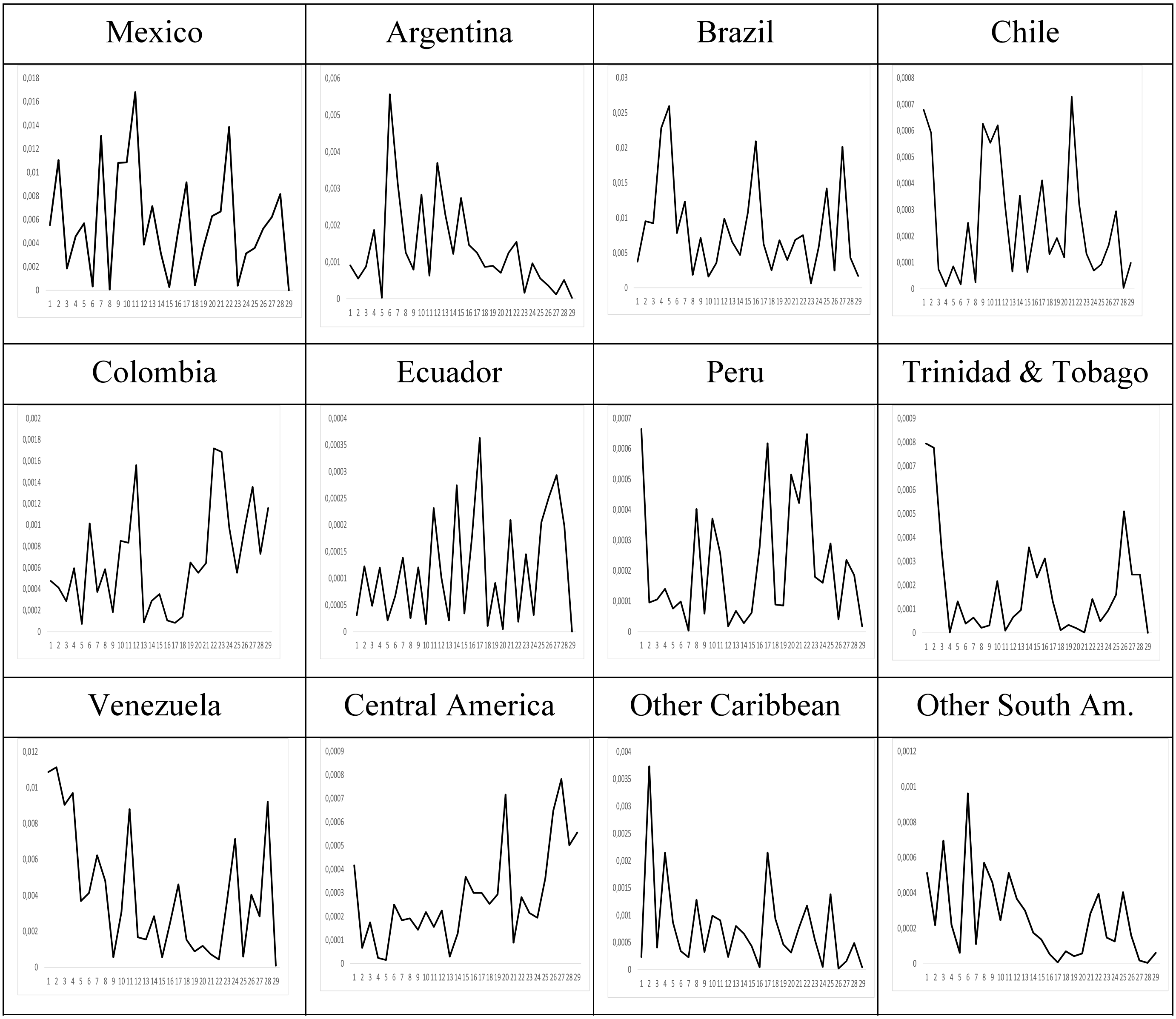

Fig. 10. Periodograms of the first differenced data. Primary per capita energy consumption
Note: The periodograms were computed on the discrete frequencies $\lambda_j = 2\pi j/T$, for j = 1, 2, …, T/2.

consumption at different periods. Chile follows with a significant deviation (23.4 GJ/person), likely due to its energy diversification. Central America has the lowest average per capita consumption (18.6 GJ/person), followed by Peru (23.1 GJ/person). Mexico (53.9 GJ/person) and Argentina (66.1 GJ/person) show intermediate consumption, characterized by stability and consistency as emerging economies.

The comparison between total consumption and per capita consumption highlights energy inequalities in the region. While Brazil and Mexico lead in total consumption, smaller countries such as Trinidad and Tobago and Venezuela show significantly higher per capita consumption, highlighting the uneven distribution of energy in Latin America.

Regarding the methodology applied in the research, the fractionally integrated models showed that primary energy consumption exhibits mean reversion patterns in three cases: Ecuador, Colombia, and Central America. This indicates that, after increases or decreases in energy consumption, the series tend to stabilize in the long term. However, in Colombia, this process is slower, likely due to structural characteristics of the energy market. On the other hand, most countries and subregions such as Venezuela, Trinidad and Tobago, and other Caribbean islands exhibit non-stationary behavior, reflecting permanent effects and persistent growth in energy consumption, possibly linked to structural changes or sustained demand.

As for linear trends, most countries require a trend component to capture long-term growth. The most pronounced trends are found in Mexico and Brazil, suggesting sustained energy consumption growth primarily driven by industrialization and urbanization. Regarding per capita energy consumption, mean reversion patterns were identified in Central America and Colombia, reflecting a quicker adjustment in average levels after a disturbance. However, for Colombia, this adjustment is slightly slower due to structural characteristics of the energy market. In most countries, values of $d \geq 1$ indicate a persistent pattern in per capita consumption, where shocks have lasting effects.

A notable case is Trinidad and Tobago, with an estimate of $d = 1.20$, significantly higher than the others, suggesting non-stationary growth related to its energy-dependent economy and role as a regional natural gas producer.

Overall, countries with mean reversion in total consumption, such as

Table 4
Estimates of the differencing parameter. primary energy consumption in Latin America.

Country	No terms	With intercept	A linear time trend
ARGENTINA	0.93 (0.72, 1.21)	1.01 (0.83, 1.45)	**1.01 (0.76, 1.45)**
BRAZIL	1.03 (0.86, 1.35)	1.03 (0.89, 1.34)	**1.04 (0.83, 1.32)**
CENTRAL AMERICA	0.88 (0.81, 1.00)	0.89 (0.83, 0.99)	**0.84 (0.74, 0.98)**
CHILE	1.00 (0.88, 1.19)	1.05 (0.95, 1.23)	**1.06 (0.93, 1.27)**
COLOMBIA	0.92 (0.79, 1.13)	0.84 (0.75, 0.99)	**0.80 (0.67, 0.99)**
ECUADOR	0.85 (0.76, 0.99)	0.85 (0.76, 0.98)	**0.78 (0.63, 0.98)**
MEXICO	0.92 (0.71, 1.29)	0.98 (0.84, 1.27)	**0.98 (0.81, 1.23)**
OTHER CARIBBEAN	1.08 (0.89, 1.35)	**1.15 (0.95, 1.42)**	1.14 (0.96, 1.40)
OTHER SOUTH AM.	1.23 (0.97, 1.62)	1.21 (1.00, 1.59)	**1.21 (1.00, 1.56)**
PERU	1.00 (0.90, 1.18)	0.98 (0.89, 1.11)	**0.98 (0.87, 1.13)**
TRINIDAD &TOBAGO	1.12 (0.99, 1.30)	**1.19 (1.07, 1.35)**	1.19 (1.07, 1.35)
VENEZUELA	1.21 (1.02, 1.46)	**1.22 (1.06, 1.46)**	1.22 (1.06, 1.45)

Note: We report estimates of d along with 95 % confidence intervals. In bold, the selected specification in relation with the deterministic terms.

Table 5
Estimated coefficients on the selected models in Table 4.

Country	No terms	With intercept	A linear time trend
ARGENTINA	1.01 (0.76, 1.45)	1.137 (12.36)	0.042 (3.45)
BRAZIL	1.04 (0.83, 1.32)	0.777 (3.41)	0.221 (6.45)
CENTRAL AMERICA	0.84 (0.74, 0.98)[a]	0.124 (3.11)	0.023 (7.92)
CHILE	1.06 (0.93, 1.27)	0.235 (5.97)	0.026 (4.13)
COLOMBIA	0.80 (0.67, 0.99)[a]	0.310 (5.12)	0.031 (8.02)
ECUADOR	0.78 (0.63, 0.98)[a]	0.005 (2.22)	0.013 (8.73)
MEXICO	0.98 (0.81, 1.23)	0.930 (4.89)	0.127 (5.55)
OTHER CARIBBEAN	1.15 (0.95, 1.42)	0.778 (11.60)	–
OTHER SOUTH AM.	1.21 (1.00, 1.56)	0.134 (3.53)	0.019 (1.81)
PERU	0.98 (0.87, 1.13)	0.182 (4.96)	0.017 (4.02)
TRINIDAD &TOBAGO	1.19 (1.07, 1.35)	0.116 (3.73)	–
VENEZUELA	1.22 (1.06, 1.46)	0.677 (4.55)	–

Note:
[a] Evidence of mean reversion at the 95 % level.

Table 6
Estimates of the differencing parameter. Per capita data.

Country	No terms	With intercept	A linear time trend
ARGENTINA	0.94 (0.76, 1.19)	0.95 (0.74, 1.36)	**0.94 (0.68, 1.36)**
BRAZIL	1.08 (0.85, 1.35)	1.17 (0.89, 1.44)	**1.13 (0.94, 1.39)**
CENTRAL AMERICA	0.78 (0.71, 0.89)	0.79 (0.72, 0.88)	**0.69 (0.56, 0.84)**
CHILE	0.97 (0.80, 1.22)	1.10 (0.96, 1.33)	**1.11 (0.96, 1.34)**
COLOMBIA	0.99 (0.81, 1.22)	0.70 (0.57, 0.93)	**0.71 (0.53, 0.95)**
ECUADOR	0.76 (0.60, 0.09)	0.79 (0.68, 1.03)	**0.78 (0.62, 1.03)**
MEXICO	1.00 (0.80, 1.26)	1.10 (0.94, 1.34)	**1.09 (0.95, 1.31)**
OTHER CARIBBEAN	1.03 (0.86, 1.27)	**1.12 (0.94, 1.39)**	1.12 (0.94, 1.38)
OTHER SOUTH AM.	1.19 (0.94, 1.52)	**1.30 (1.09, 1.64)**	1.29 (1.09, 1.63)
PERU	1.04 (0.88, 1.29)	0.98 (0.86, 1.18)	**0.99 (0.85, 1.19)**
TRINIDAD &TOBAGO	1.09 (0.95, 1.28)	**1.20 (1.08, 1.37)**	1.20 (1.08, 1.37)
VENEZUELA	1.01 (0.83, 1.27)	**1.10 (0.95, 1.32)**	1.09 (0.95, 1.31)

Note: We report estimates of d along with 95 % confidence intervals. In bold, the selected specification in relation with the deterministic terms.

Table 7
Estimated coefficients on the selected models in Table 6.

Country	No terms	With intercept	A linear time trend
ARGENTINA	0.94 (0.68, 1.36)	53.152 (22.51)	0.459 (1.85)
BRAZIL	1.13 (0.94, 1.39)	10.776 (8.47)	0.917 (3.41)
CENTRAL AMERICA	0.69 (0.56, 0.84)[a]	0.044 (1.85)	0.023 (9.54)
CHILE	1.11 (0.96, 1.34)	28.006 (12.10)	1.064 (2.34)
COLOMBIA	0.71 (0.53, 0.95)[a]	19.267 (14.06)	0.378 (5.51)
ECUADOR	0.78 (0.62, 1.03)	5.003 (2.95)	0.695 (6.68)
MEXICO	1.09 (0.95, 1.31)	23.954 (12.81)	0.711 (2.09)
OTHER CARIBBEAN	1.12 (0.94, 1.39)	35.213 (17.81)	–
OTHER SOUTH AM.	1.30 (1.09, 1.64)	14.593 (7.82)	–
PERU	0.99 (0.85, 1.19)	16.488 (11.74)	0.329 (1.87)
TRINIDAD &TOBAGO	1.20 (1.08, 1.37)	127.95 (5.55)	–
VENEZUELA	1.10 (0.95, 1.32)	71.095 (12.71)	–

Note:
[a] Evidence of mean reversion at the 95 % level.

Ecuador and Central America, probably benefit from effective energy policies or stable consumption patterns. For non-stationary cases, long-term planning is crucial to manage persistent growth in energy demand. Economic development, urbanization, and industrialization are key factors in the observed increases, particularly in countries such as Mexico, Brazil, Argentina, and Chile, which lead in modernization and energy infrastructure.

While there is an abundant body of literature analyzing the relationship between economic growth and energy consumption in Latin America, much of it agrees that sectors such as mining, industry, and transportation have been key drivers in the increase of energy demand in the region, which in turn has contributed to a rise in CO_2 emissions [5,90,91]. Although this economic development has been tangible, its effects have been heterogeneous, with varying levels of progress and unequal patterns of energy consumption across Latin American countries.

This relationship presents a complex dilemma: on the one hand, energy is essential to sustain economic growth; but on the other, an unregulated increase in energy consumption can exacerbate the effects of climate change and worsen environmental crises. Moreover, access to energy remains unequal within countries: while urban areas generally enjoy broader coverage, many rural communities face energy poverty, which limits their development and quality of life.

These inequalities are partly determined by economic structures, the availability of natural resources, institutional capacity, and access to energy technologies. Considering the contributions of Chavarry Galvez & Revinova [92]; Georgescu et al. [93]; Hernández Téllez [94]; Li et al. [95]; Stringer & Ramírez-Melgarejo [96]; and Valencia-Herrera et al. [97], which contextualize the diversity and limitations of energy realities in Latin American countries, the need to design differentiated policies tailored to each specific context becomes evident. A one-size-fits-all energy policy would not only be inefficient but also potentially unjust, as it would ignore the different starting points and needs of the countries in the region. While some must focus on advancing the decarbonization of their economies, others still face the urgent challenge of guaranteeing basic energy access.

Acknowledging this diversity requires positioning energy policy from a long-term perspective, avoiding the reproduction of extractivist

Table 8
Non-linear trend model with I(d) errors. Estimated coefficients.

Country	d (95 % c.i.)	θ_1 (t-value)	θ_2 (t-value)	θ_3 (t-value)	θ_4 (t-value)
Mexico	0.83 (0.58, 1.20)	**4.936 (11.37)**	**−2.395 (-9.75)**	−0.188 (−1.27)	−0.145 (−1.36)
Argentina	0.92 (0.49, 1.45)	**2.228 (9.73)**	**−0.795 (-4.79)**	0.098 (1.08)	−0.039 (−0.63)
Brazil	1.04 (0.73, 1.36)	**6.665 (6.12)**	**−3.859 (-5.95)**	0.208 (0.67)	**−0.368 (-1.81)**
Chile	0.91 (0.68, 1.20)	**0.847 (7.26)**	**−0.514 (-7.66)**	**0.080 (2.16)**	0.020 (0.79)
Colombia	0.66 (0.42, 0.97)[a]	**1.126 (13.85)**	**−0.519 (-11.34)**	**0.081 (2.50)**	**−0.098 (-3.07)**
Ecuador	0.66 (0.46, 0.95)[a]	**0.366 (10.63)**	**−0.233 (-12.02)**	**0.028 (2.02)**	**−0.035 (-3.32)**
Peru	0.38 (0.11, 0.76)[a]	**0.565 (35.89)**	**−0.272 (-26.47)**	**0.102 (11.66)**	**−0.072 (-9.46)**
Trinidad & T	1.06 (0.93, 1.24)	**0.330 (2.13)**	**−0.233 (-2.52)**	0.042 (0.98)	0.041 (1.48)
Venezuela	1.14 (0.93, 1.42)	**2.046 (2.06)**	−0.817 (−1.34)	−0.271 (−1.04)	0.129 (0.79)
Central Am.	0.58 (0.38, 0.83)[a]	**0.676 (17.69)**	**−0.414 (-18.87)**	**0.091 (5.48)**	**−0.036 (-2.73)**
Other Caribbean	1.13 (0.94, 1.42)	**1.089 (2.51)**	−0.191 (−0.72)	−0.064 (−0.56)	0.037 (0.52)
Other South American	1.12 (0.77, 1.55)	**0.676 (2.87)**	**−0.404 (-2.82)**	0.0001 (0.03)	0.031 (0.78)

Note: The values in column 2 are the estimates of d (with their 95 % confidence intervals in brackets). The other columns report the estimates of the Chebyshev polynomials with their associated t-values in brackets. In bold, the estimated coefficients from the selected model specification.
[a] Evidence of mean reversion at the 95 % level.

models that predominated during the 20th century. This calls for rethinking economic growth in light of the planet's ecological limits, strengthening state planning, diversifying economies, and promoting a culture of energy efficiency and environmental respect.

In terms of public policy—aligned with the publication by Barragán-Ocaña et al. [98]—this means formulating strategies that respond to concrete national realities. From this heterogeneous perspective on economic and energy development, energy-related decisions must not only ensure supply and promote growth, but also guarantee social inclusion and environmental sustainability. This implies, for example, encouraging the rational use of energy and promoting regional cooperation mechanisms that facilitate the exchange of best practices, institutional capacities, and technical resources.

Considering that, as mentioned above, the Latin American region has heterogeneous energy consumption standstills, we can mention the specific cases of Brazil and Mexico [99], since the series clearly reflects long-term patterns with large and consolidated economic structures. This can provide a basis for planning strategies for gradual transition to cleaner energy sources. Continuing to plan for the reduction of energy inequalities in its vast territories.

Chile has made impressive progress in renewable energy and shows consistent energy performance. This makes it a leading country in the region's energy transition [100]. Colombia and Peru share relatively stable consumption patterns, which can be translated into an opportunity to move towards strengthening energy infrastructure, especially in rural areas, and supporting critical sectors such as mining and transportation with cleaner and more efficient energy sources. In the case of Ecuador, which has a significant component of subsidies on energy consumption, it will be key to avoid dependence and focus on inclusive and sustainable solutions [101].

The situation of Venezuela, on the other hand, is fairly unique. The instability of its energy system is evident in the data, implying the need for a complete restructuring of the infrastructure, the rebuilding of institutional capacity and the importance of establishing a more efficient and sustainable energy system [102].

On the other hand, in the case of Argentina [103,104], with its more variable energy behavior, flexibility is required. The country can rely on its natural gas resources in the short term while moving toward a more diversified and resilient energy matrix.

In Central America and the Caribbean, where many countries operate with fewer resources and smaller systems, the key lies in regional cooperation. Sharing knowledge, technologies, and strategies could make a huge difference. For these nations, bringing electricity to rural areas, installing solar panels, or strengthening local grids is not just a technical issue; it is about reducing inequality and improving quality of life [105].

The analysis of energy and climate dynamics highlights the urgency of moving towards sustainable models that integrate renewable energy and reduce dependence on fossil fuels.

The fractional integration model offers advantages in studying energy consumption and its impact on GHG emissions, as it captures long-term dependencies, persistent effects, and permanent effects. This allows for the identification of short- and long-term patterns, facilitating the design of more effective mitigation strategies. Additionally, the analysis can highlight unsustainable consumption and production practices, emphasizing the need to transform the region's economies

Table 9
Non-linear trend model with I(d) errors. Estimated coefficients. Per capita data.

Country	d (95 % c.i.)	θ_1 (t-value)	θ_2 (t-value)	θ_3 (t-value)	θ_4 (t-value)
Mexico	0.93 (0.72, 1.23)	**51.841 (8.77)**	**−12.615 (-3.69)**	**−4.953 (-2.67)**	−1.597 (−1.25)
Argentina	0.88 (0.54, 1.35)	**63.881 (9.85)**	**−8.966 (-2.42)**	1.721 (0.81)	0.1392 (0.09)
Brazil	1.15 (0.94, 1.42)	**35.810 (4.07)**	**−13.839 (-2.56)**	−1.128 (−0.49)	−2.204 (−1.54)
Chile	0.85 (0.60, 1.18)	**54.829 (10.01)**	**−23.325 (-7.50)**	2.069 (1.12)	**3.311 (2.52)**
Colombia	0.57 (0.30, 0.90)[a]	**29.966 (21.25)**	**−5.733 (-7.04)**	0.612 (0.98)	**−1.774 (-3.53)**
Ecuador	0.62 (0.39, 0.95)[a]	**27.317 (13.86)**	**−11.639 (-10.40)**	**−1.605 (-1.95)**	**−2.092 (-3.21)**
Peru	0.51 (0.22, 0.94)[a]	**22.647 (22.49)**	**−4.418 (-7.39)**	**3.281 (6.92)**	**−1.915 (-4.86)**
Trinidad & T	1.08 (0.94, 1.27)	**240.167 (1.95)**	**−142.702 (-1.92)**	27.689 (0.81)	36.385 (1.61)
Venezuela	1.00 (0.80, 1.27)	**98.853 (4.33)**	−9.000 (−0.67)	**−12.409 (-1.85)**	1.841 (0.41)
Central Am.	0.39 (0.18, 0.66)[a]	**0.629 (23.02)**	**−0.410 (-23.23)**	**0.088 (5.90)**	**−0.037 (-2.87)**
Other Caribbean	1.10 (0.92, 1.37)	**33.184 (2.88)**	1.440 (0.20)	−1.025 (−0.33)	1.021 (0.51)
Other South American	1.19 (0.88, 1.59)	**35.516 (2.38)**	−14.372 (−1.55)	−2.882 (−0.77)	2.551 (1.10)

Note: The values in column 2 are the estimates of d (with their 95 % confidence intervals in brackets). The other columns report the estimates of the Chebyshev polynomials with their associated t-values in brackets. In bold, the estimated coefficients from the selected model specification.
[a] Evidence of mean reversion at the 95 % level.

towards increasingly resilient, low-carbon, and sustainable models which has also been discussed in recent work of Stern and Stiglitz [106], Zhao & Liu [107] Petrović [108], Greiner et al. (2024) and Vásquez Coronado et al. [109], especially in a region such as Latin America, which is highly vulnerable to extreme weather events such as hurricanes, droughts and floods.

Among the limitations of the present work we could mention the specific deterministic structure and based on the Chebyshev polynomial imposed for the non-linear structure. Other alternatives still in the context of fractional integration include the use of Fourier functions in time (Gil-Alana and Yaya, 2021) or neural networks (Furuoka et al., 2024). Stochastic non-linear models based on long memory processes are being investigated at present. The incorporation of energy policy projections, simulations and scenarios is an essential element in making studies more practical and accessible to decision makers. However, this study has focused on detailing and examining long-term structural patterns of energy use in Latin America in order to develop a comparative regional diagnostic framework. Understanding the importance of these forecasting tools, the inclusion of forecasting and scenario simulation models is proposed as a future project. These will facilitate the exploration of possible pathways under various energy policy configurations, thus providing more concrete resources for governments and regional entities that aspire to progress in energy transition, emissions reduction and planning.

Credit author statement

LAGA was in charge of the computer programming, the empirical results and the interpretation of them. LRA proposed the original idea; he wrote the introduction and literature review along with the conclusions. BL contributed with the dataset, the literature review and conclusions.

Declaration of competing interest

There are no competing interests with the publication of the present manuscript.

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Data availability

Data will be made available on request.

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