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EVALUATION OF THE TECHNICAL EFFICIENCY AND CARBON FOOTPRINT REDUCTION POTENTIAL OF SPRING BARLEY CULTIVATION[1]

Key words: spring barley, cultivation efficiency, carbon footprint, DEA, FRM

ABSTRACT. The aim of this study is to evaluate the efficiency of spring barley cultivation to indicate the reasons for its inefficiency and assess the possibility of the carbon footprint reduction potential. Survey data from 113 farms cultivating spring barley in 2016 were used. DEA (Data Envelopment Analysis) input oriented models were applied to assess technical, pure technical and scale efficiency. The carbon footprint of crop cultivation and its reduction potential for inefficient farms were estimated. The Fractional Regression Model (FRM) was used to explain how farm specific variables (structural and environmental factors) influence the efficiency of spring barley cultivation. Results indicate that the improvement of spring barley cultivation technology, through the effective use of inputs, especially mineral fertilizers, could lead to a reduction in the carbon footprint of its cultivation by an average of 32%, which, in turn, leads to a reduction in greenhouse gas emissions by 744 kg CO_2e per ha. The economic size of farms, farm area, soil quality and annual rainfall significantly affect the results of technical efficiency.

INTRODUCTION

Agricultural greenhouse gas emissions (GHG), expressed in a carbon dioxide equivalent CO_2e, account for 8.2% of total GHG emissions reported by Poland. Plant production accounts for 2/3 of total N_2O emissions, mainly composed of soil emissions induced by the decomposition of plant residue and the use of mineral and natural fertilizers [KOBiZE 2018]. The carbon footprint of crop cultivation is the sum of greenhouse gas emissions occurring during cultivation and associated with the production of inputs, such as: fertilizers, biocides, fuel and seeds. The effective use of these resources can reduce the impact of cultivation on the environment, by limiting GHG emissions. Efficiency, defined as an indicator determining the effectiveness with which agricultural inputs are transformed into outputs (yield), can be examined by methods classified into three main groups: classical - using indicators (e.g. index of nitrogen use by the plant); parametric methods (e.g. SFA – Stochastic Frontier Analysis); nonparametric methods, the most popular of which is DEA

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(e.g. Data Envelopment Analysis) [Kucharski 2014]. DEA models allow the assessment of the relative efficiency of decision-making units (farms), without making assumptions as to the functional relation between the variables. Ineffective units can improve their efficiency, by reducing input levels or increasing result levels and, thus, reduce the carbon footprint of the crop. The approach combining the Life Cycle Assessment (LCA) and DEA is widely used to assess the possibility of reducing the environmental impact of crop production [Picazo-Tadeo et al. 2011, Syp et al. 2015, Pang et al. 2016, Karimov 2013, Khoshnevisan et al. 2013, Mohammadi et al. 2013, Beltrán Esteve 2012, Żyłowski et al. 2018].

The analysis of additional structural and environmental variables affecting the efficiency of farms can be carried out using statistical methods, especially regression methods. In this approach, the determined efficiency score becomes a variable in the regression model explained by independent variables, affecting the result of effectiveness. Doubts as to the admissibility of using simple OLS regression (Ordinary Least Squares) and censored models (Tobit) have been raised by Leopold Simar and Paul W. Wilson [2007], who present the ‹conventional› approach and indicate that the efficiency results, obtained by the DEA method, are burdened with an unknown error. L. Simar and P.W. Wilson point to the advantage of bootstrap models based on the truncated regression model. On the other hand, an ‹instrumental› approach is used, treating the results of efficiency determined by the DEA method as based on a certain observation, not affected by errors. In the study, the method described by Esmeralda Ramalho et al. [2010] was used to investigate the effect of structural and environmental variables, allowing to find the correct functional form of the expected efficiency by statistical tests, using the Fractional Regression Model.

In this study, the efficiency of spring barley cultivation and carbon footprint reduction potential will be assessed through the reduction of the inputs used. Spring barley is the main fodder grain cultivated in Poland. Its share in cereal crop structure is about 10%, with an average yield of 3.8 tonnes [GUS 2018].

MATERIAL AND METHODS

Survey data from 113 farms cultivating spring barley in 2016 were used for the analysis. The data contain detailed information on the location of farms, yield, cultivation treatments, applied biocides, fuel consumption and soil (bonitation class, pH). Surveys were collected among farms belonging to the Polish FADN, with three types of production (TF8): crop cultivation (CC), dairy cattle (D), and swine farm (S). The farms are located in 4 FADN regions: region A (785) includes Pomorze and Mazury; B (790) Wielkopolska and Śląsk; C (795) Mazowsze and Podlasie; D (800) Małopolska and Pogórze. The farms belong to three classes of economic size (ES6): small (8-25 thousand Euro), medium (25-100 thousand Euro), and big (100-500 thousand Euro). Descriptive statistics of the most important variables are presented in Table 1. Meteorological data come from the Agri4Cast JRC database [JRC 2017].

Data Envelopment Analysis is a non-parametric method of linear programming that allows to measure relative efficiency in the analysed set of decision making units DMU, in this case farms cultivating spring barley. The input oriented model was used in this study, because the farmer has more control over the inputs used than the outputs (yield).

Table 1. Characteristics of farms cultivating spring barley [a]

Variable	Economic class			Type of production			Summary
	small	medium	big	D	S	CC	
Number of farms	16	61	36	31	48	34	113
Crop area [ha]	2.26	6.96	12.2	3.45	7.63	12.56	7.96
	(1.66)	(6.44)	(12.19)	(4.69)	(5.62)	(12.83)	(9.00)
Yield [t/ha]	3.6	4.48	4.68	4.1	4.58	4.48	4.42
	(0.91)	(1.28)	(1.03)	(0.88)	(1.17)	(1.44)	(1.21)
Seeds [kg/ha]	195.33	170.54	163.26	180.36	160.81	179.29	171.73
	(83.54)	(24.86)	(19.69)	(32.31)	(17.14)	(59.03)	(39.34)
N [kg/ha]	57.01	85.10	80.11	64.06	85.69	84.94	79.53
	(36.92)	(43.04)	(43.34)	(37.63)	(40.82)	(48.10)	(43.03)
P [kg/ha]	27.26	28.92	35.65	27.75	27.39	38.49	30.83
	(20.74)	(22.81)	(30.43)	(26.32)	(20.79)	(28.82)	(25.24)
K [kg/ha]	36.73	44.86	50.52	42.39	44.13	50.53	54.18
	(29.38)	(32.16)	(33.57)	(35.46)	(29.28)	(33.67)	(32.27)
N manure [kg/ha]	40.94	44.10	77.14	60.97	79.84	11.76	54.18
	(52.06)	(60.73)	(84.53)	(71.55)	(73.40)	(34.40)	(69.44)
Fuel [l/ha]	94.19	97.25	99.52	97.81	100.95	92.49	97.54
	(18.69)	(25.09)	(33.48)	(22.15)	(27.64)	(30.41)	(27.15)
Biocides [kg/ha]	1.96	2.72	2.26	2.48	2.71	2.13	2.47
	(1.32)	(2.66)	(1.61)	(1.93)	(2.87)	(1.28)	(2.24)

[a] The table shows average values and standard deviations (in brackets), broken down by economic size and types of production. The amounts of mineral fertilizers used were expressed in terms of quantities of pure components: nitrogen N, phosphorus P, potassium K; N manure means the amount of pure nitrogen applied in the form of a natural fertilizer (solid or liquid)
Source: own elaboration

In the DEA method, the efficiency of a decision unit can be defined as: TE_{CRS} technical efficiency, TE_{VRS} pure technical efficiency, and SE scale efficiency. The technical efficiency calculated by the CCR model [Charnes et al. 1978] is expressed as the ratio of weighted sums of output to the weighted sum of input. This model assumes a constant return to scale, which means that the increase in inputs leads to a proportional increase in output.

Rajiv Banker et al., [1984] introduced a different form of the DEA model, known as the BCC model. This model introduces an additional convexity condition for the linear combination of inputs and results. The assumption of variable returns to scale (VRS) means that changes in inputs can cause disproportionate changes in the results. Technical efficiency determined by the CCR model consists of two components: pure technical efficiency TE_{VRS} (the ability to make the best use of technology) and efficiency of the SE scale (the impact of production volume on the manner of transferring input to output):

$$SE = \frac{TE_{CRS}}{TE_{VRS}}$$

The decision unit operates at the optimal scale (SE = 1), if any modification of its size causes its efficiency to drop. For inefficient units (SE < 1), it is possible to determine in which area of scale effects a given unit is located, by comparing efficiency under the VRS assumption efficiency under the DRS (Decreasing Return to Scale) assumption. If $TE_{VRS} = TE_{DRS}$, this means that DMU is below the optimal production scale, otherwise it is above [Bogetoft, Otto 2011]. Calculations of the optimal technology in the CCR model (in relation to effective units) for unit i (x_i*) can be made using the equation:

$$x_i^* = \lambda_i x_i$$

where: λ_i is a vector of coefficients, obtained as a result of using the DEA model, x_i is the input vector for unit number *i*.

The agricultural inputs (amount of pure components N, P, K (kg)) in a fertilizer, the amount of nitrogen in natural fertilizers (kg), fuel (l), seeds (kg), biocides (kg) were used as inputs, and the yield of spring barley grain (kg) was used as a result for DEA models. All data refer to the declared cropping area. The R language and the *Benchmarking* package were used for the analyses [Bogetoft, Otto 2011].

The Fractional Regression Model, FRM, is described by Leslie Papke and Jeffrey Wooldridge [1996]. It requires the assumption of a functional form of the predicted mean of efficiency score values (θ), as follows:

$$E(\theta|z) = G(z_i, \beta),$$

where G is a non-linear function that satisfies the condition $0 \leq G \leq 1$, z_i – is a vector of variables affecting efficiency θ, β – a vector of regression coefficients. The most commonly used functional forms of G distribution are: *logit* $G(z\beta)=e^{z\beta}/(1+e^{z\beta})$, *probit* $G(z\beta)=\phi(z\beta)$, *loglog* $G(z\beta)=e^{e^{-z\beta}}$, *clogcog* $G(z\beta)=1-e^{e^{-z\beta}}$, where ϕ is the probability density function of standard normal distribution.

The selection of the best functional forms is made using the RESET and P-test tests. More detailed information on the applied method can be found in the studies of E. Ramalho et al. [2010, 2011]. A description of explanatory variables is presented in Table 2. The model uses variables describing the location of farms in specific Polish FADN regions, soil quality class and its pH, type and economic size of the farm, weather conditions, farm and crop area, cultivation on organic soil or the method of managing crop residue. The analysis was conducted based on R language, RStudio [RStudio Team 2015] and the *frm* package [Ramalho et al. 2011].

The carbon footprint is defined as the balance (emission or sink) of greenhouse gases caused by cultivation and expressed in the carbon dioxide equivalent – CO_2e [Wiedmann, Minx 2008]. The potential of global warming in the 100-year time horizon GWP_{N2O} (the amount of heat retained by a given gas in comparison with carbon dioxide) was assumed to be 298 for N_2O [IPCC 2007]. In this work, functional units corresponding to "area"

Table 2. Description of the variables used in the regression model [a]

Variable	Description	Range
FADN	Belongs to FADN region	{A*, B, C, D}
Soil	Soil bonitation class (o2,o3a,o3b -3; o4a,o4b-4; o5,o6-5)	{3, 4, 5*}
Climate	IPCC Climate classification, Cool Temperate	{Dry*, Moist}
Size	Economic class according to FADN	{Small, Medium, Big*}
Type	Type of production: crop cultivation, dairy, swine	{CC*, D, S}
Soil_pH	pH scale	(4.0; 7.6)
Farm_area	UUA [ha]	(6.24; 281.02)
Crop_area	Crop area [ha]	(0.41; 52.77)
Organic_soil	Organic soil cultivation	{Yes, No*}
Intercrop	Intercrop cultivation	{Yes, No*}
Residue	Management of crop residue	{Collection, Intercorp*}
Avg_temp	Mean annual temperature [°C]	(7.86; 10.47)
Spring_temp	Mean spring temperature III-V [°C]	(14.50; 15.96)
Precip_sum	Yearly sum of precipitation [mm]	(420.2; 967.5)
Precip_winter	Sum of winter precipitation XII-II [mm]	(63.0; 162.7)
Precip_summer	Sum of summer precipitation VI-VIII [mm]	(138.3; 452.9)

[a] Categorical variables appear in the model in a zero-one coded form (dummy variables). This means that, for example, the FADN variable occurs in the model in the form decomposed into variables FADN.B, FADN.C, FADN.D, taking the value 1 when the holding is in the appropriate region, 0 otherwise. Region A is the reference level (occurs when all variables FADN.B, FADN.C, FADN.D have the value 0).
The ranges of quantitative variables are given in round brackets, qualitative -in curly brackets. Reference levels for dummy variables are marked *

Source: own elaboration

[kg CO_2e/ha] and "product" [kg CO_2e/(kg grain)] are used. Direct and indirect (volatilization of ammonia, leaching and runoff of nitrogen compounds) N_2O emissions were calculated using the IPCC guide and default emission factors at Tier1. CO_2 emissions from the use of urea and lime fertilisers were taken into account [IPCC 2006]. Emissions related to the production of inputs used (mineral fertilizers: total NPK, fuel, seeds, biocides) were calculated using the same indicators as in the Biograce project [Neeft 2011]. Nitrogen content in natural fertilizers was adopted in accordance with the agricultural production standards for 5 kg of N per t of manure and 4 kg of N per t of slurry [CDR 2018]. The study does not take into account changes in soil organic matter due to a lack of information on changes in land development and cultivation technology.

RESULTS AND DISCUSSION

The results revealed that the average values of technical, pure technical and scale efficiency scores were 0.72 (± 0.20), 0.80 (± 0.19), 0.91 (± 0.13), respectively. From the total of 113 farms considered for analysis, 19% were found to be technically efficient. Hassan Ghasemi Mobtaker et al., [2013] analysed the energy efficiency and CO_2 emission of barley farms in Iran. Among a total of 67 farms, 19.4% were found to be technically efficient, with an average score of 0.79. The average technical efficiency of ineffective farms is 0.66 (± 0.16), which indicates the possibility of reducing expenditure by 34%. This, in turn, translates into the possibility of reducing the amount of used inputs: mineral fertilizers (N – 33.49%, P – 31.70%, K – 33.15%), natural fertilizers (26.50%), fuel (32.07%), biocides (36.77%) and seeds (29.54%). The quantity of agricultural inputs and yield for efficient and inefficient farms is represented in Table 3. The results indicate that effective farms consume less mineral fertilizers (N – 43%, P – 10%, K – 21%) and fuel (15%) than inefficient farms. On the other hand, the average yield of efficient farms was by 19% higher than that of inefficient ones. Taking into account the impact of the scale effect, in which farms operate, increases the number of effective farms from 21 (CCR model) to 40 (BCC model). The results indicate that 21 farms operate at an optimal scale, 30 above and 62 below optimal production scale.

Table 3. Comparison of technically efficient and inefficient farms [a]

Variable	$TE_{CRS} = 1$ (21 farms)	$TE_{CRS} < 1$ (92 farms)	Difference [%]
Yield [t/ha]	5.27	4.26	19.17
Seeds [kg/ha]	172.41	168.12	2.49
N [kg/ha]	59.03	84.21	-42.66
P [kg/ha]	28.43	31.37	-10.34
K [kg/ha]	38.85	47.03	-21.06
N manure [kg/ha]	53.19	54.40	-2.27
Fuel [l/ha]	87.20	99.90	-14.56
Biocides [kg/ha]	1.67	2.62	-56.89

[a] The table shows the average values of inputs and results (yield). The last column indicates the average difference (in %) between efficient and inefficient farms
Source: own elaboration

The results of tests conducted using the RESET and P-test for selecting correct functional forms of the conditional mean $E(\theta|z)$ for the second stage of DEA analysis did not allow to reject any of the functional forms to explain the technical efficiency of the TE_{CRS}; in the case of pure technical efficiency, the cloglog form was rejected. Regression coefficients for all four functional forms are identical in terms of signs and significance. Technical efficiency is affected by the economic size of the farm; farms with a standard output of less than 25 thous. Euro have a significantly lower efficiency than large farms. In the case of medium-sized farms, this relationship is not statistically significant. The type of production does not affect the score of technical efficiency or pure technical efficiency. The farm's location in the zone classified by the IPCC as the moist climate (Cool Temperate Moist) adversely affects the obtained technical and pure technical efficiency scores. This zone covers the northern and southern part of Poland [JRC 2010].

The average annual rainfall there is about 10% (68 mm) higher than in the dry climate zone, covering the central part of Poland, from the regions of Lubuskie, Wielkopolskie, Łódzkie to Lubelskie. The cultivation of catch crops reduces the technical efficiency score, which may be due to the need for additional treatments and worse sowing conditions. Technical efficiency increases due to the increase of annual rainfall, while it decreases with higher rainfall in the summer months. The positive effect of soil quality on TE_{CRS} and TE_{VRS} indicated all the functional forms of the models. The cultivation of spring barley on relatively better soils (classes o2, o3a, o3b) is more effective than on worse soils. None of the models indicated the area of cultivation as significantly affecting technical efficiency, which may indicate that if the agricultural inputs are appropriately used, it is possible to effectively cultivate spring barley in smaller areas. The increase in the farm area has a positive effect on the amount of pure technical efficiency. The negative impact of the average annual temperature on pure technical efficiency may be related to the unfavourable rapid increase of the air temperature in relation to the temperature of the soil, which causes root growth inhibition and excessive growth of above-ground parts. The decrease of barley yield in the relatively warmer season compared to the cooler ones was indicated by Miroslava Váňová et al. [2011].

The estimated carbon footprint of spring barley cultivation falls within the range of 568-8,435 kg CO_2e/ha (median 2048, average 2,484 kg CO_2e/ha). Carbon footprint calculated for 1 kg of grain amounted to 0.60 kg CO_2e/kg (0.11-2.94 kg CO_2e/kg). Mari Rajaniemi et al., [2011] investigated the carbon footprint of barley cultivation in Finland, taking into account the average value of yield and means of production, obtaining 0.57 kg of CO_2e/kg. Results of Monia Niero et al., [2015] indicate a carbon footprint of 0.53 kg CO_2e/kg. The carbon footprint of half of the farms falls between 1,655 and 2,641 kg CO_2e/ha. Farms with the highest carbon footprint (13 farms with CF > 4,815 kg CO_2e/ha) declare cultivation on organic soils. The high score is related to the IPCC methodology, where cultivation on organic soil results in the additional emission of 8 kg N_2O per ha

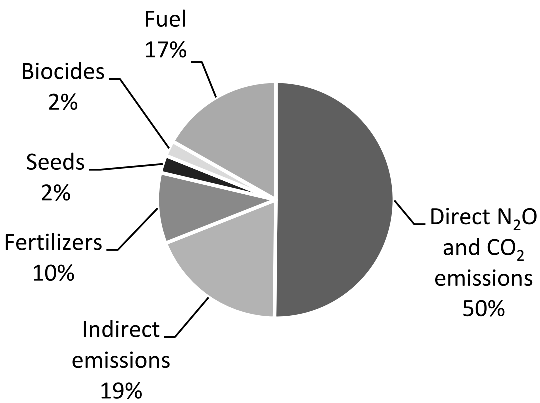

Figure 1. Percentage share of individual emission sources in the carbon footprint of winter barley cultivation. The terms Fertilizers, Seeds, Biocides, Fuel refer to indirect emissions associated with the production of used inputs

Source: own elaboration

Table 4. Results of using the FRM model to explain the obtained scores of technical and pure technical efficiency [a]

Explanatory variables	Technical efficiency TE_{CRS}								Pure technical efficiency TE_{VRS}					
	logit		probit		loglog		cloglog		logit		probit		loglog	
constant	-2.498		-1.553		-1.740		-1.975		-0.801		-0.434		-0.222	
Farm_area	0.002		0.001		0.002		0.001		0.013	**	0.007	**	0.011	**
Crop_area	-0.015		-0.009		-0.014		-0.007		-0.034		-0.018		-0.030	
Soil_pH	0.013		0.001		0.019		-0.014		0.067		0.029		0.054	
Avg_temp	-0.167		-0.088		-0.144		-0.063		-0.561	**	-0.302	*	-0.491	**
Spring_temp	0.303		0.179		0.255		0.171		0.360		0.197		0.309	
Precip_sum	0.004	*	0.002	*	0.004	*	0.002		0.006	**	0.003	*	0.005	**
Precip_winter	0.001		0.001		0.000		0.002		0.001		0.001		0.000	
Precip_summer	-0.006	*	-0.003	*	-0.005	*	-0.003		-0.007	*	-0.004	*	-0.007	**
FADN=B	-0.286		-0.149		-0.286		-0.109		0.076		0.058		0.040	
FADN=C	-0.341		-0.176		-0.332		-0.119		-0.579		-0.294		-0.527	
FADN=D	-0.188		-0.092		-0.196		-0.056		0.077		0.043		0.071	
Size=small	-1.041	***	-0.620	***	-0.876	***	-0.589	***	-0.370		-0.187		-0.334	
Size=medium	-0.219		-0.138		-0.173		-0.145		0.015		0.034		-0.013	
Type=D	-0.444		-0.273		-0.351		-0.280		0.233		0.120		0.244	
Type=S	-0.327		-0.200		-0.254		-0.202		-0.110		-0.062		-0.057	
Organic_soil=yes	0.565		0.341	*	0.477		0.324	**	0.548		0.318	*	0.477	
Soil=3	0.631	*	0.370	*	0.553	*	0.339	*	0.768	*	0.445	**	0.668	*
Soil=4	0.092		0.055		0.085		0.048		0.263		0.153		0.216	
Residue=collected	0.229		0.141		0.178		0.144		-0.009		0.008		-0.046	
Intercrop=yes	-0.472	*	-0.290	*	-0.377	*	-0.298	*	-0.509		-0.314		-0.384	
Climate=Moist	-0.732	***	-0.433	***	-0.608	***	0.405	***	-1.312	***	-0.735	***	-1.140	***
R^2	0.327		0.324		0.33		0.319		0.436		0.427		0.442	

[a] The table presents the determined values of coefficients for the non-rejected functional forms of the conditional mean for predicted values of efficiency scores,
*,**,*** denote coefficients which are significant at 10, 5, 1 %, respectively, R^2 – coefficient of determination
Source: own elaboration

(GWP_{N2O} = 298; 298 × 8 kg N_2O = 2,384 kg CO_2e/ha). Figure 1 shows the share of emission sources in the carbon footprint of spring barley cultivation. Field emissions (direct and indirect) related to the use of mineral and natural fertilizers constitute approx. 69%. Next, in the order of emission sources, is the production and combustion of fuel (17%) and then the production of mineral fertilizers (10%). The results obtained by recalculating carbon footprint for optimal technology (inefficient units), determined by the DEA model, indicate the possibility of reducing the carbon footprint in spring barley cultivation by an average of 744 kg CO_2e/ha (1.76 to 2,920 kg CO_2e/ha), which is 31.72% (0.09-73.85%), provided that farms use agricultural inputs at full efficiency.

CONCLUSIONS

In this study, a two-stage methodology was applied to analyse the efficiency of spring barley cultivation in selected farms in Poland. In addition, the carbon footprint of spring barley cultivation was estimated at the current and optimal production technology indicated by input oriented DEA models. Technical, pure technical and scale efficiency of the analysed farms were determined. The average values of the mentioned indicators are 0.72; 0.80; 0.91, respectively. The obtained results indicate that farms inefficiently using their resources could save an average of 34% of inputs, without decreasing yield. Inefficient farms obtain yield by 19% lower than technically efficient farms, using more mineral fertilizers, biocides and fuel. The improvement of spring barley cultivation technologies through more efficient agricultural inputs could lead to a reduction in the carbon footprint in its cultivation by 31.72%. The results showed a total reduction of greenhouse gas emissions by 744 kg CO_2e/ha. Due to the structure of greenhouse gas emissions, the improvement of cultivation technology should primarily include the better use of mineral fertilizers. The obtained results indicate a positive impact of the size of farms, the soil quality class and the annual amount of rainfall on the technical efficiency of farms.

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OCENA EFEKTYWNOŚCI TECHNICZNEJ ORAZ MOŻLIWOŚCI OGRANICZENIA ŚLADU WĘGLOWEGO UPRAWY JĘCZMIENIA JAREGO

Słowa kluczowe: jęczmień jary, efektywność uprawy, ślad węglowy, DEA, FRM

ABSTRAKT

Celem pracy jest ocena efektywności uprawy jęczmienia jarego, wskazanie przyczyn jej nieefektywności oraz zbadanie możliwości ograniczenia śladu węglowego. Wykorzystano dane ankietowe pochodzące ze 113 gospodarstw uprawiających jęczmień jary w roku 2016. Do oceny efektywności zastosowano modele DEA (Data Envelopment Analysis) uwzględniające stałe i zmienne korzyści skali, zorientowane na nakłady. Oszacowano ślad węglowy uprawy i oceniono możliwości jego ograniczenia, przez gospodarstwa nieefektywne. Podjęto próbę wyjaśnienia przyczyn nieefektywności wykorzystując model regresji ułamkowej FRM (Fractional Regression Model), używając jako zmiennych niezależnych czynników strukturalnych i środowiskowych. Wyniki wskazują, iż ulepszenie technologii uprawy jęczmienia jarego poprzez efektywne korzystanie ze środków produkcji, zwłaszcza nawozów, mogłoby doprowadzić do ograniczenie śladu węglowego w jego uprawie średnio o 32%, co przekłada się na redukcje emisji gazów cieplarnianych o 744 kg CO_2e/ha. Wielkość ekonomiczna gospodarstw, powierzchnia, jakość gleby i roczna suma opadów wpływają istotnie na wyniki efektywności technicznej.

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