ENERGY CROPS: ASSESSMENTS IN THE EUROPEAN UNION AGRICULTURAL REGIONS THROUGH MACHINE LEARNING APPROACHES

Vítor João Pereira Domingues MARTINHO
Coordinator Professor with Habilitation, Agricultural School (ESAV) and CERNAS-IPV Research Centre, Polytechnic Institute of Viseu (IPV), Portugal
vdmartinho@esav.ipv.pt

Abstract

There is an enormous potential to produce bioenergy from agriculture, forestry and other land use in the European Union (EU) farms. The agricultural sector in the EU member-states has conditions to increase the contributions of renewable energies through better use of the residues and the production of energy crops. Nonetheless, the profitability of these alternative agricultural outputs, in some circumstances, and the need for land for food production, for example, have been obstacles to effective positioning of the EU farms as sources of bioenergy. From this perspective, this study intends to assess the current context of the energy crops in the farms of the EU agricultural regions and identify a model that supports the prediction of these frameworks. For that, data from the Farm Accountancy Data Network (FADN) were considered for the year 2020. This statistical information was analysed through machine learning approaches, namely those associated with multilayer perceptron (MLP) algorithms from the artificial neural networks (ANN) methodologies. The results from these data show that energy crops do have not relevant importance in the European Union farms. On the other hand, when these crops appear, they are produced by larger farms, with greater competitiveness and which receive more subsidies.

Keywords: Agriculture 4.0, Artificial Neural Networks, Multilayer Perceptron
JEL classification: C45, Q12, Q42

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1. Introduction

The artificial neural networks approaches and more specifically the multilayer perceptron algorithms have been considered by the researchers for studies focused on the different domains of knowledge and using diverse developments from the theory. In fact, these methodologies have been taken into account, for example, in assessments since the credit risk (Assef et al. 2019), until the agricultural sector (Bakhshi, Pourtaheri, and Eftekhari 2016), passing by the energy dimensions (Sajid, Khan, and Santibanez Gonzalez 2022), ozone concentration prediction (Bekesiene, Meidute-Kavaliauskiene, and Vasiliauskiene 2021), natural hazards forecast (Costache et al. 2022) and health fields (Bourbonne et al. 2021), including clinical diagnoses (Cleophas and Cleophas 2010), treatments (Dias et al. 2005) and medical practices (Goyal et al. 2021).

The artificial neural networks algorithms are considered, by the literature, adjusted methodologies (Navas, Prakash, and Sasipraba 2020) with good accuracies (Ismaila, Odedoyin, and Ajisegiri 2016), showing the relevance of the associated models (Zhang and Tang 2020) for prediction assessments (Kargi 2014), that present in some cases better results compared with other approaches (Mirzakhani et al. 2022). The ANN has several advantages, such as the capacity to deal with the absence of preliminary information and assumptions about the relationships between the dependent variable and the predictors (Nagesha, Kumar, and Singh 2019). In addition, the ANN techniques are flexible and simple, making these models preferred by researchers for specific cases (Vanus, Gorjani, and Bilik 2019).

Specifically, about the energy scenarios in the EU agricultural regions, several dimensions can be deeper explored, even more in the current contexts where the rise of the energy prices contributed to promote inflation worldwide. It is important to improve the efficiency of the energy use in the farms, to support the reduction of the dependency of the countries from external sources and reduce the costs, but it is also fundamental to increase the contribution of the farming sector as a source of renewable energy. This is important for the EU strategy of decarbonisation, as well as to promote the multifunctionality of agriculture and diversify the income of the farmers. The EU agricultural policy instruments in the framework of the CAP (Common Agricultural Policy) play here a determinant role (Martinho 2020).

Considering these scenarios, this research aims to identify a model that can be used to predict the energy crops area in the farms of the EU agricultural regions. These insights may be useful for several stakeholders, namely the national and EU institutions to design policy instruments that better deal with land use for bioenergy production. The land can be used for diverse finalities and these generate often conflicts among the several demands, even more in the current situations resulting from the Covid-19 pandemic and Russia-Ukraine conflict (Martinho 2022b). In any case, it is crucial to bring more contributions and insights about the bioenergy domains in the EU frameworks, namely in terms of land use and more specifically about the energy crops area.

2. Literature survey

The ANN has several advantages compared to other methodologies, some of them are related to the flexibility to deal with incomplete information and this is particularly important in assessments carried out for contexts where the availability of data is limited (Antanasijevic et al. 2013). In some cases, the ANN models are considered among the most appropriate approaches to assess some specific issues, such as fuel use and emissions (Bishop et al. 2016).

There are close relationships between energy use and production and environmental conditions (Jaramillo-Moran and Garcia-Garcia 2019). The European Union energy framework has still, in some circumstances, a problematic and non-sustainable relationship with the environment, namely in cases where the energy resources are obtained from mining activities (Brodny and Tutak 2020). These scenarios call for more responsible and efficient energy use in diverse social and economic activities (Di Gia and Papurello 2022). Better efficiency in energy use is one of the keys to improve the sustainability of the associated systems (Oprea, Bara, and Reveiu 2018), namely in households (Szuts 2014).

In this way, energy production from renewable sources is a concern for researchers and policymakers in EU member-states (Brodny, Tutak, and Saki 2020), namely in the current conjunctures, where artificial intelligence developments may bring relevant contributions (Garcia Marquez and Peinado Gonzalo 2022). A particular focus of the studies carried out in these domains is the prediction of renewable energy production (Buturache and Stancu 2021). To promote a more sustainable and efficient use of energy, the EU institutions have been designing measures and instruments within the framework of energy and environmental policies (Dozic and Urosevic 2019), with implications in the member-states (Khayatian, Sarto, and Dall'O' 2016). This is visible, for example, in the European Green Deal strategy and the Covenant of Mayors initiative, created in 2008 (Javier Abarca-Alvarez et al. 2019). Nonetheless, the impacts of policies to reduce the use of energy from non-renewable sources are not always expected (Mrowczynska et al. 2020), especially for the poorest social classes.

The ANN models are applied by the scientific community with diverse developments (Vistica, Banovac, and Pavlovic 2015) and adjustments (Urosevic and Dozic 2021) for specific contexts (Moustris et al. 2014), and complementing other methods (Data Envelopment Analysis, for instance) (Vlontzos and Pardalos 2017). In some cases, they are applied through new approaches (Magazzino, Mele, and Schneider 2022) and particular methodologies, considering, for example, different presentations of the layers (Tutak and Brodny 2022), such as the Kohonen ANN without a hidden layer (Tutak et al. 2020).

In summary, global warming and the new contexts created by the Covid-19 pandemic and the Russia-Ukraine crisis increased concerns about energy use and its impacts on the environment and global sustainability. These concerns are particularly visible in the EU context. Bioenergy and the agricultural sector have here an important role to play (Martinho 2022a).

3. Material and methods

To achieve the objectives proposed, statistical information, for the year 2020 and the EU agricultural regions, from the Farm Accountancy Data Network (FADN 2022) was considered. The data in this database are presented through a weighting system per farm. The energy crops (ha) variable was considered as output, and as predictors were taken into account the following variables: total utilised agricultural area (ha); total livestock (LU); total crops output (euros/ha); total livestock output (euros/LU); specific crop costs (euros/ha); specific livestock costs (euros/LU); subsidies on investments (euros); farm net value added (euros/AWU); gross investment on fixed assets (euros); total direct payments (euros); and LFA subsidies (euros). The energy crops (ha) variable was categorised in the following categories (to deal with the great number of farms with zero hectares and a small number of cases with a large area for these productions): energy crops area=0, for zero hectares; energy crops area=1, for more than 0 and less or equal to 1 hectare; energy crops area=2, for more than 1 and less or equal to 2 hectares; and energy crops area=3, for more than 3 hectares. The selection of these variables follows, for example, the Martinho (Martinho 2020) findings and intends to capture the effects from the dimension and the competitiveness of the farms.

These data were analysed through multilayer perceptron algorithms from the ANN approaches (McCulloch and Pitts 1943), following IBM SPSS procedures (IBM Corp 2021; IBM SPSS 2022), to identify a model to predict the energy crops area, based on a set of predictors related to the EU farms dimension and dynamics. These methodologies are based on a set of layers for input, output and hidden constituted by units (neurons) that are connected through a network that acquires synaptic weights, imitating the human brain (Aryadoust and Goh 2014; Aryadoust and Baghaei 2016). To complement the assessment, correlation analyses were carried out through a pairwise matrix (Galton 1888; Pearson 1896; Pearson and Filon 1898), following Stata (StataCorp 2017a; 2017b; Stata 2022) software procedures.

4. Data analysis

The information presented in table 1 shows that, in general, the European Union agricultural regions with the highest energy crops area (nominal variable ranging between 0 and 3, obtained from values in hectare) have also the greatest total utilised agricultural area (ha), total livestock units (LU (livestock unit)), farm net value added (euros/AWU (annual work unit)), gross investment on fixed assets (euros) and total direct payments (euros). This is confirmed by the relevant pairwise correlations (with statistical significance at 1%) between the energy crops area and these variables, with the following coefficients, respectively: 0.680; 0.616; 0.465; 0.632; and 0.689.

This means that the EU agricultural regions farms with the biggest energy crops area are the largest ones (more area and livestock units), with the highest competitiveness (more farm net value added/AWU and gross investment on fixed assets) and that receive more direct payment subsidies.

The EU agricultural regions with the greatest results for the energy crops area are the following from Germany or neighbour countries: Czechia; Denmark; Germany, Niedersachsen; Germany, Nordrhein-Westfalen; Germany, Saarland; Germany, Hessen; Germany, Thüringen; Germany, Sachsen-Anhalt; Germany, Sachsen; Germany, Brandenburg; Germany, Mecklenburg-Vorpommern; Germany, Schleswig-Holstein/Hamburg; and Slovakia.

Table 1. Statistical information for the year 2020 across the European Union agricultural regions

Country/Region	Energy crops area[a]	Total Utilised Agricultural Area (ha)	Total livestock units (LU)	Total crops output (€/ha)	Total livestock output (€/LU)	Specific crop costs (€/ha)	Specific livestock costs (€/LU)	Subsidies on investments (€)	Farm Net Value Added (€/AWU)	Gross Investment on fixed assets (€)	Total direct payments (€)	LFA subsidies (€)
Belgium, Vlaanderen	0	39	165	3587	1180	1194	770	2447	39256	59697	14656	0
Belgium, Wallonie	0	74	97	1059	1143	376	560	2485	48072	27012	24506	811
Bulgaria, Yuzhen tsentralen	0	34	19	887	757	245	450	213	10755	9834	11593	628
Bulgaria, Yugoiztochen	0	86	31	593	917	212	559	185	13762	11221	21850	705
Bulgaria, Severozapaden	0	107	16	925	693	251	393	80	24290	36421	21869	320
Bulgaria, Severen tsentralen	0	90	20	841	756	254	482	284	17314	12155	19047	156
Bulgaria, Severoiztochen	0	93	24	708	1163	236	675	154	15940	11775	19916	102
Bulgaria, Yugozapaden	1	36	11	850	919	194	388	88	11854	3444	9245	2241
Czechia, Czechia	3	247	117	863	1323	294	879	7804	27536	65394	75353	11381
Denmark, Denmark	2	132	198	1587	1664	459	970	425	99034	79248	41404	0

Country/Region	Energy crops area[a]	Total Utilised Agricultural Area (ha)	Total livestock units (LU)	Total crops output (€/ha)	Total livestock output (€/LU)	Specific crop costs (€/ha)	Specific livestock costs (€/LU)	Subsidies on investments (€)	Farm Net Value Added (€/AWU)	Gross Investment on fixed assets (€)	Total direct payments (€)	LFA subsidies (€)
Germany, Niedersachsen	3	86	144	1264	1426	424	801	117	49158	45685	25351	19
Germany, Nordrhein-Westfalen	2	60	113	1810	1339	569	769	119	42433	39877	18508	485
Germany, Bayern	1	52	58	1085	1653	325	685	200	35608	39670	15569	2065
Germany, Baden-Württemberg	1	58	54	1194	1582	313	753	728	35517	33993	16901	976
Germany, Saarland	2	117	53	514	1676	187	688	0	37786	36870	33428	1623
Germany, Rheinland-Pfalz	1	60	28	2459	1619	542	680	28	39887	39484	17635	2
Germany, Hessen	2	87	59	804	1503	278	704	792	35601	37493	24834	2264
Germany, Thüringen	3	455	220	1050	1475	315	946	2698	46709	160884	140737	12592
Germany, Sachsen-Anhalt	3	421	159	966	1544	306	972	49	51638	92286	114210	2048
Germany, Sachsen	2	330	194	1021	1740	339	1039	4583	41684	109672	100300	6260
Germany, Brandenburg	3	455	207	997	1630	340	1495	828	31199	132040	138722	8263
Germany, Mecklenburg-Vorpommern	3	488	155	1063	1868	379	960	0	64841	186603	127871	20
Germany, Schleswig-Holstein/Hamburg	3	102	119	1111	1591	399	745	7	50872	44472	28481	16
Estonia, Estonia	0	137	37	527	1380	177	948	3706	27228	31313	24368	0
Ireland, Ireland	0	47	66	260	953	162	492	707	25255	11892	13143	2258
Greece, Makedonia-Thraki	1	12	5	1674	1005	401	594	20	15658	1324	6489	655
Greece, Ipiros-Peloponissos-Nissi Ioniou	0	7	6	2265	965	255	506	84	12011	2800	2568	417
Greece, Sterea Ellas-Nissi Egaeou-Kriti	0	9	7	1900	828	350	467	11	12530	765	4145	726
Greece, Thessalia	0	10	6	1707	1166	425	536	8	16625	313	6647	500
Spain, Navarra	0	65	45	1019	1096	251	489	587	43022	18567	16296	1134
Spain, Asturias	0	26	49	509	1154	92	749	6	15613	1196	12063	1799
Spain, Cantabria	0	37	51	116	1264	14	716	31	19243	1171	11736	2244
Spain, País Vasco	0	38	32	985	1475	276	724	730	21717	13744	10408	2648
Spain, La Rioja	0	33	17	1782	631	461	378	129	33334	7539	8857	5
Spain, Galicia	0	22	49	845	1056	209	560	93	23625	3965	7176	778
Spain, Castilla y León	0	68	57	770	1090	238	628	9	34484	1829	13639	195
Spain, Madrid	0	71	25	391	1507	72	798	34	15352	591	7429	88
Spain, Islas Baleares	0	54	20	828	1232	164	609	420	24998	9142	9263	3319
Spain, Castilla-La Mancha	0	63	28	940	1872	133	814	27	35206	960	8799	441
Spain, Cataluña	0	44	100	1538	506	354	263	713	27086	12635	11449	557
Spain, Aragón	0	76	68	965	543	164	203	74	38887	9070	15222	522
Spain, Andalucía	0	37	15	2345	716	396	339	17	34939	2228	8578	186
Spain, Extremadura	0	72	38	570	1399	125	691	0	25810	198	10062	328
Spain, Comunidad Valenciana	0	14	21	4545	1387	816	666	28	35007	3153	2529	105
Spain, Murcia	0	43	48	2806	388	426	128	6	31892	2984	6184	354
Spain, Canarias	0	4	12	25359	2942	3598	917	140	23541	5673	18181	0
France, Centre	0	141	44	1098	950	406	355	582	36422	36120	31540	1673
France, Basse-Normandie	0	108	137	512	1233	263	416	1983	34263	57673	28385	3371
France, Picardie	1	129	52	1410	1148	521	428	1020	44916	50645	30875	5
France, Haute-Normandie	1	119	75	1334	1161	471	391	1346	35276	51329	28247	120
France, Bourgogne	0	136	78	1099	726	261	306	1464	41810	37119	33724	5066
France, Champagne-Ardenne	1	85	28	1912	1117	435	441	743	48442	27482	20419	1408
France, Île-de-France	0	151	4	1617	2776	555	949	243	49387	40784	33990	0
France, Bretagne	1	69	192	1133	1182	368	500	1118	36414	49682	18168	0
France, Poitou-Charentes	0	107	54	1505	1206	350	536	611	51439	35941	24950	1846
France, Pays de la Loire	1	98	158	846	1215	314	510	1896	32718	39165	26747	651
France, Alsace	0	49	32	2488	1504	565	680	875	31864	29948	12342	495
France, Franche-Comté	1	131	93	438	1748	207	467	882	39946	69435	31216	10638
France, Nord-Pas-de-Calais	0	78	75	1710	1368	608	557	958	32699	49161	19925	0
France, Lorraine	0	161	107	520	1144	237	424	1352	42771	49860	39757	6568
France, Auvergne	0	106	99	223	994	124	340	2690	24916	32811	30079	13981
France, Languedoc-Roussillon	1	47	10	3093	1119	532	424	2550	26128	18541	7754	3383
France, Rhône-Alpes	1	68	58	1256	1309	325	407	2666	27120	40536	16996	7019
France, Provence-Alpes-Côte d'Azur	0	43	11	4834	745	705	285	2094	34201	29938	9987	4704
France, Limousin	0	109	113	147	731	108	286	1758	22329	26815	33925	11835
France, Midi-Pyrénées	0	86	49	708	970	261	369	2579	20961	25973	23702	6980
France, Aquitaine	0	55	36	2019	1422	526	599	1274	18313	26049	15011	2293
France, Corse	0	88	29	1202	1053	172	281	4601	27658	36639	15986	7484
France, Guadeloupe	0	9	10	5826	677	1216	433	1656	16563	8720	21179	774
France, La Réunion	0	10	15	9067	1511	1492	970	4851	23872	33725	17069	1780
Croatia, Jadranska Hrvatska	0	12	4	1771	1471	227	1097	0	12514	1742	3172	1176
Croatia, Kontinentalna Hrvatska	0	16	9	1157	1119	356	869	0	11832	4754	5833	643
Italy, Valle d'Aosta	1	46	24	503	1594	45	627	1503	27808	-7680	15526	6176
Italy, Piemonte	1	27	26	2540	1387	564	781	48	40533	1381	10177	352
Italy, Veneto	1	19	50	3712	1085	887	501	524	48852	7049	9217	612
Italy, Trentino	0	7	5	6892	2250	1368	1122	100	33786	6565	2037	1486
Italy, Alto Adige	0	10	11	4506	2392	649	1339	349	29500	21322	4786	1747
Italy, Lombardia	1	30	78	2119	1424	600	696	0	52799	-3936	15409	149
Italy, Emilia-Romagna	1	26	21	2719	1962	718	837	44	43644	-1194	8751	302
Italy, Toscana	1	24	6	2700	1169	693	427	143	26038	1635	7475	257
Italy, Liguria	0	7	4	8165	1375	2270	386	636	28864	676	2697	936
Italy, Friuli-Venezia Giulia	1	20	16	2891	1216	695	577	730	32762	6167	5802	711
Italy, Lazio	0	20	13	2560	1598	478	658	301	33540	4339	6092	420
Italy, Umbria	1	26	11	1627	1050	391	404	54	34056	-667	10660	460
Italy, Marche	1	24	4	1682	992	400	365	144	26932	1922	7814	781
Italy, Calabria	0	11	3	2266	992	330	375	0	17473	1319	5311	85
Italy, Campania	0	15	14	2993	1176	731	452	29	29381	1043	5195	2014
Italy, Puglia	0	17	3	2253	1704	456	815	152	26237	1992	7382	0
Italy, Molise	0	21	14	1126	996	245	304	163	22322	3610	7083	1362
Italy, Abruzzo	0	15	5	2281	1582	508	468	253	21001	2958	3995	415
Italy, Sicilia	0	20	6	1774	835	355	320	14	26680	2900	5533	378
Italy, Sardegna	1	45	21	645	1127	147	565	569	31454	-1068	10779	1307
Italy, Basilicata	0	32	8	1258	1330	266	497	1077	24655	3795	9062	397
Cyprus, Cyprus	0	11	12	1579	2096	386	1275	411	12121	3117	3913	377
Latvia, Latvia	1	66	24	686	1149	216	711	2376	15491	14457	12451	0
Lithuania, Lithuania	0	46	12	679	1055	220	624	2654	14215	15406	8725	913
Luxembourg, Luxembourg	1	87	110	488	1440	279	619	15030	54770	77533	25109	10938
Hungary, Észak-Magyarország	0	57	13	820	1262	213	717	19	31665	6676	16143	0
Hungary, Alföld	1	40	18	1147	1134	256	790	149	28123	10372	12012	0
Hungary, Dunántúl	0	52	24	1094	1084	343	797	126	25842	15809	15027	0
Malta, Malta	0	3	12	7083	1863	1689	1220	212	10227	4669	1575	503
Netherlands, The Netherlands	0	41	148	6336	1697	2032	941	2503	54854	81635	14983	0
Austria, Austria	1	33	30	906	1755	255	684	864	28863	26879	7516	3124
Poland, Pomorze i Mazury	1	38	19	753	1347	281	785	285	14022	4557	8889	651
Poland, Mazowsze i Podlasie	0	15	11	853	1363	257	757	209	7340	3931	4123	432
Poland, Wielkopolska and Slask	0	26	16	1011	1158	357	621	233	12083	4407	6289	443
Poland, Malopolska i Pogórze	0	11	5	998	1008	294	521	130	5128	1833	2788	265
Portugal, Ribatejo e Oeste	0	13	3	4916	616	1699	155	75	13417	25580	4610	107
Portugal, Alentejo e Algarve	0	72	23	425	479	85	262	50	18981	10771	10344	1745

Country/Region	Energy crops area[a]	Total Utilised Agricultural Area (ha)	Total livestock units (LU)	Total crops output (€/ha)	Total livestock output (€/LU)	Specific crop costs (€/ha)	Specific livestock costs (€/LU)	Subsidies on investments (€)	Farm Net Value Added (€/AWU)	Gross Investment on fixed assets (€)	Total direct payments (€)	LFA subsidies (€)
Portugal, Açores e Madeira	0	13	15	955	950	268	521	667	15133	5374	6020	1569
Portugal, Norte e Centro	1	14	13	1371	912	332	648	538	10964	4173	3861	1262
Romania, Sud-Est	0	28	9	580	923	231	597	45	8045	2507	5994	81
Romania, Sud-Muntenia	0	22	7	634	1027	252	584	0	9585	3475	5681	0
Romania, Sud-Vest-Oltenia	0	11	4	636	1051	220	588	2	4031	501	2322	0
Romania, Nord-Vest	0	14	9	830	741	195	535	0	6951	1268	3379	0
Romania, Centru	0	16	12	768	1068	180	767	21	8391	901	4670	0
Romania, Nord-Est	0	14	7	686	807	211	578	13	7086	1514	3001	0
Romania, Vest	0	25	10	821	814	203	554	12	12146	3457	5816	0
Romania, Bucuresti-Ilfov	0	38	2	554	2030	108	1307	0	11548	-394	6991	0
Slovenia, Slovenia	0	11	11	1336	934	295	737	624	6742	9090	3185	1023
Slovakia, Slovakia	3	438	141	806	1417	271	1139	2476	26009	68870	92281	16363
Finland, Pohjanmaa	0	66	38	1018	1996	320	1226	2362	43570	47289	27512	16648
Finland, Pohjois-Suomi	0	77	34	726	2251	245	1751	2445	32792	40150	41032	19242
Finland, Sisä-Suomi	0	60	29	675	2123	232	1445	1401	25837	30330	27229	15175
Finland, Etelä-Suomi	0	70	25	986	1441	315	910	1007	39863	30591	21725	16059
Sweden, Slättbyggdslän	1	106	54	1229	1442	393	948	6	43302	54677	23396	2235
Sweden, Skogs- och mellanbygdslän	1	108	67	517	1488	173	1056	1	31839	37494	24994	6778
Sweden, Län i norra Sverige	0	93	59	399	1422	135	1089	830	28962	30196	37594	22238

Note: [a], Nominal variable ranging between 0 and 3; Coloured cells identify the highest values for each variable.

5. Results

The machine learning approach, through artificial neural networks, for the model proposed, considered for training a sample of 68% and for testing 32% (table 2). For this approach, 3 layers were considered, with 11, 3 and 4 units for the input hidden and output layers, respectively (table 3). The synaptic weights between the different units of these layers, including bias units, are presented in figure 1. Table 4 complements the information of this figure and both highlight the strong connections, for example, among the hidden units and the following predictors: total utilised agricultural area (ha); farm net value added (euros/AWU); and total direct payments (euros). For the interrelationships between the hidden layer units and the output units, the strongest connections are with the “energy crops area=3” (output layer unit for the farms with the highest energy crops (ha)).

Table 5 reveals that the percent incorrect predictions are 27.6% for the training sample and 29.3% for the testing part. The main difficulties of the model were with the prediction of the intermediate categories (1 and 2) of the dependent variable (table 6). Similar results were found in figure 2 for the relationships between the observed categories and the predicted pseudo-probability of categories. The ROC (Receiver Operating Characteristic) curve (figure 3) and the area under the curve (table 7) for the chance that the predicted pseudo-probability of being in one category is bigger for a randomly selected example in that category than for a randomly selected example not in that category confirm the difficulties of the approach here considered with the classification of the categories 1 and 2. The cumulative gain (figure 4), related to the percentage of the whole number of cases in a category increased by considering a percentage of the total number of cases, shows that for the curve of the energy crops area=3, the top 10% would contain approximately 100% of the cases for this category. The lift curves (figure 5) are obtained from the cumulative gains curves and the values on the yaxis represent the ratio of the cumulative gain for each case to the baseline.

Table 8 and figure 6 show the most important predictors, with the following decreasing order: farm net value added; total direct payments; total utilised agricultural area; specific livestock costs; total crops output; total livestock units; gross investment of fixed assets; LFA subsidies; subsidies on investments; total livestock output; specific crop costs.

Table 2. Information for case processing summary

		Number	Percent
Sample	Training	87	68.0%
	Testing	41	32.0%
Valid		128	100.0%
Excluded		0	
Total		128	

Table 3. Outputs for network information

Network Information			
Input Layer	Covariates	1	Total Utilised Agricultural Area (ha)
		2	Total livestock units (LU)
		3	Total crops output (€/ha)
		4	Total livestock output (€/LU)
		5	Specific crop costs (€/ha)
		6	Specific livestock costs (€/LU)
		7	Subsidies on investments (€)
		8	Farm Net Value Added (€/AWU)
		9	Gross Investment on fixed assets (€)
		10	Total direct payments (€)
		11	LFA subsidies (€)
	Number of Units[a]		11
	Rescaling Method for Covariates		Standardized
Hidden Layer(s)	Number of Hidden Layers		1
	Number of Units in Hidden Layer 1[a]		3
	Activation Function		Hyperbolic tangent
Output Layer	Dependent Variables	1	Energy crops area
	Number of Units		4
	Activation Function		Softmax
	Error Function		Cross-entropy

Note: [a], Excluding the bias unit.

Figure 1. Synaptic weights between the several layers

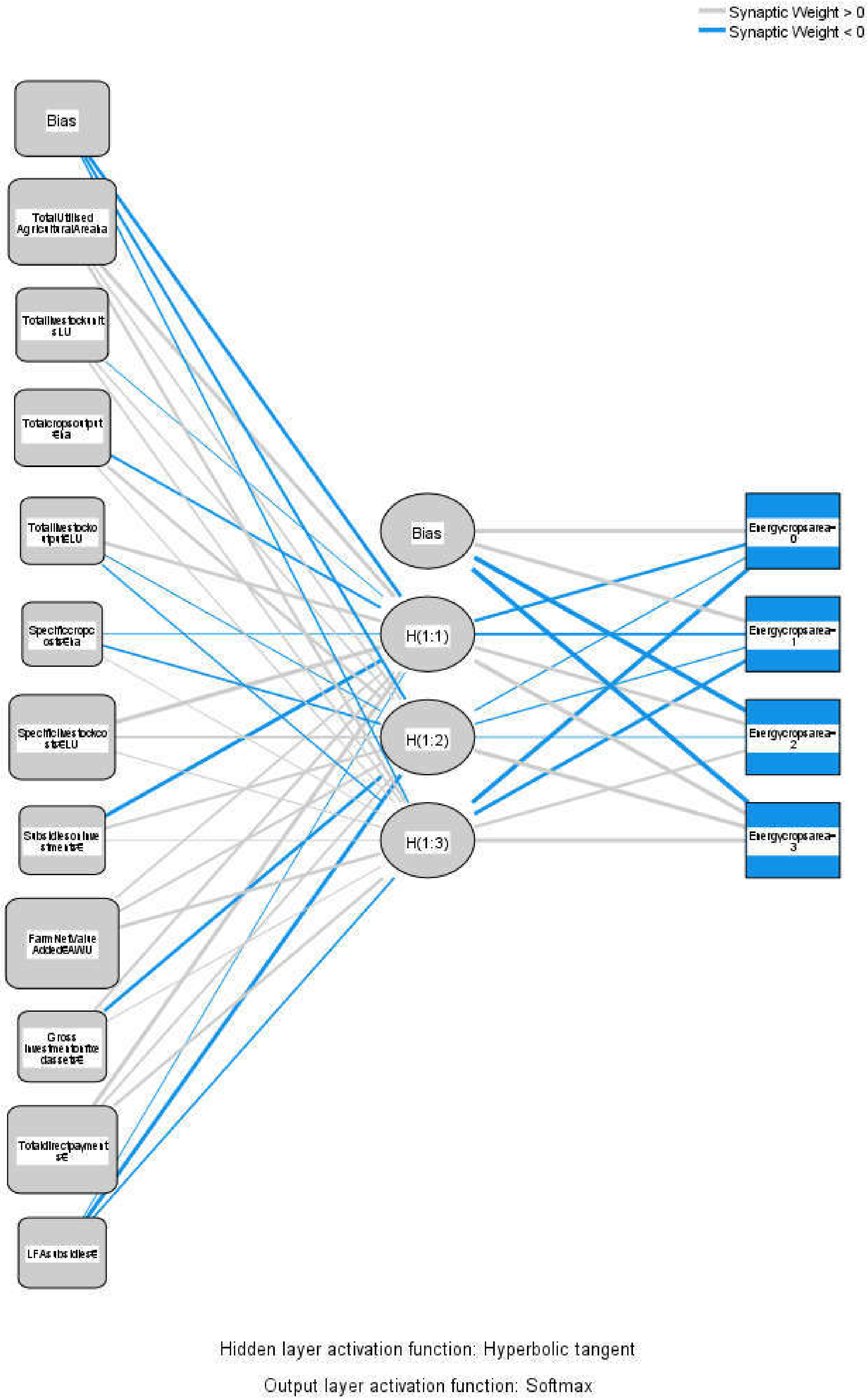


Table 4. Outputs for the parameter estimates

		Predicted						
		Hidden Layer 1			Output Layer			
	Predictor	H(1:1)	H(1:2)	H(1:3)	[Energy crops area=0]	[Energy crops area=1]	[Energy crops area=2]	[Energy crops area=3]
Input Layer	(Bias)	-0.629	-0.495	-0.337				
	Total Utilised Agricultural Area (ha)	0.699	0.421	0.547				
	Total livestock units (LU)	-0.081	0.336	0.397				
	Total crops output (€/ha)	-0.465	0.564	0.258				
	Total livestock output (€/LU)	0.660	-0.157	-0.278				
	Specific crop costs (€/ha)	-0.003	-0.427	0.121				
	Specific livestock costs (€/LU)	1.126	0.462	0.208				
	Subsidies on investments (€)	-0.762	0.491	0.044				
	Farm Net Value Added (€/AWU)	0.430	0.489	0.574				
	Gross Investment on fixed assets (€)	0.501	-0.613	0.192				
	Total direct payments (€)	0.858	0.455	0.531				
	LFA subsidies (€)	-0.084	-0.762	-0.426				
Hidden Layer 1	(Bias)				1.549	0.905	-1.722	-1.784
	H(1:1)				-0.554	-0.475	0.672	0.995
	H(1:2)				-0.269	-0.269	-0.019	0.917
	H(1:3)				-1.014	-0.678	0.531	1.209

Table 5. Model summary statistics

Model Summary		
Training	Cross Entropy Error	59.398
	Percent Incorrect Predictions	27.6%
Testing	Cross Entropy Error	27.421
	Percent Incorrect Predictions	29.3%
Dependent Variable: Energy crops area		

Table 6. Classification information

		Predicted				
Sample	Observed	0	1	2	3	Percent Correct
Training	0	56	0	0	0	100.0%
	1	19	0	0	0	0.0%
	2	3	0	0	2	0.0%
	3	0	0	0	7	100.0%
	Overall Percent	89.7%	0.0%	0.0%	10.3%	72.4%
Testing	0	28	0	0	0	100.0%
	1	12	0	0	0	0.0%
	2	0	0	0	0	0.0%
	3	0	0	0	1	100.0%
	Overall Percent	97.6%	0.0%	0.0%	2.4%	70.7%
Dependent Variable: Energy crops area						

Figure 2. Results for the predicted pseudo-probability

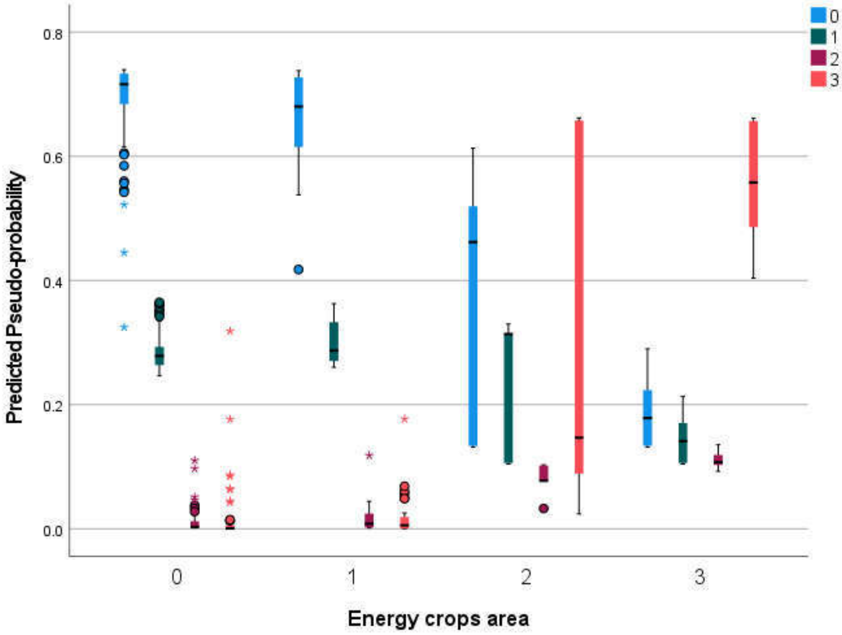


Figure 3. Results for the sensitivity/specificity

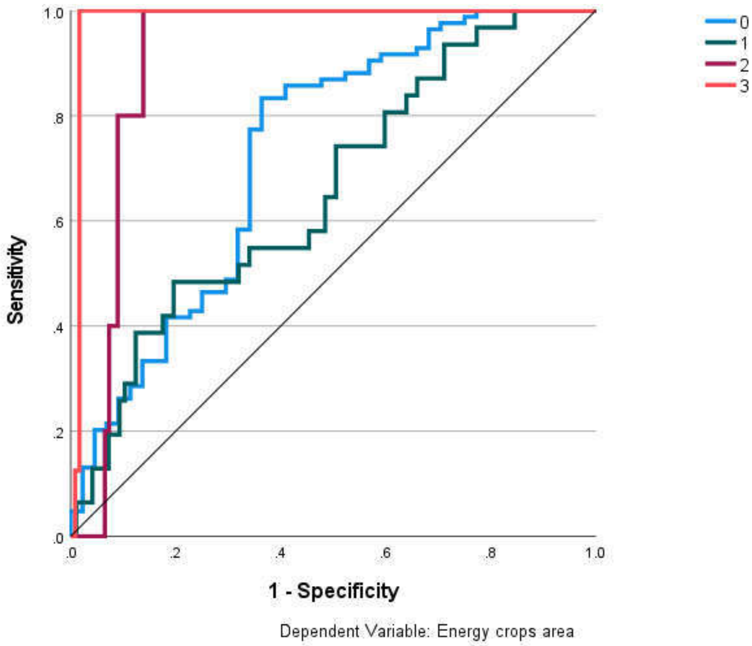


Table 7. Information for the area under the curve

		Area
Energy crops area	0	0.729
	1	0.658
	2	0.909
	3	0.984

Figure 4. Results for the gain

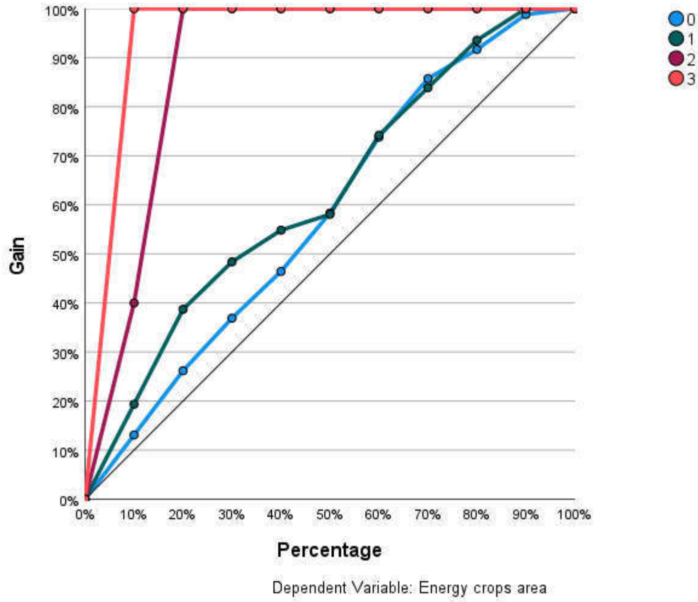


Figure 5. Results for the lift

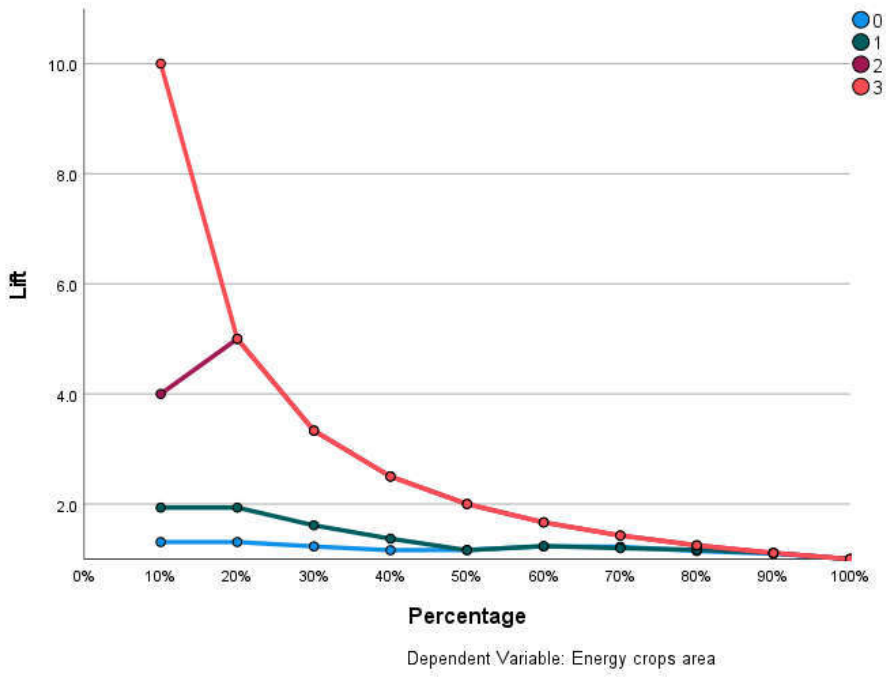
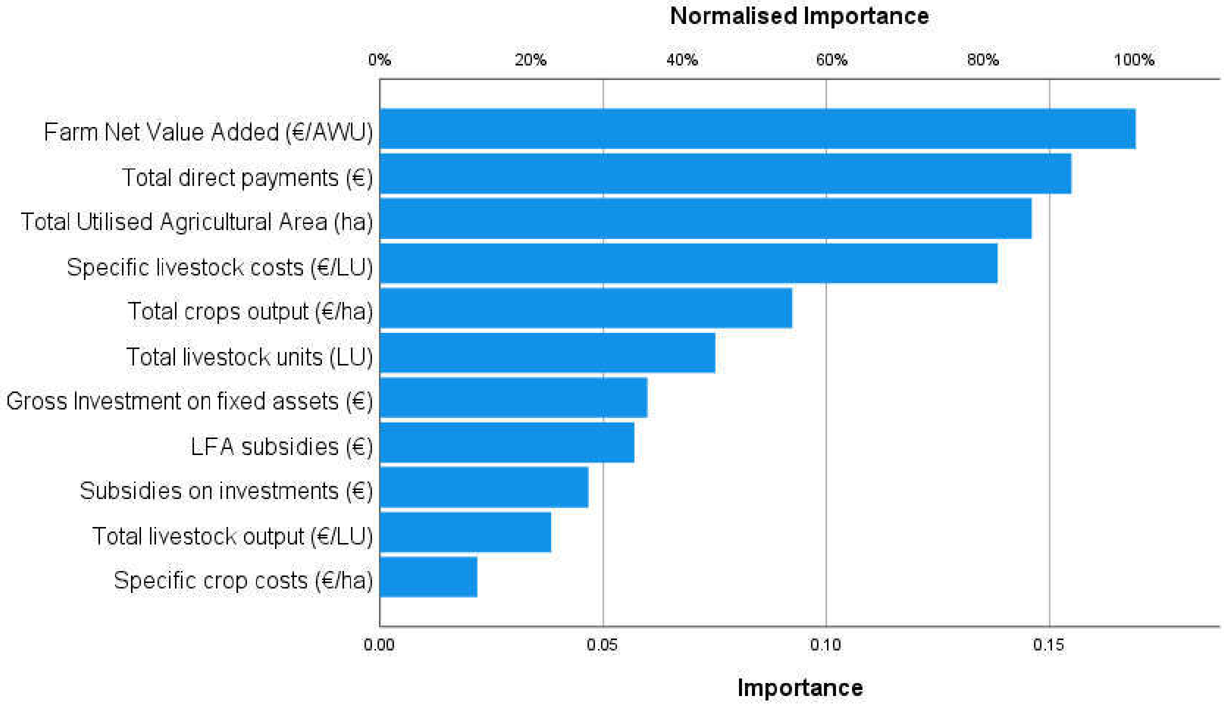


Table 8. outputs for independent variable importance

	Importance	Normalized Importance
Total Utilised Agricultural Area (ha)	0.146	86.2%
Total livestock units (LU)	0.075	44.3%
Total crops output (€/ha)	0.092	54.5%
Total livestock output (€/LU)	0.038	22.6%
Specific crop costs (€/ha)	0.022	12.9%
Specific livestock costs (€/LU)	0.138	81.7%
Subsidies on investments (€)	0.047	27.6%
Farm Net Value Added (€/AWU)	0.169	100.0%
Gross Investment on fixed assets (€)	0.060	35.4%
Total direct payments (€)	0.155	91.5%
LFA subsidies (€)	0.057	33.7%

Figure 6. Results for the normalised importance of the predictors



6. Discussion and conclusions

This research aimed to identify a model to predict the energy crops area, in the framework of the EU bioenergy, based on a set of predictors related to the farms' dimension and competitiveness (through variables weighted by the number of hectares and annual work units). This statistical information was obtained from the Farm Accountancy Data Network for the year 2020 and the agricultural regions. To analyse this information, artificial neural networks methodologies were considered through multilayer perceptron algorithms.

The literature review highlights the concerns of the EU institutions with energy use sustainability, namely to deal with the global warming challenges and to increase self-sufficiency to satisfy energy needs, specifically in times of crisis as those verified currently worldwide. Renewable energy sources may bring here relevant contributions, where the bioenergy from land use activities (agriculture and forestry, for example) is included. These concerns of the EU policymakers have been represented in the environmental and energy policies (European Green Deal strategy, for instance). In addition, the literature survey reveals the importance of the new technologies, particularly those associated with artificial intelligence, where artificial neural networks models are encompassed.

The data analysis (with data from the FADN database) shows that there is still a long way to run in the domains of EU energy crops production. A relevant number of farms from the EU agricultural regions has zero, or close to zero, hectares of these crops. Of course, several factors explain these scenarios, but maybe there are conditions and potentialities to increase the energy crops area, with added value for the farmers, without compromising the food production. In general, there is a relevant correlation among the energy crops area (categorised) and the following variables: total utilised area; total livestock units; farm net value added; gross investment on fixed assets; and total direct payments. These correlations show the interrelationships between the energy crops area and dimensions and competitiveness of the EU farms from Germany and neighbouring countries.

The results from the ANN approaches reveal that it is possible to predict the energy crops area through the model proposed with accuracies above 70%. On the other hand, the model confirms the importance of variables, such as the farm net value added, total direct payments and total utilised area in the frameworks of the EU energy crops.

In terms of practical implication, there are here relevant insights for several EU stakeholders, namely farmers, researchers and policymakers, showing that there is here potential to be assessed and explored in the farms of the European agricultural regions. On the other hand, for policy recommendations, it is suggested more adjusted instruments in the context of the CAP to better address these frameworks. For future research, it is suggested to bring more insights about the factors that justify the reduced (or even null) area for energy crops in the farms of the member-states.

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