Evaluation of Economic and Green Logistics Performance of African Countries Through Fuzzy Linear Regression and MCDM Approaches

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Abstract— **Logistics performance plays a key role in promoting greener supply chains and reducing the environmental impact of the transport sector, a major source of greenhouse gas emissions. This study analyzes the relationship between the Logistics Performance Index (LPI) and transport-related emissions, while ranking African countries based on logistics efficiency and environmental sustainability. A comprehensive framework is developed using data from the World Bank LPI 2018. A composite Green Logistics Index is proposed to evaluate countries by integrating logistics performance and environmental outcomes. The methodology combines the Entropy Method for objective weighting, the Simple Additive Weighting (SAW) method for performance aggregation, and Peters' Fuzzy Regression to model uncertainty in the relationship between logistics and emissions. The study contributes a country-level assessment of African logistics performance considering economic, operational, and environmental dimensions. It also demonstrates the usefulness of fuzzy linear regression in capturing uncertainty and complex relationships between variables.**

Green supply chain, Logistics performance index, fuzzy regression, MCDM, uncertainty, African countries.

I. Introduction

Logistics encompasses activities such as transportation, storage, customs procedures, and payment management. Efficient logistics is crucial for economic growth, competitiveness, and poverty reduction, as it lowers costs, facilitates trade, and supports development. In contrast, poor logistics increases costs and causes delays, negatively affecting both countries and businesses by reducing productivity and income.

Most existing studies on logistics performance have mainly focused on firm-level benchmarking, its impact on economic growth, and the influence of related policies. In recent years, many researchers have increasingly used the Logistics Performance Index (LPI) as a comprehensive tool for comparing logistics performance across countries. Developed by the World Bank [1], the LPI was the first global indicator specifically created to assess and compare the level of logistics development among nations. It is used not only for benchmarking but also as a strategic tool to identify the strengths, weaknesses, challenges, and opportunities in a country's trade and logistics systems. Together, these factors offer a complete understanding of national logistics performance and influence a country's position in global rankings. LPI rankings are usually based on surveys of logistics professionals. However, recent studies have used advanced multi-criteria decision-making (MCDM) methods to improve and refine these rankings, making the evaluation more structured and objective. For instance, Çakır [2] proposed a novel approach based on Fuzzy linear regression to measure and rank the logistics performance of OECD countries, primarily focusing on logistics costs, overall financial performance, and the economic impact of logistics. Ju et al. [3] developed a methodology based on a combined subjective–objective MCDM approach to rank the LPI of EU countries using the CRiteria Importance Through Intercriteria Correlation (CRITIC), MEthod based on the Removal Effects of Criteria (MEREC), and Fuzzy Range of Value (F-ROV) methods. Moreover, Isik et al. [4] combined the Statistical Variance and Multi-Attributive Border Approximation Comparison (MABAC) methods in an integrated MCDM model to assess logistics performance in 11 Central and Eastern European countries. Özceylan et al. [5] evaluated the logistics performance of Turkish provinces using the Analytic Hierarchy Process (AHP)- Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) and Analytic Network Process (ANP), TOPSIS models, based on 16 geographic and economic indicators In their study, Gürler et al. [6] employed 11 analytical techniques to evaluate the logistics performance of EU countries using 33 indicators grouped into key dimensions, namely economy and growth, trade, trade openness, transport infrastructure, and transport. They proposed a logistics performance assessment framework in which criteria weights were determined using a genetic algorithm (GA). The use of multiple MCDM techniques enhanced the robustness and consistency of the evaluation results. To address missing data, median, mean, linear regression, and k-nearest neighbor (KNN) imputation methods were applied. Among these approaches, linear regression was identified as the most effective imputation technique for the dataset used in the study. Silva [7] applied the CRITIC method to determine objective weights and uses MARCOS, TOPSIS, and Simple Additive Weighting (SAW) to generate alternative rankings. The results show that Finland ranks first in the LPI, however, several countries experience noticeable changes in their positions depending on the weighting scheme adopted. These findings underline the sensitivity of logistics performance assessments to methodological choices and weighting approaches.

Previous studies mainly used the economic, operational LPI and did not properly include sustainability aspects, even though sustainability has become an important priority in logistics. In this context, Starostka-Patyk et al. [8] aimed to clarify key concepts related to green logistics and ecological

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concerns in Europe and, more importantly, to demonstrate the need to combine two existing indexes to develop a new, more comprehensive and universal measure: the Green Logistics Performance Index (GLPI).

Currently, few studies have examined logistics sustainability, which involves simultaneously considering economic efficiency, environmental protection, and social responsibility in logistics activities. Wang et al. [9] extended their concerns to environmental concern. They compared logistics systems across OECD countries using a network DEA method. Their analysis included customs, infrastructure, international shipments, logistics skills, tracking, delivery time, as well as energy use in transport and greenhouse gas emissions.

Research shows a strong link between logistics performance and economic growth. The LPI is widely used to assess countries' logistics systems, often combined with Data Envelopment Analysis and MCDM[10], [11]. However, most studies mainly focus on economic factors, while environmental aspects are less considered. This shows a clear need to include sustainability and green logistics in performance evaluation. In addition, many previous works use subjective weighting methods based on expert judgment, which can lead to bias and less objective results. Therefore, there is a growing need for data-based weighting methods that are more transparent and reliable. [12], [13]. In real decision-making, logistics factors are often linked and not independent. They are also uncertain and unclear, especially when environmental issues are included. In this case, traditional methods based on exact values cannot properly handle this uncertainty and the complex links between criteria.

To address these limitations, this study uses Fuzzy Linear Regression (FLR), which models uncertain and unclear relationships between logistics performance and sustainability factors. Unlike standard regression methods, FLR captures fuzzy relationships and allows criteria importance to be estimated based on their fuzzy effects instead of fixed values [14], [15]. This makes the model more realistic and flexible for complex logistics systems under uncertainty, and improves the reliability of the evaluation.This approach provides a more realistic and flexible representation of complex logistics systems operating under uncertainty, thereby improving the robustness of the evaluation process.

The main objective of this research is to fill an important gap in logistics performance assessment by combining the Logistics Performance Index (LPI) with environmental factors in a framework that can handle uncertainty and complex links between variables. This study provides a more complete and realistic evaluation by considering both economic efficiency and environmental sustainability. Specifically, it aims to: (1) extend the use of the LPI database to evaluate both logistics performance and environmental impact together; (2) build a strong method that combines Entropy-based objective weighting, the Simple Additive Weighting (SAW) method, and Fuzzy Linear Regression (FLR); and (3) provide, to the best of our knowledge, the first integrated assessment of logistics performance across African countries using this hybrid approach.

The remainder of this paper is structured as follows. Section II details the proposed research methodology. Section III reports and discusses the empirical findings, demonstrating the effectiveness and practical relevance of the proposed approach. Finally, Section IV concludes the paper and suggests directions for future research.

II. Proposed Methodology

In this study, we use the last recent available data from the World Bank's 2018 report, covering 31 African countries. The LPI is evaluated based on nine criteria: C1: The ability to track and trace consignments, C2: The competence and quality of logistics services, C3: The ease of arranging competitively priced shipments, C4: The efficiency of the clearance process, C5: The frequency with which shipments reach consignee within scheduled or expected time, C6: The quality- of trade and transport-related infrastructure, C7: The Carbon dioxide (CO2) emissions from Transport, C8: The Methane (CH4) emissions from Transport, C9: The Nitrous oxide (N2O) emissions from Transport. Table I presents a brief description of the criteria adopted in this study.

TABLE I

Description of criteria

Criteria	Description	References
C1	Refers to the effectiveness of tracking and monitoring shipments throughout transportation.	[2], [3], [16], [9]
C2	Checks how well major logistics providers perform, such as transport companies, freight forwarders, customs services, and border control agencies.	[3], [9], [17]
C3	Refers to how easy it is to organize shipments at competitive and affordable prices.	[2], [3], [9], [17]
C4	Evaluates how efficient the clearance process is, including how fast, simple, and predictable it is, showing how easily trade can be carried out.	[2], [3], [9], [17], [16]
C5	Measures how often shipments arrive at consignees within the scheduled or expected delivery times.	[2], [3], [9], [17], [16]
C6	Assesses the quality of trade and transport infrastructure, including ports, railways, roads, and information technology systems.	[2], [3], [9], [17], [16]
C7	Measures the amount of carbon dioxide (CO_2) released from transport activities.	[18], [19]
C8	Measures the amount of methane (CH_4) released from transport activities.	[19]
C9	Measures the amount of nitrous oxide (N_2O) released from transport activities.	[19]

Considering the selected alternatives (African countries) and the evaluation criteria (Logistics Performance Index (LPI) indicators), we propose an integrated decision-making framework to assess logistics performance in Africa. First, the Entropy method is used to objectively calculate the importance of each criterion based on the information contained in the data. Then, these weights are applied in the SAW and FLR methods to evaluate and rank African countries according to their overall logistics performance while accounting for uncertainty.

A. Entropy Approach for Determining Criteria Weights

Giving proper weights to criteria is an important step in MCDM, because it affects the final results and the reliability of decisions. So, using objective weighting methods is necessary to get more accurate and reliable results and improve decision quality. In this study, we use the Shannon Entropy method, first introduced by Shannon [20], because it has clear advantages, as shown in the review by Kumar et al.[12].This method is based on probability theory and is used to measure uncertainty or information entropy. It works by looking at how much the values of each criterion differ across alternatives. A criterion that varies more provides more useful information and gets a higher weight. In contrast, a criterion with little variation gives less information and gets a lower weight [13]. The steps of the Entropy method are given in Kumar et al. [12].

B. Integrated SAW-FLR approaches for ranking African countries

After determining the criteria weights, the next step is to evaluate the performance of the African countries. At this stage, each country's overall score is calculated using the Simple Additive Weighting (SAW) method, a common MCDM technique introduced by Hwang and Yoon [10]. SAW combines the weighted normalized values of all criteria to provide a single score, allowing easy comparison of countries based on their overall performance as expressed by the following formula [21]:

$$S_i = \sum_{j=1}^{M} w_j \, r_{ij} \tag{1}$$

Where S_i is total score of the i^{th} objectives, w_j is the weight of criteria obtained by Entropy, r_{ij} is the normalized rating of the i^{th} criterion, N is the number of objectives, M is the number of criteria.

After calculating the overall scores using the SAW method, the next step is to evaluate and rank the countries using fuzzy linear regression. Fuzzy linear regression, first introduced by Asai et al. [14], is a basic method used to deal with uncertainty in regression models.

$$\tilde{y}_i = \tilde{A}_0 + \tilde{A}_1 x_{i1} + \cdots + \tilde{A}_k x_{ik} \tag{2}$$

In this approach, the regression coefficients $\tilde{A}_j$ $(j = 0 \ldots k)$ are modeled as symmetric triangular fuzzy numbers. Each coefficient has a central value a_j, where the membership is 1, and a spread c_j with $c_j \geq 0$. The dependent variable is also represented as a symmetric triangular fuzzy number with a center value and a spread. In the same way, the independent variables are expressed as symmetric triangular fuzzy numbers defined by their centers and non-negative spreads.

Asai et al. [14] introduced a linear programming–based formulation for estimating the fuzzy regression coefficients A_j, $j = 0, \ldots, k$:

$$\min \sum_{j=0}^{k} \left(c_j \sum_{i=1}^{n} |x_{ij}| \right) \tag{3}$$

subject to:

$$\sum_{j=0}^{k} \left(a_j + (1-H)c_j\right) x_{ij} \geq \bar{y}_i + (1-H)e_i, \quad i = 1, \ldots, n \tag{4}$$

$$\sum_{j=0}^{k} \left(a_j - (1-H)c_j\right) x_{ij} \leq \bar{y}_i - (1-H)e_i, \quad i = 1, \ldots, n \tag{5}$$

However, this model has some limits. One main issue is that, for each confidence level, the estimated interval must fully cover the observed interval. This can lead to very large spreads c_j, especially when the data is highly dispersed. Here, e_i represents the tolerance (allowed error) for observation i, which defines how far the estimate can deviate from the observed value. Because of this, the spreads c_j can become too large when the dependent variables have high variability. To overcome this, we use the improved FLR model with fuzzy intervals proposed by Peters [15]. The aim of FLR is to model the relationship between inputs and outputs when data is uncertain. Peters' method is useful because it adjusts the model so that all data points fit within the estimated interval, making it better for real-world uncertain data. The mathematical form of this model, with crisp inputs and fuzzy outputs, is given below:

$$\max \bar{\lambda} \tag{6}$$

$$\text{subject to } \sum_{j=0}^{k} (a_j + c_j) x_{ij} \geq \bar{y}_i + (1-\lambda_i) p_i, \quad i = 1, \ldots, n \tag{7}$$

$$\sum_{j=0}^{k} (a_j - c_j) x_{ij} \leq \bar{y}_i - (1-H) p_i, \quad i = 1, \ldots, n \tag{8}$$

$$\bar{\lambda} = \frac{\lambda_1 + \lambda_2 + \cdots + \lambda_n}{n} \tag{9}$$

$$\sum_{i=1}^{n} \sum_{j=0}^{k} c_j x_{ij} \leq P_0 (1 - \bar{\lambda}) \tag{10}$$

$$0 \leq \lambda_i \leq 1, \quad i = 1, \ldots, n \tag{11}$$

$$a_j = \textit{free}, \quad c_j \geq 0, \quad j = 0, \ldots, k, \qquad \bar{\lambda} \geq 0 \tag{12}$$

The parameter p_i represents the uncertainty in the fuzzy dependent variable $\tilde{y}_i$, while λ_i shows how well a solution fits the set of good solutions. P_0 defines the width of the tolerance interval for the objective function. Although these parameters may vary by problem, Peters [15] recommends using $p_i = 1$ and $P_0 = 1000$ in practice. The value of λ_i balances the objective function with the worst-case observation $\tilde{y}_i$: observations outside the tolerance interval have full membership ($\lambda_i = 1$), while those inside have membership values $\lambda_i \leq 1$.

III. Results and Discussion

In this section, we present and discuss the results obtained from the proposed approach.

A. Results of Criteria Weighting Based on the Entropy Method

To objectively assess the importance of the criteria, the Shannon Entropy method was applied using Python. This allowed us to automate normalization, entropy calculation, degree of diversification, and weight estimation, ensuring accurate and reproducible results.

A decision matrix with 31 alternatives and 9 criteria was used. First, the matrix was normalized using the following formula:

$$p_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}}$$

where p_{ij} denotes the normalized value of criterion j for alternative i, and m represents the number of alternatives. Next, the entropy value for each criterion was computed as follows:

$$E_j = -k \sum_{i=1}^{m} p_{ij} \ln(p_{ij}), \quad \text{with} \quad k = \frac{1}{\ln(m)}$$

The degree of diversification was then determined by:

$$d_j = 1 - E_j$$

Finally, the criteria weights were obtained using:

$$w_j = \frac{d_j}{\sum_{j=1}^{n} d_j}$$

where w_j represents the final weight associated with criterion j.

By applying the Entropy method, the criteria weights were calculated and are presented in Table II. The results show that criteria with higher variation receive higher weights, as they provide more information for distinguishing between alternative

TABLE II
PRIORITY WEIGHTS OF THE LPI CRITERIA

Criteria	Weights
C1	0.1094
C2	0.1802
C3	0.1157
C4	0.0815
C5	0.1103
C6	0.1049
C7	0.1196
C8	0.0865
C9	0.0918

Among all criteria, C2 is the most important, with the highest weight of 0.1802, showing its key role in improving logistics performance. This result matches the focus on service quality and operational capacity in logistics assessment frameworks. C7 comes next with a weight of 0.1196, showing the growing importance of environmental sustainability and emission reduction. Similarly, C3 and C5 have weights of 0.1157 and 0.1103, respectively, highlighting the importance of cost efficiency and timely delivery in logistics operations. C1 and C6 have close weights (0.1094 and 0.1049), showing their key role in improving transparency, reliability, and connectivity in logistics systems. On the environmental side, C8 and C9 have weights of 0.0865 and 0.0918, showing their clear impact on sustainable logistics assessment. C4 has the lowest weight (0.0815), but it is still important for smooth cross-border trade and fewer delays. Overall, the results show that both service quality and environmental factors are important in measuring logistics performance in African countries, and that efficiency and sustainability should be considered together.

B. Ranking of African countries based on SAW-FLR

Within the FLR framework, the dependent variable is the overall performance score obtained from the SAW method using Eq. (1). We set $p_0 = 100$ and $p_i = 1$ to rank the countries. The results from the regression model are shown below.

$$\begin{aligned} S = {} & (0,0) + (0.110164,0)C_1 + (0.144560,0)C_2 \\ & + (0.111929,0)C_3 + (0.097476,0)C_4 \\ & + (0.097858,0)C_5 + (0.079895,0)C_6 \\ & + (0.118680,0)C_7 + (0.124127,0)C_8 \\ & + (0.115311,0)C_9 \end{aligned} \tag{13}$$

We then ranked the countries using regression residuals. A higher residual means a larger gap between observed and predicted values, showing an unusual or outlying result. Since higher performance is better, a positive residual means a country performs better than expected. Therefore, the country with the highest residual is ranked first. Table III shows the SAW–FLR results. These residuals, seen as the difference between observed Logistics Performance Index (LPI) values and FLR predictions, give extra insight into country performance. Positive residuals mean better-than-expected performance, while negative ones indicate lower performance.

The results show that Estonia, Egypt, and Nigeria have the highest residual values, meaning they perform better than expected and are the most efficient countries in the sample. In contrast, Guinea has the lowest residual value, showing a large gap between expected and actual performance, and is therefore the lowest-performing country in terms of LPI. Overall, these results add to the ranking analysis by showing both the absolute performance and the relative efficiency of countries. This provides a clearer and more detailed understanding of country performance under the SAW–FLR framework.

C. Robustness analysis

To check the robustness of the proposed method, we compared it with other well-known MCDM approaches. Each method has its own advantages and limits in selecting the

TABLE III
RESULTS OF SAW-FLR METHODS

Countries	y_i	y_i^*	$e_i = y_i - y_i^*$
Central African Republic	1.536690	1.413039	0.12365026
Algeria	2.125226	1.991598	0.13362812
Angola	2.285971	2.151073	0.13489822
Benin	2.733750	2.569829	0.16392167
Burkina Faso	2.125145	1.967416	0.15772914
Burundi	1.522106	1.383229	0.13887695
Cameroon	2.226340	2.066546	0.1597938
Comoros	1.780599	1.645282	0.13531809
Congo, Dem. Rep.	2.087847	1.942004	0.14584316
Congo, Rep.	1.886726	1.743909	0.14281733
Egypt	8.818544	8.625558	0.19298625
Estonia	2.608176	2.413007	0.19516883
Gabon	1.541087	1.406422	0.13466498
Ghana	2.815474	2.658047	0.15742619
Guinea	1.731245	1.624954	0.10629082
Guyana	1.734618	1.603877	0.13074102
Kenya	3.152428	2.979839	0.17258938
Lesotho	1.625370	1.501443	0.12392673
Libya	3.513313	3.369335	0.14397815
Liberia	1.597221	1.456784	0.1404373
Madagascar	1.819266	1.678435	0.14082991
Malawi	1.899391	1.743549	0.15584232
Mali	2.149101	1.994628	0.15447288
Morocco	3.984317	3.819798	0.16451929
Mauritania	1.893524	1.753502	0.14002179
Niger	1.589357	1.457395	0.13196202
Nigeria	8.456175	8.273653	0.1825215
Rwanda	2.146640	1.966153	0.18048705
Senegal	1.922276	1.786257	0.13601924
Sudan	3.228146	3.072815	0.15533077
Tunisia	2.710923	2.563652	0.14727138

best option. To make the results more reliable, we also used TOPSIS and VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR). These methods are widely used in many fields and are effective for solving complex MCDM problems [11].

- Comparative analysis with TOPSIS method

TOPSIS, introduced by Hwang and Yoon [10], is a popular MCDM method. It is valued for its simple structure, easy interpretation, and low computational effort, making it suitable for complex decision problems [22]. In this study, TOPSIS is used as a reference method to test the robustness of the ranking of African countries based on LPI criteria. The method ranks alternatives by measuring their distances from the positive ideal solution (PIS) and the negative ideal solution (NIS), and then computing a relative closeness value. Countries with higher closeness coefficients (CC_i) are considered to have better performance. Based on the TOPSIS results, Estonia is the best-performing country, which is consistent with the FLR results, with a score of 0.9661. Rwanda ranks second with a score of 0.9351.

- Comparative analysis with VIKOR method

VIKOR, introduced by Opricovic and Tzeng [23], is a well-known MCDM method used to rank alternatives under conflicting criteria. It has been further improved and widely applied by many researchers [24]. The method identifies a compromise solution among alternatives with conflicting and non-comparable attributes. Countries are ranked based on their VIKOR scores, where lower values indicate better performance. The results show that Estonia is the best-performing country, followed by Egypt and Rwanda.

Table IV presents the rankings from the TOPSIS and VIKOR methods. The results show strong agreement between the two approaches, with Estonia consistently ranked as the best-performing country. This consistency confirms the reliability of the proposed framework, as it identifies the same top country across different methods. However, some differences appear in the rankings of the other countries. This is normal because Peters' FLR model uses a different mathematical approach compared to the MCDM methods. These differences affect how criteria are evaluated and how results are combined, which leads to changes in the final rankings.

- Test rank correlation

To strengthen the robustness analysis, we use the Spearman rank correlation coefficient to measure how similar the rankings are from different methods and in what direction they agree. The Spearman rank correlation coefficient (r) is calculated using the following formula:

$$r = 1 - \frac{6\sum_{i=1}^{n} d_i^2}{n(n^2-1)} \tag{14}$$

x_i is the difference between the ranks of each country, and n is the total number of countries. These values are used to calculate Spearman's rank correlation coefficient, which shows how similar the two ranking methods are.

The results show a strong correlation (0.868) between SAW-FLR and VIKOR, meaning both methods give very similar rankings. In contrast, the correlation between SAW-FLR and TOPSIS is low (0.185), showing weak agreement. The correlation between TOPSIS and VIKOR is also low to moderate (0.255). Overall, SAW-FLR is closer to VIKOR, while TOPSIS differs more from the other methods.

IV. CONCLUSION

Logistics plays a key role in economic growth and business development and is widely studied in supply chain management. The LPI is commonly used to measure logistics performance, but many studies ignore environmental indicators such as the Green Logistics Index. These gaps are mainly due to rapid logistics growth with limited focus on sustainability, although its impacts are global.

To address this, we extend the LPI by adding environmental indicators like transport emissions. Since performance factors are interrelated in reality, we propose a framework for African countries using World Bank data. The Entropy method is used for weighting, and SAW-FLR is applied to rank 31 countries. We validate results using TOPSIS and VIKOR, with a Spearman correlation test showing strong agreement between SAW-FLR and VIKOR and weaker agreement with TOPSIS. Estonia is consistently the best-performing country.

The Peters' FLR method better handles uncertainty and complex relationships than standard MCDM methods, as it works with both precise and imprecise data. This framework helps decision-makers improve logistics performance and supports better policy design. Future work may use other weighting and ranking methods such as CRITIC and MULTIMOORA to further validate the results.

TABLE IV
RESULTS OBTAINED BY TOPSIS AND VIKOR APPROACHES

Countries	TOPSIS (CC_i)	VIKOR (Q_j)
Central African Republic	0,8232	1,0633
Algeria	0.6062	0.5485
Angola	0.7754	0.8255
Benin	0.8514	0.37267
Burkina Faso	0.8743	0.4580
Burundi	0.8188	0.8927
Cameroon	0.8707	0.4464
Comoros	0.8622	0.9443
Congo, Dem, Rep,	0.8505	0.5681
Congo, Rep,	0.8563	0.5779
Egypt	0.1586	0.2763
Estonia	**0.9661**	**0**
Gabon	0.8217	1
Ghana	0.8153	0.4730
Guinea	0.8124	0.7683
Guyana	0.8422	0.7046
Kenya	0.8276	0.2919
Lesotho	0.8286	0.8208
Libya	0.6642	0.7941
Liberia	0.8258	0.8917
Madagascar	0.8486	0.6395
Malawi	0.8823	0.5127
Mali	0.8658	0.4648
Morocco	0.7002	0.4839
Mauritania	0.8353	0.6633
Niger	0.8117	0.8432
Nigeria	0.1782	0.4860
Rwanda	0.9351	0.2776
Senegal	0.8229	0.7157
Sudan	0.7620	0.5423
Tunisia	0.8209	0.5027

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