# Mean Reversion and Convergence of Ecological Footprint in the MENA Region: Evidence from a Fractional Integration Procedure

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# Abstract

This paper deals with the analysis of mean reversion and convergence of the ecological footprint (EF) in the MENA region. Using a long memory model based on fractional integration, we find that the results are very heterogeneous across countries depending on the assumptions made on the error term and the use of original versus logged data. Nevertheless, some conclusions can be obtained. Thus, mean reversion is decisively found in the case of Tunisia, and other countries showing some degree of reversion to the mean include Israel, Syria, Yemen, and Iran. Dealing with the issue of convergence within the MENA countries, similar conclusions hold and only Tunisia reports statistical evidence of convergence for the two types of errors. Additional evidence is found in the case of Syria, Yemen, and Jordania with uncorrelated errors and for Iran with autocorrelation. It is recommended that environmental policies targeted at stabilizing the trends in EF in the MENA region should not be indiscriminately applied in consideration of the heterogeneous nature of the series in the region

# 1. Introduction

One of the most difficult tasks facing the modern world is the quest to ensure the attainment of the 2030 Agenda for Sustainable Development (ASD) as envisioned by the United Nations[1]. At the heart of the 17 Sustainable Development Goals (SDGs) are three environmentally related goals including combating climate change (goal 13), conserving and sustaining life below water (goal 14), and protecting, restoring, and promoting life on land (goal 15). Thus, issues relating to the environment are critical to the attainment of the SDGs. If the SDGs are to be met, proper management and understanding of trends in the environment are vital. One environmental indicator that should be well understood is the Ecological Footprint (hereinafter referred to as EF) as it gives the most environmental consideration to the dynamics of sustainable development, and it has been largely adopted due to its lucidity (Moffatt, 2000). EF can unambiguously discern how waste behaviors and consumption patterns affect the environmental quality (Wiedmann & Barrett, 2010). The importance of EF as a measure of SD has also been acknowledged by Kates et al. (2001), Robert et al. (2005), and Moran et al. (2008) among many others.

EF refers to the surface areas (such as land and sea areas) that are biologically productive which are required for a particular nation to generate its resources and absorb the resultant waste from the consumption of such resources using the available technology (Wackernagel & Silverstein, 2000). It is essentially a metric that gauges what is available from nature and what we consume from nature. EF bothers with the demands of human endeavors such as consumption of resources and production of goods and services on the planet’s regenerative biological capacity (Kitzes & Wackernagel, 2009). An important aspect of the methodology of EF is that it envelopes a wide range of indices on the environment into a sole and comprehensive index (Costanza, 2000). Organizations such as European Energy Agency (EEA), European Union (EU), European Commission (EC), and United Nations (UN) have also incorporated it as an indicator of evaluating SD as it serves as a yardstick for designing environmental goals and selecting the appropriate action(s) to achieve the stated objectives (Borucke et al., 2013). The EF is a crucial environmental aggregate index because it aids governments, community leaders, and people in understanding and improving health, getting the most out of investments in public projects, and comprehending their global impacts (Global Footprint Network, 2021). It may be used as a probable mechanism to appraise planetary limits and the extent to which humans are putting pressure on them. It determines the rate at which ecological services are being used relative to the rate the earth can replenish.

There are profound variations in the trends and levels of EF across the different regions of the world, indicating heterogeneity in the structure of natural endowment as well as the level of environmental management. Tracking the trends and trajectory of EF across regions requires the understanding of its stochastic behavior by studying its mean reversion and convergence characteristics. The knowledge of mean reversion and convergence in EF can serve as guides on ways of setting reasonable ecological constraints, whereby the demands of human endeavors, such as consumption of resources and production of services and goods are met, in a way that guarantees the protection of the natural environment not only in the present but in the indefinite future. This becomes more imperative as the continuous rise in Greenhouse Gasses (GHGs) emissions has led to increased global warming and the global consensus is that dramatic and decisive actions must be taken to reverse the trend and avoid an impending ecological disaster [Intergovernmental Panel on Climate Change (IPCC) (2014); Lu and Stern (2016)]. This has been underscored by several climate treaties and international protocols of the United Nations Framework Convention Climate Change (UNFCCC), including the Kyoto Protocol[2], Montreal Protocol[3] as well as the Paris Agreement[4] aiming to minimise the depletion of the ozone layer beyond the level that could prove catastrophe for the survival of the human existence.

Understanding the mean reversion properties of EF is essential as it provides intuition about the characteristics of EF in the foreseeable future based on the available past trends. More precisely, the knowledge of the mean reversion of EF gives an insight into its stochastic behavior in determining if the impacts of shocks to it are transient or persistent (Ulucak and Lin, 2017). According to Hasanov and Telatar (2011), understanding the stochastic behavior of a series can facilitate the ability to forecast its future values especially if the series is found to be stationary. This has important implications for the formulations of policies relating to tackling climate change, global warming, and other environmental issues. In the same vein, understanding the pattern of convergence in EF is germane as it has implications for how policies are adopted and implemented not only towards combating climate change and global warming but also at eradicating environmental deterioration in energy, agriculture, industries, cities, buildings, forests, and fishing grounds (Erdogan & Okumus, 2021). The existence of convergence in pollutants is essential for designers of environmental policies in both advanced and emerging economies to initiate appropriate environmental policies.

Convergence of pollution indicators, especially EF, can have an impact on international climate accords. When there is no convergence of pollutants, for example, the distribution of emissions licenses may result in a significant migration of pollution-intensive companies (Payne, 2010). Pollutant convergence is a key element of many climate agendas such as the Intergovernmental Panel on Climate Change (IPCC) report of 2000. If pollutants are not predicted to be converging in the future, environmental designs that are egalitarian in dimension will not be successful. This is because countries with relatively low levels of emissions will be more likely to support egalitarian agreements since these sorts of agreements would suggest that countries with higher levels of pollution would share much of the pollution mitigation burden (Churchill et al., 2018). Furthermore, knowing the non-stationary property of relative pollution is critical for conducting cointegration analysis as well as generating reliable long-run estimates of the relative pollution series (Solarin, Tiwari, et al., 2019).

Due to its crucial importance, analyzing the mean reversion [Ulucak and Lin (2017); Solarin and Bello (2018); Yilanci et al. (2019)] and the convergence [Ulucak and Apergis (2018); Solarin, Tiwari, et al. (2019); Ulucak et al. (2020); Erdogan and Okumus (2021)] of EF is beginning to attract the interest of researchers in recent times. Our aim is to contribute to this growing list of research in at least three ways. First, we combined mean reversion and convergence analysis in a single study in order to provoke a more robust policy inference. Second, we applied the fractional integration technique which relies on integer degrees of differentiation, allowing for fractional values, thus proving to be superior over the traditional methods that relies on strict dichotomisation between I(0) and I(1). The method thus provides information about the nature of shocks to a series with greater degree of flexibility that suits our purposes of mean reversion and convergence. Third, and equally important, we have focused on the MENA region, which has attracted less attention on studies on analyzing the patterns and trajectory of its environmental indicators.

The importance of focusing on the MENA region is two-fold. First, the region is one of the most strategic regions in the world as it accounts for 60% of the global oil reserves, and 45% of the global natural gas reserves. These substantial energy resource reserves have implications for the global environment via the energy-environment nexus. Secondly, the region is one of the most susceptible regions to climate change around the globe, with rising temperature, water shortages, and more severe weather scenarios on the horizon,, all of which will have critical implications for water and food security in the region (Sieghart et al., 2018). Countries in the MENA have a combined biocapacity deficit[5] of 15000% including Israel (2,450%), Bahrain (1,690%), United Arab Emirates (1,570%), Kuwait (1,570%), Qatar (1,420%), Saudi Arabia (1,290%), Lebanon (1,200%), and Jordan (1,100%). Others with less than a thousand percent biocapacity deficit are Iraq (874%), Libya (436%), Oman (400%), Algeria (360%), Egypt (341%), Iran (333%), Djibouti (241%), Tunisia (218%), Syria (161%), Morocco (141%), and Yemen (63%) (Global Footprint Network, 2021). To put this in perspective, if everyone lived like the residents of these countries, humanity would need 169.6 earths which average 9.4 earths to survive (Earth Overshoot Day, 2021). Thus, it is important to study the mean reversion and convergence patterns of EF in these countries in order to infer appropriate environmental policy prescriptions.

The following is how the remainder of this paper has been structured. What follows in the next section is a review of the existing empirical studies on the mean reversion and convergence of environmental indicators. This is then followed by the section on the methodology, which covers the data and method. In Section 4, we discuss the empirical exercise and conclude in Section 5 with policy implications and recommendations.

[1]https://news.un.org/en/story/2016/01/521002-interview-worlds-most-difficult-task-ensuring-un-sustainable-development-agenda

[2] https://unfccc.int/kyoto_protocol

[3] https://www.unep.org/ozonaction/who-we-are/about-montreal-protocol

[4] https://unfccc.int/process-and-meetings/the-paris-agreement/the-paris-agreement

[5] An ecological deficit occurs when the Ecological Footprint of a population exceeds the biocapacity of the area available to that population

# 2. Literature Review

Modeling the stochastic characteristics of environmental series has a rich history. The origin of convergence can be conveniently traced to the novel research of Solow (1956) on long-run economic growth. Solow (1956) showed that the path to a long-run steady-state equilibrium of economic growth is determined by the variation in savings and investment rates across countries such that if countries with an initial low level of development save and invest more, their capital accumulation would increase relative to the more developed countries which would eventually lead to economic convergence of countries' national income and the eventual disappearance gaps in the per capita income across countries. The concept of convergence has since become popular and applied to different fields of human endeavors including energy [Akram et al. (2020), Shi et al. (2020)]; health [Oyedele and Adebayo (2015), Odhiambo et al. (2015)] house prices [Montanés and Olmos (2013), Meng et al. (2015)], and commodity markets [Bukenya and Labys (2005), Sensoy et al. (2015)].

However, owing to the crucial importance of environmental quality to the actualization of the sustainable development agenda and the rising challenges of global warming and climate change, convergence analysis of environmental indices is increasingly becoming popular among researchers. Though, credit for the seminal paper on the convergence of environmental indices belongs to List (1999) who examined the convergence of emissions from sulfur dioxides and nitrogen oxides in the United States over the period 1929 to 1994, the work of Strazicich and List (2003), which is based on the stochastic and conditional convergence of $CO_2$ emissions in 21 industrial countries for the period 1960 to 1972 has become more notable for popularising the research on the convergence of environmental indices. Since then, a plethora of studies have been carried out on the convergence of environmental indicators, and while several indices including $S0_2$ [Hao et al. (2015), Solarin and Tiwari (2020)] and nitrogen oxide [Solarin, Yilanci, et al. (2021), He and Jiang (2021)], have been analyzed, $CO_2$ remains the frontline candidate [Rios and Gianmoena (2018), Presno et al. (2018), Churchill et al. (2018), Magazzino (2019), Ye et al. (2020), Churchill et al. (2020) Apergis and Payne (2020), Payne and Apergis (2021), Tiwari et al. (2021), Marrero et al. (2021)]. A survey of empirical studies on convergence has already been provided by Payne (2020).

With specific reference to studies on convergence of EF, three patterns can be observed including coverage, methodology, and the dichotomy between convergence and divergence evidence in the series. In terms of coverage, two distinct patterns include studies that have focused on a global sample of world economies and those that have concentrated on a specific region or economic block. Among the studies that focused on a global sample of the world's economies include Solarin, Tiwari, et al. (2019) who tested the convergence of per capita EF and its six components in 92 countries for the period 1961–2014; Bilgili et al. (2019) whose study on the convergence of EF cut across 4 continents including Asia, Africa, America, and Europe, and Sarkodie (2021) whose study includes a sample of 188 countries across the globe. Studies focusing on specific regions or economic block includes Ulucak and Apergis (2018) on the European Union countries, Yilanci and Pata (2020b) on five Association of South-East Asian Nations, Bilgili and Ulucak (2018) on G-20 countries, Solarin (2019) on 27 OECD countries, Ulucak et al. (2020) on sub-Saharan African countries, and Işık et al. (2021) on the countries that make up the North American Free Trade Agreement (NAFTA) including USA, Mexico, and Canada.

Across the studies, various methods of analysis have also emerged including club convergence analysis [Ulucak and Apergis (2018), Solarin, Tiwari, et al. (2019), and Tillaguango et al. (2021)], non-linear panel unit root test [Yilanci and Pata (2020b)], the log t regression [Ulucak et al. (2020)], bootstrap-based panel KPSS test [Bilgili et al. (2019), Bilgili and Ulucak (2018)], residual augmented least squares regression [Solarin (2019)], and a combination of both econometric and machine learning-based estimation methods [Sarkodie (2021)]. The results have also been varied between evidence of convergence and divergence. For instance, while authors including Bilgili and Ulucak (2018), Solarin, Tiwari, et al. (2019), Solarin (2019), Sarkodie (2021), and Yilanci and Pata (2020b), have provided evidence in support of the convergence hypothesis for EF, others such as Ulucak and Apergis (2018) and Ulucak et al. (2020), have provided evidence to negate the existence of convergence and conclude that EF diverges. Others have also reported mixed results of convergence and divergence in the same study including Işık et al. (2021) who showed mixed results of convergence and divergence between two regimes, Tillaguango et al. (2021) who reported three converging clubs and two diverging clubs among 16 Latin American countries, and Bilgili et al. (2019) who provided evidence to validate the existence of EF convergence for Europe, Africa, and America, while, in the case of Asia, EF is found to diverge.

In terms of the mean reversion of the EF, the pioneering work belongs to Ulucak and Lin (2017) who analyzed the persistence of policy shocks to EF in the United States. The study employed the Fourier unit root test to test for stationarity of EF and its six components and found evidence in support of the non-stationarity of the EF in the U.S. Other prominent studies in this strand of literature include Solarin and Bello (2018) who focused on 128 developed and developing countries, Yilanci et al. (2019) on 25 OECD countries, Caglar et al. (2021) on 5-European Union countries, Yilanci, Pata, et al. (2022) on the big ten emerging economies, and Yilanci, Ulucak, et al. (2022) focusing on the Mediterranean countries. Other authors have also focused on a component among the six components of the EF including carbon footprint (Solarin, Gil-Alana, et al., 2019) and fishing ground footprint (Solarin, Gil-Alana, et al., 2021), while others have focused on ecological balance, integrating both the demand and supply sides of the ecological account [(Pata & Yilanci, 2021; Yilanci & Pata, 2020a)]. The results have been mixed with some authors including Yilanci et al. (2019), Yilanci and Pata (2020a), Yilanci, Ulucak, et al. (2022), Pata and Yilanci (2021), and Yilanci, Pata, et al. (2022) establishing mean reversion for EF and or its components for the majority of the sampled countries, while others including Ulucak and Lin (2017), Solarin and Bello (2018), Solarin, Tiwari, et al. (2019), Caglar et al. (2021), and Solarin, Gil-Alana, et al. (2021) have found evidence to negate the existence of mean reversion in EF and or its components for the majority of the sampled countries.

The above x-ray of the literature reveals two important implications within the context of the current study. First, while other regions and economic blocks have been considered in the analysis of mean reversion and convergence of EF, the MENA region has been conspicuously ignored, this is despite the fact that the region significantly contributes to global EF. Second, while some authors have applied the fractional integration procedure to analyze the mean reversion of EF for other regions other than the MENA, none of the previous studies have employed the method for the convergence analysis of EF despite its advantages. This study, therefore, adds to the extant literature by applying the fractional integration method to examine the convergence in the MENA region.

## 3. Methodology

# 3.1 Data

This empirical exercise employs yearly data on EF measured in global hectares (gha) per person for 10 countries in the MENA region for the period 1961 to 2018[6]. The data has been scooped from the latest edition of data on the EF provided by the Global Footprint Network. Table 1shows the descriptive statistics of the series for each country in its original form. It is seen that the mean per capita EF ranges from 0.862 gha (Yemen) to 4.549 gha (Israel). Israel has the maximum value of EF per capita at 6.238 gha while Yemen and Algeria have the minimum values of 0.509 gha and 0.528 gha respectively. Algeria, Djibouti, Egypt, and Iran have positive skewness while Israel, Jordan, Lebanon, Syria, Tunisia, and Yemen are negatively skewed. In terms of distribution, with the exception of Djibouti and Iran, the rest of the countries do not follow a normal distribution as indicated by the Jarque-Bera statistics. In the end, all series were transformed into their natural logarithm forms before the commencement of formal empirical analysis.

Table 1
Descriptive statistics

| Country | Mean | Minimum | Maximum | Std. Dev. | Skewness | Jarque-Bera |
|---|---|---|---|---|---|---|
| Algeria | 1.425 | 0.528 | 2.513 | 0.538 | 0.216 | 1.620 (0.445) |
| Djibouti | 1.548 | 0.780 | 3.099 | 0.500 | 1.347 | 24.050*** (0.000) |
| Egypt | 1.386 | 0.801 | 1.963 | 0.370 | 0.003 | 3.345 (0.188) |
| Iran | 1.929 | 0.853 | 3.399 | 0.919 | 0.396 | 6.398** (0.041) |
| Israel | 4.549 | 2.408 | 6.238 | 0.970 | -0.243 | 1.960 (0.375) |
| Jordan | 1.597 | 0.798 | 2.288 | 0.390 | -0.388 | 2.493 (0.288) |
| Lebanon | 2.924 | 1.694 | 3.968 | 0.606 | -0.446 | 2.957 (0.228) |
| Syria | 1.541 | 0.790 | 2.231 | 0.355 | -0.341 | 2.322 (0.313) |
| Tunisia | 1.549 | 0.826 | 2.220 | 0.435 | -0.146 | 3.657 (0.161) |
| Yemen | 0.862 | 0.509 | 1.151 | 0.113 | -0.176 | 3.042 (0.218) |
| Parenthesized figures are probability values. *** implies a 1% level of significance; ** implies a 5% level of significance. | | | | | | |

Table 1 **ABOUT HERE**

# 3.2 Method/Model

The model under examination employs a fractional integration structure though at the same time allows for deterministic terms like a constant and a linear time trend. It is specified as follows:

$$y(t) = \alpha + \beta t + x(t); \qquad (1 - L)^d x(t) = u(t). \qquad (1)$$

where y(t) is the variable corresponding to the observed data; α and β are unknown parameters referring respectively to a constant and a linear time trend; x(t) are the residuals in the regression on time; L is the lag operator, i.e., Lx(t) = x(t-1); d is a real value, and thus including potentially fractional values; u(t) are the I(0) errors that will adopt the form of a white noise process first, and then, allowing for weak autocorrelation.

Note that the fact that x(t) is I(d) and that d can be any real value, allows for a greater degree of flexibility in the modelization of the data, from anti-persistence ($d < 0$) to short memory ($d = 0$), stationary long memory ( $0 < d < 0.5$), nonstationary though mean reverting processes ( $0.5 \leq d < 1$), unit roots ($d = 1$) an explosive patterns ($d > 1$). The estimation of the parameters in Eq. (1) is based on the Whittle function expressed in the frequency domain.

[6] The 10 countries included in the empirical analysis are Algeria, Djibouti, Egypt, Iran, Israel, Jordan, Lebanon, Syria, Tunisia, and Yemen. The remaining countries in the region that have been excluded on grounds of insufficient data are Bahrain, Iraq, Kuwait, Libya, Oman, Qatar, Saudi Arabia, and the United Arab Emirates.

# 4. Empirical Results And Discussion

This section is divided into three parts. The first deals with the issue of mean reversion of the individual series, the second part focuses on the convergence issue, and the last part discusses the overall results.

### 4a. Mean Reversion

The results displayed across Tables 2–5 are based on the assumption that u(t) in (1) is a white noise process, so the time dependence is then only captured by the differencing polynomial. In Tables 6–9u(t) is supposed to be autocorrelated by using a non-parametric approach due to Bloomfield (1973) and that approximates AR structures. Tables 1, 2, 6, and 7refer to the original data, while the remaining ones to the logged transformed data.

We start presenting the results under the assumption of white noise errors. Table 2 displays the estimates of d (and the 95% confidence bands) for the three standard cases examined in the literature on unit roots, i.e., 1) with no deterministic terms, 2) with a constant, and 3) with a constant and a linear time trend. We mark in bold in the tables the selected specification for each series. We observe that the time trend coefficient is found to be statistically significant in half of the series, in particular, for Algeria, Egypt, Iran, Israel, and Tunisia. For the remaining five (Djibouti, Jordania, Lebanon, Syria, and Yemen) only an intercept is required. Looking now at the estimated values of d (along with the other estimated coefficients), in Table 3, we see that there are four series where the estimated values of d are significantly smaller than 1, thus showing reversion to the mean. They correspond to Tunisia (d = 0.31), Israel (0.64), Syria (0.66), and Yemen (0.70), while the unit root null (i.e., d = 1) cannot be rejected for the remaining countries, the values of d ranging then from 0.84 (Algeria) to 0.95 (Iran). The estimated time trend coefficient is positive in the four series which was found to be statistically significant.

Table 2
Estimates of d: White noise errors. Original data

| Series | No terms | An intercept | An intercept and a linear time trend |
|---|---|---|---|
| Algeria | 0.81 (0.65, 1.10) | 0.87 (0.76, 1.05) | **0.84 (0.68, 1.05)** |
| Djibouti | 0.82 (0.65, 1.10) | **0.86 (0.75, 1.00)** | 0.84 (0.73, 1.00) |
| Egypt | 0.91 (0.65, 1.10) | 0.94 (0.78, 1.22) | **0.93 (0.70, 1.23)** |
| Iran | 0.81 (0.65, 1.10) | 0.97 (0.86, 1.17) | **0.95 (0.79, 1.18)** |
| Israel | 0.66 (0.65, 1.10) | 0.64* (0.57, 0.82) | **0.64*** **(0.50, 0.82)** |
| Jordania | 0.75 (0.65, 1.10) | **0.88 (0.72, 1.12)** | 0.89 (0.70, 1.12) |
| Lebanon | 0.89 (0.65, 1.10) | **0.91 (0.76, 1.15)** | 0.92 (0.77, 1.15) |
| Syria | 0.66* (0.44, 0.89) | **0.66*** **(0.55, 0.82)** | 0.66* (0.53, 0.82) |
| Tunisia | 0.38* (0.30, 0.74) | 0.63* (0.56, 0.72) | **0.31*** **(0.12, 0.56)** |
| Yemen | 0.72* (0.52, 0.99) | **0.70*** **(0.42, 0.99)** | 0.73* (0.52, 0.98) |
| *: Statistical evidence of mean reversion at the 5% level. In parenthesis, 95% confidence bands. | | | |

Table 3
Estimated coefficients based on the models selected in Table 2

| Series | No terms | An intercept | An intercept and a linear time trend |
|---|---|---|---|
| Algeria | 0.84 (0.68, 1.05) | 0.6931 (6.83) | 0.0287 (3.72) |
| Djibouti | 0.86 (0.75, 1.00) | 1-6194 (9.06) | — |
| Egypt | 0.93 (0.70, 1.23) | 0.8268 (12.28) | 0.0182 (2.73) |
| Iran | 0.95 (0.79, 1.18) | 0.9410 (7.67) | 0.0406 (3.02) |
| Israel | 0.64* (0.50, 0.82) | 2.6026 (2.25) | 0.0486 (3.61) |
| Jordania | 0.88 (0.72, 1.12) | 1.703 1(10.11) | — |
| Lebanon | 0.91 (0.76, 1.15) | 1.7303 (9.56) | — |
| Syria | 0.66* (0.55, 0.82) | 1.0958 (6.93) | — |
| Tunisia | 0.31* (0.12, 0.56) | 0.8222 (13.42) | 0.0247 (13.86) |
| Yemen | 0.70* (0.42, 0.99) | 0.9149 (12.27) | — |

*: Statistical evidence of mean reversion at the 5% level.

Table 4
Estimates of d: White noise errors. Logged data

| Series | No terms | An intercept | An intercept and a linear time trend |
|---|---|---|---|
| Algeria | 0.89 (0.77, 1.06) | 0.84 (0.72, 1.02) | **0.81 (0.65, 1.02)** |
| Djibouti | 0.87 (0.76, 1.02) | **0.92 (0.81, 1.08)** | 0.92 (0.80, 1.08) |
| Egypt | 0.91 (0.77, 1.13) | 0.95 (0.76, 1.26) | **0.95 (0.73, 1.26)** |
| Iran | 0.85 (0.73, 1.13) | 0.85 (0.74, 1.13) | **0.77 (0.52, 1.14)** |
| Israel | 0.84 (0.69, 1.02) | 0.72* (0.59, 0.91) | **0.75* (0.61, 0.92)** |
| Jordania | 0.71* (0.54, 0.95) | **0.81 (0.66, 1.02)** | 0.81 (0.64, 1.02) |
| Lebanon | 0.89 (0.72, 1.11) | 0.89 (0.75, 1.11) | **0.90 (0.77, 1.19)** |
| Syria | 0.59* (0.48, 0.76) | 0.62* (0.52, 0.76) | **0.62* (0.50, 0.77)** |
| Tunisia | 0.66* (0.56, 0.81) | 0.65* (0.58, 0.76) | **0.52* (0.38, 0.71)** |
| Yemen | **0.87 (0.66, 1.13)** | 0.82 (0.53, 1.09) | 0.84 (0.64, 1.09) |

*: Statistical evidence of mean reversion at the 5% level. In parenthesis, 95% confidence bands.

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

| Series | No terms | An intercept | An intercept and a linear time trend |
|---|---|---|---|
| Algeria | **0.81 (0.65, 1.02)** | -0.3392 (-3.81) | 0.0211 (3.49) |
| Djibouti | **0.92 (0.81, 1.08)** | 0.4849 (4.89) | — |
| Egypt | **0.95 (0.73, 1.26)** | -0.2154 (-4.14) | 0.0143 (2.51) |
| Iran | **0.77 (0.52, 1.14)** | -0.0685 (-1.80) | 0.0229 (4.45) |
| Israel | **0.75* (0.61, 0.92)** | 0.9165 (12.45) | 0.0125 (3.00) |
| Jordania | **0.81 (0.66, 1.02)** | 0.5099 (4.05) | — |
| Lebanon | **0.90 (0.77, 1.19)** | 0.5326 (8.47) | 0.0099 (1.71) |
| Syria | **0.62* (0.50, 0.77)** | 0.0185 (1.15) | 0.0080 (1.78) |
| Tunisia | **0.52* (0.38, 0.71)** | -0.1479 (-2.49) | 0.0168 (8.39) |
| Yemen | **0.87 (0.66, 1.13)** | — | — |

*: Statistical evidence of mean reversion at the 5% level.

Tables 2–5 **ABOUT HERE**

We next repeat the analysis but this time using the logged data (Tables 3 and 4). The time trend is now significant in seven out of the ten countries examined, in all except for Djibouti, Jordania, and Yemen, and mean reversion is now only found in the cases of Tunisia (d = 0.52), Syria (0.62), and Israel (0.75). For the rest of the countries, though the estimates of d are still smaller than 1, the unit root null hypothesis cannot be rejected.

Table 6
Estimates of d: Autocorrelated errors. Original data

| Series | No terms | An intercept | An intercept and a linear time trend |
|---|---|---|---|
| Algeria | 0.58* (0.42, 0.87) | 0.95 (0.71, 1.31) | **0.87 (0.36, 1.32)** |
| Djibouti | 1.00 (0.80, 1.26) | **1.31 (0.96, 2.22)** | 1.31 (0.97, 2.08) |
| Egypt | 0.40* (0.30, 0.93) | 0.80 (0.65, 1.18) | **0.35 (-0.52, 1.21)** |
| Iran | 0.68* (0.57, 0.89) | 0.88 (0.74, 1.11) | **0.81 (0.48, 1.11)** |
| Israel | 0.99 (0.36, 1.33) | **0.91 (0.55, 1.33)** | 0.91 (0.53, 1.31) |
| Jordania | 0.41 (0.20, 1.25) | **0.85 (0.55, 1.29)** | 0.85 (0.13, 1.29) |
| Lebanon | 0.80 (0.34, 1.25) | 0.84 (0.58, 1.21) | **0.85 (0.61, 1.18)** |
| Syria | 0.68 (0.23, 1.25) | **1.01 (0.70, 1.42)** | 1.01 (0.70, 1.41) |
| Tunisia | 0.37* (0.30, 0.90) | 0.73* (0.60, 0.99) | **0.30* (-0.22, 0.93)** |
| Yemen | 0.02* (-0.08, 0.88) | **0.10 (-0.26, 1.32)** | 0.59 (-0.34, 1.29) |
| *: Statistical evidence of mean reversion at the 5% level. | | | |

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

| Series | No terms | An intercept | An intercept and a linear time trend |
|---|---|---|---|
| Algeria | 0.87 (0.36, 1.32) | 0.6972 (6.75) | 0.0286 (3.34) |
| Djibouti | 1.31 (0.96, 2.22) | 1.6591 (9.99) | — |
| Egypt | 0.35 (-0.52, 1.21) | 0.7956 (11.44) | 0.0201 (9.98) |
| Iran | 0.81 (0.48, 1.11) | 0.9008 (7.38) | 0.424 (5.10) |
| Israel | 0.91 (0.55, 1.33) | 2.4685 (7.23) | — |
| Jordania | 0.85 (0.55, 1.29) | 1.6898 (109.15) | — |
| Lebanon | 0.85 (0.61, 1.18) | 1.7084 (9.47) | 0.0236 (1.69) |
| Syria | 1.01 (0.70, 1.42) | 0.9761 (5.45) | — |
| Tunisia | 0.30* (-0.22, 0.93) | 0.8219 (8.43) | 0.0242 (8.71) |
| Yemen | 0.10 (-0.26, 1.32) | 0.8814 (50.49) | — |
| *: Statistical evidence of mean reversion at the 5% level. | | | |

Table 8
Estimates of d: Autocorrelated errors. Logged data

| Series | No terms | An intercept | An intercept and a linear time trend |
|---|---|---|---|
| Algeria | 1.30 (0.80, 1.84) | 0.91 (0.65, 1.34) | **0.83 (0.34, 1.33)** |
| Djibouti | 1.07 (0.86, 1.40) | **1.17 (0.90, 1.79)** | 1.17 (0.90, 1.66) |
| Egypt | 0.92 (0.67, 1.41) | 0.79 (0.63, 1.25) | **0.60 (-0.05, 1.26)** |
| Iran | 0.62* (0.48, 0.79) | 0.65* (0.53, 0.80) | **0.04* (-0.19, 0.56)** |
| Israel | 1.06 (0.73, 1.45) | **1.01 (0.44, 1.42)** | 1.02 (0.63, 1.35) |
| Jordania | 0.64 (0.36, 1.43) | **0.92 (0.58, 1.39)** | 0.92 (0.36, 1.36) |
| Lebanon | 0.91 (0.52, 1.31) | 0.86 (0.57, 1.20) | **0.88 (0.68, 1.20)** |
| Syria | 1.01 (0.70, 1.40) | **1.00 (0.73, 1.38)** | 1.00 (0.71, 1.38) |
| Tunisia | 0.83 (0.58, 1.26) | 0.75 (0.59, 1.07) | **0.66 (0.36, 1.07)** |
| Yemen | 0.86 (0.37, 1.58) | **0.04 (-0.35, 1.49)** | 0.79 (-0.48, 1.46) |

*: Statistical evidence of mean reversion at the 5% level.

Table 9
Estimated coefficients based on the models selected in Table 8

| Series | No terms | An intercept | An intercept and a linear time trend |
|---|---|---|---|
| Algeria | 0.83 (0.34, 1.33) | -0.3370 (-3.72) | 0.0211 (3.20) |
| Djibouti | 1.17 (0.90, 1.79) | 0.5007 (5.18) | — |
| Egypt | 0.60 (-0.05, 1.26) | -0.1794 (-3.41) | 0.0149 (7.28) |
| Iran | 0.04* (-0.19, 0.56) | -0.2820 (-4.63) | 0.0279 (5.77) |
| Israel | 1.01 (0.44, 1.42) | 0.8755 (11.81) | — |
| Jordania | 0.92 (0.58, 1.39) | 0.5357 (4.12) | — |
| Lebanon | 0.88 (0.68, 1.20) | 0.5344 (8.55) | 0.0099 (1.85) |
| Syria | 1.00 (0.73, 1.38) | — | — |
| Tunisia | 0.66 (0.36, 1.07) | -0.1590 (-2.19) | 0.0165 (5.12) |
| Yemen | 0.04 (-0.35, 1.49) | -0.1581 (-9.40) | — |

*: Statistical evidence of mean reversion at the 5% level.

Tables 6–9 **ABOUT HERE**

The results reported so far are based on the strong assumption that u(t) displays no autocorrelation. In order to relax this assumption, in what follows, we permit weak autocorrelation. However, rather than restricting the specification to a particular ARMA structure, with the difficulty that it suppose the choice of the short-run AR and MA orders and the inconsistency that it may cause on the estimate of d such misspecification, we propose here the use of an old non-parametric technique due to Bloomfield (1973) and that is implicitly specified with respect to its spectral density function and which logged form is very similar to the one produced by an AR structure. Using this technique, the results are reported in Tables 6 and 7 (for the original data) and Tables 8 and 9 for the logged form.

Starting with the original values, the time trend is now significant for Algeria, Egypt, Iran, Lebanon, and Tunisia (in all these cases with significantly positive coefficients), and mean reversion is only found for the case of Tunisia, with an estimated value of d of 0.30. In fact, the I(0) hypothesis (d = 0) cannot be rejected now for this country. In some other countries like Yemen and Egypt, the estimates of d are also very low (0.10 and 0.35 respectively for these two countries) but the confidence intervals are so wide that we cannot reject either the I(0) and the I(1) hypotheses.

Looking at the results based on the logged values, the time trend is significant in the same five cases as with the original data, and mean reversion occurs now only for Iran with an estimated value of d of about 0.04. The result failed to reject the specified short memory of the I(0) hypothesis for this country along with Yemen and Egypt. Thus, the results seem to be very heterogeneous depending on the assumption made on the error term and the use of original versus logged data. In an overall conclusion, we observe that Tunisia is the country displaying more evidence of mean reversion, followed by Israel, Syria, Yemen, and Iran under some circumstances. For the rest of the countries, i.e., Algeria, Djibouti, Egypt, Jordania, and Lebanon, there is no evidence of mean reversion in any single case, supporting thus the hypothesis of permanency of shocks.

## 4b. Convergence

For convergence, we computed the per capita relative EF of each country using the following equation:

$\mathrm{Re}lative\ per\ capita\ EF_{it} = \ln\left[\frac{Per\ capita\ EF_{it}}{Mean\ per\ capita\ EF_{t}}\right]$. The results are now displayed across Tables 10–13. As in the previous cases, we start presenting the results for the differencing parameter under the assumption that u(t) is a white noise process (Tables 10 and 11), while those based on autocorrelation are displayed in Tables 12 and 13.

If u(t) is white noise, the first thing we observe is that the time trend is required in the cases of Algeria, Iran, Tunisia, and Yemen, and the slope coefficient is significantly positive in the first three countries but negative for Yemen. Focussing on d, we see that evidence of mean reversion (i.e., d < 1) is found in four countries: Tunisia (d = 0.43), Syria (0.58), Yemen (0.69), and Jordania (0.76), while in the remaining six cases the unit root null hypothesis cannot be rejected.

## RESULTS OF CONVERGECE

Table 10

Estimates of d: White noise errors. Relative EF

| Series | No terms | An intercept | An intercept and a linear time trend |
|---|---|---|---|
| Algeria | 0.88 (0.75, 1.05) | 0.81 (0.68, 1.02) | **0.81 (0.66, 1.02)** |
| Djibouti | 0.96 (0.86, 1.11) | **0.98 (0.87, 1.14)** | 0.98 (0.88, 1.14) |
| Egypt | 0.78 (0.64, 0.98) | **0.88 (0.65, 1.19)** | 0.88 (0.66, 1.19) |
| Iran | 0.85 (0.72, 1.08) | 0.77 (0.65, 1.01) | **0.68 (0.47, 1.01)** |
| Israel | 0.92 (0.79, 1.09) | **0.82 (0.66, 1.01)** | 0.82 (0.67, 1.01) |
| Jordania | 0.72 (0.54, 0.95) | **0.76* (0.55, 0.99)** | 0.78* (0.62, 0.99) |
| Lebanon | 0.93 (0.78, 1.14) | **0.85 (0.71, 1.07)** | 0.84 (0.70, 1.07) |
| Syria | 0.60* (0.49, 0.75) | **0.58*** **(0.47, 0.72)** | 0.56* (0.45, 0.71) |
| Tunisia | 0.65* (0.51, 0.85) | 0.46* (0.35, 0.63) | **0.43* (0.29, 0.64)** |
| Yemen | 0.84 (0.59, 1.09) | 0.59* (0.45, 0.94) | **0.69* (0.47, 0.96)** |
| *: Statistical evidence of mean reversion at the 5% level. | | | |

Table 11
Estimated coefficients based on the models selected in Table 10

| Series | No terms | An intercept | An intercept and a linear time trend |
|---|---|---|---|
| Algeria | **0.81 (0.66, 1.02)** | -0.575 (-6.73) | 0.0098 (1.68) |
| Djibouti | **0.98 (0.87, 1.14)** | 0.242 (2.67) | — |
| Egypt | **0.88 (0.65, 1.19)** | -0.437 (-8.87) | — |
| Iran | **0.68 (0.47, 1.01)** | -0.330 (-4.38) | 0.0116 (3.28) |
| Israel | **0.82 (0.66, 1.01)** | 0.664 (10.22) | — |
| Jordania | **0.76* (0.55, 0.99)** | 0.222 (1.90) | — |
| Lebanon | **0.85 (0.71, 1.07)** | 0.300 (4.73) | — |
| Syria | **0.58*** **(0.47, 0.72)** | -0.260 (-3.02) | — |
| Tunisia | **0.43* (0.29, 0.64)** | -0.382 (-8.01) | 0.0044 (3.01) |
| Yemen | **0.69* (0.47, 0.96)** | -0.295 (-3.49) | -0.0177 (-4.36) |
| *: Statistical evidence of mean reversion at the 5% level. | | | |

Table 12
Estimates of d: Autocorrelated errors. Relative EF

| Series | No terms | An intercept | An intercept and a linear time trend |
|---|---|---|---|
| Algeria | 1.30 (0.80, 1.93) | 0.82 (0.53, 1.23) | **0.78 (0.36, 1.22)** |
| Djibouti | 1.10 (1.00, 1.56) | **1.25 (1.01, 1.71)** | 1.25 (1.01, 1.63) |
| Egypt | 0.93 (0.60, 1.33) | **0.77 (0.40, 1.42)** | 0.75 (0.23, 1.47) |
| Iran | 0.71* (0.52, 0.92) | 0.60* (0.47, 0.77) | **0.19* (-0.11, 0.64)** |
| Israel | 1.17 (0.86, 1.54) | **0.98 (0.39, 1.39)** | 0.98 (0.30, 1.38) |
| Jordania | 0.76 (-0.15, 1.46) | **0.89 (-0.11, 1.39)** | 0.90 (0.44, 1.35) |
| Lebanon | 0.89 (0.67, 1.28) | **0.78 (0.57, 1.09)** | 0.78 (0.53, 1.09) |
| Syria | 1.07 (0.80, 1.43) | **0.96 (0.68, 1.38)** | 0.95 (0.67, 1.38) |
| Tunisia | 0.72 (0.38, 1.10) | 0.47* (0.23, 0.83) | **0.47* (0.17, 0.85)** |
| Yemen | 0.48 (0.07, 1.47) | 0.36 (0.11, 1.30) | **0.47 (-0.19, 1.23)** |
| *: Statistical evidence of mean reversion at the 5% level. | | | |

Table 13
Estimated coefficients based on the models selected in Table 12

| Series | No terms | An intercept | An intercept and a linear time trend |
|---|---|---|---|
| Algeria | 0.82 (0.53, 1.23) | -0.579 (-6.80) | 0.0097 (1.84) |
| Djibouti | 1.25 (1.01, 1.71) | 0.263 (3.10) | — |
| Egypt | 0.77 (0.40, 1.42) | -0.416 (-8.97) | — |
| Iran | 0.60* (0.47, 0.77) | -0.497 (-10.47) | 0.0141 (10.52) |
| Israel | 0.98 (0.39, 1.39) | 0.635 (9.56) | — |
| Jordania | 0.89 (-0.11, 1.39) | 0.276 (2.28) | — |
| Lebanon | 0.78 (0.57, 1.09) | 0.306 (4.98) | — |
| Syria | 0.96 (0.68, 1.38) | -0.266 (-2.37) | — |
| Tunisia | 0.47* (0.23, 0.83) | -0.385 (-7.33) | 0.0044 (2.65) |
| Yemen | 0.36 (0.11, 1.30) | -0.312 (-3.75) | -0.0162 (-6.13) |

*: Statistical evidence of mean reversion at the 5% level.

Tables 10–13 **ABOUT HERE**

Focussing now on the case of autocorrelation (Tables 12 and 13) the time trend is found to be significant in the same four countries as with white noise errors (i.e., Algeria, Iran, Tunisia, and Yemen), and mean reversion takes now place only in the cases of Iran (with d = 0.19) and Tunisia (d = 0.47). In all the other cases, though the estimates of d are lesser than 1 in most of the results, the confidence intervals are so large that it fails to reject the null of the unit root.

#### 4c. Discussion of the results

The foregoing results indicate a dichotomy between reverting and non-reversing means and between convergence and divergence of EF amongst the sampled countries in the MENA region. The outcomes also show that the mean reversing nature of the series in each country generally reinforces the nature of convergence as countries with mean reversion in EF are also converging in terms of EF, while countries exhibiting non-reversing means are diverging in terms of EF. The only exceptions to this are Israel and Jordania with the latter converging without mean-reversion while the former exhibits mean reversion but diverges. This outcome is consistent with some of the previous research efforts, including Bilgili et al. (2019), Işık et al. (2021), Tillaguango et al. (2021) which have provided evidence for mixed results of convergence and divergence in EF among a group of countries.

The heterogeneous nature of the stochastic behavior of EF in terms of mean reversion and convergence among the MENA countries may be due to a variety of factors. Such factors include the rising physical and economic fragmentations of cities across the countries in the region, which have resulted in spatial disparities and creating converging and diverging countries across the regions which are being reinforced by the nature of the mean reversion in EF.

Though the MENA region comprises countries with common heritage and culture, differences in the endowments of natural resources are also responsible for the heterogeneous nature of the result. For instance, while some are rich in oil resources (Algeria, the Islamic Republic of Iran, and Yemen) others including Egypt and the Islamic Republic of Iran are endowed with a considerable amount of freshwater with the majority of the rest of the countries in the region depending on sources outside their borders for their water supply. Egypt is also reputable for being richly endowed with an abundant supply of cotton. EF is essentially a stock embodied measure of the environment that comprises various components such as fishing ground, built-up land, land for crops, land for grazing, forest product, carbon, and fishing ground; differences in the level of endowments of these natural resources across the countries in the region could thus cause differences in their stochastic nature as manifested in the mean reversion and convergence.

Linked with the forgoing factors are differences in the form and shape of the economic activities and the disparities in the level of economic development of the countries that made up the MENA. Economic activities involving some of the components of the EF including fishing, grazing, and forestry are influenced by the level of economic development of the countries in the region. Different level of development implies a different level of exploitation and economic activities around fishing, grazing, and forestry, which can cause a disparity in the pattern of mean reversion and convergence in EF amongst the MENA countries. For instance, while countries such as Israel, Egypt, Algeria, the Islamic Republic of Iran, and to some extent, Tunisia have experienced a considerable economic development relative to other countries, others such as Yemen and Djibouti have remained largely stagnated economically.

# 5. Conclusions

Projected to encounter rising temperatures, water shortages, and more severe weather scenarios on the horizon, with critical implications for water and food security, the MENA region is among the world's most vulnerable regions to climate change (Sieghart et al., 2018). In order to address these challenges in the region, it is important to broaden the understanding of the trends and patterns of the environment. In this regard, this paper simultaneously analyzed the mean reversion and convergence characteristics of the EF in the MENA region using the long memory that is based on the flexibly superior fractional integration procedure for the period between 1961 and 2018. Overall, the findings reveal a combination of mixed behavior in EF both in terms of reversing and non-reversing means and in terms of convergence and divergence. These outcomes are laced with a number of important policy inferences.

The findings give intuition into the interconnection between the mean reversing nature of a series and its convergence among countries. A series with mean reversion has the tendency to result in convergence while non-reversion of means reinforces divergence. Thus, policymakers can better understand the convergence nature of series among a group of countries, and proffer appropriate policy prescriptions, by understanding the mean reversing nature of the series for the individual country. If there is empirical evidence for mean reversion in a series, it means that the series follows a stationary process and, in that instance, policies would not have a long-lasting and permanent effect as the series would always revert to its mean value. In order words, the effect of policy shocks would be transient and not permanent. In contrast, a non-stationary series will have a permanent response to policy shocks.

On one hand, countries such as Israel, Syria, Tunisia, Yemen, and Iran with stationary and converging EF have a higher probability of predicting and forecasting the desired future values of EF based on their current and past behaviors. However, policies would not have a persistent effect on the EF in these countries as the series would always revert to its average values over time. On the other hand, countries such as Algeria, Egypt, Djibouti, and Lebanon with nonstationary and diverging EF have a lower capacity for predicting and forecasting the desired future values of EF based on their current and past behaviors. However, policies would have a persistent effect on the EF in these countries as the series does not have the tendency to revert to any value over time.

The main policy thrust is that the fact that the results show a mixture of stationary and non-stationary behavior for EF among the MENA countries indicates that reaction to environmental policies on EF would not be uniform across broad. Therefore, policies aiming to enhance the environment including carbon tax imposition, provision of green energy subsidies, and the strengthening of regulations on land use act to protect land, forest, and water should not be adopted indiscriminately. Special attention should be particularly put on Algeria, Djibouti, and Egypt with non-stationary but diverging EF. Although, the non-stationarity of the EF in these countries implies that the series is not reverting to its mean and as such policies will have long-term lasting impacts, the divergence nature of the EF means the series can explode if left unchecked. Indeed, these countries are among the countries within the MENA region that have been recording the deficit biocapacity of EF. Algeria, Egypt, and Djibouti have a combined average biocapacity deficit of 341% and if everyone lived like the residents of these countries, humanity would need about 4.2 earths to survive (Earth Overshoot Day, 2021; Global Footprint Network, 2021).

Lastly, we conclude by noting the unavoidable limitation of the present study which stems from the limited number of countries in the MENA region that have been incorporated into the study. This is due to the unavailability of up-to-date data for the countries that have been dropped as we opted to maximize the robustness of a large sample size by considering only the countries with the most available up-to-date data within the MENA region. In this regard, it is recommended that future studies can consider a larger number of MENA countries when data become available.

# Declarations

- **Ethical Approval**

Not applicable

- **Consent to Participate**

Yes

- **Consent to Publish**

Yes

- **Author Contributions**
- **BELLO, Mufutau Opeyemi (Ph.D.):**

    1. Main idea conception.
    2. Introductory Background.
    3. Literature Review.

- **Prof. Luis A. Gil-Alana (Ph.D.):**

    1. Methodology.
    2. Empirical results.

- **Assoc. Prof. Kean Siang(Ph.D.):**

    1. Discussion of results.
    2. Conclusion.

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- **Competing Interests**

We declare that we have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

- **Availability of data and materials**

The datasets are available in:

1. https://data.footprintnetwork.org/?_ga=2.177663078.2124187604.1644918995-941887846.1644918995#/countryTrends?cn=5001&type=BCpc,EFCpc
2. https://www.overshootday.org/how-many-earths-or-countries-do-we-need/

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