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Energy use in cropping systems: A regional long-term exploratory analysis of energy allocation and efficiency in the Inland Pampa (Argentina)

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ABSTRACT

As agricultural system comprises natural processes that are ruled by thermodynamics, the energy utilization is well suited for assessing the sustainability in the management of natural resources. The goals of this paper are 1) to assess the energy use efficiency of the main crops during the 1992–2005 period in Inland Pampa (Argentina); 2) to evaluate the database structure in terms of energy allocation; 3) to assess the changes in technical efficiency using frontier analysis and 4) to identify the best explanatory variables for energy efficiency variability. Results showed an upward trend in productivity per unit area in the crops analyzed (excluding sunflower). Summer soybean and sunflower showed higher energy efficiency values by the end of time series. The main shift in the energy use pattern was the reduction of the energy allocated to tillage. The overall performance of the wheat and soybean crops in the study area appears to be closer to the energy usage pattern shown by the top 5% energy use efficiency crop fields. The exploratory analysis using classification and regression trees (CART) revealed that the energy allocation to tillage; and the crop specie were the attributes that mainly explained the energy efficiency changes.

1. Introduction

Modern agricultural systems are artificially arranged in order to produce food and fiber [1,2]. Current agricultural practices reduce the plant component of these systems to one or two dominant species. The persistence of this artificially ecosystem design involves the use of complementary sources of energy in order to control the growth and development of undesired community components (e.g. pests). This additional energy requirement substantially reduces the energy efficiency of agroecosystems compared with natural systems [3–5]. Furthermore, the potential negative impact over the function and structure of agroecosystems due to this intensification usage of natural resources has led to the need for developing environmental indicators under the headings of sustainability [6].

Environmental indicators should be characterized by such factors as the simplicity and transparency of the assessment method, and should indicate items and trends obviously relevant in terms of importance for sustainability [7] Several environmental indexes have been developed as tools to more usefully aggregate and simplify information about environmental impact [8]. These indexes vary greatly in terms of methodology, input variables and the aspects of the environmental impact they address. However, as there are many conflicting frameworks to develop indicators, it is unclear the best way to collect data [9] or reach consensus not only in qualitative but also in the quantitative issues [10]. These limitations have led in recent times to seek other dimensions to assess the provision of environmental services. The efforts made under the Millennium Environmental Assessment [11], allowed to rediscover the role of physics on the concepts of cost and value, and the opportunity to explore the implications of ecosystems under the laws of thermodynamics [12,13]. Therefore, as agricultural system comprises natural processes that are ruled by thermodynamics, the energy utilization has to be analyzed with the aim of assessing the energetic efficiency in the management of natural resources [14–16].

The intensification process of natural resource usage in modern agriculture and, particularly the higher energy-dependent production systems, has also modified the Argentinean cropping systems [17]. One of this agroecosystem, the Inland Pampa, is a representative region for showing this modifications due to recent land-use changes [18]. The Inland Pampa is a sub region of a fertile plain originally covered by grasslands, which during the 1900s and 2000s was transformed into an agricultural land mosaic by grazing and farming activities. However, since 1990 the traditional mixed grazing–cropping systems were being replaced by

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permanent agriculture [19,20]. The goal of this paper is to study the energy use efficiency of the four main crops in Inland Pampa (Argentina) using a large production database. The specifics goals are 1) to assess the energy use and energy use efficiency of maize, sunflower, soybean and wheat crops during the 1991–2005 period in the Inland Pampa (Argentina); 2) to evaluate the database structure in terms of energy allocation; 3) to assess the changes in technical efficiency using frontier analysis and 4) to identify the best explanatory variables for energy efficiency variability.

2. Materials & methods

2.1. Site analyzed

The Inland Pampa (Argentina) (34–35°S; 61–63°W) comprises a land area of about 4.5 million ha in the center of Argentina and is located in the centre and the west side of the Province of Buenos Aires. The most frequently cropped soils in the region are Mollisols, developed from eolian sediments of the Pleistocene era, with dominantly udic and thermic water and temperature regimes, respectively [21]. Average annual rainfall decreases from about 900 mm in the east to 750 mm in the west [22]. In the eastern part of the gradient the moisture range of the soil changes from udic to ustic [23] and is mainly ustic in the western part [24].

2.2. Database structure

The study was conducted by using a 185-farm database (1992–2005) obtained by the AACREA farmers association, from Inland Pampa (Argentina) [25]. From this dataset we used data from the four main crops in the area: maize (*Zea mays L.*), sunflower (*Helianthus annuus L.*), wheat (*Triticum aestivum*) and soybean (*Glycine max L.*). Soybean was considered both as spring or summer crop (i.e. in a wheat-soybean double crop). The database contains 21,278 cases and it was split into seven two-year period subsets (Table 1). For every individual crop field harvested in each year, records contain information about crop yield, tillage operations, pesticides and fertilizer used (name and dose applied), and area occupied.

2.3. Method of energy balance accounting

A process analysis was used in this study to measure energy flow in the database analyzed [26,27]. According to this method, all energy inputs (direct and indirect) to an agricultural system are considered, based on physical material flows and the indirect energy use is only included one step backwards from the farm (i.e. the so-called farm gate approach [28]). This means that energy required for packing, storing, drying and transporting products were not accounted in final calculations. For each year analyzed, total indirect and direct energy (MJ) were calculated for each one single crop field. Direct energy input was considered as the energy used on farm, comprising diesel and lubricants for tillage operations. The electricity consumption was not considered, as previous on-farm estimations of energy use [29] showed a low allocation of energy use in electricity, as no irrigation systems are commonly applied in the study site. Indirect energy input includes the energy needed for the production of mineral fertilizers, plant protection agents and farm machinery. For assessing the energy input allocation, total energy input were split in three main categories: fertilizers, tillage, and pesticides (each one includes both direct and indirect energy costs). Human labor was not include in final accounting as it represents very low percentages (<0.02%) of energy input for modern production systems [30]. Solar energy was either not included in the energy balance, because it exceed few times the fossil energy used and it would mask the variation in the input of fossil energy [31]. Each energy input was considered on an area-based account and they were lately multiplied by their corresponding energetic values. Output energy of each field was calculated by multiplying the crop yield (from the database) with the energy crop content. All energetic values were extract from scientific literature sources [28,30–39]. Values of energy input and output (expressed in MJ/ha) were used to calculated the energy balance (Output/Input ratio), which express the total of crop energy produced per unit of energy output. A series of Spearman rank correlations were used for assessing the correlation between response variables and time. Differences among crops were assessed using a Kruskal-Wallis test followed by a Dunn's multiple-comparison test [40].

2.4. Energy use efficiency frontier

In order to assess the difference between each crop field and the most energy-efficient ones (in each crop and year combination), we compared the average energy use values of the 5% most energy records with those of all crop fields, using quantile regression (QR). QR is a suitable statistical method for analyzing the upper limit of a response variable distribution [41]. Thus, for each one of the crop × year subset, the 95% QR ($\tau = 0.95$) was calculated in order to estimate the highest achievable crop field performance regarding energy return. QR was performed using Blossom software (available at www.fort.usgs/gov/products/software/blossom.asp). In Fig. 1, it is represented the regression line using 5% of the dataset. Using the QR linear regression line as frontier of high efficiency achievable, it is possible to define a technical efficiency value [42], assuming constant returns to scale (i.e. the amount of energy input needed to produce an additional energy output is constant, no matter what is the level of energy input used):

$$\mathrm{TEff} = AB/AC \tag{1}$$

where, TEff has always values lower than 1 and shows the proportion of energy used in each crop field in relation to the energy use level by the top 5% performing crop fields. An alternative data envelopment analysis (DEA) [43] could be applied to database analysis, for allowing scale efficiency calculations due to

Table 1
Number of crop fields analyzed in the database analyzed.

Crop specie	Two-year period						
	1992–1993	1994–1995	1996–1997	1998–1999	2000–2001	2002–2003	2004–2005
Maize (M)	544	645	744	1104	1169	309	549
Wheat (W)	206	503	763	717	1187	672	999
Spring soybean (S1)	170	106	143	547	1413	514	1267
Summer soybean (S2)	92	66	150	330	356	153	302
Sunflower (Su)	526	1062	1247	1240	1222	201	60

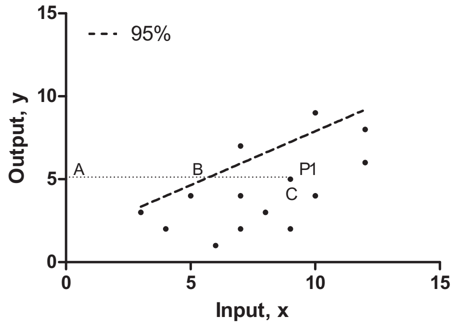


Fig. 1. A demonstrative output and input relationship. The broken line represents the linear regression using the top 5% performing crop fields. Letters on the dotted line represents the segments for technical efficiency (TEff) calculation procedure (see text for details).

variable scale returns. However, the election of the QR approach has the main advantage of allowing statistical inferences to be drawn from the results, and to distinguish between real technical inefficiencies and statistical noise [44]. Eventually, when variable returns to scale are considered, the technical efficiency indices are greater than, or equal to, the efficiencies under constant returns to scale.

2.5. Explanatory factors for TEff

Finally, in order to find the best explanatory factors for TEff, we analyzed the database using k-means cluster analysis and classification and regression trees (CART) [45,46]. Firstly, field crops were clustered using Teff through an unsupervised k-means cluster algorithm [47]. The clustering algorithm is based on a least sum-of-squares estimation, and attempts to group the crop fields increasing cluster internal homogeneity and external or between-group heterogeneity. A standard cross-validation procedure was applied for determining the final number of cluster. In cross-validation, repeated (v) random samples are drawn from the data for the analysis, and the respective model is then applied to compute predicted values. After obtaining the final configuration, a subset of the most contrasting k-means clusters was analyzed using CART. CART is a non-parametric statistical method that recursively partitions the multidimensional space defined by the explanatory factors into subsets as homogeneous as possible [48]. Also, CART is extremely robust to the effect of outliers as well as they are able of dealing with missing values by minimizing or eliminating the effect of such values on model performance. Basically, a regression tree partitions the space of all possible field attributes (both categorical and continuous), starting with all field attributes (at the root of the tree) and successively splitting that space in subsets as different as possible [45]. Initial CART analysis results in very large trees (i.e. the algorithm extracts complete descriptive information from the data, including noise), which are pruned back to an optimal sized tree based on relative error rates (misclassification error) for minimizing its cost–complexity. There are several pruning methods; in this study, the pruning method on misclassification error within one standard deviation of the minimum relative error was used [45]. Validation is an important component to test the learning status of the model. In this work, crop fields were randomly separated into two different datasets, one for training (2/3 of the original dataset: the learn set) and another for the testing of the developed tree (1/3 of the original dataset: the test set). A standard cross-validation procedure was applied for calculating both the whole misclassification error of both the learn set (i.e. CV learn) and the error set

Table 2
Variable importance ranking [0–1] of the explanatory variables used in the CART analysis.

Explanatory variable	Abbreviation	Importance
Crop specie	CROP	0.73
Year analyzed	YEAR	0.50
Area of the crop field (ha)	AREA	0.04
Fraction of total energy input allocated to fertilizers	F	0.37
Fraction of total energy input allocated to pesticides	P	0.45
Fraction of total energy input allocated to tillage	T	1.00

(CV error). In CART the equivalent to the R2 of linear regression is (1 − CV error) [45]. This estimates the "portion of variance explained by the model" [49]. Finally, the CART procedure considers the importance of the independent variables, which are ranked in descending order of their contribution to tree construction. The procedure looks at the improvement measure attributable to each variable in its role as a surrogate to the primary split. The values of these improvements are summed over each node of the tree and scaled relative to the best performing variable. The variable with the highest sum of improvements is scored 100, and all other variables have lower scores ranging downwards towards zero [48]. The explanatory factors used in CART were those described in Table 2.

3. Results and discussion

Although at the beginning of the data period studied all crops (except summer soybean) showed similar values of energy use by the end of this series, wheat (W) and maize (M) exhibited two- and three-fold values of energy use compared with the other non-cereal crops (Fig. 2a). The average energy input per hectare increased from 1992 to 2005 in maize, wheat and summer soybean

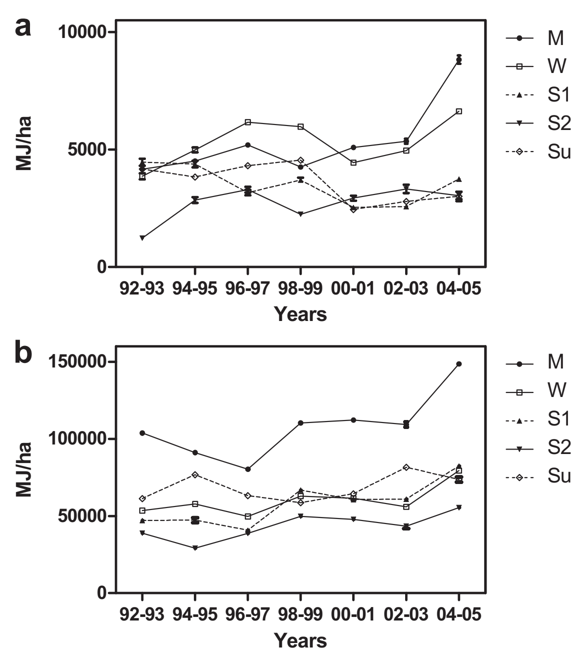
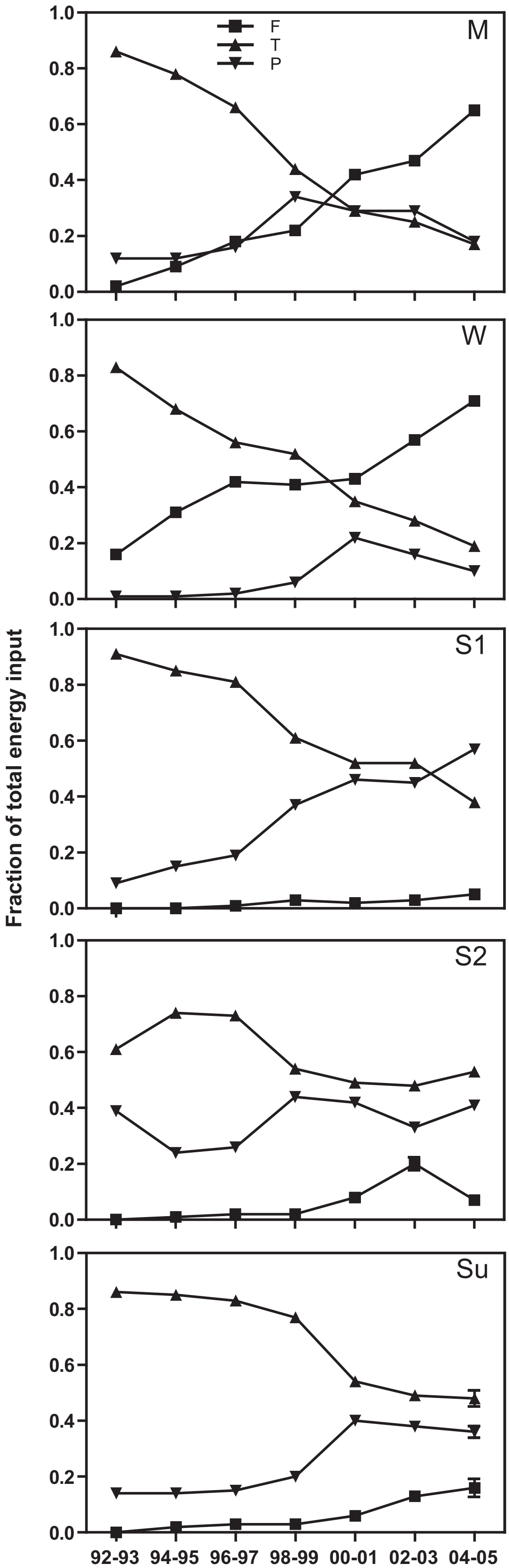


Fig. 2. Mean and standard error of energy input a) and output b) of each crop during the period studied. Crops are: sunflower (Su); maize (M); spring soybean (S1); soybean after wheat (S2); and wheat (W). Full line only connects the mean symbols to highlight the time trend.

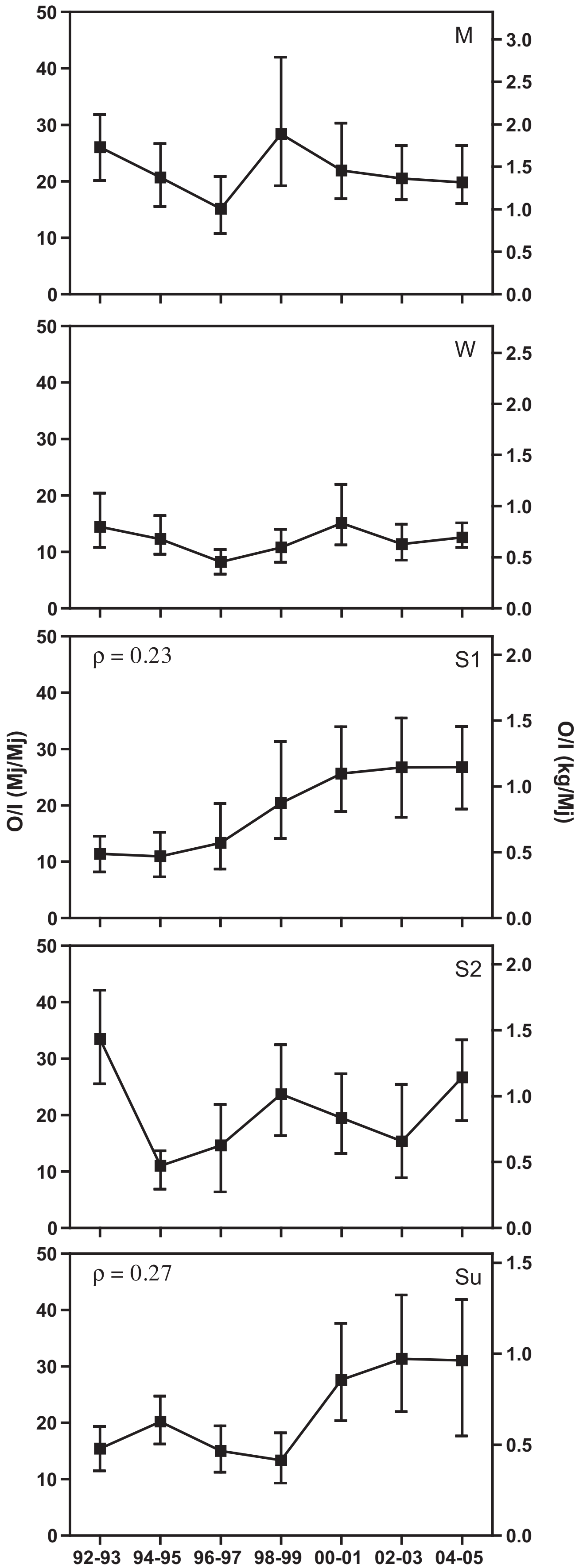


(S2) (Spearman rank correlations (SRC) = 0.26; 0.11; 0.07, respectively). Spring summer (S1) did not show a significant time trend regarding energy input, while sunflower (Su) was the only crop that showed a significant negative trend regarding energy use per hectare during the period studied (SRC = −0.38). When energy output (i.e. crop yield adjusted by the grain specific energy) was assessed, maize showed the highest values during all the period studied, and these differences increased by the end of the time series (Fig. 2b). Sunflower was the only crop that showed a non-significant correlation between time and energy output. The rest of the studied crops showed an increased in energy output (SRC: M = 0.36; S1 = 0.46; S2 = 0.31; W = 0.36, Fig. 2b).

When energy allocation is studied all the crops showed a remarkable reduction in tillage energy use (Fig. 3). In all cases (except summer soybean) tillage represented ca. 85% of total energy use by 1992–1993. Maize and wheat showed the highest reductions in tillage energy allocation, reaching values of 20% by the end of the time series (Fig. 3). Moreover, these two cereal crops showed a significant changed in energy allocated to fertilizers increasing the partition in the total energy budget from values lower than 20 % to 65 % (maize) and 70% (wheat) (SRC = 0.63 and 0.58, for maize and wheat, respectively). Non-cereal crops (i.e. soybean and sunflower) showed different energy allocation patterns from maize and wheat (Fig. 3). Energy allocated to fertilizer showed a low significant increased only in sunflower, and this energy fraction never exceeded 20% of total budget in the non-cereal crops, during the whole period studied. Regarding energy allocated to pesticide use, all crops showed increments in this fraction. The lowest increment value was observed in summer soybean (SRC = 0.10) while the highest increment value was observed in spring soybean (SRC = 0.55) increasing from 10% in 1992 to almost 60% of total energy use by 2005.

The calculated ratio between total energy used and crop yield (i.e. O/I) for maize, wheat and summer soybean showed no significant trend during the period studied, with mean O/I values of 21.4, 12.3, and 20.7 MJ/MJ, respectively (Fig. 4). The significant reduction in total energy use for sunflower (Fig. 1a) was the main cause for the observed improved in the O/I ratio for this crop, by the end of the period studied (Fig. 4). Also, spring soybean showed a consistent pattern of increasing in O/I values during the period studied raising from an average of 12 to 28 by the end of the time series. Although there were significant differences among the time periods studied (Kruskal Wallis, $P < 0.05$), technical efficiency (TEff) for the whole database showed no significant linear trend ($P > 0.05$) during the period studied (Fig. 5). Mean values range from 0.42 to 0.58, with an overall mean of 0.50. It means that, in average, the most efficient crop fields in each year used ca. 50% less energy for the same output level than the mean value of the whole database. Regarding each crop distance from the high-efficiency frontier (i.e. TEff = 1) as an average of the outcome from 1992 to 2005 (Fig. 6), both wheat and soybean showed more closer values to the highest achievable efficiency value determined by the top 5% performing crop fields analyzed. Finally, it was possible to assess some specific patterns when changes in time of the different crops are analyzed (Fig. 7). Both maize and sunflower exhibited a negative and significant trend in TEff values during the period studied (SRC = −0.04 and −0.09, respectively). In contrast, both wheat and summer soybean showed a positive and significant time trend in TEff during the period studied

Fig. 3. Mean and standard error of the fraction of total energy input allocated to fertilizer (F); tillage (T); and pesticides (P) of each crop during the period studied. Crop legends as in Fig. 2. Full line connects the mean symbols as in Fig. 2.



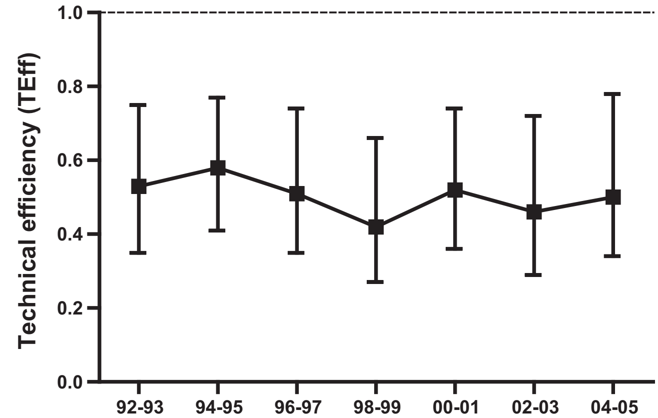


Fig. 5. Mean and interquantile range (25–75 percent) of technical efficiency (TEff) values of the crop fields measured as the ratio between total input energy used in the higher 5% of performing crop fields and the energy used in each crop field. The closer the TEff value to 1, the closer the energy used compared with the higher 5% performing fields (see Fig. 1 for further explanation). Crop legends as in Fig. 2. Full line connects the mean symbols as in Fig. 2. Spearman's rank correlation (ρ) was not significant ($P > 0.05$).

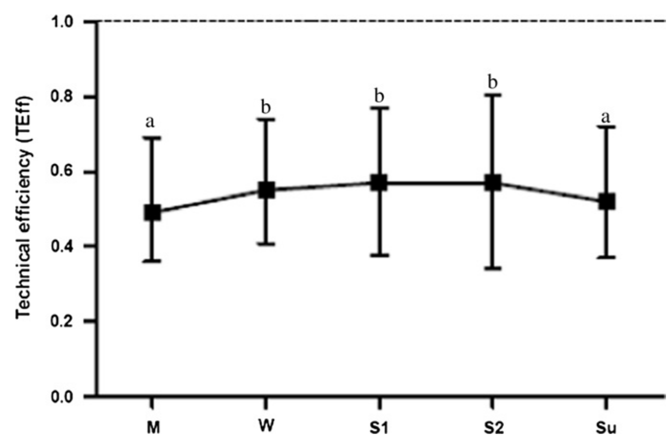


Fig. 6. Mean and interquantile range (25–75 percent) of technical efficiency (TEff) values of the crop species during the whole period studied (1992–2005). Crop legends as in Fig. 2. Full line connects the mean symbols as in Fig. 2. Different letters indicates significant differences (Dunn's multiple comparison test, $P < 0.05$). Full line connects the mean symbols as in Fig. 2.

(Fig. 7). Summer soybean showed no significant TEff trend in the 1992–2005 intervals and also depicted the higher interquantile ranges during the period studied.

The k-means cluster analysis initially selected sixteen crop field sets. Five of these clusters were lately selected for CART analyses (Fig. 8). These five clusters represent a gradient of TEff values and their selection increase the chance to find a significant explanation model. CART analysis using this subset was able to explain 40% of the total variability ($1 - CV = 0.40$) and defined ten terminal nodes (Fig. 9). At the top of the tree, the CART model use CROP for splitting the maize crop fields from the rest

Fig. 4. Mean and interquantile range (25–75 percent) of output to input (O/I) energy ratio expressed both in MJ/MJ and kg/MJ of each crop during the period studied. Crop legends as in Fig. 2. Full line connects the mean symbols as in Fig. 2. Only significant spearman's rank correlation (ρ) are showed ($P > 0.05$).

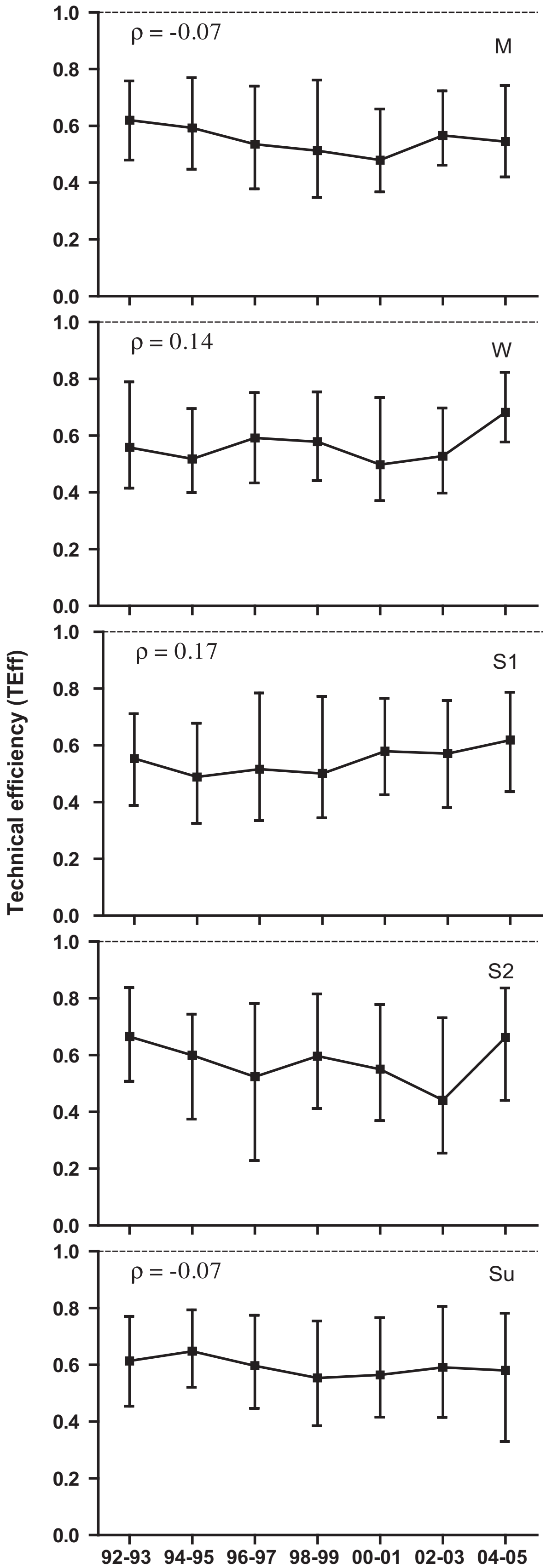


Fig. 7. Mean and interquantile range (25–75 percent) of technical efficiency (TEff) values for each crop and year analyzed. Crop legends as in Fig. 2. Full line connects the mean symbols as in Fig. 2. Only significant spearman's rank correlations (ρ) are showed ($P > 0.05$).

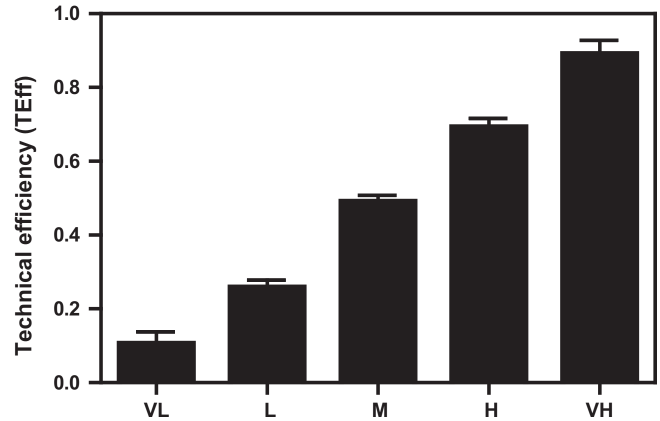


Fig. 8. Mean and standard deviation of technical efficiency (TEff) of a subset of the most contrasting k-means clusters obtained from the whole database. Abbreviations of k-means cluster of TEff: VL (very low); L (low); M (medium); H (high); and VH (very high). Number of fields in each cluster: VL = 301; L = 981; M = 1737; H = 1840; and VH = 1364.

of the other crops. The right side of the CART tree was subsequently splitted (Fig. 9, ID3) using the fraction of energy input allocates to tillage (T). The splitting value (SV) for this node was 0.526. When this condition was satisfied (i.e. the right branch of ID3) the CART model selected T and YEAR for splitting four terminal nodes, representing all k-means cluster except very high (VH) TEff (Fig. 9). In the right part of the CART (i.e. T >= 0.526), the CART model determined five more splitting nodes (with six terminal nodes), and the fraction of energy allocates to pesticides (P) were selected in three of them. These terminal nodes represent the k-means cluster subset of medium (M), high (H) and very high (VH) TEff values, with the exception of a terminal node with only eight outlier values (Fig. 9, ID17). At the bottom of the tree, the CART model was able to split two terminal nodes that represent very high values of TEff (Fig. 9, ID18 and ID20). Both terminal nodes came from a common splitting condition associated to the fraction of energy allocated to fertilizer (Fig. 9, ID13). The SV of this splitting node indicates that the VH classification was achieved in crop fields that invest equal or less that ca. 5% (i.e. F <=0.056) of the total energy input in fertilizers. The CART model revealed the non-linear nature of the relationship between TEff and the explanatory factors, as it was possible to get an equal classification through different CART paths. For example, the CART classified two terminal nodes (Fig. 8, ID11 and ID12) as medium (M) TEff nodes. However, this status can be achieved either under the condition of low tillage investment (ID4) and during the most recent years (ID11) or under higher investment in tillage (ID5) and under an pesticide energy investment equal or lower than ca. 20% of total energy input (Fig. 9 ID12). When the variable importance for CART selection was assessed (Table 2), the algorithms showed that the fraction of energy allocated to tillage (T) was the most important variable for building the final CART model of Fig. 8. The importance of other variables is explained on the value of T. In this sense, the crop specie (CROP) and year (YEAR) were able to explain 73 and 50%, respectively, as explained by the fraction of energy assigned to tillage. The remaining fractions of energy allocation (pesticides and fertilizers) reached relative values of less than 50%. Finally, the area of each crop field (AREA), a possible indirect estimator of landscape effects, reached a very low value of importance in terms of building the CART model (Table 2).

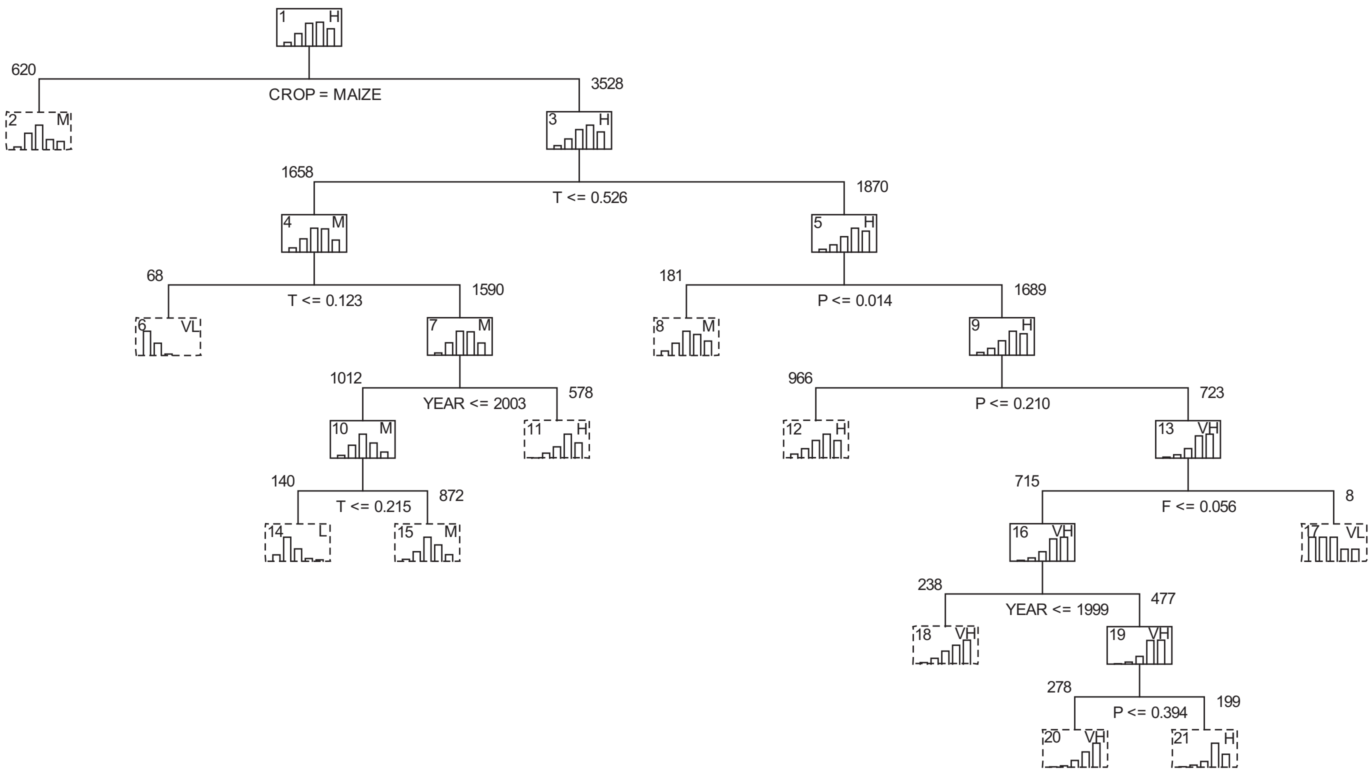


Fig. 9. Classification and regression tree (CART) of a subset of the k-means clusters depicted in Fig. 8. Right and left branches indicate that the group satisfies, or do not satisfy, respectively, the split condition at a decision node (for variable abbreviations see Table 2). The number associated to each branch shows the number of crop fields splitted to each child node. Columns inside each box indicate the frequency of distribution each k-means clusters in that node, and the top-left number is the node number (ID). The top-right abbreviation inside the boxes indicates the most frequent cluster (the column order is VL-L-M-H-VH; see Fig. 8 for cluster abbreviations). Dotted boxes indicate terminal nodes. Cross-validation (CV) cost for the learning set (4148 cases) = 0.60. CV cost for test set (2041 cases) = 0.61 (no significant difference, $P < 0.05$). Variance explained by the model: 1 − CV learning set = 0.40.

4. Conclusions

This work constitutes the first approach for studying the energy efficiency in the long term in Argentine agroecosystems. The evidence showed an upward trend in productivity per unit area in the production systems studied, with the exception of sunflower crop. Genetic progress is an aspect not considered in the estimates of this work and it is often associated with changes in productivity over time [50]. However, these increases were of a magnitude greater than the increases in input use (via fertilizers, pesticides or crops) only for summer soybean (S1) and sunflower (Su), which resulted in higher energetic efficiencies by the end of the time series analyzed. In the study area, the most remarkable shift in the energy use pattern was the reduction of the energy allocated to tillage, mainly from 1996. This coincides with the introduction of soybeans genetically modified to tolerate glyphosate, and its subsequent explosive expansion in the Pampean agroecosystems [51]. The balance between energy use and output in each crop through the study period showed a plateau tendency of the O/I parameter. The O/I values were higher than similar cropping systems [31,35,52,53], mainly in the non-cereal crops, where the relative low usage of fertilizers in Argentinean crops is more evident [54]. In particular, the spring soybean and sunflower crops appear to have improved their performance in terms of the O/I during the studied period, doubling their initial values, but also showed an apparent trend towards the stabilization of this parameter. Also, it was possible to detect that the within-crop variation was higher in soybean and sunflower compared with those for wheat and maize. These variations are important because they denote that there is scope to adjust the production technologies for controlling energy consumption within the same crop. Although some of this variability can be awarded to changes in natural resource availability, these results show that there is scope to work on the efficiency determined by the parameter O/I. The greatest variation detected within than between crops could also be referred to TEff results. Through this parameter it was possible to detect slight changes on technical efficiency (i.e. the difference in energy use in each field crop in relation to the most energy-efficient ones). The efficiency denoted by the TEff parameter is different from the O/I traditional measurement. Mainly, TEff indicates how far are each overall crop performance with respect to the highest achievable efficiency value (i.e. the one determined by the frontier analysis). Thus, the overall performance of the wheat and soybean crops in the study area appears to be closer to the energy usage pattern shown by the top 5% energy use efficiency crop fields. However, the most obvious pattern is the low variability among production systems, which would indicate that a genuine impact in reducing energy use (or increases in efficiency) would be achieved through internal production systems adjustments rather than a radical system change (i.e. crop species change). The exploratory analysis for explaining the variability of technical efficiency (TEff) using CART revealed that the energy allocation to tillage and the crop specie were the attributes that most strongly explain the energy efficiency changes. Finally, and based on the values of productivity and energy efficiency, it was possible to identify some benchmarks in terms of energy allocation that could serve as indicators for clustering groups of varying energy efficiency. Moreover, to get a full indication of changes in energy use at regional level, it should be also considered the crop rotation effects and productivity variations due to changes in resource availability not associated to external energy inputs (e.g. soil type or rainfall).

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