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Research article

Development of agri-environmental footprint indicator using the FADN data: Tracking development of sustainable agricultural development in Eastern Europe ☆

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ABSTRACT

The emphasis put on environmental issues of the European Union (EU) agricultural sector in the strategies like the European Green Deal, Biodiversity and Farm to fork strategy give new directions to the Common Agricultural Policy (CAP) changing the EU agricultural practice into a more environment-and climate-friendly manner. The modified support rules and obligations for farmers will necessitate adopting new farm management practices on farms. This paper proposes the Agri-environmental Footprint Index (AFI) as a tool to identify the current state of the environmental situation and to track the changes and achievements on farms. The proposed approach is applied for the case study in Lithuania for 2017. The farm-level data from the Lithuanian Farm Accountancy data Network (FADN) are exploited. The paper relies on the multivariate statistical techniques (Shannon Entropy and Principal Component Analysis) and multi-criteria approach (Simple Additive Weighting) to construct the composite indicators. The results are analyzed across farming types and farm size classes. The most environmentally beneficial farms are characterized as medium-sized (in economic terms) and specialized in field crops-grazing livestock. The highest share of farms with a low value of AFI was found for the largest farm size class and for farms specialized in horticulture (using Shannon entropy weighting) and orchards (using Principal Component Analysis (PCA) weighting). The results of AFIs using Shannon entropy and PCA weighting across farming types tended to differ. Therefore, in order to apply the proposed tool in practice, testing different weighting schemes is preferable.

1. Introduction

The Common Agricultural Policy (CAP) is the European Union (EU) policy addressed to the agricultural sector. Over the years it has evolved to meet the changing needs of the agricultural society and citizens (Baldock, 2020). The main priorities of the CAP for the 2021–2027 are provided in the nine specific objectives and three of them relate to the environmental sector. We refer to the aforementioned three objectives as Environmental Objectives (EC, 2021b):

1 *Contribute to climate change mitigation and adaptation, as well as to sustainable energy;*
2 *Foster sustainable development and efficient management of natural resources such as water, soil and air;*
3 *Contribute to the protection of biodiversity, enhance ecosystem services and preserve habitats and landscapes.*

These objectives and the EU strategies such as the European Green Deal (EC, 2019b), Biodiversity (EC, 2020b) and Farm to fork (EC, 2020c) give new directions to the CAP changing the EU agricultural practices into a more environment-and climate-friendly manner. As stated by Peeters et al. (2020), the current CAP by its first pillar payments acted as an accelerator for environmental degradation of the agricultural sector, and at the same time, the second pillar payments acted partially as a brake mitigating the sector's negative impacts to the environment. The modified

Abbreviations: **:** EU, European Union; RISE, Response-Inducing Sustainability Evaluation; SAFE, Sustainability Assessment of Farming and the Environment; IDEA, Indicateurs de Durabilité des Exploitations Agricoles, MOTIFS, Monitoring Tool for Integrated Farm Sustainability; FADN, Farm Accountancy Data Network; CAP, Common Agricultural Policy; DPSIR, Driver-Pressure-State-Impact-Response; AI, Agri-environmental Indicator; AFI, Agri-environmental Footprint Index; OECD-JRC, Organization for Economic Cooperation and Development-Joint Research Centre; PCA, Principal Component Analysis; COP, specialist cereals, oilseeds and protein crops; SO, Standard Output; UAA, Utilised Agricultural Area; AWU, Agricultural Work Unit; SD, Standard Deviation; Min, minimum value; Max, maximum value; RACER, Relevant, Accepted, Credible, Easy, Robust; GHG, Greenhouse Gas; Ha, hectare; MCDM, Multi-Criteria Decision Making; OECD, Organization for Economic Cooperation and Development.

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Nomenclature

H_S	Shannon diversity index
E_S	Shannon Evenness Index
i	index for farms
j	index for agri-environmental indicators
I	number of farms
J	number of agri-environmental indicators
B	set of the benefit indicators
C	set of the cost indicators
x_{ij}	the j-th agri-environmental indicator for the i-th farm
y_i	agri-environmental index for the i-th farm
w_j^P	weight of the j-th indicator based on the PCA
w_j^E	weight of the j-th indicator based on the entropy

support rules and obligations for farmers will necessitate adopting new farm management practices. In line with that, it is essential to identify the current environmental state and to track the changes and achievements on farms.

The environmental impacts of the agricultural sector have been analyzed in numerous studies (Purvis et al., 2009; Westbury et al., 2011; Mauchline et al., 2012; Nowak et al., 2019; Kasztelan and Nowak, 2021). Some environmental pressure variables like GHG emissions, biodiversity measured by the bird population index, phosphorus management and others cover a broad spectrum of the environmental impacts and, therefore, have commonly adopted for the quantification of the environmental pressures (Vlontzos and Pardalos, 2017; Svanbäck et al., 2019). Therefore, frequently, studies draw attention on a single environmental pressure element. For example, Overmars et al. (2014) developed an indicator to analyze biodiversity in the European Union (EU); Vlontzos and Pardalos (2017) assessed greenhouse gas (GHG) emissions efficiency in the EU agriculture; Svanbäck et al. (2019) explored nutrient flows for the Baltic Sea catchment; Garske and Ekardt (2021) addressed the issues related to the phosphorus management in the agricultural sector. Since the agricultural sector is responsible for a complex of negative impacts on the environment (soil degradation, soil, water and air pollution, loss of biodiversity and climate change) (EC, 2019b) it has prompted researchers to develop various tools comprising numerous environmental pressure elements which facilitate to take the appropriate decisions for the policy-makers ensuring the agricultural sector's development in a sustainable way (Vlontzos et al., 2017; Kasztelan and Nowak, 2021).

In the EU, one the most important farm-level data source is the Farm Accountancy Data Network (FADN). The data are collected annually, representing the structure of the agricultural sector in a given Member State. However, the assessment of farm environmental performance is sometimes cumbersome, e.g., when as many as 71 indicators are used to evaluate environmental situation on farms (Sauvenier et al., 2005). Still, the FADN system has proved to be a valuable data source in terms of the assessment of environmental issues on farms in many studies (Westbury et al., 2011; Gerrard et al., 2012; Dabkienė et al., 2020; Lynch et al., 2018; Czyżewski et al., 2019; Tzouramani et al., 2020; Santos et al., 2020). The different scope of the issues covered by developed indicators or sets of indicators were used by scholars and thus, on the one hand, the simplified view or not a full picture of the environmental situation on farms is provided, and on the other hand, the comparison of the results obtained in these studies is limited. The changes in FADN database (the EU Member States collect some additional indicators to the main FADN survey (Vrolijk et al., 2016) and the main FADN survey is often updated by DG AGRI (EC, 2021c)) and new legislative environment at the EU agriculture (the goals set for the EU agricultural sector in the strategies, like the European Green Deal (EC, 2019b), Biodiversity strategy (EC, 2020b), Farm to fork strategy (EC, 2020c) and a country-wise policy actions (for example, new rules for Lithuanian farmers concerning the use of underground water laid down in the Underground Law (LRS, 2020)) are the main reasons for the development of new indicators, sets of indicators or frameworks.

(Van Cauwenbergh et al., 2007; Sauvenier et al., 2007) distinguished two sustainability assessment approaches: the action and evaluation path. The action path is based on sustainability issues linked to the targets, strategies, and tasks. This path refers to the R (which stands for Response) in the DPSIR framework (OECD, 1993). The evaluation path takes into account sustainability principles which are designed according norms, criteria, and indicators. This path reflects the DPSI (which stands for Driver, Pressure, State and Impact) in the framework.

Based on the presented background above, the goal of this paper is to present the agri-environmental composite indicator as a tool to capture the current state of environmental performance of farms, which refers to the action path. The tool consists of agri-environmental indicators (AIs) customized to the FADN data which cover three aforementioned CAP specific environmental objectives.

In this study, we take Lithuania, an EU Member State, as an example. Indeed, this country provides an interesting example where the effects of the CAP unfold (and are amplified in many instances) amid the consequences of the economic transition. Indeed, the agricultural sector is a priority sector in Lithuania which faces multiple challenges in achieving environmental sustainability (EC, 2020a).

The remainder of the paper is organized as follows: Section 2 provides short literature review related to the environmental studies of agriculture assessment using composite indicators. Section 3 gives a description of the data used and methods applied to calculate an agri-environmental index at farm level that were used for empirical research. Section 4 presents the results of agri-environmental performance indicators and indices calculated for Lithuanian family farms and discusses the results in the light of the earlier literature. Finally, Section 5 concludes.

2. Literature review

In response to the Rio Earth Summit in 1992, the Environmental Sustainability Index and Environmental Performance Index are the first attempts of academia to develop sets of indicators attaining to measure environmental performance and sustainability providing practical guidance ensuring ways towards sustainable development (Hsu et al., 2013; EC (European Commission) 2021a). Agricultural sector and rural areas play an important role in terms of resource use and sustainability, therefore the agricultural sustainability assessment has received much attention with particular measures and frameworks (Hani et al., 2003; Sauvenier et al., 2005; Zahm et al., 2008; Wang et al., 2019). The three dimensions of sustainable development are environmental, economic, and social. The environmental list of indicators for the agricultural sector has been developed in a standalone manner (Purvis et al., 2009; Westbury et al., 2011; Mauchline et al., 2012; Kasztelan and Nowak, 2021) or as an environmental dimension of sustainability assessment (Zahm et al., 2008; Gómez-Limón and Sanchez-Fernandez, 2010; Nowak et al., 2019). In order to improve the selection of indicators and to structure the farms' sustainability assessment, many frameworks were developed (Talukder and Hipel, 2018). The examples of sustainability analysis frameworks include RISE (Hani et al., 2003), SAFE (Sauvenier et al., 2005), IDEA (Zahm et al., 2008), and MOTIFS (Meul et al., 2008). As pointed out by Talukder and Hipel (2018) RISE, SAFE, and IDEA frameworks emphasize the assessment at individual indicator level rather than as composite indicator. In order to support decision-makers with comprehensible information on the environmental state of the agricultural sector, the indices have been developed in many studies (Purvis et al., 2009; Westbury et al., 2011; Mauchline et al., 2012; Nowak et al., 2019; Dos Santos and Ahmad, 2020; Kasztelan and Nowak, 2021).

The methodology of the Agri-environmental Footprint Index (AFI) presented by Purvis et al. (2009) was designed and tested for seven EU Member States in order to investigate the differences of the environmental impacts of farms that embarked on participation in agri-environmental schemes compared to those that opted out. Based on three main agri-environmental management strategies, namely output structure, farm physical properties, manifestations of natural and cultural heritage on farms, and policy objectives, the matrix as a framework for indicators was developed. The same indicators can be assigned to the different criteria of the matrix. The involvement of experts in the evaluation process is a core feature of AFI methodology of Purvis et al. (2009). The authors suggested normalizing indicators according to the relationships between original indicator values and index (linear or nonlinear). The original methodology or those with some modifications were tested empirically in several studies (Westbury et al., 2011; Mauchline et al., 2012; Vesterager et al., 2012; Diti et al., 2015). Westbury et al. (2011) used the AFI framework based on English FADN data in 1995, 2000 and 2005. Two Assessment Criteria Matrices were proposed for arable and livestock farms and each farming system was measured by the set of nine indicators. The authors pointed out that the results of the AFI were driven by the developed indicators, and the inclusion of more indicators to the assessment could perform more precise analysis. Mauchline et al. (2012) tested the AFI methodology in 14 case studies across Europe during 2006–2007. The AFI framework also was tested by Vesterager et al. (2012) in twenty-five Danish farms. Mauchline et al. (2012) pointed out that the AFI framework could be used for the assessment of farms' environmental performance without the participatory in the agri-environmental schemes element and Vesterager et al. (2012) suggest using this framework for assessing complex policies concerning agriculture. Diti et al. (2015) developed a tool using the AFI and geographical information system to classify the Italian rural areas and to identify the policy actions for rural areas management in a sustainable manner.

The guidelines for composite indicators (indices) construction elaborated by OECD-JRC (2008) discuss various methods of data normalization, weighting, and aggregation of indicators. The presented methods and in combination with other techniques were employed in many agricultural studies (Gómez-Limón and Sanchez-Fernandez, 2010; Barnes and Thomson, 2014; Bachev, 2017). Gómez-Limón and Sanchez-Fernandez (2010) constructed the index for farm sustainability assessment based on ten index construction stages presented by OECD-JRC (2008). The indicators were selected following SAFE (Sauvenier et al., 2007) hierarchical framework. The farm data was gathered through questionnaires from 349 Spanish farms in 2008. Nine indicators were devoted to account the environmental sustainability in farms. The indicators were normalized using linear normalization with respect to maximum and minimum values. The different aggregation techniques, namely the weighted sum of indicators, the product of weighted indicators and the multicriterion function based on the distance to the ideal point were opted in the research. In order to assign weights to indicators, the Principal Component Analysis (PCA) and Analytic Hierarchy Process were chosen. Barnes and Thomson (2014) measured Scottish beef farms sustainable intensification over the period of 2000–2010. The authors have chosen the positive matrix factorization approach to estimated weights to indicators and the geometric mean of individual weightings to sum the indicators to an overall index. Bachev (2017) evaluated the sustainability of 190 Bulgarian farms in 2006. The expert panel and farm managers were involved in establishing the reference values and a qualitative meaning to the indicators. The equal weighting method was used to aggregate indicators into the index. Dos Santos and Ahmad (2020) opted to construct an agricultural sustainability index based on the aggregate data from the EU FADN. To standardize the indicators the linear normalization with respect to maximum and minimum values of the EU-28 were used. The weights to the indicators were estimated by factorial analysis.

EC (2019a) provides a list of twenty eight agri-environmental indicators, which track the integration of environmental impacts into the CAP at EU, country – wise or regional level. Some of the indicators are still under the development stage and some already are utilized as the CAP indicators. The CAP context socio-economic, sectorial and environmental indicators were employed by Nowak et al. (2019) to construct a synthetic measure to compare the agricultural sustainability in the EU Member States. The EU countries were ranked by Agri-Environmental Index in Kasztelan and Nowak (2021) research using Organization for Economic Cooperation and Development (OECD) and Eurostat indicators.

Summing up, it can be concluded that a wide range of different index compositing methods have been applied in previous studies. Therefore, this paper tests whether different weighting methods (Shannon entropy and Principal Component Analysis (PCA)) used for the index construction come to different results in regard to agri-environmental index presented as agri-environmental footprint index (AFI) across farm groups.

3. Data and methods

3.1. Data sources

Lithuanian FADN data of 1,300 farms representing 58,618 family farms of the year 2017 were used. The environmental index was performed for farms groups according to type of farming and farm economic farm size. Following the EU FADN classification the results are presented for specialist cereals, oilseeds and protein crops (COP), field crops, horticulture and orchards, specialist dairying, grazing livestock, specialist granivores, field crops-grazing livestock combined and various crops and livestock combined for six economic farm size classes according to the Standard Output (SO) value. Descriptive statistics of the Lithuanian family farms FADN sample according to farm type of farming and economic farm size class are depicted in Table 1.

The development of agri-environmental footprint index (AFI) follows the stages outlined by OECD-JRC (2008) and Gaviglio et al. (2017). The paper is organized correspondingly. Thus, selection of indicators in dealt with in Section 3.2, data preparation is discussed in Section 3.3, and AFI analysis proceeds in Section 4.

3.2. Selection of agri-environmental performance indicators

Based on scientific literature review on farm environmental performance (Purvis et al., 2009) and sustainability (Hani et al., 2003; Zahm et al., 2008; Gaviglio et al., 2017; Sulewski and Kłoczko-Gajewska, 2018) the main themes/components for farms agri-environmental performance assessment were derived, namely agricultural practices, energy, diversity, organisation of spaces, natural resources, farmer's agricultural skills. Then the data availability were analysed in the Lithuanian FADN. When constructing the AIs based on the FADN data, it is important to find proxy indicators for variables used in the literature due to data inconsistency. In order to cover the selected components for

Table 1
Main characteristics of the family farms across farming types and economic size classes.

	Number of observations	Number of farms represented	Economic farm size (thou. EUR SO) average±SD [min/max]	UAA (ha) average±SD [min/max]	AWU average±SD [min/max]	LU average±SD [min/max]
Farming type						
COP	490	17,070	44.3±80.8 [4.0/1,451.3]	75±118 [7.5/1,807.0]	1.5±1.1 [1.0/30.1]	1.5±4.4 [0.0/79.8]
Field crops	100	3,452	22.9±60.8 [4.0/1,245.0]	30±62 [2.6/1,206.7]	1.5±1.1 [0.4/18.3]	1.1±3.1 [0.0/29.3]
Horticulture	31	740	27.3±84.7 [5.4/1,016.5]	11±26 [0.2/324.8]	1.9±2.5 [0.7/22.9]	0.3±0.5 [0.2/1.4]
Orchards	30	320	25.9±29.4 [4.0/145.2]	34±32 [3.1/161.8]	1.7±0.6 [0.4/2.8]	0.1±0.5 [0.0/2.1]
Dairying	313	18,042	23.1±42.5 [4.7/1,619.6]	28±40 [2.3/978.1]	1.6±0.8 [1.0/32.2]	15.2±28.9 [1.9/879.1]
Grazing livestock	102	4,461	14.0±15.4 [4.0/229.8]	34±34 [5.9/332.9]	1.5±0.5 [1.0/5.4]	17.6±22.3 [2.3/288.7]
Granivores	15	45	130.9±227.3 [9.0/823.9]	32±63 [0.0/333.0]	2.6±2.2 [1.0/11.9]	129.0±220.6 [4.4/796.4]
Field crops-grazing livestock	162	7,669	22,0±48.5 [4.2/983.2]	43±58 [4.0/1,000.6]	1.4±0.9 [1.0/20.1]	11.8±21.8 [1.0/356.6]
Various crops and livestock	57	6,819	9,3±8.9 [4.0/255.9]	13±15 [0.0/345.4]	1.3±0.4 [0.4/6.7]	4.4±6.2 [0.0/103.6]
Farm economic size, thou. EUR SO						
2–8	99	24,289	6.5±1.2 [4.0/8.0]	12±10 [0.2/81.0]	1.3±0.3 [0.4/2.8]	3.1±2.9 [0.0/16.2]
8–25	277	21,487	13.9±4.2 [8.0/25.0]	27±16 [0.0/117.2]	1.4±0.5 [0.4/5.1]	6.6±6.8 [0.0/39.6]
25–0	222	5,990	36.5±6.7 [25.0/49.7]	62±33 [2.1/271.0]	1.5±0.5 [1.0/3.7]	14.3±16.2 [0.0/109.3]
50–100	252	3,793	70.8±14.9 [50.0/99.9]	105±42 [6.9/300.1]	1.8±0.6 [1.0/4.4]	20.2±25.4 [0.0/139.0]
100–500	279	2,919	183.3±83.5 [100.0/499.4]	246±123 [2.5/783.5]	3.3±2.0 [1.0/9.6]	39.2±62.6 [0.0/288.7]
>500	171	140	736.3±238.7 [502.1/1,619.6]	847±399 [0.0/1,807.0]	10.6±6.1 [2.2/32.2]	89.1±190.0 [0.0/879.1]
Total	1,300	58,618	27.0±57.4 [4.0/1,619.6]	42±77 [0.0/1,807.0]	1.5±0.9 [0.4/32.2]	8.7±21.4 [0.0/879.1]

farms' agri-environmental assessment, the accessibility and farms participation in agri-environmental programs were approximated based on the continuous monetary variables (Purvis et al., 2009; Westbury et al., 2011). Note that one should avoid excessive use of the dichotomous indicators (Purvis et al., 2009). Ideally, the developed indicators should be RACER: Relevant, Accepted, Credible, Easy, and Robust (Wieck and Hausmann, 2019). There is no developed and publically available tool (as a user-friendly spreadsheet) based on FADN to calculate Greenhouse Gas (GHG), therefore the calculation of GHGs on farms is not straightforward.

In order to avoid of double counting the same environmental impact element on farms (OECD-JRC, 2008), the nonparametric Spearman tests were performed to examine the relationships between AIs. The result showed a strong relationship for the use of inorganic fertilizers and pesticides and for livestock density and meadows and pastures, with correlations of r = 0.881 and r = 0.753, respectively (Fig. 1). These AIs were included in the final list of indicators as they address different environmental impacts and were proposed to be used together in the literature (Westbury et al., 2011; Kelly et al., 2015; Table 2).

The AIs and the AFIs are designed in order to use them for identification of agri-environmental problem issues on farms, encouraging farmers to achieve better results and monitoring their achievements. Therefore it is important to ensure that AIs are in line with the CAP objectives for 2021–2027 (EC, 2021b) and, especially, AIs coverage of the environmental objectives (see the three objectives listed in Introduction). The AIs developed according to the CAP objective "Contribute to climate change mitigation and adaptation, as well as to sustainable energy" are illustrated in Fig 2.

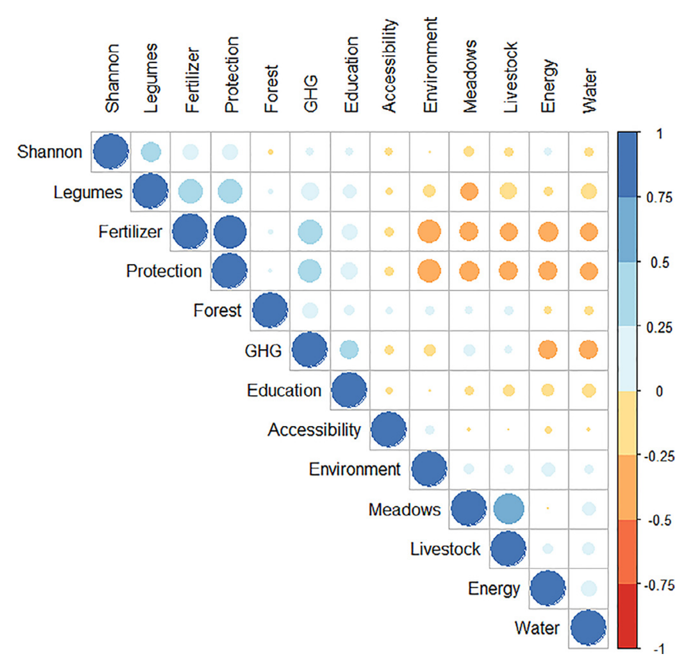

Fig. 1. Correlogram of agri-environmental indicators.

Use of fertilizers

The on-farm use of fertilizers is an essential indicator of environmental impacts caused by agricultural activity (Gaviglio et al., 2017; Czyżewski et al., 2019; Tzouramani et al., 2020). The EU

Table 2
Description and summary statistics of agri-environmental indicators.

Indicator	Dimension	Impact of indicator	Average±SD	Weights	
				PCA	Shannon entropy
Fertilizers use	kg/ha UAA	Min	69.6±110.9	0.08	0.08
Crop protection use	EUR/ha UAA	Min	21.6±51.2	0.07	0.08
GHG emissions	t CO_{2eq}/farm	Min	61.3±126.2	0.12	0.08
Energy intensity	EUR/thou. EUR	Min	130.9±103.1	0.11	0.08
Environment-friendly farming	%	Max	4.7±12.9	0.04	0.08
Water use	EUR/thou. EUR	Min	9.1±10.9	0.08	0.08
Shannon Evenness Index	index	Max	0.7±0.3	0.09	0.08
Legumes area	%	Max	7.6±13.8	0.08	0.08
Meadows and pastures	%	Max	12.7±21.8	0.08	0.08
Livestock density	units/ha forage	Min	0.3±1.8	0.11	0.08
Forest area	%	Max	2.1±7.7	0.06	0.08
Accessibility	score	Max	0.1±0.2	0.02	0.08
Education	score	Max	0.3±0.4	0.05	0.08

Note: min (resp. max) indicates that the minimum (resp. maximum) value indicates better agri-environmental performance.

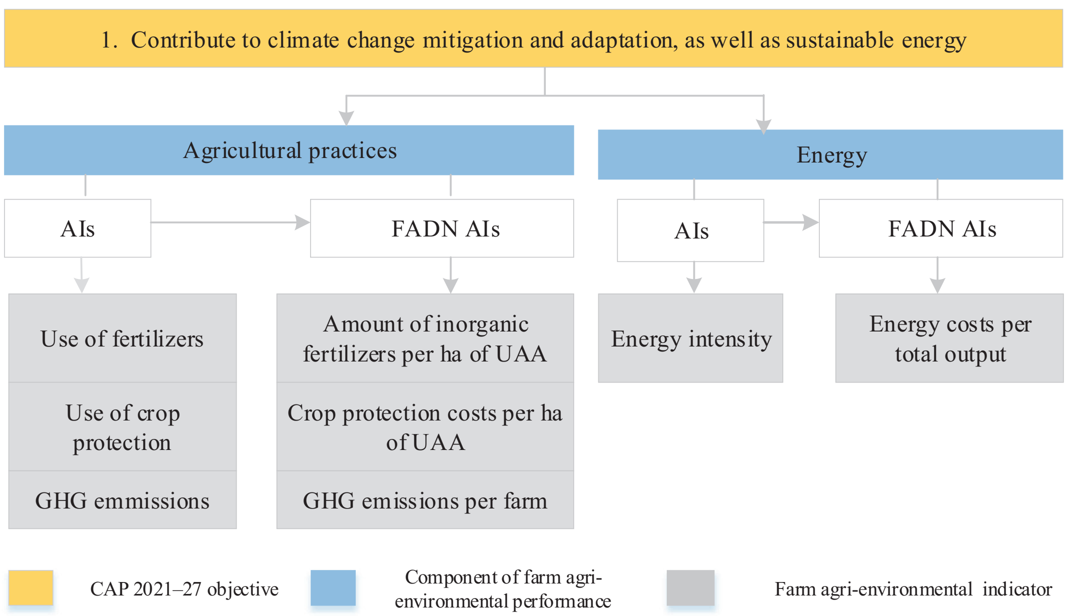

Fig. 2. Agri-environmental indicators linked to Environmental Objective 1.

FADN has been collecting data on the quantities of fertilizers used on farms across the EU Member States since 2017. These data are presented by variables SE296, SE297, and SE298. On Lithuanian farms, on average in 2017–2019, the application rate of inorganic fertilizers was 145 kg per hectare of UAA, by 14 kg more than the EU-28 level (EU FADN, 2021). What is more, in Lithuania the annual growth rate of inorganic nitrogen consumption was 2.8% from 2009 to 2019 (Eurostat, 2021).

The use of crop protection

Crop protection products (herbicides, fungicides and insecticides) use on farms measured as costs per hectare or per output, pesticide treatment index, pesticide usage were analysed by scholars (Sauvenier et al., 2007; Vesterager et al., 2012; Uthes and Herrera, 2019).

In 2009–2019, on average, on Lithuanian farms the costs for crop protection per hectare of UAA amounted to EUR 43 and it was 1.9 times lower than the EU-28 average. However the crop protection costs rose at an annual growth rate of 4.2% on Lithuanian farms during 2009–2019 (EU FADN, 2021).

GHG emissions

The GHGs on farms in previous studies were measured using indicators like GHGs per farm and per output, and GHGs balance (Lynch et al., 2018; Uthes and Herrera, 2019; Tzouramani et al., 2020). For present research GHG emission per farm was taken into account. See Dabkienė et al. (2020) for an in-detail description of GHG emission calculation.

Lithuanian agricultural sector is the second most significant source of GHGs in Lithuania and accounted for 21.1% of the total emissions in 2018. Agricultural sector is the main contributor of CH_4 and N_2O emissions, which originate from enteric fermentation and agricultural soils, respectively. The reduction of GHG emissions in Lithuanian agricultural sector (including the absorption from Land Use, Land-Use Change and Forestry sector) to 25% by 2030 compared to the reference year of 2005 is set in the National climate change management agenda (LRS, 2021). In 2018 the Lithuanian agricultural emissions (sectors 3.A, 3.B, 3.C, 3.D, 4.C and 4.B) were 22.7% higher than in 2005 (Eurostat, 2021).

Energy intensity

Various indicators related to energy use on farms can be developed (Sauvenier et al., 2007; Vesterager et al., 2012;

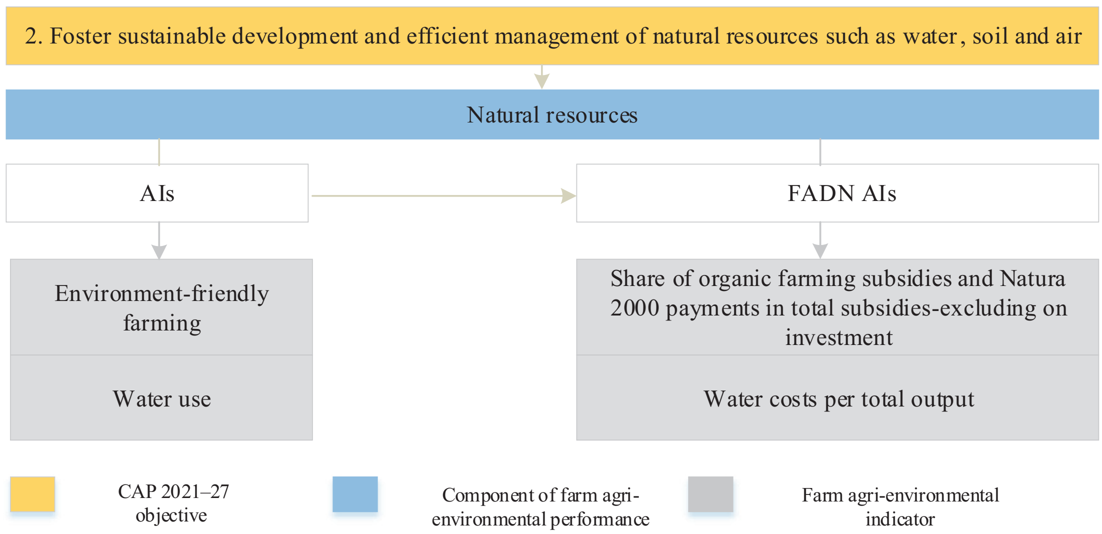

Fig. 3. Agri-environmental indicators linked to Environmental Objective 2.

Czyżewski et al., 2019). The Lithuanian FADN provides the information related to the costs of electricity and fuel on farms. The energy costs (EUR) per total output (thousand EUR) during the 2009–2019 experienced a negative annual growth rate of 1.0%, however in the Lithuanian farms the energy use intensity was 42% higher than the EU-28 average (EU FADN, 2021).

The AIs linked to the CAP specific objective “Foster sustainable development and efficient management of natural resources such as water, soil and air” are presented in Fig 3.

Environmental-friendly farming

Farmers’ participation in agri-environmental programs is a key element of farms sustainability assessment (Areal et al., 2018; Uthes and Herrera, 2019). In Lithuania the UAA area fully converted to organic farming rose at an annual growth rate of 9.8% between 2012 and 2019 (Eurostat, 2021).

Water use

Water intensity measure was taken into account by researchers (Westbury et al., 2011; Gaviglio et al., 2017; Tzouramani et al., 2020) emphasizing water resource protection and adequate use on farms and its importance to farms’ sustainability. The regulation of flooding and runoff is a problem in the Lithuanian agriculture (EC, 2020a). Lithuanian farmers have favourable conditions for water use (LRS, 2020) and it is common to use water for irrigation from ponds and streams, therefore water use measured in volume from all sources would be fairer and more targeted.

The AIs related to the CAP specific objective “Contribute to the protection of biodiversity, enhance ecosystem services and preserve habitats and landscapes” are shown in Fig. 4.

Shannon Evenness Index

A plethora of indicators is proposed by researchers to evaluate the biodiversity on farms. In the present paper the Shannon Evenness Index was opted. The areas of twenty eight land use elements are collected by Lithuanian FADN. Small farms are essential in terms of supporting agricultural biodiversity (Guarín et al., 2020). Therefore, in the present research, the maximum level of biodiversity was assumed for farms up to 5 hectares of UAA irrespectively of the land use structure. For the rest of farms, the Shannon Diversity and Evenness Indices were calculated according to Shannon and Weaver (1949):

$$H_S = -\sum_{l=1}^{L} p_l \ln p_l \,, \tag{1}$$

$$E_S = \frac{H_S}{H_S^{\max}} = \frac{H_S}{\ln L}, \tag{2}$$

where H_S is the Shannon diversity index, p_l is the surface proportion of land use element l; L is the number of different land use elements, E_S is the Shannon Evenness Index. E_S takes values from zero (when a single land use element dominates) and one (when all land use elements are equally abundant). In Lithuania, biodiversity measured by common farmland bird index declined at an annual rate of 2.9% over 2009–2019 and in 2019 was by 38.3 percentage points lower compared to the reference year (2000=100) (Eurostat, 2020).

Legumes area

The benefits of legumes to the sustainability of agriculture has been extensively analysed by Stagnari et al. (2017). The use of legumes in crop rotations as a wish indicator was introduced by Kelly et al. (2015). The annual growth rate in the incline of the area of legumes accelerated to 9.9% during 2010–2020 in Lithuania (Statistics Lithuania, 2021).

Meadows and pastures

In order to measure the environmental sustainability of farms, the grassland area was included in the indicator set in lines with the previous studies (Vesterager et al., 2012; Barnes and Thomson, 2014; Areal et al., 2018). Between 2009 and 2019, the area of permanent grasslands rose at an annual growth rate 7.3 % in Lithuanian family farms (EU FADN, 2021). Soussana et al. (2010) emphasized the role of grasslands in terms of carbon sequestration and the mitigation of GHGs, namely partly offsetting the emissions generated by ruminant production systems. In Lithuania, this potential decreased by 27.4% in 2019, as compared to 2009 (Eurostat, 2021).

Livestock density

A high livestock density often causes large nitrogen and phosphorus surpluses (Svanbäck et al., 2019). The environmental impact of livestock density to farms environmental performance was evaluated in several studies (Westbury et al., 2011; Gerrard et al.,

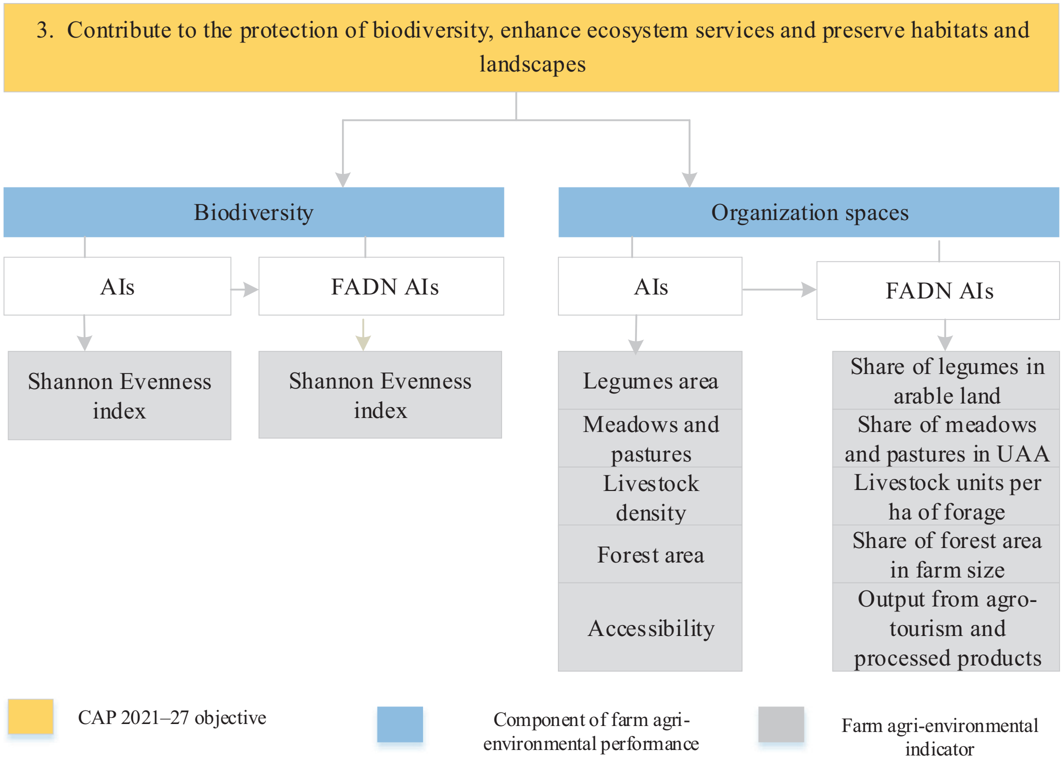

Fig. 4. Agri-environmental indicators linked to Environmental Objective 3.

2012; Czyżewski et al., 2019). In Lithuania, total livestock units per hectare of forage area per farm declined at an annual growth rate of 2.6% over the 2009–2019 (EU FADN, 2021). This was essentially caused by a decrease of cattle number during 2009–2019 at annual growth rate of 1.7% (Statistics Lithuania, 2021).

Forest area

Forest area on farm holdings has been acknowledged as a contributor to environmental sustainability by Purvis et al. (2009), Westbury et al. (2011), and Migliorini et al. (2018). In Lithuanian family farms, the share of forest area in the total farm area per farm remained stable during 2009–2019 at around 2.7% (LAEI, 2021).

Accessibility

The evaluation of farms accessibility in terms of recognition and conservation of agricultural heritage systems was included in environmental performance evaluation in several studies (Purvis et al. 2009; Vesterager et al., 2012, Goswami et al., 2017). The preservation of traditional production/processing methods on Lithuanian family farms was assessed as a binary indicator (yes-no) indicating the output on farms generated from agro-tourism and processed products. The output of agro-tourism share in the total output per Lithuanian farm constituted only 0.12% over 2009–2019 (EU FADN, 2020).

The proposed set of the AIs covers CAP 2021–2027 cross-cutting objective "Foster knowledge, innovation, digitalization in agriculture and rural areas" by taking into account **farmers' level of education.** The education level of farmers has a positive impact on farms' environmental sustainability (Sulewski and Kłoczko-Gajewska, 2018). In line with the information provided in Lithuanian FADN (farmer with full agricultural training, basic training and with practical experience only) the present research used a three-value scale (1, 2, 3) to measure farmer's education.

3.3. Multi-criteria analysis

The Multi-Criteria Decision Making (MCDM) procedure involves the three key elements: (i) regularization; (ii) normalization, (iii) weighting, and (iv) aggregation. The normalization ensures comparability across the criteria. The weighting allows taking the preferences of the decision maker(s) into account. The aggregation returns a single number that can be used for benchmarking.

3.3.1. Regularization

The decision matrix comprises the data for all farms indexed over $i = 1, 2, \ldots, I$ and indicators indexed over $j = 1, 2, \ldots, J$. Prior to the construction of the composite scores, the data are regularized by modifying the extreme values for each indicator. Let there be lower and upper quantiles, q_{l_i} and q_{u_i}, chosen for a certain variable i, where $0 \le l_i < u_i \le 1$. Then, the values below q_{l_i} are equated to the lower quantile and those above q_{u_i} are related to the upper quantile:

$$x^*_{ij} = \begin{cases} q_{l_i}, x_{ij} < q_{l_i}, \\ x_{ij}, q_{l_i} \le x_{ij} \le q_{u_i}, \\ q_{u_i}, x_{ij} > q_{u_i}. \end{cases} \quad (3)$$

In our case, we set $l_i = 0.05$ and $u_i = 0.95$ for $i = 1, 2, ..., m$. This implies that 5% highest and 5% highest values of each indicator are replaced by the 5-th and 95-th percentiles respectively. Note that the regularization is not applied for categorical variables.

3.3.2. Normalization

The decision matrix comprises the data for all farms indexed over $i = 1, 2, \ldots, I$ and indicators indexed over $j = 1, 2, \ldots, J$. The indicators are expressed in different dimensions and oriented towards different directions (maximization or minimization). The benefit criteria need to be maximized (these are denoted by $B \subseteq j$), whereas the cost criteria need to be minimized (denoted by $C \subseteq j$) in order to improve the sustainability of a certain farm. There have been a number of normalization techniques proposed (Vafaei et al., 2016).

Linear normalization with respect to the maximum is carried out with respect to the extreme values observed for each criterion. In this case, the maximum is considered. The other values of the indicators are disregarded, i.e., data range or distribution is not taken into account. For cost criteria, the negation and subtraction from unity (i.e., maximum possible value) is applied. The linear normalization with respect to maximum is defined as follows (Vafaei et al., 2016):

$$\hat{x}_{ij} = \begin{cases} x^*_{ij}/\max_i x^*_{ij},\ j \in B \\ 1-\left(x^*_{ij}/\max_i x^*_{ij}\right),\ j \in C \end{cases}, \tag{4}$$

where $\hat{x}_{ij}$ is the normalized value bounded at 1 from above.

3.3.3. Weighting

The weighting can be either subjective or objective (data-driven). The equal weighting can be considered as the simplest subjective instance where decision is taken to assume all the criteria are equally important. The data-driven approaches can follow a number of statistical techniques. In this paper, we consider the entropy and PCA weights. The entropy weights maximize the variation in the data without considering the correlation among the criteria. The PCA seeks to exploit the correlation among the criteria.

The Shannon entropy is a popular tool to identify the weights. It attaches higher importance on the criteria that show higher variation across the alternatives (farms). The entropy-based weights are obtained via the four-step procedure (Wang and Lee, 2009; Shemshadi et al., 2011). In our study, we are interested in weighting indicators comprising the AFI. The construction of the weights based on the Shannon entropy proceeds as follows:

Step 1. The original data are scaled with respect to the sums of the columns of the decision matrix to construct the evaluation matrix for measurement of the entropy:

$$x^{**}_{ij} = \frac{x_{ij}}{\sum_{i=1}^{I} x_{ij}}, \tag{5}$$

For zero values of x^{**}_{ij}, a small number κ is added (we set $\kappa = 0.1$).

Step 2. The entropy is calculated for values obtained in Eq. 5:

$$e_j = -\frac{1}{\ln I}\sum_{i=1}^{I} x^{**}_{ij}\ln x^{**}_{ij}. \tag{6}$$

Step 3. The entropy scores from Eq. 6 are inverted:

$$d_j = 1 - e_j. \tag{7}$$

Step 4. The weights are calculated by normalizing the values of d_j with respect to their sum:

$$w^E_j = d_j / \sum_{j=1}^{J} d_j. \tag{8}$$

The Principal Component Analysis weighting finds the loadings of the criteria under consideration on the principal components explaining the variation of the data in the decision matrix. The weights for environmental performance indicators are computed using rotated factor loadings and eigenvalues in two steps. First, the squared loadings are normalized with respect to the sum of the eigenvalues of the factors retained after the rotation. The maximum values are identified for each criterion:

$$b_j = \max_k \frac{a^2_{jk}}{\sum_{k=1}^{K}\lambda_k} \tag{9}$$

where a_{jk} is the factor loading of indicator j on principal component k; λ_k - eigenvalue of principal component k. Second, the PCA-based weights are calculated as shown in the following equation:

$$w^P_j = \frac{b_j}{\sum_{j=1}^{J} b_j}, \tag{10}$$

where w^P_j - weight of the j-th indicator based on the PCA. Note that principal components with eigenvalues above 1 are kept in the analysis.

3.3.4. Aggregation

The weighted normalized decision matrix needs to be aggregated across the criteria so that the sustainability of each farm could be expressed by a single dimensionless number. This allows establishing the ranking of the farms. The two basic approaches can be considered: the additive and multiplicative utility functions (Chakraborty and Zavadskas, 2014). Here, we rely on additive aggregation.

The additive aggregation can be related to the Simple Additive Weighting approach. The linear combination of the normalized values is used to construct the composite indicator:

$$y_i = \sum_{j=1}^{J} w_j \hat{x}_{ij}, \tag{11}$$

where w_j is the weight of the j-th criterion chosen from entropy weighting or PCA weighting and $\hat{x}_{ij}$ is the normalized value obtained by either maximum linear normalization. Higher values of y_j indicate higher environmental sustainability of a farm.

The descriptive statistics for the AIs and the weights obtained by PCA and the Shannon entropy are presented in Table 2. As one can note, Shannon entropy weights are basically equal due to the data structure. The rounding errors are present as the weights are actually lower than 0.08.

Values of the AFI closer to one indicate a higher level of agri-environmental performance of farm within farms sample. Besides the average values, the distribution of the AFI is also important for decision making. In order to classify farms according to the obtained values of the AFI, the three levels of environmental performance (low, medium and high) are defined in terms of average value and standard deviation of the AFI. Rather than simply dividing the resulting range of the AFI into three equal parts, a statistical approach is followed (Kasztelan and Nowak, 2021). Thus, one standard deviation is chosen as the threshold for delineating the farm performance levels with respect to the average value. Note that one standard deviation is considered as a sufficient distance in our case, yet further studies could embark on picking some different values as well. The lower (resp. upper) bound for the medium level AFI was defined as the average value minus (resp. plus) one standard deviation. The values falling below (resp. above) the lower (resp. upper) bounds represented low (resp. high) levels of the AFI.

4. Results and discussion

The results for the whole Lithuanian family farms sample showed that farmers' participation in agri-environmental programs and diversification of farming activity was low (Fig. 5). The normalized values of the fertilizers use per hectare of UAA ranged

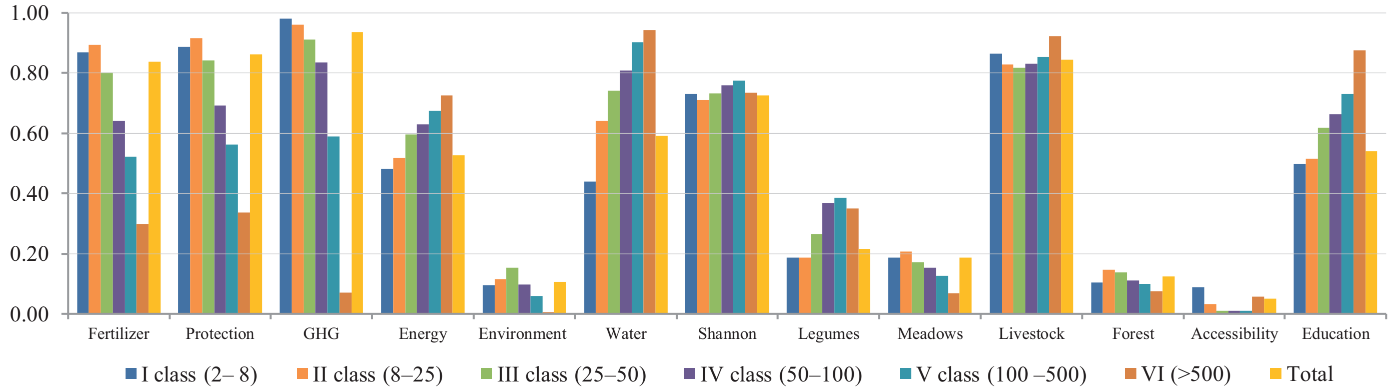

Fig. 5. Normalized agri-environmental indicators across economic farm size classes.

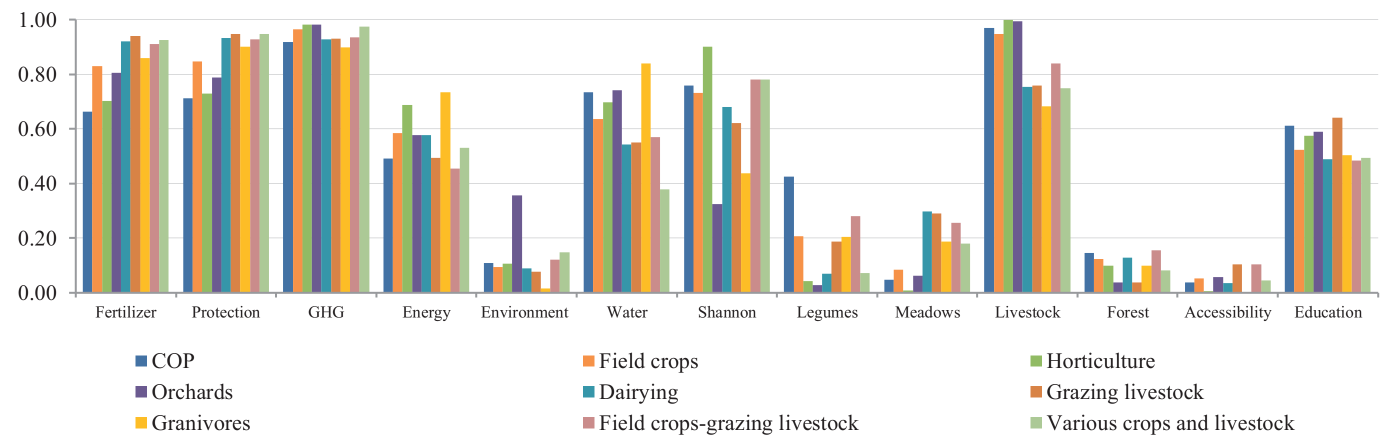

Fig. 6. Normalized agri-environmental indicators across farming types.

from 0.30 to 0.89, in economic farm size classes VI and II, respectively. The same tendency is observed for the use of the crop protection products on farms. The GHG emissions normalized values decrease with the economic farm size class. Even so, the large differences are observed between farms in economic size classes V and VI. The energy and water use intensity and the education of farmers follow the opposite trend and the normalized values increase with the economic farm size class. The energy use intensity findings are in line with Westbury et al. (2011). The uptake of agri-environmental production methods was mostly performed by farms with SO of 25–50 thousand EUR. The normalized values of Shannon's Evenness Index and legumes area in arable land increased within 25–500 thousand EUR SO farms. The Shannon's Evenness Index values were relatively similar in the observed farm size classes and this result is in line with Uthes et al. (2020). Westbury et al. (2011) identified a direct relationship of farm size in hectares and land use diversity and this could be tested empirically in future research in the Lithuanian case. The normalized values of the meadows and pastures area in UAA ranged from 0.07 for farms with more than 500 thousand EUR SO up to 0.21 for farms with 8–25 thousand EUR SO. Farms of 25–50 thousand EUR SO had the lowest livestock density. The spread of normalized values of forest area in total farm area across economic farm size classes was low with values ranging from 0.08 for the largest farms with SO exceeding 500 thousand EUR to 0.15 for farms with SO of 8–25 thousand EUR. The smallest farms with SO of 2–8 thousand EUR were most open for tourists and most engaged in food processing (that is represented by the accessibility indicator).

The highest levels of inorganic fertilizers and crop protection products use per hectare were found on COP farms followed by horticulture farms, whereas the lowest levels were achieved on grazing livestock and various crops and livestock combined farms (Fig. 6). These results are in line with the findings by Gerrard et al. (2012) where English horticultural farms spent most for fertilizers and crop protection products. Normalized indicator values of GHG emissions per farm ranged from 0.90 to 0.98 for granivore and orchards farms, respectively. The GHG emissions on granivore farms did not reach the highest level within considered farming types in a study by Dabkienė et al. (2020). These differences could be related to the small sample of those farms in FADN and elimination of outliers in the present research. The highest energy intensity (energy costs per total output) was found for field crops-grazing livestock combined farms, while the lowest energy intensity was identified for granivore farms. The agri-environmental schemes were adopted most in orchards farms, while least in granivore farms. The lowest water use intensity (costs per total output) was on granivore farms, the highest intensity was observed for various crops and livestock farms. The Shannon's Evenness index ranges from 0.32 to 0.90, on orchards and horticulture farms, respectively. A low land use diversity obtained by livestock farms agree well with results obtained by Gerrard et al. (2012). The lowest level of land use biodiversity for orchards farms is obtained due to limited data availability in the Lithuanian FADN database on tree varieties on these farms. The data availability in database for biodiversity assessment is highlighted in previous studies based on FADN data (Uthes et al., 2020).

The highest share of legumes in arable land was found on COP farms. The lowest value of legumes area achieved by orchards farms can be linked to the first CAP pillar support requirements (when only the orchards area on a farm is declared, a farm ful-

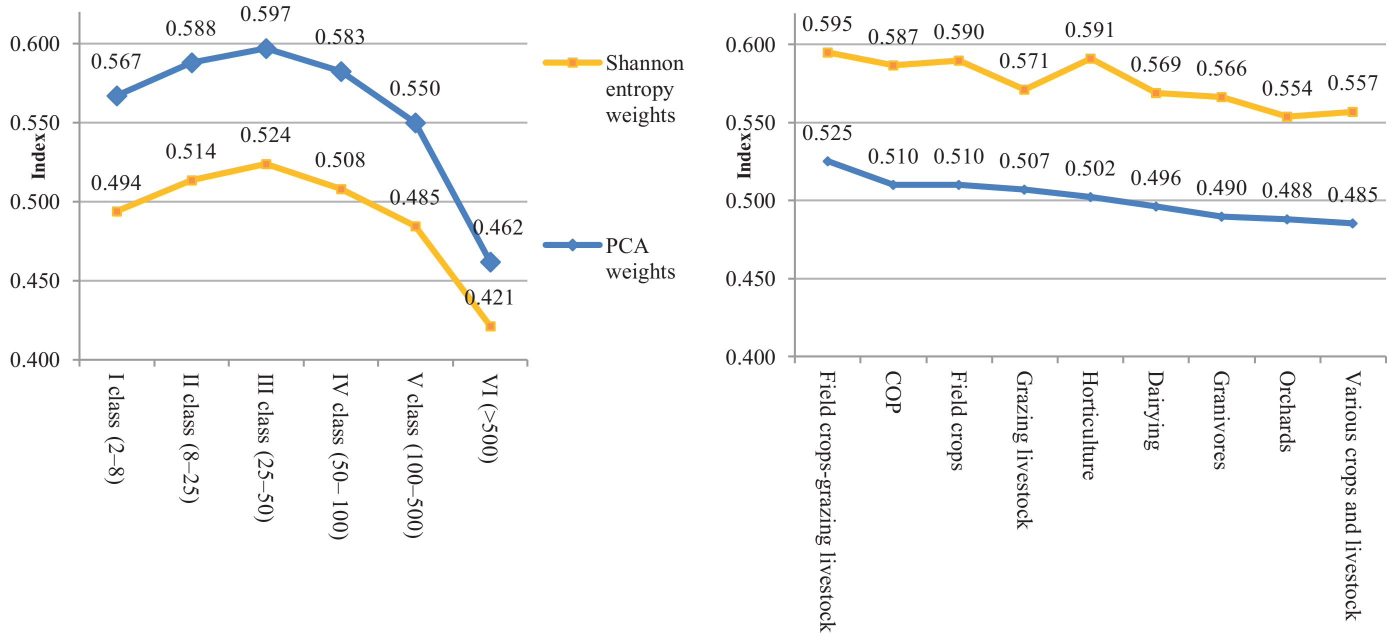

Fig. 7. Agri-environmental footprint indices by type of farming and economic farm size.

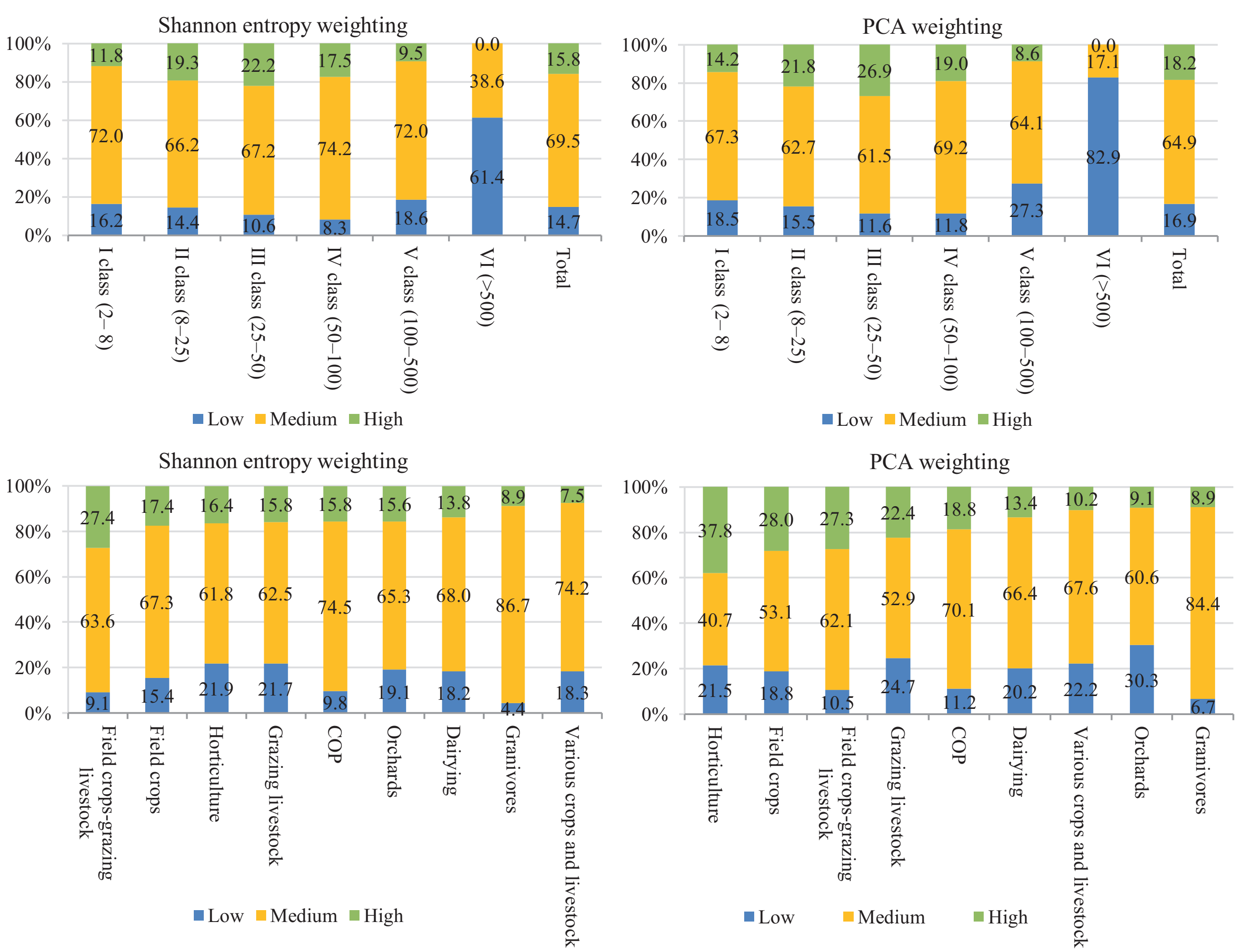

Fig. 8. Distribution of the agri-environmental footprint indices.

fils the greening payment requirements). The results of the ratio of meadows and pastures to UAA across types of farming are associated with farms specialization: the highest ratio is observed for dairying and grazing livestock farms, whilst the lowest ratio for horticulture farms. The livestock density was the most environmentally unfavourable on granivore farms, whereas the most environmentally favourable density was on horticulture and orchards farms. The forest area is small in all farms and normalized values ranged from 0.04 (on grazing livestock farms) to 0.15 (on COP and field crops-grazing livestock farms). The conservation of traditional heritage was developed mostly in grazing livestock and field crops-grazing livestock farms and least in granivore farms. Within types of farming a better agricultural education had farmers specialized in grazing livestock.

The entropy- and PCA-based AFIs initially increase their values with economic farm size (until 50 thousand EUR is reached) and then decline. Thus, the medium-sized farms were found to be the most environmentally beneficial. This result agrees to some extent with findings by Czyżewski et al. (2019). The most favourable agri-environmental performance was achieved by field crops-grazing livestock farms using both weighting approaches. At the other end of the scale, the lowest agri-environmental performance was found for various crops and livestock and orchards farms, using Shannon entropy and PCA, respectively (Fig. 7). The differences in AFIs were larger among economic farm size classes than among farming types. The average AFI values (irrespectively of the weighting used) for all farming types fell within the medium agri-environmental performance level (interval), whereas the low level was observed for the largest farms as their AFIs were below the lower bound of the medium interval threshold ($AFI_S < 0.43$; $AFI_{PCA} < 0.51$).

Approximately two-thirds of Lithuanian family farms fell into the medium agri-environmental performance category (Fig. 8) which can be related to the law of normal distribution. These measures are relative to the sample average. The position of Lithuanian average performance among the other countries can be ascertained by considering earlier results reported by Dos Santos and Ahmad (2020) who put the New Eastern Member States (including Lithuania) in the stratum of moderate environmental sustainability. Even worse results were obtained by Kasztelan and Nowak (2021) who ranked Lithuanian agricultural sector as the second last out of twenty EU Member States. In order to alleviate environmental pressures rendered by farm activities, the actions are needed across different farm groups. The low agri-environmental performance farm groups identified in this study can be the primal objective of the agricultural support programmes. The highest share of farms with a low level agi-environmental performance is registered on the largest farms class (SO, thousand EUR > 500) and specialized in horticulture (using Shannon entropy weighting) and orchards (using PCA weighting).

The major issues related to the index construction are selection of the criteria, weighting normalization and aggregation methods. These are pertinent to the main stages of index construction and may have an impact to the final results index (Talukder et al., 2017; Greco et al., 2019). Different approaches towards normalization and aggregation of indicators into the final score were tested by Talukder et al. (2017) who concluded that the design of approach lies with the researcher and usually depends on the properties of the dataset. Greco et al. (2019) emphasized the robustness analysis in each stage of index construction as a quality assurance tool. The influence of the weighting approach to the constructed indices can be tested by the correlation analysis (Talukder et al., 2017).

The Pearson correlation coefficient ($r = 0.950$) between the AFIs based on the PCA and entropy weights is rather high. Thus, the differences rendered by the use of the different methods for construction of the weights are more of a quantitative nature rather than qualitative. Still, the ranking of, e.g., farming types based on the point estimates of the average AFI scores differ across the two weighting schemes. Thus, the use of the different weighting methods and interpretation of the results requires certain caution.

5. Conclusions

This article presented the agri-environmental indicators and footprint index methodology for assessing agri-environmental performance in agriculture at farm level. The agri-environmental footprint index is based on 13 constructed indicators which are adjusted to Farm Accountancy Network data. The agri-environmental indicators and footprint index methodology allows the comparison of the agri-environmental performance situation and changes in various farm groups. In addition, the stakeholders (farmers, researchers, policy-makers and public) can identify the environmental impacts of farms with the highest pressure on the environment. Moreover, the policy interventions (in particular, the second pillar payments) can be directed more precisely towards implementation of sustainable farm management solutions in a certain group of farms.

In Lithuania, the most environmentally beneficial farms are medium-sized ones (in terms of economic size measured by the Standard Output) and those specialized in field crops-grazing livestock. The highest share of farms with a low value of agri-environmental footprint index was found in the largest farm size class and farms specialized in horticulture (using Shannon entropy weighting) and orchards (using Principal Component Analysis weighting). The values of the agri-environmental footprint indices for approximately two-thirds of the Lithuanian family farms were close to average value, i.e., within the range of one standard deviation value.

Two agri-environmental footprint indices were computed, using Shannon entropy and Principal Component Analysis weighting approaches. The results of agri-environmental footprint indices using Shannon entropy and Principal Component Analysis weighting tended to differ. Therefore, future farm sustainability research should test different weighting schemes and, possible, involve expert judgements to ensure the robustness. The most cost-effective way is to use the results of the experts' survey assessing the needs of the national Common agricultural Policy Strategic Plan. One of the key steps towards the national Strategic Plan development is prioritisation and ranking of the sector's needs by stakeholders. The ranks are provided separately to specific objectives of the Common Agricultural Strategic Plan within the sustainability dimension (economic, environmental, and social) and to the needs (problem areas) within each specific objective. As an outcome, the obtained ranking could serve as weights for given components (indicator group) or indicator of farms agri-environmental performance assessment.

Several suggestions for agricultural support policy can be made based on the results of this study. Horticultural farms in Lithuania (along with other groups of environmentally underperforming farms) could be assigned with additional priority points when distributing the support payments (especially, the second pillar measures). In general, to effectively cope with environmental pressures related to farming, we recommend evaluating the situation across different farm groups and avoid implementing "one-size-fits-all" solutions. Moreover, educational programmes and advisory services should emphasize farmers' role in adopting climate-friendly practices. The assessment tools of agri-environmental performance benchmarking at the farm level could be designed in order to make farmers familiar with their performance and facilitate mutual learning.

Although the present research focuses on a single-year data, the developed agri-environmental footprint index can be considered a useful tool for panel data as well. As regards data normalization, future research could embark on applying the reference values (e.g., standards and norms or values obtained from an expert panel) for a multi-criteria assessment. Besides, future research could focus on the assessment of the policy interventions targeted to certain aspects of farm environmental performance. The AFI obtained via the multi-criteria assessment would serve as a benchmark. Moreover, future research could seek to perform an international comparison by using the developed set of indicators for analysing the agri-environmental performance of farms in the other European Union Member States. Also, the developed indicators could serve as a block of a wider system of agricultural sustainability indicators.

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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References

Areal, F.J., Jones, P.J., Mortimer, S.R., Wilson, P., 2018. Measuring sustainable intensification: combining composite indicators and efficiency analysis to account for positive externalities in cereal production. Land Use Policy 75, 314–326. doi:10.1016/j.landusepol.2018.04.001.

Bachev, H., 2017. Socio-economic and environmental sustainability of Bulgarian farms. Agricult. Resour. Econ. 3 (№ 2), 5–21.

Baldock, D., 2020. Locating the CAP in an escalating green agenda. Italian Rev. Agricult. Econ. 75 (3), 13–18. doi:10.13128/rea-12704.

Barnes, A.P., Thomson, S.G., 2014. Measuring progress towards sustainable intensification: how far can secondary data go? Ecol. Indic. 36, 213–220. doi:10.1016/j.ecolind.2013.07.001.

Chakraborty, S., Zavadskas, E.K., 2014. Applications of WASPAS method in manufacturing decision making. Informatica 25 (1), 1–20.

Czyżewski, B., Matuszczak, A., Muntean, A., 2019. Approaching environmental sustainability of agriculture: environmental burden, eco-efficiency or eco-effectiveness. Agricult. Econ. 65 (7), 299–306. doi:10.17221/290/2018-AGRICECON.

Dabkienė, V., Baležentis, T., Štreimikienė, D., 2020. Estimation of the carbon footprint for family farms using the Farm Accountancy Data Network: a case from Lithuania. J. Cleaner Prod. 121509. doi:10.1016/j.jclepro.2020.121509.

Diti, I., Tassinari, P., Torreggiani, D., 2015. The agri-environmental footprint: a method for the identification and classification of peri-urban areas. J. Environ. Manage. 162, 250–262. doi:10.1016/j.jenvman.2015.07.058.

Santos, Dos, L., M.J.P., Ahmad, N, 2020. Sustainability of European agricultural holdings. J. Saudi Soc. Agricult. Sci. 19 (5), 358–364. doi:10.1016/j.jssas.2020.04.001.

EC (European Commission). 2019a. CAP context indicators –2019 update. https://ec.europa.eu/info/food-farming-fisheries/farming/facts-and-figures/performance-agricultural-policy/cap-indicators/context-indicators_en. Accessed 8 October 2020.

EC (European Commission). 2019b. The European Green Deal. https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=COM%3A2019%3A640%3AFIN. Accessed 8 March 2021.

EC (European Commission). 2020a. Commission recommendations for Lithuania's CAP strategic plan. https://eur-lex.europa.eu/legal-content/EN/TXT/HTML/?uri=CELEX:52020SC0395&rid=9#endnote7. Accessed 8 March 2021.

EC (European Commission). 2020b. EU 2030 Biodiversity strategy. https://ec.europa.eu/commission/presscorner/detail/en/fs_20_906. Accessed 8 October 2020.

EC (European Commission). 2020c. Farm to fork strategy – for a fair, healthy and environmentally-friendly food system. https://ec.europa.eu/food/farm2fork_en. Accessed 8 October 2020.

EC (European Commission). 2021a. Agri-environmental indicators. https://ec.europa.eu/eurostat/web/agriculture/agri-environmental-indicators. Accessed 8 October 2020.

EC (European Commission). 2021b. Key policy objectives of the future CAP. https://ec.europa.eu/info/food-farming-fisheries/key-policies/common-agricultural-policy/future-cap/key-policy-objectives-future-cap_en. Accessed 8 March 2021.

EC (European Commission), 2021c. RICC 1750 Standard Results v Sep 2020 https://circabc.europa.eu/ui/group/880bbb5b-abc9-4c4c-9259-5c58867c27f5/library/17a3cb1f-8199-4df2-b857-161fefc4c857/details.

EU FADN, 2021. FADN public database https://ec.europa.eu/agriculture/rica/database/database_en.cfm.

Eurostat., 2021. Eurostat Database https://ec.europa.eu/eurostat/data/database.

Garske, B., Ekardt, F., 2021. Economic policy instruments for sustainable phosphorus management: taking into account climate and biodiversity targets. Environ. Sci. Eur. 33 (1), 1–20. doi:10.1186/s12302-021-00499-7.

Gaviglio, A., Bertocchi, M., Demartini, E., 2017. A tool for the sustainability assessment of farms: selection, adaptation and use of indicators for an Italian case study. Resources 6 (4), 60. doi:10.3390/resources6040060.

Gerrard, C.L., Padel, S., Moakes, S., 2012. The use of Farm Business Survey data to compare the environmental performance of organic and conventional farms. Int. J. Agricult. Manage. 2 (1), 5–16.

Gómez-Limón, J.A., Sanchez-Fernandez, G., 2010. Empirical evaluation of agricultural sustainability using composite indicators. Ecol. Econ. 69 (5), 1062–1075. doi:10.1016/j.ecolecon.2009.11.027.

Goswami, R., Saha, S., Dasgupta, P., 2017. Sustainability assessment of smallholder farms in developing countries. Agroecol. Sustain. Food Syst. 41 (5), 546–569. doi:10.1080/21683565.2017.1290730.

Greco, S., Ishizaka, A., Tasiou, M., Torrisi, G., 2019. On the methodological framework of composite indices: a review of the issues of weighting, aggregation, and robustness. Social Indicators Res. 141 (1), 61–94. doi:10.1007/s11205-017-1832-9.

Guarín, A., Rivera, M., Pinto-Correia, T., Guiomar, N., Šūmane, S., Moreno-Pérez, O.M., 2020. A new typology of small farms in Europe. Global Food Secur. 26, 100389. doi:10.1016/j.gfs.2020.100389.

Hani, F., Braga, F.S., Stampfli, A., Keller, T., Fischer, M., Porsche, H., 2003. RISE, a tool for holistic sustainability assessment at the farm level. *International food and agribusiness management review*, 6.

Hsu, A., Lloyd, A., Emerson, J.W., 2013. What progress have we made since Rio? Results from the 2012 Environmental Performance Index (EPI) and Pilot Trend EPI. Environ. Sci. Policy 33, 171–185. doi:10.1016/j.envsci.2013.05.011.

Kasztelan, A., & Nowak, A. 2021. Construction and Empirical Verification of the Agri-Environmental Index (AEI) as a Tool for Assessing the Green Performance of Agriculture. *Energies*, 14(1), 45. 10.3390/en14010045.

Kelly, E., Ryan, M., Finn, J., Hennessy, T., 2015. Farm-Level Indicators for Evaluating Sustainability and Emerging New Policy Topics *Flint Project*.

LAEI, 2021. FADN survey results https://www.laei.lt/?mt=vt_UADT_tyrimas.

LRS, 2020. The Underground Law https://e-seimas.lrs.lt/portal/legalAct/lt/TAD/TAIS.19879/asr.

LRS, 2021. National climate change management agenda (project) https://e-seimas.lrs.lt/rs/legalact/TAP/093497e071f511eb9fc9c3970976dfa1/#_ftn17. Accessed 8 March 2021.

Lynch, J., Skirvin, D., Wilson, P., Ramsden, S., 2018. Integrating the economic and environmental performance of agricultural systems: a demonstration using Farm Business Survey data and Farmscoper. Sci. Total Environ. 628, 938–946. doi:10.1016/j.scitotenv.2018.01.256.

... Mauchline, A.L., Mortimer, S.R., Park, J.R., Finn, J.A., Haysom, K., Westbury, D.B., Yli-Viikari, A., 2012. Environmental evaluation of agri-environment schemes using participatory approaches: experiences of testing the Agri-Environmental Footprint Index. Land Use Policy 29 (2), 317–328. doi:10.1016/j.landusepol.2011.07.002.

Meul, M., Van Passel, S., Nevens, F., Dessein, J., Rogge, E., Mulier, A., Van Hauwermeiren, A., 2008. MOTIFS: a monitoring tool for integrated farm sustainability. Agron. Sustainable Dev. 28 (2), 321–332. doi:10.1051/agro:2008001.

Nowak, A., Krukowski, A., Różańska-Boczula, M., 2019. Assessment of sustainability in agriculture of the European Union countries. Agronomy 9 (12), 890. doi:10.3390/agronomy9120890.

, 1993. Core set of indicators for environmental performance reviews. Environmental Monograph, p. 83.

OECD-JRC, 2008. Handbook on Constructing Composite Indicators. Methodology and user guide http://www.oecd.org/std/42495745.pdf.

Overmars, K.P., Schulp, C.J., Alkemade, R., Verburg, P.H., Temme, A.J., Omtzigt, N., Schaminée, J.H., 2014. Developing a methodology for a species-based and spatially explicit indicator for biodiversity on agricultural land in the EU. Ecol. Indic. 37, 186–198. doi:10.1016/j.ecolind.2012.11.006.

... Peeters, A., Lefebvre, O., Balogh, L., Barberi, P., Batello, C., Bellon, S., Wezel, A., 2020. A Green Deal for implementing agroecological systems: Reforming the Common Agricultural Policy of the European Union doi:10.3220/LBF1610123299000.

Purvis, G., Louwagie, G., Northey, G., Mortimer, S., Park, J., Mauchline, A., Knickel, K., 2009. Conceptual development of a harmonised method for tracking change and evaluating policy in the agri-environment: the Agri-environmental Footprint Index. Environ. Sci. Policy 12 (3), 321–337. doi:10.1016/j.envsci.2009.01.005.

... Sauvenier, X., Valckx, J., Van Cauwenbergh, N., Wauters, E., Bachev, H., Biala, K., Peeters, A., 2005. Framework for assessing sustainability levels in Belgium agricultural systems-SAFE.

Shannon, C.E., Weaver, W., 1949. The mathematical theory of communication. University of Illinois Press, Illinois.

Shemshadi, A., Shirazi, H., Toreihi, M., Tarokh, M.J., 2011. A fuzzy VIKOR method for supplier selection based on entropy measure for objective weighting. Expert Syst. Appl. 38 (10), 12160–12167. doi:10.1016/j.eswa.2011.03.027.

Soussana, J.F., Tallec, T., Blanfort, V., 2010. Mitigating the greenhouse gas balance of ruminant production systems through carbon sequestration in grasslands. Animal 4 (3), 334–350. doi:10.1017/S1751731109990784.

Stagnari, F., Maggio, A., Galieni, A., Pisante, M., 2017. Multiple benefits of legumes for agriculture sustainability: an overview. Chem. Biol. Technol. Agricult. 4 (1), 1–13 10.1186/s40538-016-0085-1.

Lithuania, Statistics, 2021. Database of indicators https://osp.stat.gov.lt/statistiniu-rodikliu-analize#/. Accessed 1 March 2021.
Sulewski, P., Kłoczko-Gajewska, A., 2018. Development of the sustainability index of farms based on surveys and FADN sample. Probl. Agricult. Econ. 3 (356). doi:10.30858/zer/94474.
Svanbäck, A., McCrackin, M.L., Swaney, D.P., Linefur, H., Gustafsson, B.G., Howarth, R.W., Humborg, C., 2019. Reducing agricultural nutrient surpluses in a large catchment–Links to livestock density. Sci. Total Environ. 648, 1549–1559. doi:10.1016/j.scitotenv.2018.08.194.
Talukder, B., Hipel, WK., 2018. The PROMETHEE framework for comparing the sustainability of agricultural systems. Resources 7 (4), 74.
Talukder, B., W Hipel, K., W vanLoon, G., 2017. Developing composite indicators for agricultural sustainability assessment: effect of normalization and aggregation techniques. Resources 6 (4), 66. doi:10.3390/resources6040066.
Tzouramani, I., Mantziaris, S., Karanikolas, P., 2020. Assessing Sustainability Performance at the Farm Level: examples from Greek Agricultural Systems. Sustainability 12 (7), 2929. doi:10.3390/su12072929.
Uthes, S., Kelly, E., König, H.J., 2020. Farm-level indicators for crop and landscape diversity derived from agricultural beneficiaries data. Ecol. Indic. 108, 105725. doi:10.1016/j.ecolind.2019.105725.
Uthes, S., Herrera, B., 2019. Farm-Level Input Intensity, Efficiency and Sustainability: A Case Study Based on FADN Farms (No. 2240-2019-3061).
Vafaei, N., Ribeiro, R.A., Camarinha-Matos, L.M., 2016. Normalization techniques for multi-criteria decision making: analytical hierarchy process case study. In: Doctoral conference on computing, electrical and industrial systems. Springer, Cham, pp. 261–269.
Van Cauwenbergh, N., Biala, K., Bielders, C., Brouckaert, V., Franchois, L., Cidad, V. G., Peeters, A., 2007. SAFE—A hierarchical framework for assessing the sustainability of agricultural systems. Agriculture, ecosystems & environment 120 (2–4), 229–242.
Vesterager, J.P., Teilmann, K., Vejre, H., 2012. Assessing long-term sustainable environmental impacts of agri-environment schemes on land use. Eur. J. Forest Res. 131 (1), 95–107. doi:10.1007/s10342-010-0469-x.
Vlontzos, G., Pardalos, P.M., 2017. Assess and prognosticate greenhouse gas emissions from agricultural production of EU countries, by implementing, DEA Window analysis and artificial neural networks. Renewable Sustainable Energy Rev. 76, 155–162. doi:10.1016/j.rser.2017.03.054.
Vlontzos, G., Niavis, S., & Pardalos, P. 2017. Testing for environmental Kuznets curve in the EU agricultural sector through an Eco-(in) efficiency index. *Energies*, 10(12), 1992. doi:10.3390/en10121992.
Vrolijk, H., Poppe, K., Keszthelyi, S., 2016. Collecting sustainability data in different organisational settings of the European Farm Accountancy Data Network. Studies in Agricultural Economics 118 (3), 138–144. doi:10.7896/j.1626.
Wang, J., Ma, Y., Collins, A.R., 2019. Measuring benefits of rural-to-urban water transfer: a case study from Puyang River basin, China. Chin. J. Popul. Resour. Environ. 17 (4), 352–358.
Westbury, D.B., Park, J.R., Mauchline, A.L., Crane, R.T., Mortimer, S.R., 2011. Assessing the environmental performance of English arable and livestock holdings using data from the Farm Accountancy Data Network (FADN). J. Environ. Manage. 92 (3), 902–909. doi:10.1016/j.jenvman.2010.10.051.
Wieck, C., Hausmann, I., 2019. Indicators everywhere: The new accountability of agricultural policy? (No. 2230-2019-1957).
Zahm, F., Viaux, P;, Vilain, L., Girardin, P., Mouchet, C., 2008. Assessing farm sustainability with the IDEA method–from the concept of agriculture sustainability to case studies on farms. Sustainable Dev. 16 (4), 271–281. doi:10.1002/sd.380.
Sauvenier, X., Lambert, R., & Vanclooster, M. (2007). *Towards a process-based" C&N" model for Belgian agro-ecosystems: the WAVE-DNDC model* (UCL-Université Catholique de Louvain).