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THE MEASUREMENT OF AGRICULTURAL PRODUCTIVITY CHANGE IN OECD COUNTRIES WITH FUZZY DATA

Kazim Baris Atici[*], Aydin Ulucan and Irmak Uzun Bayar

Abstract. In this paper, we aim to measure agricultural productivity change of 34 OECD countries between years 1990 and 2014. The methods employed are data envelopment analysis (DEA) and malmquist productivity index (MPI). DEA is a relative efficiency method in a production technology, whereas MPI is based on DEA to measure the changes in the production technology over time. Our challenge is the existence of missing data points over the years in the initial dataset, which correspond to approximately 9% of the data. Removing units, factors or years with missing data as commonly practiced in DEA, would cause loss of information and makes it very difficult to draw conclusions in such a macro-data. We present the idea of using averages of available data points for a given factor and average variations over the years in those data to produce intervals for the missing points and handle the problem without any dimension reduction in the available data. Fuzzy DEA approach is employed using the calculated factor-specific intervals followed by MPI calculations to conduct a productivity change analysis. We suggest and empirically illustrate that instead of narrowing down the scope of the analysis by excluding the points missing, applying fuzzy approaches is an option worth considering by which it can be possible to make the best out of the available information. The results of the analysis are interpreted with respect to years, countries, regions and economic size of the countries.

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1. Introduction

The availability of relevant, reliable and complete data is an essence of macro-level evaluations especially in quantitative research. Methods may vary in terms of the output information provided, however, the produced results are meaningful only if the data utilized is relevant, reliable and complete. Missing data hold an important place in quantitative analysis that omitting them can change the findings and therefore can change the interpretations. In some cases, existence of vast missing data is the main barrier for analyzing them in the first place.

The measurement of agricultural performance and its change over time at macro-level is one of the interest areas of quantitative performance measurement literature. Data envelopment analysis (DEA) is one of the major methods that is widely applied in this research area. It is a well-established efficiency measurement method, relying on the calculation of the efficiency score of a unit in a production technology relative to an

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Department of Business Administration, Hacettepe University, Ankara, Turkey.

[*] Corresponding author: kba@hacettepe.edu.tr

efficient Frontier established by units performing similar operations. DEA identifies the best-practice Frontier of the units and measures the relative efficiency scores of the less efficient units in relation to the Frontier. The method is introduced by Charnes *et al.* [4] and it is based on linear programming. In general, DEA is applied to measure efficiency at a point in time. When the efficiency score of a unit at a specific year and the score of the same unit in the following year are compared, the change from one year to another reflects only a part of the story since both scores are obtained relative to different Frontiers. If one is interested to see the change in efficiency over time using DEA, then it is essential to calculate malmquist productivity index (MPI), [3, 9, 17], which also acknowledges the change in the Frontier from one period to another.

The research employing DEA and MPI has been conducted at different levels of agricultural policy making from evaluating farms in a specific region to evaluating productivity of countries. Country level evaluations of agricultural productivity change work on macro-agriculture data-sets of sample countries varying between studies depending on the regional differences such as samples of African countries, [15, 20, 23, 27, 29], Asian countries [26, 28], Middle East and North African countries [2] and European Union countries [8, 19, 31] or on the economic differences such as samples of least developed countries [10], developing countries [21], OECD countries [18] and industrialized countries [22].

DEA and MPI are deterministic methods in nature. Despite the fact that the DEA is introduced as a deterministic method, by time, several derivations of the technique have been developed to handle the uncertain data (especially data in the form of intervals). Imprecise DEA [6] and Fuzzy DEA [11, 12, 13, 16, 24, 25, 30] approaches construct two main stream when dealing with interval data in DEA.

Measuring efficiency with DEA and measuring its change over time with MPI require the completeness of data over a time period. Therefore, the existence of missing data is a challenge to be faced with when such analyses are intended. As indicated by Kao and Liu [14], in practice, units with values missing are usually excluded to apply DEA. However, this has consequences as the loss of information contained in those deleted units and an overestimation of the efficiencies of the remaining units.

Country-level agricultural performance measurement is an area to come up with missing data because of its macro-nature. This paper deals with such a case. We aim to measure the agricultural productivity of 34 member countries of organization for economic co-operation and development (OECD) between years 1990 and 2014. However, approximately 9% of the data are missing in the data-set consisting of commonly used input and output factors for 34 countries over the mentioned years. We propose to tackle the given missing data problem using fuzzy DEA approach of Saati *et al.* [24]. In order to measure the change over time, we make the use of MPI approach derived to work with fuzzy data by Hatami-Marbini *et al.* [12], which is based on fuzzy DEA approach of Saati *et al.* [24].

The main motivation of using fuzzy approaches instead of data removal is that none of excluding the units or years or factors with the missing data provides us a consecutively complete data-set to proceed. The exclusions shrink the overall data-set to a smaller bit which makes it very difficult to draw conclusions. Therefore, in order to keep the country, factor and year dimensions of the data as intended, it is necessary to find a way to fill up the missing data points with a reasonable approach.

To apply the given fuzzy methodologies, we require intervals for the missing data points. We suggest that available data over the years can be used to estimate an interval for any missing data point. At this point, we come up with an approach relying on average of available values for the given factor as well as the average percent changes throughout the years in the given factor. Lower and upper limits for the missing data points are obtained as moving to both directions from the average value with the calculated average percent change. When missing values are replaced with factor-specific interval values, we apply fuzzy DEA and MPI approaches to measure efficiency and its change without any loss of any countries, factors and years in the data-set.

The paper contributes with the use of such an approach to a macro-level agricultural productivity analysis for the first time in the literature. We show that fuzzy DEA can be a powerful tool to handle missing data if no loss of information is intended. It is important to note that the paper reveals a thinking on the trade-off between excluding the missing data and modelling them as fuzzy intervals. We apply tests of reliability where actual data are replaced with fuzzy ones and the changes are observed. The findings reveal that fuzzy data are worth consideration when there exists missing data rather than losing information *via* exclusions. We interpret the findings of the analysis with respect to both regional position and economic size of the countries.

The paper is organized as follows: Section 2 provides the modelling basics of fuzzy DEA and MPI. Section 3 presents the model design considerations on our data where the selection of variables are explained, the size of missing data in our set is discussed, the framework of fuzzy data generation is provided and finally reliability of the fuzzy intervals are examined. Section 4 focuses on the findings of the analysis on 34 OECD countries taking the modelling approaches in previous section into account. Finally, Section 5 concludes.

2. Methodology

DEA is a well-established non-parametric performance measurement approach for identifying relative efficiency of decision making units (DMUs) considering multiple outputs and multiple inputs with a simple restriction that all DMUs in a production technology lie on or below an efficient Frontier. DEA has been presented to the literature by the study of Charnes *et al.* [4].

The conventional DEA models process with deterministic data. Relying on the defined input and output values of DMUs, they measure relative efficiency for each unit by making use of linear programming models established and solved for each unit. (See [7] for more details of DEA modelling). Efficiency measurement with DEA focuses on a certain period in time. When a time-based analysis is required, MPI introduced by Malmquist [17] and Caves *et al.* [3] and improved further by Färe *et al.* [9] is a widely known method to employ, which also processes with deterministic data in the conventional setting. Nevertheless, both DEA and MPI approaches are further improved in order to handle fuzzy data. In this section, we provide the considered fuzzy DEA and MPI modelling in the scope of this study.

2.1. Fuzzy DEA

Fuzzy DEA model developed by Saati *et al.* [24] is of interest in this part. Consider n decision making units. Assume that each decision making unit j for $j = 1, 2, \ldots, n$ uses m different inputs x_{ij} ($\mathrm{i} = 1, 2, \ldots, m$). and produces s different outputs. y_{rj} $(r = 1, 2, \ldots, s)$. DEA measures relative efficiency of the units at a specific time period (t). Fuzzy DEA model assumes input and output values are in terms of fuzzy intervals where L, M, U. represent lower limit value, average value and upper limit values, respectively. Linear fuzzy DEA model for a specific unit (k) in time period t is given in (2.1). The value of $\theta^{t,t}$ represents the efficiency score of the unit in time period t relative to the efficient Frontier of time period t.

$$
\begin{aligned}
&\theta^{t,t} = \max \sum_{r=1}^{s} \bar{y}_{rk}^{t} && (2.1)\\
&\text{s.t.}\\
&\sum_{i=1}^{m} \bar{x}_{ik}^{t} = 1\\
&\sum_{r=1}^{s} \bar{y}_{rj}^{t} - \sum_{i=1}^{m} \bar{x}_{ij}^{t} \leq 0 \quad \forall j\\
&v_i \left[\alpha x_{ij}^{Mt} + (1-\alpha)\, x_{ij}^{Lt}\right] \leq \bar{x}_{ij}^{t} \leq v_i \left[\alpha x_{ij}^{Mt} + (1-\alpha)\, x_{ij}^{Ut}\right] && \forall i, j\\
&u_r \left[\alpha y_{rj}^{Mt} + (1-\alpha)\, y_{rj}^{Lt}\right] \leq \bar{y}_{rj}^{t} \leq u_r \left[\alpha y_{rj}^{Mt} + (1-\alpha)\, y_{rj}^{Ut}\right] && \forall i, j\\
&u_r, v_i \geq 0 \quad \forall i, r
\end{aligned}
$$

Above model applies the α-cut concept in handling the fuzzy data where $\alpha \,\epsilon\, [0, 1]$. This is a parameter that extracts a smaller range of the original interval where the actual value is thought be most likely belonging in. The original fuzzy model defined in Saati *et al.* [24] is linearized binterval alterations and variable substitutions where below definitions hold:

$$\begin{aligned}
&\bar{x}_{ij} = v_i \hat{x}_{ij} \\
&\bar{y}_{rj} = u_r \hat{y}_{rj} \\
&\alpha x_{ij}^m + (1-\alpha) x_{ij}^l \le \hat{x}_{ij} \le x_{ij}^m + (1-\alpha) x_{ij}^u \quad \forall i, j \\
&\alpha y_{rj}^m + (1-\alpha) y_{rj}^l \le \hat{y}_{rj} \le y_{rj}^m + (1-\alpha) x_{ij}^u \quad \forall i, j
\end{aligned}$$

2.2. Fuzzy MPI

MPI is a DEA-based measure to evaluate the changes in the productivity over time. It is a nonparametric measure of productivity change which also contains information about the source of this change. The index represents the magnitude of improvement (or decrease) in productivity of the evaluated unit from time period t to $t+1$. The calculation of the index relies on evaluation of the unit in both periods t and $t+1$ followed by cross evaluations of each periods' performance within the data of the other period by making use of the fundamental CCR DEA model developed by Charnes *et al.* [4].

In the presence of fuzzy data, the standard MPI calculation needs further improvement so that the fuzzy data can be handled. The first step to deal with is updating the abovementioned cross efficiency calculations. Following the fuzzy DEA model by Saati *et al.* [24], Hatami-Marbini *et al.* [12] integrate fuzzy data considerations to the cross efficiency measurement as given in (2.2). The value of $\theta^{t+1,t}$ represents the efficiency score of the unit k in time period $t+1$ relative to the efficient Frontier of time period t. The value of $\theta^{t,t+1}$ can also be calculated with relevant transformations to (2.2).

$$\begin{aligned}
&\theta^{t,t+1} = \max \sum_{r=1}^{s} \bar{y}_{rk}^{t+1} \qquad (2.2)\\
&\text{s.t.}\\
&\sum_{i=1}^{m} \bar{x}_{ik}^{t+1} = 1\\
&\sum_{r=1}^{s} \bar{y}_{rj}^{t} - \sum_{i=1}^{m} \bar{x}_{ij}^{t} \le 0 \quad \forall j\\
&v_i \left[\alpha x_{ij}^{Mt} + (1-\alpha)\, x_{ij}^{Lt}\right] \le \bar{x}_{ij}^{t} \le v_i \left[\alpha x_{ij}^{Mt} + (1-\alpha)\, x_{ij}^{Ut}\right] \quad \forall i, j\\
&u_r \left[\alpha y_{rj}^{Mt} + (1-\alpha)\, y_{rj}^{Lt}\right] \le \bar{y}_{rj}^{t} \le u_r \left[\alpha y_{rj}^{Mt} + (1-\alpha)\, y_{rj}^{Ut}\right] \quad \forall i, j\\
&v_i \left[\alpha x_{ik}^{Mt+1} + (1-\alpha)\, x_{ik}^{Lt+1}\right] \le \bar{x}_{ik}^{t+1} \le v_i \left[\alpha x_{ik}^{Mt+1} + (1-\alpha)\, x_{ik}^{Ut+1}\right] \quad \forall i\\
&u_r \left[\alpha y_{rk}^{Mt+1} + (1-\alpha)\, y_{rk}^{Lt+1}\right] \le \bar{y}_{rk}^{t+1} \le u_r \left[\alpha y_{rk}^{Mt+1} + (1-\alpha)\, y_{rk}^{Ut+1}\right]. \quad \forall i\\
&u_r, v_i \ge 0 \quad \forall i, r,
\end{aligned}$$

with the performance data in hand for two time periods, for the specific unit k, firstly, the efficiency scores of the unit in t and $t+1$ are calculated separately using (2.1). Then, each periods' performance data are cross evaluated relative to other periods' performance data using (2.2). Finally, we come up with the below MPI measure (given in (2.3)) representing the productivity change for the given unit k from time period t to $t+1$ using the relevant scores of both models (2.1) and (2.2).

$$MPI_k^{t,t+1} = \sqrt{\frac{\theta^{t+1,t+1}\theta^{t+1,t}}{\theta^{t,t}\theta^{t,t+1}}}. \qquad (2.3)$$

In general, MPI consists of two components namely as efficiency change (EC) and Frontier shift (FS), where product of these components provides the overall index. Efficiency change, which is also referred as catching up index or technical efficiency change, represents the change ratio of the efficiency score form one period to another. It is calculated by dividing efficiency scores of a unit in adjacent periods. Frontier shift (also referred as technical change), on the other hand, is the measure of the movement of the efficient Frontier at the given point between two adjacent time periods and it is calculated for a unit by making use of cross efficiency scores of the unit. The efficiency change and Frontier shift components of MPI score is calculated as given in (2.4) and (2.5).

$$EC_k^{t,t+1} = \frac{\theta^{t+1,t+1}}{\theta^{t,t}} \tag{2.4}$$

$$FS_k^{t,t+1} = \sqrt{\frac{\theta^{t,t}\theta^{t,t+1}}{\theta^{t+1,t+1}\theta^{t+1,t}}} \tag{2.5}$$

3. Model design

The study aims to evaluate the change in agricultural productivity of member countries of OECD[1] over time (from 1990 to 2014) using widely known DEA-based method: malmquist productivity index. We benefit from databases of the World Bank,[2] food and agriculture organization of the united nations (OSTAT)[3] and international fertilizer industry association (IFA)[4] for the relevant data. The challenge to face here is the vast amount of missing data over the years. Instead of omitting units, factors or years containing the missing data, we propose to incorporate a fuzzy DEA approach developed by Saati *et al.* [24] and MPI approach developed in line with the given fuzzy approach by Hatami-Marbini *et al.* [12] in order to handle the missing data.

3.1. Input/output variables

The choice of the input/output factors is an important point in any efficiency assessment with non-parametric methods such as DEA and MPI. As a widely studied research area, it is possible to induce the common input and output variables the majority of the agricultural efficiency measurement studies consider into main categories. On the output side agricultural production (of different kinds such as crop or livestock in terms of money or actual production) is the main factor to be considered. On the input side, we can mention four main categories of variables as land use, labor (in monetary terms, hours or number of workers), capital (mostly in terms of machinery use) and cost-related variables to cultivate or raise livestock such as seed, feed, fertilizer, pesticide uses or monetary terms related to those uses.

The selected variables in this study to evaluate agricultural performance of countries are in line with the abovementioned categories of factors commonly used (for a similar study, see Coelli and Prasada Rao's work [5]). Table 1 summarizes the input and output variables considered with their units of measurement and the sources of the data.

3.2. Size of missing data

The data consist of 34 OECD countries, nine factors and 25 years, which add up to 7650 data points. Of those, 656 data points are missing that corresponds to approximately 9% of the data.

In the case of missing data, it is possible to think about narrowing down the scope of the analysis by eliminating countries, years or factors with missing data. However, considering this leads to dramatic results for our case where we can only analyze four years (2000–2003) if we consider to continue with fully available data. In terms of factors, there exists no factor without a missing data that leaves us with the choice of eliminating countries with missing data where almost half of the countries should be excluded from the analysis.

[1]https://www.oecd.org/
[2]http://databank.worldbank.org/data/home.aspx
[3]http://faostat3.fao.org/home/E
[4]http://www.fertilizer.org/statistics

TABLE 1. Input and output variables.

	Input variables	Unit of measurement	Source of data
1	Cultivated land	Hectares	World bank
2	Agricultural machinery/tractors	Number	FAOSTAT
3	Labor	Active population	World bank
4	Fertilizer use	Tonnes	IFA
5	Livestock	Number	FAOSTAT
6	Pesticides	Tonnes	FAOSTAT
	Output variables		
1	Crop Production	US dollars	FAOSTAT
2	Livestock production	US dollars	FAOSTAT
3	Food production	US dollars	FAOSTAT

TABLE 2. Illustrative example on calculation of intervals.

	Year 1	Year 2	Year 3	Year 4	Year 5	Average
Factor value	105	108	Missing	112	109	**108.50**
% change		2.86%		3.70%	−2.68%	**1.29%**

The factors with the most missing data points are the agricultural machinery and pesticide use with 35% and 18% of missing data points, respectively. It should be noted that removing those factors does not ensure the completeness of the data because other factors also have missing data points for some years or for some countries. Similarly, exclusion of the countries with the largest missing data (Luxembourg, Belgium, Slovakia, Slovenia and Israel) does not provide us a complete data-set either.

On the other hand, fortunately, there exists no factor with all the data points are missing for all 25 years in all countries. Therefore, for each country, we have enough number of data in the yearly basis that can serve to fill in the data for the missing years. The data-set is rich enough to draw conclusions when the missing ones are handled in a realistic way. We benefit from fuzzy logic here. The proposition is to develop fuzzy ranges for the missing data using the existing data points and their variation over the years. We explain the generation of such ranges in the following part.

3.3. Generating fuzzy data

In generating fuzzy intervals for the missing data points, we consider two types of information from the available data for a country in each factor:

- Average of the available data in the given factor over the years.
- Average of % changes in the available data of the given factor over the years.

For a given factor, lower and upper limits of the missing data points are identified as below to be used in efficiency and cross efficiency score calculations (see (2.1) and (2.2)) in order to come up with Malmquist indices (see (2.3)).

Lower Limit Value = Average Value – (Average Value × Absolute Value (Average % change))

Upper Limit Value = Average Value + (Average Value × Absolute Value (Average % change))

To illustrate how the intervals are obtained, suppose we have five years of data in a factor for a country with a missing data point as given in Table 2.

In order to generate the interval for year-3 data point, we use the above formulation relying on the average value of currently available data points and % changes throughout the years. The available data points have an average of 108.50 and the data variates by 1.29% in average through years. Lower and upper limit values are calculated as:

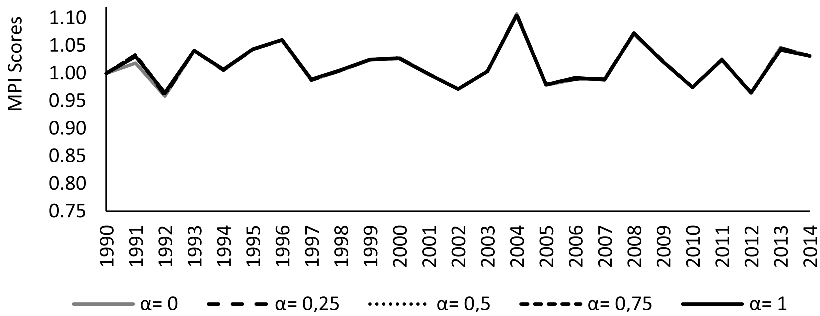

FIGURE 1. MPI scores over the years wrt different α values reason behind seeing almost a single line in Figure 1 is that we do not observe substantial changes in the MPI scores when the α values are changing for our data. Since this preliminary test reveals that the results are insensitive to changes in α values, we choose the α value as zero where the largest interval is possible is pursued.

Lower Limit Value = 108.50 − (108.50 × 1.29%) = 107.10.
Upper Limit Value = 108.50 + (108.50 × 1.29%) = 109.90.

As seen above, the intervals are obtained as factor and country specific depending on the available data points in the given factor. Missing data are replaced by the interval data and fuzzy DEA models are used to calculate efficiency scores.

Fuzzy DEA model proposed by Saati *et al.* [24] and Fuzzy DEA model for cross efficiency calculations developed by Hatami-Marbini *et al.* [12] apply the α-cut concept in handling the fuzzy data. Therefore, apart from average, lower and upper values for the fuzzy data, the models require the α -cut value (see models (2.1) and (2.2)) where $\alpha\, \epsilon[0,\, 1]$. As mentioned, α is a parameter that extracts a smaller range of the original interval where the actual value is thought be most likely belonging in. Different α values yield different efficiency scores in models (2.1) and (2.2). As a usual practice, we test for the sensitivity of our results to different α values. We define five values as (0, 0.25, 0.5, 0.75, 1) and calculate MPI scores with those values. The MPI sores over the years with different α values are presented in Figure 1.

3.4. Testing for reliability of fuzzy data

In the case of missing data, there exists a trade-off between excluding the factors, units or years with missing data and modelling them as fuzzy intervals. As we discussed above, excluding factors, years or countries with missing data seriously affects the scope of the analysis. Since we omit the exclusion option and consider to move on with fuzzy intervals for missing data, we conduct a preliminary analysis to observe the sensitivity of results to fuzzy intervals. For this purpose, we test the reliability of the fuzzy data derived by making use of the existing data.

A two-dimensional procedure is followed here. First, we conduct a factor-based analysis by testing the sensitivity of MPI scores to fuzzy ranges when actual data are changed to fuzzy ones. For years 2000 and 2001, we have the complete data for all countries and all factors. Therefore, we are able to calculate MPI values with the actual data for those years. Then, we replace the actual data with fuzzy ones for the input agricultural machinery following the procedure explained in above section. (Agricultural machinery is the factor that has the most data points missing all over the data-set). MPI scores with actual data and fuzzy machinery data are presented for all countries in Table 3.

Secondly, a country-based analysis is conducted to observe the changes in MPI scores when actual data for a country is changed to fuzzy data in all factors. Belgium is the country with the most missing data points among others. However, the data for this country are complete between years 2001 and 2005, which makes it possible to calculate actual MPI scores. After calculations with actual data, Belgium data are replaced with the fuzzy

Table 3. Comparisons between actual and fuzzy MPI scores for 2000–2001.

	Country	Actual MPI	Fuzzy MPI	% Change
1	Australia	1.03	1.03	0.0%
2	Austria	1.04	1.03	−1.0%
3	Belgium	0.95	0.95	0.0%
4	Canada	0.86	0.86	0.0%
5	Chile	1.07	1.07	0.0%
6	Czech republic	1.01	1.02	1.0%
7	Denmark	0.95	0.94	−1.1%
8	Estonia	0.82	0.82	0.0%
9	Finland	1.12	1.12	0.0%
10	France	1.00	1.00	0.0%
11	Germany	1.00	1.00	0.0%
12	Greece	1.02	1.02	0.0%
13	Holland	0.97	0.97	0.0%
14	Hungary	1.28	1.22	−4.7%
15	Iceland	0.98	0.98	0.0%
16	Ireland	0.91	0.87	−4.4%
17	Israel	0.99	1.00	1.0%
18	Italy	1.02	1.02	0.0%
19	Japan	1.03	1.03	0.0%
20	Luxemburg	0.84	0.88	4.8%
21	Mexico	1.07	1.05	−1.9%
22	New Zealand	1.05	1.05	0.0%
23	Norway	1.04	1.04	0.0%
24	Poland	1.06	1.06	0.0%
25	Portugal	1.00	1.00	0.0%
26	Slovakia	1.09	1.09	0.0%
27	Slovenia	1.15	1.15	0.0%
28	South Korea	1.01	0.95	−5.9%
29	Spain	0.97	0.98	1.0%
30	Sweden	0.99	0.98	−1.0%
31	Switzerland	0.93	0.93	0.0%
32	Turkey	0.97	0.96	−1.0%
33	United Kingdom	0.88	0.89	1.1%
34	USA	0.98	0.98	0.0%

Table 4. Comparisons for actual and fuzzy MPI scores for Belgium.

Period	Actual MPI	Fuzzy MPI	% Change
2001–2002	1.06	1.12	−5.5%
2002–2003	1.04	1.05	−0.9%
2003–2004	1.03	1.02	0.8%
2004–2005	0.92	0.95	−2.9%

data points derived using the procedure explained in above section. The MPI scores of Belgium with actual and fuzzy data are presented in Table 4.

When both tables are analyzed, it can be concluded that the results are not very sensitive to changing actual data to fuzzy data. When t-test (paired two sample for means) for actual and fuzzy data results in Table 3 is applied, p-value ($\alpha = 0.95$) is obtained as 0.198, which indicates no significant difference between two series. As

TABLE 5. Mean MPI, EC and FS scores by years.

Period	Mean MPI	Mean EC	Mean FS
1990–1991	1.018	1.036	0.983
1991–1992	0.958	0.947	1.012
1992–1993	1.041	1.032	1.009
1993–1994	1.006	1.008	0.997
1994–1995	1.043	1.012	1.031
1995–1996	1.060	1.019	1.041
1996–1997	0.987	1.008	0.979
1997–1998	1.005	0.983	1.022
1998–1999	1.024	1.019	1.005
1999–2000	1.028	0.993	1.035
2000–2001	0.999	1.023	0.976
2001–2002	0.971	0.968	1.003
2002–2003	1.003	1.026	0.978
2003–2004	1.108	0.985	1.124
2004–2005	0.979	1.002	0.977
2005–2006	0.989	0.996	0.993
2006–2007	0.990	0.981	1.009
2007–2008	1.071	1.026	1.044
2008–2009	1.021	0.993	1.028
2009–2010	0.974	1.020	0.955
2010–2011	1.025	1.008	1.017
2011–2012	0.964	1.003	0.961
2012–2013	1.046	1.004	1.042
2013–2014	1.031	0.986	1.045
Mean	1.014	1.003	1.011

a result, fuzzy data ranges derived for missing data points seem to be reliable in a sense that the results would be very close to real score if the full data were available.

4. Results and discussion

The changes in agricultural productivity of 34 OECD countries between years 1990 and 2014 are analyzed on the yearly basis considering the input and output variables given in Table 1. As explained, missing data over the years (which correspond to almost 9% of the whole data-set) are filled up with the fuzzy intervals relying on the averages and the average variations over the years as explained in Section 3.3. Agricultural efficiency scores in each year are calculated using model (2.1) where fuzzy data can be handled. Following that, cross-efficiency calculations are conducted by making use of model (2.2). Finally, the efficiency scores are composed into EC and FS components to obtain MPI scores for consecutive years. Leaning on the insensitivity of MPI scores to changing α values, which is tested beforehand, the α parameters in models (2.1) and (2.2) are taken as 0, which provides the widest ranges for the fuzzy data. In this section, results are put together to observe the agricultural efficiency changes of countries over the years.

Table 5 presents the mean MPI scores and values of their efficiency change and Frontier shift components with respect to time periods. Values of MPI less than 1 indicate a decline in productivity from one year to another. The most recent drop in productivity is observed in 2011–2012 period where the results indicate a 3.6% decline in productivity from 2011 to 2012. The main factor behind this decline is the Frontier shift component. Although it seems that mean efficiency change points out an improvement within this period, a 3.9% technical change

TABLE 6. Mean MPI, EC and FS scores by countries.

	Country	Mean MPI	Mean EC	Mean FS
1	Australia	1.003	0.992	1.009
2	Austria	1.019	1.014	1.010
3	Belgium	1.002	1.000	1.009
4	Canada	1.037	1.010	1.021
5	Chile	1.018	1.019	0.998
6	Czech Republic	0.995	0.994	1.006
7	Denmark	1.018	1.000	1.032
8	Estonia	1.000	0.995	1.005
9	Finland	1.028	1.013	1.019
10	France	1.029	1.007	1.026
11	Germany	1.029	1.015	1.019
12	Greece	0.998	0.983	1.007
13	Hungary	0.982	1.000	0.979
14	Iceland	1.006	1.000	1.004
15	Ireland	1.009	1.001	1.011
16	Israel	1.018	1.000	1.017
17	Italy	1.032	1.012	1.015
18	Japan	1.001	1.000	0.993
19	South Korea	0.996	1.000	0.996
20	Luxembourg	0.990	1.000	0.997
21	Mexico	1.028	1.021	1.007
22	Netherlands	1.027	1.003	1.024
23	New Zealand	1.035	1.008	1.028
24	Norway	1.001	1.000	1.006
25	Poland	1.000	0.988	1.014
26	Portugal	1.005	1.000	1.006
27	Slovakia	0.988	1.001	0.996
28	Slovenia	1.024	1.004	1.017
29	Spain	1.030	1.008	1.014
30	Sweden	1.006	0.993	1.014
31	Switzerland	1.017	1.000	1.016
32	Turkey	1.030	1.011	1.014
33	United Kingdom	1.008	0.998	1.016
34	USA	1.028	1.013	1.014

in the whole technology is observed resulting in a decrease in productivity in the mean terms. We observe a decline in some other periods as well (see the shaded rows of Tab. 5). However, the values are relatively closer to 1 revealing less than 5% declines over the years. It is possible to note that in the majority of regressing time periods, the cause lies behind the Frontier shift component which indicates a shift in the production technology rather than the efficiency changes of individual units.

The mean MPI score for all years is 1.014, which indicates a productivity growth of 1.4% globally. The largest growth observed is in 2003–2004, which is interestingly followed by a decline over the following three periods (2004–2007). Following in this section, we provide the changes specific to regions of the countries by years which can provide an insight for this three-period major decline in productivity.

Before analyzing the results with respect to regions, in Table 6, we provide the results by country. The mean MPI, EC and FS scores with respect to countries given in Table 6 reveal that 28 out of 34 countries experienced a productivity growth in agriculture on mean terms over the 25 years analyzed. The countries with the leading MPI scores are Canada, New Zealand and Italy. The top countries in efficiency change component of MPI can be listed as Mexico, Chile and Germany whereas the leading ones in Frontier shift (technical change) are Denmark,

Table 7. Mean cumulative MPI, EC and FS scores by regions.

	Cumulative mean MPI	Cumulative mean EC	Cumulative mean FS
Americas	1.368	1.345	1.017
Asia-Pacific	0.897	1.000	0.897
Australia	1.302	1.084	1.201
Europe	1.157	1.009	1.146
Middle East	1.223	1.057	1.157

Table 8. Cumulative mean MPI, EC and FS scores by economic size.

	Cumulative mean MPI	Cumulative mean EC	Cumulative mean FS
Overall	1.174	1.050	1.118
Developed economies	1.173	1.026	1.143
Developing economies	1.181	1.202	0.982

New Zealand and France. It can be noted that Canada owes its leading growth to its increase in efficiency together with its strong position relative to shifting Frontier over the years. Of the countries with the most missing data (Luxembourg, Belgium, Slovakia, Slovenia and Israel), only Slovenia and Israel exhibit a productivity growth. Belgium has the mean score of approximately 1, which indicates neither of growth or of regression.

The results are also evaluated with respect to regions that the countries belong to. Table 7 presents cumulative mean productivity growth for five regions. Americas (including both north and south countries) has experienced the highest cumulative growth rate of 36.8%. If we consider only North America (Canada, USA and Mexico), the growth is even higher with the rate of 44.1%. The only region with the recession in the cumulative MPI is the Asia-Pacific (consisting of Japan and South Korea).

In order to observe the breakdown of the cumulative mean growth data given in Table 7 over the years, Figure 2 can be examined, where dark grey series represent the mean cumulative growth of all countries in the sample. It is seen that the Asia-Pacific region exhibits the most severe drop between 2001 and 2003 followed by a rapid growth. This can be presumably attributed as a reflection of the major drought of 1998–2001 to the agricultural production (see [1] for more on 1998–2001 drought in Asia).

Americas and Australia regions exhibit a rapid cumulative productivity growth where all mean values are over the mean cumulative MPI scores of the full sample. It is possible to notice an expanding growth in the Middle East countries in the sample (which includes Israel) after 2007. There exists an increasing trend for all sample from 2012 to 2014 and this trend is mostly caused by increasing cumulative productivity in Europe, which is the only region with only consistent trend over 2012 to 2014.

The results are also aggregated to analyze the productivity change regarding the economic classification of the countries. 34 OECD countries in the sample belong to two main groups of United Nations Country Classification (2014)[5] as: developed countries and developing countries. Table 7 summarizes the cumulative mean MPI, EC and FS scores of these two groups of countries. The developing countries class consists of five countries namely as Chile, Israel, South Korea, Mexico and Turkey. Individual mean MPI, EC and FS scores of those countries can be seen in Table 7.

Results in Table 8 indicate that developing countries have more cumulative growth than developed countries over the 25-year period. The cumulative mean MPI for the developed countries is approximate to the cumulative mean of the whole sample, which is 17.4%. The developing countries attain a cumulative growth of 18.1% although a decline in cumulative FS component is observed.

Figure 3 consists of the cumulative MPI scores with respect to country classifications over the years. It can be observed that the cumulative mean data of developed countries are more in line with the whole sample in

[5]United Nations (2014) World Economic Situation and Prospects - Country Classifications http://www.un.org/en/development/desa/policy/wesp/wesp_current/2014wesp_country_classification.pdf.

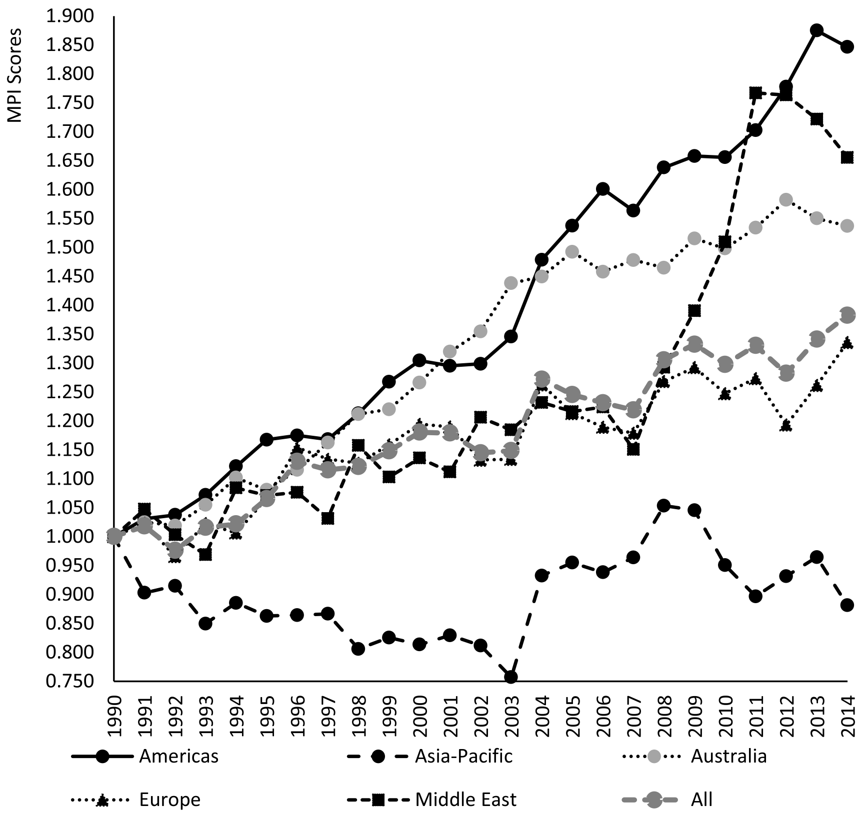

FIGURE 2. Mean cumulative MPI scores by regions over years.

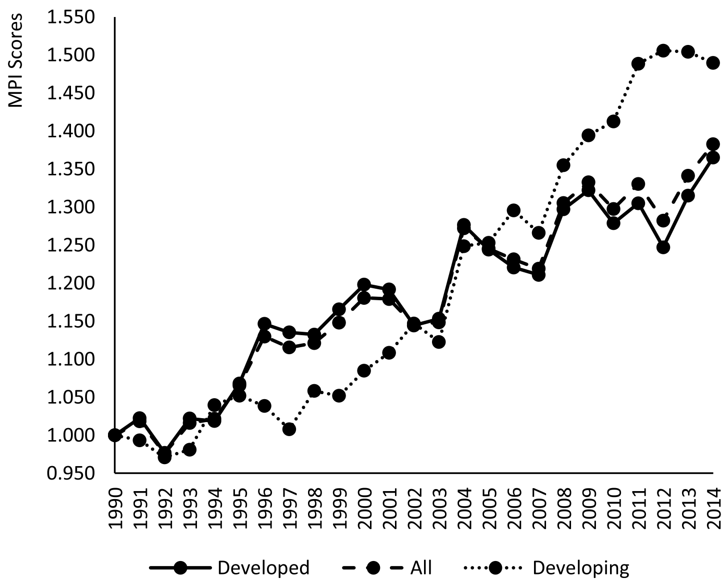

FIGURE 3. Cumulative mean MPI by years.

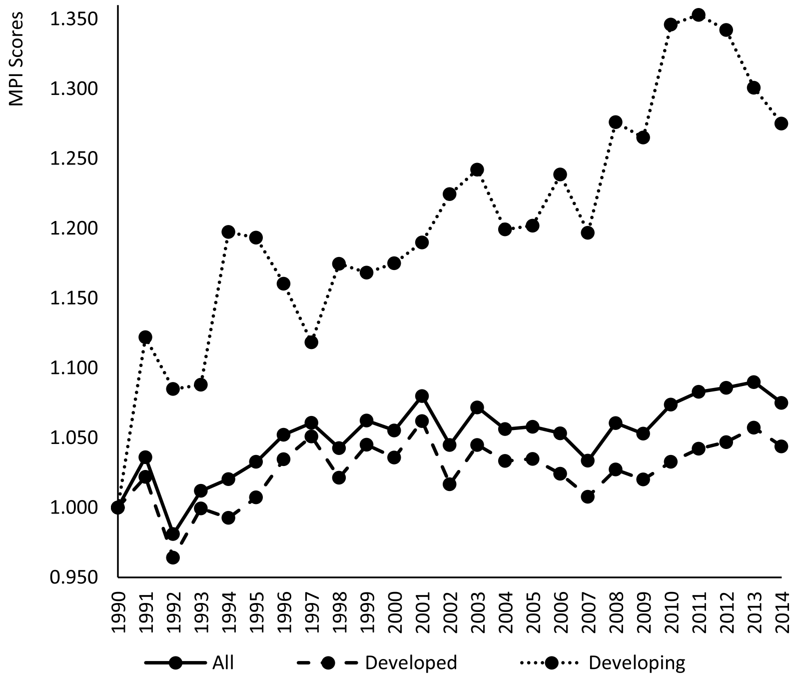

FIGURE 4. Cumulative mean EC by years.

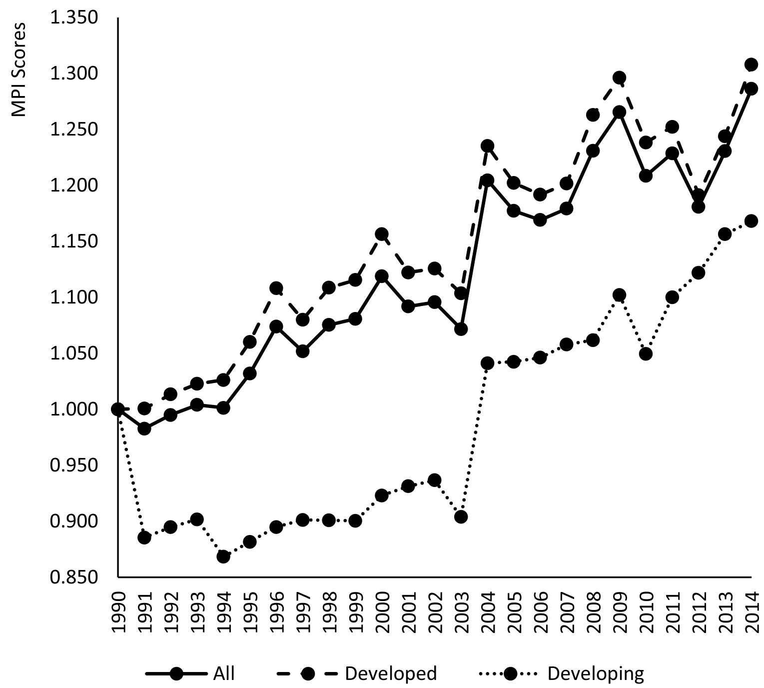

FIGURE 5. Cumulative mean FS by year.

terms of cumulative MPI; whereas developing countries exhibit an aggressive increase after 2004 (especially after 2007). The developed countries pursue a more stationary pattern. On the other hand, an increasing trend can be recognized for developing countries, which is slightly interrupted in recent years.

The EC and FS components of the cumulative mean MPI are presented in Figures 4 and 5, respectively. As can be seen, cumulative EC scores of developing countries exhibit an increasing trend and they are all above the sample and developed country means. On the technical change part, the cumulative FS scores of developing countries are below 1 until 2004. The technical growth mostly occurs after 2004 for those countries, which results in a boost in cumulative MPI scores as seen in Figure 3. In both EC and FS components developed country means are highly in line with the overall sample. Whether developed or developing countries are of interest, a decline is observed in efficiency change component and an increase is observed in Frontier shift component in the most recent years.

5. Concluding remarks

Quantitative analysis on the agricultural productivity change over time at a macro-level is important to observe global trends in agricultural production and therefore, to shape agricultural policy making. The databases of global agriculture organizations contain rich and valuable information to serve as an input for such analyses. However, macro-level data have a high potential to involve data completeness issues due to the fact that collected data are originated from different sources. In this paper, we demonstrate that it is possible to take the opportunity of drawing conclusions out of such data resources even if there exist missing data points. For our case where we use Data Envelopment Analysis and Malmquist Productivity Index approaches to measure agricultural productivity of 34 OECD countries over 25 years, we propose to benefit from fuzzy approaches developed specific to these methods for the first time in a country-level agricultural productivity analysis. Using the averages and average variations of the complete data points, we provide interval estimations for the missing data points which enable us to accomplish the analysis we intended for. Accordingly, we are able to derive results without sacrificing any factor, any country or any year from the initial scope. We suggest and empirically illustrate that instead of shrinking the scope of the analysis by excluding the points missing, applying fuzzy approaches is an option worth considering by which it can be possible to make the best out of the available information. Note that such a suggestion is applicable for any other macro-level analysis regardless of the application area and scope of the research problem.

Based on above, the results of conducted analysis on agricultural productivity change of OECD countries with the data of reliable data resources as World Bank and FAO reveal a 1.4% of mean growth in OECD agriculture from 1990 to 2014 when six input variables related to four main categories of factors (land, labor, capital and costs) considered to produce crop, livestock and food outputs. If the cumulative growth is of interest the mean growth is identified as 17.4%. The countries experiencing the lead growth are detected as Canada, New Zealand and Italy. In the regionals sense, Americas and Australia have the largest growth; whereas the Middle East has an increasing trend in the recent years. In the economic size sense, developed countries represent the whole agricultural sector better; whereas developing countries experience a larger cumulative growth. We believe that results provide an insight to put potential benchmark countries in agricultural development forward for the agricultural policy makers.

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