Research Article

Vítor João Pereira Domingues Martinho*

Five models and ten predictors for energy costs on farms in the European Union

https://doi.org/10.1515/opag-2025-0441
received February 28, 2025; accepted April 10, 2025

Abstract: Energy costs are the main concerns of the agricultural stakeholders, because of their economic, environmental, and social impacts on the farms and the development of interrelated activities. In fact, it is important to save costs with the energy use to improve the profitability of the farms, but the level of these costs is often interlinked with the options to manage the energy consumption and the respective implications on sustainability. This framework highlights the importance of good management and planning for energy utilisation in the farming sector, namely to promote a balanced and integrated rural development. Considering these perspectives, this research intends to identify which factor, and how, impacted the energy costs in the European Union farms over the last decades. To achieve these objectives data from the Farm Accountancy Data Network database were considered for the European Union agricultural regions and the period 2013–2021. This statistical information was analysed through machine learning approaches following the procedures proposed by the software IBM SPSS Modeler. The linear support vector machine, regression, random forest, random trees, and the classification and regression tree are the most accurate models. On the contrary, the level of production, the size of farms, the economic and financial structure, and policy measures are the most important predictors. The findings here may be important insights for the European Union farming stakeholders, specifically to allow the design of policies for a more adjusted energy resources management.

Keywords: agricultural regions, artificial intelligence, digital transition, econometric methodologies

* **Corresponding author: Vítor João Pereira Domingues Martinho**, Agricultural School (ESAV) and CERNAS-IPV Research Centre, Polytechnic Institute of Viseu (IPV), Viseu, 3504-510, Portugal, e-mail: vdmartinho@esav.ipv.pt

1 Introduction

There is growing concern about social and territorial equilibrium, which calls for new approaches to managing territories and the various socio-economic activities that take place there [1]. Agriculture and the corresponding agricultural policies play an important role in territorial balance in rural areas [2]. It is therefore important to ensure the rational and appropriate use of resources by the agricultural sector in order to promote more sustainable rural development. Energy sources and the related farming costs are examples of how more rational management of these resources will lead to interesting gains in terms of sustainability.

The framework understanding of energy use in the farming sector is fundamental to supporting the farmers' decisions and the policy design for better agricultural management. The digital transition and the respective approaches brought innovations that may contribute significantly to more sustainable development in different fields [3], including the agrifood chains. This is mainly essential to assess and implement more eco-friendly practices and processes, such as those related to circular economy [4] and bioeconomy. This transition is also central to supporting the development of new biotechnology fields [5].

These new methodologies may have a relevant added value, for example, in the following contexts: tomato disease identification through the deep convolutional neural network [6] and tea leaf disease prediction at the early phase [7]; assessing the potential for bioenergy production [8] and agricultural biomass use in the energy supply [9]; unmanned aerial vehicles challenges management [10]; solar energy prediction through neural networks in precision agriculture [11]; internet of things application [12]; leaf area index evaluation in vineyards considering small unmanned aerial systems [13]; contributions for the food, energy, and water frameworks understanding [14]; energy management approaches for vehicles used in agriculture [15]; farming production efficiency [16]; and corn production prediction [17].

These innovative technologies, associated with the concept of smart farming [18], allow us to collect of data with alternative approaches (unmanned aerial vehicles, for example), transmitting (through the Internet of Things innovations) the information in real-time to be assessed and process these data with methodologies of artificial intelligence (with higher accuracy). The implementation of smart farming methods promotes improvements in the quality of agricultural products and consequently increases the profitability of the farmers [19].

The relevance of the digital transition for agricultural and forestry activities seems to have acceptance in the scientific community [20]. Nonetheless, there is still some work to do [21], particularly to improve the efficiency of the related methodologies and consequently to reduce the costs associated with their application. Energy efficiency, network period and model accuracy have been concerns for the researchers [22] who work with the new technologies and procedures.

Considering this scenario, this study aims to analyse factors that influence the energy costs in the European Union farming sector, considering microeconomic data for the period 2013–2021 obtained from the Farm Accountancy Data Network (FADN) [23] database for the agricultural regions. The statistical information is presented in this database for representative farms of each European Union agricultural region. These data were assessed through machine learning approaches following the IBM SPSS Modeler [24] procedures and taking into account the findings of Martinho [25,26]. For the literature review the most relevant documents were identified (for the topics "energy," "agricultur*," and "machine learning") through bibliometric analysis [27] and considering the VOSviewer [28–30] software procedures for bibliographic data and bibliographic coupling links. The selection of these topics, on 24 February 2024, for the bibliometric assessment was based on a compromise between obtaining a reasonable number of studies for the literature survey and their relation with the objectives of this research. Panel data regression techniques were also taken into account following Stata software [31–33] procedures, Torres-Reyna [34] suggestions, and developments of Hoechle [35]. To better understand the relationships between some variables a Spearman's rank correlation [36] matrix was obtained. The assessments carried out using these methodologies took into account potential problems related, among others, to multicollinearity, data partitioning, cross-validation, the most important metrics for evaluating the models used. These analyses were made following the procedures proposed by the software used (IBM SPSS Modeler and Stata).

The main contribution and innovation of this study lies in the consideration of machine learning approaches to identify the best-fitting models and the most important predictors of energy costs on farms in the agricultural regions of the European Union, using microeconomic information from the FADN. The perspective here is that more rational uses of energy resources in agriculture will ensure greater sustainability in the sector and promote better territorial balance. The scientific literature available on the topics addressed, namely agricultural energy, machine learning approaches, and FADN data is scarce and warrants new contributions.

2 Literature review

The several dimensions related to energy use in diverse socio-economic activities and processes, particularly in agriculture, have motivated different researchers over time. More recently, the relevance of artificial intelligence in these fields has been the focus of a significant number of studies. Some of these scientific contributions have given special attention, for example, to the following domains:

– Data analysis and the supply chain planning [37];
– Pest detection in precision agriculture [38];
– Crop production assessment [39];
– Internet of Things vulnerabilities [40];
– Cattle behaviour analysis [41];
– Privacy and trustworthiness on Internet of Things systems [42];
– Spray management in vineyards [43];
– Robustness of Internet of Things data transmission [44];
– Triboelectric nanogenerators and Internet of Things [45];
– Farm monitoring [46];
– Mapping the soil [47];
– Net radiation estimation [48];
– Greenhouse climate regulation [49];
– Crop landscape mapping [50];
– Solid fuels classification [51];
– Artificial neural networks applications in greenhouse [52];
– Photosynthetic capacities estimation [53];
– Solar energy use in greenhouses [54];
– Evapotranspiration analysis [55–57];
– Sorghum biomass prediction [58];
– Well-organised agrophotovoltaic structure [59];
– Weed control [60];
– Environmental implications of corn farms [61];
– Rubber tree evolution [62];
– Irrigated areas mapping [63];
– Deep learning constraints [64];

– Agricultural practices and food security [65];
– Wireless sensor network and precision agriculture [66];
– Drought forecast [67];
– Variety temperature forecast [68];
– Soil moisture prediction [69]; and
– Wireless sensor networks quality in terms of efficiency, privacy, and security [70].

These studies focused on the trustworthiness of the new approaches related to artificial intelligence, specifically on the collection and transmission of data through the Internet of Things technologies and wireless sensor networks. The prediction and mapping of the resources needed for agricultural production is another motivation for the researchers, as well as the farming yield forecast. The use of these new methodologies for a more adjusted management and planning of the activities inside the farms was also highlighted in the scientific literature.

The use of artificial intelligence opens, indeed, new opportunities for the different socio-economic sectors; nonetheless, some constraints may compromise, in some cases, the effective adoption of these innovations. Some of these limitations are related to the complexity of the methodologies, the needed resources, skills requirements, and some distrust of the society about these approaches (namely because of the use of non-humans in some jobs) [71].

In any case, the use of smart farming approaches may be a plausible solution to deal with the current challenges created for the agricultural sector by climate change and the increased need for food for the world population, which has been growing. In these frameworks, water use is a concern for the agricultural stakeholders, and here, smart irrigation answers may bring relevant added value [72] for more sustainable agricultural management. Wireless sensor network plays a relevant role in smart farming innovation [73]. Global warming also brings new worries with the air and soil temperature forecast [74,75]. Data analysis is another motivation for the scientific community where digital innovations may contribute significantly [76].

The agricultural sector has specificities, and some of them need complex approaches to be managed. In these contexts, the contributions of novel solutions may support the decisions of the stakeholders for better options related, for instance, with the insemination practices in dairy cattle [77], energy use on dairy farms [78], food supply chain analysis [79], and agricultural land management [80].

Disease and pest control, crop selection, and water use are among the most critical decisions for farmers, and this requires innovative approaches for more adjusted agricultural plan design [81]. The application of new technologies for more sustainable water use in agriculture has attracted the interest of researchers [82–84], as well as crop productivity [85] and fruit harvesting [86].

3 Data analysis

On average, the energy cost/total input cost ratio in the European Union with 27 countries, after Brexit in 2020 (EU27_2020), presents a decreasing tendency over the period considered (2013–2021) and represents around 8% (Figure 1). This trend may represent good news, signifying

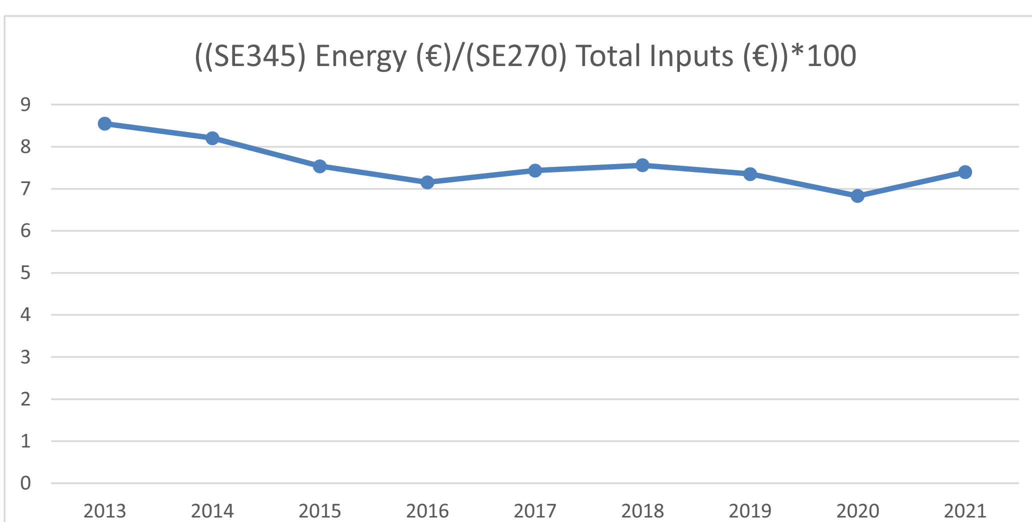

Figure 1: Weight of energy costs in total input costs for the EU27_2020 representative farms over the period 2013–2021.

Table 1: Energy costs on average for the European Union agricultural regions over the period 2013–2021

Member state, region	**Average energy costs (Euros)**
Austria, Austria	5,409
Belgium, Vlaanderen	18,712
Belgium, Wallonie	7,683
Bulgaria, Severen tsentralen	8,714
Bulgaria, Severoiztochen	9,108
Bulgaria, Severozapaden	8,764
Bulgaria, Yugoiztochen	7,036
Bulgaria, Yugozapaden	2,751
Bulgaria, Yuzhen tsentralen	3,389
Croatia, Jadranska Hrvatska	1,237
Croatia, Kontinentalna Hrvatska	1,886
Cyprus, Cyprus	3,768
Czechia, Czechia	32,225
Denmark, Denmark	18,271
Estonia, Estonia	13,274
Finland, Etelä-Suomi	13,937
Finland, Pohjanmaa	18,699
Finland, Pohjois-Suomi	14,293
Finland, Sisä-Suomi	12,465
France, Alsace	9,458
France, Aquitaine	10,128
France, Auvergne	9,153
France, Basse-Normandie	12,969
France, Bourgogne	10,760
France, Bretagne	18,092
France, Centre	13,478
France, Champagne-Ardenne	8,507
France, Corse	7,381
France, Franche-Comté	11,735
France, Guadeloupe	3,058
France, Haute-Normandie	14,122
France, La Réunion	3,979
France, Languedoc-Roussillon	5,854
France, Limousin	8,052
France, Lorraine	14,998
France, Martinique	4,286
France, Midi-Pyrénées	8,966
France, Nord-Pas-de-Calais	13,443
France, Pays de la Loire	14,831
France, Picardie	13,555
France, Poitou-Charentes	11,232
France, Provence-Alpes-Côte d'Azur	8,618
France, Rhône-Alpes	9,311
France, Île-de-France	14,568
Germany, Baden-Württemberg	13,173
Germany, Bayern	13,299
Germany, Brandenburg	74,026
Germany, Hamburg	18,661
Germany, Hessen	15,722
Germany, Mecklenburg-Vorpommern	75,419
Germany, Niedersachsen	20,321
Germany, Nordrhein-Westfalen	18,563
Germany, Rheinland-Pfalz	12,302
Germany, Saarland	15,523
Germany, Sachsen	63,137
Germany, Sachsen-Anhalt	66,397
Germany, Schleswig-Holstein	21,438
Germany, Schleswig-Holstein/Hamburg	25,275
Germany, Thüringen	86,127
Greece, Ipiros-Peloponissos-Nissi Ioniou	1,600
Greece, Makedonia-Thraki	2,918
Greece, Sterea Ellas-Nissi Egaeou-Kriti	1,964
Greece, Thessalia	2,850
Hungary, Alföld	6,940
Member state, region	**Energy costs average (Euros)**
Hungary, Dunántúl	10,362
Hungary, Észak-Magyarország	7,786
Ireland, Ireland	3,595
Italy, Abruzzo	3,637
Italy, Alto Adige	2,475
Italy, Basilicata	4,092
Italy, Calabria	2,277
Italy, Campania	4,082
Italy, Emilia-Romagna	6,506
Italy, Friuli-Venezia Giulia	5,356
Italy, Lazio	5,834
Italy, Liguria	3,706
Italy, Lombardia	10,893
Italy, Marche	4,346
Italy, Molise	4,203
Italy, Piemonte	5,984
Italy, Puglia	3,756
Italy, Sardegna	3,694
Italy, Sicilia	3,275
Italy, Toscana	5,280
Italy, Trentino	2,555
Italy, Umbria	4,431
Italy, Valle d'Aosta	3,315
Italy, Veneto	6,377
Latvia, Latvia	7,987
Lithuania, Lithuania	3,846
Luxembourg, Luxembourg	12,230
Malta, Malta	3,843
Netherlands, The Netherlands	30,447
Poland, Malopolska i Pogórze	1,795
Poland, Mazowsze i Podlasie	2,133
Poland, Pomorze i Mazury	4,740
Poland, Wielkopolska and Slask	4,180
Portugal, Alentejo e Algarve	3,049
Portugal, Açores e Madeira	1,619

(*Continued*)

Table 1: *Continued*

Member state, region	Energy costs average (Euros)
Portugal, Norte e Centro	1,816
Portugal, Ribatejo e Oeste	3,898
Romania, Bucuresti-Ilfov	2,292
Romania, Centru	1,260
Romania, Nord-Est	1,013
Romania, Nord-Vest	1,187
Romania, Sud-Est	2,297
Romania, Sud-Muntenia	2,051
Romania, Sud-Vest-Oltenia	1,235
Romania, Vest	2,099
Slovakia, Slovakia	57,888
Slovenia, Slovenia	2,686
Spain, Andalucía	3,690
Spain, Aragón	6,530
Spain, Asturias	2,865
Spain, Canarias	4,676
Spain, Cantabria	3,378
Spain, Castilla y León	5,226
Spain, Castilla-La Mancha	5,191
Spain, Cataluña	6,021
Spain, Comunidad Valenciana	1,618
Spain, Extremadura	4,608
Spain, Galicia	3,217
Spain, Islas Baleares	5,313
Spain, La Rioja	3,989
Spain, Madrid	6,036
Spain, Murcia	4,823
Spain, Navarra	5,519
Spain, País Vasco	4,532
Sweden, Län i norra Sverige	16,792
Sweden, Skogs-och mellanbygdslän	15,174
Sweden, Slättbyggdslän	19,663

Note: The red cells represent the ten higher values, and the green ones are relative to the ten agricultural regions with the lower average energy costs.

a propensity for a more sustainable development; nonetheless, there are here several factors that may impact this evolution and need to be properly and deeper analysed in this research and future studies.

Table 1 shows the results for the average energy costs in the European Union agricultural regions over the period 2013–2021. It should be noted that in these values, not all years have statistical information for the agricultural regions of Hamburg and Martinique.

Czechia, a relevant number of German agricultural regions, The Netherlands, and Slovakia agricultural regions have higher energy costs per representative farm, in some cases because of the dimension of the farms, in other cases due to the requirements of energy of the agricultural systems adopted and in other circumstances because of the economic conjuncture.

Some regions of Croatia, Greece, Poland, Portugal, Romania, and Spain have lower energy costs per farm. These findings need, however, to be further analysed to try to understand if these costs are a consequence of the prices, for example, or derived from the level of consumption related to the dynamics of the farm (or lower efficiency in the energy use). In particular, it is important to understand the importance of factors such as the type of crop and the size of the farm.

4 Machine learning approaches to identify important predictors of energy costs and accurate models

Linear support vector machine (LSVM), regression, random forest, random trees, and classification and regression (C&R) tree approaches are the most accurate models, considering the relative error (lower results) for the testing set (Table 2). The relative error is the way considered by the software used (IBM SPSS Modeler) to analyse the accuracy of the models tested. In any case, this way of analysing accuracy is considered the most relevant [87]. The higher accuracy of these models to predict the energy costs in the European Union farming regions is confirmed by Figure 2 for the relationships among the observed values and the predicted ones. The statistical information considered was obtained from the European Union FADN, and the results of the models were found using IBM SPSS Modeler procedures. LSVM is specifically relevant for datasets with a large number of variables. The regressions are common linear regressions, and the random forest is a tree model implemented in Python. Random trees are models characterised by multiple decision trees, and C&R tree is a classification and predictive method [24].

Table 2: Accurate models to predict the energy costs in the European Union agricultural regions over the period 2013–2021

Model	Build time	Correlation	Number fields used	Relative error
LSVM	4	1.000	168	0.000
Regression	4	0.999	135	0.003
Random forest	4	0.991	168	0.018
Random trees	4	0.986	168	0.028
C&R tree	4	0.982	52	0.039

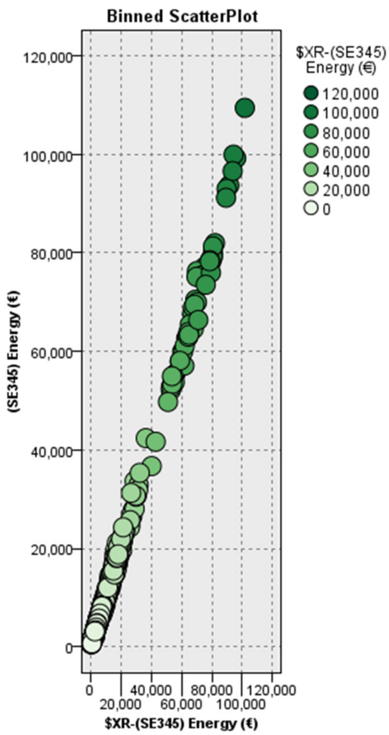

Figure 2: Relationships between the observed energy costs and the predicted ones in the European Union agricultural regions over the period 2013–2021.

The most important predictors identified are, for example, the following (Table 3): cereals output, long and medium-term loans, total liabilities, cows' milk production, total utilised agricultural area, total assets, and decoupled subsidies.

These results reveal the importance of some productions for the level of energy costs in the European Union representative farms, as well as the dimension of these farms and their economic and financial structures.

Table 3: Important predictors of energy costs in the European Union regions over the period 2013–2021

Nodes	Importance
(SE155) Sugar beet (€/farm)	0.025
(SE160) Oil-seed crops (€/farm)	0.025
(SE630) Decoupled payments (€)	0.034
(SE436) Total assets (€)	0.038
(SE025) Total Utilised Agricultural Area (ha)	0.040
(SE216) Cows' milk and milk products (€/farm)	0.048
(SE485) Total liabilities (€)	0.057
(SE256) Other output (€/farm)	0.059
(SE490) Long and medium-term loans (€)	0.068
(SE140) Cereals (€/farm)	0.069

Another interesting finding is the relevance of the Common Agricultural Policy (CAP) instruments to explain and predict energy costs. This means that the CAP measures may be considered to mitigate some of these costs.

In the following subsections, the findings for each one of the five models with higher accuracy will be presented, considering the most important predictors identified.

4.1 Linear support vector machine results

Table 4 summarises the linear support vector machine model information, considering the energy costs as the target field and ten predictors input. Table 5 shows the importance of the total utilised agricultural area to predict the energy costs in the European Union agricultural regions (in the period 2013–2021), as well as the level of output of some specific productions. This is confirmed in Figure 3 for the relative importance of the predictors. The summary records of the model are highlighted in Table 6.

Table 4: LSVM model information to predict energy costs in the European Union agricultural regions, over the period 2013–2021

Model information	
Target field	(SE345) Energy (€)
Model building method	Linear SVM
Number of predictors input	10
Number of predictors in final model	8
Regularisation type	L2
Penalty parameter (Lambda)	0.1
Regression precision (Epsilon)	0.1

Table 5: LSVM parameter estimates to predict energy costs in the European Union agricultural regions, over the period 2013–2021

Parameter	Estimates
Intercept	1072.519
(SE025) Total Utilised Agricultural Area (ha)	40.442
(SE140) Cereals (€/farm)	0.038
(SE155) Sugar beet (€/farm)	−0.018
(SE160) Oil-seed crops (€/farm)	0.044
(SE216) Cows' milk and milk products (€/farm)	0.053
(SE256) Other output (€/farm)	0.187
(SE436) Total assets (€)	0.003
(SE485) Total liabilities (€)	0.001
(SE490) Long and medium-term loans (€)	−0.005
(SE630) Decoupled payments (€)	0.015

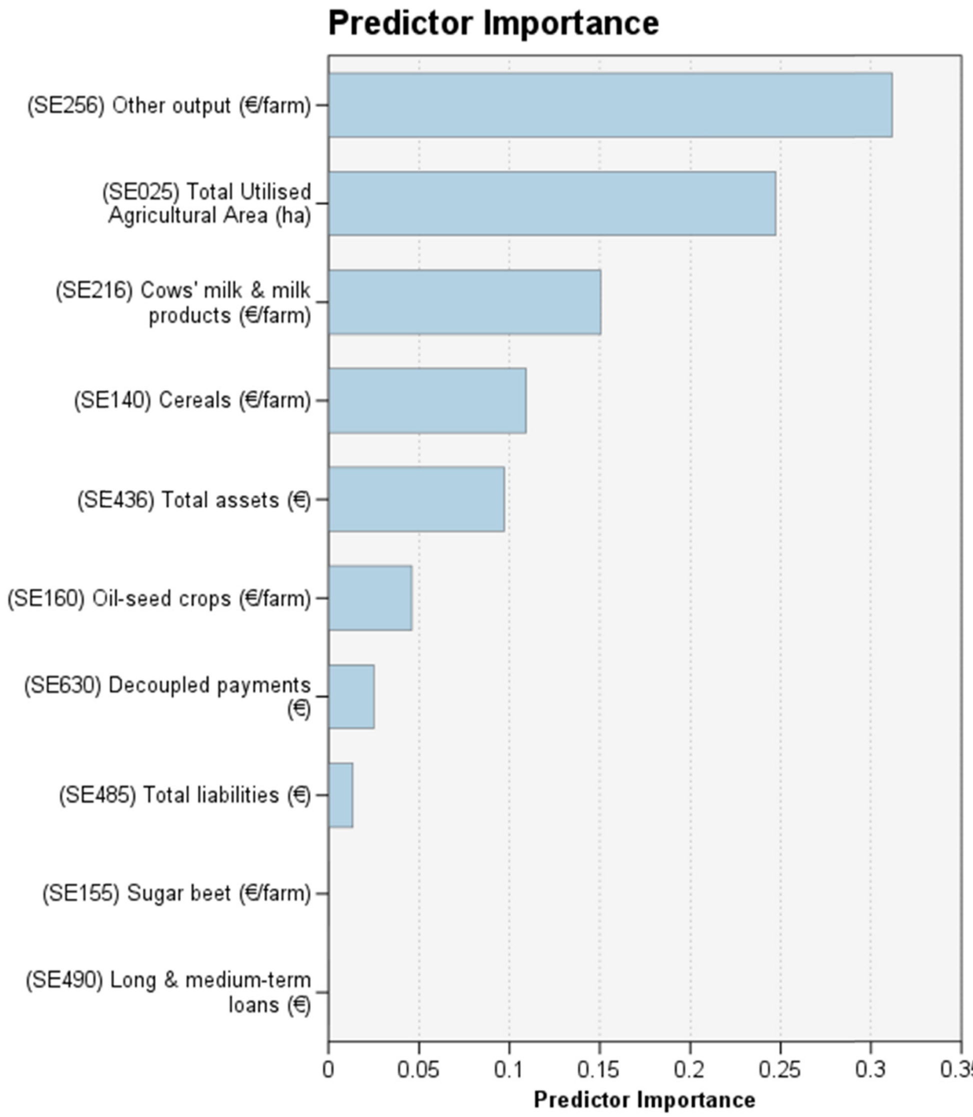

Figure 3: Predictor importance of the energy costs in the European Union agricultural regions, over the period 2013–2021, considering LSVM model.

Table 6: LSVM records summary to predict energy costs in the European Union agricultural regions over the period 2013–2021

Records	Number	Percentage
Included	579	99.66
Excluded	2	0.34
Total	581	100

4.2 Regression model findings

The results for the regression model confirm the importance of some farming productions and the dimension of the farms to predict the energy costs (Tables 7 and 8). Another relevant

Table 7: Predictor importance of the energy costs in the European Union agricultural regions, over the period 2013–2021, considering a regression model

Nodes	Importance
(SE155) Sugar beet (€/farm)	0.000
(SE490) Long and medium-term loans (€)	0.000
(SE140) Cereals (€/farm)	0.019
(SE485) Total liabilities (€)	0.049
(SE160) Oil-seed crops (€/farm)	0.077
(SE436) Total assets (€)	0.121
(SE216) Cows' milk and milk products (€/farm)	0.128
(SE630) Decoupled payments (€)	0.166
(SE025) Total utilised agricultural area (ha)	0.207
(SE256) Other output (€/farm)	0.233

Table 8: Regression coefficients to predict energy costs in the European Union agricultural regions over the period 2013–2021

	Unstandardised coefficients	Standard error	Standardised coefficients	*t*	Significance
(Constant)	390.694	181.179		2.156	0.031
(SE025) Total utilised agricultural area (ha)	35.802	5.490	0.220	6.521	<0.001
(SE140) Cereals (€/farm)	0.007	0.010	0.022	0.723	0.470
(SE155) Sugar beet (€/farm)	−0.028	0.030	−0.010	−0.958	0.338
(SE160) Oil-seed crops (€/farm)	0.084	0.017	0.104	4.838	<0.001
(SE216) Cows' milk and milk products (€/farm)	0.062	0.004	0.177	13.862	<0.001
(SE256) Other output (€/farm)	0.149	0.008	0.291	18.702	<0.001
(SE436) Total assets (€)	0.005	0.001	0.167	8.671	<0.001
(SE485) Total liabilities (€)	0.004	0.005	0.069	0.915	0.360
(SE490) Long and medium-term loans (€)	−0.014	0.005	−0.192	−2.824	0.005
(SE630) Decoupled payments (€)	0.115	0.028	0.181	4.118	<0.001

finding is the relative importance of the decoupled payments to predict the energy costs in the European Union farms. This means that the CAP instruments may be taken into account to improve the efficiency in energy use and in this way mitigate the respective costs that represent about 8%, on average (for the representative farms and over the period here considered) in the total input costs.

4.3 Random forest results

Figure 4 also highlights the relative importance of the following predictors: decoupled payments, total utilised agricultural area, long and medium-term loans, total assets, and cereals output. Nonetheless, considering the results from the regression model, the long and medium-term

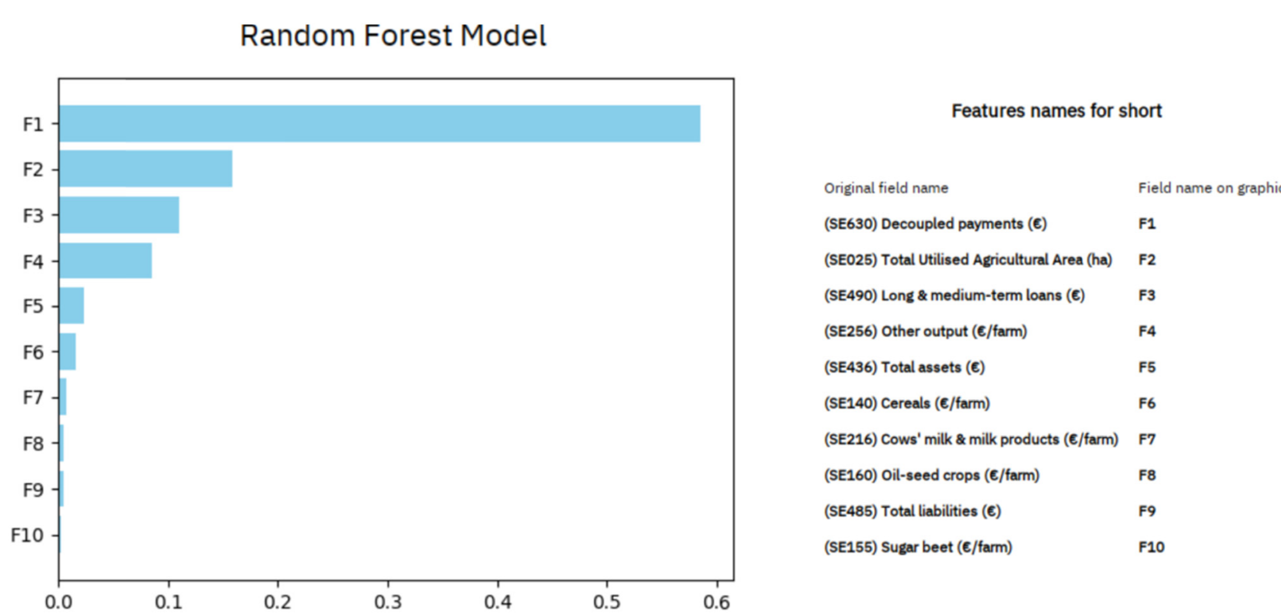

Figure 4: Predictor importance of the energy costs in the European Union agricultural regions, over the period 2013–2021, considering a random forest model.

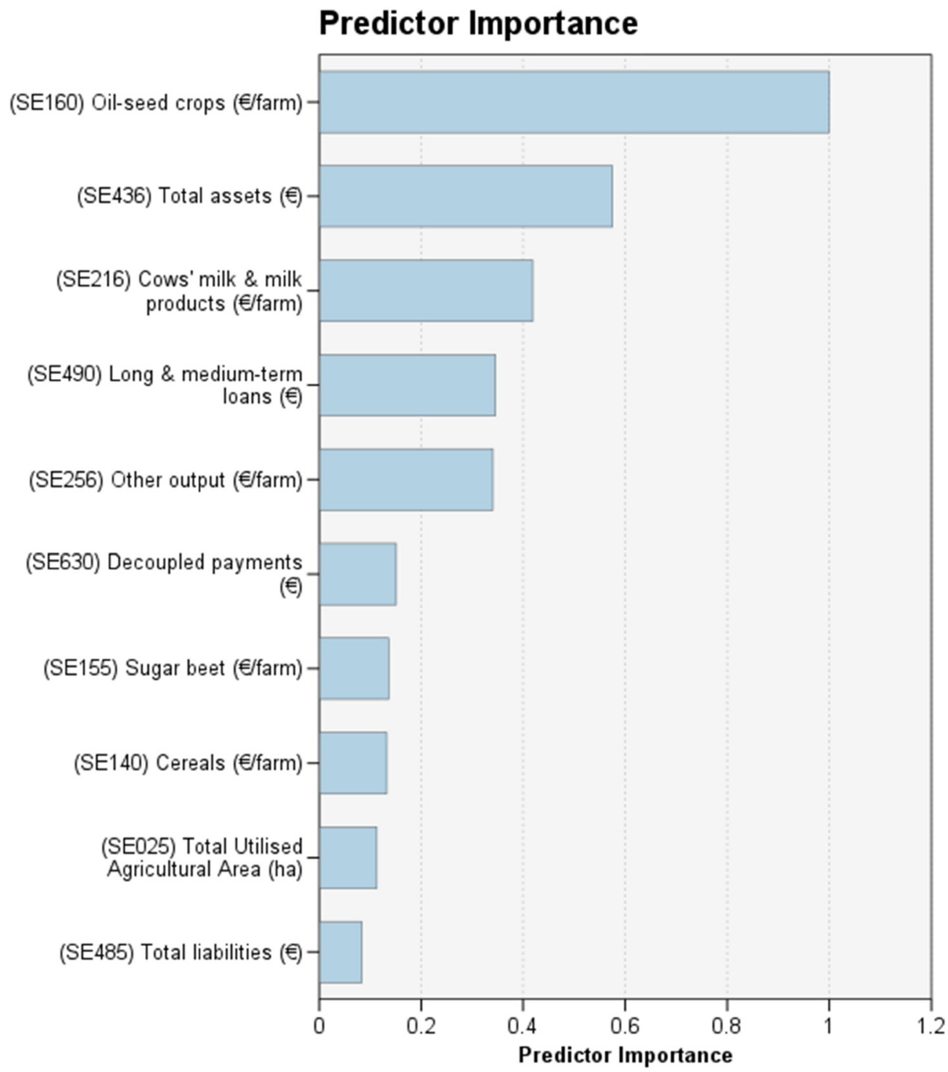

Figure 5: Predictor importance of the energy costs in the European Union agricultural regions, over the period 2013–2021, considering a random trees model.

loans predict the energy costs in the farming context of the agricultural regions in the European Union member-states with a negative relationship.

4.4 Random tree findings

For this model, the results reveal that the most important predictors are in decreasing order as follows (Figure 5): oil-seed crops output, total assets, cows' milk output, long and medium-term loans, decoupled payments, sugar beet output, and cereals output. The total utilised agricultural area appears for this approach with a lower relative importance. In this model, the levels of output of some productions and the economic and financial structures have higher importance.

4.5 C&R tree results

Considering the results presented in Figure 6, node 1 contains the observations when a representative farm of the European Union agricultural region has an oil-seed crop output lower, or equal, to 40,749 euros. A random European Union agricultural region has a 97% probability of belonging to this node with a predicted value for energy costs of 7809 euros. Terminal node 6 reveals that farms with higher oil-seed crop output have greater energy costs, and terminal

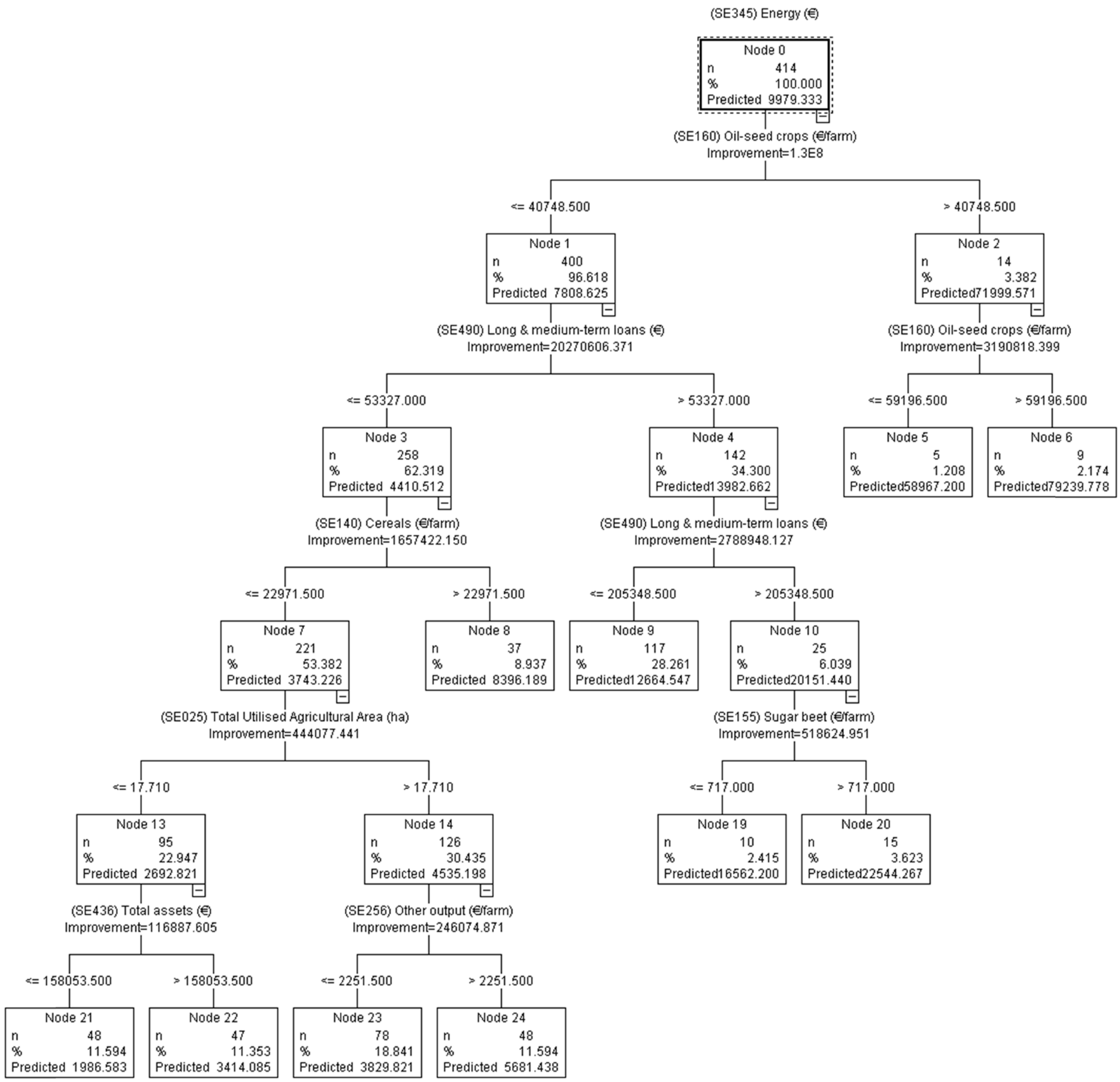

Figure 6: C&R tree results to predict the energy costs in the European Union agricultural regions, over the period 2013–2021.

node 21 presents that farms with lower oil-seed crop output, lower long and medium-term loans, lower hectares, and lower total assets have inferior energy costs.

5 Regression results with panel data

To bring more insights into the energy cost explanation in the representative farms of the European Union agricultural regions, it seems interesting to simulate, through panel data approaches, the relationships between the energy costs in these farms and the variables identified in the previous sections to predict these costs. The independent variables were selected, taking into account the findings obtained before with machine learning methodologies and the variance inflation factor (VIF) test for multicollinearity.

In general, Table 9 shows that the energy costs in the European Union farming regions have strong (and statistically significant) correlations with the dimension of the farms, the level of output of some agricultural activities, the financial structure, and the amount of decoupled

Table 9: Spearman's rank correlation matrix between energy costs and important predictors in the European Union agricultural regions over the period 2013–2021

	(SE345) Energy (€)	(SE025) Total utilised agricultural area (ha)	(SE140) Cereals (€/farm)	(SE155) Sugar beet (€/farm)	(SE160) Oil-seed crops (€/farm)	(SE216) Cows' milk and milk products (€/farm)	(SE256) Other output (€/farm)	(SE436) Total assets (€)	(SE485) Total liabilities (€)	(SE490) Long and medium-term loans (€)	(SE630) Decoupled payments (€)
(SE345) Energy (€)	1.000										
(SE025) Total utilised agricultural area (ha)	0.817	1.000									
	(0.000)										
(SE140) Cereals (€/farm)	0.792	0.844	1.000								
	(0.000)	(0.000)									
(SE155) Sugar beet (€/farm)	0.475	0.403	0.593	1.000							
	(0.000)	(0.000)	(0.000)								
(SE160) Oil-seed crops (€/farm)	0.623	0.721	0.897	0.556	1.000						
	(0.000)	(0.000)	(0.000)	(0.000)							
(SE216) Cows' milk and milk products (€/farm)	0.738	0.640	0.623	0.469	0.469	1.000					
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)						
(SE256) Other output (€/farm)	0.844	0.632	0.624	0.471	0.500	0.677	1.000				
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)					
(SE436) Total assets (€)	0.799	0.621	0.593	0.493	0.406	0.751	0.791	1.000			
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)				
(SE485) Total liabilities (€)	0.860	0.790	0.700	0.485	0.599	0.730	0.817	0.750	1.000		
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)			
(SE490) Long and medium-term loans (€)	0.854	0.766	0.683	0.490	0.567	0.766	0.822	0.785	0.985	1.000	
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		
(SE630) Decoupled payments (€)	0.868	0.934	0.880	0.517	0.739	0.725	0.715	0.736	0.798	0.791	1.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	

Table 10: Panel data regression results, through a linearised model with logarithms, for the European Union agricultural regions over the period 2013–2021

Prais–Winsten regression, heteroskedastic panels corrected standard errors, ln((SE345) Energy (€))	**Coefficient**	**Standard error**	***z***	***P* > |*z*|**
ln((SE025) Total utilised agricultural area (ha))	0.423	0.025	17.140	0.000
ln((SE155) Sugar beet (€/farm))	−0.008	0.006	−1.290	0.196
ln((SE160) Oil-seed crops (€/farm))	0.040	0.013	3.030	0.002
ln((SE216) Cows' milk and milk products (€/farm))	0.111	0.013	8.530	0.000
ln((SE436) Total assets (€))	0.500	0.021	24.180	0.000
_cons	−0.458	0.204	−2.240	0.025
VIF	3.570			
Hausman test	6.050 (0.417)			
Modified Wald test for groupwise heteroskedasticity	1.6×10^{29} (0.000)			
Wooldridge test for autocorrelation	58.856 (0.000)			

subsidies. When the total utilised agricultural area, oil-seed crops output, cows' milk output, and total assets, in these farms, increase by 1%, the energy costs increase, respectively 0.42, 0.04, 0.11, and 0.50% (Table 10). To deal with statistical problems related to heteroscedasticity and autocorrelation, Prais–Winsten regressions were considered.

To analyse the potential effects of inflation over the period considered and the differences in the prices between the European Union countries, the values in euros were deflated through the harmonised indices of consumer prices (HICP, all-items, 2015 = 100) and adjusted with the price level indices (PLI, gross domestic product, EU27_2020 = 100). These indices were obtained from the Eurostat [88]. Generally, the results for Spearman's rank correlation coefficients (Table 11) and the panel data regressions (Table 12) are not so different from those presented in Tables 9 and 10, showing a non-relevant impact in these relationships from the prices.

Tables 13 and 14 present the results for the values in euros corrected with the HICP and PLI and considering the ratio (SE345) Energy (€)/(SE025) total utilised agricultural area (ha) instead of the variable (SE345) energy (€). The intention is to assess the energy costs corrected by the dimensions of the representative farms. In this case, Spearman's rank correlation coefficients among the ratio and the other variables are all negative (Table 13), and the strongest correlations were found for the total utilised agricultural area (−0.607) and the decoupled payments (−0.419). When the total utilised agricultural area increases by 1%, the energy costs by hectare decrease by 0.62% (Table 14). The impacts from the other independent variables are similar to those verified before.

6 Discussion

The energy costs represent a relevant part of the total inputs in the European Union farms, and in this perspective, it is important to bring more knowledge for a better understanding of these frameworks, namely to highlight the main predictors and variables that may explain the level of these costs. Another dimension is related to the identification of accurate models and algorithms to assess the associated contexts. In these conditions, this study aims to bring more insights into the explanation and prediction of the energy costs in the European Union agriculture, taking into account statistical information from the FADN and Eurostat databases, as well as machine learning approaches and panel data methodologies. The period of 2013–2021 was the period considered for the assessment here presented. The intention was to consider a period after the last enlargement of the European Union.

The literature review highlighted the relevant contribution of the digital transition for a better understanding of several socio-economic dimensions, particularly for a better analysis of the energy use in the farming sector [54]. An efficient use of energy resources is crucial for more sustainable development in the farming sector. The new technologies associated with era 4.0 have contributed to the different fields of energy use in the farms, since a more accurate prediction of the crop's diseases until a more adjusted management of the related supply chains. This may contribute to improving the profitability of the farmers and increase the quality if the agrifood supply chains. Nonetheless, the use of smart farming approaches has not only advantages; there are also some concerns of the stakeholders with the use of these new techniques, and some of them are linked with the

Table 11: Spearman's rank correlation matrix between energy costs and important predictors in the European Union agricultural regions, over the period 2013–2021, with the variables in euros deflated with the HICP and corrected with the PLI

	(SE345) Energy (€)	(SE025) Total utilised agricultural area (ha)	(SE140) Cereals (€/farm)	(SE155) Sugar beet (€/farm)	(SE160) Oil-seed crops (€/farm)	(SE216) Cows' milk and milk products (€/farm)	(SE256) Other output (€/farm)	(SE436) Total assets (€)	(SE485) Total liabilities (€)	(SE490) Long and medium-term loans (€)	(SE630) Decoupled payments (€)
(SE345) Energy (€)	1.000										
(SE025) Total utilised agricultural area (ha)	0.814	1.000									
	(0.000)										
(SE140) Cereals (€/farm)	0.792	0.795	1.000								
	(0.000)	(0.000)									
(SE155) Sugar beet (€/farm)	0.462	0.395	0.577	1.000							
	(0.000)	(0.000)	(0.000)								
(SE160) Oil-seed crops (€/farm)	0.675	0.670	0.913	0.537	1.000						
	(0.000)	(0.000)	(0.000)	(0.000)							
(SE216) Cows' milk and milk products (€/farm)	0.689	0.633	0.569	0.472	0.456	1.000					
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)						
(SE256) Other output (€/farm)	0.767	0.631	0.554	0.463	0.467	0.637	1.000				
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)					
(SE436) Total assets (€)	0.707	0.629	0.554	0.513	0.429	0.703	0.736	1.000			
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)				
(SE485) Total liabilities (€)	0.829	0.800	0.662	0.488	0.584	0.715	0.797	0.714	1.000		
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)			
(SE490) Long- and medium-term loans (€)	0.818	0.780	0.642	0.498	0.553	0.753	0.806	0.752	0.985	1.000	
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		
(SE630) Decoupled payments (€)	0.847	0.921	0.883	0.502	0.784	0.667	0.630	0.655	0.767	0.752	1.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	

Table 12: Panel data regression results, through a linearised model with logarithms, for the European Union agricultural regions, over the period 2013–2021, with the variables in euros deflated with the HICP and corrected with the PLI

Prais–Winsten regression, heteroskedastic panels corrected standard errors, ln ((SE345) energy (€))	Coefficient	Standard error	Z	P > |z|
ln((SE025) Total utilised agricultural area (ha))	0.347	0.023	15.030	0.000
ln((SE155) Sugar beet (€/farm))	−0.004	0.006	−0.720	0.470
ln((SE160) Oil-seed crops (€/farm))	0.062	0.013	4.980	0.000
ln((SE216) Cows' milk and milk products (€/farm))	0.106	0.011	9.670	0.000
ln((SE436) Total assets (€))	0.466	0.023	20.030	0.000
_cons	−3.260	0.106	−30.720	0.000
VIF	2.980			
Hausman test	3.690 (0.718)			
Modified Wald test for groupwise heteroskedasticity	5.7×10^{30} (0.000)			
Wooldridge test for autocorrelation	83.887 (0.000)			

Internet of Things vulnerabilities, for example. The privacy and trustworthiness of the systems, particularly in the transmission of data, have concerned the scientific community. In addition, the competition of these approaches with the humans in some jobs, the skills and resources needed and the complex structure of these systems are other focus of discussion for the researchers [71].

The data analysis shows that for the period considered, the energy costs represented around 8% of the total input costs in the European Union farms. On the contrary, the farms from Czechia, Slovakia, The Netherlands, and some German agricultural regions have higher energy costs, because of the dimension of these agricultural units, the farming systems implemented, and the specificities of the economic/financial context of the countries. Inversely, agricultural regions from Croatia, Greece, Poland, Portugal, and Romania have inferior energy costs in their respective farms.

The assessment of the data through machine learning approaches highlighted the accuracy of the LSVM, regression, random forest, random trees, and C&R tree models to predict the energy costs in the farms of the European Union agricultural regions. The important predictors identified are related to the level of output of some productions (cereals, for example), the dimension of the farms (total utilised agricultural area), economic and financial structure (total assets and liabilities), and policy measures (this means that the CAP instruments may be eventually adjusted to mitigate energy costs).

The regressions carried out with panel data methodologies confirmed the importance of the total utilised agricultural farms of the farms to explain the energy costs, as well as the level of output of some farming productions and the level of total assets, including when the variables in euros were corrected for the inflation and the differences in the level of prices between the diverse European Union member-states. When the energy costs are adjusted by the dimension of the farms (energy costs/hectare), the strongest and negative Spearman's rank correlation coefficients appeared for the number of hectares and the decoupled payments. Again, the CAP instruments appear here as a tool that may be reanalysed to better deal with the energy costs in the European Union agricultural regions.

7 Conclusions

In terms of practical implications, for a more efficient use of energy resources and to mitigate energy costs, the farms of some European Union agricultural regions, particularly the bigger and more dynamic ones, need to identify innovative approaches to make compatible these dimensions with a more sustainable development. Without a harmonious development of the agricultural sector, the consequence will be the abandonment of the activity with the risk of desertification of the most disadvantaged rural areas. Another implication will be the appearance of new focuses on territorial asymmetries due to inappropriate land management and incorrect definitions of policy instruments. For policy recommendations, it is suggested to adjust the CAP instruments (namely the decoupled payments) to promote the strongest sustainability in the European Union farms. For future research, it could be interesting to analyse further the impacts of the CAP measures on the energy costs of the farms, to better rethink them. It would be important, also, to make more inferences with the results, namely validate them with the context of each country.

Table 13: Spearman's rank correlation matrix between energy costs/total utilised agricultural area and important predictors in the European Union agricultural regions, over the period 2013–2021, with the variables in euros deflated with the HICP and corrected with the PLI

	(SE345) Energy (€)/(SE025) Total utilised agricultural area (ha)	**(SE025) Total utilised agricultural area (ha)**	**(SE140) Cereals (€/farm)**	**(SE155) Sugar beet (€/farm)**	**(SE160) Oil-seed crops (€/farm)**	**(SE216) Cows' milk and milk products (€/farm)**	**(SE256) Other output (€/farm)**	**(SE436) Total assets (€)**	**(SE485) Total liabil-ities (€)**	**(SE490) Long and medium-term loans (€)**	**(SE630) Decoupled payments (€)**
(SE345) Energy (€)/(SE025) total utilised agricultural area (ha)	1.000										
(SE025) Total utilised agricultural area (ha)	−0.607	1.000									
	(0.000)										
(SE140) Cereals (€/farm)	−0.261	0.795	1.000								
	(0.000)	(0.000)									
(SE155) Sugar beet (€/farm)	−0.026	0.395	0.577	1.000							
	(0.370)	(0.000)	(0.000)								
(SE160) Oil-seed crops (€/farm)	−0.182	0.670	0.913	0.537	1.000						
	(0.000)	(0.000)	(0.000)	(0.000)							
(SE216) Cows' milk and milk products (€/farm)	−0.142	0.633	0.569	0.472	0.456	1.000					
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)						
(SE256) Other output (€/farm)	−0.044	0.631	0.554	0.463	0.467	0.637	1.000				
	(0.135)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)					
(SE436) Total assets (€)	−0.134	0.629	0.554	0.513	0.429	0.703	0.736	1.000			
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)				
(SE485) Total liabilities (€)	−0.270	0.800	0.662	0.488	0.584	0.715	0.797	0.714	1.000		
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)			
(SE490) Long- and medium-term loans (€)	−0.259	0.780	0.642	0.498	0.553	0.753	0.806	0.752	0.985	1.000	
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		
(SE630) Decoupled payments (€)	−0.419	0.921	0.883	0.502	0.784	0.667	0.630	0.655	0.767	0.752	1.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	

Table 14: Panel data regression results, through a linearised model with logarithms, for the European Union agricultural regions, over the period 2013–2021, with the variables in euros deflated with the HICP and corrected with the PLI

Prais–Winsten regression, heteroskedastic panels corrected standard errors, ln ((SE345) Energy (€)/(SE025) Total Utilised Agricultural Area (ha))	Coefficient	Standard error	z	$P > \|z\|$
ln((SE025) Total utilised agricultural area (ha))	−0.618	0.029	−21.220	0.000
ln((SE155) Sugar beet (€/farm))	0.006	0.011	0.510	0.612
ln((SE160) Oil-seed crops (€/farm))	0.061	0.020	3.110	0.002
ln((SE216) Cows' milk and milk products (€/farm))	0.070	0.011	6.390	0.000
ln((SE436) Total assets (€))	0.444	0.026	17.020	0.000
_cons	−3.256	0.169	−19.310	0.000
VIF	2.980			
Hausman test	3.690 (0.718)			
Modified Wald test for groupwise heteroskedasticity	3.8×10^{30} (0.000)			
Wooldridge test for autocorrelation	83.887 (0.000)			

Acknowledgments: Furthermore, we would like to thank the CERNAS Research Centre and the Polytechnic Institute of Viseu for their support.

Funding information: This work was funded by National Funds through the FCT – Foundation for Science and Technology, I.P., within the scope of the project Refª UIDB/00681 (https://doi.org/10.54499/UIDP/00681/2020). This work was developed under the Science4Policy 2023 (S4P-23): annual science for policy project call, an initiative by PlanAPP - Competence Centre for Planning, Policy and Foresight in Public Administration in partnership with the Foundation for Science and Technology, financed by Portugal's Recovery and Resilience Plan.

Author contribution: The author confirms the sole responsibility for the conception of the study, presented results and manuscript preparation.

Conflict of interest: Vítor João Pereira Domingues Martinho, who is the author of this article, is a current Editorial Board member of Open Agriculture. The author states no conflict of interest.

Data availability statement: The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.

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