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Relationships between agricultural energy and farming indicators

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ABSTRACT

Cutting costs in farms is the main concern for several stakeholders, specifically for farmers. Reducing energy costs allows for, at the very least, two relevant outcomes, one concerning increases in the net farm income and the other relating to the environment and the promotion of more sustainable farming and rural development. In turn, the agricultural sector may itself be a relevant source of renewable and clean energies. Considering these motivations, this research/study has intended to explore the concept of agricultural energy, highlighting the main insights from literature, and to stress the relationships between this concept and relevant farming indicators. The findings obtained may provide interesting support for the several related stakeholders, namely, policymakers, farmers and researchers. To achieve these objectives, literature available on scientific platforms was explored and statistical relationships were established, through econometric approaches (allowing for spatial effects), between structural characteristics from farms in the European Union. The findings reveal that the several instruments within the Common Agricultural Policy (CAP) should further address the relationships between financial support and sustainability. For example, it could be interesting to index the direct payments from the 1st CAP Pillar with farm indicators that consider dimensions related with the efficiency and savings in costs. In the current context, it is possible to increase the output and area with energy cost growths of 0.423 and 0.375% points, respectively, and increase the total crops output/ha growth and the utilised agricultural area with energy costs/ha growth of 0.243 and −0.225% points, respectively.

1. Introduction

The concept of agricultural energy may, in fact, be considered from two perspectives associated with energy consumption and production in the agricultural sector [1]. The energy consumed by the agricultural sector does not represent a large part of the global energy consumption in, for example, the European Union [2], however, the associated costs within farms may achieve, on average, around 31% of the specific costs, 18% of the intermediate consumption and 12% of the total input [3].

On the other hand, in these percentages of energy consumption in-farms, namely, direct consumptions of motor fuels and lubricants, electricity and heating fuels were considered [3]. Nonetheless, in addition to the direct energy consumption, several sectors, including the farming sector, also consume energy indirectly through fertilizers and crop protection products, for instance [4] and here, sometimes the statistics are underestimated. This underestimation of the several socio-economic impacts occurs across several domains of society, as happens, for example, in environmental assessments [5]. Other dimensions to take into account are the relationships of the input consumption with agricultural policies and with economic dynamics [6]. Another field is the relevance of the efficiency concept as a basis for sustainable development, where the assessment of several interrelationships may bring about useful contributions [7].

In this context, the main objective of this study is to further explore the concept of agricultural energy and identify the main relationships between energy consumption and several indicators from farms in the European Union. For this reason a bibliometric analysis with the VOSviewer [8] software was first carried out. For this bibliometric approach 98 documents (namely articles) from the Web of Science Core Collection [9] were considered for the topic “agricultural energy”. This previous analysis allows us, amongst other insights, to better organize the literature survey. In fact, with the information from the bibliometric analysis, the various documents were clustered. These documents were, later, analysed further through a literature review. To bring out more highlights, on this topic, for the several stakeholders, namely policymakers (for instance), the relationships between energy consumption by European Union farms and other agricultural indicators were explored, through econometric approaches, including spatial autocorrelation methodologies. Statistical information from the Farm Accountancy Data Network (FADN), as well as, shapefiles for spatial analysis were also

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considered. The econometric approaches were performed following the procedures of GeoDa [10] and Stata [11].

1.1. Main motivations and contributions

Considering the relevance of the energy concept on farms and the weight of energy costs within the agricultural sector, as described before, it seems pertinent to further explore the several dimensions related with "agricultural energy". On the other hand, it seems that there appear to be several gaps in literature related to these topics, at least in an integrated manner. For example, a search performed in the Web of Science All Databases [12] shows that there are no documents for the topics "agricultural energy" and "bibliometric", as are there none for the topics "agricultural energy" and "FADN" and very few (about ten and a half, with a relevant part for the years before 2010 and from meetings) for the topics "agricultural energy" and "review".

From this perspective, this study carried out here may provide an interesting contribution for the several interested parties. In fact, the combination of bibliometric analysis with literature review and with empirical analysis using statistical and econometric approaches (including spatial autocorrelation methodologies) brings about new and relevant insights to the topic "agricultural energy" in an integrated dimension. Bibliometric analysis highlights some bibliographic indicators and supports a better organization and systematization of the literature review. On the other hand, the statistical and econometric approaches bring insights into the relationships between the "agricultural energy" domains and the European farm indicators.

2. Bibliometric approach with bibliographic data

Considering the 98 documents from the Web of Science and following the VOSviewer procedures for bibliographic data, Fig. 1 was obtained for the link bibliographic coupling (references shared) and item documents [13]. With the files obtained from the Web of Science, the VOSviewer software has two options (bibliographic data and text data) to create new network visualization maps. For the text data it is possible to consider co-occurrence links and item terms. For the bibliographic data, the software allows to take into account several links (and respective items), such as the following: co-authorship (authors, organizations and countries); co-occurrence (keywords); citation (documents, sources, authors, organizations and countries); bibliographic coupling (documents, sources, authors, organizations and countries); and co-citation (cited references, cited sources and cited authors). In order to avoid being exhaustive and considering the objectives of bibliometric analysis for this research (supporting, namely, the literature review), only documents for bibliographic coupling were considered in this study. In the maps obtained from VOSviewer, the dimension of the circles is related, for example, with the number of documents or citations (citations in this map) and the proximity (relatedness) is associated, in this case, to the references shared.

Only 58 documents are connected with each other for these links and items. In any case this analysis provides its contribution to the bibliometric analysis outcome and is a useful basis for the organization of the literature review. In fact, as mentioned before, the bibliometric analysis performed in this section is intended to provide support towards a better design in the structure of the literature review presented in the next section.

Fig. 1 and the information obtained from VOSviewer show that this software organised the 58 documents as being interconnected into 10 clusters. On the other hand, the study by Schmer (2008) is the most cited with 679 citations, followed by, for example, the studies of Refsgaard (1998) and Wood (2006) with, respectively 124 and 109 citations. On the other hand, these documents have great relatedness (number of references they share), because they appear in close proximity to each other in the figure. For the normalised citations (removing batch effects, in the number of citations, from the number of years the published document has had) the works of Harchaoui (2019) and Hussain (2019) have higher scores. Finally, these 58 documents began being published from 1992 to 2019, however, 2018 was the year with the most publications.

3. Literature survey

This section was organised considering the bibliometric analysis performed in the previous section. Subsections were created considering the clusters identified, related with the topic of agricultural energy. The 10 clusters found through the VOSviewer software were merged into the following two groups: agricultural energy and pollution; demand and supply of energy by farms.

3.1. Agricultural energy and pollution

The agricultural sector is an important source of energy production for human needs [14] and would be sufficient if some energy wastage were mitigated. Some of these energy losses are, also, sources of pollution. Crop production alone could supply about 85% of human requirements [15].

The rural population structure may play a determinant role in mitigating greenhouse gas emissions from agriculture. This is true for China, but, with specific adjustments, is applicable for many countries around the world. In the specific case of China, for example, between 2005 and 2013, agricultural production increased by 37.1% and the agricultural CO_2 emissions 15.6% [16]. The energy consumption, in China, to obtain unit groundwater has increased, in recent years, about 22% and greenhouse gas emissions increased by 42% [17]. To address these frameworks, changes in agricultural practices, related to land use and water savings, are needed [18]. Water management is and will be one of the most relevant challenges for the planning of farming [19], where the efficiency concept may bring relevant contributions [20]. In farms, the efficiency of energy use may be improved through several operations, such as in irrigation activities, machinery utilization and conditioning processes [21]. These possibilities of farming efficiency improvements

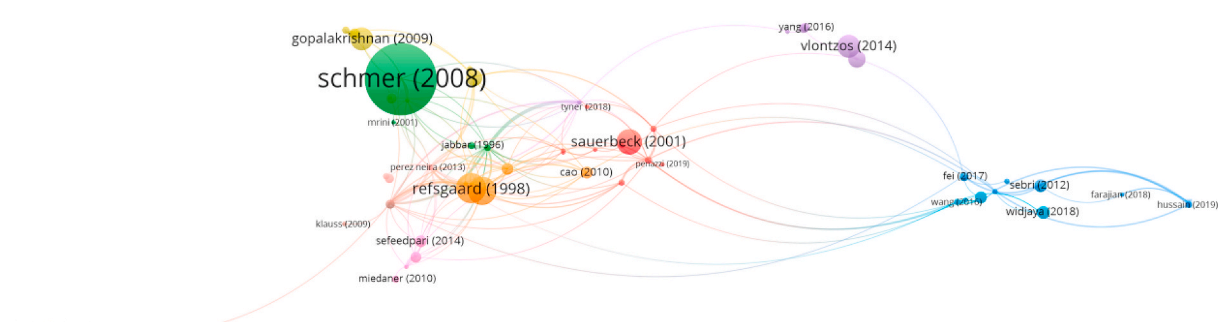

Fig. 1. Network visualization map for bibliographic coupling and items documents.

have an enormous potential impact around the world [22].

On the other hand, in Cyprus, it was found that livestock breeding has an impact of 16% on global agricultural energy greenhouse gas emissions and the agricultural sector has an impact of 0.7% on total energy emissions. In any case, the emissions from energy use (in pigs, poultry and cattle) represent only 3% of the total livestock breeding emissions (from energy use, enteric fermentation and manure management) [23]. Increasing energy independence of farms, through self-sufficiency approaches, may be a solution in reducing emissions from agriculture [24], where the integration of crops and livestock may provide important outcomes [25].

In these contexts of relationships between agriculture and sustainability, the agricultural policies and efficiency improvements are crucial, however, due to patterns of human adaption, sometimes, the results are not always those which are expected, in line with the so called rebound effects, well described within the literature [26].

Integrated urban-rural ecosystems in urban planning may be a way to mitigate the emission effects from the concentration of populations in urban areas and the consequent needs for product transportation [27]. In fact, the farming sector is a relevant source of carbon emissions, but may have, also, significant contributions for development which is compatible with the environment, including CO2 sequestration [28]. In turn, agricultural energy is a relevant concept [29] and is related with energy use in farms and with energy production from agricultural activities [30], such as the production of biofuels, for example [31], from diverse farming sources [32], is therefore environmentally compatible. Agricultural energy consumption may, also, be direct and indirect. The main indirect energy consumption in farms is related with fertilizers and machinery use [33]. Agricultural and industrial energy utilization in some countries represents a significant part of the total consumption [34]. Biofuels are fuels (bioethanol, biodiesel and methane) that can be produced from agricultural residues, such as crops and livestock waste [35], and also from seeds [36]. In general, the sustainability of the several dimensions related with agricultural energy depends, often, on off-farms factors [37], such as fuel and food prices, for instance [38].

In the state of Nebraska, for example, the use of marginal land may produce feedstocks to supply 22% of energy needs [39] having low environmental impact. The target for renewable energy use, for 2020, is 20% in the European Union and 38% in Finland [40]. Climate change and global warming are, indeed, some of the main incentives for the growth in renewable energy sources, however, environmental impacts from these sources are not unanimous between the several stakeholders [41]. The energy deficit is, also, an important agent for renewable energy sources [42]. This controversy is due to the great diversity of realities in farms, from structural facilities, to the potentialities for various agricultural productions [43], that call for multivariable analysis [44] and specific approaches [45]. In any case, biodiesel [46] and the new agricultural energies [47] have motivated and still motivate several studies. On the other hand, the energy requirements for agriculture depend on the kind of productions considered and on the global location being assessed [48], including for realities in organic farming systems [49].

3.2. Demand and supply of energy by farms

The demand for energy, from the varying socioeconomic sector, has increased over recent years (or at the very least, changed in its structure), as a result of several factors, as shown in the contexts from Bangladesh [50], for instance, which combined with the volatility of international energy markets [51] and climate change, increased the production of energy from alternative sources [52]. The volatility of market commodities is, in fact, a focus of attention for several stakeholders [53], as well as, the liquidity commonality [54], or inflation [55]. This trend is, also, true in the countries that traditionally produce fossil fuels as a main source of energy [56]. Climate change has, indeed, its impact on agricultural and rural dynamics [57].

In China, for example, the agricultural energy demand has increased with agricultural production and mechanization and decreased with agricultural structuring, fiscal frameworks and energy prices [58]. Similar patterns were found in Tunisia, where the agricultural output is dependent on energy consumption [59]. In Germany, the feed production and dietary characteristics are some of the dairy farming dimensions that have relevant energy requirements, as well as, machinery and facilities. It is in these dimensions where energy savings may be more pertinent [60]. In the Australian farming context, organic farming seems to be an interesting alternative towards reducing global (direct and indirect) energy demand [61]. Nonetheless, the relationships between energy domains and organic farming motivated little research [62]. Sometimes, the positive relationships between economic growth, across the several sectors, and energy consumption create self-reinforced processes [63], including contexts in the Chinese agricultural sector [64], where the public policies are claimed to have promoted more balanced developments [65]. In general, there are relationships between the energy dimensions, environmental fields [66], and economic growth. There are, too, interlinkages from the energy fields with other scientific domains [67], socioeconomic dimensions [68], such as water management/administration [69], water pollution [70], phytoremediation [71], soil fields [72], or microbial communities [73].

The diversity of instruments from the several policies play a determinant role in sustainability [74], namely, interlinking different dimensions related with the farming sector, such as those associated with food, energy and water, in the European Union [75] and in other world countries [76]. There is, definitely, a close interrelationship across energy issues and water domains [77], addressed more or less markedly [78] and where the agricultural policies have their influence, as shown in examples from Mexico and India [79]. For example, in European Union countries, there are promising expectations for energy efficiency with the more recent Common Agricultural Policy (CAP) instruments [80] and the several legislations for the use of renewable energies having increased, at least, the attention of the several operators in these fields [81]. Energy efficiency in the Chinese agricultural sector could be, also, improved and is higher in the eastern than in the western regions. The main sources of agricultural inefficiency are more related with management specificities than with technological circumstances [82]. The public Chinese institutions have here, and in other aspects [83], issues to consider in their strategies for agricultural [84], namely to mitigate the environmental impacts from an inefficient use of fossil fuel intensive materials [85]. However, sometimes the environmental outcomes from agricultural policies are not always those expected, as is the case with the grain-for-green policy in China [86]. The agricultural sector is, indeed, complex having several different alternatives for each assessment and the adequacy of each proposal depends on several interactions between productions and inputs [87] and specific particularities of each country [88]. The farms adaptation to new realities, related with energy contexts, is influenced by the farmers' perceptions, traditions and institutional frameworks [89].

Contributions from the agricultural sector for energy supply may be improved, around the world, through the production of renewable energies [90], with the diverse amount of technologies available [91]. A well organised plan to recover all agricultural residues may significantly improve farming contributions for the sustainability of energy in agriculture [92]. For example, the use of rice straw, in India, for the production of biofuel increases the agricultural energy supply and reduces the environmental impact from straw burning [93]. The use of non-wood waste around the world regions is another alternative [94], or choosing the most adjusted techniques and raw materials [95]. Biomass appears as a relevant source of renewable energy [96], where there are, still, many areas to explore and improve upon [97]. New technologies, such as artificial intelligence [98], or smart agriculture tools [99] are relevant instruments for agricultural energy demand and supply evaluations, as well as, the insights from scientific assessment approaches

[100] and methodologies of analysis [101]. The continuous assessment of energy contexts is crucial and requires adjusted indicators [102]. Agricultural energy analysis and modelling has always motivated the scientific community [103], through several assumptions [104] and conceptual frameworks [105], including policy aims [106], farm management [107], potentialities highlighting [108] and methodological adjustments [109]. Farm management and, maybe even, agricultural policies are the main determinants for an efficient energy use in farming [110], where, for instance, tillage practices may have its influence [111].

3.3. Main insights from the literature review

The main concern in the fields of agricultural energy should be the mitigation of energy wastage in the several farming activities. On the other hand, changes in farm structures and their interrelationships with rural dynamics could bring interesting insights into these contexts. These changes should promote greater farm efficiency in the use of resources, namely for productions having a higher energy consumption, and could reposition the agricultural sector as being a relevant supplier of energy for local populations and economic dynamics. The use of marginal and abandoned land could play an interesting role here, namely in the production of biomass as a source of renewable energy.

Climate change and global warming have changed consciousness and paradigms in various sectors, including the agricultural sector, and this has promoted changes in energy demand and supply, however, this may not be enough to promote effective sustainability due to the pressures from the needs for economic growth. These contexts need tax and subsidy instruments adjusted to the framework of agricultural policy around the world and, particularly in the European Union countries. For effective compliance by farmers, it is important that the policy framework is simple and with a reduced number of instruments.

4. Data analysis and spatial autocorrelation assessment

In this section, the energy costs (euros) and the energy costs by hectare (euros/ha) of utilised agricultural area were analysed, first through descriptive and spatial autocorrelation approaches and subsequently considering pairwise correlation matrices between these two variables and others associated with the structural characteristics of European Union farms, namely, the following: total utilised agricultural area (ha); energy crops area (ha); total livestock units (lu); total output (euros); total output/total input; total crops output/ha (euros/ha); total livestock output/lu (euros/lu); total inputs (euros); farm net value added/awu (euros/awu); total subsidies-excluding investments (euros); subsidies on investments (euros); energy costs (euros); taxes (euros). These data, disaggregated at regional level (for the European Union agricultural regions), were obtained from the FADN [3] database, for the year 2017. The monetary data (with the exception of the energy costs) were corrected by the Price level indices (EU28 = 100) for the Gross

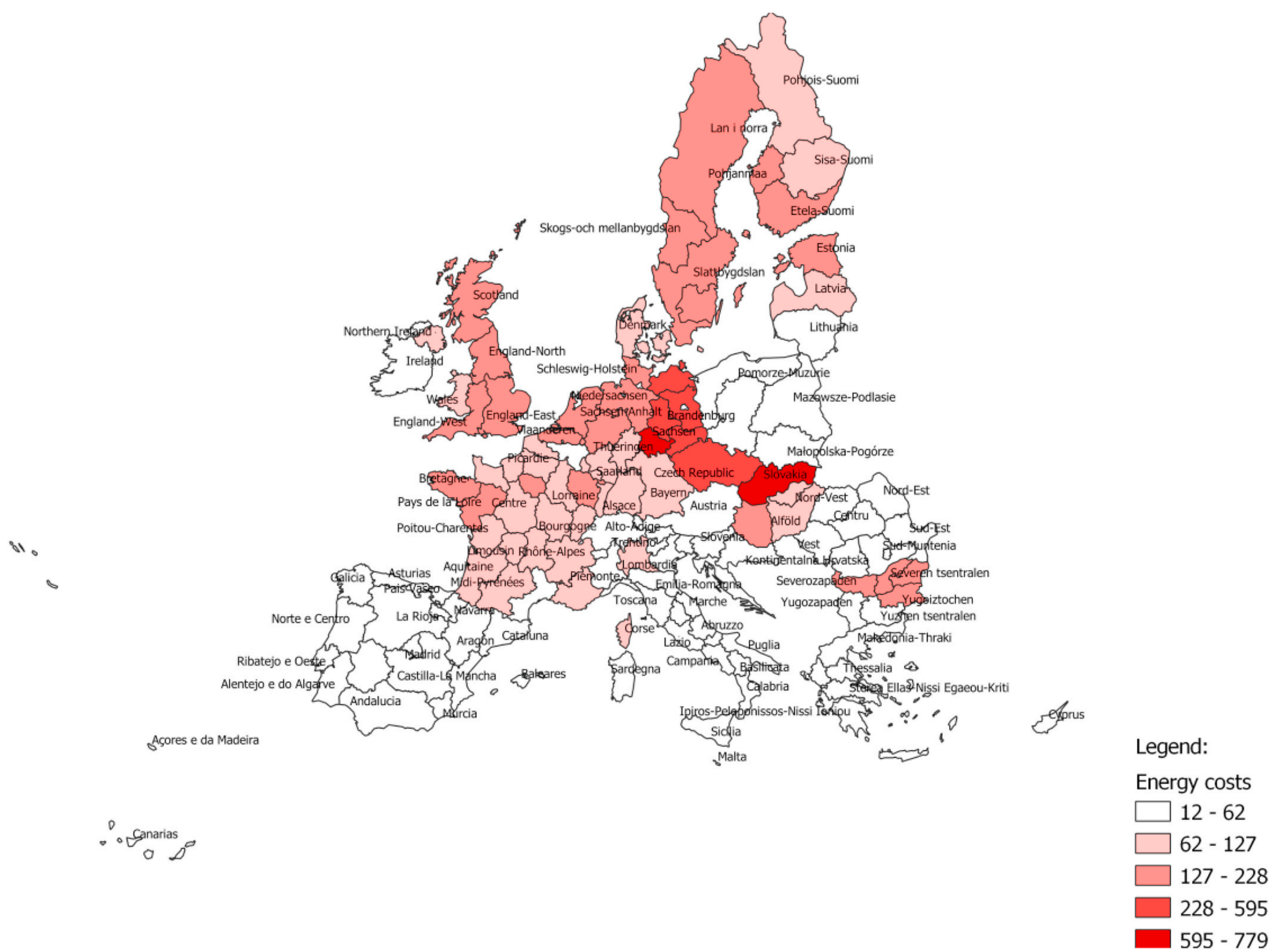

Fig. 2. Energy costs (corrected by the Price level indices (EU28 = 100) for Electricity, gas and other fuels) across European Union agricultural regions, for the year 2017.

domestic product. The energy costs were corrected by the Price level indices (EU28 = 100) for Electricity, gas and other fuels. The price level indices were obtained from the Eurostat [2]. For the spatial autocorrelation analysis, the overseas regions Guadeloupe, Martinique and La Réunion were removed. Highlighting that the values for each region are average values for a representative farm. Figs. 2 and 3 were obtained with the QGIS [112] software, Figs. 4 and 5 through the GeoDa [10] software and Tables 1 and 2 by Stata [11]. The local spatial autocorrelation maps obtained with the GeoDa software are based on Moran's I statistics [113] and developments of Anselin [114] on these subjects. The correlation matrices presented in Tables 1 and 2 were obtained considering the Pearson coefficients [115,116].

Fig. 2 shows that the Czech Republic, Slovakia and the neighbouring German agricultural regions are those where the farms have, on average, higher energy costs. The farms from the Czech Republic and Slovakia, for example, have, on average, high dimension and this partially explain the higher energy costs. A great part of the regions from the United Kingdom and Sweden presents medium energy costs. The same occurs for The Netherlands, Estonia and some regions from France, Finland, Belgium and Bulgaria, for instance. In turn, if the energy costs by ha are considered (Fig. 3), the higher values appear in Malta (14.73 euros/ha), Canarias (in Spain with 9.97 euros/ha) and The Netherlands (6.41 euros/ha).

Figs. 4 and 5 confirm these tendencies and show that there are several signs of positive local spatial autocorrelation amongst the European agricultural regions. These figures were obtained with the GeoDa software considering the Moran statistics for the identification of spatial clusters. In these figures the clusters high-high and low-low represent positive spatial autocorrelation for higher and lower values, respectively, of the variable analysed. The clusters high-low and low-high represent negative spatial autocorrelation. For example, for energy costs (Fig. 4), there is positive high-high spatial autocorrelation for the Czech Republic and the neighbouring German regions and positive low-low spatial autocorrelation, for example, in some regions from Greece, Italy, Spain and Portugal. There is, also, negative spatial autocorrelation low-high in Austria and some regions from Poland. This means that the lower energy costs are influenced negatively by the higher energy costs in the neighbouring regions from Slovakia, Czech Republic and Germany. The same happens for the German region Bayern. For the energy costs/ha the signs of local spatial autocorrelation are not so visible. However, there is positive spatial autocorrelation low-low for the Spanish and French regions and some from the United Kingdom. These findings could afford relevant support in implementing policy changes, taking advantage from spatial autocorrelation frameworks, since policy interventions in some regions may spread to spatially autocorrelated neighbours.

4.1. Correlations analyses

Tables 1 and 2 were obtained following the procedures proposed by the Stata software. Table 1 shows a pairwise correlation matrix for the energy costs and other structural variables for European farms. In Table 2, the energy costs and some structural variables were divided by the area to correct for the effects of the farms' sizes.

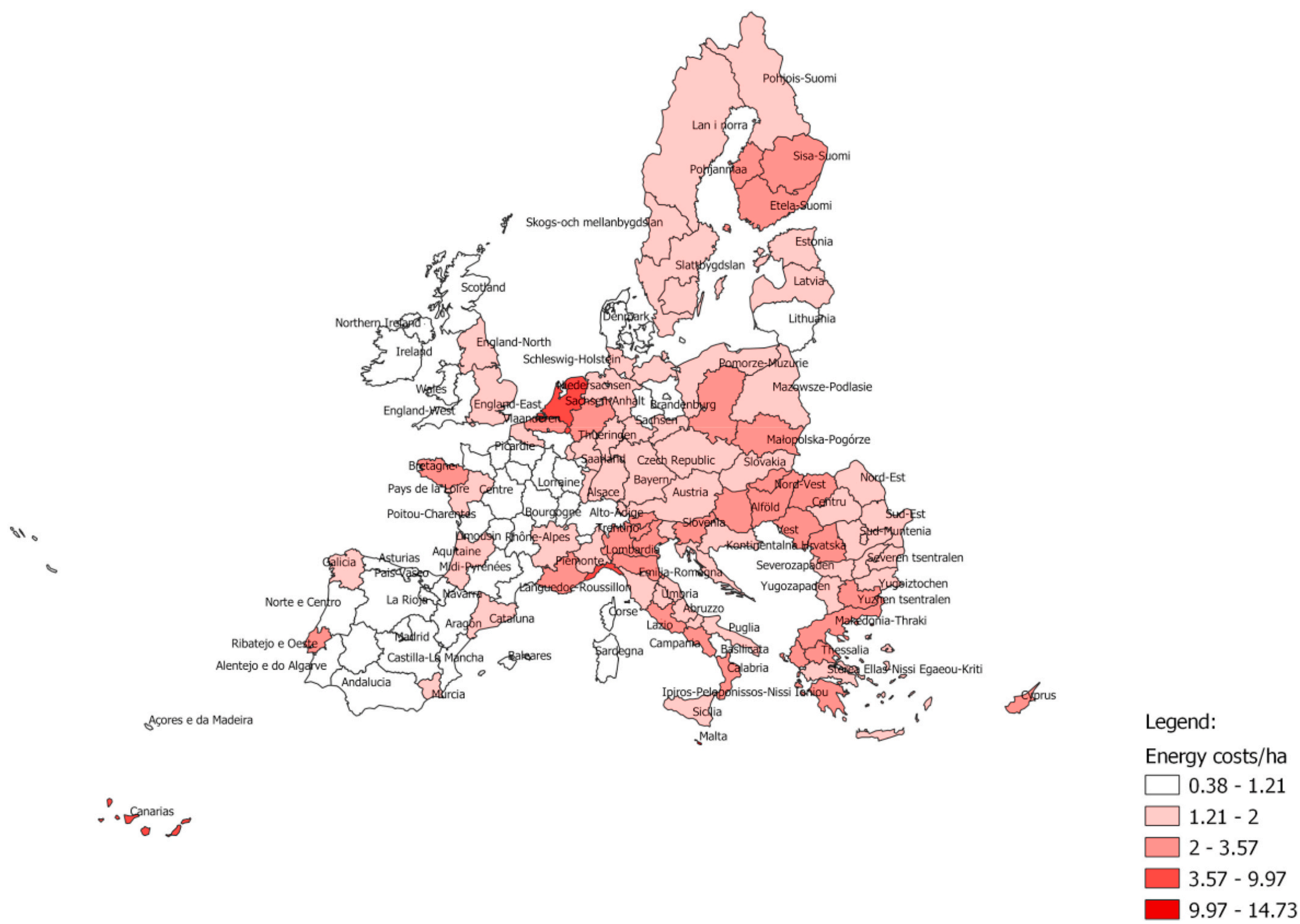

Fig. 3. Energy costs/ha (corrected by the Price level indices (EU28 = 100) for Electricity, gas and other fuels) across European Union agricultural regions, for the year 2017.

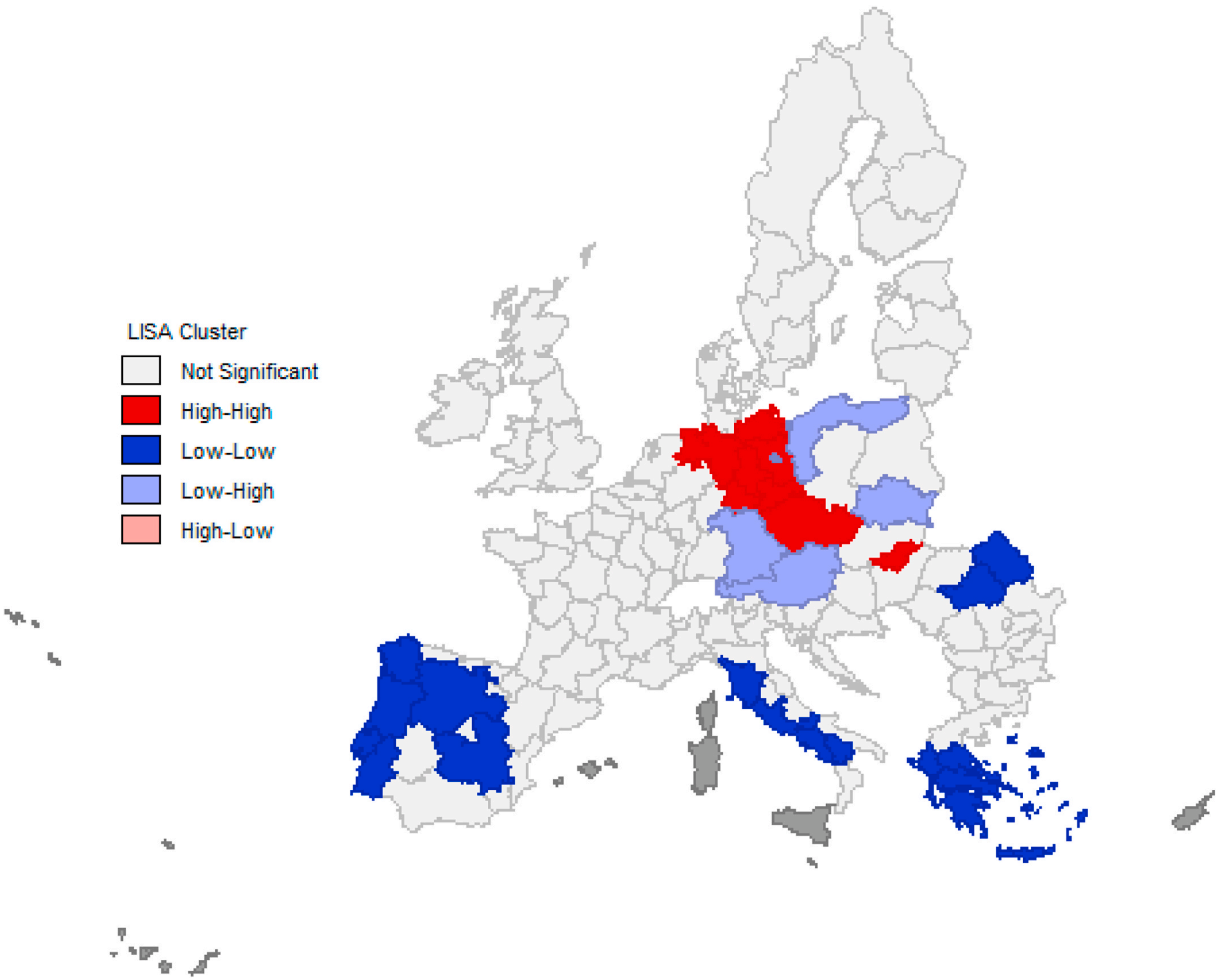

Fig. 4. Local spatial autocorrelation for energy costs (corrected by the Price level indices (EU28 = 100) for Electricity, gas and other fuels) across European Union agricultural regions, for the year 2017.

Table 1 reveals that the energy costs, on average, are positive and strongly correlated with the following farm variables: utilised agricultural area (0.933); energy crops area (0.670); total livestock units (0.745); total output (0.961); total input (0.979); total subsidies-excluding investments (0.955) and taxes (0.849). This context shows that the farm's dimension, the level of output and input, the total subsidies-excluding investments and taxes, in general, are directly accompanied by the level of energy costs. On the other hand, the energy costs are positive, but weakly, correlated with the Farm Net Value Added/AWU and the subsidies on investment, negatively correlated with the total output/total inputs and, finally, not correlated with the Total crops output/ha and Total livestock output/LU. This reveals that, in general, the energy costs are weakly, or negatively, or without statistical significance associated with variables related with competitiveness.

For energy costs by ha (Table 2) the positive and stronger correlations are with the total crops output/ha, the total output/ha and the total inputs/ha. With the farm net value added/awu there is no correlation. This framework demonstrates that there is, in this case, strong correlation with the farm area productivities (namely crops area productivity), but, also, with the inputs/ha and there is no relation with the farm competitiveness indicator (farm net value added/awu).

5. Regressions results allowing for spatial autocorrelation effects

To try to identify the main farming structural variables that explain the energy costs for European agricultural regions, classification and regression binary tree approach were first performed and the results are those presented in Figs. 6 and 7 for energy costs and energy costs/ha, respectively. These methodologies were performed following the IBM SPSS Modeler [117] procedures. The classification and regressions trees are based on the developments of, for example, Breiman et al. [118]. In this section, the monetary data were corrected by the Price level indices (EU28=100) and those with time series were deflated with the HICP (2015 = 100).

Fig. 6 shows that initially two nodes were created, the note 1 for observations when the farms have utilised agricultural areas up to 393 ha. If a random representative farm from the European Agricultural regions belongs to this node its predicted energy costs, for the year 2017, is 90.7 euros. On the other hand, the probability of a random agricultural region to belong to this node is 94.2%. The terminal node 20, for the higher predicted energy costs (342.6 euros), reveals that it is the farms with higher inputs, outputs and area that have more energy consumption costs. The inverse happens for farms with lower energy

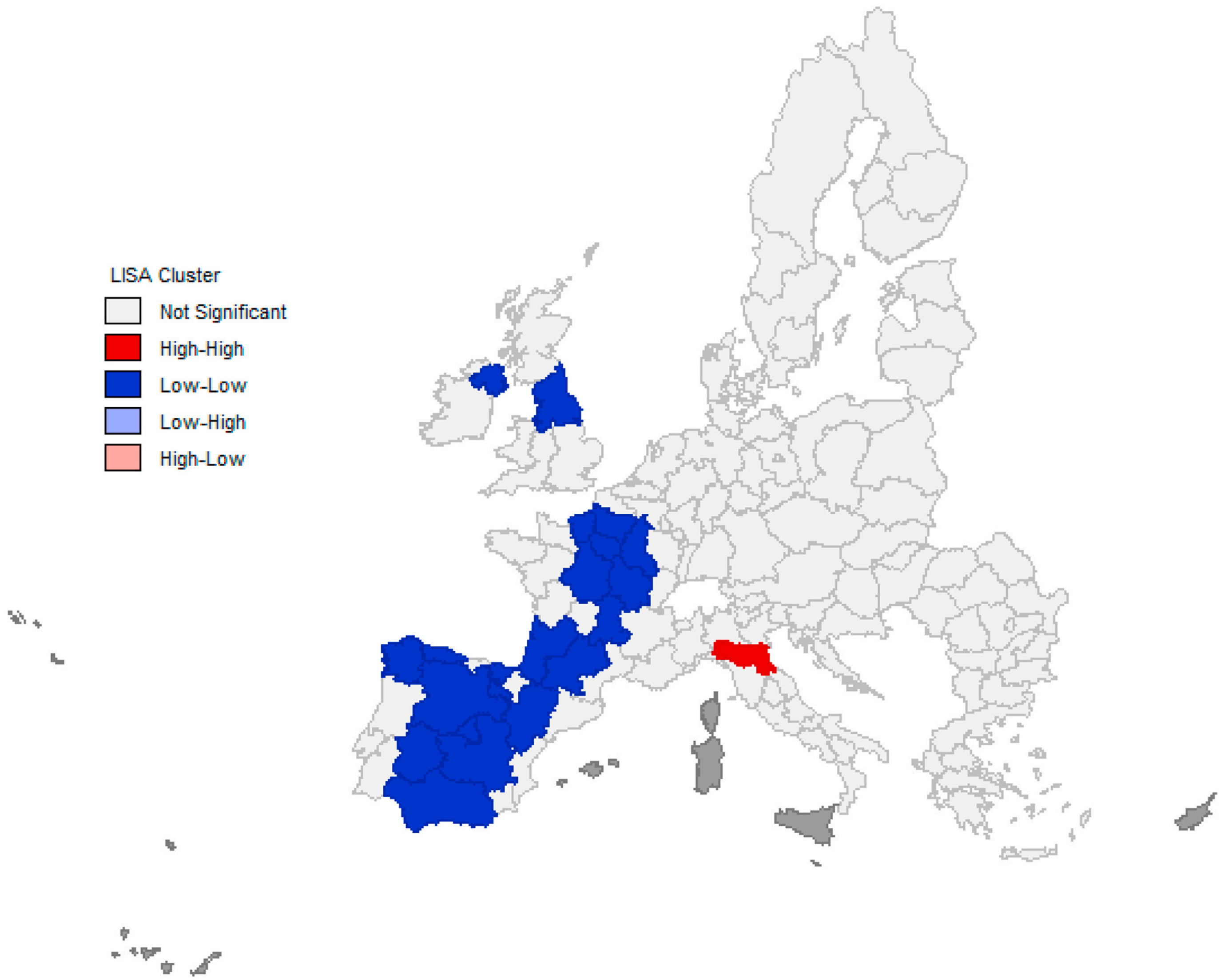

Fig. 5. Local spatial autocorrelation for energy costs/ha (corrected by the Price level indices (EU28 = 100) for Electricity, gas and other fuels) across European Union agricultural regions, for the year 2017.

costs, as presented by node 13.

The results presented in Table 3 confirm, in fact, that the energy costs are mainly predicted by the total utilised agricultural area, total outputs and total inputs. This framework reinforces the need to promote more efficiency and productivity in the use of energy resources, implementing more adjusted management plans and increasing the effectiveness of farmers' vocational training initiatives.

Considering the insights found previously, following the procedures proposed by the Stata software and Torres-Reyna [119] for panel data with spatial effects, the results presented in Table 4 were obtained. The period of 2012–2017 was considered and since, in some years, the FADN database has a lack of data for the regions Hamburg (Germany), Bucuresti-Ilfov (Romania), as well as, for Croatia, these regions were removed. For the construction of the regression model as a base, the Verdoorn/Kaldor laws [120–123] from the Keynesian theory [124,125] was taken into account, where the productivity/employment growth is endogenous and dependent on the output growth. From this perspective the energy costs growth is regressed by the area and the output growth, allowing for spatial effects. These results show that, for the period 2012–2017, the spatial effects are, namely, random. In turn, when the output and area growth change 1% point the energy costs growth change 0.423 and 0.375% points, respectively, showing that the changes in energy costs growth are lower than 0.5. This means that the increases in the energy costs are significantly lower than the changes in the output or area growths. However, the growth in energy costs may still be significantly reduced, considering that values close to zero are the ideal objectives for these coefficients, taking into account developments in the theory. Yet again, the vocational training (learning-by-doing), efficiency and productivity improvements must be key aspects in the design of new policies.

The inverse is, also, true, where European Union counties are able to reduce 0.423 and 0.375% points in the energy costs growth for each 1% point reduction in output and area growth. Land management may play a key role here.

Table 5 shows the adequacy of the model to predict energy costs for the European Union agricultural regions and, in this way, highlights its relevance as an important tool to simulate agricultural policy instruments related to the management and planning of farming energy consumption.

Considering the energy costs and other farm structural variables divided by the utilised agricultural area, Fig. 7 reveals that the farms having higher predicted energy costs/ha (terminal node 22) have a higher utilised agricultural area, lower crops output/ha, higher total subsidies (excluding on investments/ha) and higher total inputs/ha. In

Table 1
Pairwise correlation matrix between several variables from European Union agricultural regions, for the year 2017.

	UAA	ECR	TLU	TOU	OBI	COH	LOL	TIN	VAA	TSE	SOI	ENE	TAX
UAA	1.000												
ECR	0.7087* (0.000)	1.000											
TLU	0.7685* (0.000)	0.5875* (0.000)	1.000										
TOU	0.9104* (0.000)	0.6937* (0.000)	0.8137* (0.000)	1.000									
OBI	−0.4726* (0.000)	−0.2225* (0.010)	−0.4294* (0.000)	−0.4028* (0.000)	1.000								
COH	−0.2417* (0.005)	−0.097 (0.263)	−0.2364* (0.006)	−0.104 (0.230)	0.2360* (0.006)	1.000							
LOL	0.014 (0.874)	0.068 (0.436)	−0.1739* (0.044)	0.084 (0.334)	0.006 (0.945)	0.1999* (0.020)	1.000						
TIN	0.9315* (0.000)	0.6958* (0.000)	0.7911* (0.000)	0.9930* (0.000)	−0.4473* (0.000)	−0.122 (0.159)	0.102 (0.238)	1.000					
VAA	0.4220* (0.000)	0.3570* (0.000)	0.5593* (0.000)	0.5635* (0.000)	−0.054 (0.534)	−0.054 (0.537)	−0.162 (0.061)	0.4888* (0.000)	1.000				
TSE	0.9245* (0.000)	0.6706* (0.000)	0.6801* (0.000)	0.9072* (0.000)	−0.5205* (0.000)	−0.135 (0.118)	0.127 (0.143)	0.9452* (0.000)	0.3404* (0.000)	1.000			
SOI	0.2042* (0.018)	0.039 (0.653)	0.126 (0.147)	0.2098* (0.015)	−0.2352* (0.006)	−0.076 (0.379)	0.048 (0.584)	0.2292* (0.008)	0.077 (0.376)	0.2708* (0.002)	1.000		
ENE	0.9327* (0.000)	0.6701* (0.000)	0.7452* (0.000)	0.9608* (0.000)	−0.4733* (0.000)	−0.158 (0.067)	0.128 (0.138)	0.9788* (0.000)	0.4397* (0.000)	0.9554* (0.000)	0.2307* (0.007)	1.000	
TAX	0.8319* (0.000)	0.7534* (0.000)	0.6636* (0.000)	0.8895* (0.000)	−0.1953* (0.023)	−0.069 (0.424)	0.115 (0.186)	0.8844* (0.000)	0.4511* (0.000)	0.8137* (0.000)	0.085 (0.329)	0.8490* (0.000)	1.000

Note: UAA, Total Utilised Agricultural Area; ECR, Energy crops; TLU, Total livestock units; TOU, Total output; OBI, Total output/Total input; COH, Total crops output/ha; LOL, Total livestock output/LU; TIN, Total Inputs; VAA, Farm Net Value Added/AWU; TSE, Total subsidies-excluding on investments; SOI, Subsidies on investments; ENE, Energy; TAX, Taxes.

Table 2
Pairwise correlation matrix between several variables (some divided by the utilised agricultural area) from European Union agricultural regions, for the year 2017.

	UAA	ECR	TLU	OBI	COH	LOL	VAA	TOH	TIH	TEH	SIH	ENH	TAH
UAA	1.000												
ECR	0.7087* (0.000)	1.000											
TLU	0.7685* (0.000)	0.5875* (0.000)	1.000										
OBI	−0.4726* (0.000)	−0.2225* (0.010)	−0.4294* (0.000)	1.000									
COH	−0.2417* (0.005)	−0.097 (0.263)	−0.2364* (0.006)	0.2360* (0.006)	1.000								
LOL	0.014 (0.874)	0.068 (0.436)	−0.1739* (0.044)	0.006 (0.945)	0.1999* (0.020)	1.000							
VAA	0.4220* (0.000)	0.3570* (0.000)	0.5593* (0.000)	−0.054 (0.534)	−0.054 (0.537)	−0.162 (0.061)	1.000						
TOH	−0.2364* (0.006)	−0.077 (0.376)	−0.119 (0.168)	0.2129* (0.013)	0.9442* (0.000)	0.2482* (0.004)	0.005 (0.951)	1.000					
TIH	−0.168 (0.052)	−0.043 (0.620)	−0.058 (0.503)	0.020 (0.820)	0.9225* (0.000)	0.2343* (0.006)	0.003 (0.975)	0.9719* (0.000)	1.000				
TEH	−0.1696* (0.049)	−0.062 (0.473)	−0.1822* (0.035)	−0.108 (0.214)	0.8071* (0.000)	0.168 (0.052)	−0.165 (0.056)	0.7228* (0.000)	0.8165* (0.000)	1.000			
SIH	−0.051 (0.558)	−0.077 (0.373)	−0.056 (0.519)	−0.098 (0.256)	0.044 (0.611)	0.070 (0.419)	−0.038 (0.666)	0.058 (0.506)	0.078 (0.370)	0.033 (0.702)	1.000		
ENH	−0.2338* (0.006)	−0.083 (0.340)	−0.152 (0.079)	0.096 (0.269)	0.7399* (0.000)	0.2678* (0.002)	−0.108 (0.215)	0.8609* (0.000)	0.8512* (0.000)	0.5704* (0.000)	0.082 (0.346)	1.000	
TAH	−0.1958* (0.023)	−0.038 (0.663)	−0.155 (0.072)	0.5096* (0.000)	0.4338* (0.000)	0.2310* (0.007)	0.067 (0.443)	0.4500* (0.000)	0.3094* (0.000)	0.127 (0.142)	−0.067 (0.439)	0.2624* (0.002)	1.000

Note: UAA, Total Utilised Agricultural Area; ECR, Energy crops; TLU, Total livestock units; OBI, Total output/Total input; COH, Total crops output/ha; LOL, Total livestock output/LU; VAA, Farm Net Value Added/AWU; TOH, Total output/ha; TIH, Total Inputs/ha; TEH, Total subsidies-excluding on investments/ha; SIH, Subsidies on investments/ha; ENH, Energy/ha; TAH, Taxes/ha.

turn, the farms with lower predicted energy costs/ha have lower total livestock output/lu, higher total output/ha and lower total subsidies (excluding those on investments) and lower crops output/ha. Table 6 confirms that the energy costs by hectare are mainly predicted by the utilised agricultural area and by the total crops output/ha.

Considering the insights and developments considered for Table 4, the results in Table 7 present that in this case the spatial effects are, again, random and when the total crops output/ha growth and the utilised agricultural area change 1% point, the energy costs/ha growth change between 0.243 and −0.225% points, respectively. This shows that the gains in crop area productivity is possible with increases in the energy costs/ha, however with changes close to zero. This reinforces the importance of improvements in farm productivity as a key to saving energy costs.

Table 8 reveals, in this case, the adequacy of the model to be considered as support for the several agricultural energy stakeholders in

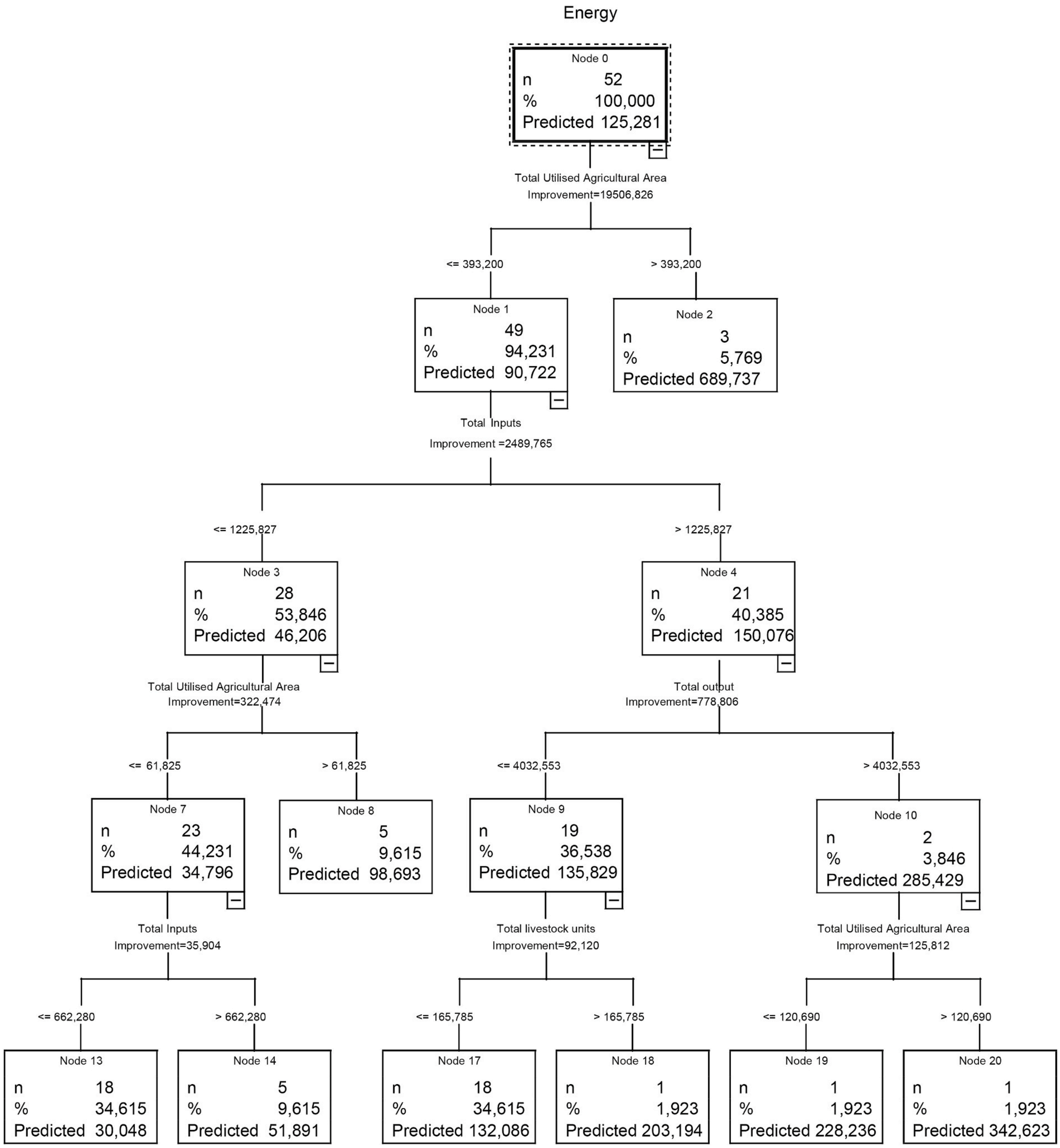

Fig. 6. Classification and regression tree for several variables from European Union agricultural regions, for the year 2017.

farming management and for policy design by agricultural policymakers.

6. Conclusions

The main objective of this research was to explore the concept of "agricultural energy". For this purpose, 98 documents obtained from the Web of Science were reviewed. This literature survey was supported through a bibliometric analysis performed based on the VOSviewer software procedures. Finally, considering the data available in the FADN database, for the period 2012–2017, statistical analyses were performed for energy costs from farms of European Union agricultural regions. For these statistical approaches spatial autocorrelation, classification and regression binary trees and panel data methodologies were all considered.

The bibliometric analysis stresses that this is not a new topic, however 2018 was the year with more publications, revealing that there has been an increased interest in these subjects, from the scientific community, in recent years. In fact, climate change and global warming has brought about an increased interest regarding the ecological footprint mitigation and, here, the agricultural sector as a renewable energy producer and energy consumer may contribute toward these new greener goals. This approach also showed, that the analysed documents could be clustered into 10 groups, however, considering the close relationships of the subtopics, the literature review was organised into 2 sets, as the following: agricultural energy and pollution; and demand and supply of energy by farms.

The literature review concerning "agricultural energy and pollution" highlights that there is a relevant relationship between energy consumption, economic development and negative environmental impacts. This is one of the greatest challenges for the several stakeholders to solve over the coming years. Indeed, this economic model that calls for

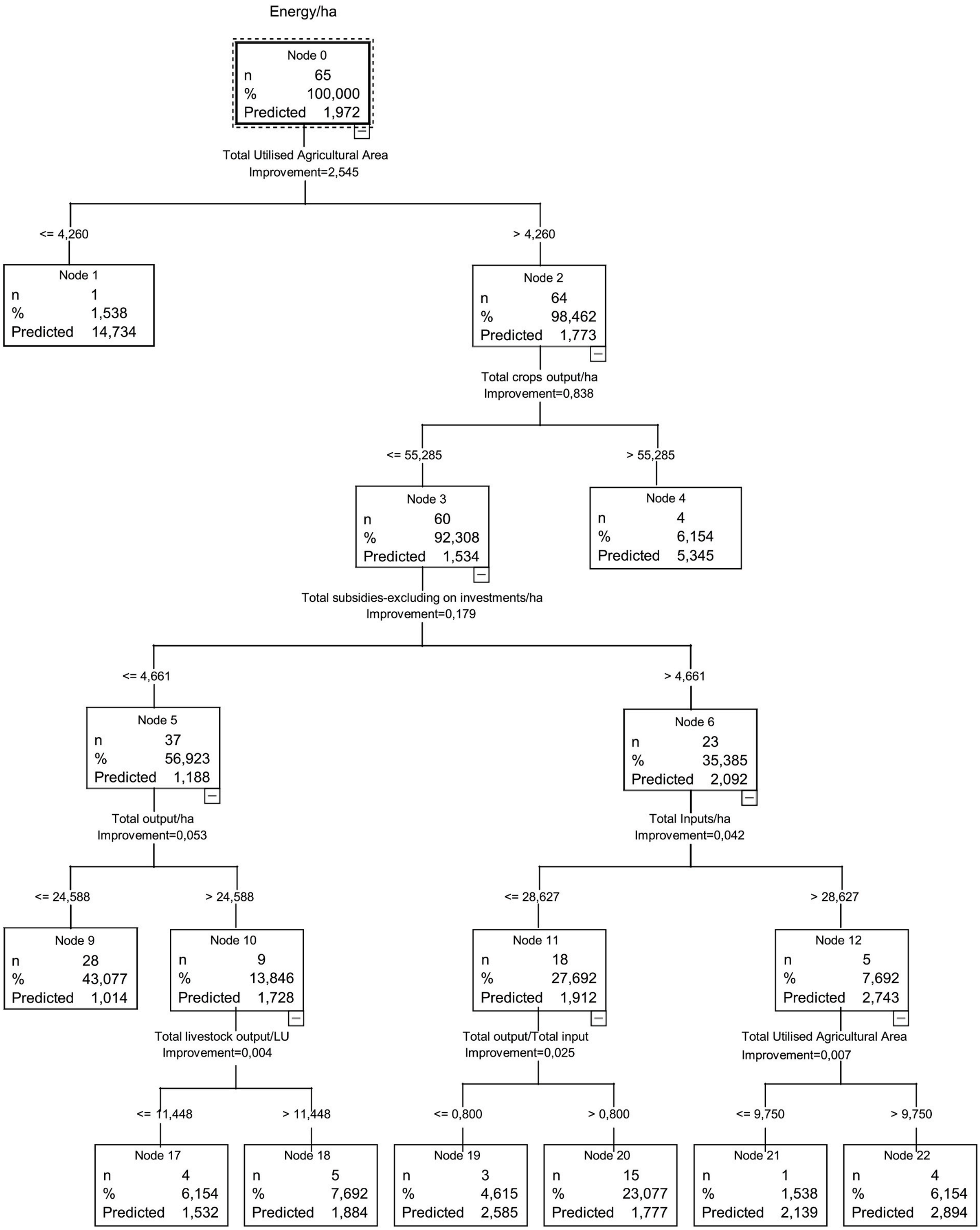

Fig. 7. Classification and regression tree for several variables (some divided by the utilised agricultural area) from European Union agricultural regions, for the year 2017.

permanent and increasing GDP growth rates, may, in fact, be incompatible with global and integrated sustainability. More support for family farming and for agriculture developed through sustainable systems could be an interesting approach. On the other hand, more efficient agricultural systems could, also, bring more sustainable contributions. For instance, in the Chinese context the energy consumption to obtain groundwater increased by more than twenty percent in recent years whilst greenhouse gas emissions increased by more than forty percent. In turn, in Cyprus, livestock breeding has an impact of almost twenty percent on the global agricultural energy greenhouse gas emissions and the agricultural sector has an impact of almost one percent on the total energy emissions. To mitigate these frameworks better resource management and efficiency are, in fact, the keywords, as well as, the design of better adjusted policies. Nonetheless, in these frameworks there is

Table 3
Predictor importance for several variables from European Union agricultural regions, for the year 2017.

Variables	Predictor importance (%)
Total utilised agricultural area	57
Total inputs	11
Total output	11
Total livestock units	8

Table 4
Regression results between the energy costs growth and other variables from European Union agricultural regions, in panel data for the period 2012–2017.

Model	GLS
Constant	−0.010**
	(-1.730)
	[0.084]
Total output growth	0.423*
	(10.330)
	[0.000]
Total utilised agricultural area growth	0.375*
	(6.670)
	[0.000]
Independent variable (total utilised agricultural area growth) spatially lagged	−0.010
	(-0.050)
	[0.958]
Dependent variable spatially lagged	0.110
	(0.610)
	[0.544]
Error term spatially lagged	0.314**
	(1.790)
	[0.074]
Hausman test	1.740
	[0.884]
VIF	1.690

Note: *, statistically significant at 5%; **, statistically significant at 10%; The variables were spatially lagged with a contiguity matrix.

Table 5
Summary statistics for the energy costs growth (EN) and the energy costs growth predicted by the model (EN_predict) across the several European agricultural regions, over the period 2012–2017.

Variable	Observations	Mean	Standard deviation	Min	Max
EN	645	0.007985	0.145606	−0.47875	0.812027
EN_predict	645	0.007505	0.094309	−0.28371	0.715586

Table 6
Predictor importance for several variables (some divided by the utilised agricultural area) from European Union agricultural regions, for the year 2017.

Variables	Predictor importance (%)
Total utilised agricultural area	55
Total crops output/ha	27
Total inputs/ha	9
Total subsidies-excluding on investments/ha	2

both bad and good news. For example, some studies concerning "demand and supply of energy by farms" reveal that the demand for energy has increased over the last few years, which in conjunction with global warming and the volatility in traditional energy markets has promoted an increase in demand for alternative sources of energy, including producers of traditional fossil fuels. Agricultural planning, the fiscal structure and energy prices may be useful tools to reduce the demand for energy in some contexts. In any case, the farming sector consumes energy directly, but, also, indirectly (through fertilizers and crop protection products, for example) and it is here where agriculture may

Table 7
Regression results between the energy costs/ha growth and other variables from European Union agricultural regions, in panel data for the period 2012–2017.

Model	GLS
Constant	−0.008
	(-1.350)
	[0.178]
Total crops output/ha growth	0.243*
	(7.570)
	[0.000]
Total utilised agricultural area growth	−0.225*
	(-4.730)
	[0.000]
Independent variable (total utilised agricultural area growth) spatially lagged	0.249*
	(2.180)
	[0.029]
Dependent variable spatially lagged	0.013
	(0.070)
	[0.942]
Error term spatially lagged	0.456*
	(3.030)
	[0.002]
Hausman test	2.270
	[0.811]
VIF	1.000

Note: *, statistically significant at 5%; **, statistically significant at 10%; The variables were spatially lagged with a contiguity matrix.

contribute to a more environmentally compatible energy use. These insights may be interesting contribution, considering the European Union targets for renewable energy use in 2020.

The data analysis, for the year 2017, shows that the Czech Republic, Slovakia and the neighbouring regions of Germany are where the energy costs, on average (for representative farms), are higher in European Union agricultural regions. Nonetheless, when the energy costs are divided by the dimension, the higher costs/ha appear in Malta and The Netherlands. In turn, there are strong signs of spatial autocorrelation for energy costs in European farms, which may support the implementation of policy instruments in the framework of the Common Agricultural Policy to improve energy consumption in the European context. This may, in fact, be considered in the several instruments designed for the first and second CAP Pillars, namely inside the Greening and Young Farmers measures. There are, also, positive relationships among energy costs and variables related with farm size, level of output, level of inputs, subsidies (excluding investments), taxes and some area productivities, however there is weak, or an absence of correlation between energy costs and the subsidies on investments and competitiveness indicators (farm net value added/awu), for instance. This could be better addressed by the European institutions, namely in designing, also, CAP policy and tax instruments that promote further relationships between energy costs and competitiveness. This is due to the fact that in the current context energy costs are correlated with taxes and total subsidies (excluding investments), for example, but are weakly, or not at all, correlated with the subsidies on investments and competitiveness. In addition, the gains in the area productivities are only ever possible, in some cases, with increases in energy costs.

Finally, for the period 2012–2017, the output and area growth changed the energy costs growth by 0.423 and 0.375% points, respectively, and the total crops output/ha growth and the utilised agricultural area changed the energy costs/ha growth by 0.243 and −0.225% points, respectively. These values of less than 0.5 are good news for a more efficient energy use in European farms. In any case, as highlighted before, there are margins here to improve these relationships and to save energy costs in the farms, with better management, more efficiency, more farming multifunctionality, and more vocational training for farmers.

In summary, the following policy measures, under the CAP framework, are recommended:

Table 8
Summary statistics for the energy costs/ha growth (Enha) and the energy costs/ha growth predicted by the model (Enha_predict) across the several European agricultural regions, over the period 2012–2017.

Variable	Observations	Mean	Standard deviation	Min	Max
Enha	645	−0.01105	0.120852	−0.451	0.80734
Enha_predict	645	−0.01138	0.04084	−0.17727	0.255473

- Create new policy instruments in the first and second Pillars to promote more sustainability in the use of agricultural energy;
- Promote more vocational training for farmers in order to improve efficiency and management performance in farms;
- Support family farming and the sustainable systems with more and better adjusted funds that promote compliance by farmers;
- Create more adjusted instruments which reduce surplus productions;
- Promote circular economies in farms;
- Support more research in order to design optimization models enabling farms to reduce energy consumption;
- Create a more effective tax framework that encourages the use of renewable energy sources in the agricultural sector.

In future researches, it could be interesting to address other dimensions related with agricultural energy and renewable sources such as those related to stochastic management [126,127] or load management [128].

Credit author statement

I am the sole author.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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