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A DYNAMIC SPATIOTEMPORAL ANALYSIS OF GROWTH CONVERGENCE, NATURAL DISASTERS, AND CLIMATE CHANGE IN THE MENA REGION

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Abstract

This study investigates economic growth convergence within the MENA region using a spatial econometric approach. The empirical findings reveal that environmental factors significantly influence the convergence process. Growth convergence appears to be shaped not only by each country's idiosyncratic characteristics but also by environmental feedback effects from neighboring countries and the intensity of ecological spillovers. These spillovers are not limited to immediate (first-order) or contiguous neighbors; they also extend to higher-order neighbors and may ultimately impact the entire region.

Keywords: Growth convergence, Spillover effects; Spatial models; Climate change.
JEL Classifications: O47, D62, C31, Q54.

ملخص

تبحث هذه الدراسة في تقارب النمو الاقتصادي في منطقة الشرق الأوسط وشمال أفريقيا باستخدام نهج القياس الاقتصادي المكاني. تكشف النتائج التجريبية أن العوامل البيئية تؤثر بشكل كبير على عملية التقارب. ويبدو أن تقارب النمو لا يتشكل فقط من خلال الخصائص الفريدة لكل بلد، بل أيضًا من خلال تأثيرات التغذية الراجعة البيئية من الدول المجاورة وكثافة التداعيات البيئية. ولا تقتصر هذه التداعيات على الدول المجاورة المباشرة (من الدرجة الأولى) أو المتجاورة؛ بل تمتد أيضًا إلى دول مجاورة من الدرجة الأعلى، وقد تؤثر في نهاية المطاف على المنطقة بأكملها.

1. Introduction

Exploring the concepts of economic growth and income convergence[3] in the context of climate change is a prominent and widely debated issue. This debate is especially relevant to the MENA region, which has been severely cursed by recurrent chaotic events—some of extreme violence—including internal and external conflicts, economic crises, population displacement, and natural disasters. The interconnection of these economies, combined with the shocks associated with such events, necessitates a holistic and ambitious analysis to understand the underlying logic behind the region's chronic economic lethargy despite its abundant human and natural resources. Some primary queries arise from both environmental and economic perspectives. First, will climate factors raise the convergence speed across the MENA region or will they instead exacerbate regional disparities? Second, to what extent do spatial factors shape the development trajectories of MENA countries? Third, do neighboring countries with similar environmental factors converge faster? Finally, are there spillover effects within the region, and if so, what kinds are they and how far do they extend geographically?

This exploratory spatial and ecological analysis investigates the spatial correlation between MENA economies in terms of economic convergence while accounting for the potentially significant influence of ecological factors. The contribution of this study is twofold. First, it examines the impact of environmental degradation and climate change on economic growth convergence, thereby addressing a notable gap in the empirical literature on the MENA region. Second, it implements various spatial models and techniques to improve upon previous studies by explicitly considering spatial interdependence as a source of externalities that may spill over to neighboring or even distant countries. To this end, a panel dataset covering 18 MENA countries over the period 1996-2019 is constructed to explore the aforementioned questions.

2. Economic growth-ecological footprint nexus: why does spatial analysis matter?

Lesage (2010, p.20) states that "spatial econometrics is a field whose analytical techniques are designed to incorporate dependence among observations (regions or points in space) that are in close geographical proximity. Extending the standard linear regression model, spatial methods identify cohorts of 'nearest neighbors' and allow for dependence between these regions/observations." Indeed, a spatial econometric framework represents a promising approach to address the importance of territorial interdependencies in the context of both economic growth and environmental issues. In reality, what happens in one country is likely to directly or indirectly affect others—whether neighboring or more distant—through various transmission channels.

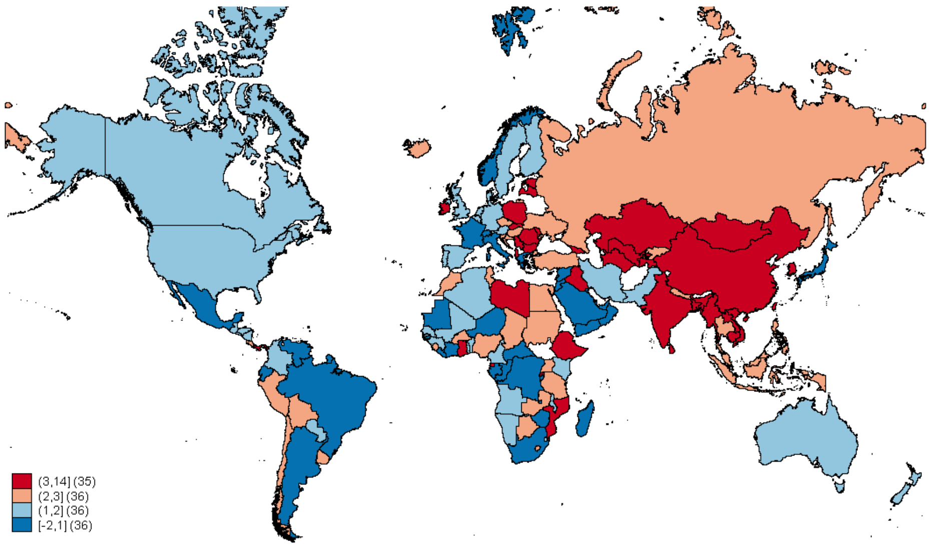
[3] Broadly speaking, the economic convergence theory postulates that all economies will eventually converge in terms of per-capita output. Accordingly, economic divergence occurs when we observe an income growth differential between a sample of countries and a list of benchmark countries. Baumol (1986), Barro and Sala-I Martin (1997), Lee et al. (1997), Bernard and Durlauf (1995), and Luginbul and Koopman (2004) have meaningfully shaped the economic convergence analysis.

The restrictive Ordinary Least Squares (OLS) assumption of independence among observational units may lead to serious misspecification problems, resulting in biased and inconsistent coefficient estimates. Another relevant point to emphasize is the difficulty in properly detecting and measuring spillover effects. While these externalities are recognized within the OLS framework, they are rarely quantified due to its technical limitations. Spatial econometric models are specifically designed to address this shortcoming. Therefore, in the presence of geographical interactions, spatial models offer a promising alternative to OLS (or non-spatial regressions) by explicitly accounting for spatial autocorrelation affecting both dependent and explanatory variables (LeSage and Pace, 2009).

In recent years, spatial effects have been increasingly recognized as a key factor in the process of economic convergence (Rey and Montouri, 1999). Global income distribution is not uniform; wealthy countries and fast-growing economies tend to be geographically clustered—i.e., located near one another. This is implicitly revealed in Figure 1, where the concentration of similar color tones in regions such as Asia, Europe, and the Americas presumes the presence of a positive spatial correlation in GDP per capita growth at the continental level. Figure 1 clearly indicates that clusters of countries tend to exhibit similar levels of GDP per capita growth, with darker tones representing higher values and lighter tones representing lower ones. A key benefit of spatial econometrics lies in its ability to ascertain whether this phenomenon is driven by an underlying spatial structure or arises merely by chance. Determining whether there is a definite logic or simply a random coincidence behind such a phenomenon is one of the key advantages of using spatial econometrics. Nevertheless, it is important to recognize that spatial interdependence plays a significant role in the context of economic growth (Tian and Chen, 2010). There appears to be a shadow growth effect—growth spillovers originating from other countries—that should be taken into account when examining economic convergence. For instance, over the past decade, a stream of empirical research on economic convergence has demonstrated the importance of accounting for spatial dependence. It is crucial to emphasize that neglecting spatial interactions can lead to serious model misspecifications. Income growth and economic convergence in one country do not depend solely on its own conditions but are also influenced by those prevailing in other countries. Space, in fact, is not composed of units isolated from each other. What happens in each of them can influence others; in other words, there is spatial interaction (Jayet, 1993).

The disparities in economic growth depicted in Figure 1 stand in stark contrast to the neoclassical theory of absolute convergence. Empirical evidence suggests that significant economic differences persist, with less developed countries neither attaining the same steady state growth rates nor catching up to the income levels of developed nations. In fact, it is imperative to consider alternative theoretical frameworks beyond the often-contested and overly simplistic assumption of absolute convergence.

Figure 1. Panorama of the GDP/Capita growth in the world (period average: 1996-2019, 143 countries)



Source: Authors' calculation using World Bank data.

3. The empirical work

To estimate the convergence of GDP per capita determinants in the MENA region, we use a dataset of 18 economies[4] over the period 1996-2019. The time frame and countries are selected to supply both balanced panel data and a rather large sample size dataset to properly run the spatial regressions. Data are collected from the Penn World Table database (PWT.10.01) from the University of California and the University of Groningen,[5] the World Bank (World Development Indicators and the Worldwide Governance Indicator), and the International Monetary Fund.

3.1. The OLS regression results

As a first step, we estimate the basic Solow model using the OLS [Eq.1], serving as a benchmark for testing absolute convergence (Table 1). We then extend the analysis by conducting spatial regressions based on an augmented Solow specification, which includes additional economic and environmental idiosyncratic covariates to align with the spirit of conditional convergence.

[4] Algeria, Bahrain, Egypt, Jordan, Kuwait, Iran, Libya, Oman, Mauritania, Morocco, Qatar, Saudi Arabia, Sudan, Syria, Tunisia, Turkey, and the United Arab Emirates.

[5] Feenstra, R. C., Inklaar, R., and Timmer, M. P. (2015). The Next Generation of the Penn World Table. American Economic Review, 105(10), 3150-3182, available for download at: www.ggdc.net/pwt.

$$G_r = \beta_0 + \beta_1 Y_0 \qquad \text{[Eq.1]}$$

Hence, in the second step, we regress the growth of real GDP per capita $G_r = \frac{GDP/Cap_t - GDP/Cap1996}{T}$ on the following variables: the initial real GDP per capita[6] [per capita GDP of the year 1996: GDP/Cap_{1996}]; the capital stock (*CapStock*), which serves as a proxy of the physical capital accumulation; and the sum of population growth, technology growth rate, and capital depreciation rate (*NGD*)[7] [*NGD*= $(nn + gg + \delta\delta)$].[8] In addition, the variable natural resource endowment (*ResEndow*), [9] approximated by total natural resource rents (percentage of GDP), is included in the estimation. The environmental regressors (retrieved from the IMF online database)[10] cover carbon dioxide emissions (*CO2*) in kiloton (kt) as a proxy of environmental pollution, and the annual sum of natural climate disasters (measured by the combined frequency of droughts, extreme temperatures, floods, landslides, storms, and wildfires). Except for the governance variable (*Gov*)[11] and the natural disaster indicator (*NatDisaster*), all the other variables are expressed in logarithm.

Table 1. OLS estimates of the β-convergence regression of per-capita income in the MENA region, period: 1996-2019

Variables	**(1)** **Gr**
GDP/Cap1996	-0.371***
	(-2.579)
Constant	3.849***
	(2.836)
Observations	432
Number of id R-sq	18
	0.17

*Notes: Robust z-statistics in parentheses. *** p<0.01, ** p<0.05, * p<0.1*

The OLS results[12] indicate that the coefficient of $\beta\beta$-convergence for the entire period is highly significant with the expected negative sign, confirming the presence of convergence over the years

[6] At constant 2017 national prices (in mil. 2017US$).
[7] Following the economic growth literature, $gg + \delta\delta$ is supposed to be equal to 0.05.
[8] GDP/cap, ck, nn, $\delta\delta$ are extracted from PWT.10.01.
[9] WDI
[10] https://climatedata.imf.org/
[11] Measured as the average of five governance indicators: Voice and Accountability, Political Stability and Absence of Violence/Terrorism, Government Effectiveness, Regulatory Quality, Rule of Law and Control of Corruption, ranging from -2.5 (weak) and 2.5 (strong) performance.
[12] Based on the absolute convergence hypothesis since the regression equation does not include explanatory variables measuring the countries characteristics.

1996-2019. The negative coefficient of initial per capita GDP aligns with the theoretical prediction of growth convergence: poorer countries tend to grow faster than richer ones. The estimated value of -0.371 implies an annual rate of convergence of approximately 1.9 percent, corresponding to a half-life of 38.48 years.[13]

Table 2. OLS Estimation of the determinants of conditional convergence in MENA18 period: 1996-2019

Variables	(1) Gr
GDP/Cap1996	-1.011***
	(-7.237)
CapStock	-0.125**
	(-2.255)
NGD	0.440**
	(2.175)
ResEndow	0.183***
	(5.311)
CO2	2.352***
	(4.002)
CO2sq	-0.0880***
	(-3.161)
NatDisaster	-0.0605**
	(-2.193)
GOV	0.656***
	(4.511)
Constant	-2.513
	(-0.749)
Observations	432
Number of id	18
R^2	0.23

*Notes: statistics in parentheses. *** p<0.01, ** p<0.05, * p<0.1*

The OLS conditional convergence results (see Table 2), which incorporate both economic and ecological factors, support the convergence hypothesis, as evidenced by the negative coefficient of initial GDP per capita. Moreover, resource endowment, CO_2 emissions, and governance exhibit positive and statistically significant effects at the one percent level. The *NGD* variable also shows a positive effect, although significant only at the five percent level. In contrast, the squared term of CO_2 emissions (*CO2sq*), capital stock, and natural disasters display significant negative impacts on growth convergence in the MENA region. Specifically, both natural disasters and capital stock have significant detrimental effects on convergence (at the five percent level), while the negative effect of *CO2sq* is highly significant at the one percent level.[14]

[13] $Speed\ convergence: b = -\frac{ln(1+\beta)}{T} = 0.019\ ;\ t_{half-life} = \frac{ln\,(2)}{b} = 38.48$

[14] Further information on this point is provided in the findings of the spatial regression later on.

3.2. The spatial econometric regressions

Broadly speaking, four popular spatial models are widely used in applied research: the Spatial Lag Model or Spatial Autoregressive Model (SAR), the Spatial Error Model (SEM), the SAC model (also known as SARAR or the Cliff-Ord model), and the Spatial Durbin Model (SDM). The Spatial Lag or SAR model [Eq.2] posits that the level of the dependent variable y depends on the levels of y in neighboring units, as captured by the spatial weights matrix W and represented by the term ρW_y.

In the Spatial Error Model (SEM) [Eq.3], the spatial influence arises exclusively through the error term, specified as terms $\mu = \lambda W_\mu + \varepsilon$, and it is not suitable for detecting spillover effects. The SAC model [Eq.4] is a mixed spatial autoregressive specification that includes both endogenous interactions among the dependent variable (Wy) and autoregressive disturbances (λW_μ.). If $\lambda = 0$, the model simplifies to the SDM [Eq.5], which incorporates the lagged dependent variable (ρW_y, often reported as "*Rho*" in regression tables) as well as spatially related residuals. Compared to the SEM, the SDM additionally includes spatially lagged independent variables, expressed as $WX\theta$, thereby capturing the potential spatial spillover effects of covariates.

SAR:	$y = \rho W_y + \alpha + \beta X + \varepsilon$		[Eq.2]
SEM:	$y = \alpha + \beta X\mu \quad \mu = \lambda W_\mu + \varepsilon$		[Eq.3]
SAC:	$y = \rho W_y + \alpha + \beta X + WX\theta + \varepsilon$	$\mu = \lambda W_\mu + \varepsilon$	[Eq.4]
SDM:	$y = \rho W_y + \alpha + \beta X + WX\theta + \varepsilon$		[Eq.5]

3.2.1. The space configuration

In order to run spatial econometric regressions, a spatial weights matrix must be specified. This matrix defines the spatial structure and parameterizes the potential interactions between pairs of observations (countries), denoted by i, j. The positive and symmetric $n \times n$ spatial weights matrix[15] is composed of elements $W_{i,j}$ at location i, j that capture the degree of interaction between locations i and j By convention, the diagonal elements are set to zero ($W_{i,j} = 0$), indicating that a location cannot be its own neighbor.

$$W = \begin{pmatrix} w_{1,1} & \cdots & w_{1,n} \\ \vdots & \ddots & \vdots \\ w_{n,1} & \cdots & w_{n,n} \end{pmatrix}$$

A variety of techniques are available to define the structure of the spatial weight matrix, which reflects the spatial relationships between observational units. One common approach is contiguity-

[15] n is the number of spatial units.

based weighting, where spatial units that share a common boundary or vertex are considered neighbors.[16] An alternative is to use an inverse distance or a threshold distance.[17] Another popular method is the k-nearest neighbors' approach, where each spatial unit is assigned a fixed number (k) of the closest units as neighbors, regardless of the actual distance. In this study we use an inverse distance $w_{i,j} = \frac{1}{e^{d_{ij}}} = e^{-d_{ij}} \quad \forall\, i \neq j; i,j = 1, \ldots\ldots, N$ relating a primitive and canonical principle of geographic law described concisely by Tobler (1970, p.236)[18] "Everything is related to everything else, but near things are more related than distant things." Also, a contiguity matrix is applied on some regressions for robustness checks.

3.2.2. Completing the growth convergence equation with the spatial model

To implement the spatial regression models, we follow Tian et al. (2010), Fingleton and López-Bazo (2006), Arbia (2006), and Kubi and Schneider (2016), who adapt and extend the Cobb-Douglas production function to incorporate spatial dependence. In line with the Marshallian literature, which distinguishes between two types of externalities—technological and pecuniary—the authors argue that the primary source of spatial effects arises from externalities generated through regional interactions. These interactions manifest in the form of knowledge spillovers, factor mobility, and trade linkages, all of which contribute to interregional growth dynamics.

The Solow Cobb-Douglas equation proposed by the authors is a classical constant return to scale function taking the following form:

$$y_i(t) = A_i(t) K_i^{\alpha}(t) L_i^{1-\alpha}(t), 0 < \alpha < 1 \qquad \text{[Eq.6]}$$

Where $y_l(t)$, $A_i(t)$, $K_i(t)$ and $L_i(t)$ represent, respectively, the output, aggregated level of technology, capital, and labor in region *i* and time *t,* while $\propto$ is a parameter representing the capital elasticity.

After the rearrangement, we obtain the Spatial Durbin Model of the augmented Solow function expressed by the following equation:

$$G_r = \beta_0 + \beta_i X_i + W X_i + \rho W G_r + \varepsilon \qquad \text{[Eq.7]}$$

[16] i, j locations interact when they are contiguous, i.e., sharing a common border. Then, we obtain a binary matrix with value 0 (countries are not contiguous) and 1 (countries are contiguous). We distinguish Rook contiguity (defines neighbors as those sharing a common edge) and Queen contiguity (is more inclusive and defines neighbors as those sharing either an edge or a vertex).

[17] i, j locations interact when being within a critical distance band.

[18] Tobler, W. (1979). Cellular Geography." In *Philosophy in Geography*, edited by S. Gale and G. Olsson, pp. 579-86. Dordrecht: Reidel. Cited in Anselin (1988, p.8).

Where, G_r W_l , WX_l, and $\rho W G_r$ represent, respectively, the dependent variable, the selected independent variables (GDP/Cap1996, *CapStock*, *NGD*, ResEndow, *CO_2*, *CO2sq*, and *NatDisaster*), and the spatially lagged independent variables (preceded by the weighted matrix W, and the spatially dependent variable ($\rho W G_r$).[19]

3.2.3. The selection of the spatial model and the regression results

We estimate several spatial regression models using the maximum likelihood (ML) method, which is widely regarded as appropriate for handling spatial dependence in econometric models. In the case of the spatial lag model (SAR), applying the OLS leads to biased and inconsistent estimates due to endogeneity. Specifically, the inclusion of the spatially lagged dependent variable introduces a simultaneity bias, as this lag is correlated with the error term (Anselin, 1988; Elhorst, 2014). The ML estimator corrects for this endogeneity by jointly estimating the spatial parameter and the regression coefficients, thus producing consistent and efficient estimates.

In contrast, in the spatial error model (SEM), the spatial dependence enters through the error term rather than the dependent variable. In this case, the OLS estimates of the regression coefficients are still unbiased, but they are inefficient because the standard errors are misestimated due to the violation of the Gauss-Markov assumption of independently distributed errors (LeSage and Pace, 2009). The ML estimation improves efficiency by explicitly modeling the spatial autocorrelation in the error structure.

Given the existence of a plethora of spatial models, we run some tests to detect the spatial model with the best goodness-of-fit. As proposed by Belotti et al. (2017), we start by regressing the most general specification of our model, namely the SDM. In the second step, to test the spatial autoregressive model (SAR) specification, we check econometrically whether the parameters are $\rho \neq 0$ and $\theta = 0$. Then, we test the specification of a spatial error model (SEM) by examining if $\theta = -\beta\rho$. Next, we use the Akaike information criterion (AIC) to evaluate the specification of the SDM with an autoregressive disturbance model (SAC).[20] Based on the estimation tests, we find that the best model is the dynamic SDM (DSDM). The specification tests between the SDM and SAR models, as well as between the SDM and SEM models, reject the null hypothesis at the one percent significance level, thereby favoring the SDM in both cases. Subsequently, we compare the information criteria of the SAC and the SDM, with the SDM displaying lower values of *AIC*.[21]

[19] Formally this can be expressed by the following equation: $G_r = \beta_0 + \beta_1$ GDP/Cap1996 + β_2CapStock + β_3NGD + β_4ResEndow + β_5CO2 + β_6CO2sq + β_7NatDisaster + β_8GOV + θ_1GDP/Cap1996 + θ_2WCapStock + θ_3WNGD + θ_4WResEndow + θ_5WCO2 + θ_6WCO2sq + +θ_7WNatDisaster+θ_8WGOV + $\rho W G_r$+$\varepsilon\varepsilon$.

[20] Since the SAC and SDM are non-nested, we can rely on information criteria to test whether the most fitting model is the SDM or the SAC model. In this empirical work, the Akaike's information criterion favors the SDM compared to the SAC model (see Table 6 in the Appendix).

[21] For more details, see Table 5 and Table 6 in the Appendix.

Henceforward, we find that the DSDM provides goodness-of-fit. Furthermore, the potential bias caused by the omitted variables may be corrected using this model (LeSage and Pace, 2010).

According to the econometric estimations, the coefficient of initial GDP per capita is negative and statistically significant at the one percent level across all estimated models. This result provides strong evidence in support of the growth convergence hypothesis. In addition, the regression results indicate that the variable *NGD*—defined as the sum of the population growth rate, technological progress, and the capital depreciation rate—contributes positively and significantly to growth convergence, with statistical significance at the one percent level. However, this result is not confirmed in the SAR models, whether using the contiguity-based spatial weight matrix or the inverse distance matrix. Nevertheless, the results from the spatial dynamic model indicate that this variable contributes strongly and positively to the growth convergence process in the MENA region, with statistical significance at the one percent conventional level. At the same significance level (one percent), the results from the SDM suggest that physical capital accumulation contributes to growth divergence in the MENA region. In contrast, this variable is not statistically significant in the SAR model. Resource endowment and governance indicators, however, support the growth convergence process, a finding that holds true across both the SAR and dynamic SDM models. Environmental factors—particularly air pollution—have a significant impact on the MENA region's growth convergence trajectory, as evidenced by both the SAR and dynamic SDM regression results.

The indicator of natural disasters—measured by the incidence of droughts, extreme temperatures, floods, landslides, storms, and wildfires—is found to be statistically significant and negative at the five percent level in the SAR model, but it is not significant in the DSDM. According to the SAR model, the occurrence of natural disasters increases disparities among MENA countries. This may be explained by the varying intensity of shocks and the heterogeneous capacity of countries to absorb and manage these events, which can create or exacerbate development gaps across the region.

Table 3. SAR estimation of the impact of climate change on growth convergence in MENA18

	Model 1: Contiguity Weighted Matrix						Model 2: Inverse Distance Weighted Matrix					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Variables	**Main**	**Spatial**	**Variance**	**LR_Direct**	**LR_Indirect**	**LR_Total**	**Main**	**Spatial**	**Variance**	**LR_Direct**	**LR_Indirect**	**LR_Total**
GDP/Cap1996	-0.999***			-1.044***	-0.437***	-1.481***	-1.029***			-1.039***	-0.562**	-1.601***
	(-5.613)			(-5.398)	(-3.751)	(-5.057)	(-5.729)			(-5.519)	(-2.144)	(-4.109)
CapStock	-0.0805			-0.0869*	-0.0358	-0.123*	-0.130**			-0.135**	-0.0724*	-0.207**
	(-1.547)			(-1.650)	(-1.614)	(-1.658)	(-2.377)			(-2.506)	(-1.716)	(-2.360)
NGD	0.282			0.317*	0.131	0.449*	0.271			0.297	0.152	0.449
	(1.529)			(1.713)	(1.630)	(1.708)	(1.366)			(1.543)	(1.246)	(1.509)
ResEndow	0.194***			0.203***	0.0844***	0.287***	0.189***			0.191***	0.101**	0.292***
	(5.281)			(5.486)	(4.167)	(5.389)	(4.780)			(4.969)	(2.404)	(4.517)
CO2	2.348***			2.459***	1.028***	3.487***	2.079***			2.104***	1.111**	3.215***
	(4.139)			(4.307)	(3.441)	(4.186)	(3.425)			(3.578)	(2.159)	(3.375)
CO2sq	-0.0896***			-0.0936***	-0.0391***	-0.133***	-0.0715**			-0.0720**	-0.0376*	-0.110**
	(-3.334)			(-3.407)	(-2.911)	(-3.341)	(-2.483)			(-2.541)	(-1.872)	(-2.499)
NatDisaster	-0.0361			-0.0376	-0.0156	-0.0532	-0.0540**			-0.0545*	-0.0293	-0.0838*
	(-1.454)			(-1.391)	(-1.351)	(-1.391)	(-2.042)			(-1.958)	(-1.469)	(-1.870)
GOV	0.786***			0.815***	0.343***	1.158***	0.695***			0.695***	0.380*	1.076***
	(5.607)			(5.576)	(3.516)	(4.973)	(4.705)			(4.704)	(1.934)	(3.464)
Rho			0.326***						0.346***			
			(7.879)						(3.889)			
lgt_theta			-1.843***						-1.765***			
			(-8.353)						(-7.804)			
sigma2_e			0.265***						0.302***			
			(14.08)						(14.24)			
Constant			-3.397						-1.748			
			(-0.999)						(-0.489)			
Observations			432									
R-squared			0.258									
Number of id			18									

*Notes: (W: Contiguity and Inverse Distance) Period: 1996-2019, (Blue color: Spatial indicators, LR: Long-run spillovers). z-statistics in parentheses. *** p<0.01, ** p<0.05, * p<0.1*

Table 4. The effect of climate change on growth convergence in MENA18: A dynamic SDM model estimation

Variables	(1) Main	(2) *Wx*	(3) Spatial	(4) Variance	(5) SR_Direct	(6) SR_Indirect	(7) SR_Total	(8) LR_Direct	(9) LR_Indirect	(10) LR_Total
L.Gr	0.881***									
	(44.91)									
L.WGr	-0.00123									
	(-0.00702)									
GDP/Cap1996	0	0			0.00341	-0.00196	0.00146	2.802	-2.799	0.00289
	(omitted)	(omitted)			(0.111)	(-0.0883)	(0.0520)	(0.0502)	(-0.0502)	(0.0487)
CapStock	-0.0195	0.365***			-0.0485	0.253***	0.205***	-9.809	10.24	0.431***
	(-0.643)	(7.483)			(-1.478)	(5.819)	(5.592)	(-0.0382)	(0.0399)	(3.833)
NGD	0.0528	0.597***			0.0106	0.365***	0.375***	-15.98	16.77	0.786***
	(0.653)	(3.679)			(0.138)	(3.587)	(3.150)	(-0.0360)	(0.0378)	(2.814)
ResEndow	0.0362**	-0.0357			0.0408**	-0.0391*	0.00164	1.936	-1.933	0.00311
	(1.978)	(-1.163)			(2.210)	(-1.802)	(0.0768)	(0.0367)	(-0.0366)	(0.0683)
CO2	5.330***	8.848***			4.849***	3.435***	8.284***	13.98	3.435	17.41***
	(15.29)	(17.46)			(14.43)	(4.583)	(10.05)	(0.0198)	(0.00487)	(4.941)
CO2sq	-0.256***	-0.461***			-0.230***	-0.189***	-0.419***	0.0925	-0.973	-0.881***
	(-14.42)	(-18.02)			(-13.94)	(-5.038)	(-10.11)	(0.00176)	(-0.0185)	(-4.959)
Natdisaster	0.00587	0.0104			0.00606	0.00474	0.0108	0.0669	-0.0443	0.0226
	(0.580)	(0.805)			(0.591)	(0.469)	(1.095)	(0.0335)	(-0.0222)	(1.046)
GOV	0.753***	1.322***			0.682***	0.533***	1.215***	-1.660	4.214	2.554***
	(9.964)	(11.87)			(9.238)	(4.312)	(8.801)	(-0.0116)	(0.0295)	(4.711)
Rho			0.731***							
			(4.646)							
sigma2_e				0.0371***						
				(15.20)						
Observations	414									
R-squared	0.172									
Number of id	18									

*Notes: Blue color: Spatial Indicators L.Gr: Tme-Lagged Dependent Variable, L.WGr: Spatial-Time-Lagged Dependent; Wx: Spatial lagged Independent Variable, LR: Long-Run spillovers, SR: Short-Run spillovers, z-statistics in parentheses *** p<0.01, ** p<0.05, * p<0.1*

Regarding environmental degradation, CO_2 emissions are used as a proxy for air pollution. The regression results from both the SAR and DSDM models reveal a nonlinear (inverted U-shaped) relationship between air quality degradation and economic growth. Specifically, CO_2 emissions are associated with improved growth convergence, as indicated by a positive and statistically significant coefficient at the one percent level, while the square of CO_2 emissions shows a negative and significant effect (also at the one percent level), confirming the inverted U-shape. This suggests that the relationship between economic growth and environmental quality is complex, involving bidirectional causality and feedback loops. Increases (or decreases) in one variable tend to influence the other. These findings are consistent with previous empirical studies that have identified various nonlinear relationships, including N-shaped, U-shaped, and inverted U-shaped patterns. One plausible explanation for these discrepancies is the wide diversity of covariates and modeling techniques employed in the econometric analyses.

Spatial regression models capture the complex interdependence between observational units—in this case, countries. A change in an explanatory variable in one country can affect not only that country directly but also others indirectly. This structure implies the presence of total marginal effects, which can be decomposed into direct effects (or feedback effects) and indirect effects (spillovers). The direct effect measures the impact of a change in the growth convergence covariate on the dependent variable within the same country. In contrast, the indirect effect captures how a change in that covariate influences growth convergence in neighboring countries. The variables reflecting spatial dependence—particularly the $RRhcc$ coefficient **(**$\rho\rho$**)** and spatially weighted explanatory variables **(**WW_{xx}**)**—are key components of the SAR and DSDM models. The estimation results from both models reveal a positive feedback effect of economic growth in the MENA region, indicating that spatial dependence fosters convergence toward a steady-state growth path across countries.

The SDM, which nests the SAR model, includes both the spatially lagged dependent variable (ρWG_{rr} or Rho) and the spatial lags of the explanatory variables (W_x). The advantage of the DSDM over SAR and other spatial models lies in its ability to disaggregate total marginal effects into short-term direct and indirect components. The DSDM results point to the existence of short-term positive spillover effects in the MENA region, particularly through variables such as physical capital accumulation (*CapStock*), *NGD*, CO_2 emissions, and governance (*GOV*). However, variables such as the square of CO_2 emissions (*CO2sq*) and resource endowment **(***ResEndow***)** are associated with short-term negative spillovers, suggesting potential externalities or diminishing returns. Notably, the DSDM did not reveal any statistically significant long-term spillover effects.

4. Conclusion

This study aims to examine economic growth convergence within the MENA region through the lens of a spatial econometric framework. The empirical findings highlight that environmental factors play a significant role in the convergence process. This process is influenced not only by the idiosyncratic characteristics of each country but also by neighboring countries' feedback effects and substantive spillovers, both positive and negative, as captured by the spatially lagged variables (ρWG_r and W_x). Moreover, the environmental impacts are both direct and indirect, transmitted through various spatial mechanisms. These spillover effects are global in scope; they are not confined to immediate or first-order neighbors but extend to higher-order neighbors and may affect the entire MENA region. This has important policy implications.

Policymakers should adopt a proactive and regionally coordinated strategy to amplify the positive externalities while mitigating negative ones. Given the broad geographic extent of environmental spillovers, both environmental policy and economic growth strategies must be approached from a regional and global perspective. Enhanced regional cooperation and sustained commitment to environmental protection represent a win-win strategy to promote a more inclusive and environmentally sustainable growth trajectory.

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Appendix

Table 5. Specification tests for spatial model selection

SAR Test	SEM Test
(1) [Wx]GDP/Cap1996 - [Wx]CapStock = 0	(1) [Wx]ln_cn = -[Spatial]rho*[Main]CapStock
(2) [Wx]GDP/Cap1996 - [Wx]NGD = 0	(2) [Wx]lnNGD = -[Spatial]rho*[Main]NGD
(3) [Wx]GDP/Cap1996 - [Wx]ResEndow = 0	(3) [Wx]ln_ResEndow = -[Spatial]rho*[Main]ResEndow
(4) [Wx]GDP/Cap1996 - [Wx] CO_2 = 0	(4) [Wx]ln_co2kt = -[Spatial]rho*[Main]CO_2
(5) [Wx]GDP/Cap1996 - [Wx]CO2sq = 0	(5) [Wx]ln_co2ktsq = -[Spatial]rho*[Main]CO2sq
(6) [Wx]GDP/Cap1996 - [Wx] Nat_Disaster = 0	(6) [Wx]disaster_total = -[Spatial]rho*[Main]Nat_Disaster
(7) [Wx]GDP/Cap1996 - [Wx] GOV = 0	(7) [Wx]gov = -[Spatial]rho*[Main] GOV
(8) [Wx]GDP/Cap1996 = 0	
Chi2(8) = 141.03 Prob > chi2 = 0.0000	Chi2(7) = 136.29 Prob > chi2 = 0.0000

Table 6. Akaike's information criterion

Model	Obs	ll(model)	df	AIC
SDM	432	-329.0055	20	7085.797
SAC	432	-340.9169	10	7094.223