https://doi.org/10.17221/235/2023-AGRICECON

Structural and weather-related factors of the sustainable intensification process in agriculture of the European Union regions

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Citation: Staniszewski J., Muder A. (2023): Structural and weather-related factors of sustainable intensification in agriculture of the European Union regions. Agric. Econ. – Czech, 69: 385–393.

Abstract: Sustainable intensification (SI) is a widely discussed concept that aims to increase agricultural production without harming the environment. This study assessed the process of SI that took place in the EU regions from 2004 to 2018 and the impact of structural and weather-related factors. In doing so, a single index based on DEA environmentally adjusted efficiency and kernel regression were applied to data from the Farm Accountancy Data Network (FADN) Public Database and the Agri4Cast resource portal. The study found an overall positive trend of SI in the EU regions in which land and animal concentration had a significant impact on this process. Sun radiation, as the only significant weather variable, had a decreasing impact on efficiency due to potential droughts. The findings emphasise the need for political support for regions with a low degree of SI and for those particularly affected by climate change.

Keywords: concentration; data envelopment analysis; environmentally adjusted efficiency; non-parametric regression; productivity; performance

The United Nations predict that by 2050, the global population will exceed 9.7 billion (United Nations 2022), resulting in a significant increase in food demand (FAO et al. 2018). Climate change, including extreme weather conditions, rapid urbanisation, leading to the loss of agricultural land and biodiversity, and changing consumption patterns to resource-intensive diets pose additional challenges.

To tackle these challenges, it is crucial to prioritise more efficient and sustainable approaches to meeting future food demand (Rockström et al. 2017). Sustainable intensification (SI) is a widely discussed concept in this context since it combines the issues of improving global food production and ecological sustainability (Weltin et al. 2018). The aim of SI is to improve resource productivity without causing significant damage to the environment (Buckwell et al. 2014). However, no uniform definition of this approach exists (Lyu et al. 2021). Originally, SI was introduced by Pretty (1997) in the context of agriculture to improve the livelihoods of smallholders in the Global South while fostering ecological gains. Later on, the concept has also been adjusted to the European context but there has been an ongoing discussion on how to define it (Weltin et al. 2018). In this paper, we consider SI with a holistic view, taking into account the social, en-

Supported by the National Science Centre in Poland Grant No. 2018/29/N/HS4/01799.

https://doi.org/10.17221/235/2023-AGRICECON

vironmental and economic dimensions (Godfray and Garnett 2014). We will base the definition on the one by Lampkin et al. (2017), which states that SI means to 'improve overall agricultural productivity by increasing resource efficiency and reducing the environmental impact per unit of production' .

Since the late 1990s, SI has been addressed by a number of scholars, and particularly in the last ten years, the topic has been gaining increasing attention, with an annual literature growth rate of 35% (Lyu et al. 2021). As SI cannot be measured directly, proxies are necessary, and the choice of indicators should be made carefully (Barnes and Thomson 2014). However, there is no uniform way to do so, and research that assesses SI is still scarce.

Most existing studies applied an aggregated index of eco-efficiency to assess SI (e.g. Gadanakis et al. 2015; Weltin and Hüttel 2022). While many of these studies have a rather static view (e.g. Barnes and Thomson 2014), Staniszewski et al. (2023) focus on the assessment of which progress of SI has been made so far. However, there is still a research gap in controlling for the impact of weather (Staniszewski et al. 2023). So far, only a few studies have included weather variables in environmentally adjusted efficiency models. They found a significant negative impact of higher temperatures on efficiency (Skevas and Lansink 2013; Skevas and Serra 2016; Soliman and Djanibekov 2020). The findings regarding rainfall were ambiguous across studies. They found either that higher precipitation increases efficiency as rainfall has a beneficial impact on the growth of the plants (Skevas and Lansink 2013; Skevas and Serra 2016), or has no impact at all (Soliman and Djanibekov 2020).

The method and procedures used for our analysis were built on the presented research and aimed to contribute further to the field. In particular, we propose a new SI index combining socio-economic and eco-efficiency components and use kernel regression to explore the relation between the sustainable intensification process and structural and climate features of EU Farm Accountancy Data Network (FADN) regions.

In doing so, the following three main research questions will be addressed:

(*i*) How has the process of SI progressed in the EU regions from 2004 to 2018?

(*ii*) Which structural variables explain the process of SI?

(*iii*) How does the weather affect SI?

According to the earlier studies, we can formulate the following hypotheses as answers to the stated questions.

H_1: In the years 2004–2018 we could observe a progress in sustainable intensification among EU regions (Staniszewski 2018; Expósito and Velasco 2020; Baležentis et al. 2021).

H_2: The most important structural feature for the SI process is land concentration (Skevas and Serra 2016; Žáková Kroupová et al. 2018).

H_3: High radiation negatively affects the SI process (Skevas and Lansink 2013; Skevas and Serra 2016; Soliman and Djanibekov 2020).

MATERIAL AND METHODS

The first challenge of this study was to measure the sustainable intensification (SI) process in the form of a single index. To best capture the environmental component, crucial for the concept of SI, we employed an approach based on environmentally adjusted efficiency. An explanatory variable for the model was an SI index constructed according to the modified formula proposed by Czyżewski and Staniszewski (2018), which is based on data envelopment analysis (DEA) results, a productivity index, and angular and Euclidean distance measures. The SI index consists of two components – environmental and socio-economic performance, which are calculated as TFP (total factor productivity) indices. Further, two values are aggregated, based on the baseline level of socio-economic efficiency and the desired direction of change in these areas. This direction was set in accordance with the assumption that more improvement should be sought in the area of greater inefficiency. The SI indicator takes on positive values when there has been sustainable intensification on a farm in a given year, meaning that there has been improvement in at least one dimension without worsening in another. The method is described in detail in the Electronic Supplementary Material (ESM).

The kernel regression was chosen as the best-suited technique to check for the impact of structural, weather and other features of farming in EU FADN regions on the sustainable intensification process. The choice was driven by the fact that the distribution of the SI measure is bimodal (Figure S3 in the ESM) and that many structural variables are expressed as proportion data, which is by nature bounded by 0 and 1 (Table S1 in the ESM). Under such conditions, standard econometric approaches such as ordinary least square (OLS) regression are not suitable due to the lack of normal distribution in the data. In this paper, we follow the approach proposed by Czekaj and Henningsen (2013), who proved the usefulness of kernel regression for

https://doi.org/10.17221/235/2023-AGRICECON

panel data. This approach makes it possible to estimate a conditional mean of SI indicators, controlling for the impact of structural, weather and other features. Kernel regression is described in detail in the Electronic Supplementary Material (ESM). This method was also successfully applied in the studies of agricultural performance factors conducted by Baležentis et al. (2014), Ferreira and Almeida (2021) and Song et al. (2022).

The goal of the research was to verify the hypothesis that structural features remain significant predictors of SI process after controlling for the impact of other features and the impact of weather conditions. To verify this hypothesis, a stepwise, backward regression was conducted. Predictors were excluded from the model based on their P-values until all the variables in the model were significant at a 0.01 level. A basic set of structural variables, described in detail in Table S1 in the ESM, was reduced using cluster analysis (for details see the ESM). Similar clustering was conducted for weather and control variables. Descriptive statistics of variables taken into account in modelling are presented in Table 1.

Data for the study was acquired from two sources on September 26, 2020. The first one was the Farm Accountancy Data Network (FADN) Public Database. We can obtain from it standardised economic results for different types of farms in all EU member states. The annual sample currently covers approximately 80 000 holdings. They represent a population of about

Table 1. Descriptive statistics of variables used in modelling, N = 1 554

Variable	Mean	Median	SD	Min.	Max.
SI	1.39	1.20	1.43	–1.32	7.49
Concentration					
LSU_S	0.74	0.75	0.16	–0.17	1.01
LAB_S	0.62	0.61	0.07	0.36	0.89
UAA_S	0.65	0.64	0.09	0.41	0.89
O_S	0.73	0.72	0.70	0.23	0.94
Specialisation					
ABS_SPEC	0.33	0.30	0.17	0.07	1.00
REL_SPEC	0.51	0.51	0.08	0.28	0.72
MIXED	0.14	0.12	0.11	0.00	0.58
Direction					
ANIMAL	0.41	0.40	0.20	0.03	0.96
Weather					
PREC	414.75	415.13	134.36	38.50	857.84
RADIATION	16 416.85	15 967.00	3 046.253	6 068.49	23 777.10
Control variables					
CAP_UAA	1 914.95	1 552.97	1 585.267	217.75	13 980.8
SUBSIDIES	0.2	0.18	0.12	0.01	0.94
RENTED_LAND	0.56	0.57	0.23	0.04	0.97
HIRED_LAB	0.28	0.22	0.20	0.01	0.94

SI – sustainable intensification index; *ANIMAL* – share of livestock output in total output; *ABS_SPEC* – distribution of total output among farms of different production type measured with Hirschman-Herfindahl Index (HHI); *REL_SPEC* – distribution of total output among farms of different production type measured in relation to average value with Krugman Index; *LSU_S* – distribution of livestock among farms of different economic size measured with standard concentration index (*C*); *LAB_S* – distribution of labour among farms of different economic size measured with *C*; *UAA_S* – distribution of land among farms of different economic size measured with *C*; *O_S* – distribution of livestock among farms of different economic size measured with *C*; *MIXED* – share of output generated by non-specialised farms in total output; *PREC* – sum of precipitation (in mm) in the growing season (from March 1 to October 31); *RADIATION* – average daily radiation (KJ·m^{-2}) in the growing season; *CAP_UAA* – capital/land ratio; *SUBSIDIES* – ratio of total subsidies (excluding on investments) to total output; *RENTED_LAND* – share of rented utilised agricultural area; *HIRED_LAB* – share of paid labour input; for detailed description see supplementary materials

Source: Authors' own study

https://doi.org/10.17221/235/2023-AGRICECON

5 000 000 farms in the EU, which covers approximately 90% of the total utilised agricultural area (UAA) and accounts for about 90% of the total agricultural production. The sample can be divided into different types of farming and economic size classes according to standard output (SO) expressed in EUR, which is the average monetary value of the agricultural output at the farm-gate price of each agricultural product (crop or livestock) in a given region. The SO is calculated by member states per ha or per head of livestock, by using basic data for a reference period of 5 successive years (European Commission 2020).

Data in this work is aggregated at FADN regional level, which has some similarities with a standard Nomenclature of Territorial Units for Statistics (NUTS) and can be situated between NUTS-1 and NUTS-2 delimitation level. This aggregation is justified by the willingness to evaluate structural features, such as concentration, specialisation and orientation, which cannot be obtained at a farm level. In this study, we analysed representative farms in 111 FADN regions in the 15-year period 2004–2018. The number of FADN regions included in the study was reduced from the overall number due to several reasons. First, to keep the panel balanced, we excluded regions from Bulgaria, Romania and Croatia, which joined the EU after 2004. Second, non-European regions such as Canarias, Açores e Madeira, La Réunion, Guadeloupe and Martinique were not taken into account due to the completely different specificity of agricultural production. Third, regions Sterea Ellas-Nissi Egaeou-Kriti, Castilla-La Mancha and Saarland were excluded as outliers. The final sample size includes 1 554 observations. All the values expressed in EUR have been cleared from the impact of price and exchange rate changes and are expressed in constant 2010 prices.

The second source of the data is Agri4Cast resource portal, which provided the data from JRC MARS Meteorological Database. Observations are available from weather stations interpolated on a 25 km × 25 km grid on a daily basis. Regional value is an average for all the grids in the region, weighted by the share of a given grid cell crop area in the total crop area in the given region in the given year. Only records for the growing season (March 1 to October 31) were used to calculate the average.

RESULTS AND DISCUSSION

SI Index change. The first question to be answered in this work is how the process of SI has progressed in the EU regions. The changes from the 2004–2018 period are presented in Figure 1. Importantly, even though the SI index represents a bimodal distribution in the overall sample, its distribution within each region over the years was normal in 106 of 111 cases (basing on Shapiro-Wilk test, $P > 0.01$), which is why we used average values in the map.

The fastest progress toward SI was achieved in the Baltic countries (Lithuania, Latvia, Estonia), as well as in the regions of England (North, East, West) and Northern Ireland. Positive examples from Southern Europe include the Hungarian region Alfold and Greek Makedonia-Thraki. However, the sources of good results are different for the regions. For example, Lithuania, a region with the highest average score 4.66, was characterised in the whole period by low average efficiency scores: 17.5% for socio-economic and 4.35% for environmental efficiency. Notably, those scores improved from 7.79 to 20.75% and from 2.28 to 5.16%, respectively, throughout the studied period. The direction of improvement was also adequate because farms in the region improved relatively more in the environmental scope, where more inefficiency existed in the beginning. Therefore, a base effect worked here. The situation was similar in the case of Makedonia-Thraki and Alfold, where although environmental efficiency was particularly low for the whole period, it improved from ‘very low‘ to just ‘low‘ level. On the other hand, Latvia and Estonia improved more in socio-economic aspects. The British regions were slightly different case where the starting level of efficiency was higher; however, this did not prevent these regions from achieving a significant improvement in performance. On the other side, there were five regions where a process opposite to SI occurred. These are Italian Trentino and Spanish Madrid, Comunidad Valenciana, Murcia and Extremadura. We observed a decline in both socio-economic and environmental performance. Average results for all the regions are presented in Table S2 in the ESM. To sum up, for most of the regions, SI indicator took a positive value (77% of 1 554 observations), which leads to the conclusion that, in general, a process of sustainable intensification can be assumed to have taken place in the FADN regions of the EU in the 2004–2018 period, and that H_1 is verified positively. This corresponds with the results of some earlier studies conducted at the country level (Staniszewski 2018; Expósito and Velasco 2020; Baležentis et al. 2021). Other studies, particularly those where a different approach to efficiency estimation was assumed (Staniszewski and Kryszak 2022; Staniszewski et al. 2023), tend to report a decline in SI;

https://doi.org/10.17221/235/2023-AGRICECON

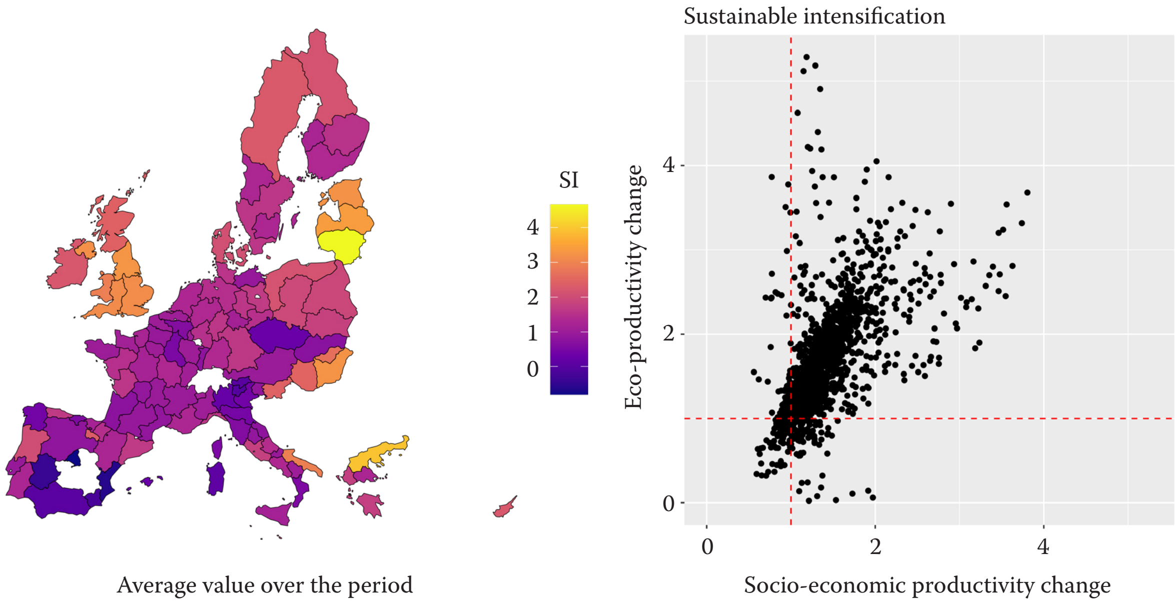

Figure 1. Sustainable intensification (SI) process in EU FADN regions in years 2004–2018

FADN – Farm Accountancy Data Network
Source: Authors‘ own study

however, the directional distance function approach in those works was more strict.

SI determinants. In the second part of the research, obtained SI measures were explained by a set of structural and weather-related factors. The results of panel kernel regression are summarised in Table 2. All the models estimated in the stepwise backward procedure are presented. In some cases, exclusion of one variable made estimation infeasible. In such a case, we also excluded another variable with the second highest *P*-value. Standard errors were estimated using a bootstrap procedure with 50 replications. To check whether the number of replications was sufficient, errors were also estimated in a procedure with 400 replications. Increasing the number of replications only slightly changed the error estimate, and we therefore considered 50 replications to be sufficient (Table S4 in the ESM).

From the results, we can draw the conclusion of a stable, robust impact of some structural variables. When it comes to concentration, interestingly, it is beneficial for the SI process when land (*UAA_S*) in the region is concentrated but not when livestock is (*LSU_S*). This can be explained by the fact that larger crop-producing farms have a higher potential and proper scale to invest in modern technologies which improve productivity and decrease environmental impact. Larger farms also have more land resources which they can allocate to permanent grassland. Finally, if animal production is combined with field crops or grassland cultivation, manure spreads on a larger surface, causing less environmental impact. Regarding concentration in animal production, it is not beneficial from the point of view of the sustainable intensification process. With the over-concentration of livestock production come problems such as deterioration in animal welfare or an increase in point-source ammonia emissions and the risk of creating a nitrogen imbalance in the soil. Similar results regarding land concentration emerge from the works of Žáková Kroupová et al. (2018), based on results for Czech dairy farms. According to the work of Skevas and Serra (2016) concerning Dutch arable farms, concentration increases technical efficiency but decreases environmental efficiency. Gadanakis et al. (2015) found that the most beneficial factor for the sustainable intensification of arable farms in the UK is a medium size. For animal concentration, previous studies (Sintori et al. 2019; Kuhn et al. 2020; Soteriades et al. 2020) suggest a rather opposite direction of the relationship than the one revealed in our study. However, all these studies were conducted at the farm level, which may indicate the existence of the fallacy of composition. Increasing the number of animals increases the environmental efficiency of individual farms, but at the regional, aggregated level, the effect is opposite.

https://doi.org/10.17221/235/2023-AGRICECON

Table 2. Results of kernel regression; in parenthesis bootstrapped standard errors with 50 replications

Variable	Model configuration								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	**(8)**	(9)
LSU_S	−2.13*** (0.32)	−1.81*** (0.29)	−1.97*** (0.33)	−0.64* (0.25)	−0.65** (0.2)	−0.62** (0.22)	−0.61*** (0.16)	**−0.54*** **(0.25)**	−0.22 (0.32)
LAB_S	1.28 (0.88)	1.09 (0.77)	–	–	–	–	–	–	–
UAA_S	1.28* (0.51)	1.42* (0.56)	1.44*** (0.41)	1.7*** (0.49)	1.72** (0.62)	1.78*** (0.44)	1.72*** (0.45)	**1.49**** **(0.54)**	1.41*** (0.4)
O_S	2.46** (0.83)	1.86 (1.01)	2.58*** (0.81)	0.22 (0.66)	0.2 (0.72)	–	–	–	–
ABS_SPEC	0.89* (0.35)	0.71*** (0.2)	0.7*** (0.21)	−0.72* (0.3)	−0.65*** (0.17)	−0.66*** (0.18)	−0.55** (0.18)	**−0.69***** **(0.17)**	−0.73*** (0.2)
REL_SPEC	−3.95*** (0.66)	−3.89*** (0.51)	−3.78*** (0.48)	0.16 (0.53)	–	–	–	–	–
MIXED	0.47 (0.34)	–	–	–	–	–	–	–	–
ANIMAL	−0.15 (0.19)	–	–	–	–	–	–	–	–
PREC	–	–	–	−1.7E−4 (1.5E−4)	−1.7E−4 (2.5E−4)	–	–	–	–
RADIATION	–	–	–	−1.5E−4*** (1.1E−5)	−1.5E−4*** (1.1E−5)	−1.5E−4*** (1.1E−5)	−1.6E−4*** (1.1E−5)	**−1.4E−4***** **(1.3E−5)**	−1.6E−4*** (1.3E−5)
CAP_UAA	–	–	–	–	–	–	−2.4E−5 (2.4E−5)	–	–
SUBSIDIES	–	–	–	–	–	–	−0.69* (0.3)	–	0.43 (0.4)
RENTED_LAND	–	–	–	–	–	–	–	**−0.08** **(0.14)**	–
HIRED_LAB	–	–	–	–	–	–	–	**0.34*** **(0.16)**	1.14*** (0.25)
R^2	0.439	0.388	0.412	0.545	0.509	0.547	0.498	**0.744**	0.627
N					1 554				
Region fixed effects					yes				
Time fixed effects					yes				

*, **, *** $P < 0.5$, $P < 0.01$, and $P < 0.001$ respectively; *N* – number of observations; *SI* – sustainable intensification index; *ANIMAL* – share of livestock output in total output; *ABS_SPEC* – distribution of total output among farms of different production type measured with Hirschman-Herfindahl Index (HHI); *REL_SPEC* – distribution of total output among farms of different production type measured in relation to average value with Krugman Index; *LSU_S* – distribution of livestock among farms of different economic size measured with standard concentration index (*C*); *LAB_S* – distribution of labour among farms of different economic size measured with *C*; *UAA_S* – distribution of land among farms of different economic size measured with *C*; *O_S* – distribution of livestock among farms of different economic size measured with *C*; *MIXED* – share of output generated by non-specialised farms in total output; *PREC* – sum of precipitation (in mm) in the growing season (from March 1 to October 31); *RADIATION* – average daily radiation ($KJ \cdot m^{-2}$) in the growing season; *CAP_UAA* – capital/land ratio; *SUBSIDIES* – ratio of total subsidies (excluding on investments) to total output; *RENTED_LAND* – share of rented utilised agricultural area; *HIRED_LAB* – share of paid labour input; for detailed description see the Electronic Supplementary Material (ESM)

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Regarding specialisation, understood as a high share of output generated in fewer types of farms (*ABS_SPEC*), its impact was significant but ambiguous. The sign changed after including weather variables in the model, which may indicate a moderation effect. Finally, a negative relationship was found in the better-fitted models, which can be explained by the diminishing biodiversity coming with specialisation in one production type. Results from other studies are inconclusive in this case. The relationship is positive among Greek sheep dairy farms (Sintori et al. 2019), for Czech dairy farms the lowest greenhouse gases (GHG) shadow price was estimated in medium-specialised units (Žáková Kroupová et al. 2018), while for Spanish horticultural farms, the relationship is rather negative (Godoy-Durán et al. 2017). In summary, among the structural variables, the effect of concentration proved to be the most stable and significant, allowing H_2 to be positively verified.

An important conclusion from this work is that structural variables remained significant even after controlling for the impact of weather and other factors. Regarding weather, primarily two variables describing the sum of precipitation (*PREC*) and average daily radiation (*RADIATION*) were included. However, only the impact of sun radiation remained significant in the end. The negative direction comes from the fact that high radiation may lead to droughts, which lower the efficiency of agricultural production. Weather variables are rarely included in other studies. Only in the study of Skevas and Serra (2016) we found a conclusion that higher temperature increases the technical and environmental inefficiency of Dutch arable farms. The authors explain this with higher weed growth and pest activity, which demands higher application of plant protection products. The empirical results therefore also allow us to accept H_3.

CONCLUSION

Within this study, SI in the EU FADN regions was assessed, taking into account socio-economic and environmental aspects. The findings brought to light that in the majority of EU regions (106 out of 111 investigated regions), SI did take place from 2004 to 2018, while the degree of SI varied largely among regions. It was particularly striking that in several countries which joined the EU (e.g. Baltics, Slovenia, Hungary) in 2004, a great change in SI took place between 2004 and 2018. Therefore, we conclude that the accession to the EU had a significant positive impact on the SI of agricultural production in many member states. We argue that the high environmental standards of the Common Agricultural Policy (CAP) and the support for investments from the CAP made this rapid change not just required but also possible.

Although we conclude that the accession to the EU pushed the process of SI forward in many countries, our paper cannot explain the differences in the change of SI among all regions (e.g. the great progress in Great Britain). Hence, further research at the country or regional level is necessary to identify further drivers of SI. Such research could include qualitative methods that investigate national (or regional) policies and include stakeholder interviews. Further quantitative research could also expand our model with other factors such as consumer preferences or trends in prices (Staniszewski et al. 2023) to control if, and in which way, these affect SI.

Even though a large number of papers on the topic of SI appeared during the last decade, research on measuring SI in different EU regions is still scarce compared to the studies on the farm level. Our paper makes an important contribution to recent literature by helping to bridge this gap. We also found that on the regional level of analysis, weather affects the process of SI, and therefore weather variables should be included in such models. In our model, only one weather variable (the daily radiation) had a significant negative effect on the process of SI. This correlation could explain why in a few regions of Spain, one of the warmest countries in the EU, no SI but an opposite process could be observed. Daily radiation is expected to increase further in the future due to climate change. Therefore, we conclude that measures to protect crops and livestock from heat and drought are highly needed. Policies should support farmers' investments in sustainable protection measures, e.g. drip irrigation systems in the crops sector. In the livestock sector, investment support for modern barns and barn technologies to optimise the temperature inside (e.g. dairy fans) to avoid heat stress of the animals is highly needed.

Furthermore, we prove a stable relationship between production concentration and the SI process. While land concentration had a positive impact, animal production concentration affected SI negatively. These findings can be used in the future to better shape the instruments of the CAP so that they support a properly targeted concentration of production, for example, changes in the redistributive payment mechanism which would promote medium-sized farms to increase their utilised agricultural area.

Although our study provides valuable insights into structural and weather-related factors of SI in EU agriculture, it is essential to acknowledge certain limitations of our study. As SI is not directly quantifiable, the included variables are only proxies to measure SI. Therefore, it is important to note that the use of proxies introduces a level of uncertainty, and the selected proxies might not fully capture the complexity of SI. Furthermore, our study only considers aggregated farm-level data and no individual farm-level data, which restricts the ability to capture the full complexity and variability of the studied farms. Therefore, future research should strive to apply this model to individual farm-level data and to validate and expand upon our results.

To sum up, we conclude that EU policies had successfully pushed SI in the EU member states. In the future, special support is needed for regions which still have a low level of SI to catch up, and furthermore, for regions whose SI is particularly at stake due to global warming.

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Received: July 13, 2023
Accepted: September 4, 2023
Published online: October 24, 2023