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Long-term trends in functional crop diversity across Swedish farms

Henning Schaak[a,*,1], Riccardo Bommarco[b,2], Helena Hansson[c,3], Brian Kuns[d,4], Pia Nilsson[c,5]

[a] University of Natural Resources and Life Sciences, Vienna, Department of Economics and Social Sciences, Institute of Agricultural and Forestry Economics, Vienna, Austria
[b] The Swedish University of Agricultural Sciences, Department of Ecology, Uppsala, Sweden
[c] The Swedish University of Agricultural Sciences, Department of Economics, Uppsala, Sweden
[d] The Swedish University of Agricultural Sciences, Department of Urban and Rural Development, Uppsala, Sweden

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ABSTRACT

The diversity of cultivated crops is relevant on various spatial scales, from the field and farm to the landscape. We apply a decomposition of the Shannon diversity index that allows the differentiation of functional diversity of production. The decomposition separates diversity of functional crop groups from related diversity, which shows the species diversity within the crop groups. Using population-based field and farm-level data from Sweden 2001–2018, we are able to study the development of overall (Shannon), functional and related crop diversity among a total of 83770 farms. Crop diversity indices are calculated by farm and year based on the Swedish Land Parcel Identification system (LPIS). We find that functional crop diversity has declined among Swedish farms over the period. Related crop diversity has declined but regained in recent years. Accounting for farm size and pedoclimatic conditions, organic farms have a higher functional diversity, and the uptake of organic practices leads to an increase in functional crop diversity over the period.

1. Introduction

Land use is the common denominator of agriculture and landscapes (Vejre et al., 2007). The diversity of cultivated crops at the farm and in the landscape is a defining factor for both agricultural production and the landscape as an ecosystem. Crop diversity affects biodiversity associated to agriculture (Aguilera et al., 2020; Sirami et al., 2019) and ecosystem functions such as pest control (Redlich et al., 2018) and microbial soil health (Guzman et al., 2021). The relationships can be complex. For example, positive effects of crop diversity can be offset by simultaneous increases in management intensity (Hass et al., 2018). Beyond ecological aspects, crop diversity also influences the visual appeal of a given landscape, thereby affecting the provisioning of cultural ecosystem services such as recreational values (van Zanten et al., 2014). Importantly, crop diversity can have major though diverse impacts on agricultural production. Diverse crop production can support climate change mitigation and adaption (Altieri et al., 2015; Marini et al., 2020), contribute to food security (Egli et al., 2021; Renard and Tilman, 2019), reduce reliance on external inputs for crop production (Bennett et al., 2012; D'Annolfo et al., 2017) and improve farm performance (Di Falco et al., 2010). Other landscape elements also play important roles in determining ecosystem functioning and biodiversity, but these can be more difficult to change quickly than the crops. For example, changes in field boundaries and semi-natural habitats are subject to ownership of the land, local cultural traditions, as well as legal restrictions (Clough et al., 2020). Thus, changing which crops to cultivate, for instance in a rotation, are comparably straightforward to implement when aiming to change the ecological functioning and appearance of an agricultural landscape.

Crop diversity is typically examined in terms of species richness and relative abundance. A commonly used indicator for crop diversity is the Shannon diversity index, or the effective number of crop species

* Corresponding author.
E-mail addresses: henning.schaak@boku.ac.at (H. Schaak), riccardo.bommarco@slu.se (R. Bommarco), helena.hansson@slu.se (H. Hansson), brian.kuns@slu.se (B. Kuns), pia.a.nilsson@slu.se (P. Nilsson).
[1] OCRID: 0000-0002-7659-4795
[2] ORCID: 0000-0001-8888-0476
[3] ORCID: 0000-0001-9609-4387
[4] ORCID: 0000-0001-5687-9307
[5] ORCID: 0000-0002-5664-3115

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(Aguilar et al., 2015; Hijmans et al., 2016; Liu et al., 2018). The Shannon measure implies a unidimensional conceptualization of crop diversity that ignores differences in functional traits among crop species. We take an alternative approach on the measurement of crop diversity by focusing on the functional complementarities or similarities that arise between and within groups of crop species as suggested by Di Falco et al. (2010). The main arguments for our approach is that functionally distinct crop species co-occurring in an ecosystem occupy more niche space, complement each other and thereby draw resources and suppress build-up of antagonists more efficiently than functionally less diversified species combinations (Díaz et al., 2016). Biologically diverse ecosystems thereby have high functional integrity and resource use efficiency (Gamfeldt et al., 2013; Hooper et al., 2012), which is shown to be particularly important for agroecosystem biodiversity and multifunctionality (Finney and Kaye, 2017; Gagic et al., 2015; Josefsson et al., 2017; Martin et al., 2019; Wood et al., 2015). Diverse cropping is also shown to reduce losses to pests and stabilize yields under adverse climate conditions (Altieri et al., 2015; Bowles et al., 2020; Degani et al., 2019; Holt-Giménez, 2002; Marini et al., 2020; Philpott et al., 2008). Separating functional and related diversity in tracking changes in crop diversity over time can improve our understanding of crop diversity trends and the associated potential benefits on the farm and in the landscape. Functional and related crop diversity affect the farm economy differently. Economic performance and input self-sufficiency are for example higher and increase over time with on-farm functional diversity (Nilsson et al., 2022), but the cropping trends of these diversity indices have not been established for larger geographic areas.

Swedish agriculture, which is our empirical focus, is on a path towards fewer, and more specialized farms with larger acreage, as also observed elsewhere in Europe (Baráth and Fertő, 2017; Djurfeldt and Gooch, 2002; Hansson et al., 2013; Neuenfeldt et al., 2019). This development is associated with a tendency of farms to simplify production and replace integrated crop-livestock production with high-input crop production (Neuenfeldt et al., 2019). However, this does not necessarily imply a continuous decline in crop diversity over spatial and temporal scales when moving towards further industrialization of agriculture (Aguilar et al., 2015; Crossley et al., 2021; Hijmans et al., 2016; Liu et al., 2018; Mariani et al., 2021; Smith et al., 2019). Instead, crop diversity trends can be both nonlinear and highly context specific.

Empirical assessments of functional crop diversity trends, in Europe and elsewhere, are needed to understand the build-up of potential capacities on farms in the face of price volatility and varying environmental pressure (IPBES, 2019; IPCC, 2021; Mariani et al., 2021). Still, the actual change in functional crop diversity taking place on farms over time is not known for major agricultural regions including Europe and Sweden. Most research has been limited to the county-level addressing landscape attributes other than crop diversity with little consideration given to variations at the farm level and to changes in policy over time (c.f. Aguilar et al., 2015; Crossley et al., 2021; Hijmans et al., 2016; Liu et al., 2018).

In assessing farm-level responses in crop diversity over time, we argue that it is necessary to account for the relevant policies that could influence farmers' cropping decisions. Policies to encourage crop diversification were introduced in the 'Greening' of the EU Common Agricultural Policy (CAP) reform for 2015–2020 with the aim to stimulate diversification of European farming systems based on monoculture. This includes agri-environmental measures to support organic farming and other measures to support farm crop diversification, permanent grassland retention and the establishment of ecological focus areas (Council Regulation (EC), 2013). As cropping decisions are made by farmers, we further argue that the farm is a relevant scale at which to examine factors influencing crop diversity changes over time and when investigating potential influences of CAP reforms. Since farming is often concentrated to certain regions in a country, crop diversity changes in the farm population also indicate crop diversity changes in the wider landscape.

Our objective is to assess farm-level changes in crop diversity from 2001 to 2018. We examine crop diversity trends by applying a decomposed measure of crop diversity that reflects trends in the cultivation of ecologically and thereby functionally differing groups of crop species, such as cereals, legumes, oilseeds, perennial pasture and forage, with contrasting traits. We contrast this to an examination of trends in crop species richness and relative abundance which can attain high values with functionally similar species, such as multiple species of cereals. By analysing the population of Swedish farms, we account for potential structural farm-level factors driving differences in crop diversity. In the analysis we account for the three CAP reforms in the time period covered. This gives us indications about whether changes in agricultural policy are associated with changes in crop diversity trends.

Using crop field-level data from the Swedish Land Parcel Identification system (LPIS), we perform a population-based assessment including nearly all Swedish farms 2001–2018. The LPIS includes 99.7 % of Swedish arable land (Jordbruksverket, 2021) and identifies on average 1,022,732 unique cropped parcels over the study period. We build a unique field and farm-level panel dataset to track changes in crop diversity among a total of 83,770 Swedish farms, accounting for three CAP reforms and varying biophysical conditions 2001–2018. Following Nilsson et al. (2022) we calculate farm-level diversity indices by additively decomposing the Shannon diversity index into two indices to distinguish between the average diversity of crops grown on a farm that are *i)* functionally unrelated, measuring diversity across functional groups of crop species, and *ii)* functionally related, measuring diversity within functional groups. We include variables from farm to EU level that influence crop diversity, such as farm size, soil quality, weather conditions, organic production and changes in agricultural policy.

2. Materials and methods

2.1. Measurement of functional and related crop diversity

In defining functional crop diversity, we consider that groups of crop species grown on a farm complement each other ecologically. To account for the functional diversity of crops grown on a farm, we extend the commonly used unidimensional measures of crop diversity. The Shannon index (H^S) is among the most applied of such measures and represents the basis and starting point for our decomposition approach. For a farm growing n different crops, it is calculated from the shares p_c of the individual crops $c = 1, \ldots, n$:

$$H^S = -\sum_{c=1}^{n} p_c * \ln(p_c) \tag{1}$$

The index ranges between 0 and $\ln(n)$. A value of 0 represents the special case when the farm only produces one crop (so that $n = 1$), whereas $\ln(n)$ is the result when all n crops are grown on identical shares of land.

Crop species can have more or less similar ecological roles in the cropping ecosystem (Roscher et al., 2012). The Shannon index (1) is based on the relative abundance of the crop species, and functional similarities or differences among crop species are not accounted for. In contrast to the Shannon approach, but in line with the research cited above on functional diversity, we bin crop species into nine functional groups: i) legumes, ii) oilseeds, iii) cereal, iv) fruits, berries, v) vegetables, herbs, potatoes, beets, vi) forage crops, vii) energy crops, and viii) pasture, hay, meadow. We consider also the land use group of ix) fallow, protection zones, wetlands on arable land. Our choice of the nine functional groups (Table S1) follows the approach in Nilsson et al. (2022) who group crop species that have distinct ecological roles in the agroecosystem, and use measures of diversity within and between the functional groups to reflect the degree of functional integrity and resource use efficiency of crops grown on a farm. The rationale is that increasing crop species richness can have a small impact on agroecosystem functioning if the added species are closely related and have similar traits, such as multiple species of cereals, whereas increasing functional crop diversity by introducing crops from several plant families could enhance the multifunctionality of the agroecosystem (Finney and Kaye, 2017). We therefore group crop species with functionally similar traits into functional groups (e.g. de Bello et al., 2010; Roscher et al., 2012; Westoby and Wright, 2006). This approach resembles that of Finney and Kaye (2017), who assembled crop species with similar traits to form four functional groups. In line with their approach, our grouping is focused on crop species that tend to be grown as monocultures, i.e., species of cereal and legume crops and other distinct groups of crops such as oilseeds, and fruits and vegetables. Still, they can be combined to assemble polycultures, which have varying degrees of species richness and functional composition.

In addition, we consider other land uses such as energy crops, forage crops and pastures, that can add to the diversity of a farm as productive complementarities can arise in integrated production e.g. in combined crop and livestock production systems (Russelle et al., 2007). Farmers are faced with technology and land-use options that may involve several complementarities or trade-offs in dealing with production constraints and in exploiting current and potential opportunities in response to changes in external and internal conditions (de Roest et al., 2018; Panzar and Willig, 1981). Synergies between input factors in seemingly different production specializations could thereby provide incentives to choose alternative ways for enhancing farm diversity to achieve economies of scope in production. Analyses of crop diversity trends that ignore these complex inter-relationships in land-uses may therefore underestimate or overestimate the drivers of diversification.

To account for these complex inter-relationships in land uses, we additively decompose the Shannon diversity H^S into two components to capture (i) the functional diversity (H^F), Eq. (2) and (ii) the related diversity (H^R), Eq. (3), meaning the average diversity of crops closely related with each other, i.e. within the same crop group (Nilsson et al., 2022).

When each crop c belongs to one of k functional crop groups, H^F can be obtained by first summing the shares of all crops in crop group $g = 1, \ldots, k$ to the group share p_g. H^F can then be calculated in a way analogous to H^S:

$$H^F = -\sum_{g=1}^{k} p_g * \ln(p_g) \tag{2}$$

Like H^S, H^F can take values between 0 and $\ln(k)$. Naturally, it is also possible to calculate a group-specific Shannon index, using Eq. 1, but only considering crops and their shares in crop group g, respectively. Based on this crop group diversity, which we denote as H_g^S, we can obtain the related diversity H^R by weighting all H_g^S with their respective share of p_g and calculating their sum:

$$H^R = \sum_{g=1}^{k} p_g * H_g^S \tag{3}$$

As mentioned, Eqs. (2) and (3) have the appealing property that they represent an additive decomposition of H^S:

$$H^S = H^F + H^R \tag{4}$$

A proof can be found in Jacquemin and Berry (1979). Further, the decomposition is equivalent to decompositions used in other empirical contexts (e.g. Aarstad et al., 2016; Frenken et al., 2007; Fritsch and Kublina, 2018; Jacquemin and Berry, 1979). It also corresponds to a special case of biodiversity measure decompositions (Jost, 2007). The definition of the indices is mathematically straightforward. Still, the indices can respond differently to similar changes in different cropping systems. The supplemental material contains a more detailed explanation of the diversity indices used here, including illustrative numerical examples (supplementary material S1) and more information on the considered crops (Table S1).

2.2. Data

Our primary data source is the Swedish implementation of the LPIS, which is a nationally implemented Geographic Information System created to fulfil the guidelines of the Integrated Administration and Control System (IACS). This system is used in EU-member countries for monitoring the farm support payments of the Common Agricultural Policy. Within the 44 LPIS implementations in the EU, there are several common database designs, with the farmer parcel system that Sweden uses being similar to the LPIS in France, Finland, Austria and southern-eastern Germany (European Court of Auditors, 2016, p. 12). The Swedish LPIS is available from 2001 and identifies each field (*block* in Swedish) as a spatially referenced polygon and provides information on any sub-field parcels (*skifte* in Swedish) and the area and crops grown in the field. The majority of Swedish fields are cropped as one parcel, meaning that the cropped parcel is the same as the field. Roughly a third of all fields, though this number varies from year to year, are divided into parcels where different crops are cultivated during the production year. The cropped parcels themselves are not spatially referenced in the version of the LPIS that we used for this research, rather they are all given the same field (block) ID, and are thus connected to the spatially referenced fields in which they are located.

The LPIS information can be linked to farms through the organizational identity of the person or legal entity that applied for farm support for specific crops and fields. Most of the agricultural land in Sweden is included in the LPIS. In fact only 10,900 ha of arable land can be identified outside of the LPIS, most of which are part of very small land holdings (Jordbruksverket, 2021). This “unspecified” arable land was temporary grass (*slåtter- och betesvall* in Swedish) in 85 % of the cases according to a 2013 study (cited in Jordbruksverket, 2021: 21). For example, in 2018, a total of 59,004 Swedish farmers applied for support payments for 1,208,899 unique cropped parcels, totalling 3,017,311 ha of agricultural land. Because the organizational identifier of a farm can change over time, for example when the farm ownership changes, the total number of farms for the entire period is greater than for any given year. Of particular interest in this study is to use the LPIS to calculate the crop diversity indices at the farm-level using the approach described in Section 2.1. In contrast to previous studies that have used the LPIS to measure crop diversity (Latruffe and Piet, 2014; Uthes et al., 2020), we calculate indices that differentiate between related and functional crop diversity. In contrast to Nilsson et al. (2022), who use a sub-sample of medium to large farms in the LPIS and focus on economic outcomes linked to crop diversification, we include the vast majority of farms in the LPIS with the main interest to analyse changes and drivers of crop diversity on farms over time.

2.3. Variables and summary statistics

We include variables to account for farm area size as large farms usually have a more diversified production structure and they typically also need to undergo only relatively small area adjustments to diversify (Louhichi et al., 2017). To account for differences in pedoclimatic conditions of the farm, we include information on weather as average annual temperature and precipitation, using the E- OBS datasets (v.22) of the Copernicus-project (Cornes et al., 2018). To better account for the actual agricultural production cycle in Sweden, we calculate these values for the period July-June, rather than for calendar years, in order to mimic the production period relevant for a given harvest. With respect to the diversity of grown crops, it is reasonable to assume that farmers have to make their decisions before they know (respectively observe) the weather conditions until the harvest. Hence, it is plausible to assume that their initial cropping decisions can only be based on their expectations of the weather conditions. Assuming that these expectations are formed by previous experiences, we include the weather conditions of the previous year (“lag(Temperature)” and “lag (Precipitation)”) as proxy variables in the analysis. Additionally, we include the clay content as a proxy for soil quality. Using the gridded data with a 50 m resolution (Piikki and Söderström, 2019), we calculate the average clay content of each individual field. Annual farm-level averages are then calculated by averaging over fields linked to the respective farm in LPIS data for a given year.

To account for the presence of organic production, we include a dummy variable indicating whether a farm has received support payments for organic production in a given year, using information provided by the Swedish Board of Agriculture. Organic farms are usually more diversified with higher overall biodiversity (Bengtsson et al., 2005; Tuck et al., 2014). Following the assumption that farmers, on average, modify their crop mix as a result of changes in the prices of major crops (Bertoni et al., 2021) we include a producer price index for cereal prices from (FAOSTAT, 2021). The merged data forms an unbalanced panel dataset covering the period 2001–2018, containing a total of 835,878 observations from 83,770 farms.

Summary statistics are given in Tables 1 and 2. Variables include H^s, H^F and H^R in Table 1, as well as the crop group specific diversity measures (H^S_g in Eq. 3) in Table 2. Over the full period, average Shannon diversity is 0.84, the greater part of which stems from the functional diversity (0.64) than the related diversity (0.20). Average farm size is 52 ha, with a standard deviation of 87 (Table 1). At the crop group level, cereal production is the most diversified on average (0.51) but also the one with the largest SD (0.45). The lowest diversity is found for energy crops (0.02). In Table 2, the numbers of observations give an indication of how frequently these crop groups were grown during the full period and we present them only to suggest some guidance on how to interpret the diversity indices, and not for inclusion in the estimated model. We can see that fruits/berries as well as energy crops are only rarely grown (by around 1000 farms/year).

2.4. Estimated models

To assess the influence of structural differences between farms and CAP-reforms on crop diversity over time, as well as the temporal trend in general, we apply a Random-effects within-between-model (REWB-model, also called hybrid-panel-model; Bell et al., 2019). This model allows us to assess the effects of overall differences between farms (between effects) and the effects of changes at the farm level over time (within-effects). While the REWB model in principle is a reparameterisation of the well-established 'Mundlak-model' (Mundlak, 1978), it has only gained interest in recent years (Bell et al., 2019; Schunck, 2013). It should also be noted that so-called fixed- and random-effects models (FE-, respectively RE-model) used in the economic literature represent special cases of the general REWB.

We consider the following model:

$$y_{it} = \beta_0 + \boldsymbol{\beta}'_W(\boldsymbol{x}_{it} - \overline{\boldsymbol{x}_i}) + \boldsymbol{\beta}'_B\overline{\boldsymbol{x}_i} + \boldsymbol{\beta}'_z\boldsymbol{z} + \upsilon_i + \epsilon_{it} \tag{5}$$

where, for each individual i, y_{it} denotes the dependent variable observed at time t i.e. the respective diversity index and where β_0 denotes the overall intercept. The vector $\boldsymbol{x}_{it}$ contains the time-variant farm level variables: the log of farm size (in ha), the local temperature and depreciation in the previous year, as well as the average soil quality of the farm and the involvement in organic production. The farm-level means over the observation period are given by $\overline{\boldsymbol{x}_i}$. $\boldsymbol{\beta}_W$ and $\boldsymbol{\beta}_B$ contain the within- and between-effects, respectively. The within-effects are identical to the within-effects obtained by an FE-model. Further, $\boldsymbol{z}$ denotes a vector of farm-invariant variables. In the main model, this includes a time effect and its quadratic covariate (t and t^2) to allow for non-linearities in the temporal trend (cf. Fig. 1). The model also include the first two lags of the producer price index for cereals and dummy variables (CAP_{P2}, CAP_{P3}) to account for the CAP-periods 2007–2013 and 2020, with the reference period being 2000–2006. Their effects are represented by $\boldsymbol{\beta}_z$. The random effect for each individual is denoted υ_i and ϵ_{it} represents the usual observation-specific residual. This model is estimated for each of the three diversity measures.

Compared to an FE- (or RE-) model, the model outlined above has some advantages. While the within-effects capture the effects of farm-level changes in the same way as standard panel models, the between-effects allow for comparisons between farms, for example with respect to differences in farms of different sizes. Further, the model structure automatically includes biophysical conditions in two ways. First, by including the previous year's conditions (i.e. the first lags), the within-effects reflect the effect of short-run conditions on the outcome, as in a FE-model. Second, because the between effects are based on the average conditions over the observed period, they proxy the mid-run conditions faced by the farmer. An alternative would be to explicitly include rolling-averages of biophysical conditions. While this would be preferred from a theoretical perspective, the chosen specification still allows a correlational interpretation of differences between farms (or farmers) facing different biophysical conditions.

The lags of the cereal price index are included in the model to proxy general market conditions for crop products. We also considered a general agricultural producer price index, as well as a single-product price index (for wheat). The cereal price index was chosen as it is more strongly correlated with the outcome variables and as it improves the fit of the models more than the other indices. The CAP-dummies are introduced to account for potential shifts in the temporal development, as the CAP aims to change agricultural production practices. For example, it is likely that the crop diversity developments are also driven by requirements in the CAP-periods, like the introduction of specific regulations (see supplementary material S3).

All analyses are carried out using R (R Core Team, 2021), the main packages being *panelr* (Long, 2020), *lme4* (Bates et al., 2015) and *plm* (Croissant and Millo, 2008). The data preparation strongly rely on the packages *dplyr* (Wickham et al., 2021), *raster* (Hijmans, 2021) and *exactextractr* (Baston, 2021).

3. Results

In the beginning of the considered period, crop diversity decreased with respect to all three diversity measures in Swedish agriculture. The Shannon and related diversity have regained recently, whereas functional diversity has remained at a lower level (Fig. 1). Still, comparing the first and the last observed year, the overall diversity (H^S) has decreased. The same holds for the functional diversity (H^F), where the decrease is more pronounced. In contrast to this development, the average related diversity (H^R) has increased from 2001 to 2018. At the

Table 1
Descriptive statistics of variables used in the analysis.

		Full sample	Conventional	Organic
Variable	Unit	Mean (SD)/ %	Mean (SD)/ %	Mean (SD)/ %
Shannon diversity (H^S)	Index value (Eq. 1)	0.84 (0.56)	0.82 (0.57)	0.92 (0.49)
Functional diversity (H^F)	Index value (Eq. 2)	0.64 (0.42)	0.62 (0.42)	0.77 (0.37)
Related diversity (H^R)	Index value (Eq. 3)	0.20 (0.27)	0.20 (0.28)	0.15 (0.22)
lag(Temperature)	Degree Celsius	7.24 (1.19)	7.29 (1.19)	6.92 (1.12)
lag(Precipitation)	mm	358 (95)	359 (95)	354 (91)
Clay	%	18 (11)	18 (11)	19 (11)
Area	ha	52 (87)	49 (83)	70 (109)
Organic	1 =yes, 0 =no	14	–	–
N		835,878	716,373	119,505

Note: Results for all observations, pooled over complete period.

Table 2
Summary statistics of functional groups.

		Full Sample		Conventional		Organic	
$g = 1, \ldots, G$	Variable	N	Mean (SD)	N	Mean (SD)	N	Mean (SD)
g_1	Legumes	59,663	0.04 (0.15)	43,307	0.03 (0.13)	16,356	0.07 (0.20)
g_2	Oilseeds	80,736	0.06 (0.19)	73,659	0.06 (0.19)	7077	0.07 (0.20)
g_3	Cereals	448,599	0.51 (0.45)	376,745	0.52 (0.45)	71,854	0.42 (0.47)
g_4	Berries/Fruit	12,426	0.07 (0.19)	9549	0.07 (0.18)	2877	0.09 (0.22)
g_5	Vegetables	91,432	0.12 (0.27)	79,914	0.12 (0.27)	11,518	0.13 (0.26)
g_6	Fodder	697,156	0.08 (0.19)	582,517	0.08 (0.19)	114,639	0.07 (0.17)
g_7	Energy crops	18,777	0.02 (0.11)	16,239	0.02 (0.11)	2538	0.02 (0.11)
g_8	Pasture	508,641	0.05 (0.15)	419,901	0.04 (0.15)	88,740	0.06 (0.17)
g_9	Fallow	359,710	0.07 (0.19)	306,931	0.07 (0.18)	52,779	0.09 (0.21)

Note: Results for all observations, pooled over complete period.

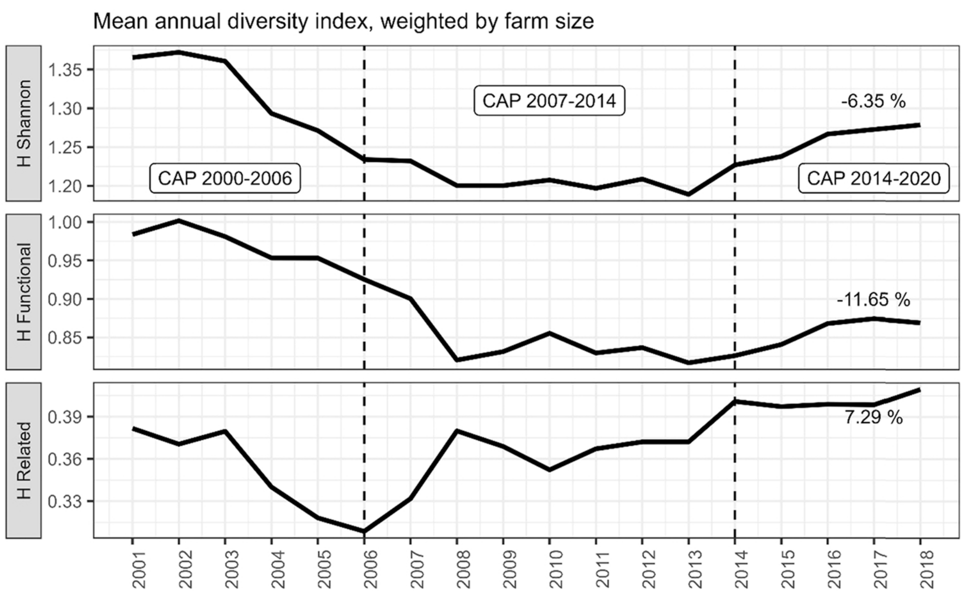

Fig. 1. Mean values of the crop diversity indices, weighted by farm size, and percentage change 2001–2018.

farm level, three main indicators (H^S, H^F and H^R) are strongly correlated with the diversity of cereal production. Diversity in fodder, vegetable and fallow production shows the lowest correlations with the main indices (see Table S4).

We estimate the regression model according to (5) for each of the three diversity measures. With respect to the variables concerning the temporal development, we also estimate two more parsimonious, nested model specifications: one only containing the quadratic time trend, excluding the CAP variables and one with only a linear time trend. The comparison of these variants using Likelihood-ratio-tests can be found in Table S5. For all three measures, the tests reject the Null hypotheses, indicating that the model specification according to (5) is preferred over the simpler nested specifications. Further, it is possible that the within- and between-effects do not differ. In this case, the more parsimonious RE-model can be used (Bell et al., 2019). To test whether the simpler model can be applied, we follow Bell et al. (2019) and jointly test for equivalence of the between- and within-effects. A comparable test using the Mundlak-parameterisation is often used to guide the decision between FE and RE models (Bell et al., 2019; Pinzon, 2015). For the three dependent variables, the Null hypothesis of parameter equivalence is rejected (see Table S6). This reveals that simpler, restricted panel specifications should not be used in the present case. As expected, the within-effects of the REWB and FE-model (which only estimates the within-effects, see Table S7) are practically identical. Differences are likely due to numerical differences in the estimation methods. The regression results for the alternative specifications are presented in Table S8.

As we show in Section 2.1, H^F and H^R are an additive decomposition of H^S. From the results in Table 3, it is noteworthy that the estimated effects decompose in the same way ($\beta^{HS} = \beta^{HF} + \beta^{HR}$, apart from numerical differences). While the relative size of β^{HF} and β^{HR} differs, the effect sizes have the same order of magnitude in many cases and differ at most by one (with one exception). In the following, we describe the results for each variable, considering both the between- and the within-effects. The between effects can the thought of as the cross-sectional effects of the average differences between the farms in the sample, indicating overall diversity differences of farms with varying characteristics. In contrast, the within-effects represent the average change if a given variable changes on the farm over time.

Between-effects among Swedish farms (2001–2018) show that large farms are on average more diversified than smaller farms, in terms of all three crop diversity measures. We also find growth in farm size to be positively associated with increases in crop diversity (within-effects), in all three crop diversity measures. For farms engaged in organic production we find less overall diversity (H^S), but greater functional diversity (H^F) and lower related diversity (H^R). The uptake of organic practices does not lead to a change in overall diversity on the farm over time ($p > 0.001$), but does increase functional and decrease related crop diversity.

Between farms, those with high clay content in their land, which indicates higher soil quality, are overall less diversified (H^S). Interestingly, when considering, H^F and H^R, the results indicate that this

Table 3
Regression results for the diversity indices.

Effect type	Variable	Shannon crop diversity	Functional crop diversity	Related crop diversity
Within effects	ln(area)	0.277879 *	0.187841 *	0.090039 *
		(0.000761)	(0.000659)	(0.000505)
	organic	-0.001168	0.022978 *	-0.024375 *
		(0.001126)	(0.000976)	(0.000748)
	clay	0.000519	-0.003073 *	0.003589 *
		(0.000234)	(0.000203)	(0.000156)
	lag(temperature)	0.022409 *	0.017967 *	0.004524 *
		(0.000403)	(0.000349)	(0.000267)
	lag(precipitation)	-0.000026 *	0.000012	-0.000039 *
		(0.000005)	(0.000004)	(0.000003)
Between effects	(Intercept)	-0.285890 *	0.021060	-0.308268 *
		(0.010659)	(0.008893)	(0.005797)
	ln(area)	0.312273 *	0.207064 *	0.105474 *
		(0.000937)	(0.000781)	(0.000507)
	Organic	-0.049538 *	0.064864 *	-0.115108 *
		(0.004191)	(0.003494)	(0.002268)
	Clay	-0.001690 *	-0.003571 *	0.001891 *
		(0.000106)	(0.000088)	(0.000057)
	lag(temperature)	0.059497 *	0.030986 *	0.028724 *
		(0.001207)	(0.001006)	(0.000653)
	lag(precipitation)	-0.000187 *	-0.000047 *	-0.000140 *
		(0.000015)	(0.000013)	(0.000008)
Controls	T	-0.021151 *	-0.010635 *	-0.010546 *
		(0.000370)	(0.000320)	(0.000245)
	t^2	0.001358 *	0.000720 *	0.000637 *
		(0.000019)	(0.000016)	(0.000012)
	lag(Cereal prices)	-0.000460 *	-0.000679 *	0.000219 *
		(0.000016)	(0.000014)	(0.000011)
	lag(Cereal prices)2	-0.000656 *	-0.000591 *	-0.000067 *
		(0.000015)	(0.000013)	(0.000010)
	CAP-P2	-0.024280 *	-0.040055 *	0.015713 *
		(0.001357)	(0.001176)	(0.000900)
	CAP-P3	-0.129039 *	-0.123570 *	-0.005661 *
		(0.002134)	(0.001850)	(0.001416)
Model statistics	Random Effect (SD)	0.310799	0.258287	0.164960
	AIC	95,719.7	-149481.8	-622596.4
	N (farms)	83770	83770	83770
	N (observations)	835,878	835,878	835,878
	R^2_{Total}	0.840736	0.791552	0.689058

Note: Standard errors in parentheses, * $p < 0.001$

specialization is even more pronounced for the functional diversity, and is partially offset by an increase in related diversification. Hence, farms with high clay content diversify, but only within specialized sets of crop groups. When the average soil quality improves for a farm during the considered period, e.g., by acquiring additional land parcels, functional diversity and overall diversity decreases and related diversity increases, i.e., a tendency to shift towards specific crop groups.

With respect to temperature we find that farms in warm conditions are more diversified. Assuming that these conditions allow for larger number of crops to be grown, this would make it easier to diversify production. Similarly, the production in a year following a warm year is more diversified in all diversity dimensions. Given the great latitudinal coverage of the Swedish geography there is a north-south diversification gradient. For precipitation, farms operating under more humid conditions are less diversified than farms in dry places. Similarly, in the short run the farm's production program will on average be more diversified the year after a dry year.

For the additional variables, we find that cereal prices are related with the diversity in Swedish agriculture. We observe that the overall diversity (H^S) decreases when prior cereal prices are higher. The same holds for the functional diversity. In contrast, the related diversity increases when cereal prices are higher in the previous year. Interestingly, the second-order lag of the price index has an opposing effect sign. The estimates of the CAP dummies for the overall and functional diversity (H^S and H^F) suggest that it decreased during the CAP periods 2007–2013 and 2014–2020, relative to the reference period of 2000–2006. In contrast, it appears that related diversity (H^R) increase in the CAP period of 2007–2013, but that this increase is completely offset in the following period.

4. Discussion

Over all Swedish farms, an initially negative time trend in crop diversity has reversed for Shannon and related diversity but not for functional diversity, which declined until about 2008 and has thereafter remained more or less constant (Fig. 1). After adjusting for farm level changes in structure, biophysical and price conditions, the unadjusted crop diversity trends (Fig. 1) are confirmed by the time trends in the regression models. These represent the systematic temporal changes in diversity that are not explained by other variables. They can rather be interpreted as changes in the production decisions under otherwise constant conditions (ceteris paribus), i.e. as changes unrelated to changing structural factors in the model. We find that the linear component has a negative sign, whereas the quadratic has a positive sign for all three diversity measures. Using the parameter estimates to calculate the estimated minima of the models' time trends shows that under constant conditions, a farms production program became on average more specialized initially, but that this trend changed during the studied period. The parameter estimates indicate that the negative trend reversed around 2009 for all three diversity measures. This result provides first evidence that, after adjusting farm growth and potential shifts due to CAP requirements, trends towards less diversified production programs have reversed. This means that keeping everything else equal farmers started choosing more diverse crop production programs in recent years again. Note, however, that crop diversity overall was still lower in 2018 than in 2001.

Closely linked to the time trends, the results for the CAP-effects serve as first indications of the potential effects of CAP on crop diversity in Sweden. Our results suggest that the CAP greening reform in 2015–2020 has, contrary to the stated purpose, led to specialization in crop production instead of diversification among Swedish conventional farms. On the one hand, the potential negative effect of the last CAP period appears surprising at first, giving that this CAP reform explicitly introduced a "crop diversity"-measure (Council Regulation (EC), 2013). On the other hand, the crop diversity measure in CAP has been criticized for not being demanding enough and thereby allowing "further conversion into monocultures rather than maintaining or increasing crop diversity" (Pe'er et al., 2017, p. 21). Also, most farmers in Sweden and other EU countries already fulfilled the requirements before the reform was imposed (Josefsson et al., 2017; Louhichi et al., 2017; cf. also supplementary material S1).

Thus, it does not appear unreasonable to infer that the combination with other CAP-components could have led to an incentive to specialize into related crops rather than diversify crop production. Still, the effects of CAP on related diversity are relatively small in comparison with the effect on functional diversity, differing by more than a magnitude in the last period (−0.124 vs. −0.006). This can be an indication that the CAP influenced the functional diversity more strongly. In this context, it should also be noted that the effect sizes are relatively small in comparison to the time trend. While our results do not allow for causal interpretations, they serve as an indication of potential policy failures of the CAP greening reform, in line with the findings of Louhichi et al. (2017). The identification of casual effects of CAP as a whole on crop diversity would be challenging, if not impossible. The core issue is that with such a general conceptualisation, all farms would have to be considered as treated units. When the interest is on causal effects of the CAP, it would be more fruitful to consider specific measures. In the context of the crop diversity rule introduced in the last CAP period, one could take threshold sizes for the binding of individual rules into consideration and apply a regression discontinuity design for example.

We find that larger farms are, on average, more diversified. This could be linked to scale economies in that larger farms can grow more crop types, and where additional crops give smaller increase in additional fixed costs (Louhichi et al., 2017). The finding that functional diversity is greater on farms with organic production is reasonable from an agronomic perspective where organic farms cultivate a higher number of crop groups, but fewer crops within each group. The negative estimate for organic dummy variable on the Shannon diversity can be explained through higher management requirements of diversified systems, limiting the total number of crops typically grown. The finding that diversity changes after changes in soil quality is supported by Di Falco and Zoupanidou (2017) who argue that crop diversity and soil can act as substitutes. We have focused here on diversity on the farm, but we argue that our findings can be transferred also to greater spatial scales as the farm is fundamental decision-making unit in agriculture. Considering crop diversification as a risk management strategy (Moschini and Hennessy, 2001), it appears reasonable that the production will on average be more diversified the year after a dry year.

The present work focuses on the status and trends of farm crop diversity over time and only accounts for spatial heterogeneity in terms of basic biophysical conditions (weather and soil), but not other potential sources of spatial heterogeneity like the degree of urbanization (Meraner et al., 2015). Future research could explicitly include the spatial dimension and account for potential effects of collaboration, interactions and information exchange between farmers on the uptake of more diversified practices (Vroege et al., 2020). While the data we used is the most comprehensive available, other sustainable practices that influence crop composition, such as mixed cropping or sub-seeding, were not represented in the data. Particularly, when only the main crop is recorded, the LPIS data might lead to underestimated levels of functional diversity. In addition, crop diversity is only one diversity dimension, both at the farm and landscape level. At the farm level, farmers can take other actions to (economically) diversify, e.g. through alternative distribution channels or agro-tourism (Vroege et al., 2020).

To define functional crop diversity we have binned crops into nine ecologically and agronomically distinct functional groups of crop species adhering to different botanical families. Swedish cropping is dominated by cereals, which are all grasses (i.e. related diversity). Including crops from other plant families in the crop rotation (i.e. increasing functional diversity) on the farm is well known to efficiently break pest build-up and enhance nutrient capture and use efficiency in a rotation sequence otherwise characterized by ecologically similar cereals (Bennett et al., 2012). Plants can be functionally grouped in more ecologically informed ways based on their respective traits reflecting their particular ecological niches (Díaz et al., 2016). More refined trait-based definitions of crop and variety functional groups, in line with Díaz et al. (2016), would be ideal, but new comprehensive databases would need to be built. Ours is a first step in this process and we find separate trends for Shannon, related and functional diversity when crops are grouped according to separate ecological and agronomic characteristics.

Our findings have methodological implications. We find that empirical findings can change depending on which definition of crop diversity is used. While the distinction between count-based and entropy-based indices is relatively straightforward, it is more complicated when different definitions of the same index (e.g. the Shannon index) are applied. For example, diversity is most often defined based on species (e.g. Hass et al., 2018), but can also be based on broader crop categories (Redlich et al., 2018). Depending on how such categories are defined, they may or may not correspond to other definitions of functional diversity. The decomposition we propose could be fruitful in reducing ambiguity when communicating results. Explicitly considering functional diversity is furthermore relevant when designing agricultural policies, which increasingly need to account for effects on functionalities beyond agricultural production (Wittwer et al., 2021). For example, to achieve heterogeneous agricultural land cover and multifunctional cropping systems beyond production, policies might orient crop diversity regulations stronger on functional requirements.

5. Conclusions

Using comprehensive farm-level data from Sweden for the period 2001–2018, we examined the development of overall, as well as functional and related crop diversity. We calculate crop diversity metrics that capture functional traits among crop groups based on the LPIS (Nilsson et al., 2022), analogous to approaches applied in ecology research (e.g., Wood et al., 2015; Josefsson et al., 2017).

The observed decline in functional crop diversity over time could indicate an average decline in the provisioning of ecosystem services on conventional Swedish crop producing farms over the last decade (Egli et al., 2021; Finney and Kaye, 2017; Hajjar et al., 2008; Iverson et al., 2014; Josefsson et al., 2017). This implies a fall in the capacity of Swedish crop producing farms to generate, capture and cycle resources within the farm, e.g., for crop protection and nutrition, making farms more dependent on externally acquired inputs and more exposed to changes in input prices (Bommarco et al., 2013; D'Annolfo et al., 2017). Given the positive association between farm size and all three metrics of crop diversity over the study period, it seems that larger farms currently are better equipped to tackle such challenges compared with smaller farms and, if correct, policies would need to be instituted that increase possibilities for small farms to diversify. To validate our findings, next steps would be to better differentiate overarching structural trends (like regional specialization) in crop production and the effects of the CAP reforms, and confirm such effects in additional national contexts. Decomposing the Shannon index could be fruitful also in other settings, for example in analyses of effects of crop diversification on farm economic performance. Furthermore, it would be interesting to explore behavioural factors, such as attitudes, norms and values among farmers that influence the adoption of more functional or related diversified production programs.

Although the population-based register data on which we have based our analysis are unique in their detail and allow us to calculate decomposed diversity indices at the farm level, our index-based approach also has limitations. One limitation is that the analysis does not disentangle how specific crops contribute individually to the observed trends. More detailed future analysis, e.g., based on methods that analyze the contribution of main species per different taxonomic category as well as examining functional diversity based on plant traits could complement our approaches.

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.

Data Availability

The data that has been used is confidential.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.agee.2022.108269.

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