EVALUATION OF THE PRODUCTIVITY, EFFICIENCY AND RESILIENCE OF FOOD PRODUCTION SYSTEMS DURING THE COVID 19 PERIOD (2020-2022): A CASE STUDY FOR GLOBAL REGIONS

Luis Angel Figueroa-Campos

Estudiante de maestría, Posgrado en Sistemas Agrícolas y Alimentarios Resilientes, Wageningen University, Paises Bajos

***Author for correspondence: angel.figueroacampos@wur.nl**

Citation: Figueroa-Campos LA. 2025. Evaluation of the productivity, efficiency and resilience of food production systems during the COVID 19 period (2020-2022): a case study for global regions. **REMEVAL** 1(2): 180-200. https://doi.org/10.63121/6yn6ey68

Received: July 7, 2025
Accepted: August 2, 2025
Published: August 29, 2025

Abstract

To operationalize the term resilience in food systems, it is necessary to indirectly quantify this attribute, so that the impact caused by external phenomena can be measured. One way to think of resilience is in terms of maintaining productive efficiency over time. It is assumed that resilience is an intrinsic property of complex adaptive systems, which should be measured as a comparison across time of the behavior of the system under study (time series) and comparing similar cases (data panels). This paper integrates the concepts and results of econometric analyses based on total agricultural production (TFP), data envelope analysis (DEA) and Malmquist index to identify nations that in the period from 2020 to 2022 serve as an example in terms of maintaining their productive efficiency under adverse contexts such as the COVID pandemic. The results are discussed with a complex adaptive systems approach.

Introduction

There are global phenomena whose aggregate effects on decision-making units are more frequent and imminent, such as extreme weather events, aggressive and unpredictable economic policies and pandemics, among others. These risks of different natures have an asymmetrical impact across organizational scales and ecological, economic and social dimensions on complex systems, this includes food production and distribution systems.

To analyze the effect of global phenomena on agrifood systems and their resilience, this paper proposes to analyze the productivity of nations and discuss the results from a complex systems approach. Resilience is then considered in terms of productive efficiency and the ability to maintain such efficiency after an external phenomenon that disrupted the usual plans and behaviors of food chains, such as the COVID 19 pandemic.

Resilience is assumed to be an intrinsic attribute of systems that, in this case, reflects the continuity of aggregate behavior. However, since there is no universal approach to this concept, the present work suggests a way to indirectly quantify this attribute of systems by integrating econometric analysis tools.

The general objective of this work is to analyze from a national scale, the productivity efficiency of agricultural sector activities in different regions of the world, with emphasis on the Latin American region, but integrating North America, Asia, Europe and Oceania into the study, during the period 2020 to 2022, through three econometric analysis tools: first, an overview of the Total Agricultural Productivity (TFP) indicator, second, a data envelope analysis (DEA) and finally, a Malmquist analysis, in order to identify the regions and countries that show greater resilience post-COVID-19.

Methodology

Next, a brief description of the conceptual tools used for the analysis of productivity and efficiency is made, as well as a reference to the database where the information of the different nations has been compiled that has been used for the research. The literary sources used as a reference for the discussion of the results are also mentioned.

The International Agricultural Productivity report measures agricultural productivity using the Total Agricultural Productivity (TPF) indicator. It compares the proportion of the total products of agricultural activities with the combined inputs used in their production of land, human labor, capital, and material resources used in field production. Most of the information used to develop the indicators comes from FAOSTAT, also integrating information from multiple other databases (Department of Agriculture, U.S., 2025). In (a) describes the calculation of the indicator, defined as a proportion of outputs (outputs) and inputs (inputs):

$$TFP = \frac{Y}{X} \qquad 1)$$

Total Factor Productivity (Department of Agriculture, U.S., 2025).

$$ln\left(\frac{TFP_t}{TFP_{t-1}}\right) = \sum_i R_i ln\left(\frac{Y_{it}}{Y_{it-1}}\right) - \sum_j S_j ln\left(\frac{X_{jt}}{X_{jt-1}}\right) \qquad 2)$$

Weighted difference of value (costs)-share between total product growth and total input growth (Department of Agriculture, U.S., 2025).

Y= Total products
X = Total inputs
Ri = revenue share of the i-th product
Sj = share of the costs of the j-th input

Total output growth is estimated by adding the growth rates of each output, weighted by its revenue share, represented in (b), is the weighted value-share difference between total output growth and total input growth. These growth rates are used to estimate the annual index, where the base year *t* has a value of 0. If total outputs grow faster than total inputs, it is called an improvement in productivity per total factor (Department of Agriculture, U.S., 2025).

Now, there are multiple products and inputs that make up agricultural activities as a whole, also, competitive markets in equilibrium are assumed, where the underlying technology is represented by production functions of constant returns to scale, so technological improvements have a "positive" effect on yield, it is also assumed that an agricultural product *i* will have its elasticity defined by the participation of an input *j* in its cost for each input present. (Department of Agriculture, U.S., 2025).

These growth rates of Total Agricultural Productivity (TPF) are compared to generate the TPF Index, which is based on the year 2015, since its last update in 2024, assigned a value of 100, so a value of 115 in the year 2020 would be an increase of 15% in the TFP in relation to 2015. This increase in technical efficiency is driven by changes in the set of available technologies, extension and education, market access and institutional reforms, derived from public policies.

In this context, and to provide a valid analysis and interpretation, the TFP values are referenced to 2020, therefore, it is assumed that:

$$\text{TFP Index}_t^{\text{base 2020}} = \frac{\text{TFP}_t}{\text{TFP}_{2020}} \times 100 \qquad 3)$$

Value of the index in year t, assigning a score of 100 to the year 2020.

and

$$\text{TFP}_t = \text{TFP Index}_t^{\text{base 2015}} \times \left(\frac{\text{TFP}_{2015}}{100} \right) \qquad 4)$$

Value in year t, assigning a score of 100 to the year 2015 to the index.
then

$$\text{TFP Index}_t^{\text{base 2020}} = \frac{\text{TFP Index}_t^{\text{base 2015}}}{\text{TFP Index}_{2020}^{\text{base 2015}}} \times 100$$

5)

Clearing of the Total Agricultural Productivity index for the year 2020 with a value of 100.

In such a way that new TFP values are generated, by region, based on the year 2020, given in (c), (d) and (e), these are structured as a data panel for a descriptive statistical analysis.

Subsequently, a data envelope analysis (DEA) was performed to evaluate and identify those countries in the Americas, Oceania, Europe and Asia that define an efficiency frontier by having a score of =1, which serves as a reference for "inefficient" countries (*Coelli, et al.*, 2005), the score is obtained by estimating the minimum distance to get as close as possible to its virtual efficient versions, *theta*. This procedure was carried out for the year 2020, 2021 and 2022. Broadly speaking, it consists of defining inputs (inputs) and outputs (profitable products) to generate an efficiency frontier established by decision-making units (in this case countries), for each year, by means of a linear optimization approach. An input-oriented analysis was performed, with a constant return-to-scale (CRS) approach, also with variable return-to-scale (VRS) to finally estimate the efficiency at scale (SE).

$$\begin{aligned}
&\min_{\theta,\,\lambda} \quad \theta \\
&\text{s.t.} \quad \sum_{j=1}^{n} \lambda_j x_{ij} \le \theta x_{io}, \qquad i = 1, \ldots, m, \\
&\qquad\;\; \sum_{j=1}^{n} \lambda_j y_{rj} \ge y_{ro}, \qquad r = 1, \ldots, s, \\
&\qquad\;\; \lambda_j \ge 0, \qquad\qquad\qquad j = 1, \ldots, n.
\end{aligned}$$

6)

Approach to the linear DEA problem, with constant return of scale, oriented to outputs (Coelli, *et al.*, 2005).

Where x is the quantity of inputs, y the quantity of outputs, i is the index of inputs, r is the index of outputs, j is the index of decision-making units, in this case countries. Theta(θ) is the efficiency score, it refers to the total percentage of inputs that are necessary to generate the same amount of outputs, while the percentage of possible reduction (improvement in processes) of inputs for each decision-making unit is $1-\theta$. Lambda(λ) is the weight assigned to each decision unit j that serves as a reference for the most inefficient decision units and that have similar values in terms of scale/efficiency (Coelli, *et al.*, 2005).

For the model with variable return to scale (VRS) one more limitation is added to the optimization problem, which forces the reference values when generating the boundary to have as 1 the value of the total sum (figure 7), this controls the size at scale unlike CRS according to Thanassoulis, 2001, who also describes scale efficiency as:

$$\sum_{j=1}^{n} \lambda_j = 1 \tag{7}$$

Limitation added to the linear problem to propose a variable return of scale (VRS)

"... measures the divergence between the efficiency score (θ) of a DMU under CRS and VRS respectively... the greater the divergence between the efficiency ratings of VRS and CRS, the lower the value of scale efficiency and the more adverse the impact of scale size on productivity" (Thanassoulis, 2001:140) (h).

$$\mathbf{SE}_o = \frac{\theta_o^{\mathrm{CRS}}}{\theta_o^{\mathrm{VRS}}} \tag{8}$$

Calculation of Scale Efficiency.

The linear optimization problem is solved in *RStudio*, using the *Benchmark* package, which in turn uses the *lpsolve* package to solve the problem, using a simplex algorithm.

The variable established as the total product (*y*) is defined as the gross value of agricultural production of crops, livestock and aquaculture multiplied by $1000 at constant 2015 prices. The following are the variables used (Table 1) as inputs (*J*), this information is part of the database with which the TFP was calculated, in it you can consult the sources of information and explanation of the units.

The final component of the present work consists of a Malmquist analysis (i) for adjacent periods, which *"measures productivity changes over time and can be decomposed with a non-parametric approach like DEA... it represents changes in efficiency and technological changes"* (Lee, 2011:1). A variable return scale model was used to consider differences around the countries.

$$\mathrm{MPI}^I_{t,t+1}(x_t, y_t, x_{t+1}, y_{t+1}) = \underbrace{\frac{D^I_{t+1}(x_{t+1}, y_{t+1})}{D^I_t(x_t, y_t)}}_{Efficiencychange(EC)} \times \underbrace{\left[\frac{D^I_t(x_{t+1}, y_{t+1})}{D^I_{t+1}(x_{t+1}, y_{t+1})} \cdot \frac{D^I_t(x_t, y_t)}{D^I_{t+1}(x_t, y_t)}\right]^{1/2}}_{Technicalchange(TC)}. \tag{9}$$

Table 1. Description of the variables used as inputs for the data envelope analysis (DEA) and the Malmquist analysis, source: Department of Agriculture, U.S., 2025.

Input	Description
Earth	Agricultural area adjusted for quality; cropland irrigated with rainfall.
Farmland	Total cropland (including arable land and land with permanent crops)
Irrigated land	Total Area with Irrigation Equipment
Grasslands	Total area of permanent pasture
Work	Number of workers in agricultural sectors
Capital	Net Equity Stock Value, $1000 at constant 2015 prices
Fertilizer	Total nitrogen (N), phosphate (P2O5) and potassium/potash (K2O) nutrients from inorganic fertilizers and N from organic fertilizers applied to soils
Feed for animal production	Total metabolizable energy from animal feed, M Cal

Source: Self-elaborated.

Estimation of the Malmquist index, proposed as a change in efficiency between two adjoining periods (Färe *et al.,* 1994).

Where D_t^I is a function that results in the distance of a decision-making unit (countries in this exercise) in period *t,* to the efficiency frontier, given a set of technologies, inputs and outputs, (Färe *et al*., 1994), this value is a score like theta, where it takes the value of 1 if it is at the efficiency frontier.

$$\mathrm{EC} = \frac{\hat{\theta}_t + 1(x_t + 1, y_t + 1)}{\hat{\theta}_t(x_t, y_t)}, \qquad \mathrm{TC} = \sqrt{\frac{\hat{\theta}_{t+1}(x_t, y_t)}{\hat{\theta}_t(x_t, y_t)} \cdot \frac{\hat{\theta}_t(x_{t+1}, y_{t+1})}{\hat{\theta}_{t+1}(x_{t+1}, y_{t+1})}}, \qquad 10)$$

Definition of efficiency change and technological frontier change (Färe *et al*., 1994).

The change in efficiency between these two adjacent periods is driven by two components, efficiency change, which refers to the resources and technologies available, and that is how far or close one is to the efficiency frontier. The change of the technological frontier refers to the sets of technologies available in each year and can be understood as a contraction or expansion of the frontier (Chang & Ross, 2024, Färe *et al*., 1994). In this approach, an improvement in efficiency can be explained by the fact that there were more technologies available or that it was more efficient with the available technologies, which allowed better results in terms of quantities of proportions of inputs and outputs obtained.

$$\mathrm{MPI} = \mathrm{EC} \times \mathrm{TC}. \qquad 11)$$

Simplification of the Malmquist index defined by the change in efficiency and the change in the technological frontier

In (k) simplifies the index, where values >1 indicate growth in productivity while values <1 indicate a decrease; The formal definition and breakdown of the method used as a reference are by Färe et al., 1994 and Chang & Ross, 2024. To visualize the contribution of each component of the index, the multiplication is decomposed to generate an additive visualization.

$$\underbrace{\mathrm{MPI}-1}_{totalchange} = \underbrace{(\mathrm{EC}-1)}_{catch-up} + \underbrace{(\mathrm{TC}-1)}_{frontiershift} + \underbrace{(\mathrm{EC}-1)(\mathrm{TC}-1)}_{interaction}. \quad 12)$$

Additive visualization of the contribution of each component to the indicator.

For Malmquist's analysis, a set with all countries with data available in the selected regions was used in the regional comparison, for the intraregional comparison subsets by region were used.

In order to discuss the final results within an already established and broader context of analysis with applicable theoretical approaches on resilience of complex adaptive systems, concepts established in the assessment framework for food systems ABCD (Agency, Buffer, Connectivity and Diversity) (Fonteijn et al., 2022), Analysis of Complex Adaptive Systems (Carmichael & Hadzikadic, 2019, Cumming, 2011, Adger *et al*., 2005), Resilience of socio-ecosystems (Folke, 2006), Adaptive cycles and Panarchy (*Resilience Alliance - Panarchy*, n.d., Meuwissen *et al*., 2019) are used as a framework of analysis.

Results and Discussion

The section is semi-structured, comparing the interregional and intraregional data, first, of the values of Total Agricultural Productivity, then the results of the analysis by data envelope, the results of the Malmquist analysis and finally a correlation between the three.

In terms of the change in the gross value of agricultural crop, livestock and aquaculture production in 2020, Oceania has the best yields, followed by Latin America and Asia (Figure 1).

Given that in a complex system there are variables of rapid and slow qualitative change, the variability in behavior in a relatively short period of time (2020 to 2022) can be attributed to rapidly changing variables and interactions, and to the fact that the

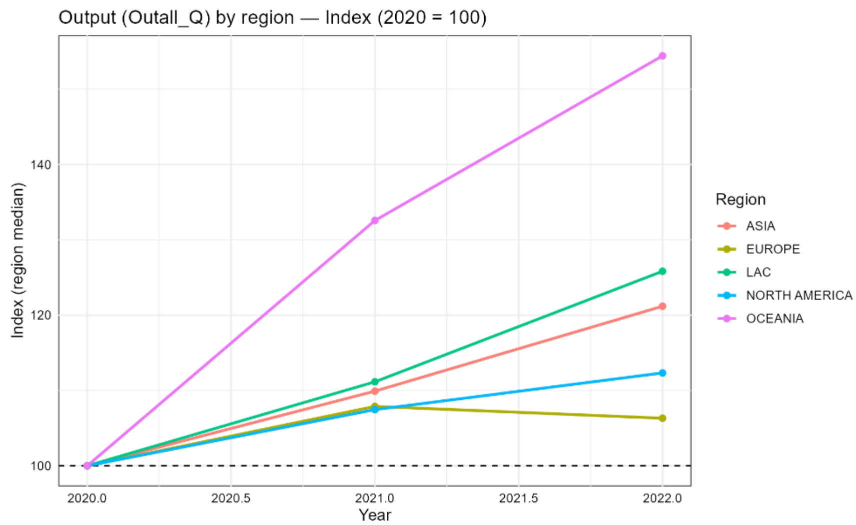

Figure 1. Values of the Output variable (gross value of total agricultural production base 2020).

response of institutions is usually when phenomena impact the daily life of society (*Resilience Alliance - Panarchy*, n.d., Folke, 2006) for example, assuming that there have been more changes in the quantities and/or prices of fertilizers, livestock feed, and capital value, their effect on process efficiency, both in the uncertainty for strategic planning and operational issues in shorter periods of action, will have a greater impact on the set of available technology and possibly on technical efficiency in the use of resources, than the sizes or holdings of production areas, as well as drastic institutional changes.

In this case, "Total Factor Productivity (TFP) growth reflects the ability to produce more with less: higher production with a given set of inputs" (Bureau & Antón, 2022: p. 4) because, in this case, the indicator uses a reference year to assess change over time, It is interesting to see the changes before and after 2020; in this sense, the impact on the trend of efficiency behavior is observed at the regional scale, where Oceania initially stands out with high values in the indicator both before and after 2020. Latin America and North America have TFP values lower than the reference year, both before and after, without recovering (Figure 2).

In reference to inputs, although it is usually presented as second place, Oceania does not stand out for having values as high as North America, only in the total area of permanent pastures (Pasture_Q), however, its gross value of total production (Output_Q) and value in Total Agricultural Productivity show resilience in terms of maintaining its efficient productive capacities or technological improvement through the process of managing COVID-19, given that by 2022, they approached their maximum values in 2017, even though there was a decline prior to 2020.

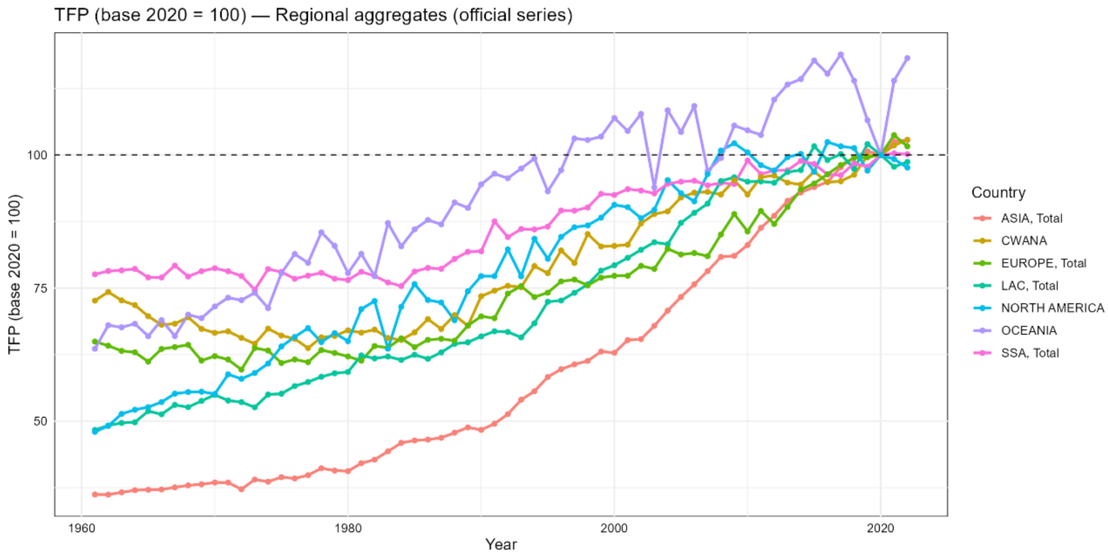

Figure 2. Time series from 1961 to 2022 with Total Agricultural Productivity (TFP) values base 2020.

As can be seen in Figure 3, some countries increased their values of the indicator. In Latin America, it is observed that Peru had an increase of 110.15 in 2021 and 118.66 in 2022, being the highest value in the total agricultural productivity

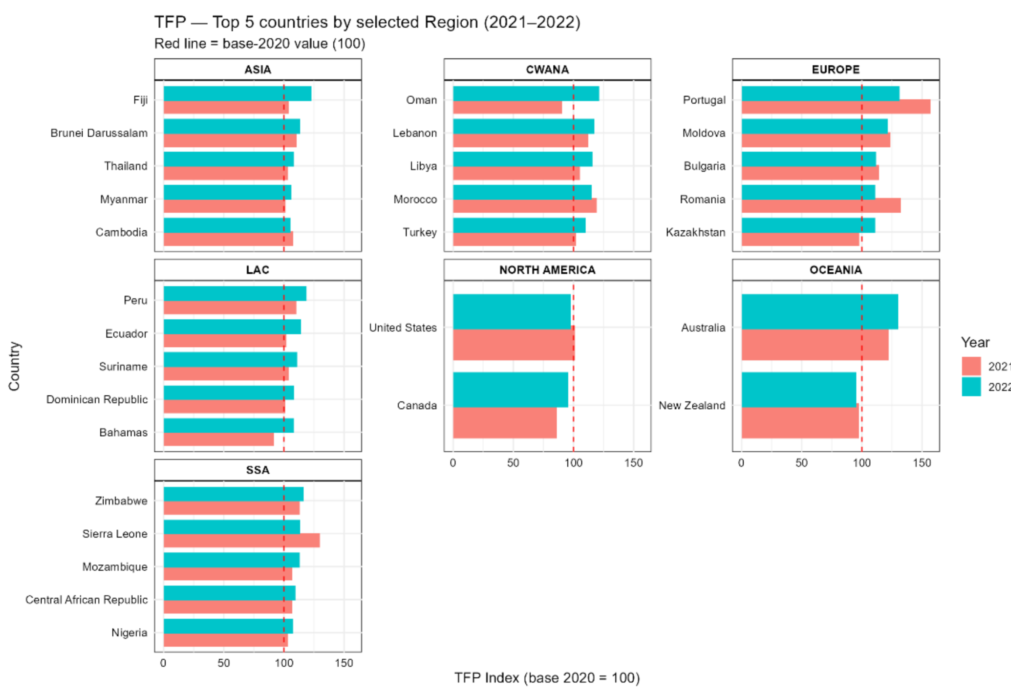

Figure 3. The 5 countries with the highest values in Total Agricultural Productivity 2021 and 2022.

index during the two years of the analysis, with Ecuador, the Dominican Republic and Suriname remaining in the top 5 during the two years of analysis.

Brunei, Fiji, Oman, Morocco, Portugal, Moldova, Romania, Peru, Sierra Leone and Zimbabwe are the best references for their respective regions in terms of reducing production costs, because their growth in the indicator implies either an improvement in the efficiency of the processes or an improvement in the set of technologies (or both). which results in less quantity or costs than those of inputs (Bureau & Antón, 2022).

Oceania and North America represent, in this database, large areas, but only two governments, however, both have low values, indicating an impact on their ability to maintain post-COVID-19 processes. When contrasting with the results of the additive decomposition of the MPI (Figure 20), we observe that there is a negative change in the technological frontier, it may be due to the loss of labor or other available inputs that the total set of possible inputs was reduced.

The following are results of the data envelope analysis, particularly the scale efficiency values. The average presented in Figure 4 is the result of the technological and process efficiency differences between countries in these regions, in Latin America,

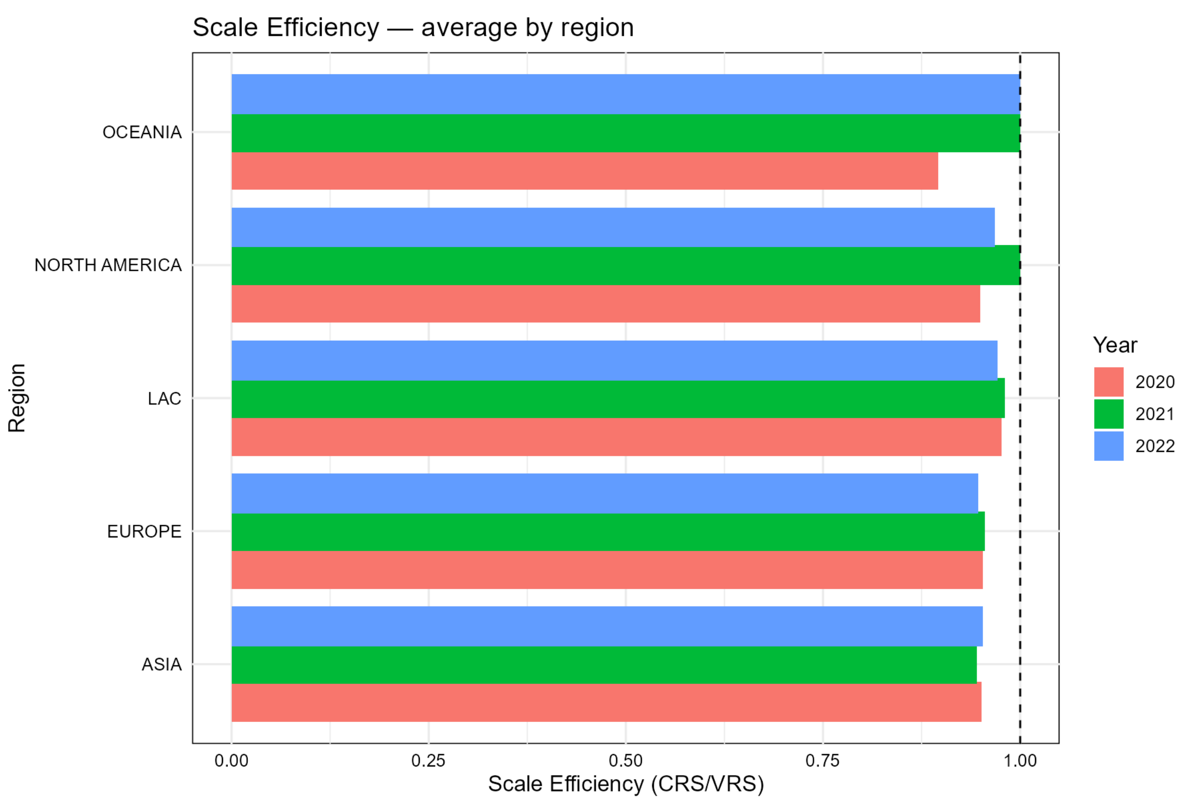

Figure 4. Average of the scale efficiency (SE) score of the countries that make up each region.

Asia and Europe, the number of countries is greater and therefore the average is more sensitive to extreme values.

In terms of efficiency of scale (SE), Oceania is part of the set that defines the border in 2021 and 2022, during this period the countries of this region operated optimally on their most productive scale (Aparicio & Santín, 2025), which reinforces the interpretation of a return to their production capacity and efficiency prior to 2020. given the production technology sets available in each year considering returns to scale as well as North America in 2021.

For those nations that have <1 values, this implies the possibility of improvement in the use of their resources (Figure 5). Values =1 coincide with the countries identified in the TFP ranking in the regions analyzed, however, Peru presents values less than 1 in the three years, not operating on an optimal scale, it was able to improve its capacity to produce the same amount with fewer inputs in the following years.

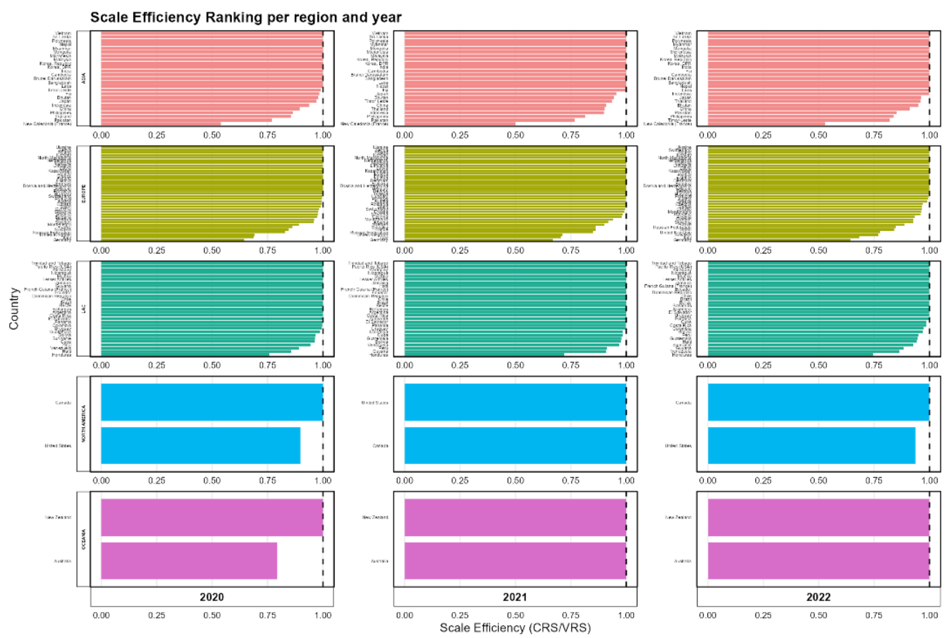

Figure 5. Score obtained by country in scale efficiency (SE).

Malmquist's analysis results:

The ranking presented in Figure 6 was made with all the mean of all the countries per region. Latin America and Europe take the 1 ranking in the period 2020 to 2021 and 2021 to 2022 respectively, Asia has number 2 in the year 2020 to 2021 and LAC in the second period. This narrative indicates the presence of feedback mechanisms between organizational scales that managed asymmetric changes and impacts on the variables of "rapid" change in supply chains, particularly those linear and nonlinear

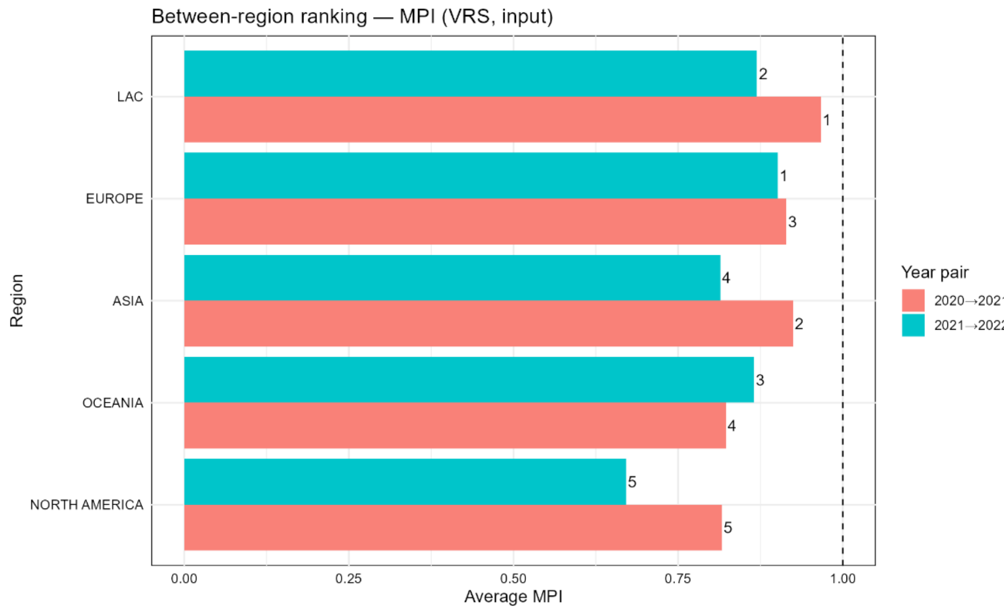

Figure 6. Average score of the Malmquist indicator of the countries that make up each region.

processes that impacted production and price levels on the farm, managing to increase efficiency in their total production after the impact produced in 2020.

This ranking was made with subsets by region (Figure 7). In Latin America, the Bahamas, Cuba and Guana stand out in the period 2020 to 2021, Honduras and Paraguay in the period 2021 to 2022. The other countries have values lower than 1, according to the indicator, that is, a decrease in the efficiency of their total agricultural productivity, after 2020, which may have previously had high values and there was a reduction in the set of available technologies, or a possible decline in the technical efficiency of the use of resources. illustrated as a distancing from the efficiency frontier.

In North America, only Canada in the period 2020 to 2021 has a value greater than 1, with a value less than 1 in both periods in the United States and the countries of Oceania. In Asia, Mongolia, Micronesia, Timos Leste and Bangladesh present values greater than 1 in the period 2020 to 2021, in the following period, this is the case only for Sri Lanka and Bhutan, which maintained their values at 1 during both periods.

In Europe, during the period 2020 to 2021, Croatia, Estonia and Slovenia have values greater than 1, Slovakia and Finland maintain a value equal to 1. In the following period, many more countries show improvements in the efficiency of their total agricultural production, including Hungary, Spain, Sweden, Ukraine and Romania, with Albania maintaining its value equal to 1.

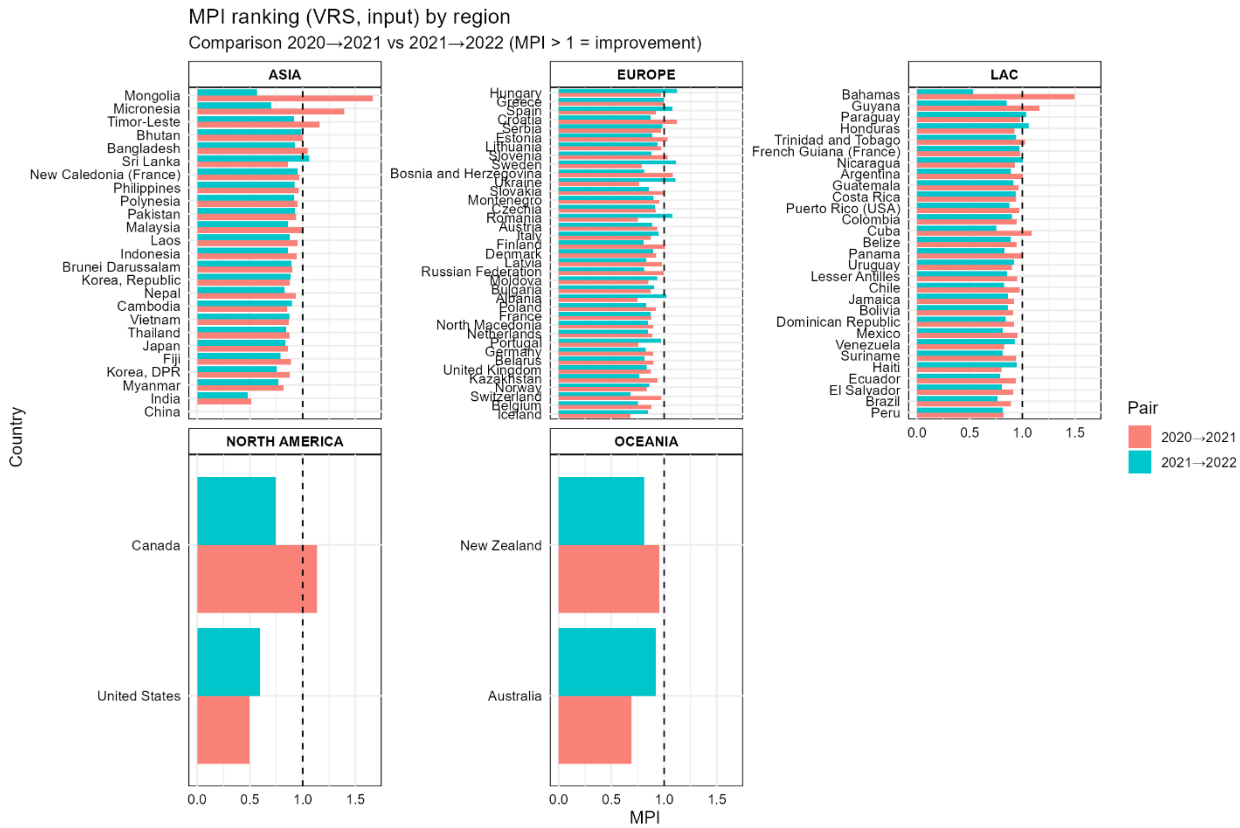

Figure 7. Score obtained from each country in the Malmquist index.

Figure 8 shows the countries with the highest value in the Malmquist indicator, this ranking being particularly useful for Latin America, Asia and Europe, and is broken down by attributing growth to a component determined by a set of available technologies and another by technical efficiency.

In the case of Latin America, the greatest growth was during the period 2020 to 2021, attributed mainly in the Bahamas and Guyana to an increase in the technological frontier and therefore a greater availability of technologies that allowed for more efficient production (with greater cost-benefit). Cuba's increase is mostly attributed to being more efficient with the same set of technologies, getting closer to the efficiency frontier. In the period 2021 to 2022 there were few changes related to the additive contribution, all related to the availability and use of sets of technologies, which may be due to an interruption in supply chains that contracted the frontier as there was less technology available (e.g. types of agrochemicals, industrial parts, workers, etc...).

Similarly in Asia, in the period 2020 to 2021, the increase in the countries is attributed to greater availability and use of technologies in the period 2020 to 2021,

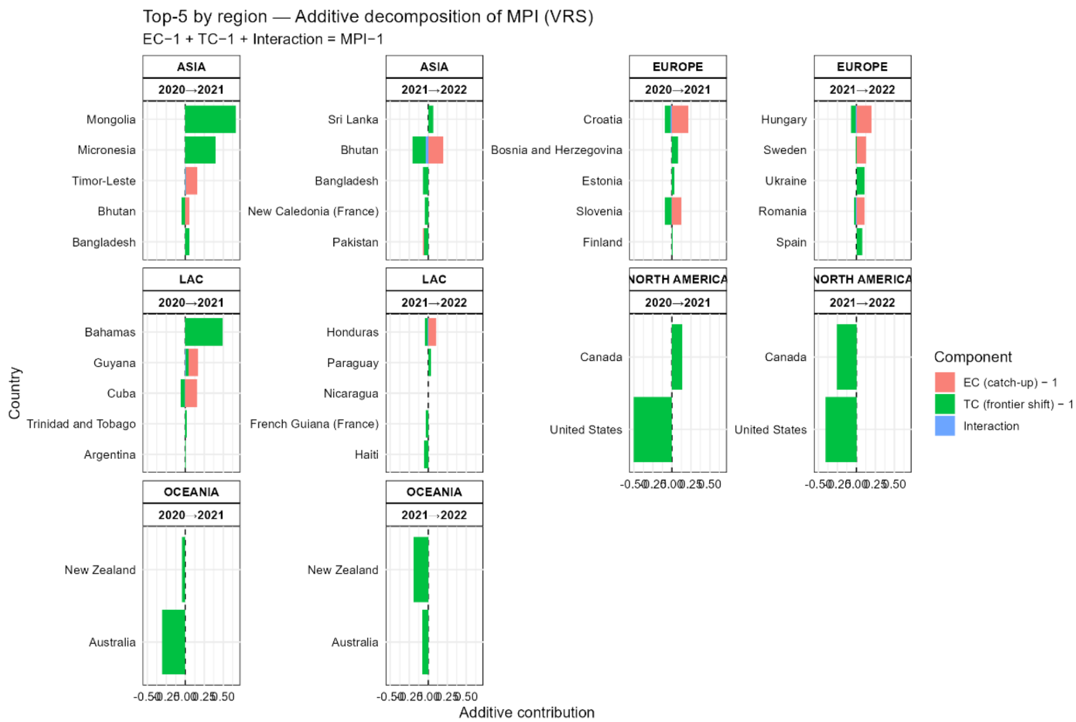

Figure 8. Additive decomposition of the Malmquist index

particularly for Mongolia and Micronesia, during the following period the largest increase is attributed to an improvement in the efficiency of the use of available resources and technologies.

In Europe, the largest increase in the period 2020 to 2021 is mostly attributed to an improvement in efficiency, particularly in Croatia, while in the following period 2021 to 2022, Ukraine stands out for an increase attributed to the subset of technologies, being this lower in Spain, while in Sweden and Hungary the increase is attributed to improving efficiency.

These analyses are performed with regional boundaries generated by the data subsets, so when these efficiency frontiers and the relative change in them are defined, by the set of available technologies, it is in relation to the countries that make up that region, "*these measures capture performance in terms of the best practices defined by the sample" (Färe et al., 1994:78).*

Consistency in the results obtained by the 3 analysis tools:

One possibility of the negative correlation (Figure 9) between TFP and MPI (also in Efficiency of Scale and MPI to a lesser extent) is that countries with high

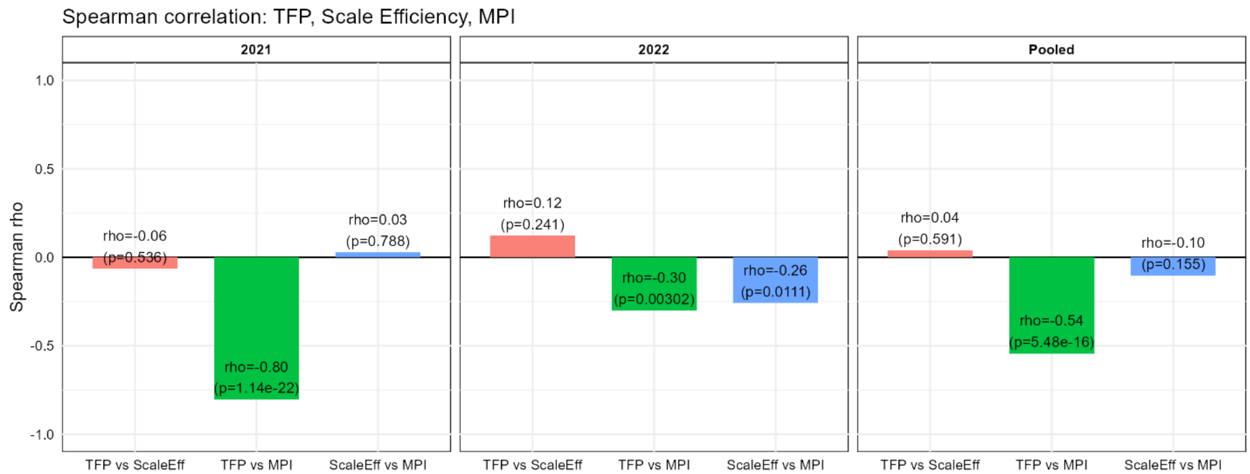

Figure 9. Results of Spearman's correlation.

total agricultural productivity and that tend to produce at their optimal scale have relatively small increases, coherent with Farnoukdia, 2023: *" can be attributed to the fact that, if a country has achieved development in a given year, it becomes increasingly difficult to achieve further development in the following year... If a country has experienced a deterioration in a given year, it is comparatively easier to achieve development in the following year through minor changes." (Farnoukdia, 2023: 3070)*

The positive correlation presented between TFP and efficiency scale, particularly in the year 2022, coincides in a monotonic relationship between operating at an optimal scale and increasing total agricultural productivity, being that it seeks to get closer to using the optimal possible amount of available resources and technologies in an efficient way (SE), there could be a more punctual correlation with an increase in technical efficiency.

Factors that determine the increase in TFP refer to the components of the Malmquist index, directly such as the change in the set of available technologies (frontier expansion) or in extension and education and market access, which indirectly refers to technical efficiency (approach to the frontier) (Deparment of Agriculture, 2025, Färe et al., 1994). These have impacts on operational processes and strategic planning, but still on the scope of actors directly related to the agricultural sector, while institutional reforms derived from public policies, which are not necessarily related to the sector, can have a broader, more asymmetrical and non-linear effect on the productivity of agricultural sectors

The Latin American region is then described in detail by comparing the values of the countries that presented the highest scores in Total Agricultural Productivity (Table 2) and the Malmquist (Table 3) index during the year 2021 and 2020, this to

Table 2. Comparison of the results for the top 5 in Total Agricultural Productivity (TFP) values.

Rank	Country	TFP 2021	SE 2021	MPI 2020-2021	Country	TFP 2022	SE 2022	MPI 2021-2022
1	Peru	110.15	0.91	0.79	Peru	118.66	0.95	0.77
2	Haiti	109.67	1	0.79	Ecuador	114.06	1	0.71
3	Bolivia	105.86	0.97	0.91	Suriname	110.87	0.92	0.84
4	El Salvador	105.63	0.99	0.90	Dominican Republic	108.39	1	0.79
5	Belize	104.51	1	0.90	Bahamas	108.06	1	0.51

Source: Self-elaborated.

Table 3. Comparison of the results for the top 5 in Malmquist index score.

Rank	Country	TFP 2021	SE 2021	MPI 2020-2021	Country	TFP 2022	SE 2022	MPI 2021-2022
1	Bahamas	91.88	1	1.44	Nicaragua	98.73	1	1.00
2	Guyana	85.09	0.90	1.27	Paraguay	76.62	1	0.98
3	Cuba	95.9	0.98	1.09	Honduras	95.21	0.71	0.95
4	Argentina	92.06	1	1.00	Haiti	107.67	1	0.94
5	Paraguay	92.69	1	0.99	French Guiana	99.09	1	0.93

Source: Self-elaborated.

highlight examples of resilience in terms of increasing and/or maintaining their TFP and the change in productivity between the periods 2020 to 2021 and 2021 to 2022.

Since the database used for this analysis aggregates the information at a national level, nations can then be defined as complex adaptive systems, with a behavior of the condition of the system (in this case TFP, SE and MPI) within a regime of attraction that involves interactions across public and private scales of organization. in economic dimensions (agriculture as an economic activity), social (given the impacts of COVID-19 on health) and ecological (considering soil management and inputs of renewable resources), these interactions are non-linear but generate dependence on paths, capturing processes and mechanisms with distinguishable and characterizable patterns. While the data directly reference inputs and outputs in terms of masses and costs, the implicit interactions warrant an approach of complex adaptive systems for their analysis (Folke, 2006, Carmichael & Hadzikadic, 2019).

It is intuitive to want to identify the public policies and practices (or identifiable processes and patterns) carried out at the multiple organizational scales that allowed these countries to be resilient and maintain or increase their productivity and efficiency through this period of health crisis, not only with primary producers but also with the industrial and marketing sector. Largely affected, by institutional structures, regulations and power interactions, as well as the monitoring and action capacity of the multiple actors, both small producers and large public companies that direct the direction of adaptation, since an improvement in econometric terms does not necessarily imply a fair distribution of profits or sustainable management of the resources involved in production. "*A management system for a natural resource has multiple scales and must be managed at different scales simultaneously" (Adger et al., 2005:1)*

One approach is to characterize the demographic groups, actors, and systems that make up the agricultural sector and identify the formal (and informal) feedback mechanisms across scales of organization present related to gender, social status, level of education and educational opportunity (Agency), savings capacity, amount of savings, statistical parameters related to financial capabilities (Buffer), merchant networks, distances to markets, percentage of inputs exchanged between whom (Connectivity), non-agricultural economic activities, type of production system or industrialization (Diversity). These variables and properties of Agency, Buffer, Connectivity, and Diversity are proposed in the ABCD approach to assess food systems resilience and can be integrated by categorizing or defining mechanisms as adaptative, transformative or robustness driving (Meuwissen et al., 2019, Fonteijn et al., 2022).

The presence of these feedback mechanisms, quantifying them over time and in horizontal and vertical interactions at the public and private organizational scales, can help to identify the designs and configurations of policies, infrastructure, and capacities of agents that, in non-linear interactions but with a recordable dependence on paths, correlate with resilience. In this way, with a reliable record, changes in domain regimes derived from external phenomena at the national level can be integrated as the decisions or selection criteria of the decision-making units to these options (or unplanned emergent behaviors, and therefore importance of having Agency in the agricultural sector). which, in a correlated change, generate adaptations that allow the efficiency of the agricultural sector to be maintained, the coherent limitation of this category of analysis being key (Folke, 2006, Carmichael & Hadzikadic, 2019, Cumming, 2011).

In this way, resilience is proposed in this paper as quantifiable indirectly in terms of maintaining or increasing efficiency; Because this attribute is intrinsic to systems, being efficient is first defined by the technological capabilities of the system and then how optimally those resources are used, this latter optimization characterization requires comparison with systems with similar capabilities and scales.

Methodologically, the presence of agency, diversity, connectivity and buffer properties can be correlated with total agricultural productivity or the Malmquist index, both individually and/or in multiple configurations and values, especially after an external event that negatively affects and threatens a change in the dominance regime. A characterization of this type is justified in a nation like Mexico, where there are great differences in the scales and production capacities of the actors that make up the agricultural sector and its entire production and value chain.

Limitations of the study

The database used for the analysis has subsets of country data that were estimated due to lack of information (Department of Agriculture, U.S. 2025), as well as multiple changes and revisions that make it subject to bias and errors. The information is highly aggregated and incorporates multiple sectors, so the results should be taken with criticism.

The efficiency scale (ES) DEA analysis such as Malquemist (MPI) was input-oriented, it was assumed that countries sought to maintain productivity levels with the same or fewer inputs due to supply chain disruptions. For the analysis of regional Malquemist, regional sets were used, while the efficiency scale used the total set of countries to make a comparison that considers interregional examples, which limits their comparison and opens up a comparative analysis of subsets of data.

The difference in complexity in terms of decision-making is evident between regions and countries of the world, with there being, for example, more countries and therefore more administrative boundaries in Latin America than in Oceania or North America; this point is not explicitly considered in the analysis, a subsequent review of the correlation between productivity, number of government regimes and participation is proposed, to identify institutional mechanisms and public policies that provide resilience in terms of agency, connectivity and diversity (Fonteijn et al., 2022) abstracted into variables and indicators of a social nature.

Conclusions

The most resilient regions and countries by region have been identified, in terms of maintaining and/or increasing their capacity to convert inputs (efficiency) into procedures and improve the set of technologies available during the period 2020 to 2022, obtaining different results depending on the analysis tool.

In Latin America, according to total agricultural production (TFP), Peru stands out for being the country that was present in the 2 years, with El Salvador and the Dominican Republic, Bolivia, Haiti and Belize in the first places during 2021 and 2022. In terms of the Malmquist index, Paraguay remained in the ranking for the analysis of both periods, in which the Bahamas, Cuba, Argentina and Nicaragua, Honduras and Haiti were also in 2021.

A negative correlation between total agricultural production (TFP) and the Malmquist index, a negative correlation between scale efficiency (SE) and the Malmquist index and a positive correlation between total agricultural production

(TFP) and scale efficiency (SE) were estimated, being consistent with the bibliographic references consulted.

Concepts, approaches, and possible methodologies that integrate multiple disciplines to characterize and quantify resilience were identified and discussed, highlighting the approach of complex adaptive systems and ABCD, which are coherently structured for integration with econometric approaches.

Literature Cited

Adger, W. N., Brown, K., & Tompkins, E. L. (2005). The Political Economy of Cross-Scale Networks in Adger, W. N., Brown, K., & Tompkins, E. L. (2005). The Political Economy of Cross-Scale Networks in Resource Co-Management. *Ecology and Society,* 10(2). https://www.jstor.org/stable/26267741

An introduction to efficiency and productivity analysis (with J. Coelli, T., Prasada, D. S., Battese, G., & O'Donell, C.). (2005). New York : Springer. http://archive.org/details/introductiontoef0000unse

Aparicio, J., & Santín, D. (2025). Global scale efficiency in data envelopment analysis. *International Transactions in Operational Research*, 32(5), 2474–2496. https://doi.org/10.1111/itor.13501

Bogetoft, P., & Otto, L. (2010). Benchmarking: Benchmark and Frontier Analysis Using DEA and SFA (p. 0.33) [Dataset]. https://doi.org/10.32614/CRAN.package.Benchmarking

Bureau, J. C., & Antón, J. (2022). Agricultural Total Factor Productivity and the environment: A guide to emerging best practices in measurement (OECD Food, Agriculture and Fisheries Papers 177; OECD Food, *Agriculture and Fisheries Papers*, Vol. 177). https://doi.org/10.1787/6fe2f9e0-en

Carmichael, T., & Hadzikadic, M. (2019). The Fundamentals of Complex Adaptive Systems (pp. 1–16). https://doi.org/10.1007/978-3-030-20309-2_1

Cumming, G. S. (2011). Spatial resilience: Integrating landscape ecology, resilience, and sustainability. *Landscape Ecology*, 26(7), 899–909. https://doi.org/10.1007/s10980-011-9623-1

DEPARMENT OF AGRICULTURE, U. S. (2025). International Agricultural Productivity—Update and Revision History | Economic Research Service. Economic Research Service U.S. DEPARTMENT OF AGRICULTURE. https://www.ers.usda.gov/data-products/international-agricultural-productivity/update-and-revision-history

FAOSTAT. (n.d.). Retrieved August 3, 2025, from https://www.fao.org/faostat/en/#search/agriculture

Färe, R., Grosskopf, S., Norris, M., & Zhang, Z. (1994). Productivity Growth, Technical Progress, and Efficiency Change in Industrialized Countries. *The American Economic Review*, 84(1), 66–83.

Farnoukdia, H. (2023). (PDF) Malmquist index evaluation of countries: 2000-2019. ResearchGate. https://doi.org/10.1051/ro/2023118

Folke, C. (2006). Resilience: The emergence of a perspective for social–ecological systems analyses. *Global Environmental Change*, 16(3), 253–267. https://doi.org/10.1016/j.gloenvcha.2006.04.002

Fonteijn, H. M. J., Van Voorn, G. A. K., de Steenhuijsen Piters, C. B., & Hengeveld, G. M. (2022). The ABCD of food systems resilience: An assessment framework. https://doi.org/10.18174/580782

Lee, C. (2011). Malmquist Productivity Analysis using DEA frontier in Stata. CHI11 Stata Conference, Article 21. https://ideas.repec.org//p/boc/chic11/21.html

Meuwissen, M. P. M., Feindt, P. H., Spiegel, A., Termeer, C. J. A. M., Mathijs, E., Mey, Y. de, Finger, R., Balmann, A., Wauters, E., Urquhart, J., Vigani, M., Zawalińska, K., Herrera, H., Nicholas-

Davies, P., Hansson, H., Paas, W., Slijper, T., Coopmans, I., Vroege, W., ... Reidsma, P. (2019). A framework to assess the resilience of farming systems. *Agricultural Systems*, 176, 102656. https://doi.org/10.1016/j.agsy.2019.102656

Resilience Alliance—Panarchy. (n.d.). Retrieved February 8, 2023, from https://www.resalliance.org/panarchy

Thanassoulis, E. (2001). Introduction to the Theory and Application of Data Envelopment Analysis. Springer US. https://doi.org/10.1007/978-1-4615-1407-7