Journal of Environmental Management 300 (2021) 113770

Contents lists available at ScienceDirect

Journal of Environmental Management

journal homepage: www.elsevier.com/locate/jenvman

Questioning the dichotomy: A Latent profile analysis of ecological management practices in Swedish agriculture

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ARTICLE INFO

Keywords:
Adoption
Ecological practices
Farms
Typology
Sweden

ABSTRACT

Currently, farmers who are not certified according to organic certification schemes are considered to be conventional farmers. Discussions in the farming sector reveal a view that the current organic classification system is too narrow and does not account for the full heterogeneity of the ecological practices that are prevalent in the agricultural sector. The failure to recognise practices within conventional farming, such as low-input farming or conservation agriculture, may therefore undermine efforts to adopt ecological practices. This study investigates heterogeneity in farmer uptake of management practices using factor analysis for dimension reduction and Latent Profile Analysis (LPA) for identification of farmer segments. The findings reveal four farmer profiles with a varying degree of use of chemicals and ecological, alternative, or mixed management approaches. Using seemingly unrelated regression, we find that being certified according to the Swedish organic certification scheme KRAV, or the EU organic label, does not have an impact on a farmer's profile, suggesting that the data do not support the organic/conventional dichotomy. Instead, age, farming income and geographical location are to a greater degree the key factors in determining the larger farmer profile compared with the smaller, more diversified farmer profiles.

1. Introduction

Organic farming practices have played an important role in European farming over the past decade. As consumption of certified organic products has increased (Eurostat, 2020), part of the agricultural sector has converted in response to the growing demand for this type of produce. Between 2007 and 2017, the farm area devoted to certified organic production increased by 70%, and 20% of the total farm area is now under conversion (numbers from 2019), reflecting the potential growth in the coming years (European Union, 2019). Certified organic farming practices are encouraged and recognised under the European organic certification scheme (Council Regulation (EC) No 834/2007). Developments within the Common Agricultural Policy (CAP) in the past two decades also underline the interconnectedness between agricultural and environmental systems (Leduc et al., 2021) and further emphasise the demand for ecological practices. In addition, previous research on Ecological Intensification (EI) has shown that practices to promote plant diversification benefit the functioning of ecosystems and promotes ecosystem services. In particular, it has been found that EI boosts the supply of natural pest control e.g. increases the abundance of predators and decreases pest abundance (e.g. Geertsema et al. (2016), Wan et al. (2019); Wan et al. (2020a); Wan et al. (2020b); Gurr et al. (2016)), and increases the abundance of pollinators (e.g. Duchenne et al. (2020); Huang and D'Odorico, 2020). Furthermore, EI decreases the negative environmental impacts, e.g. trough reduction in use of chemicals (e.g. Garibaldi et al. (2019); Gurr et al. (2016); Wan et al. (2018); Wan et al. (2019); Wan et al. (2020b)), while improving the productivity and the crop yields (e.g. Bright et al. (2017); Cardinale et al. (2010), Wan et al. (2018); Wan et al. (2020b); Gurr et al. (2016)).

However, while organic farming practices are expected to contribute to the provision of ecosystem services, such as biodiversity, carbon sequestration, and positive landscape features and to enhancing animal welfare, (Darnhofer et al. (2010); Power (2010)), only the certified organic farms themselves and the products they produce are accounted for in terms of ecological practices. Consequently, if a farm is not classified according to the organic production scheme, its products are considered conventional by default, irrespective of the farm's adoption of various ecological farming practices. This is problematic as it may lead to a significant underestimation of the actual application of ecological farming practices, as farms that partially adopt ecological

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https://doi.org/10.1016/j.jenvman.2021.113770
Received 12 April 2021; Received in revised form 9 September 2021; Accepted 16 September 2021
Available online 21 September 2021

management practices but are not certified due to size, costs, or other reasons, will not receive market premiums for the societal benefits from their production. Furthermore, as the adoption of farming practices, including the uptake of ecological practices, is affected by policy incentives (e.g. Fairweather (1999); Kuminoff and Wossink (2010); Hansson et al. (2019)), understanding and acknowledging the diversity in applied ecological practices is also fundamental for the development of appropriate agricultural policies that can further support a greening of the agricultural sector (Garibaldi et al., 2019).

Anecdotal evidence from exploratory workshops the authors organised with researchers, farmers, and other practitioners further underlines the need to better understand the diversity of applied ecological practices; participants question the strict dichotomy between organic and conventional production and point to the administrative aspects of organic certification as a disincentive, especially for small farms. Furthermore, discussions in the farming sector reveal a view that the current organic classification system is too narrow and does not account for the full heterogeneity of the ecological practices that are prevalent in the agricultural sector. The failure to recognise practices within conventional farming, such as low-input farming or conservation agriculture, may therefore undermine efforts to adopt ecological practices.

Previous research has also challenged the idea of conventional versus organic farming. Fairweather et al. (2009) also found evidence of a strong environmental orientation among conventional farmers and argued that the organic classification is too narrow to fully capture the diversity of practices that generate positive environmental outcomes. Efforts have been undertaken to organise the range of ecological practices into classification schemes, for instance by Dalsgaard et al. (1995); Hendrickson et al. (2008); Lantinga et al. (2004); Leeson et al. (1999); Stavi et al. (2016); Sutkowska et al. (2013); and Therond et al. (2017) (see Rega et al. (2018) for a comprehensive review). These studies range from efforts to define ecological sustainability and integrated farming practices to an examination of chemical input levels and varying degrees of conservation agriculture. Based on a review of these studies, Rega et al. (2018) proposed a spectrum of ecological farming practices based on a categorisation of management practices on an ecological scale.

In this study, we use the synthesis by Rega et al. (2018) and propose a procedure for classifying farms into an ecological farming typology based on information about management practices applied at the farms. Consequently, the aim of this study is to develop an approach for constructing a typology of the current uptake of ecological practices on a variety of farms, so as to understand the type of ecological practices applied in a sample. We hypothesise that farmers can be clustered into homogenous groups based on their degree of application of ecological management practices, using information about farmers' adoption of pest and plant disease management, weed management, fertilisation and soil management, crop diversification and crop rotation and grassland management. We use data from the Swedish agricultural sector to demonstrate the applicability of the approach and further explore how current organic farming certification practices relate to the typology revealed from the applied ecological practices, along with other characteristics of the farms. The primary purpose of generating typologies is to develop concepts and create categories (Collier et al., 2012). Typologies can be used to describe, communicate, and understand the complexity in relationships between multiple factors that affect farmers' behaviour (Emtage et al., 2007).

This paper contributes to the literature by developing a participatory approach for typology development related to farm uptake of ecological practices, based on which categories of farms can be formed. By allowing for a more nuanced categorisation of farms in relation to their uptake of ecological practices, such categories should be useful for future research aimed at modelling within the agricultural sector and for analyses that are interested in evaluating the driving forces for uptake of specific ecological practices. Being able to construct an ecological farming typology based on farmers' actual management practices would also be highly relevant from a policy perspective. For instance, farm typologies can be used as an instrument for policy assessment and monitoring (Andersen et al., 2007). Furthermore, in the European policy context, an ecological farming typology would provide important insights into policy development and goal fulfilment. While productivity and efficiency remain a central part of the CAP (Erjavec and Erjavec (2015); Leduc et al., 2021), the multi-functionality and environmental concerns connected to agricultural systems dominate the policy direction of the CAP (Erjavec and Erjavec (2015); Leduc et al., 2021). European farmers are therefore expected to generate ecosystem services while at the same time ensuring economic performance. An approach that allows for a broader view of what constitutes ecological farming may thus contribute to a more diverse array of tools for farmers to fulfil these goals by encouraging a less rigid ecological classification in the EU, which could promote the use of ecological practices, including among farms that have previously chosen not to certify their production as organic.

2. Method

2.1. Overview of typology development

The choice of variables and type of data collection will naturally affect the outcome of a typology. The construction of typologies therefore inherently involves a level of subjectivity (Alvarez et al. (2018); Bailey (1994); Emtage et al. (2007)), which is one of the main criticisms raised against classification methods (Bailey, 1994). Hence, prior knowledge and theoretical guidance are required in order to make the right decision about what variables to include (Rega et al., 2018). Similarly, Landais (1998) suggests that information about types should be gathered before the data collection. One way to reduce subjectivity and derive a more solid typology is to use an approach that involves both statistical methods and elements of stakeholder validation. Several authors have pointed to the benefits of applying such a mixed approach, where a qualitative part can strengthen or complement the results from a statistical method (e.g. Alvarez et al. (2018); Emtage et al. (2007); Kostrowicki (1977); Kuivanen et al. (2016); Pacini et al. (2014)). Furthermore, Emtage et al. (2007) discussed how a participatory approach strengthens the sense of ownership of the typology among the stakeholders involved. Similarly, Alvarez et al. (2018) argued that typology development should involve local stakeholders and proposed a methodological framework for typology construction using a combination of expert knowledge, participatory approaches, and statistical methods. Geertsema et al. (2016) also point out that interaction between researchers and stakeholders supports an effective implementation of measures for sustainable use of ecosystem services. Thus, in addition to a multivariate analysis, this study is based on stakeholder participation through workshops, first to validate the problem formulation as introduced above and second to discuss the results of our data analysis; see Fig. 1.

As a starting point, we conducted a review of the current literature on typologies related to ecological practices and organic farming. As mentioned above, the detailed review by Rega et al. (2018) served as a basis for the identification of previous studies of typologies in ecological farming. The validation of problem formulation was done through consultation with stakeholders and the available literature. The problem formulation was guided by a multi-stakeholder workshop (Bigot et al., 2020) in addition to the review by Rega et al. (2018). The process secured a problem formulation anchored in the current policy environment and the empirical context of the study (Swedish agriculture). Next, we defined the set of management practices to serve as input for the data analysis. This step involved theoretical findings from the literature combined with knowledge from the research team. The data analysis involved factor analysis and cluster analysis (described in detail below) in order to i) reduce dimensionality while preserving the data structure; ii) identify homogenous groups in the data, based on the degree of adoption of ecological management practices; and iii) apply

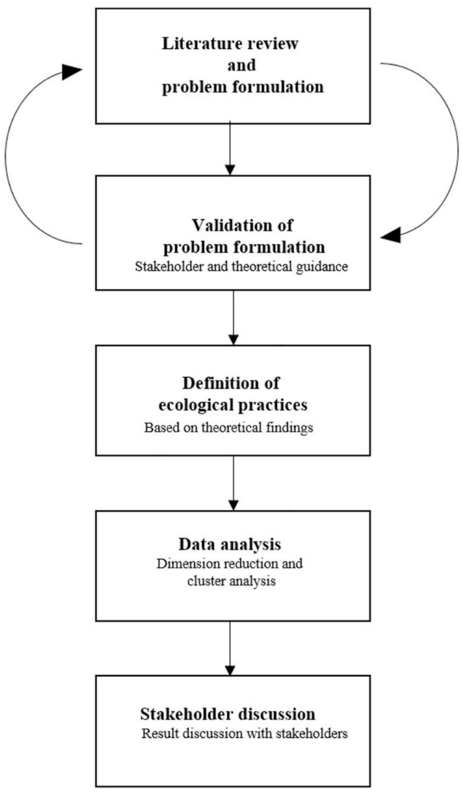


Fig. 1. Study methodology.

regression analysis to describe profile affinity as a function of socio-economic characteristics and organic certification. Finally, we performed a workshop to disseminate the results and engage in discussion with stakeholders from the Agrifood Economics Centre and the Swedish Board of Agriculture.

2.2. Ecological practices and variable selection

In our selection of ecological management practices, we depart from the overview provided by Rega et al. (2018), who referred to ecological practices as the extent of adoption of chemical input use, the use of inputs from outside the agriculture system, appropriate rotation system, tillage management, presence of semi-natural habitats as sources of functional biodiversity, water management, waste management, recycling of biomass for composting or energy, reduced carbon footprint or measures to mitigate CO2 emissions etc. We limited the inclusion of management practices to those most frequently applied in Swedish agriculture. This means that landscape features located on the farm, such as hedgerows, flower strips, tree lines, etc., were excluded. Although it can be argued that such landscape features are part of a farmer's ecological management effort (e.g. by contributing to preserving biodiversity), they are not common practices in a Swedish context. In addition, and in contrast to Rega et al. (2018), we argue that it is useful to distinguish between ecological farming practices, climate-related practices, and overarching sustainable practices. A wide range of factors, from the economic management of farm activities to animal welfare management and input use, should be considered when examining sustainable practices. For the consideration of ecological practices, we focus on management practices related to the management of fertilisers, pesticides, weeds and soil and grasslands, as well as crop diversification and crop management. This means that we opted not to consider energy management in farm infrastructure as measures taken to mitigate CO2 emissions, which relate to climate efforts but are not directly related to agricultural production. We also excluded water management as this belongs to broader sustainability concerns. In addition, we disregarded animal disease management and manure and sludge management from the analysis as these did not contribute to the model specification.

Table A1 (see Appendix) shows the groups of management practices and indicators considered in the development of a typology of ecological practices. The management practices: pest and plant disease, weeds, fertilisation and soil, crop diversification and crop rotation, and grassland management are all considered on a 6-point Likert scale, answering the question "On what % of your UAA did you use this practice in 2018?" with the following response options: did not use = 0, less than or equal to 5% = 1, between 5% and 10% = 2, between 10% and 15% = 3, between 15% and 20% = 4, more than 20% = 5. Data were collected from a large-scale survey that is part of the H2020 project LIFT (Tzouramani et al., 2019). Additionally, in our regression analyses, two variables were included to investigate the effect of organic certification, KRAV (Swedish certification scheme) and EU organic certification as well as socio economic and demographic variables.

2.3. Data analysis

2.3.1. Study area and data collection

An internet-based survey was conducted among Swedish farmers during the autumn of 2019. Data collection was part of a large-scale survey administrated to case study areas in the H2020 project LIFT (Tzouramani et al., 2019). After receiving the contact details from Statistics Sweden, invitation letters were sent by post to 1500 respondents with farms that specialised in livestock production: dairy, sheep, cattle, livestock, or mixed livestock. Only respondents with commercial farms, requiring a minimum of 1600 working hours per year, were selected in order to exclude potential hobby farmers. To fit with the regional disparities of farming activity across Sweden, the sample was stratified with i) 715 farmers randomly drawn from counties located in the Southern-plain areas of Sweden, including: Blekinge län, Skåne län, Hallands län, Västra Götalands län, Örebro lön, Västmanlands län, Södermanlands län, Uppsala län and Stockholms län and ii) 785 farmers from counties in North Sweden: Gävleborgs län; Jämtlands län, Västernorrlands län, Västerbottens län and Norrbottens län. This allowed for a comparison between two broad geographical areas (South and North), which represent areas that differ in their conditions for agriculture, in terms of both geographical conditions and access to markets and labour. A map showing the regional division of Sweden can be found in the Appendix (see Figure A1). The invitation letter was followed by three electronic reminders. The final sample consists of 387 respondents, corresponding to a response rate of 26%. After cleaning the data, we ended up with 184 observations. Table 1 and Figs. 1and2 provide descriptive statistics of the sample.

The average age in the sample was 59 years, a majority (85%) of the respondents were male, and about 14% had an agricultural education. The average area of total Utilised Agricultural Area (UAA) was 196 ha with an average turnover of SEK 1.81 million (approx. EUR 181,000).

Around 20 per cent of the respondents were dairy, sheep, and goat or mixed crop and livestock producers respectively. Around half of the respondents (96) were located in the northern regions (Gävleborg,

Table 1
Descriptive statistics of general sample characteristics.

Variable	Obs	Mean	Sd
Age (years in 2019)	172	58.576	11.334
Agricultural education (1 if yes; 0 if no)	184	.136	n/a
Gender (1 if male; 0 if female)	153	.85	n/a
UAA (Utilised agricultural area; ha)	162	196.044	158.787
Agricultural experience (years)	167	37.928	14.336
Turnover (SEK in 2018)	156	1,811,383	3,872,869

Note: Observations differ due to missing values; 10 SEK is approximately 0.988 EUR (June 2021). n/a (not applicable).

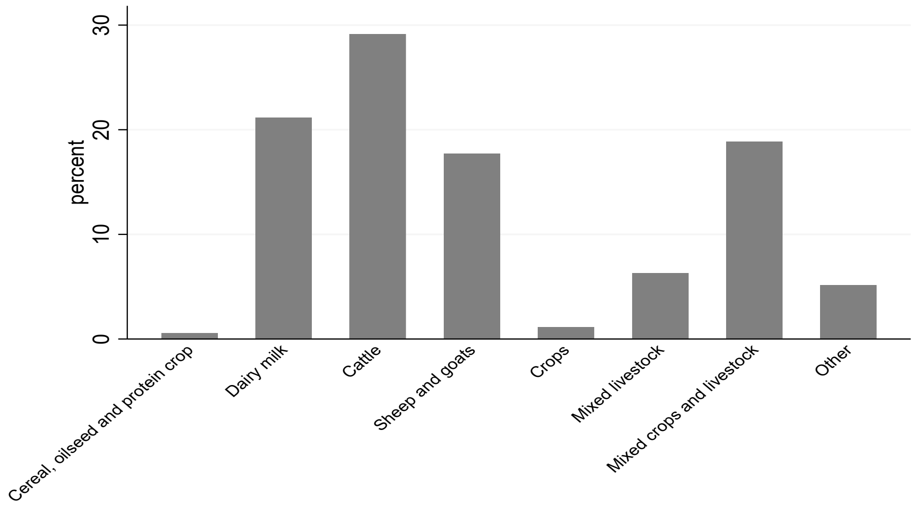


Fig. 2. Distribution of main farm types in the sample.

Västernorrland, Jämtland, Västerbotten and Norrbotten) and 86 were in the south (Stockholm, Uppsala, Södermanland, Örebro, Bleking, Skåne, Halland and Västra Götaland) (see Appendix for map of Swedish NUTS regions). Hence, the response rate in both the northern and southern regions was around 12%.

2.3.2. Statistical methods

Given the large number of management indicators (41), we used factor analysis to reduce the data dimensionality and to group the indicators. Hence, we use a multivariate analysis consisting of two parts: i) an exploratory principal component factor analysis to reduce dimensionality in the data that was applied to the practices in each management group; ii) cluster analysis, using Latent Profile Analysis (LPA) to identify potential underlying groups within the data. Using LPA, we could identify the unobserved underlying group structure in the data, i.e. the underlying latent structure, based on farmers' adopted ecological farming practices. We used the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy to evaluate whether the data was suitable for factor analysis. Test scores were between 0.577 and 0.730, which are all within the acceptable range. Management practice groups related to weed management and to crop management were in the lower, but acceptable, range although not "meritorious" (0.8–0.9) (Spicer, 2005).

For the principal component factor analysis, varimax rotation was used to extract the factors. Table 2 demonstrates the results from the factor analysis, which resulted in 12 factors, representing five groups of management practices in the data. We analysed each group of management practices separately and kept factors with an eigenvalue above one, following the Kaiser criterion (Kaiser, 1960). For interpretational purposes, indicators with loadings above 0.4 were considered (e.g. Pituch and Stevens, 2015). To avoid cross loadings, indicators with strong loadings (above 0.4) for more than one factor were excluded.

To examine clusters in the data, we used Latent Profile Analysis (LPA), the Gaussian (finite) mixture model, which is the corresponding analysis method to the more commonly known Latent Class Analysis (LCA), or the Binomial (finite) mixture model but for continuous class indicators (Oberski, 2016). Hence, the difference between LCA and LPA is conceptual and not technical. The analysis was performed on the 12 factors resulting from the factor analysis, where *weed_org_mix* was found to be non-significant for all classes and hence excluded, leaving 11 factors. The number of profiles was guided by goodness-of-fit indices. LPA assumes that the latent group structure follows a normal distribution, but that the distribution differs between the groups. The goal is to identify unobserved latent profiles based on similarities in individual observed response patterns.

Following Masyn (2013), we can represent this more formally as in Eq. (1)

$$f(y_i) = \sum_{k=1}^{K} \pi_k f_k(y_i) \tag{1}$$

where we have M continuous latent profile indicators $y_1, y_2, \dots, y_M$ on n individuals, where y_{mi} is the observed response to item m for individual i (in our case, the observed response to the item is now the value for the individual i for factor m from the factor analysis), hence, $y_i = y_{1i}, y_{2i}, \dots y_{Mi}$. We assume an underlying unordered categorical latent profile variable c, with K classes where $c_i = k$ if individual i belongs to profile k. The proportion of individuals with profile k is represented by π_k, where each individual in the population is a member of one group only and the $\sum \pi_k = 1$. $f(y_i)$ is the multivariate probability density function for the overall population, and $f_k(y_i) = f(y_i | c_i = k)$ is the group-specific density function for profile k. The observed variables are assumed to be independent, conditional on the latent variables, which is the assumption of local independence. That is, within each profile, the observed variables are uncorrelated. Membership is estimated as a probability conditional on a participants' response variable score, where the model parameters are the estimated maximum likelihood (ML) via the EM algorithm in Stata (2015). Based on Bayes' theorem, farmers are assigned to a profile based on the highest posterior profile membership probability (Eq. (2)).

$$\mathrm{P}(c_i = k | y_i) = \frac{\pi_k f_k(y_i)}{f(y_i)} \tag{2}$$

Since the number of latent profiles in the data is unknown, we used an exploratory approach, estimating each class until we find the lowest goodness-of-fit scores, using Akaikes Information criterion (AIC) (Akaike, 1974) and Bayesian information criterion (BIC) (Schwarz, 1978) values. The information criteria both tell us how well the model fits the data, with lower values indicating a better fit.

Seemingly Unrelated Regression (SUR) and Multinomial regressions (MNL) can be used to describe the relationship between the probability of profile membership and covariates, depending on the specification of the dependent variable. Alternatively, for small profile groups, logistic regression can be used (Peduzzi et al., 1996). We used an SUR model as defined in Eq. (3)

$$y_{ti} = \sum_{j=1}^{K_i} x_{tij} \beta_{ij} + u_{ti} \tag{3}$$

where y_{ti} is the t'th observation on the i'th dependent variable, x_{tij} s the t'th observation on the j'th explanatory variable in the i'th equation. β_{ij} is the coefficient associated with x_{tij} and u_{ti} is the error term (Srivastava

Table 2
Summary of factors retained from the principal component factor analysis.

Group of management practice	Management practice	labels	Mean (sd)	Factor 1	Factor 2	Factor 3
Pest and plant disease management				*pest_chem_mix*	*pest_org*	
	Chemical products	pest_chem	0.201 (0.676)	0.636		
	Biological control	pest_bio	0.033 (0.254)		0.905	
	Chemical products allowed by organic regulation	pest_chem_org	0.076 (0.538)		0.893	
	Pest/disease resistant/tolerant varieties	pest_varieties	0.342 (0.962)	0.614		
	Integrated pest management principles (IPM)	pest_IPM	0.152 (0.708)	0.708		
	Precision technologies	pest_prec	0.19 (0.818)	0.776		
Variation explained				*32%*	*29%*	
Kmo	0.585					
Weed management				*weed_chem_mix*	*weed_org_mix*	*weed_alt*
	Mulching with an inorganic material	weed_mulch_inorg	0.005 (0.074)	–	–	–
	Mulching with organic/biodegradable material	weed_mulch_org	0.043 (0.230)			0.746
	Machine weeding	weed_mach	0.255 (0.757)		0.652	
	Manual weeding	weed_man	0.245 (0.747)	–	–	–
	Thermal weed control	weed_therm	0.005 (0.074)	–	–	–
	Weed-tolerant varieties	weed_var	0.06 (0.492)			0.763
	Integrated weed management (IWM) principles	weed_IWM	0.174 (0.791)	0.905		
	Precision technologies to guide herbicide application	weed_prec	0.109 (0.644)	0.810		
	Chemical products (herbicides)	weed_chem	0.359 (1.025)	0.836		
	Products allowed by organic regulations	weed_org	0.082 (0.466)		0.861	
Variation explained				*33%*	*17%*	*17%*
Kmo	0.613					
Fertilisation and soil management of crop area				*fert_conv*	*fert_cons*	*fert_org*
	Conventional tillage	fert_convtill	1.582 (1.566)	0.852		
	Conservation tillage	fert_constill	0.141 (0.555)		0.602	
	No tillage	fert_notill	0.130 (0.548)		0.576	
	Application of inorganic fertilisers	fert_inorg	1.001 (1.812)	–	–	–
	Application of animal manure	fert_manure	1.815 (1.752)	0.839		
	Application of sewage sludge and other sludge	fert_sludge	0.022 (0.295)	–	–	–
	Application of compost	fert_compost	0.087 (0.575)	–	–	–
	Application of soil amendment	fert_soilamend	0.082 (0.489)			
	Green manuring	fert_green	0.212 (0.756)			0.827
	Leaving crop residues on soil	fert_cropres	0.277 (0.884)			0.674
	Planting of nitrogen-fixing crops	fert_nfix	0.435 (1.011)	–	–	–
	Planting of catch crop	fert_catcrop	0.092 (0.498)			
	Planting of cover crop	fert_covcrop	0.011 (0.147)	–	–	–
	Precision technologies	fert_prec	0.114 (0.711)			
	Machine controlled application	fert_machine	0.152 (0.767)		0.634	
	Soil mapping	fert_soilmap	0.299 (1.113)		0.649	
Variation explained				*20%*	*18%*	*14%*
Kmo	0.577					
Crop diversification and crop rotation				*crop_mixed*	*crop_fall*	

(*continued on next page*)

Table 2 (*continued*)

Group of management practice	Management practice	labels	Mean (sd)	Factor 1	Factor 2	Factor 3
	Crop rotation	crop_rot	1.402 (1.995)	–	–	–
	Crop diversification	crop_div	0.098 (0.654)	0.694		
	Selection of traditional/locally adapted varieties	crop_trad	0.185 (0.816)	0.674		
	Mixed cropping	crop_mix	0.217 (0.827)	0.701		
	Fallowing	crop_fallow	0.255 (0.665)		0.947	
Variation explained				*36%*	*26%*	
Kmo	0.577					
Grassland management				*grass_alt*	*grass_conv_mix*	
	Application of inorganic fertilisers	grass_inorg	0.384 (1.209)		0.682	
	Application of animal manure	grass_manure	0.380 (1.049)		0.721	
	Application of sewage sludge or other sludge	grass_sludge	0.027 (0.369)	0.982		
	Application of compost	grass_comp	0.027 (0.369)	0.982		
	Application of soil amendments	grass_soilamend	0.044 (0.429)	0.895		
	Mowing	grass_mow	1.141 (1.6)		0.539	
	Reseeding	grass_reseed	0.038 (0.242)		0.644	
Variation explained				*42%*	*25%*	
Kmo	0.730					

Note: weed_mulch_org, weed_therm, fert_sludge, and fert_compost were excluded because of no variation, and weed_man, fert_inorg, fert_soilamend, fert_nfix, fert_covcrop, fert_prec, and crop_rot were excluded because of cross-loadings in factors..

and Giles, 2020).

We also used a logistic model defined as Eq. (4), where the number of groups is $k = 1,2$

$$P(c_i = k|x_i) = \frac{e^{\beta_i x_i}}{1 + e^{\beta_i x_i}} \quad (4)$$

3. Results

3.1. Variables and dimension reduction

The factors retained from the principal component factor analysis of the management practice groups are summarised in Table 2.

For *pesticide use*, we retained two factors, which together explained 61% of the total variation. The first factor contained high loadings for use of precision technology, IPM, chemical products, and selection of varieties. The first factor was therefore labelled *pest_chem_mix*, considering the mixture of management practices. The second factor was labelled *pest_org*, since it comprises indicators related to biological control and chemicals allowed in organic production.

The factor analysis for *weed management* retained three factors after excluding three indicators due to no variation and cross-loadings, explaining 67% of total variation. The first factor was labelled *weed_chem_mix,* as the highest loadings related to weed management were usage of IWM, chemicals, and precision technologies. The second factor, with high loadings for manual weeding and chemicals allowed for organic production, was labelled *weed_org_mix*. The third factor was labelled *weed_alt*, referring to alternative practices of mulching using organic/biodegradable material and using weed-tolerant varieties.

Likewise, for the *fertiliser management* group, we retained a three-factor solution with use of conventional tillage and application of manure loading high on the first factor, labelled *fert_conv*. The factors explained 52% of total variation. The second factor had high loadings on conservation tillage, no tillage, use of machine, and soil mapping and hence was labelled *fert_cons*. The third factor contained high loadings for use of green manuring and application of crop residuals and was therefore labelled *fert_org*, referring to organic fertilisation.

For *crop diversification and crop rotation,* we retained two factors after crop rotation was excluded due to cross-loading. The first factor was labelled *crop_mixed,* as it had high loadings for crop diversification, selection of traditional/local varieties, and mixed cropping. The second factor only contained *crop_fallow*, which was included as a separate factor to facilitate interpretation. The factors explained 62% of total variation.

Finally, the factor analysis for the *grass management* group gave a two-factor solution, explaining 67% of the variation. We labelled the first factor *grass_alt,* as it comprised indicators related to use of sludge, compost, and soil amendment, therefore referring to this factor as mixed alternative usage. We labelled the second factor *grass_conv_mix,* referring to a mix of conventional approaches*:* it contained high loadings on use of manure, inorganic fertilisers, reseeding, and mowing.

3.2. Farm clusters

Eleven factors retained from the PCA were used as input for the LPA. A four-profile solution was considered the most appropriate based on the BIC (Schwarz, 1978) and AIC criteria (Akaike, 1974), which both took their minimum values at a four-class model (Table 3).

After running the four-class solution, *weed_org_mix* was not significant in any of the profiles and hence excluded. The contributions and

Table 3
Goodness-of-fit for the estimated classes.

Model	Obs	ll(model)	df	AIC	BIC
one-profile	184	−2866.417	22	5776.833	5847.562
two-profile	184	−2654.173	34	5376.346	5485.654
three-profile	184	−2536.995	46	5165.991	5313.878
four-profile	**184**	**−2427.792**	**58**	**4971.584**	**5158.050**
five-profile	184	−2469.56	70	5079.12	5304.166

significance of the factors to each of the profiles is demonstrated in Table 4. The probability for belonging to Profile 1 is the highest at 88.5%, followed by 4.5% for Profile 2, 4.9% for Profile 3, and 2.2% for Profile 4. Hence, a clear majority of the farmers are classified into Profile 1.

The four groups demonstrate differences in the level of chemical inputs and diversification, and we labelled the groups according to the contribution of the significant factors in each group.

Profile 1: Low chemical input and low alternative or conservation farming. Represents farmers with low use of chemicals, precision technologies, and decision models for integrated pest and weed management principles (IPM and IWM) in the form of negative values for *pest_chem_mix* and *weed_chem_mix*. Moreover, the factors *fert_cons* and *weed_alt* are negative and significant, indicating a low use of alternative weed and fertilisation management practices, such as mulching with organic material, using weed-tolerant varieties, and soil mapping, as well as low use of conservation tillage and no-till practices.

Profile 2: High chemical input farming with diversified crop and soil management. Farmer profile 2 represents about 4.5% of the farmers and is characterised by high use of chemicals, precision technologies, and decision models for integrated pest and weed management principles (IPM and IWM) in the form of *weed_chem_mix* and *pest_chem_mix*. In addition, the factors *fert_conv*, *fert_cons,* and *crop_mixed* represent diversified management of crops and soils for the farmer profile.

Profile 3: Low input farming with alternative soil and crop management. For Profile 3, the factors *fert_org, crop_fall,* and *weed_alt* indicate use of organic and alternative management practices, such as application of soil amendment, green manuring, mulching with organic material, using a selection of varieties for weed management, and fallowing.

Profile 4: High chemical input with ecological farming with mixed grassland management. In addition to *pest_chem_mix* and *weed_chem_mix,* Profile 4 contains respondents with a mix of crop and grassland management practices in the form of *pest_org, fert_cons,* and *crop_fall,* indicating use of biological pest control, chemicals allowed for organic production, conservation tillage, no-till, soil mapping, and machine-controlled application. Moreover, the group is characterised by the factors for alternative and conventional grassland management, *grass_alt* and *grass_conv_mix,* and was therefore labelled high chemical input and conservation or ecological farming with mixed grassland management.

The results show that a higher use of chemicals in Profiles 2 and 4 is combined with a higher use of alternative or more ecological approaches, such as crop diversification and reduced tillage, biological control, and chemicals allowed in organic production for pesticide and disease management. The higher reliance on chemicals in Profile 2 could be explained by the higher use of conservation approaches, such as no-till, conservation tillage, and crop mixing, which are the basic principles in conservation farming. Such practices are more reliant upon the application of chemicals such as glyphosate (Kudsk and Mathiassen, 2020). Profile 3, on the other hand, contains farmers using only alternative and low-input approaches, without reliance on chemicals. This group of farmers may therefore be the farmers committed to low-impact agriculture. The largest farmer profile, Profile 1, can be interpreted as the conventional or "regular farmer" profile with a lower use of chemicals, but also a lower use of alternative or conservation approaches.

3.3. Characterising the farmer groups

Using seemingly unrelated regression (SUR), we estimated the effect of being certified with KRAV or the EU organic label in addition to the socio-demographic variables: age, gender, agricultural education, agricultural experience, geographical location (north or south), and farming income (Table 5). The dependent variables are the profile-specific probabilities in each group.

An increase in age increases the likelihood of belonging to Profile 1 (although a small coefficient, indicating a small effect), as well as being located in the north. Additionally, an increase in farm income decreases the likelihood of belonging to Profile 1. Profiles 2 is negatively related to being in the north, hence it includes farmers who are more likely to be located in the southern regions. Profile 3 is negatively related to gender, where male = 1 and hence profile 3 is more likely to be characterised by female farmers. Additionally, profile 3 is related to higher farming income, although the effect is small and only significant at the 10% level. In Profile 4, farmers have a higher degree of agricultural experience and farming income, although the effect is small and only significant at the 10% level.

In addition to the SUR, we performed a logistic regression to further examine the differences between groups, with the dependent variable as a dummy variable taking the value 1 if the observation belonged to Profile 1 and 0 if the respondent belonged to any other group (Table 5). A multinomial logistic regression (MNL) would allow for differences between each group, with the dependent variable introduced as a dummy variable for profile affinity for each of the groups, but due to the small number of observations in groups 2–4, results from a MNL are likely to be biased (Peduzzi et al., 1996) and hence, a logistic regression is more appropriate.

The results from the logistic regression indicate a higher likelihood of being located in the northern regions and a lower likelihood of higher farming income for Profile 1, relative to the group with Profiles 2, 3, and 4. Hence, an increase in farming income would decrease the likelihood of belonging to Profile 1. Additionally, age is significant and above 1, indicating a higher likelihood of higher age in Profile 1 than in the group containing Profiles 2–4. Agricultural experience is significant at the 10% level and indicates that there is a lower likelihood of agricultural experience and belonging to Profile 1. Hence, the results indicate that Profile 1 is more likely to contain older farmers and less likely to contain farmers with higher agricultural experience and lower farming income,

Table 4
Expected profile probabilities and variable coefficients in each class.

	Profile 1		Profile 2		Profile 3		Profile 4	
	Coef.	*p*-value	Coef.	*p*-value	Coef.	*p*-value	Coef.	*p*-value
Profile probability	0.885***	0.000	0.045***	0.000	0.049***	0.000	0.022***	0.000
pest_chem_mix	−0.233***	0.000	2.551***	0.000	0.02	0.909	**4.2****	0.000
pest_org	−0.064	0.368	−0.27	0.397	0.202	0.505	**2.708*****	0.000
fert_conv	−0.075	0.302	1.705***	0.000	−0.227	0.462	0.064	0.891
fert_cons	−0.129**	0.037	1.09***	0.000	−0.3	0.254	**3.698*****	0.000
fert_org	−0.056	0.462	−0.246	0.493	0.852***	0.008	0.865*	0.074
crop_mixed	−0.082	0.274	1.315***	0.000	0.24	0.451	0.089	.851
crop_fall	−0.077	0.312	0.097	0.774	0.859***	0.008	**0.982****	0.042
weed_chem_mix	−0.213***	0.000	1.868***	0.000	−0.158	0.303	**5.193*****	0.000
weed_alt	−0.2***	0.000	−0.283*	0.083	3.901***	0.000	−0.086	0.709
grass_alt	−0.082	0.228	−0.059	0.847	0.089	0.760	**3.266*****	0.000
grass_conv_mix	−0.032	0.673	−0.325	0.343	0.405	0.214	**1.071****	0.029

Note: * significance at p < 0.1; ** significance at p < 0.05; *** significance at p < 0.001.

Table 5
Results from the seemingly unrelated and the logistic regression analysis.

	Seemingly unrelated regression								Logistic regression	
	Profile 1 Low chemical input and low conventional grassland and soil management		Profile 2 High chemical input farming with diversified crop and soil management		Profile 3 Low input farming and alternative soil and crop management		Profile 4 High chemical input with conservation or ecological farming and mixed grassland management			
	Coef.	*p*-value	Coef.	*p*-value	Coef.	*p*-value	Coef.	*p*-value	Odds ratio	*p*-value
Age	**0.005****	0.043	−0.002	0.214	−0.002	0.308	−0.001	0.286	**1.07****	0.036
Gender	0.044	0.550	0.033	0.464	**−0.092***	0.076	0.015	0.689	2.011	0.362
Agricultural education	−0.044	0.545	0.025	0.579	−0.034	0.501	0.053	0.142	0.649	0.514
Agricultural experience	−0.003	0.108	0.002	0.150	−0.001	0.707	**0.002***	0.051	**0.954***	0.077
North	**0.109****	0.043	**−0.056***	0.094	−0.029	0.444	−0.024	0.380	**3.375****	0.046
Certified Krav	0.031	0.658	−0.009	0.844	0.027	0.590	−0.050	0.162	1.391	0.659
Eu organic label	0.020	0.796	0.016	0.737	−0.007	0.893	−0.028	0.459	1.308	0.663
Farming income	**−0.128****	0.019	0.017	0.618	**0.065***	0.090	**0.046***	0.093	**0.188****	0.019
Constant	0.637	0.000	0.087	0.432	0.216	0.086	0.060	0.501	0.736	0.866

Note: ***p < 0.01, **p < 0.05, *p < 0.1; Obs. 145; Base for the logistic regression = Profile 1; Odds ratio >1 = higher likelihood of event; < 1 = lower likelihood of event.

and these farmers are more likely to be located in the north compared with the group containing Profiles 2–4. Interestingly, no significant between-group differences were found for KRAV certification or the EU-organic label, suggesting that being KRAV certified or having the EU organic label does not influence belonging to a certain profile. For robustness check, we excluded the variable accounting for EU organic in the SUR and logistic regressions, but this did not affect the results (results not shown). The results of between-group differences are illustrated in detail in Table 6, where we use the chi-square test for the indicator variables KRAV certified, EU organic label, gender, and region and show the distribution of the indicators in each profile. Similar to the SUR and logistic, the chi-square test demonstrates that the between-group differences in KRAV certified and EU-organic label are not significant. For the regional distribution however, the test indicates significant between-group differences, and, similar to the SUR, suggests that for Profiles 1, 2 and 3, there is a higher percentage of farmers located in the north, while in profile 4, there is a larger share located in the south.

4. Discussion and policy perspectives

The aim of this study was to examine heterogeneity in farmers' adoption of ecological management practices. While previous studies have suggested different methods to categorise farms into, for example, ecological sustainability, integrated farming practices, chemical input levels, and varying degrees of conservation agriculture, our study more broadly examines whether there is support in survey data from Sweden for a broader view of conventional farming based on farmers' uptake of ecological management practices. With this study, we contribute to the literature by developing an approach for constructing a typology of the current uptake of ecological practices using a variety of farms in Sweden as empirical examples. Novel findings point to the varying uptake of ecological practices between the farmer profiles and suggest that there is no support for the conventional/organic dichotomy. Our analysis is based on the management practices proposed by Rega et al. (2018). The suggested method of clustering on management profiles is, however, not limited to these practices. Our approach can be adjusted to other countries and contexts and to include other management practices or technologies. The importance of our findings is that a strict division of organic and conventional agriculture may fail to take into account the diversity of practices applied.

Involving stakeholders in research formulation and result discussion provided important information and highlights what others (e.g Garibaldi et al. (2019) and Geertsema et al. (2016)), have emphasised – participation and inclusion of farmers is important in the research process and strengthens implementation. Using a participatory approach that combined data analysis with stakeholder participation, we identified four farmer profiles. Our discussion with stakeholders confirmed Profile 1 as representative of practices used by "an ordinary Swedish livestock farmer". However, the smaller profiles were seen as somewhat less representative of farm types that are generally recognisable to stakeholders. Nevertheless, a conservation management approach is

Table 6
Between-group differences.

	Profile 1 Low chemical input and low conventional grassland and soil management (n = 163)		Profile 2 High chemical input farming with diversified crop and soil management (n = 8)		Profile 3 Low input farming and alternative soil and crop management (n = 9)		Profile 4 High chemical input with conservation or ecological farming and mixed grassland management (n = 4)		χ^2	*p*
	n	%	n	%	n	%	n	%		
Krav certified									1.21	0.751
Yes	22	13.5	1	12.5	2	22	0	0		
No	141	86.5	7	87.5	7	78	4	100		
EU organic label									0.661	0.882
Yes	22	13.5	1	12.5	1	11.1	0	0		
No	141	86.5	7	87.5	8	88.9	4	100		
Gender									4.936	0.177
Female	20	12.3	0	0	3	33.3	0	0		
Male	115	70.6	6	75	5	55.6	4	100		
Region									6.878	0.076
North	89	54.6	1	87.5	5	55.6	1	25		
South	72	44.2	7	12.5	4	44.4	3	75		

Note: 1: 31 missing values; 2: 2 missing values.

dependent upon the use of more chemicals, such as glyphosate, which corresponds well to what we find in Profile 2, where farmers relied more on chemical input than farmers in Profile 1. In our view, the three smaller groups represent varying degrees of use of alternative and/or conservation approaches but may be more reliant upon the use of chemicals (Profiles 2 and 4). Furthermore, it is interesting to note that whether a farm is certified according to the Swedish KRAV certification or the EU organic label does not determine profile affiliation. Hence, certified organic farms do not differ enough from non-certified farms to form their own latent profile in the data. This means that farms in Profile 1 with more conventional approaches could be certified organic, as could farms in Profile 3, which are characterised by low-input, conservation, and alternative approaches, suggesting that even though a farm is not certified organic, the farmer may use ecological practices. The strict division into certified organic or conventional is therefore not supported in our results, implying that the dichotomy may indeed be too narrow. Moreover, we find that the region where the farm is situated affects profile membership. This is not surprising considering the Swedish climate and geographical conditions. Farms in different geographical locations face different landscapes and climatic conditions, and distance to the marketplace is larger in the north. The management practices applied will therefore differ from the south. Policy incentives targeting the different conditions faced by farmers in different regions could incentivise the adoption of ecological management practices. It is also interesting to note that income from farming is a significant determinant of profile membership. This could be an effect of differences in the costs of applying certain methods and differences on farm profitability. Hence, providing support to farmers so they can adopt more ecological management practices could increase adoption. Furthermore, stakeholders confirmed that the groups vary in the degree to which the farmers use ecological management practices but requested that a connection be made to the environmental pressure for the different practices, which would make it possible to grade them on an ecological scale from most conventional to most organic.

Given the increasing attention to agriculture as a multi-functional entity and the demand that the agricultural sector supplies ecosystem services to society, our examination of heterogeneity in ecological management practices provides insight that can be applied in policy making. Widening the view of the conventional spectra and including levels of ecological management practices could incentivise farmers who are willing to adopt ecological practices, but to a lesser, or higher, extent than what is required by the current certification schemes. However, our research does not take into account the costs and benefits of the different practices on the ecosystems. Wan et al. (2017) pointed out the importance of trade-offs in measures directed towards ecosystem management. For example, grazing, chemical pesticides and chemical fertilisers have negative effects on ecosystems in terms of loss of vegetation coverage, non-point source pollution and pesticide resistance, but additional positive effects such as promoting plant productivity and diversity, increasing crop yields etc. may outweigh negative effects or vice versa. Analysis of societal costs and benefits of management practices are an interesting and important area of future empirical research, where our approach (i.e cluster on management practices) could be combined with the methodology suggested by Wan et al. (2017) and would demonstrate the societal costs and benefits related to the different farmer profiles.

A limitation of our study is that farmers with interest in organic farming may be more likely to answer the survey. Hence, the conventional farmers may be underrepresented in the survey answers. Furthermore, the use of typologies is criticised for a lack of robust validation (e.g. Guillem et al., 2012). Thereby, an interesting direction for future research would be to replicate the study with a new sample, as this would allow for the study of the robustness of the profile generation. Questions about management practices could be easily incorporated into surveys sent out to farmers and thus potentially collected alongside other data. Furthermore, research is needed on the environmental effects and connection to the management practices in relation to Swedish and European policy, such as how different management practices or farmer profiles contribute to or counteract the goals of the Swedish environmental objectives.

5. Conclusions

With this paper, we developed an approach for constructing a typology of the current uptake of ecological practices on a variety of farms in Sweden. In particular, we presented a participatory methodology for typology construction, from problem formulation to data analysis and stakeholder discussions, based on a Swedish case study. In doing so, we investigated how farm management practices could allow for the creation of a typology of ecological practices. Our results show four different farm profiles with varying degrees of use of chemicals and ecological, alternative, or mixed management approaches. No relationship between profile membership and organic certification was found, and hence no evidence of latent profile membership based on the division into conventional and organic could be identified. Instead, our results suggest that regional differences and farming income are factors that influence profile membership and thus the adoption of ecological or conventional management practices.

Credit author statement

Lisa Höglind: Conceptualization; Data curation; Formal analysis; Investigation; Methodology; Software; Validation; Visualization; Roles/Writing - original draft; Writing – review & editing. **Helena Hansson:** Conceptualization; Data curation; Funding acquisition; Investigation; Methodology; Project administration; Resources; Supervision; Validation; Roles/Writing - original draft; Writing – review & editing. **Gordana Manevska-Tasevska:** Conceptualization; Funding acquisition; Investigation, Methodology; Project administration; Resources; Supervision; Validation; Roles/Writing - original draft; Writing – review & editing.

Funding

This study is part of the LIFT ('Low-Input Farming and Territories – Integrating knowledge for improving ecosystem-based farming') project that has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement no. 770747.

Declaration of competing interest

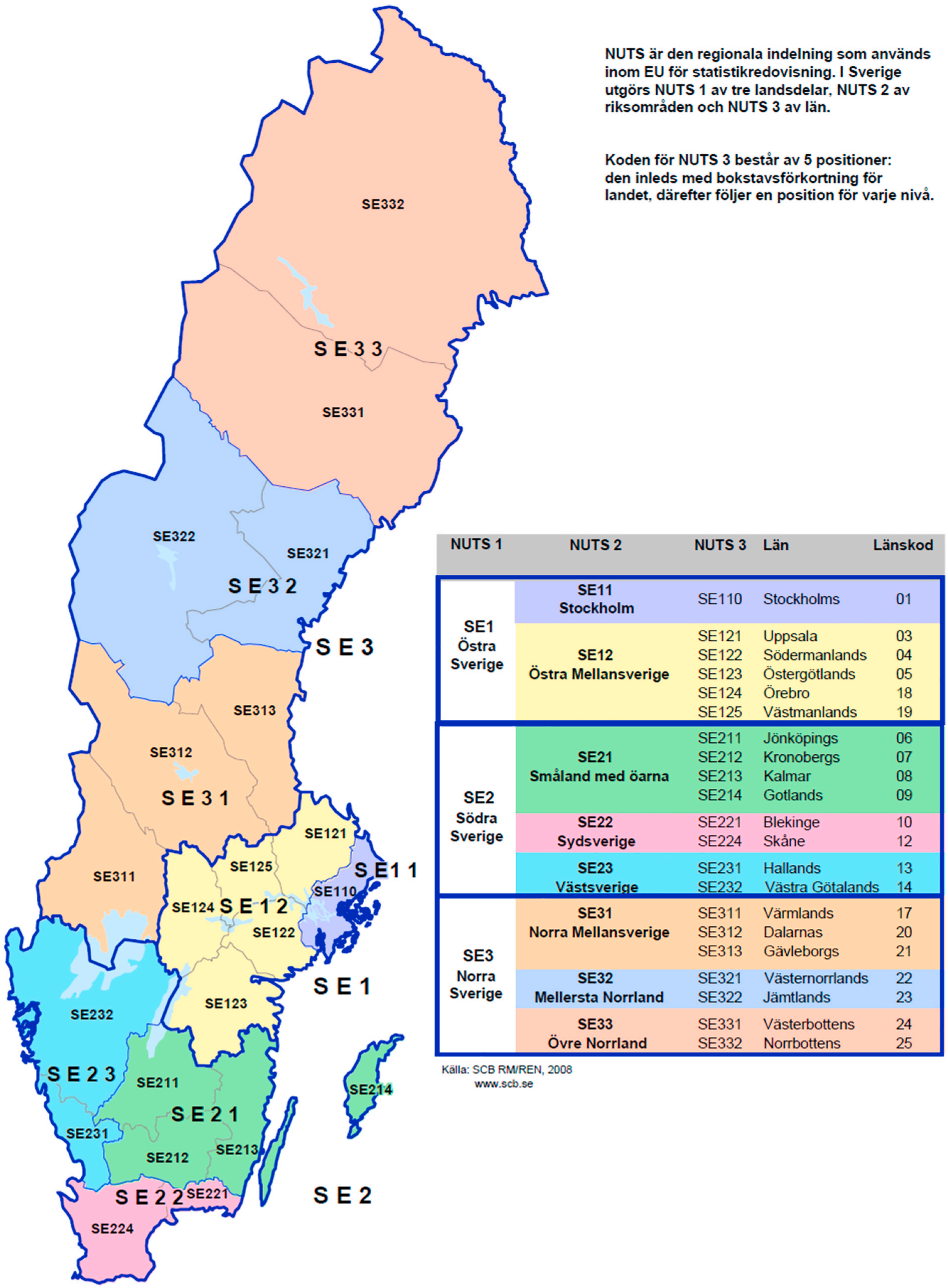
The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix

Table A1
Selected indicators used in farm type identification

Group of management practice	Variables	Labels
Pest and plant disease management	Chemical products	pest_chem
	Biological control	pest_bio
	Chemical products allowed by organic regulation	pest_chem_org
	Pest/disease resistant/tolerant varieties	pest_varieties
	Integrated pest management principles (IPM)	pest_IPM
	Precision technologies	pest_prec
Weed management	Mulching with organic/biodegradable material	weed_mulch_inorg
	Mulching with an inorganic material	weed_mulch_org
	Machine weeding	weed_mach
	Manual weeding	weed_man
	Thermal weed control	weed_therm
	Varieties tolerant of weed	weed_var
	Integrated weed management (IWM) principles	weed_IPM
	Precision technologies to guide herbicide application	weed_prec
	Chemical products (herbicides)	weed_chem
	Products allowed by organic regulations	weed_org
Fertilisation and soil management of crop area	Conventional tillage	fert_convtill
	Conservation tillage	fert_constill
	No tillage	fert_notill
	Application of inorganic fertilisers	fert_inorg
	Application of animal manure	fert_manure
	Application of sewage sludge and other sludge	fert_sludge
	Application of compost	fert_compost
	Application of soil amendment	fert_soilamend
	Green manuring	fert_green
	Leaving crop residues on soil	fert_cropres
	Planting of nitrogen-fixing crops	fert_nfix
	Planting of catch crop	fert_catcrop
	Planting of cover crop	fert_covcrop
	Precision technologies	fert_prec
	Machine controlled application	fert_machine
	Soil mapping	fert_soilmap
Crop diversification and crop rotation	Crop rotation	crop_rot
	Crop diversification	crop_div
	Selection of traditional/locally adapted varieties	crop_trad
	Mixed cropping	crop_mix
	Fields that lay in fallow	crop_fallow
Grassland management	Application of inorganic fertilisers	grass_inorg
	Application of animal manure	grass_manure
	Application of sewage sludge or other sludge	grass_sludge
	Application of compost	grass_comp
	Application of soil amendments	grass_soilamend
	Mowing	grass_mow
	Reseeding	grass_reseed

Note: Indicators were measured using a Likert scale, answering the question "On what % of your UAA did you use this practice in 2018?" with the following response options: did not use = 0, less than or equal to 5% = 1, between 5% and 10% = 2, between 10% and 15% = 3, between 15% and 20% = 4, more than 20% = 5.



NUTS 1	NUTS 2	NUTS 3	Län	Länskod
SE1 Östra Sverige	SE11 Stockholm	SE110	Stockholms	01
	SE12 Östra Mellansverige	SE121	Uppsala	03
		SE122	Södermanlands	04
		SE123	Östergötlands	05
		SE124	Örebro	18
		SE125	Västmanlands	19
SE2 Södra Sverige	SE21 Småland med öarna	SE211	Jönköpings	06
		SE212	Kronobergs	07
		SE213	Kalmar	08
		SE214	Gotlands	09
	SE22 Sydsverige	SE221	Blekinge	10
		SE224	Skåne	12
	SE23 Västsverige	SE231	Hallands	13
		SE232	Västra Götalands	14
SE3 Norra Sverige	SE31 Norra Mellansverige	SE311	Värmlands	17
		SE312	Dalarnas	20
		SE313	Gävleborgs	21
	SE32 Mellersta Norrland	SE321	Västernorrlands	22
		SE322	Jämtlands	23
	SE33 Övre Norrland	SE331	Västerbottens	24
		SE332	Norrbottens	25

Fig. A1. Nomenclature of Territorial Units for Statistics – NUTS statistical regions of Sweden

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