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Improvements and Spatial Dependencies in Energy Transition Measures

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Abstract: This article aims to improve one of the newest energy transition measures—the World Economic Forum WEF Energy Transition Index (ETI) and find its driving forces. This paper proposes a new approach to correct the ETI structure, i.e., sensitivity analysis, which allows assessing the accuracy of variable weights. Moreover, the novelty of the paper is the use the spatial error models to estimate determinants of the energy transition on different continents. The results show that ETI is unbalanced and includes many variables of marginal importance for the shape of the final ranking. The variables with the highest weights in ETI did not turn out to be its most important determinants, which means that they differentiate the analysed countries well; nonetheless, they do not have sufficient properties of approximating the values of the ETI components. The most important components of ETI (with the highest information load) belong to the CO_2 emissions per capita, the innovative business environment, household electricity prices, or renewable capacity buildout. Moreover, we identified the clustering of both ETI and its two main pillars in Europe, which is not observed in America and Asia. The identified positive spatial effects showing that European countries need much deeper cooperation to reach a successful energy transition.

Keywords: energy transition index; energy transition; composite indicators; sensitivity analysis; spatial error model

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1. Introduction

'Nothing in life is to be feared, it is only to be understood. Now is the time to understand more, so that we may fear less' Maria Skłodowska-Curie.

Energy is a crucial input in each production process and a key source of economic growth. In the economic literature, a well-known and empirically confirmed feedback hypothesis shows that energy consumption and economic growth have a bidirectional relationship, i.e., energy consumption leads to economic growth, and economic growth leads to a rise in energy consumption [1–3]. The latest analyses also indicate the positive impact of renewable energy on economic growth and vice versa, both in developed and developing countries [4,5]. As the average annual growth rate in the world economy in the last decade was around 3.5% (excluding the pandemic period), an increasing energy demand is observed, regardless of energy source [6]. Additionally, the world's population is projected to grow by around two billion over the next two decades, and the standard of living is increasing significantly in India and China. Due to the above, energy generation is expected to rise by 49 per cent by 2040 [7]. The shrinking of natural resources and world energy production based on fossil fuels (84.2% in 2019) make the energy transition process one of the most significant challenges faced by the global economy [8].

In this article, we explore the energy transition process. The global energy system is currently undergoing a transformation, driven by technological innovation and geopolitical developments. It is accompanied by the global dimensions of energy trade and the urgency of climate change, which makes the current energy transition crucial for the economic growth of many economies. The term 'energy transition' refers to the shift in energy generation and consumption methods, i.e., generating energy in ways that reduce CO_2 emissions and overall energy consumption, primarily through improved efficiency. In the literature, we can find many definitions of energy transition [9–12], but simultaneously we observe the consensus on looking at this phenomenon more broadly, considering its socioeconomic and political aspects [13]. We understand the energy transition in a broad sense, as Strunz [14] proposes, as a shift from a fossil-nuclear-powered energy system to one powered by renewable energy sources, including shifts across related technological, political, and economic structures. The importance of energy transition for many economies is proven by the inclusion of access to affordable and clean energy as one of the 17 global goals that make up the 2030 Agenda for Sustainable Development [15]. It forces economists to face the difficult task of identifying the factors, which support the energy transition and finding a proper measurement for the phenomenon [16].

The above approach to defining the energy transition focuses on the process taking place at the macro level, as the energy transition involves significant shifts in several sectors. However, we should be aware of this approach, i.e., it ignores the different impacts on specific stakeholders. The energy transition is a process that has both positive and negative impacts on different communities [17–19]. Policymakers and other proponents of new energy sources often experience positive effects of these changes in energy markets. However, consumers are negatively affected by price effects, and some employees are negatively affected by work disruptions [20].

Our paper concentrates on the measurement of the energy transition and improvements in this area. Almost all approaches to energy transition assessment are related to a composite index. It usually combines a wide range of energy indicators, which are valuable tools for decision-makers, helping them see the big picture and identify areas for improvement. Unfortunately, many energy transition indices are related to a particular aspect of this phenomenon, i.e., the Sustainable Energy Development Index [21] related to sustainability, the Energy Security Index [22] and the Multidimensional Energy Poverty Index [23] to accessibility, and the World Energy Council Energy Trilemma Index [24] to energy security. Based on the broad definition of the energy transition, we concentrate on the Energy Transition Index (ETI), a relatively new index created by the World Economic Forum. A distinctive feature of this index is its multifaceted nature, i.e., it combines many aspects of energy transition from two large dimensions: energy system performance (accessibility, security, sustainability) and a variety of indicators of transition readiness. Additionally, the ETI considers aspects related to economic growth and development, so it helps policymakers identify areas where the policy could be improved to speed up the energy transition.

Our article is part of the discussions on the development and integration of different approaches to measure energy transition and to develop a universal index. The novelty of this paper is an attempt to propose an improvement of the most comprehensive index, which we consider the EIT, rather than creating a new one. It is the first attempt in empirical literature to the best of our knowledge. The Energy Transition Index is a weighted average of 40 indicators; thus, using sensitivity-based techniques, we want to determine if the weights of individual variables accurately represent each factor's purported importance. We also examine the architecture of the index for coherence or consistency. In addition, it will aid in determining whether the index is capable of detecting differences in energy transition between countries. Finally, our analysis will propose a new ETI composition, which will better reflect the changes in the energy transformation of economies.

Additionally, we think that the energy transition process cannot be fully understood without considering its spatial implications. The existing measures of energy transformation do not take them into account, although the first attempts at conceptualising the spatial dimensions of energy transitions are observed [25–28]. In the literature, there are few studies on the effects of economic growth and the use of renewable energy and natural gas on CO_2 emissions that take into account the spatial effects in their modeling [29,30]. The novelty of our paper will be to check whether the spatial effects are important in the model explaining the ETI volatility. To fill the gap, we study the spatial dependences of the Energy Transition Index using measures of global spatial autocorrelation. Furthermore, we employ spatial error models (SEMs) to analyse the drivers of energy transition indicators, which turned out to be characterised by spatial dependence.

It turned out that the weights proposed by the WEF do not fully reflect the real importance of the individual components of the ETI. They are especially overestimated for: RISE (Regulatory indicators for sustainable energy) access, quality of transportation infrastructure, or share of global fossil-fuel reserves, which means that those variables could, in principle, be removed from the index without causing significant differences in the final ranking. On the other hand, the weights for CO_2 per capita and per TPES (total primary energy supply (kg/GJ))or renewable capacity buildout turned out to have underestimated weights. Moreover, the energy transition phenomenon is characterised by spatial clustering in Europe, while in the other analysed continents, it was rather random.

The contribution of our paper is to describe the ETI methodology with two main dimensions and 23 individual indicators to show how countries can track their progress in energy transmission and benchmark themselves against other economies. In addition, we discuss the ETI robustness assessment as a necessary step in future ETI reconstruction/modification and propose the optimization procedure of the weights that allows improving the accuracy of the variables. Finally, we would like to draw attention to an overlooked aspect in the economic literature, i.e., the energy transition is a spatial process and without considering this aspect, we cannot achieve an effective energy transition.

The paper is organised as follows. Section 2 provides an overview of the Energy Transition Index composition and methodology. Section 3 describes the methodology of the present analysis, with a particular emphasis on sensitivity analysis and spatial modelling. Section 4 contains the results, and the last section is a conclusion.

2. Energy Transition Index—Composition and Methodology

In 2013, the World Economic Forum (WEF) created the Energy Architecture Performance Index (EAPI), which aimed to help decision-makers better understand energy systems and assess the efficiency of energy architecture at the country level. Unfortunately, EAPI failed to foster a better understanding of the drivers and bottlenecks in national energy systems to make potential changes. This is why the WEF decided to introduce a new measure, the Energy Transition Index (ETI), which aims to help policymakers and companies navigate a successful energy transition path. The WEF offers a very comprehensive approach to measuring energy transition, assuming that the diverse components inside the system and their interdependencies with features outside of the energy sector contribute to the complexity of the energy transition [14].

The ETI is a composite index based on 40 indicators, which assesses 115 economies on their energy systems' current performance [14]. In 2018, these countries accounted for more than 98 per cent of global GDP and carbon emissions from the global energy system, approximately 90% of the worldwide population, and about 60% of people without access to electricity [31]. To build a reliable index, the WEF follows several rules of the data selection process, i.e., the index includes only output data instead of projections, data from reputable institutions, the best measure available, the given constraints, and the data comes from the same providers on an annual basis and includes sufficient global coverage [32]. Furthermore, each indicator before the aggregation process is arithmetically scaled between the minimum and maximum threshold values and standardised on a scale of 0 to 100 for aggregation (with a target value of 100 per cent) [14].

The ETI consists of two equally weighted indices: system performance and transition readiness score (Figure 1).

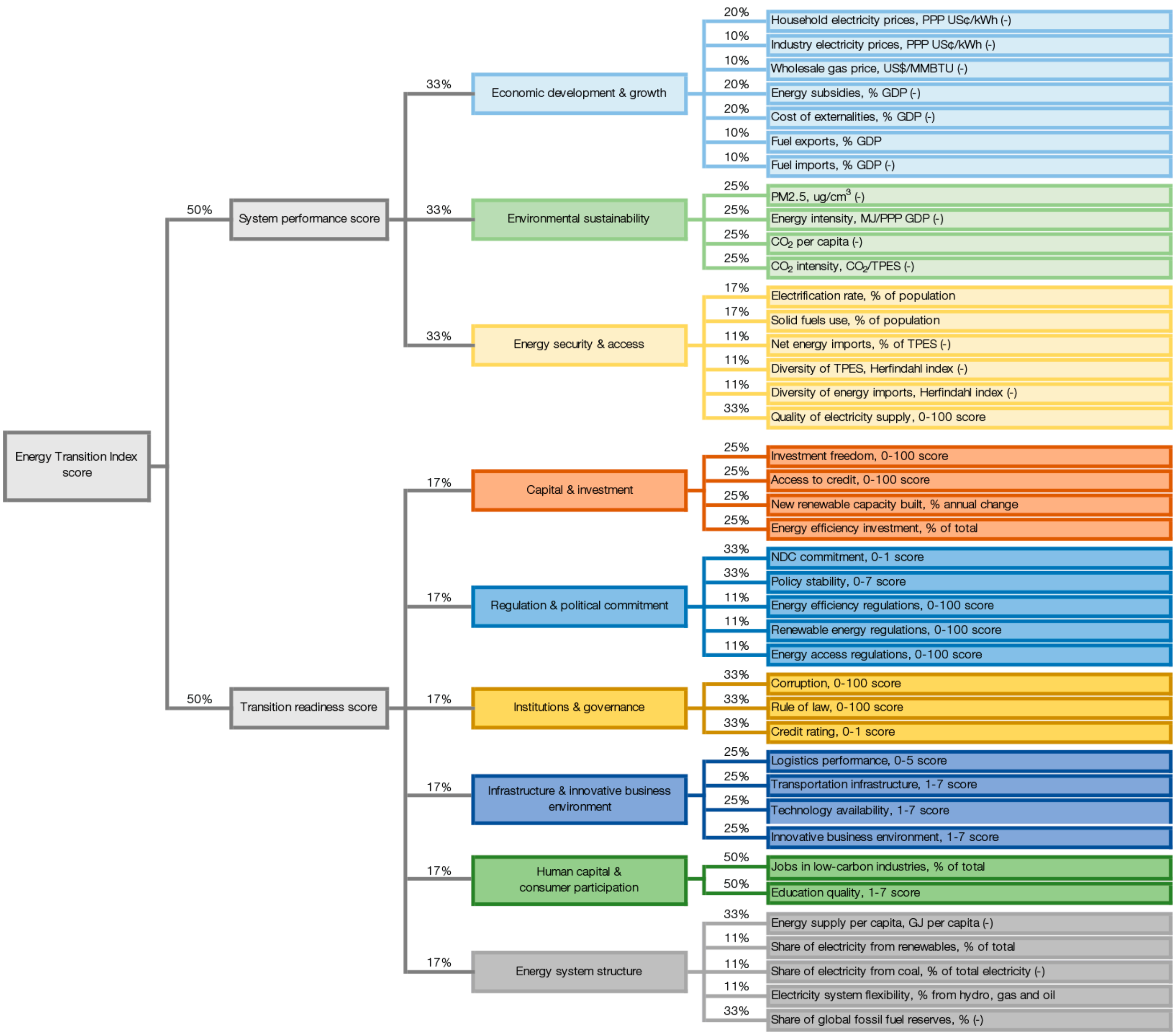

Figure 1. The Main Dimensions of the Energy Transition Index. Reproduced with pemission from [14], World Economic Forum, 2019.

The system performance score assessment uses 17 indicators showing how well a country's energy system supports three main objectives: economic development and growth, energy access and security, and environmental sustainability. To score and rank the performance of each country's energy system chosen by the WEF, the individual indicators are aggregated into three subscores, one for each of the imperatives (Figure 1).

Economic development and growth measures to what degree the energy system contributes to, rather than hinders, economic development and growth. Environmental sustainability refers to how well the energy infrastructure reduces negative environmental externalities. Finally, access to energy and security measures the degree to which the energy infrastructure jeopardises energy security and whether all population members have enough access to energy. The system performance score is calculated by averaging the three groups' subscores.

In turn, the transition readiness score measures the readiness of a country to transition to secure, sustainable, affordable, and inclusive energy systems [14]. Assessment of transition readiness is based on 23 indicators aggregated into six categories: capital and investment; regulation and political commitment; institutions and governance; infrastructure and innovative business environment; human capital and consumer participation; and energy system structure (Figure 1).

Analysing the WEF methodology of the ETI, we pay special attention to the weighting system. In the WEF reports, we did not find any substantive justification for the adopted importance of the individual indicators. The WEF applies the method of equal weights to ensure high international comparability of ETI. This weighting approach is used in some popular indices, such as the Doing Business Ranking or the Human Development Index, and is broadly discussed in the literature [33–35]. In our opinion, the arbitrary adoption of such a weighting system is the ETI's greatest weakness, so we want to determine whether the weights of individual variables accurately reflect the supposed importance of each factor.

3. Materials and Methods

In this paper, the 2019 ETI sub-component data published by the WEF [36] were used for empirical analysis, both in the sensitivity analysis and the spatial modelling. In addition, the study also uses data from the World Bank on the general condition of the economies under investigation. The sensitivity-based analysis was prepared in Matlab based on the CIAO package [37], while the spatial studies were carried out in the Geoda and ArcGIS pro software.

3.1. Sensitivity-Based Approach

The previous section describes the structure of the Energy Transition Index. Similar to most composite indicators, there are suspicions that this one also has drawbacks. In many cases, the problem concerns an overly trivial approach to the weights assigned to particular diagnostic variables [37–43]. We start our investigation by challenging the ETI's discriminatory properties by applying a consistency analysis based on a sensitivity analysis (SA). In our opinion, one of the best tools for assessing the consistency of any composite indicator is a sensitivity-based approach, which makes it possible to determine whether the assigned weights reflect the significance of each component. The coherence of the measure with its methodology is tested by considering variances and correlations among diagnostic variables. The Energy Transition Index is an additive weighted average of n-normalised variables x_i:

$$y_j = \sum_{i=1}^{d} w_i x_{ji},\ j = 1, 2, \ldots, d;\ i = 1, 2, \ldots, n, \tag{1}$$

where: y_j—the value of the composite indicator for the j-th item (country), x_{ji}—the normalised value of the i-th variable in the j-th item, and w_i—the weight assigned to the i-th variable ($\sum_{i=1}^{n} w_i = 1$ and $w_i > 0$).

Thus, the impact of x_i on y may be isolated and determined by the statistical measure of global variance-based sensitivity—the first-order sensitivity index [44–48]:

$$S_i \equiv \eta_i^2 = \frac{V_{x_i}(E_{x\sim i}(y|x_i))}{V(y)}, \tag{2}$$

where: S_i—the first-order sensitivity measure, $x_{\sim i}$—the vector containing all variables except x_i, $E_{x\sim i}(y|x_i)$—the expected value of y at a given value of x_i with the exception taken over $x_{\sim i}$, and $V(y)$—the unconditional variance of y. In our study, $E_{x\sim i}(y|x_i)$, is estimated via a non-linear regression fit using penalized splines—a technique used in so-called scatterplot smoothing [49]. This measure can be used as a measure of importance as it helps to define 'the expected fractional reduction in variance of the composite indicator that would be obtained if that variable could be fixed' [47]. By comparing the S_i values for the variables a and b with the weights assigned to these variables, it can be determined whether the index reflects the assumptions of its architects. The S_i measure provides information about the non-compliance with the assumptions of a composite indicator when: (i) $S_a \neq S_b$ while the index designers argue that the variables a and b have equal importance (if, for example, the index designer assumes that variables a and b should have weights 0.1 and $S_a = 0.6$ while $S_b = 0.35$; that means the weights given to the variables do not reflect their actual importance); (ii) $S_b > S_a$ while the index designers argue that variable a is more important than variable b; (iii) $S_a = 0$, meaning that variable a and the final rank are not associated at all (the variable can be considered 'silent' as it has virtually no effect on the final values of the composite indicator); (iv) $S_a = 1$, meaning that there is a perfect knowledge of final rank knowing just the distribution of variable a; and (v) $S_i < 0$ indicating conceptual problems with the indicator. It is, therefore, an excellent tool to spot the discrepancies between the initial assumptions and the final product—in this case, the ranking based on the ETI value. Another advantage of S_i as a measure of goodness of CI is the possibility of its decomposition into a correlated and non-correlated part:

$$S_i = S_i^u + S_i^c \tag{3}$$

where: S_i—the first-order sensitivity measure, S_i^u—the uncorrelated contribution, which is the unique variability that can only be explained by x_i, and S_i^c—the correlated contribution, which is the variability caused by all variables associated with x_i. Therefore, it is possible to indicate to what extent the significance of the given variable results from the information transferred by it and the extent to which it results from a correlation with other diagnostic variables $S_i^c \approx S_i$. If a variable has high S_a^c value and a low S_s^u value, it means that it does not contribute additional information on its own, but only duplicates the information provided by other variables. In such case, variable a can be eliminated from the set of diagnostic variables, allowing for the reduction in the set of the input variables, simplifying the calculations and reducing the cost and time of data acquisition. Knowing S_i, the uncorrelated part S_i^u can be easily estimated by performing the multivariate linear regression of x_i on $x_{\sim i}$ and finding the residuals [48]:

$$\hat{z}_i = x_i - \hat{x}_i = x_i - \left(\beta_0 + \sum_{l \neq i}^{d} \hat{\beta}_l x_i\right) \tag{4}$$

where: $\hat{z}_i$—the residuals of a regression of x_i on $x_{\sim i}$, β_0—the y-intercept from multivariate linear regression, $\hat{\beta}_l$—the coefficient from multivariate linear regression. Next, the non-linear regression of y to fitted $\hat{z}_i$ values are used to estimate S_i^u:

$$S_i^u = \frac{\sum_{j=1}^{n}\left(\hat{y}_j^{(\sim i)} - \overline{y}^{(\sim i)}\right)^2}{\sum_{j=1}^{n}\left(y_j - \overline{y}\right)^2} \tag{5}$$

where S_i^u—the uncorrelated contribution, $\hat{y}_j^{(\sim i)}$—the non-linear regression fitted values, $\overline{y}^{(\sim i)}$—the average value of $\hat{y}_j^{(\sim i)}$, y_j—the composite indicator value in the j-th item, and $\overline{y}$—the average value of y_j. With knowledge of the uncorrelated contribution, it is possible to compute the correlated part S_i^c:

$$S_i^c = S_i - S_i^u \tag{6}$$

If both the uncorrelated (5) and correlated (6) contributions are known, it is possible to apply the following optimisation algorithm to adjust the weights:

$$\widetilde{S}_i = \frac{S_i}{\sum_{i=1}^{n} S_i} \tag{7}$$

where: $\widetilde{S}_i$—the normalised correlation ratio of x_i. This is done because it makes the correlation ratio directly comparable with the weights of the composite indicator. Thus, optimal weights can be computed as:

$$w_{opt} = \text{argmin}_w \sum_{i=1}^{d} \left(\widetilde{S}_i^* - \widetilde{S}_i(w)\right)^2, \tag{8}$$

where: $\widetilde{S}_i^*$—the target normalised correlation ratio, i.e., a situation in which initial weights reflect the intended importance of each indicator $\widetilde{S}_i^* = w_i$, w—the set of weights $w = \{w_i\}_{i=1}^{d}$. The optimisation process was carried out using the Nelder–Mead simplex method [50]. The optimal weights were selected so that they sum up to one and are non-negative: $\sum_{i=1}^{n} w_{opti} = 1$ and $w_{opti} > 0$. Adjusting the weights is one of the possible solutions to weight inadequacy to the constructors' assumptions. As an alternative, one can also consider changing the aggregation method (e.g., from arithmetic to geometric mean) or changing the components in sub-pillars and then repeat the entire procedure. Therefore, it seems that the most convenient solution is to perform the weight optimization task.

Figure 2 illustrates the steps of the analysis carried out at this stage of the investigation.

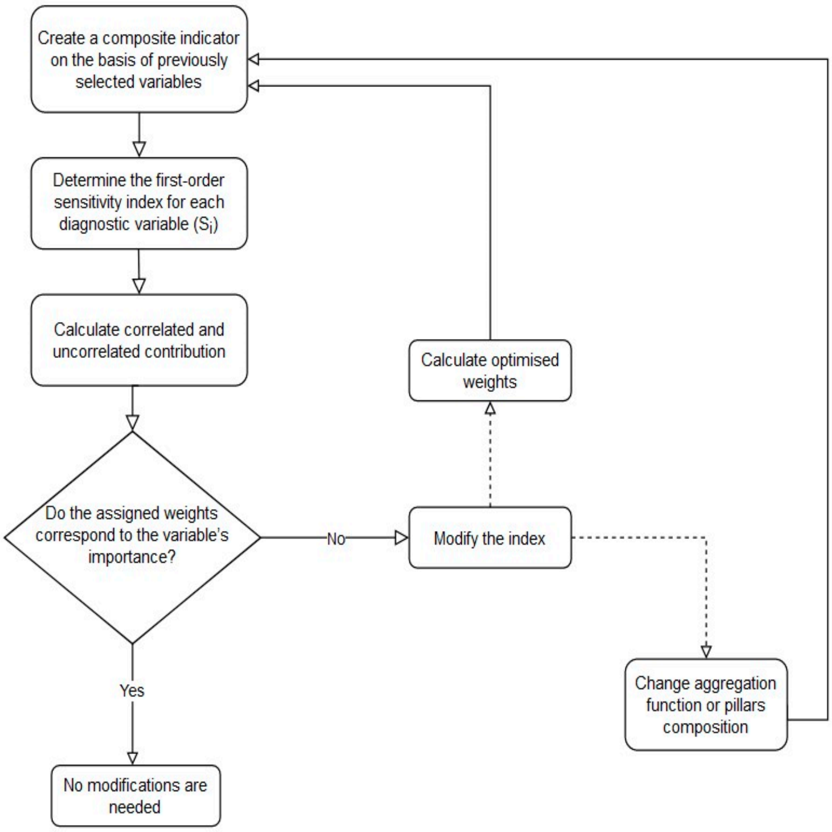

Figure 2. Composite indicator's compliance testing procedure.

3.2. Spatial Modelling

The second part of the study was devoted to analysing the spatial distribution of the ETI and its determinants; there is a suspicion that the discussed variables may tend toward spatial clustering. The central premise for this approach is Tobler's first law of geography, claiming that '*Everything is related to everything else, but near things are more related than distant things*' [51]. Moreover, when using geographical items in the analysis, assuming, in advance, their independence is a mistake because interconnections between neighbouring objects may occur [52]. In addition, the diversification of economic phenomena in an established group of regions is highly affected by the spatial conditions [53]. Finally, according to Griffith [54], it is better to use the most straightforward weight matrix than assume independence in advance.

In the first step of our analysis, we determined the Global Moran I statistics to check whether spatial autocorrelation applies to the analysed variable [55,56]:

$$I = \frac{n}{\sum_i \sum_j w_{ij}} \cdot \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} (x_i - \overline{x})(x_j - \overline{x})}{\sum_{i=1}^{n} (x_i - \overline{x})^2} \; (i = 1, \ldots, n; j = 1, \ldots, n) \tag{9}$$

where: I—the value of Moran's I statistics, n—the number of observations (countries), w_{ij}—the spatial weight matrix, x_i, x_j—the value of the analysed variable in i-th and j-th item, and $\overline{x}$—the average value of the analysed variable.

In our analysis, w_{ij} is a first-order queen contiguity matrix, meaning that items are considered as neighbouring when they share a border:

$$w_{ij} = \begin{cases} 1, \; bnd(i) \cap bnd(j) \neq \varnothing \\ 0, bnd(i) \cap bnd(j) = \varnothing \\ 0, \; i = j \end{cases} \tag{10}$$

The matrix size is equal to the number of analysed items (in our case, countries) and expresses the neighbour structure between the observations:

$$w_{ij} = \begin{bmatrix} w_{11} & w_{12} & \ldots & w_{1n} \\ w_{21} & w_{22} & \ldots & w_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ w_{n1} & w_{n2} & \cdots & w_{nn} \end{bmatrix} \tag{11}$$

The spatial weight (11) was row-standardised according to the following formula [56]:

$$w_{ij}(s) = \frac{w_{ij}}{\sum_j w_{ij}}. \tag{12}$$

First, the multiple regression model without spatial effect was estimated using ordinary least square estimation:

Then, we checked whether the Moran's I statistic in residuals of the standard regression model indicates the existence of spatial autocorrelation. If so, we checked using the Lagrange Multiplier test for lag $LM(lag)$ and error $LM(error)$ models (both classic and robust versions) [57] to indicate the type of spatial autocorrelation [58]:

The null hypothesis in $LM(lag)$ test is as follows $H_0 : \rho = 0$ (no spatial dependence), and the test statistics is given by:

$$LM(lag) = \left(\frac{e'wy}{e'en^{-1}}\right)^2 \frac{1}{H'} \tag{13}$$

where: e—error, w—the weight matrix, y—the dependent variable, $e'en^{-1}$—error variance.

The null hypothesis in the $LM(error)$ test is as follows $H_0 : \lambda = 0$ (no spatial dependence), and the test statistics are given by:

$$LM(error) = \left(\frac{e'we}{e'en^{-1}}\right)^2 \frac{1}{tr[w'w + w^2]} \tag{14}$$

where: e—error, w—the weight matrix, $e'en^{-1}$—error variance, tr—the matrix trace operator.

The Spatial Error Model (SEM) should be chosen when: (i) $LM(error)$ is significant, and $LM(lag)$ is not, (ii) if the robust version of $LM(error)$ is significant and robust $LM(lag)$ is not, (iii) in the case that both robust tests are significant, the lower p-value indicates the appropriate model, thus: $p[LM(error)] < p[LM(lag)]$. The spatial lag model (SAR) should be chosen in the converse cases.

In the SAR model, the dependent variable in the i-th item is affected by the independent variables in both i-th and j-th objects [59]:

$$y_i = \rho \sum_{j=1}^{n} w_{ij} y_j + \sum_{q=1}^{Q} X_{iq}\beta_q + \varepsilon_i \tag{15}$$

where: y_i—the dependent variable in the i-th item, ρ—the spatial autoregression parameter, w_{ij}—the spatial weight matrix, X_{iq}—the independent variable matrix, β_q—the egression parameters, ε_i—the residuals $\varepsilon \sim N(0, \sigma^2 I)$.

While in the case of the SEM model, the error terms across different spatial units are correlated. The most common specification is a first-order process given by [59]:

$$y_i = \sum_{q=1}^{Q} X_{iq}\beta_q + \varepsilon_i \tag{16}$$

where:

$$\varepsilon_i = \lambda w_{ij} \varepsilon_j + u_i \tag{17}$$

and where: λ—the autoregressive parameter, u_i—the random error term $u \sim N(0, \sigma^2 I)$.

Table 1 presents variables used in statistical modelling.

Table 1. Variables used in the investigation.

Variable	Description
ETI	The logarithm of the Energy Transition Index value
HEP	The logarithm of household electricity prices (PPP USDc/kWh)
CO_2	The logarithm of CO_2 emissions per capita (tonnes per capita)
RCB	The logarithm of renewable capacity buildout (% of installed capacity)
JLCI	The logarithm of share of renewable energy jobs as part of countries total workforce
POP	The logarithm of population size
UR	The logarithm of urban population as % of the total population
EM	The logarithm of employment in manufacturing as % of total employment

4. Results

4.1. Optimisation of ETI Weights

At the first step of our analysis, we investigated the correlation between ETI and its six subindices (Figure 3).

It appears that most of the subindices are positively correlated (deep red) with each other, but the correlation with the final ETI does not exist (white background). Moreover, the ESS subindex (Energy System Structure) is negatively correlated with all others (deep blue). Perhaps it results from the fact that two variables included in this subindex (share of global fossil-fuel reserves and share of electricity from coal generation) are desitmulants, i.e. the lower the value, the better from the point of view of the analysed phenomenon. Thus, the presence of a negative correlation between the subindices and a weak correlation with the final CI may be a symptom of ETI construction drawbacks. Moreover, a strong correlation between the remaining subindices may indicate that the significance of the given variable results from its correlation with others, not from the information load contained in it, which means that information provided by a given variable can be inferred from another variable [60].

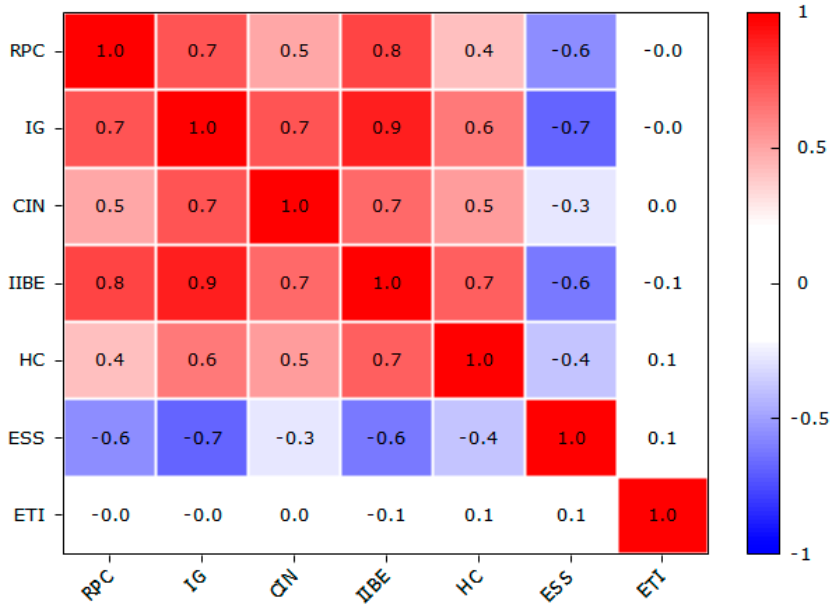

Figure 3. Correlation between the ETI and its subindices.

We applied a top-down approach—starting from checking the coherence of the ETI's subindices and ending up with individual variables within each subindex. Figure 4 presents the estimated values of the first-order sensitivity measures for System Performance (an analogous analysis was performed for all subindices and ETI).

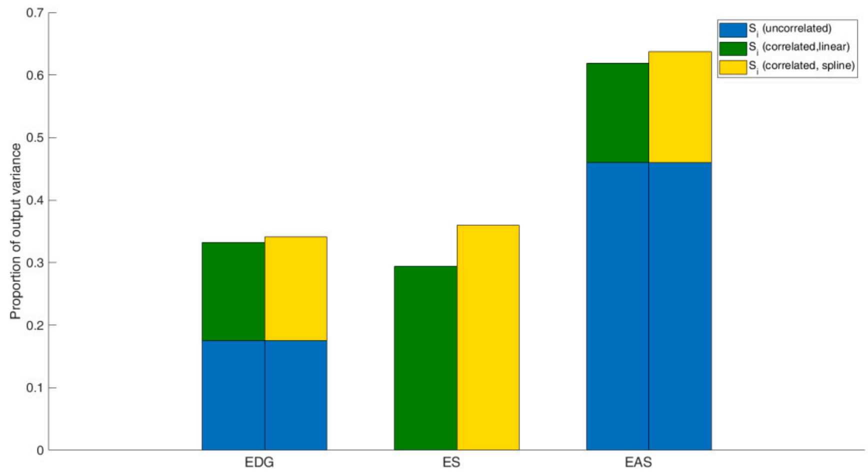

Figure 4. Penalised spline estimates of S_i (entire bar) broken down into S_i^u (blue bar) and S_i^c (green or yellow bar)* or ETI's System Performance. EGD—Economic Development and Growth, ES—Environmental Sustainability, EAS—Energy Access and Security.

When analysing the data contained in Figure 4, it can be seen that similar estimates were obtained with both the linear (green bar) and non-linear estimator (yellow bar). A slightly more significant discrepancy occurred in the case of ES (Environmental Sustainability). ES is also the only subindex in which the value of the entire S_i measure is equal to the value of its correlated part S_i^c, i.e. ES itself does not carry additional information on the development of System Performance. In other cases, the share of the uncorrelated part is 50% for EDG and 74% for EAS. The lack of negative values, which indicates a conceptual problem with the analysed indicator, is a positive phenomenon [49]. A high proportion of the correlated parts in some subindices leads to the assumption that ETI is volatile, as the correlation between subindices commands the influence—not their assigned weights. Therefore, we applied the optimisation procedure expressed by Formula (9), which allowed us to obtain weights that show the real influence of a given variable on ETI and its components. Some of the results are presented in Table 2; all are available in additional materials.

Table 2. Original and optimised weight for chosen ETI components.

Dimension	Original Weight	Optimal Weight	Direction
System performance	0.50	0.5249	Underestimated
Environmental sustainability	0.33	0.3612	Underestimated
Particular matter concentration	0.25	0.0833	Overestimated
Energy intensity	0.25	0.0260	Overestimated
CO_2 emission per capita	0.25	0.5075	Underestimated
CO_2 emission per TPES	0.25	0.3779	Underestimated

When analysing the contents of Table 2, it can be noted that the actual influence of the selected variables in many cases does not correspond to the weights given by the WEF. This is particularly noticeable in the case of particular matter concentration and energy intensity, whose influence is greatly overestimated when, in practice, the meaning of the former is slightly more than 0.02, and the latter is only 0.02. Therefore, it can be assumed that the energy intensity variable is 'silent' and removing it will not significantly affect the formation of the final ETI ranking but will only improve and simplify the calculation process. However, it should be stressed that being 'silent' does not mean that a given variable is irrelevant in the context of the country's energy transition. It only means that in the way that the ETI was constructed, this variable is either blurred or overwhelmed by other variables. To highlight such a variable, it would be necessary to change the aggregation formula or completely rebuild the composite indicator. However, in the present shape of the CI, it is practically unnoticeable.

Figures 5 and 6 present the distribution of the original and optimised values of the ETI. As can be seen, there is no significant difference between them. Of course, the order of magnitude and the values taken by the measure have changed because it results from applying different weights. Nevertheless, the pattern of countries has not changed significantly, i.e., countries with low original ETI values (bright green in Figure 5) are also countries with low modified ETI values (bright green in Figure 6). The situation is similar for the countries with the highest ETI values (dark green in Figures 5 and 6). Thus, despite changes in the value of the measure itself, the hierarchy of countries according to its value is converged. This is also confirmed by the value of Kendall's tau coefficient $\tau = 0.79$ $(p < 0.0004)$ calculated for the ranking of countries. The value of the Kendall tau coefficient indicates a significant similarity, i.e., there have been some changes in the linear order of the country, but the possible shifts in the ranking are not substantial. Table 3 presents the top five and bottom five countries in terms of the original and modified ETI values. When analyzing the data contained in this table, it can be noticed that essentially the same countries occupy places in both rankings. Even if there are some differences, they are within countries with a similar level of development of energy markets. This means that the structural changes caused by adjusting the weights to their actual significance do not contribute to considerable changes in the linear orderings of countries due to their energy transition achievements.

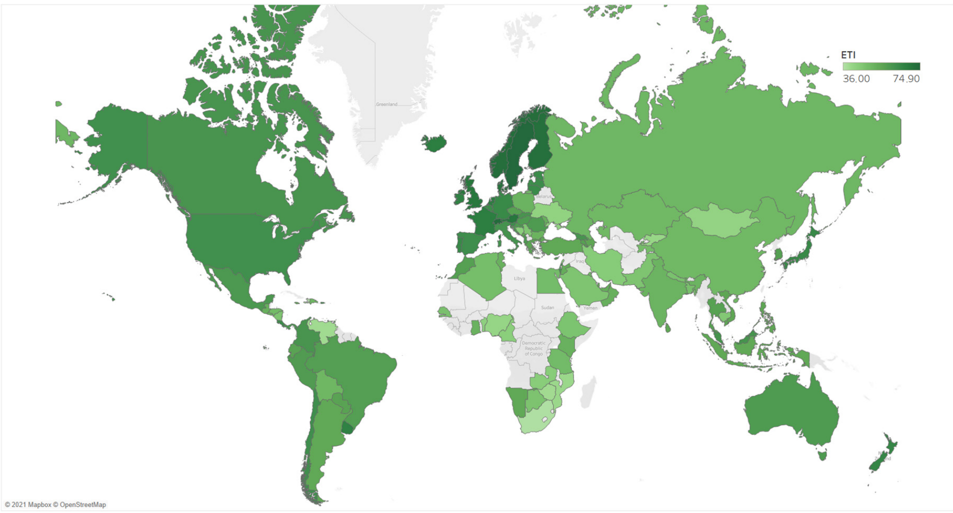

Figure 5. Distribution of original Energy Transition Index values.

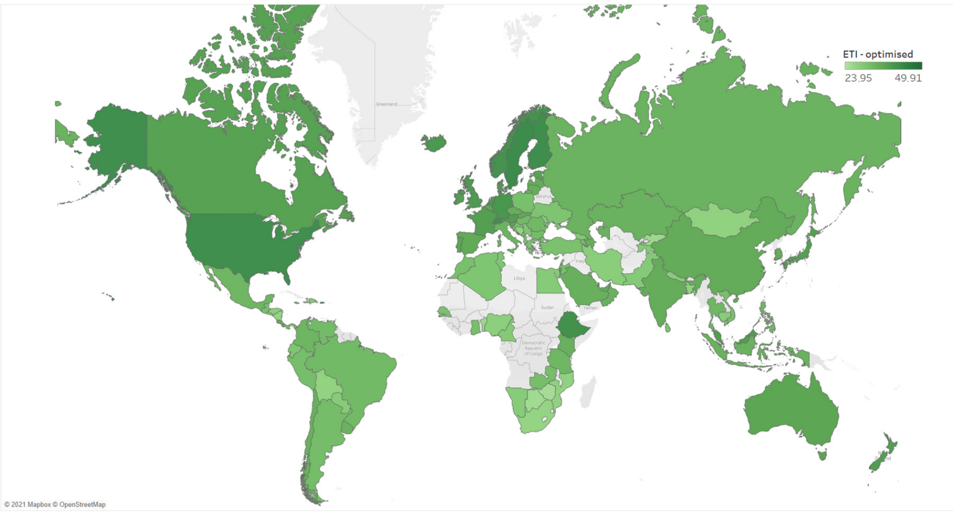

Figure 6. Distribution of optimised Energy Transition Index values.

Table 3. Top and bottom five countries according to original and optimised ETI.

Top Countries		Bottom Countries	
Original ETI	**Optimised ETI**	**Original ETI**	**Optimised ETI**
Sweden	Sweden	Mozambique	Benin
Switzerland	Finland	Venezuela	Mozambique
Norway	Switzerland	Zimbabwe	Botswana
Finland	Norway	South Africa	Zimbabwe
Denmark	United States	Haiti	Haiti

The sensitivity-based analysis also allowed us to select diagnostic variables for econometric models. Table 4 lists five variables of the highest and the lowest importance. Knowing the optimal weights, we consulted the new (optimised) ETI version. In addition, the critical variables (i.e., with the highest weights) were used in the econometric modelling of energy transition components.

Table 4. The most and least significant variables of the Energy Transition Index.

Most Significant	Least Significant
CO_2 per capita	RISE access score
Household electricity prices	Quality of transportation infrastructure
CO_2 per TPES	Energy Intensity
Renewable capacity buildout	Share of global fossil-fuel reserves
Jobs in low-carbon industries	Transparency

4.2. Spatial Models

Econometric modelling began with checking whether spatial relationships can be found in the dependent variables. The analysis was carried out separately for each continent; however, due to the insufficient number of observations and their large dispersion on the African continent, African countries were not included (ETI publishes data for approx. 40% of African countries).

Figure 7 presents the distribution of Moran I statistics for original ETI conducted for European countries, and Figure 8 shows the cluster map in Europe.

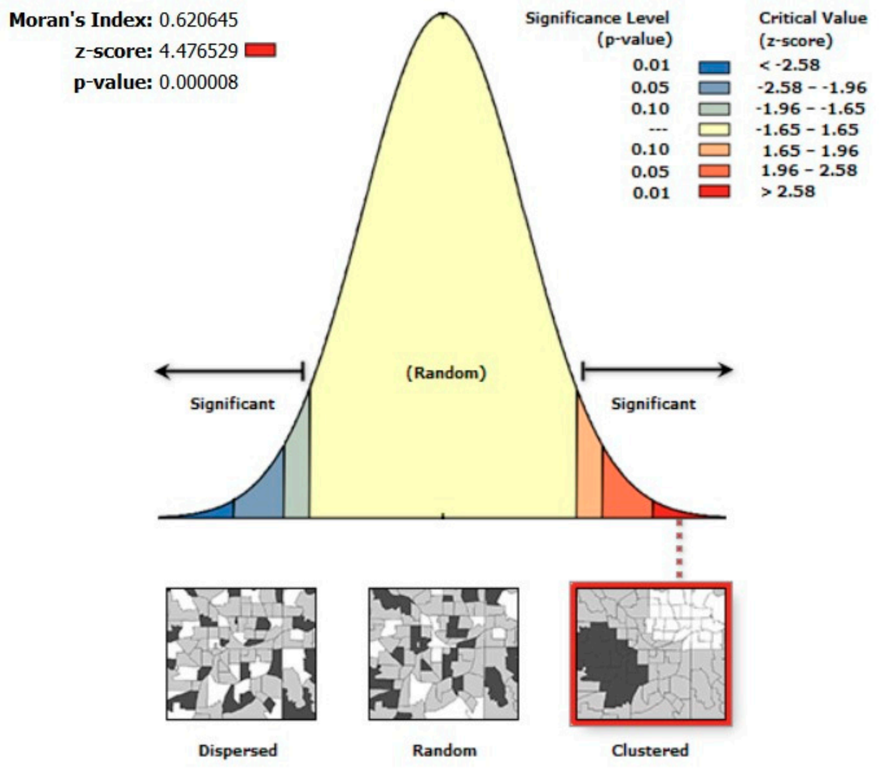

Figure 7. Moran's I distribution for ETI in Europe.

When analysing its contents, it can be noticed that the values of the Moran I statistics are positive and statistically significant, which proves that European countries are clustered; in the case of Asia, such clustering did not take place (Figures 9 and 10), and the ETI values are distributed randomly. An analogous analysis was performed for the ETI subindices (System Performance and Transition Readiness) for each continent, using both the original and optimised versions.

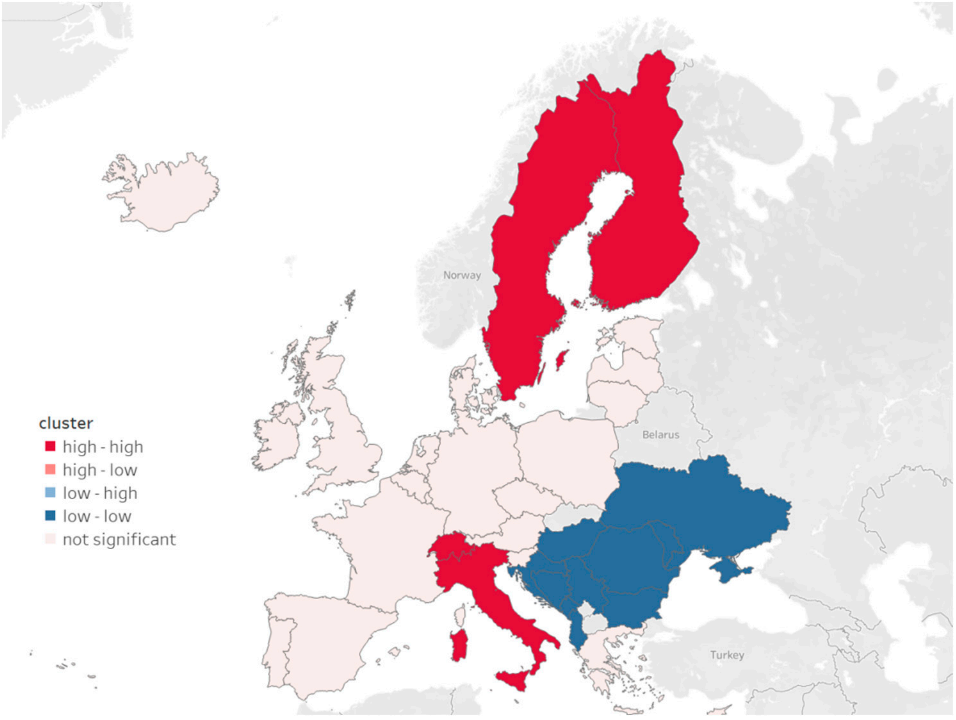

Figure 8. ETI cluster map in Europe.

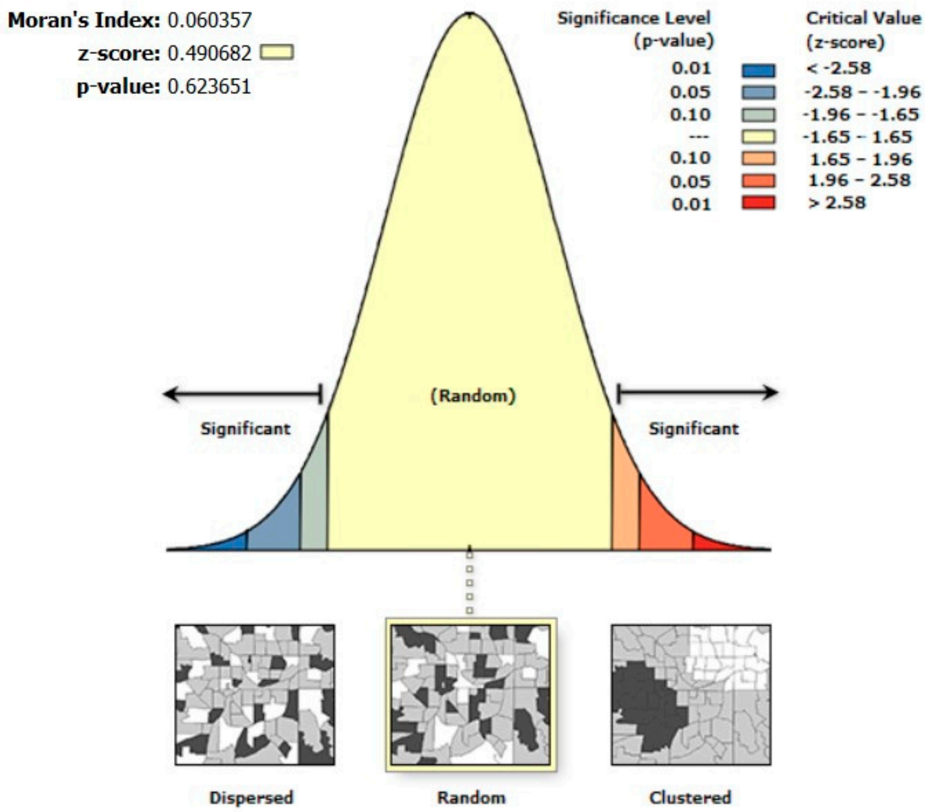

Figure 9. Moran's I distribution for ETI in North and South America.

Figure 10. ETI cluster map in North and South America.

In each case, it transpired that clustering occurs in European countries. It was not observed in Asia and only once (in the case of SP) in America. It may, therefore, prove that the effects of a jointly conducted climate policy are noticeable in Europe. Given that, in most cases, the Moran I statistics were statistically significant, the models indicating the factors influencing the Energy Transition Index, System Performance, and Transition Readiness (in both new and old versions) were estimated, using as diagnostic variables those with the highest weights according to the sensitivity-based analysis and additional variables indicating the degree of development of analysed countries (Table 5).

Table 5. Estimation results for ETI (new and optimised) for different continents.

Variable	Original ETI			Optimal ETI		
	America	Asia	Europe	America	Asia	Europe
λ	-	-	0.659 (0.0001)	-	-	0.769
HEP	0.088 (0.086)	0.014 (0.478)	−0.015 (0.655)	0.013 (0.741)	0.020 (0.220)	−0.045 (0.087)
CO_2	0.047 (0.241)	0.001 (0.981)	−0.055 (0.106)	0.109 (0.003)	0.086 (0.009)	0.014 (0.601)
RCB	−0.149 (0.798)	−0.324 (0.442)	0.331 (0.456)	0.234 (0.610)	−0.489 (0.114)	0.028 (0.933)
JLCI	4.337 (0.148)	5.665 (0.153)	2.217 (0.055)	3.318 (0.159)	4.321 (0.161)	2.477 (0.006)
POP	−0.013 (0.626)	−0.005 (0.767)	−0.003 (0.808)	0.013 (0.541)	0.016 (0.261)	0.005 (0.632)
UR	0.280 (0.148)	0.058 (0.532)	0.065 (0.524)	0.131 (0.379)	−0.033 (0.649)	0.100 (0.218)
EM	0.269 (0.040)	−0.135 (0.178)	−0.110 (0.170)	0.028 (0.767)	−0.101 (0.191)	−0.005 (0.930)
R^2	0.602	0.258	0.642	0.742	0.621	0.781

Table 5. *Cont.*

Variable	Original ETI			Optimal ETI		
	America	Asia	Europe	America	Asia	Europe
Moran's I (error)	(0.118)	(0.617)	(0.044)	(0.128)	(0.491)	(0.012)
LM (lag)	(0.226)	(0.182)	(0.117)	(0.882)	(0.483)	(0.056)
LM (lag) robust	(0.270)	(0.180)	(0.089)	(0.857)	(0.369)	(0.566)
LM (error)	(0.345)	(0.896)	(0.073)	(0.369)	(0.388)	(0.002)
LM (error) robust	(0.422)	(0.805)	(0.047)	(0.366)	(0.303)	(0.011)

Constant calculated but not reported; *p*-value is given in parentheses.

If the Moran statistics did not show spatial autocorrelation in the residues, the OLS multiple regression models were used; otherwise, the LM tests indicated the validity of SEM models; the SAR model was not pointed out in any case. The results of the estimates are presented in Tables 5–7. In addition, for the Energy Transition Index in Europe and America, the distribution of residuals from the model are shown in Figures 11 and 12.

Table 6. Estimation results for system performance (new and optimised) for different continents.

Variable	Original SP			Optimal SP		
	America	Asia	Europe	America	Asia	Europe
λ	0.617 (0.001)	-	0.563 (0.0001)	-	-	0.572 (0.0001)
HEP	0.043 (0.232)	0.028 (0.288)	−0.009 (0.812)	−0.114 (0.083)	0.038 (0.146)	−0.046 (0.276)
CO_2	−0.024 (0.538)	0.026 (0.586)	−0.081 (0.021)	0.063 (0.220)	0.199 (0.0001)	0.022 (0.600)
RCB	−0.317 (0.502)	−0.690 (0.186)	−0.110 (0.814)	−0.380 (0.611)	−0.311 (0.548)	−0.813 (0.140)
JLCI	2.226 (0.301)	3.537 (0.456)	1.293 (0.274)	1.971 (0.597)	0.100 (0.983)	0.279 (0.841)
POP	−0.015 (0.520)	−0.001 (0.985)	0.004 (0.751)	−0.007 (0.847)	0.012 (0.572)	0.0126 (0.439)
UR	0.344 (0.030)	0.011 (0.924)	0.083 (0.433)	0.422 (0.093)	−0.183 (0.116)	0.234 (0.061)
EM	0.356 (0.004)	−0.214 (0.082)	−0.144 (0.084)	−0.060 (0.703)	−0.194 (0.116)	0.017 (0.864)
R^2	0.722	0.254	0.518	0.682	0.598	0.549
Moran's I (error)	(0.019)	(0.133)	(0.047)	(0.371)	(0.278)	(0.004)
LM (lag)	(0.378)	(0.408)	(0.207)	(0.272)	(0.722)	(0.023)
LM (lag) robust	(0.495)	(0.364)	(0.120)	(0.275)	(0.815)	(0.187)
LM (error)	(0.036)	(0.331)	(0.093)	(0.811)	(0.535)	(0.008)
LM(error) robust	(0.160)	(0.298)	(0.049)	(0.837)	(0.576)	(0.060)

Constant calculated but not reported; *p*-value is given in parentheses.

Table 7. Estimation results for transition readiness (new and optimised) for different continents.

Variable	Original TR			Optimal TR		
	America	Asia	Europe	America	Asia	Europe
λ	-	-	0.670 (0.0001)	-	-	0.806 (0.0001)
HEP	0.170 (0.005)	0.001 (0.946)	−0.019 (0.622)	0.101 (0.060)	0.013	0.011 (0.118)
CO_2	0.105 (0.021)	−0.033 (0.432)	−0.022 (0.570)	0.136 (0.004)	0.038 (0.447)	0.424 (0.645)
RCB	0.058 (0.925)	0.112 (0.780)	0.847 (0.087)	0.312 (0.604)	−0.531 (0.249)	3.611 (0.173)
JLCI	4.775 (0.139)	8.043 (0.059)	3.577 (0.006)	4.266 (0.166)	6.172 (0.136)	0.001 (0.0001)
POP	−0.016 (0.578)	−0.011 (0.554)	−0.012 (0.443)	0.017 (0.526)	0.017 (0.065)	0.058 (0.911)

Table 7. *Cont.*

Variable	Original TR			Optimal TR		
	America	**Asia**	**Europe**	**America**	**Asia**	**Europe**
UR	0.124 (0.538)	0.124 (0.209)	0.088 (0.421)	0.021 (0.912)	0.035 (0.256)	−0.016 (0.453)
EM	0.189 (0.162)	−0.040 (0.691)	−0.072 (0.447)	0.095 (0.453)	−0.060 (0.653)	0.011 (0.788)
R^2	0.631	0.274	0.712	0.652	0.536	0.822
Moran's I (error)	(0.520)	(0.680)	(0.092)	(0.347)	(0.295)	(0.073)
LM (lag)	(0.117)	(0.218)	(0.571)	(0.836)	(0.516)	(0.218)
LM (lag) robust	(0.114)	(0.220)	(0.485)	(0.654)	(0.262)	(0.354)
LM (error)	(0.979)	(0.519)	(0.094)	(0.776)	(0.245)	(0.001)
LM(error) robust	(0.849)	(0.634)	(0.043)	(0.626)	(0.139)	(0.001)

Constant calculated but not reported; *p*-value is given in parentheses.

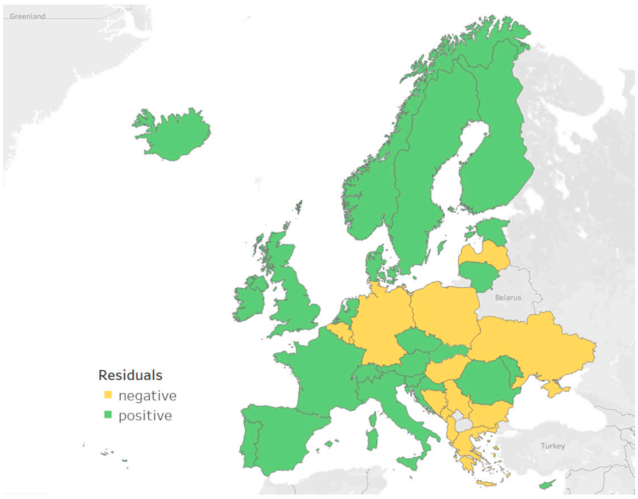

Figure 11. Moran's I distribution for residuals for the ETI OLS model in Europe.

Figure 12. Moran's I distribution for residuals for the ETI OLS model in North and South America.

When analysing data contained in Table 5 concerning the development of ETI in its original and new form, it can be noticed, as mentioned before, that the spillover effect takes place only in the case of Europe; it is not detected on other continents. Moreover, when it comes to the variables with the highest weights, HEP (household electricity prices) for the original ETI in America and optimised in Europe and the JLCI in both models for Europe are statistically significant at the level of 0.1. It should be emphasised, however, that the HEP affects America and Europe differently. Perhaps this could be explained by the fact that rising energy prices in American households will push for a faster transition to alternative energy sources, while the process is not so fast in Europe and hence harms energy transition. In the case of Europe, increasing the share of employment in the renewable energy sector (JLCI) contributes to improving the ETI value. While at first glance, comparing Figures 11 and 12, one could think that the residuals from the model are distributed similarly, and the Moran's I statistics in the case of America are statistically insignificant, indicating the lack of spatial dependencies in the development of ETI values.

In terms of System Performance, as for ETI, spatial dependencies are noticeable in Europe. In the original synthetic SP measure in America, its optimised version does not emphasise such a feature. In the case of System Performance, the explanatory abilities were better for those variables relating to the general development of the economy, i.e. the degree of urbanisation positively influences SP in America (both models) and Europe (optimised version). Employment in the industry positively impacts the SP value in America, while it is negative in Europe and Asia (original version). On the other hand, the degree of urbanisation positively influences the optimised SP values on the American and European continents.

The last of the estimated models concerned the transition readiness aspect. Also, in this case, the effect of spatial spillovers is visible only in Europe. Significant (positive) influence is again observed in the percentage of people employed in the renewable energy sector (JLCI), which can be explained by the intensively developing industry, which certainly favours the broadly understood energy transition.

5. Discussion

The energy transition is one of the biggest challenges facing the global economy due to the gradual depletion of fossil fuels and climate change. Changes in the energy sector have implications for the entire economy. The energy transition process also involves overcoming various challenges due to their complexity and uncertainty, especially in the funding of green investments [61]. According to Falcone [62], the reliability and transparency of the financial system and the management of systemic risk related to green credit will play a crucial role in a successful energy process. In addition, the approach to financing energy transition should be more hybridized, i.e., financial instruments should focus on environmental issues and the inclusion of socioeconomic and governance-related challenges. This kind of financial instrument, named green finance, enormously facilitates and accelerates the energy transition [63].

We agree with other authors [1] that energy transition should be assessed in the broader socioeconomic context. The energy policy should focus on a more holistic assessment of the interactions between the energy transition and the broader economy. For this reason, we focus our analysis on The Energy Transition Index, which takes into account macroeconomic, institutional, social, and geopolitical factors that make it possible to measure an effective energy transition. Starting our analysis, we were in line with [33] that the ETI allows, due to its complex nature, to better understand the past and current states of energy transition worldwide.

Unfortunately, the conducted research shows that the ETI is unbalanced and includes many variables of marginal importance for the shape of the final ranking. Many of them concern the perception of the analysed countries in the international arena, i.e., transparency, credit rating, or the rule of law. However, this group also includes such variables as energy access regulation (RISE access score), energy per capita, or share of electricity from renewable generation. The most important (with the highest information load) are CO_2 emissions per capita, innovative business environment, household electricity prices, or renewable capacity buildout. The research results complement the analysis of [64], which draws attention to the other set of energy transition determinants: economic growth, unemployment, and rising government debt.

Our analysis indicates the robustness evaluation should be a necessary step in ETI construction or ETI changes. Greco et al. [33] previously stressed how far off the mark a weighting scheme might be when assigned compared to its actual effect on the overall index. Therefore, we strongly recommend using one of the three tools proposed by [48] to gain better insight into the impact of the weights on the final synthetic index, i.e., estimating the effect of the weights applying Gaussian processes (or penalised splines), isolating the correlation of the indicators in the index based on Pearson's correlation ratio, or finally, perfectly fitting the given weights to their actual importance in the final index. Our results are consistent with [33], who link the usefulness of ETI in decision making to the modification of variables or weights to relevance to local circumstances.

We also believe that one of the causes of ETI's non-reliability is that it considers many variables with different directions of impact (stimulants and destimulants), which, as shown by the correlation analysis, indicates that there is a negative correlation between individual elements. It is problematic, both from the technical and computational point of view, and the political implications on the other hand. How can activities be properly balanced if improvement in one area implies a deterioration of the situation in another? The solution to this problem may be selecting diagnostic variables so that they have the same effect on the analysed phenomenon. Because, in this case, even the normalisation and unification of the direction of impact do not solve the negative correlation between the pillars. In addition, the index can be simplified by excluding variables with a marginal information load, which will reduce the time and cost of acquiring data and improve the transparency of the index.

Moreover, in our study, we identified the clustering of both the ETI and its two main pillars in Europe, which offers some policy implications. The results are in line with some studies [65], which indicate that spillover effects in many socioeconomic phenomena can be facilitated by spatial proximity and organisational, technological networks. Additionally, the presence of a specific organisational community influences the design of certain phenomena, notably the energy transition. Therefore, European countries should consider their own conditions and the effects of neighbouring countries, such as CO_2 emissions per capita, innovative business environment, household electricity prices, or renewable capacity buildout.

Our results are in line with policy priorities of the European Commission for climate and energy in the period from 2020 to 2030 [66]. The identified positive spatial effects show the European countries need much deeper cooperation to reach a successful energy transition, especially to drive the decarbonisation in line with the Paris Agreement, capitalise on the economic and industrial prospects that this global transition offers, and develop a common approach to energy stability.

We hope that our research contributes to further analyses of measuring the energy transition. Therefore, it is advisable to review all major energy transition indicators and improve them and identify the most important determinants of this phenomenon.

Our research plans are two-pronged. First, we intend to look in more detail at other composite indicators of the energy transition [21–24,67] and verify them using a sensitivity-based approach. Afterwards, based on the factors that played the most significant role in each of the indicators, we want to create a novel composite indicator, ensuring that the weights reflect the actual significance of the variables. Secondly, we want to develop an applied research tool. At the moment, it is quite problematic for those who are not so familiar with sensitivity analysis. Moreover, it does not clearly indicate when the weights should be modified: Does a 5% difference between the actual weights and those assigned by creators imply a change in weights? Is the level of discrepancy is acceptable? We want to conduct a series of simulations using the Monte Carlo method to prepare recommendations on how to proceed in specific scenarios.

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