THE ECONOMIC PERFORMANCES OF MOROCCAN REGIONS: A TOPSIS AND SPATIAL AUTOCORRELATION METHODS

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Abstract

This paper investigates the economic performance of Morocco's twelve regions from 2015 to 2022, combining a temporal and spatial analysis methods, and focusing on five key regional macroeconomic indicators: GDP per capita, HFCE per capita, contribution to national growth, start-ups created, and the activity rate. While previous studies have examined regional disparities using MCDM or spatial statistics, none have combined TOPSIS with spatial autocorrelation to evaluate regional economic-entrepreneurial performance in Morocco under its new administrative division, which enables ranking of regional competitiveness and detection of clustering patterns. Findings show that Casablanca-Settat consistently ranks in the top twelve, solidifying its position as the country’s economic capital, followed alternately by the northern Tanger-Tétouan-Al Hoceima and the emergent Rabat-Salé-Kénitra regions, while the southern regions remain at the bottom. Marrakech-Safi was severely affected by the disruption of tourist cash flows under the Covid-19 crisis, before it gradually recovered post-2020. Similarly, Béni Mellal-Khénifra progressed significantly, largely due to its phosphate exports, agro-oil industry, and remittances’ inflows, until 2020, when it retrograded remarkably. Spatial analysis reveals that Moroccan regions exhibit high autocorrelation, with both, top and low ranked regions identified by the TOPSIS method clustering together. Results can inform region-specific development strategies, equitable resource allocation, entrepreneurship promotion, and spatial regional planning. However, limitations such as the restricted set of indicators, short interval, and methodological constraints suggest future research directions that integrate broader social, environmental, and innovation variables, extend the sample interval, and apply advanced comparative and econometric approaches.

Keywords: Morocco, regions, economy, TOPSIS, spatial autocorrelation
JEL classification: C38, L26, R11, R12
pp. 93-114

1. Introduction

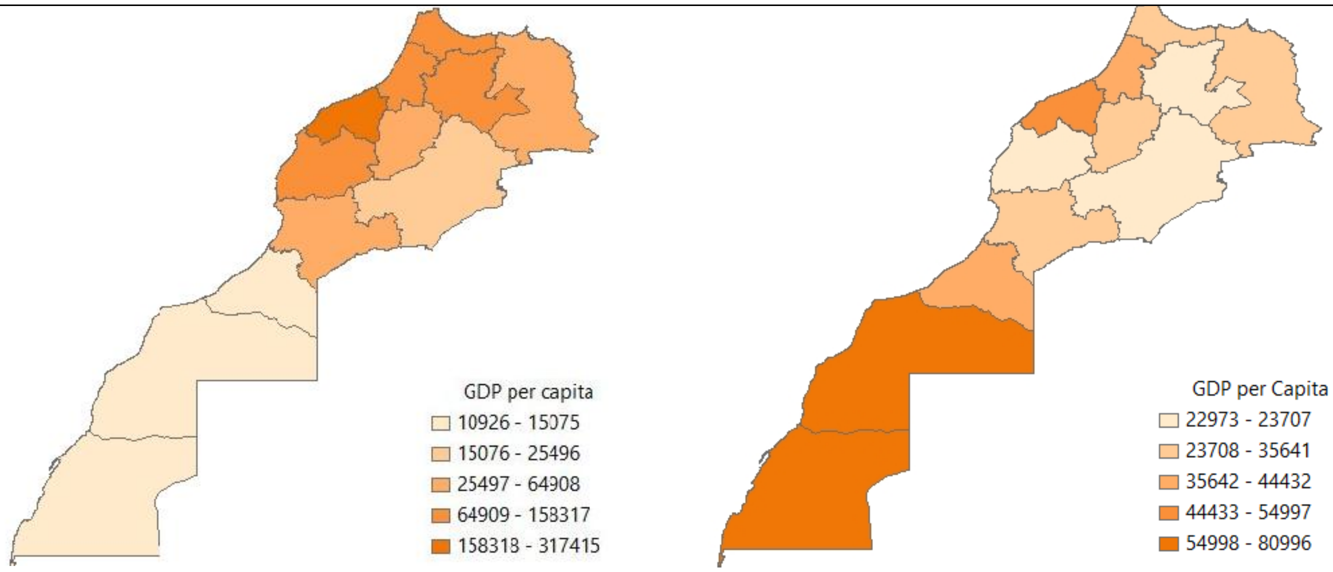
Economic and entrepreneurial disparities among regional territories remain a pressing concern for development planners, especially in contexts marked by heterogeneous resource endowments and institutional capacities. In Morocco, despite concerted efforts toward decentralization and inclusive growth, significant spatial inequalities persist, evidenced by differing regional trajectories in investment, infrastructure, and entrepreneurial activity (Afifi & Ismaili Idrissi, 2025; Ouhakki et al, 2022). This study conducts a spatiotemporal analysis of the Moroccan regions' economic and entrepreneurial performance by integrating TOPSIS and spatial autocorrelation techniques. TOPSIS will rank regions in terms of their economic and entrepreneurial efficacy, while spatial autocorrelation diagnostics will elucidate whether high-performing regions tend to cluster and whether similar patterns persist over time. This dual approach aims to yield both normative rankings and a richer understanding of spatial inequality dynamics, providing meaningful insights for policymakers seeking balanced regional development. Since 2015, Morocco has adopted a new administrative structure comprising twelve regions instead of sixteen, each with financial and governance autonomy, as part of its advanced regionalization plan to promote a political solution to the Western Sahara conflict (Zoubir, 2018). This new structure aims to ensure balanced development, reduce regional disparities, and address the unequal distribution of natural resources and demographic density by investing in local infrastructure and projects tailored to each region's unique characteristics, priorities, and economic potential. Casablanca-Settat, the country's economic heart, a major financial center, home to the largest port and numerous international companies, and a hub of industries like manufacturing, textiles, automative and aeronautics, in addition to services like banking, finance, telecommunications, and trade are predominant here, besides nearshore facilities, nevertheless, the essor of agriculture is remarkable in the plains of Chaouia, around Settat city. Rabat-Salé-Kénitra, while hosting Rabat city, the political and administrative capital of Morocco, benefits from government services, international organizations, and a growing tech sector, as well as manufacturing, logistics, and the development of new industrial zones, besides remarkable infrastructure. Tanger-Tetouan-Al Hoceima is a key industrial and logistical hub, thanks to the Tangier-Med port, one of Africa's largest ports. The region is also seeing growth in the automotive, aerospace, and electronics sectors, besides tourism, agriculture, and some light industries. Marrakech-Safi: when Marrakech city is a major tourist destination, it drives growth in hospitality, real estate, and services in Marrakech-Safi. Safi is well known for its phosphate industry and fishing activities. The region is benefiting from the first portion of arable lands at the national level. Beni Mellal – Khenifra heavily depends on agriculture, which is the backbone of the region's economy. The major crops in this region include cereals, beetroot, olives, citrus fruits, and pomegranates, and it hosts 44% Morocco reserves among 70% of the world's known phosphate rock reserves, making it the leading global supplier of this essential agricultural resource (Walan et al., 2014). Fès-Meknès: Fès is an important cultural and educational center with a growing tourism sector. Meknès is known for its historical sites, agriculture, and emerging industrial activities. The region also has a strong agriculture base especially in vine-growing. Souss-Massa, where Agadir, the main city, is a key region for agriculture, particularly citrus fruits and vegetables. It is also a popular tourist destination and has significant fishing and processing industries. The Oriental-Rif region benefits from cross-border trade with Algeria, despite political tensions. it is also developing its mining and renewable energy sectors. Drâa-Tafilalet is known for its mining resources, and a growing tourism industry focused on its desert landscapes and historical sites. Its strengths lie in high-potential sectors such as tourism, anchored by iconic desert and cultural sites, and renewable energy, notably the Noor Ouarzazate solar complex, hence, the region also benefits from niche agricultural products like dates and saffron, which can support value-added exports. The southern regions of Laâyoune-Sakia El Hamra, Guelmim-Oued Noun and Dakhla-Oued Ed-Dahab, are seeing significant investments in renewable energy, fisheries, and phosphates. Together, they embody a key aspect of Morocco's broader strategy to integrate sub-Saharan Africa (SIMIC, 2023), and to boost for a political solution of the Western Sahara conflict by the economic lever. Figure 1 maps the Moroccan regions under the updated 2015 administrative division.

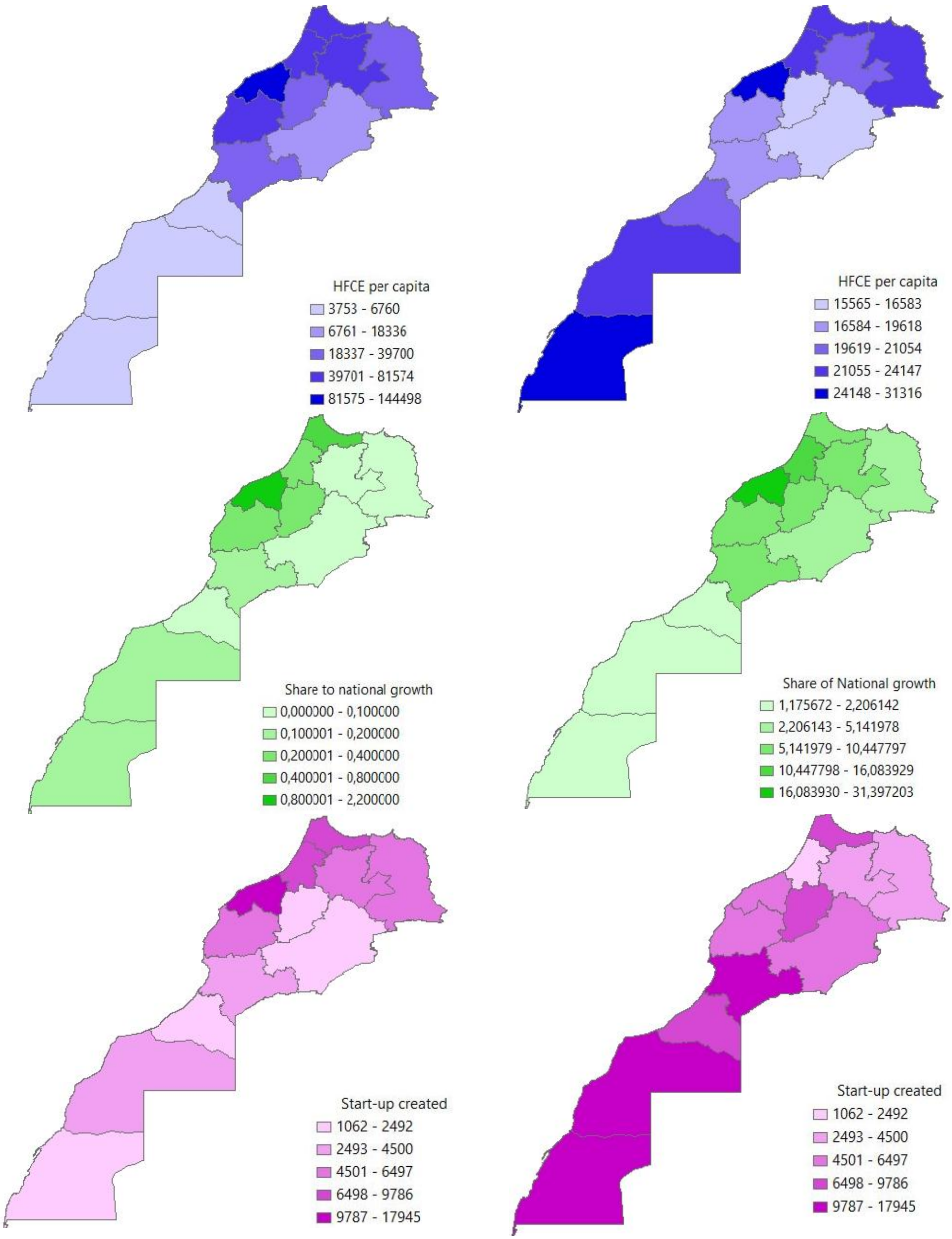
Figure 1: The administrative division of the twelve Moroccan regions

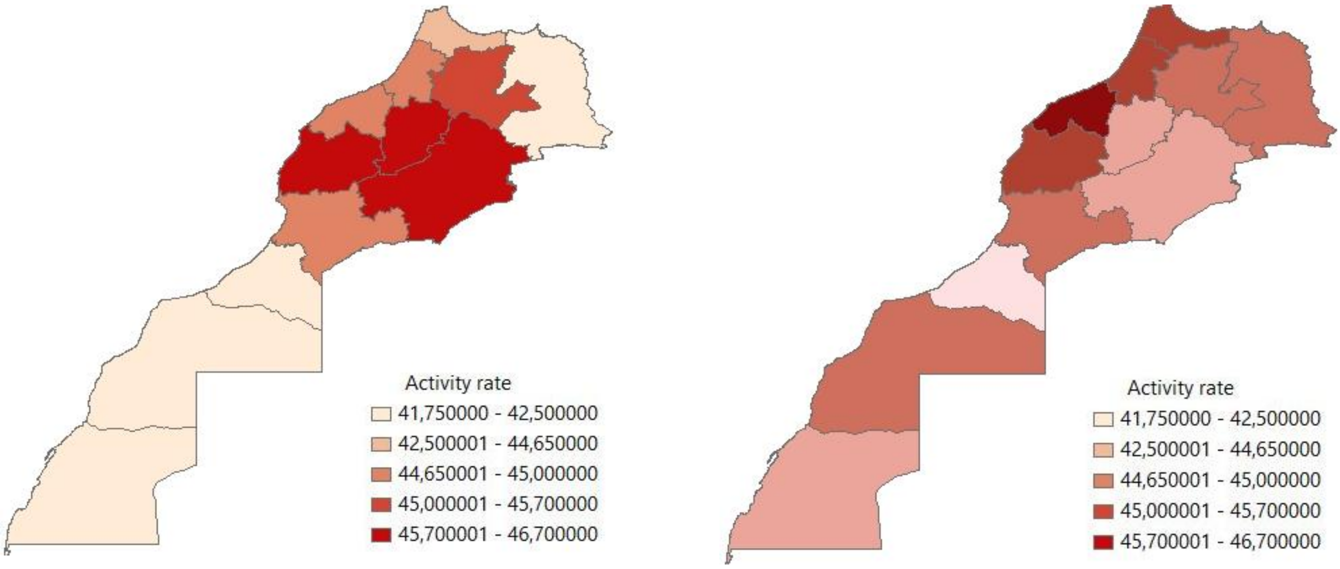
Source: Arcmap10.4 outputs based on official administrative division (Law 47-96 reform of 2015).

As shown in Figure 1, Morocco's largest regions by surface area are mostly in the south. Dakhla-Oued Ed-Dahab and Laâyoune-Sakia El Hamra, mostly deserted, dominate the list, each covering around 140,000 km², followed by Drâa-Tafilalet with nearly 89,000 km² and the Oriental region with about 83,000km². Further north, the regions get smaller: Souss-Massa has roughly 54,000 km², Béni Mellal-Khénifra around 28,000, and Marrakech-Safi and Fès-Meknès are just above 39,000 and 40,000 km² respectively. The most compact regions are Tanger-Tétouan-Al Hoceïma, Casablanca-Settat, and Rabat-Salé-Kénitra, each under 20,000 km², concentrated in Morocco's densely populated Atlantic and Mediterranean corridors. Figure 2 illustrates the evolution of the five regional macroeconomic aggregates from 2015 to 2022. The 2015 aggregates are presented on the left, and the 2022 ones are on the right, with a map key underneath each time.

Figure 2: Evolution of the economic-entrepreneurial performances of Moroccan regions




HFCE per capita
3753 - 6760
6761 - 18336
18337 - 39700
39701 - 81574
81575 - 144498
HFCE per capita
15565 - 16583
16584 - 19618
19619 - 21054
21055 - 24147
24148 - 31316
Share to national growth
0,000000 - 0,100000
0,100001 - 0,200000
0,200001 - 0,400000
0,400001 - 0,800000
0,800001 - 2,200000
Share of National growth
1,175672 - 2,206142
2,206143 - 5,141978
5,141979 - 10,447797
10,447798 - 16,083929
16,083930 - 31,397203
Start-up created
1062 - 2492
2493 - 4500
4501 - 6497
6498 - 9786
9787 - 17945
Start-up created
1062 - 2492
2493 - 4500
4501 - 6497
6498 - 9786
9787 - 17945



Source: Arcmap10.4 outputs based on authors own computations

As shown in Figure 2, in 2015, the economic and entrepreneurial performances of Moroccan regions were steadily concentrated in the northern, western, and central regions, while the southern regions remained relatively marginalized. However, over the eight years, these regions underwent a progressive evolution, ultimately catching up with the northern regions in all indicators by 2022.

2. Literaure review

Without delving in the evident correlation between economic growth and development, the relationship between entrepreneurship and economic development is complex, but it is generally agreed that entrepreneurship plays a crucial role in driving economic growth and development. Entrepreneurship drives innovation, job creation, and economic growth by creating new businesses and jobs, generating innovation, and stimulating competition, which contributes to a more productive and efficient economy (Wennekers, 2010). Empirically, entrepreneurship has an overall positive effect on economic development, although the relationship is U-shaped, with entrepreneurship initially declining but then reviving as economies grow (Piotr & Rekowski, 2008). Studies on Morocco’s territorial economy consistently reveal persistent spatial disparities in economic and entrepreneurial performance. Boumahdi and Zaoujal (2023) highlight that Morocco’s regions differ markedly in labor market conditions, human capital, innovation, and infrastructure, with the coastal and urbanized areas outperforming interior and southern regions. Such disparities persist despite national efforts toward decentralization and regional development.

Kattabi et al. (2025) confirm the existence of a convergence process of regional disparities in Morocco, indicating that specific economic variables positively influence regional development. Word bank Policy-oriented reports from reinforce this picture, all underscore reducing social and territorial inequalities as a core objective of Morocco’s development agenda. Structural factors, such as water scarcity, rural–urban divides, and the concentration of industrial agglomerations, are frequently cited as major contributors to uneven regional performance (Malouche & Partow, 2019).

From an entrepreneurship perspective, the Moroccan ecosystem has been improving but remains geographically concentrated. The 2025 Global Startup Ecosystem Index places Morocco in a competitive regional position, yet entrepreneurial activity, financing, and incubation are still largely clustered in Casablanca-Settat, Rabat-Salé-Kénitra, and Tanger-Tétouan-Al Hoceïma and together, they provide employment to 73% to the labor force (Robichaud et al., 2023). Public programs and initiatives like Technopark, Maroc PME and InnovInvest aimed at fostering entrepreneurship, the spread of entrepreneurial activities into less developed regions remains limited due to fragmented support mechanisms and investor risk aversion (Ghaziri, 2022; Robichaud et al., 2023). Furthermore, fragmentation in support mechanisms and investor risk aversion as barriers to diffusion into lagging regions (Frese and

De Kruif, 2000). This, and the urgent need for territorial development balances, and equitable wealth distribution are the main motivations behind this administrative distribution, knowing that 60% of Morocco's GDP emerge from three regions (Kattabi et al., 2025). This hub underscores the need for integrated approaches that combine composite performance ranking with spatial diagnostics for relevant policies taking. Methodologically, To comprehensively assess these disparities, it is essential to deploy methods that capture both the relative comparative performance of regions and the spatial structures underlying their development. MCDM such as TOPSIS method enable the ranking of regions based on multiple economic and entrepreneurial indicators. Meanwhile, spatial autocorrelation measures, like Moran's I and Local Indicators of Spatial Association reveal the clustering patterns and spatial dependencies that often escape purely non-spatial evaluation (Hirobe, 2014; Martinho, 2018; Akbaşoğullari & Duran, 2020; Chairat & Pechsong, 2020: Manaeva & Tkacheva, 2021; Manaeva et al, 2021). Multi-criteria decision-making (MCDM) techniques have become standard for synthesizing diverse regional indicators into composite performance scores *(*Ziāril *&* Mohammadi , 2016*)*. The TOPSIS method introduced by Hwang and Yoon (1981) ranks alternatives based on their proximity to an ideal and anti-ideal solution, offering transparency and comparability over time. Subsequent refinements, such as improved normalization procedures, have increased its robustness for regional benchmarking (Sarraf et al., 2013). It started to be used in scarcely in the fields of managements and economics with Karimi et al. (2009) who examined the location decision for FDI in ASEAN countries, with Sait (2011) who applied TOPSIS and WSA (Weighted Sum Approach) in analysis of economic activities of European Union States and candidate countries.

Complementing MCDM approaches, spatial autocorrelation techniques provide valuable insights into the geographic structure of performance. Anselin's (1995)' LISA framework allows detection of high–high and low–low clusters, as well as spatial outliers, while extensions by Chen. (2022) improves its adaptability to spatiotemporal datasets. In Moroccan applications, spatial econometrics has been employed to analyze regional convergence and inequality (Afifi & Ismaili Idrissi, 2025), consistently showing that economic performance exhibits significant spatial dependence. Several regional performance studies have combined MCDM approaches and spatial autocorrelation methods to evaluate macroeconomic aggregates in different national contexts. For example, (Yorulmaz et al., 2021) applied a based-TOPSIS to rank Turkish provinces by economic development using GDP, employment, and investment indicators, revealing persistent east–west disparities. In China, (He & Liu, 2022) integrated TOPSIS with Moran's I to assess provincial competitiveness, showing significant spatial clustering of high-growth regions along the eastern seaboard. In Spain, López-Bazo et al. (2002 used Moran's I autocorrelation for analyzing the regional distribution of unemployment, highlighting the geographic persistence of macroeconomic inequalities. In Morocco, Afifi and Ismaili Idrissi (2025) applied Principal Component Analysis (PCA) and Exploratory Spatial Data Analysis (ESDA), to the 12 regions from 2015 to 2022, to reveal the existence of spatial autocorrelation for GDP and the agricultural sector, and to show that industry has a greater impact on economic growth than agriculture, highlighting a strong heterogeneity in the distribution of wealth in Morocco. These studies demonstrate the methodological value of pairing multi-criteria rankings with spatial diagnostics to capture both the relative performance of regions and the geographical structure of economic disparities.

Research gap: While previous studies have addressed regional disparities and applied either MCDM or spatial statistics, few have integrated TOPSIS with spatial autocorrelation to assess regional economic–entrepreneurial performance in Morocco under the new administrative division. This integration enables both ranking of regional competitiveness and detection of spatial clustering patterns, offering richer policy-relevant insights. On this basis, in order to measure the economic and entrepreneurial performances of Moroccan regions, the following hypotheses are posed:

H_1: The twelve Moroccan regions have an equal economic and entrepreneurial performances

H_2: There is a spatial autocorrelation between these regions with regard to H_1

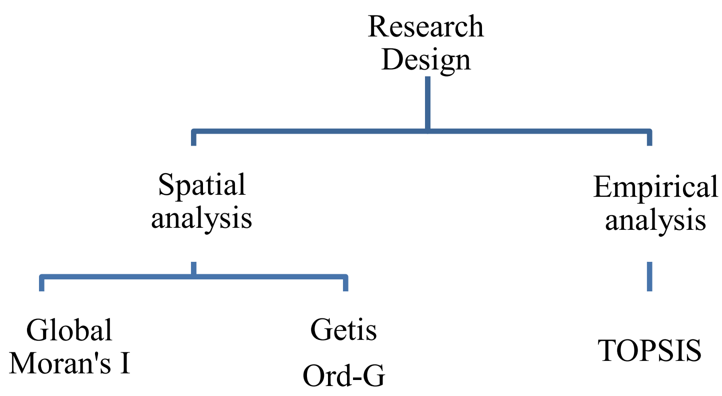
3. Methods and data

3.1. Methodology

This research is designed upon the TOPSIS method for empirical analysis, the Getis-Ord General G, the Global and Local Moran's I methods for spatial analysis, all over the period from 2015 to 2022.

The following Scheme 1 represents this methodology in a chart-flow

Scheme 1: Research design



Source: Author own computation

3.2. Data collection

The TOPSIS method is conducted based on five criterions: regional per capita GDP and HFCE (householders final consumption expenditure), both in MAD (Moroccan dirham), the contribution of each region to the national growth in percent; the number of startups created; the regional activity rate (100-unemployment rate) to total labor force.

This data has been retrieved from Moroccan statistics office, Morocco open data, and Moroccan entrepreneurship barometer.

3.3. The TOPSIS method

Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) is a tool for establishing order preference by similarity to the ideal solution, which was developed by Hwang and Yoon (1981) and Lai et al. (1994) for dealing with real-valued data. Currently it becomes one of the most popular methods for MCDM. The principle of TOPSIS is quite simple; the selected best alternative should have the shortest distance from the positive ideal solution and the greatest distance from the negative one in the geometrical (Euclidean) sense, in other words, the ideal alternative solution has the best level of all attributes considered, whereas the negative ideal solution is the one with the worst attribute value. There are three main advantages in this method: it's a practical tool incarnated by mathematical simplicity and high flexibility in the definition of the choice set. Hung and Chen (2009) listed three advantages of TOPSIS: simple, rationally comprehensible concept, good computational efficiency, and its ability to measure the relative performance for each alternative in simple mathematical form. Hence, it offers a marge of subjectivity regarding the possibility of weighting each criterion following the researcher desire.

The TOPSIS is expressed in a succession of six steps as suggested (Jahanshahloo et al., 2008).

- Step 1: Construction of the normalized decision matrix

The normalized decision matrix converts different criteria units into comparable scales. Each element r_{ij} is calculated as:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \quad (1)$$

Where, x_{ij} is the performance value of alternative ii under criterion j, and m is the number of alternatives. This ensures all criteria are unitless and comparable.

- Step 2: Construction of the weighted normalized decision matrix

Multiply each normalized value r_{ij} by its criterion weight w_j:

$$v_{ij} = w_j \cdot r_{ij} \quad (2)$$

Where, w_j is the weight of criterion j with the sum of all weights is equal to 1. This incorporates the relative importance of each criterion.

- Step 3: Determination of the Positive Ideal Solution (PIS) and Negative Ideal Solution (NIS)

While the positive ideal solution represents the best case, the negative one presents the worst:

$$V^{+} = \{v_1^{+}, v_2^{+}, \ldots, v_n^{+}\}, v_j^{+} = \max v_{ij} \text{ (benefit)}, \min v_{ij} \text{ (cost)} \quad (3)$$

$$V^{-} = \{v_1^{-}, v_2^{-}, \ldots, v_n^{-}\}, v_j^{-} = \min v_{ij} \text{ (benefit)}, \max v_{ij} \text{ (cost)} \quad (4)$$

For benefit criteria, higher values are better, and for cost criteria, lower values are better

- Step 4: Calculation of the separation measures

Compute the Euclidean distance of each alternative from the PIS (S_i^{+}) and NIS (S_i^{-}):

$$S_i^{+} = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^{+}\right)^2} \quad (5)$$

$$S_i^{-} = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^{-}\right)^2} \quad (6)$$

Distance measures quantify how far each alternative is from the ideal and anti-ideal solutions.

- Step 5: Estimations of the Relative Closeness (RC) to the ideal solution

Relative closeness of each alternative to the PIS is:

$$RC_i = \frac{S_i^{-}}{S_i^{+} + S_i^{-}} \quad (7)$$

Where, $0 \leq RC_i \leq 1$, the more is higher RC_i , the more its closer to the ideal solution

- Step 6: Ranking the alternatives

Alternatives are ranked based on RC_i in descending order, where:

$$\text{Rank}_i = \text{position of } RC_i \text{ in descending order}$$

Alternative with highest RC_i gets the first rank, and alternative with lowest RC_igets the latest

3.4. Global and local Moran's I

The Global Moran's I measures the degree to which a set of spatial features and their associated data values tend to be clustered together in space (auto-correlation). Its (Anselin, 1995)' formulas are as following, in line with (Abdulhafedh, 2017):

$$I = \frac{N}{W} \cdot \frac{\sum_{i=1}^{N} \sum_{j=1}^{N} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{N} (x_i - \bar{x})^2} \quad (8)$$

Where, N is the number of features, x_i the attribute value at location I, $\bar{x}$ the mean of the attribute, w_{ij} the spatial weight between feature i and feature j, which captures spatial relationship, such as adjacency or distance decay, $W = \sum_{i=1}^{N} \sum_{j=1}^{N} w_{ij}$ is the sum of all spatial weights ($\Sigma_i \Sigma_j w_{ij}$), which defines the closeness or influence between spatial units i and j.

The local Moran's I for local distribution can be calculated as:

$$I_i = \frac{(x_i - \bar{x})}{m_2} \sum_{j=1}^{N} w_{ij}(x_j - \bar{x}) \quad (9)$$

Where, x_i is the attribute value at location I, and w_{ij} is the spatial weight between i and j, while

$$m_2 = \frac{1}{N} \sum_{k=1}^{N} (x_k - \bar{x})^2 \quad (10)$$

The inverse distance weight approach sets:

$$w_{ij} = \begin{cases} \frac{1}{dij}, i \neq j, and\ dij \succ 0 \\ 0, i = j \end{cases} \quad (11)$$

Where, d_{ij} is the Euclidean distance between locations i and j, and diagonal elements are zero since a location does not exert spatial influence on itself.

However, while inverse distance is better for continuous spatial processes such as potential markets, migration, cross-borders diffusion, large distances can yield very small weights, which may require row-standardization, as in this study:

$$w_{ij}^{*} = \frac{w_{ij}}{\sum_{j=1}^{N} w_{ij}} \quad (12)$$

Row-standardization ensures the total influence from all neighbors for each unit sums to 1.

For both Global and Local Moran's I, it is calculated a Z-score related to a p-value based on the null hypothesis of spatial randomness, under a distance-based weight defined as the inverse distance between locations i and j (Cliff and Ord. (1975), its formula is:

$$z(I) = \frac{I - E[I]}{\sqrt{Var(I)}} \quad (13)$$

where E(I) is the expected value of I, and V(I) is the variance of I, with the following specifications $E[I] = -\frac{1}{N-1}$ (14)

$$Var(I) = E[I^2] - (E[I])^2 \quad (15)$$

If the Global Moran's I value is larger than E(I) at a chosen significance level (often $\alpha=0.05$) or the correspondent z score is higher than the critical value, it means positive spatial autocorrelation, meaning that features are clustered and if it is less than E(I), or the correspondent z score is lower than minus critical value, it indicates negative spatial autocorrelation, meaning that features are dispersed, when Global Moran's I is insignificant, this refers to random pattern.

Values for Local Moran's I range from −1 to +1, where a value of −1 indicates negative spatial autocorrelation, and a value of +1 indicates positive spatial autocorrelation.

3.5. Getis-Ord General G

The Getis-Ord G statistic is calculated with respect to a specified threshold distance instead of the inverse distance, as with the Moran's I.

The threshold distance is the maximum separation at which two observations are still considered neighbors in Moran's I calculation, and it's typically chosen to guarantee connectivity of the spatial network. its formula as reported (Getis & Aldstadt, 2004) is:

$$G = \frac{\sum_{i=1}^{N} \sum_{j=1}^{N} w_{ij} x_i x_j}{\sum_{i=1}^{N} \sum_{j=1}^{N} x_i x_j} \text{ (usually with } w_{ii} = 0\text{) (16)}$$

Where x_i is the attribute value at location i, x_j, is the attribute value at location j and w_{ij} is the spatial weight between features i and j. If high values are near other high values, the G statistic increases. and if low values are near other low values, the G statistic decreases. All things are equal.

Under a typical randomization null hypothesis (values randomly permuted among locations):

The expected value specification is

$$E[G] = \frac{\sum_i \sum_j w_{ij}}{N(N-1)} \text{ assuming } w_{ii} = 0 \text{ (17)}$$

$$z(G) = \frac{G - E[G]}{\sqrt{\mathrm{Var}\,(G)}} \quad (18)$$

Where Var(G) is the variance of G under the null hypothesis of random distribution across space.

If the is a positive z, this means a clustering of high values.

If the is a negative z, this means a clustering of low values.

In sum, while Global Moran's I is used measure the intensity of regional autocorrelation, Local Moran's I allows for a spatial distribution on a local regional scale, meantime, the Getis-Ord General G measures the degree of clustering of high or low values across the entire study area.

4. Results

4.1. Empirical evidence

The six steps of the TOPSIS method are illustrated through the 2015 observations and presented in six corresponding tables, following the six steps explained in the Methods subsection above.

Following table 1 represents the 2015 regional dataset.

Table 1: The 2015' regional dataset for the TOPSIS method

Region	GDP per capita	HFCE per capita	Share to national Growth	Regional startups created	Regional activity rate
Tanger-Tétouan Hoceima	99073	66018	0,8	9101	44,65
Oriental-Rif	47429	38495	0,1	5672	42.5
Fès Meknès	89118	63788	0	6071	45.7
Rabat-Salé- Kénitra	158317	81574	0,4	9786	45
Béni Mellal Khénifra	57806	30855	0,3	2492	46.7
Casablanca Settat	317415	144498	2,2	17945	45
Marrakech-Safi	87888	62323	0,3	6497	46.3
Drâa-Tafilalet	25496	18336	0	1572	46.4
Souss-Massa	64908	39700	0,2	4500	44.95
Guelmim- Oued Noun	13100	6741	0,1	1572	41.75
Laâyoune- Saguia Al Hamra	15075	6760	0,2	3290	41.75
Dakhla Oued Eddahab	10926	3753	0,2	1062	41.75

Source: Moroccan statistics office, Morocco open data, Moroccan entrepreneurship barometer

Table 1 show that the Casablanca-Settat region is ranking first for all the 2015 observations related to the five indicators used in testing Moroccan regions performance, excepted for activity rate which comes in secondary positions, in fact the economic capital of the country is suffering from high demographic density which obstruct the full employment of its local active population although the economic prosperity it is witnessing since decades, on the other hand it is remarkable that the southern regions are the less rated among the regions of Morocco, mainly because of low demographic intensity, which is correlated to general economic under-scoring performance.

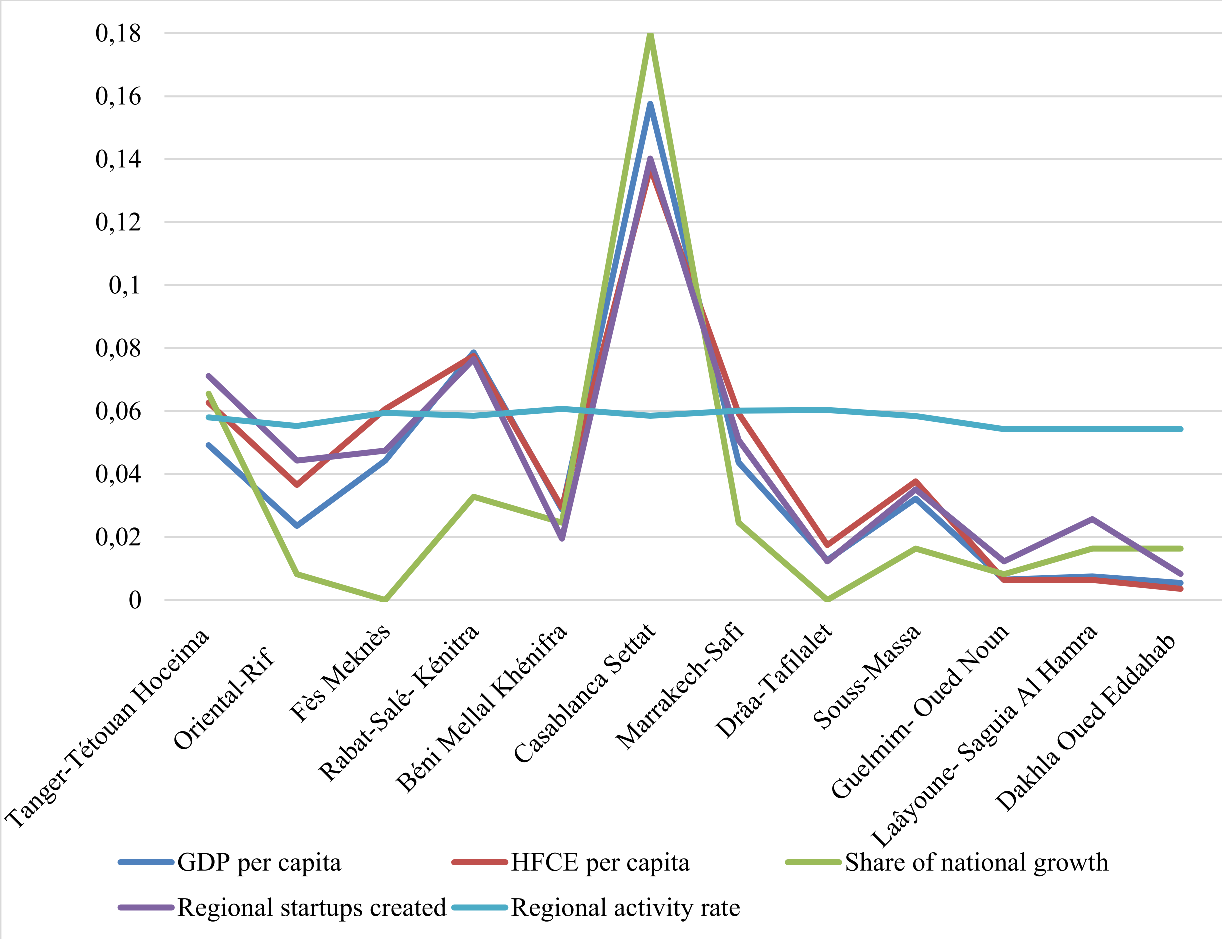
Drâa-Tafilalet and the southern regions of Guelmim- Oued Noun, Laâyoune- Saguia Al Hamra, and Dakhla Oued Eddahab, have the lowest scores, primarily due to underdevelopment issues, hard climate condition, low-value farming, limited tourism, weak infrastructure and services, low investment, and youth out-migration.

As the represented observations in Table 1 are heterogeneous and expressed in different order of scales, it was necessary to normalize the decision matrix before applying the TOPSIS method.

After a discrete uniformization of Table 1 data in the same scale of [0-1] order using the sum-based method formulated in the research design section, step 1, comes the second step of attributing an estimated weight to each singular criteria represented in reflect of the importance of each one in the general study scheme, in this matter, we have decided to attribute equal weight proportion to each indicator by multiplying each related observation from the normalized decision matrix by 0.2 considering that all criterion have the same importance degree in our study.

The multiplication' products forming the weighted matrix are represented in Figure 3 below.

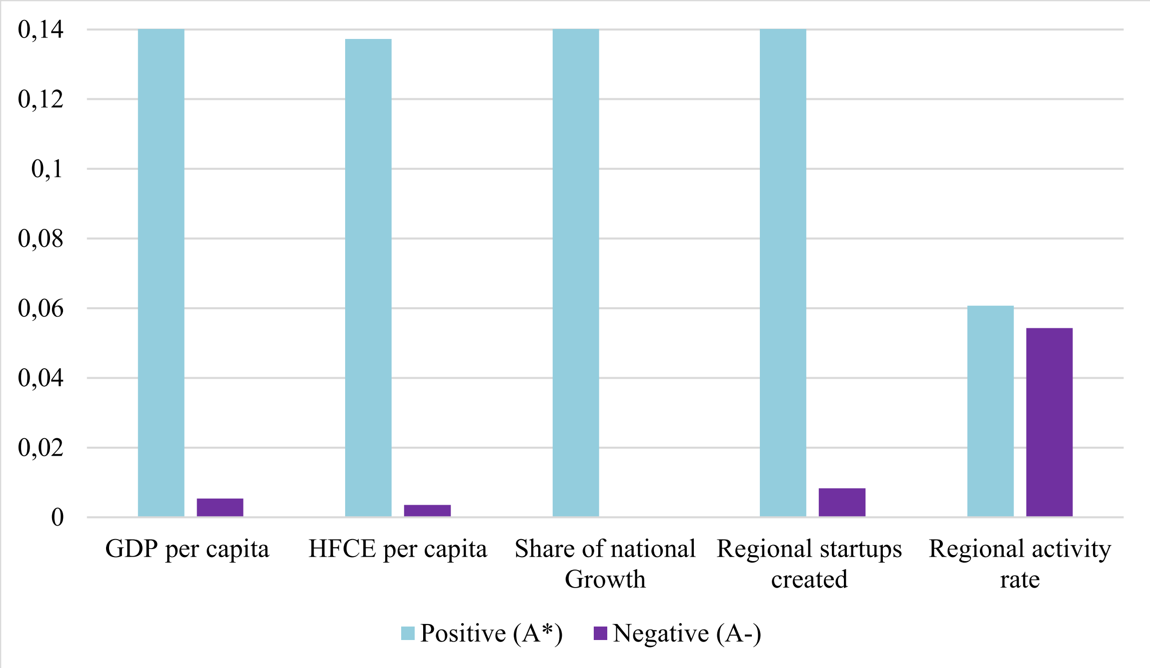
Figure 3: The weighted normalized decision matrix of the TOPSIS method



Source: Excel outputs based on the author own computations

Figure 3, which is based on Table 1, illustrates the weighted normalized observations diagram, ranking Casablanca-Settat as the top performer for all 2015 observations across the five indicators used to assess Moroccan regions, while the Southern regions consistently rank lowest. However, the weighted normalized activity rate observations for the twelve regions show a noticeable stagnation. The ideal positive and negative solutions generated results are represented in Figure 1 below.

Figure 4. Ideal solutions in both directions of the TOPSIS method

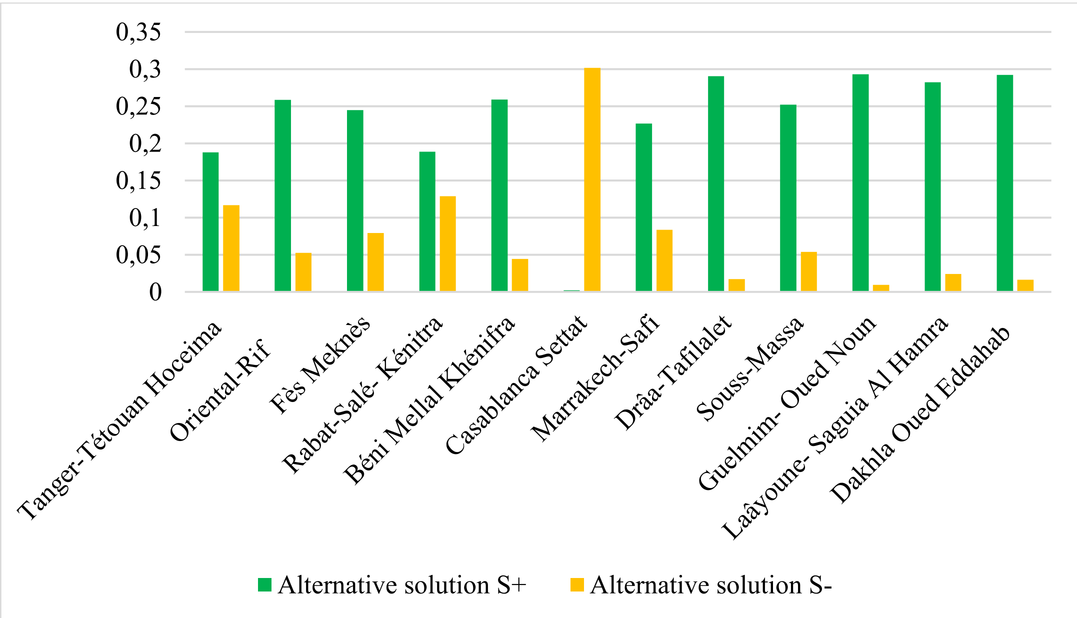


Source: Excel outputs based on the author own computations

Figure 4 above represented the resulted ideal solutions of each criterion in both directions, the best measures are represented by A^+, the worst measures by A^-.

Based on, the respective measures of separation of each alternative from the positive ideal solution (S^*) and the negative ideal solution (S^-) above are presented in the following Figure 5.

Figure 5. The TOPSIS 'measures of separation of each alternative solution

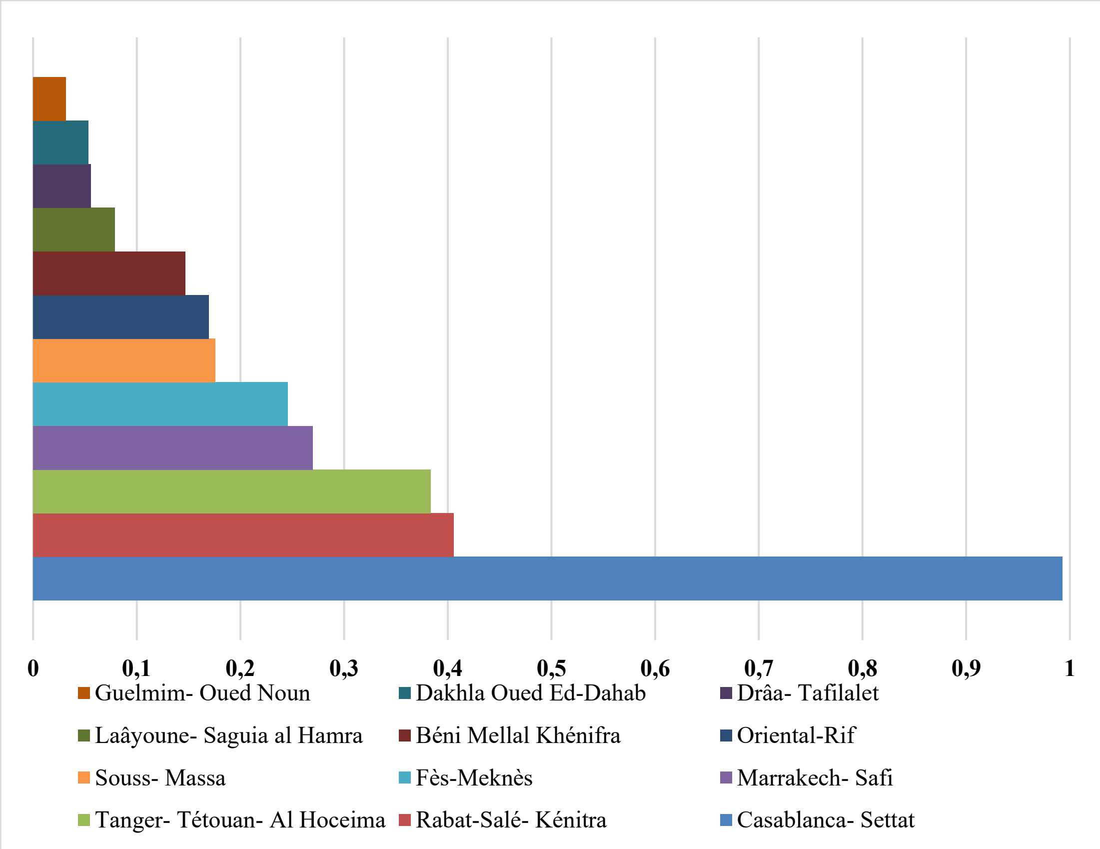


Source: Excel outputs based on the author own computations

As shown in Figure 5 above, the measures of separation, with the shortest distances to the positive ideal solutions (S^+) are considered as the best measures, and the longest distances from the negative ideal solutions (S^-) are considered as the worst measure attribute to the region of Casablanca-settat first, the shortest positive ideal solutions (S^+), and the longest negative ideal solution (S^-), and the southern regions, in addition to Deraa Tafilalet manifest exactly an opposite trend.

Based on, the following Figure 6 below retrace the 2015 final ranking based on the Relative Closeness (RC) coefficient represented on the horizontal axis:

Figure 6: The 2015 final ranking based on Relative Closeness (RC) of the TOPSIS method



Source: Based on the author own computations

Based on the RC in Figure 6 above, under the decision rule which stipulate that the more RC is high, the best the related region is placed in the ranking, vise-versa. For instance, as the region of Casablanca-Settat detains the highest RC for 2015, it is tributary to be firstly ranked, conversely to the region of Guelmim-Oued Noun, which comes last for having the less underscored performance.

Applying the same methodology to the remaining years of the study period yields the final ranking, shown in Table 2 below.

Table 2: The final ranking of the TOPSIS method over the period [2015-2022]

Region	2015	2016	2017	2018	2019	2020	2021	2022
Tanger- Tétouan- Al Hoceima	3	2	3	2	2	6	3	3
Oriental-Rif	7	8	6	7	7	7	7	8
Fès-Meknès	5	6	5	6	5	4	4	4
Rabat-Salé- Kénitra	2	3	2	3	3	2	2	2
Béni Mellal Khénifra	8	11	7	8	6	5	8	7
Casablanca- Settat	1	1	1	1	1	1	1	1
Marrakech- Safi	4	4	4	4	4	12	5	5
Drâa- Tafilalet	10	12	10	10	8	10	10	11
Souss- Massa	6	5	8	5	9	11	6	6
Guelmim- Oued Noun	12	9	11	11	11	8	12	9
Laâyoune- Saguia al Hamra	9	7	9	9	10	3	9	12
Dakhla Oued Ed-Dahab	11	10	12	12	12	9	11	10

Source: Excel outputs based on authors own computations

As shown in Table 2 above, the region's final ranking has exhibited a noticeable stagnation throughout the entire period of study, indicating a relatively stable territorial hierarchy despite economic and social fluctuations at the national level. Casablanca-Settat consistently secures a position among the top twelve performers, a result that reinforces its status as Morocco's undisputed economic capital and primary growth pole, benefiting from its diversified industrial base, concentration of financial institutions, and role as the country's main hub for trade and services. Immediately following are the regions of Tanger–Tétouan–Al Hoceima and Rabat–Salé–Kénitra, which frequently alternate their positions across the ranking periods, reflecting the dynamic nature of northern Morocco's manufacturing and logistics activities on the one hand, and the administrative and service-oriented weight of the capital region on the other.

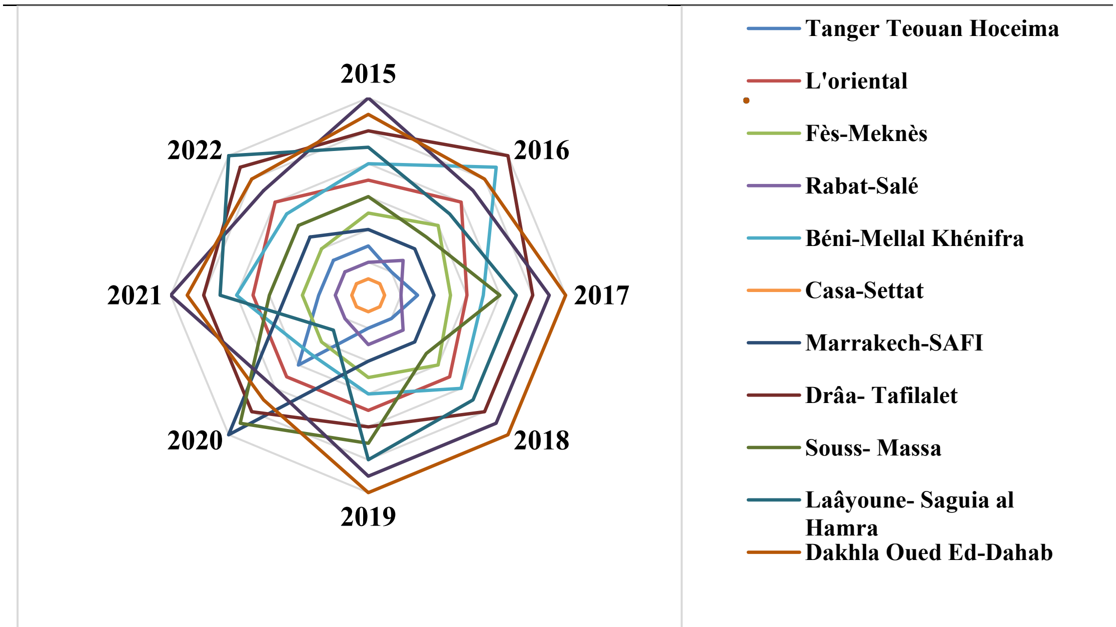
In contrast, the southern regions consistently occupy the lower end of the ranking spectrum, a situation that highlights persistent structural challenges such as limited industrial diversification, lower population density, and weaker infrastructure connectivity compared to the northern and central regions. The remaining regions occupy intermediate positions, with relatively minor movements upward or downward from one period to the next, suggesting modest but steady economic adjustments.

A notable exception is Marrakech-Safi, which experienced a dramatic and sudden decline in 2020, coinciding with the global Covid-19 crisis. The region's economy, heavily reliant on tourism and related services, was severely disrupted by travel restrictions, business closures, and the collapse of international tourist arrivals, leading to a temporary but sharp contraction in its overall performance.

Another important case is the Béni Mellal–Khénifra region, which, over the years preceding 2020, registered a remarkable upward trajectory. This improvement was largely attributable to its buoyant phosphate exports, expansion of the agro-industrial sector, particularly olive oil production, and sustained inflow of remittances from the Moroccan diaspora, which together boosted household consumption and regional investment. However, following the onset of the pandemic and subsequent economic slowdown, the region's ranking dropped by two points, underscoring its vulnerability to external shocks and global demand fluctuations.

Figure 7 below retraces the final ranking results in a graphic radar representation. The closer a region circle is to the radar plot epicenter, the more representative and well-ranked it is, indicating a stronger leader position, better ranking, and a lower radius distance. The lower a region's circle is ranked, the farther it is from the radar epicenter.

Figure 7: Graphic Radar representation of Moroccan regions performance final ranking



Source: Excel outputs based on authors own computation

As shown in the Figure 7 results, Casablanca-Settat consistently occupies the outermost layer for all years between 2015 and 2022. Tanger–Tétouan–Al Hoceima and Rabat–Salé–Kénitra follow closely, alternating their positions from one year to another but remaining near the top throughout the period. Marrakech–Safi remains relatively stable until 2020, when its curve moves sharply inward before slightly expanding again in the following years.

Béni Mellal–Khénifra shows a gradual outward movement from 2015 to 2019, followed by a contraction after 2020. Fès–Meknès, L'Oriental, and Souss–Massa are positioned around the middle of the radar, with slight upward and downward displacements across the years. Drâa–Tafilalet remains closer to the center for the entire period, showing limited variation.

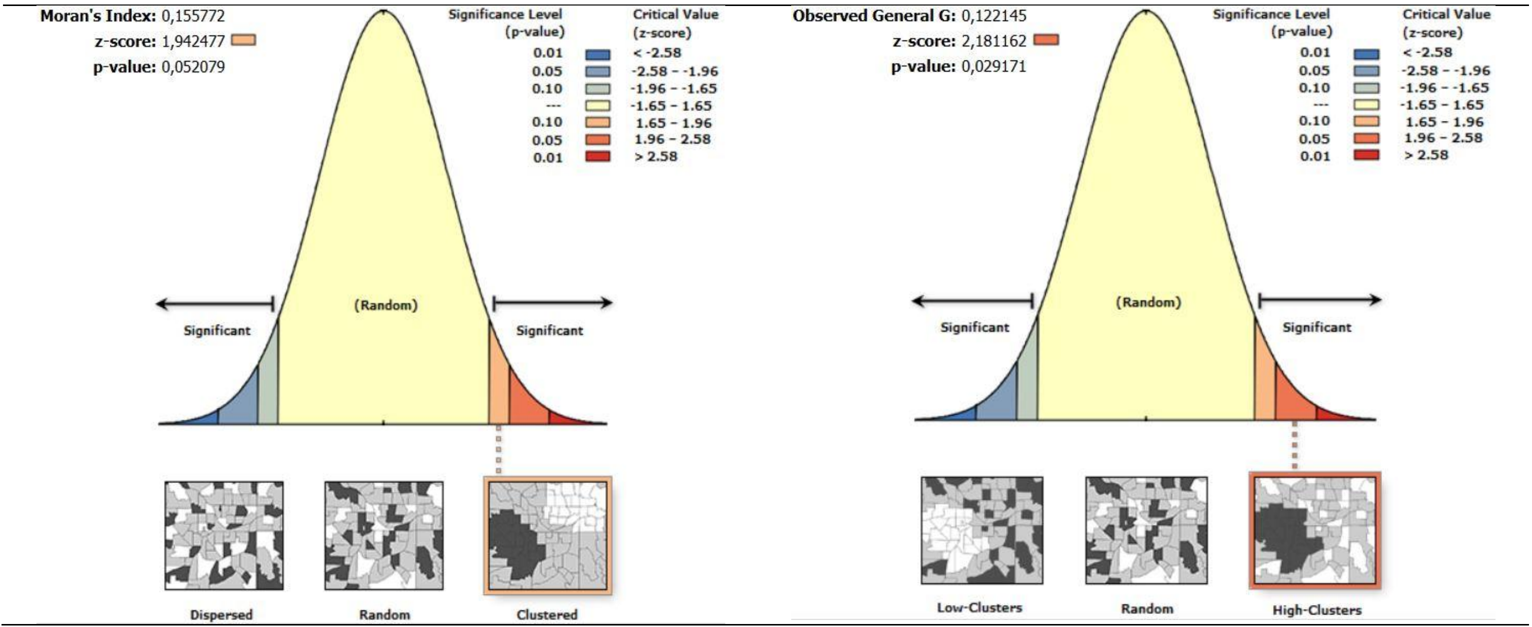
The southern regions, Laâyoune–Saguia al Hamra and Dakhla–Oued Ed-Dahab, display progressive outward shifts over time, with their lines expanding slightly year after year. Overall, the radar shows relatively stable positions for most regions, with only a few noticeable contractions or expansions during the period observed.

4.2. Spatial analysis

The spatial analysis involves three tests: Global Moran's I which measures the intensity and the nature of the regional autocorrelation; Getis-Ord General G test, which identifies the type of clustering present, and the local Moran's I which allows for a localization of these regions in four quadrants of clustering, these tests are illustrated based on GDP per capita for 2015 and 2022.

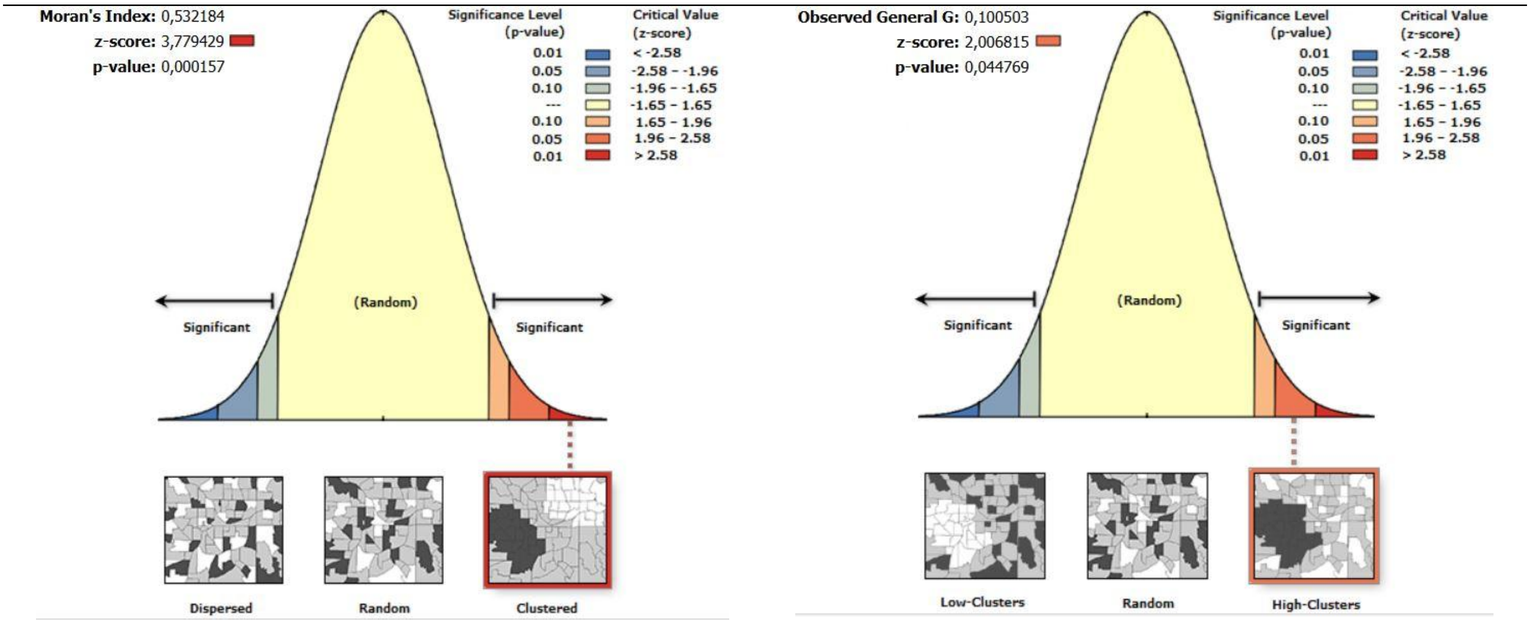
While Figure 8 represents the graphic Global Moran's I and Getis-Ord General G tests outputs for 2015, Figure 9 represents theses outputs for 2022.

Figure 8: The 2015 Global Moran's I and Getis-Ord General G



Source: Arcmap10.4 outputs based on authors own computations

Figure 9: 2022 Global Moran's I and Getis-Ord General G



Source: Arcmap10.4 outputs based on authors own computations

As shown in Figures 8 and 9 above, the respective z-scores of 1.94247681769 and 3.77942902088 of the Global Moran's I tests in 2015 and 2022 indicate a positive spatial autocorrelation, given their positive significant z-score, regions with similar values cluster spatially (high-high or low-low). According to the Getis-Ord General G results from the same figures, for 2015 and 2022, with a respective z-scores of 2.18116187332 and 2.00681504743, there is less than a 5% likelihood that this high-clustered pattern is due to random chance, furthermore, given their high positive z-score, there is clustering of high values (hot spots). Subsequently, neighboring Moroccan regions have a spillover effect on each other.

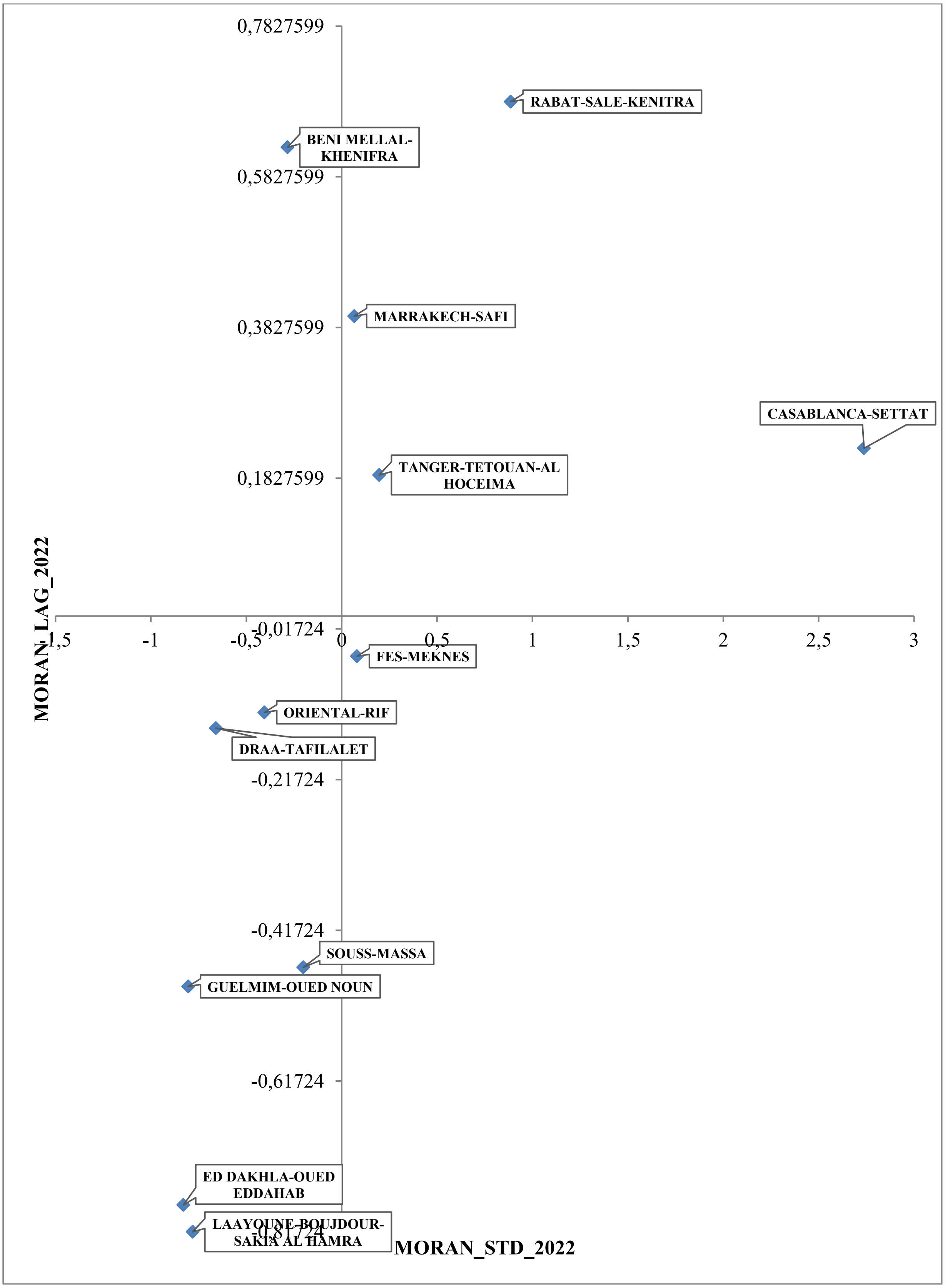
Regarding the four quadrants of Local Moran's I link directly to the values of the statistic at each location. A positive Local Moran's I occurs when a location is similar to its neighbors, which corresponds to diagonal High–High (upper-right) or Low–Low (lower left) quadrants, indicating spatial clustering.

A negative Local Moran's I arises when a location differs from its neighbors, corresponding to High–Low or Low–High outliers.

In this way, the sign and magnitude (z-score) of the Local Moran's I region value indicate both the type (cluster or outlier) and strength of local spatial association.

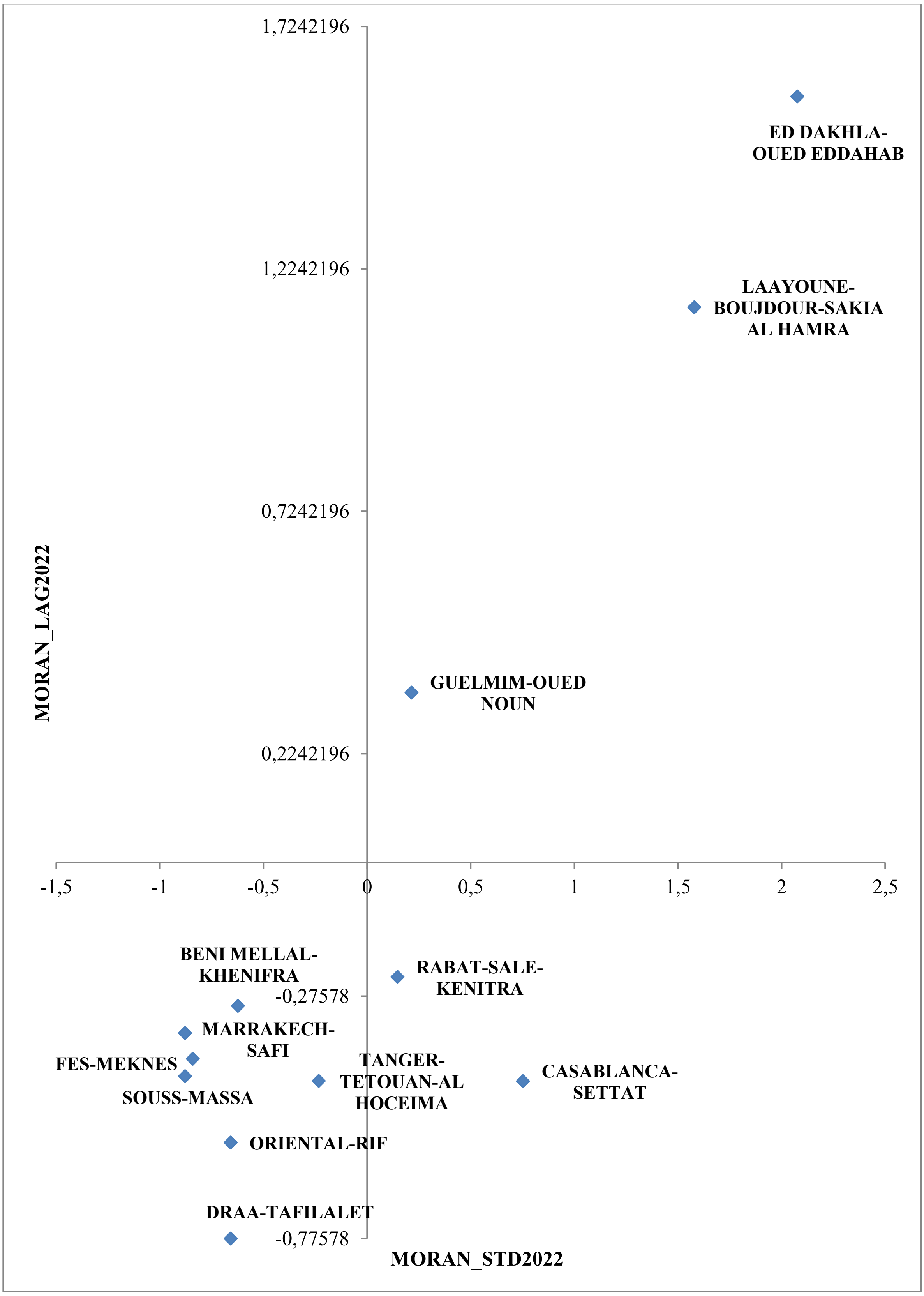
Figures 10 and 11 provide a graphic representation of the local Moran's I spatial distribution of the twelve Moroccan regions, for the years 2015 and 2022, respectively.

Figure 10: The 2015 Local Moran's I distribution of Moroccan regions



Source: QI Macros output based on Global Moran's I results

Figure 11: The 2022 Local Moran's I distribution of Moroccan regions



Source: Qi Macros outputs based on Global Moran's I results

Figure 10 reveals that the top four regions in the 2015 TOPSIS ranking, namely Casablanca-Settat, Rabat Salé Kenitra, and Tangier Tetouan Hoceima, are clustered together in the high-high quadrant, indicating that they have strong economic performance and a significant impact on each other. In contrast, the bottom-ranked regions, including Oriental-Rif-Rif, Drâa-Tafilalet, and the southern regions of Guelmim-Oued Noun, Laâyoune-Saguia al Hamra, and

Dakhla Oued Ed-Dahab, are grouped together in the low-low quadrant, suggesting that they have low economic entrepreneurial performance and affect each other in 2015.

Figure 11 reveals that, in 2022, the southern regions of Guelmim-Oued Noun, Laâyoune-Saguia al Hamra, and Dakhla Oued Ed-Dahab are positioned in the high-high quadrant, indicating that they are experiencing both economic growth and significant interdependence. In contrast, the regions of Casablanca-Settat, Rabat Salé Kenitra, and Tangier Tetouan Hoceima have shifted to the high-low quadrant, remaining clustered whereas the remaining regions have little impact on each other, situated in the low-low quadrant.

The remaining test based on the rest of criterions exhibit similar spatial distribution and the same clustering tendencies throughout the period study, and converge with the TOPSIS method outputs.

5. Discussion, policy implications, limitations and future prospects

5.1. Discussions

The results underscore a persistent hierarchical structure among the twelve regions, revealing a marked path dependency in regional rankings (Martin & Sunley, 2006). The quasi-stagnation in the final ranking suggests that structural economic asymmetries are entrenched, with limited inter-regional mobility in performance despite the rollout of successive national development strategies.

The results provide a comprehensive assessment of these rankings over time, highlighting both persistence and episodic change. Casablanca–Settat consistently occupies the outermost layer across all years, reaffirming its status as the country's primary economic pole, a finding consistent with core–periphery dynamics (Krugman, 1991) and the concentration of productive activity in major metropolitan areas. Its unchanging position underscores the self-reinforcing nature of agglomeration advantages, diversified industrial base, financial centrality, and transport and logistics infrastructure, that sustain its long-term dominance.

The second tier of regions, notably Tanger–Tétouan–Al Hoceima and Rabat–Salé–Kénitra, display alternating but relatively stable trajectories, suggesting a form of regional resilience (Pike et al., 2010). Their intermittent rise in the rankings points to the growing importance of northern coastal corridors, fueled by port expansions such as Tanger Med, foreign investment inflows, and administrative centrality in Rabat's case. The clustering of these coastal regions at the top of both TOPSIS rankings and Moran's I spatial maps highlights the role of positive spatial spillovers and agglomeration economies, where proximity-based effects in infrastructure, investment, and skilled labor mobility reinforce their performance.

In contrast, middle-ranking regions such as Fès–Meknès, L'Oriental, and Souss–Massa exhibit only modest positional shifts across the study period, remaining largely locked in place. This limited mobility resonates with Rodríguez-Pose's (2017) notion of the "revenge of the places that don't matter", where intermediate regions neither collapse nor experience transformative growth, due to structural and institutional inertia. The Oriental-Rif and Drâa–Tafilalet regions consistently remain near the center of the radar, reflecting low GDP per capita, limited industrial activity, weak market integration, and structural constraints such as water scarcity and climate vulnerability that impede competitiveness (Yakubova & Sagaffe, 2019). Persistent out-migration further erodes their human capital base, limiting endogenous development potential.

Marrakech–Safi presents a striking exception in its trajectory: its curve remains stable until 2020, when it experiences a sharp inward contraction coinciding with the Covid-19 pandemic. This drop visually captures the vulnerability of tourism-dependent economies to exogenous demand shocks (Kalaj & Barbullushi, 2023). Its gradual recovery post-2020 suggests partial adaptation, but the region's overall trajectory illustrates the slow adjustment capacity of mono-specialized economies lacking industrial or technological diversification to buffer external crises (Capello et al, 2015).

Similarly, Béni Mellal–Khénifra shows a gradual outward movement from 2015 to 2019, supported by phosphate exports, agro-industrial growth, and remittance inflows, followed by a visible contraction of more than two points after 2020. This reversal underscores the fragility of growth trajectories heavily reliant on volatile global commodity markets and external financial transfers.

The southern regions of Laâyoune–Saguia al Hamra and Dakhla–Oued Ed-Dahab trace progressive outward paths over the study period, indicating incremental improvements. However, their position remains in the lower tier, suggesting that despite targeted investments, peripherality and limited economic diversification still shape their development outcomes.

Taken together, the findings confirm the presence of geographic clustering, with high and statistically significant positive Moran's I values indicating that top-performing regions tend to neighbor other prosperous ones, while lagging regions remain spatially grouped. This spatial polarization aligns with the core–periphery model (Krugman, 1991) and suggests that the territorial distribution of economic dynamism in Morocco is governed by selective convergence (Barro & Sala-i-Martin, 1995): leading regions consolidate their dominance, while a few lagging regions progressively catch up. Nevertheless, the persistence of middle-ranking and low-performing territories implies that territorial inequalities remain a defining feature of Morocco's economic geography, requiring policies that go beyond physical infrastructure provision to address structural drivers of underperformance.

5.2. Policy implications

The persistence of regional hierarchies calls for place-based policies that go beyond infrastructure provision and target productive capacity, skills development, and innovation in lagging regions (Barca, McCann & Rodríguez-Pose, 2012). Leading regions such as Casablanca–Settat, Rabat–Salé–Kénitra, and Tanger–Tétouan–Al Hoceima should be leveraged as growth engines, with stronger supply-chain linkages to hinterland regions to diffuse agglomeration benefits.

Tourism-dependent regions like Marrakech–Safi require economic diversification strategies to reduce vulnerability to shocks, while territories such as Drâa–Tafilalet and the Oriental-Rif need targeted investments in skills, water-efficient agriculture, and entrepreneurial ecosystems to break low-performance traps.

The emerging dynamism of southern regions should be supported through connectivity upgrades, renewable energy projects, and diaspora investment programs to consolidate their role as new growth poles and foster more spatially balanced development.

5.3. Limitations and future prospects

Results can inform region-specific development strategies, equitable resource allocation, entrepreneurship promotion, and spatial regional planning. However, limitations such as the restricted set of indicators, short interval, and methodological constraints suggest future research directions that integrate broader social, environmental, and innovation variables, extend the sample interval, and apply advanced comparative and econometric approaches.

6. Conclusion

The study's integration of TOPSIS, and spatial autocorrelation analysis over the period 2015–2022 provides a multi-dimensional perspective on Morocco's regional economic–entrepreneurial performance. Taken together, these results point to structural and spatial lock-ins in Morocco's regional development. While certain regions such as Casablanca-Settat, and the northern regions have benefited from sustained agglomeration economies, port-led growth, and diversified industrial bases, others remain constrained by geographic isolation, limited economic diversification, and vulnerability to sector-specific shocks. From a policy standpoint, the persistence of such patterns suggests that place-based development strategies, targeting structural transformation in lagging regions, improving interregional connectivity, and fostering economic diversification, are essential to reducing spatial inequalities and unlocking broader national growth potential.

Declarations statement

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