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RESEARCH ARTICLE

Yield stability and weed dry matter in response to field-scale soil variability in pea-oat intercropping

Sebastian Munz · Julian Zachmann · Iman Raj Chongtham · Nawa Raj Dhamala · Jens Hartung · Erik Steen Jensen · Georg Carlsson

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Abstract
Background and aims Intercropping of grain legumes and cereals in European agriculture can provide benefits, such as an increase in yields, yield stability and weed suppression. Interactions between crops in intercropping may depend on spatial heterogeneity in soil conditions, which are present on farmers' fields. Understanding the effect of within-field variation in soil conditions on interspecific interactions might increase the benefits of intercropping by within-field adjustment of the agronomic management.
Methods Crop performance and weed dry matter were assessed together with several soil properties in grids within three large field experiments at two sites (Germany and Sweden) and during two years. Each experiment was comprised of several strips sown either with the two sole crops oat (*Avena sativa* L.) and field pea (*Pisum sativum* L.) or an oat-pea intercrop.
Results The response of crop performance to within-field variability in soil conditions was mostly species-specific. Yield stability of intercropping was consistently higher compared with pea, but not compared to oat. The highest land equivalent ratio was found for an additive intercropping design under a higher water availability. In this experiment, yield stability of both intercropped pea and oat were lower, which might be expected as a result of within-field variation in interspecific interactions. Intercropping reduced weed dry matter compared to pea, for which one experiment indicated an increase in weed dry matter with nutrient availability.
Conclusion The experimental design and the developed statistical analysis can contribute to further research about spatial variations in interspecific interactions in intercropping, which will improve the understanding of plant-plant and plant-soil interactions.

Keywords Mixed cropping · Land equivalent ratio · Precision farming · Coefficient of variation · Legumes · Cereals

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S. Munz (✉) · J. Zachmann
Agronomy, Institute of Crop Science, University of Hohenheim, Fruwirthstr. 23, 70599 Stuttgart, Germany
e-mail: s.munz@uni-hohenheim.de

I. R. Chongtham · E. S. Jensen · G. Carlsson
Department of Biosystems and Technology, Swedish University of Agricultural Sciences, P.O. Box 190, SE-234 22 Lomma, Sweden

N. R. Dhamala
Department of Plant and Environmental Sciences, University of Copenhagen, Højbakkegård Alle 13, 2630 Copenhagen, Denmark

J. Hartung
Biostatistics Unit, Institute of Crop Science, University of Hohenheim, Fruwirthstr. 23, 70599 Stuttgart, Germany

Introduction

The majority of contemporary large-scale arable cropping systems are characterized by the cultivation of a few commodity crops in short rotations, in particular cereals, managed with large inputs of fertilizers and pesticides to produce high and stable yields. These input-intensive systems cause environmental problems in terms of e.g. climate impact (greenhouse gas emissions from the use of fossil fuels and from the production and use of nitrogen (N) fertilizers), eutrophication (nutrient losses), contamination of ground water and biodiversity loss. Diversification of cropping systems through the implementation of e.g. diversified crop rotations, cover crops, and intercropping (i.e. the simultaneous cultivation of two or more crop species on the same field), is known to provide benefits by increasing resource use efficiency and resilience, reducing the reliance on external inputs and mitigating negative environmental impacts of crop production (e.g. Vandermeer 1989; Kremen et al. 2012).

Grain legumes are key components of diversified cropping systems and important crops for the sustainable development of agriculture and food systems (Voisin et al. 2014; Watson et al. 2017). Due to their ability to fix atmospheric N_2 in symbiosis with N_2-fixing bacteria, their cultivation leads to savings of N fertilizer inputs and their N-rich grains and biomass provide high-protein food and feed. Grain legumes also contribute to other ecosystem services via improved soil fertility, nutrient cycling, reduced emission of greenhouse gases and productivity of other crops in rotations, increased resource use efficiency and agrobiodiversity (Jensen et al. 2012; Stagnari et al. 2017; Voisin et al. 2014; Watson et al. 2017). However, integrating grain legumes into cropping systems is a challenge because several grain legumes have high spatial and temporal yield variability caused by a range of biotic and abiotic factors, including high susceptibility to drought, nutrient scarcity (other than N), and weeds, diseases and pest damages (Watson et al. 2017; Bedoussac et al. 2015; Manners et al. 2020).

Intercropping (IC) of grain legumes and cereals in European agriculture can provide several benefits. Increased yields compared to sole cropping (SC) particularly with a low availability of soil N promoting the complementary N use by legumes and cereals (Bedoussac et al. 2015; Hauggaard-Nielsen et al. 2008; Jensen 1996). Yield advantages in IC are further promoted by a sufficient water availability to decrease negative impacts of water competition by the cereal on the legume crop (Justes et al. 2021). Weed dry matter can be substantially reduced by intercropping a legume with a cereal compared to the legume sole crop as shown by numerous studies (Gu et al. 2021; Hauggaard-Nielsen et al. 2001). This is particularly important in organic legume production (Corre-Hellou et al. 2011) and in general for reduction or even exclusion of herbicides (Zimmermann et al. 2021). A higher yield stability of IC is often mentioned, however, results are not conclusive. A higher yield stability of IC compared to the legume sole crop in temperate regions was found in a meta-analysis by Raseduzzaman and Jensen (2017), whereas this was not confirmed by Weih et al. (2021) based on seven two-year field trials across Europe.

Yields in IC and the relative yield of each component crop are the result of several ecological mechanisms, which are described in the 'four C' concept: *Complementarity* (use of different niches by the IC components for resource acquisition), *Cooperation* (one IC component generates benefits for the other, e.g. via nutrient availability or physical support), *Competition* (one species in IC has an advantage in acquisition of resources) and *Compensation* (any loss or reduced yield of one IC component is substituted by another due to different sensitivities to stresses) (Justes et al. 2021).

Complementarity and competition between legumes and cereals in IC have a direct influence on their relative yields and weed suppression, which can also be used to provide recommendations for the agronomic management, e.g. by increasing relative sowing densities of one component crop, adjusted N fertilizer rates and sowing at different dates (Gu et al. 2021; Yu et al. 2016). An aspect not yet considered is how IC performance is affected by the heterogeneity in soil conditions inherent to larger field sizes as cultivated by farmers in contrast to often small-scale experimental plots within a more homogeneous field (Panten et al. 2010). The soil heterogeneity (e.g. texture, organic carbon content, pH) may lead to spatial variability of available growth resources (water, nutrients) and species-specific yield potential within the field. This aspect is addressed by precision agriculture technology, which is increasingly applied in conventional management of sole crops, using e.g. sensor-assisted equipment for adapting the rates of fertilizer applications to within-field variations in soil nutrient availability (Bhakta et al. 2019). Within this context, Jensen et al. (2015) considered IC of non-legume crops with grain legumes (e.g. pea) as an ‘ecological precision farming’ (EPF) principle since individual plants in IC can naturally adapt on a very small spatial scale to a given heterogeneity. According to the stress-gradient hypothesis, this would result in more complementary use of N in cereal-legume IC at sites with low N availability; while, with an increase in N availability competition by the cereal dominates (Brooker et al. 2008). However, the EPF principle and the within-field variability in soil conditions and its influence on yield and yield stability in IC have not been studied experimentally yet.

Therefore, this study investigates crop performance (yield and shoot dry matter) and weed dry matter in cereal and grain legume sole crops (SCs) and their ICs grown in fields with heterogeneous soil conditions in Sweden and Germany. The specific objectives were to determine how the field-scale spatial variability in soil physical and chemical characteristics affects the interactions between intercropped oat (*Avena sativa* L.) and field pea (*Pisum sativum* L.), and to investigate the within-field yield variability of SCs and IC of the two crops. The main hypotheses are: (i) the variability in soil conditions in the field affects the performance of crops differently in oat and pea grown as SC or IC, and (ii) within-field yield stability of IC (both crops together) is higher compared to SCs; and, (iii) within-field weed dry matter is consistently, i.e. irrespective of soil conditions, lower in SC-Oat and IC compared with SC-Pea.

Materials and methods

Experimental sites

Field experiments were conducted at the research stations “Ihinger Hof” of the University of Hohenheim (UHOH), Stuttgart, Germany (48° 44’ N, 8° 55’ E) in 2018 and 2019 and “SITES Lönnstorp” of the Swedish University of Agricultural Sciences (SLU), Alnarp, Sweden (55° 40’ N, 13° 6’ E) in 2019. Compared to the long-term average (2000–2020), the weather at the German site was rather warm and dry in 2018, especially in June and July, while it was more similar to the long-term average in 2019 (Table 1). Weather conditions at the Swedish site were rather dry with lower precipitation in particular in April and July in 2019. The field experiment at SLU in 2018 was abandoned due to severe drought during the growing season.

Experimental design and characterization of soil spatial variability

In all experiments, field pea and oat were grown both as SCs and in IC in replicated, parallel strips on large fields with heterogeneity in soil properties. Heterogeneous fields were selected based on variations in topography and measurements of apparent soil electrical conductivity (ECa; Doolittle and Brevik 2014).

Table 1 Mean monthly temperature and cumulative precipitation during the vegetation period at the experimental site in Germany (March – July, 2018 and 2019) and Sweden (April – August, 2018 and 2019) and the long-term averages (2000–2020)

Location	Month	Mean temperature (°C)			Precipitation (mm)		
		2018	2019	2000–2020	2018	2019	2000–2020
Germany	March	2.9	6.1	4.9	21.2	47.1	45.7
	Apr	12.4	8.6	9.3	17.4	26.7	37.3
	May	14.9	10.1	13.1	75.1	107.2	82.0
	Jun	17.4	18.5	17.0	32.5	52.2	68.9
	Jul	19.9	18.7	18.4	32.0	53.9	83.8
Sweden	Apr	9.3	7.8	7.7	29.6	9.4	35.5
	May	15.8	10.8	12.3	3.0	27.8	38.7
	Jun	18.1	17.8	16.0	14.8	58.0	59.8
	Jul	20.9	17.8	18.0	13.4	26.6	65.7
	Aug	19.2	18.6	17.7	91.8	63.0	102.6

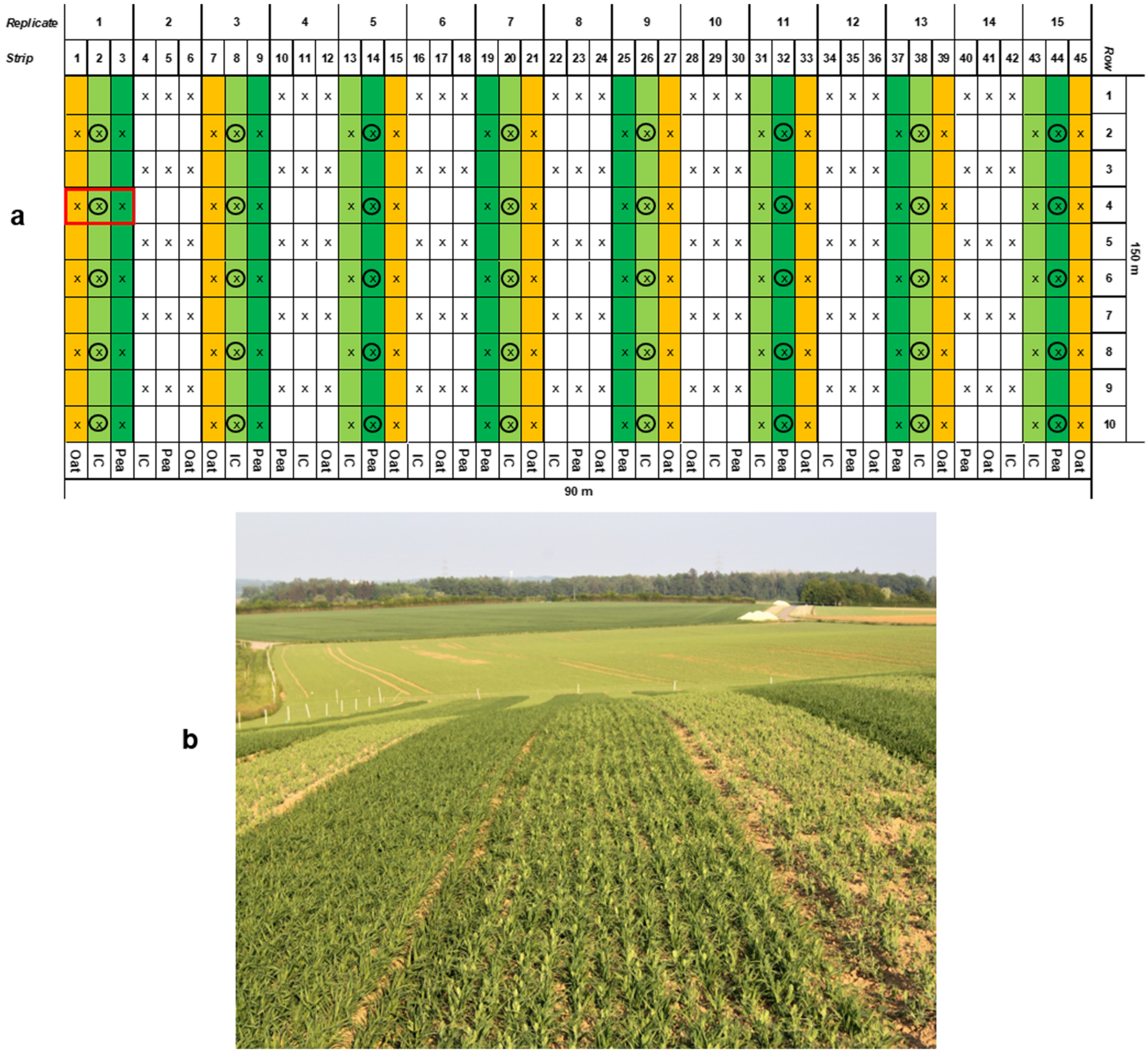

Fig. 1 Experimental design (**a**) in Germany in 2018 with the factors replicate ($n=15$), strip ($n=45$), row ($n=10$), and block ($n=80$, indicated by red rectangle), and the treatments Pea, Oat, and the intercrop (IC) and an exemplary image of the three treatments in one replicate (**b**). The "x" indicates the plant sample plots ($n=120$), circles denote the soil sample plots ($n=40$). Note that the white areas were harvested with a combined-harvester and not included in this study

On each field, treatments were allocated to strips according to a randomized complete block design with repeated measures within strips.

German site

Field sizes of the experiments in Germany were different with 1.35 ha (150 × 90 m²) in 2018 and 0.29 ha (80 × 36 m²) in 2019. The soil of both fields was a silty clay loam. The three treatments (Oat-SC, Pea-SC, IC) were sown in parallel strips of 2 m width along the slope in E-W direction in 2018 and N-S direction in 2019. The field experiments in 2018 and 2019 were comprised of different numbers of replicates, strips, and rows (Figs. 1 and 2).

Both fields were selected for slope (variation of 10 m from highest to lowest point) (illustrated in Figs. 1b and 2b) and measurements of ECa (18.5–34.0 mS m^{-1} in 2018 and 13.3–30.3 mS m^{-1} in 2019) indicating heterogeneity in soil conditions within the

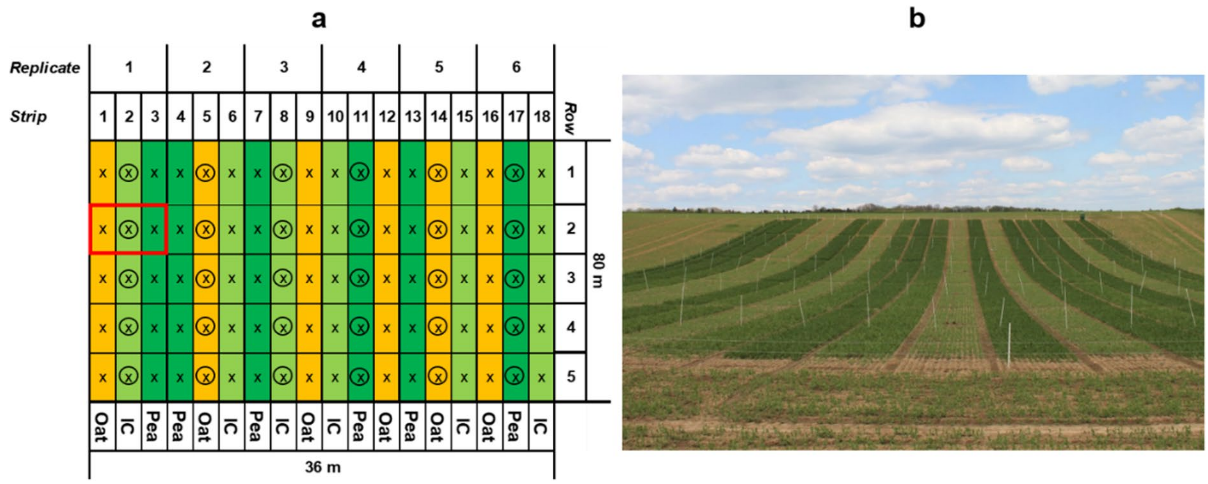

Fig. 2 Experimental design (**a**) in Germany in 2019 with the factors replicate ($n=6$), strip ($n=18$), row ($n=5$), and block ($n=30$, indicated by red rectangle), and the treatments Pea, Oat, and the intercrop (IC) and an exemplary image illustrating the parallel strips of the three treatments and the slope of the field (**b**). The "x" indicates the plant sample plots ($n=90$), circles denote the soil sample plots ($n=30$)

field. In 2018, the replicates were divided into hand-harvested areas (coloured) and areas harvested with a combined harvester (white) (Fig. 1a). In this study, only data of hand-harvested areas were used.

In total, there were 120 and 90 sample plots in 2018 and 2019, respectively. The strips were sown with oat (cv. Troll (I.G. Pflanzenzucht GmbH, Ismaning, Germany), 320 seeds m^{-2}) and pea (cv. Respect (InterSaatzucht GmbH, Hohenkammer, Germany), 80 seeds m^{-2}) as SCs and as IC on 12 April 2018 and 28 March 2019. IC was sown in an additive design with 50% of Oat-SC density (160 seeds m^{-2}) and 75% of Pea-SC density (60 seeds m^{-2}). Row distance was 12 cm and sowing depth 3.5 cm. Oat and Pea in IC were mixed within the row. The higher sowing density of pea in IC was chosen due to the expected high competitiveness of oat growing on this fertile soil and in accordance to agronomic recommendations for similar pedo-climatic conditions (Dierauer et al. 2017). Density of Oat-IC was kept at 50% like in a replacement design to assure a high potential of compensation growth if Pea-IC would be negatively affected by environmental conditions.

Before sowing, the variability in soil conditions was determined by measuring volumetric soil moisture in situ with a TDR probe (FieldScout100; Spectrum Technologies Ltd, Bridgend, Wales) to a depth of 20 cm followed by the collection of soil samples to a depth of 60 cm from the central plot within each replicate and row (indicated by circles in Figs. 1 and 2). Soil texture, organic carbon (Corg), mineral N (Nmin), total C (Ct) and N (Nt) were analyzed. This resulted in 40 and 30 analyzed soil samples in 2018 and 2019, respectively. The ECa was measured continuously across the field using the EM38-MK2 and later ECa values were extracted for 40 sample plots in 2018 and for all 90 plots in 2019. Soil texture was determined with sieving-sedimentation method (Thun and Hoffmann 2012). Concentrations of Nt, Ct and Corg were measured by dry combustion with an elemental analyzer (vario Macro cube, Elementar Analysensysteme GmbH, Langenselbold, Germany). Nmin was measured according to Thun and Hoffmann (2012), using a flow injection analyzer (FIAstar 5000 Analyzer, FOSS GmbH, Hamburg, Germany).

Nitrogen was applied at a rate of 60 kg N ha^{-1} in 2018 and 55 kg N ha^{-1} in 2019 broadcast as calcium ammonium nitrate based on the mean mineral N across all soil samples in the respective year and the target value of 70 kg N ha^{-1}. Plant protection measures were only performed once on 7 May in 2019 by applying the insecticide Lambda against the pea leaf weevil (*Sitona lineatus* L.). No irrigation was applied.

Swedish site

The design for the field experiment in Sweden was aligned with the previously described experiments

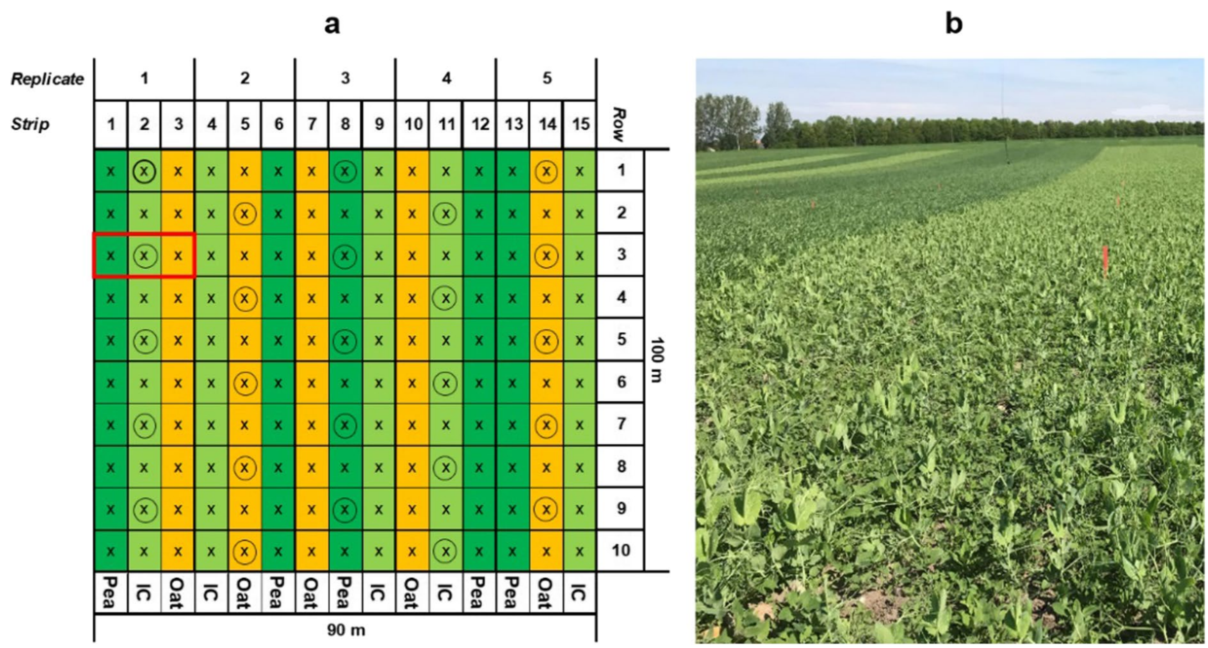

Fig. 3 Experimental design (**a**) in Sweden in 2019 with the factors replicate ($n=5$), strip ($n=15$), row ($n=10$), and block ($n=50$, indicated by red rectangle), and the treatments Pea, Oat, and the intercrop (IC) and an image illustrating the parallel strips of the experiment (**b**). The "x" indicates the sample plots ($n=150$), and circles in the grid denote the soil sample plots ($n=25$) for soil variables not measured in all 150 sample plots

in Germany. The field experiment covered an area of 0.9 ha (100 × 90 m^2) on a loamy sand soil with variations in topography (undulating field with variation of 1.8 m from highest to lowest point) and ECa values between 11.2 and 24 mS m^{-1} measured using an electromagnetic induction sensor (EM38-MK2; Geonics Ltd., Mississauga, Canada). Fifteen parallel strips measuring 100 × 6 m^2 were laid along the length of the field in N-S direction (Fig. 3). The field was divided into ten, equally spaced rows with 10 m length resulting in a grid with 150 sample plots.

On 16 April 2019, each strip was sown with either Oat-SC (cv. Nike (Lantmännen Seed, Malmö, Sweden), 320 viable seeds m^{-2}), Pea-SC (cv. Ingrid (Lantmännen Seed, Malmö, Sweden), 80 viable seeds m^{-2}) or IC in a replacement design with 50% of SC seeding densities. Row distance was 12.5 cm and sowing depth 3.5 cm. Oat and Pea in IC were mixed within the row.

The variability in soil conditions was determined before sowing of crops by measuring volumetric soil moisture content in situ with a TDR probe (FieldScout TDR 300, Spectrum Technologies Ltd, Bridgend, Wales) to a depth of 10 cm followed by the collection of soil samples to a depth of 25 cm in the center of each sample plot (indicated by circles in Fig. 3). The sampling depth at the Swedish site was shallower expecting less influence of nutrient and water availability of the loamy sand soil compared with the silty clay loam at the German sites. Concentrations of Ct and Nt were analyzed in all sample plots, while soil texture, pH, soil organic matter (SOM), and concentrations of Nmin and P were measured in 25 sample plots covering the entire field in a triangular pattern (indicated by a circle in Fig. 3). Nitrogen fertilization was 50 kg N ha^{-1} supplied as ammonium nitrate. No plant protection measures and irrigation were performed.

Ct and Nt were analyzed by dry combustion using an elemental analyzer (Thermo Scientific™ Flash 2000 CHNS/O, Thermo Fisher Scientific, Walthman, MA, USA). Soil texture was determined with sieving-sedimentation method. The pH was measured potentiometric in a 1:5 soil:water suspension. SOM was determined by loss on ignition method. Nmin was extracted with 2 M KCl and plant available phosphorus with acid ammonium acetate lactate (AL-P, Egnér et al. 1960). Nmin and AL-P were determined by air-segmented continuous flow analysis (AutoAnalyzer 3 h, SEAL Analytical Inc., Mequon, WI, USA).

Harvest

At crop maturity, plant samples were collected in all sample plots to measure grain yield, shoot dry matter and weed dry matter. The plant sampling was done by manually cutting all plants at the ground level from 1 m^2 in the center of each sample plot (1.04 m x 0.96 m in the German trials and 1.0 m x 1.0 m in the Swedish trial), sorting the samples into crop and weed plants, sorting oat from pea in IC samples, threshing the crop plants (separating seeds from straw, which included all non-seed aboveground biomass) and drying all plant samples at 60 ºC for 48 h. The harvest was conducted in Germany on 23 July in 2018 and 29 July in 2019, and in Sweden on 2 August in 2019, respectively.

Statistical analysis

All analyses were performed within the developed mixed model framework in SAS 9.4 (SAS Institute, 2016). Separate analyses were performed for the three experiments. Each experiment was laid out in a randomized complete block design (RCBD) with the treatments Oat-SC, Pea-SC and IC allocated to strips (Figs. 1, 2 and 3). Repeated data were taken from plots within each strip. Plots were arranged in rows being orthogonal to the direction of strips. As strips were allocated along the gradient within the field, we expected large variation between plots within strips and small covariance between plots within a strip, respectively. Therefore, the three neighbouring plots within one row and one replicate were defined as an additional block as illustrated in Figs. 1, 2 and 3.

Weed dry matter was measured for SC-Oat, SC-Pea, and IC (three observations per block), while shoot dry matter and yield were measured for SC-Oat, SC-Pea, IC-Oat, and IC-Pea (four observations per block).

For traits with three observations per block, the following model was fitted:

$$y_{ijklm} = \mu + r_j + s_{jk} + b_{jl} + \tau_i + e_{ijklm} \tag{1}$$

where y_{ijklm} is the m-th observation of treatment i in block l of strip k and replicate j, μ is the intercept, r_j, s_{jk}, and b_{jl} are random effects of replicate j, strip k within replicate j and block l within replicate j, τ_i is the i-th treatment effect and e_{ijklm} is the error of y_{ijklm}.

The model of an RCBD was extended by adding strip and block effects. It can be assumed that strip effects within a replicate are more similar compared to strip effects of different replicates. The covariance of strip effects within a replicate is covered by the replicate effect. Analogously, the three plot effects within a block can be assumed to be more similar compared to plots from different blocks and is covered by the block effect. Thus, in (1) the covariances are modelled by replicate and block effects. Alternatively, strip and replicate effects (block and plot effects) can be modelled jointly resulting in a 3 × 3 variance-covariance structure. Model (1) can therefore be simplified to:

$$y_{ijkl} = \mu + s_{jk} + \tau_i + e_{ijkl} \tag{2}$$

where the covariance between strip effects s_{jk} of the same replicate j and between error effects e_{ijkl} of the same block is now fitted by a 3 × 3 compound symmetry structure with heterogeneous variances. The term τ_i has three (Oat-SC, Pea-SC and IC for weed dry matter) levels.

Analogously, for traits with four observations per block (Oat-SC, Pea-SC, Oat-IC, and Pea-IC for grain yield and shoot dry matter), model (2) was fitted and a 4 × 4 variance-covariance structure was assumed for the s_{jk} effects in the same replicate and e_{ijkl} in the same block.

The variance-covariance structure should account for both, the covariance due to occurrence in the same replicate or block and the competition in IC due to growth on the same strip or plot. Thus, in the current study and for traits with observations available four times per block, the variance-covariance structure R was defined for each block as follows:

$$R = \begin{bmatrix} \sigma^2_{Oat-SC} & \sigma_1 & \sigma_1 & \sigma_1 \\ \sigma_1 & \sigma^2_{Pea-SC} & \sigma_1 & \sigma_1 \\ \sigma_1 & \sigma_1 & \sigma^2_{Oat-IC} & \sigma_1 + \sigma_2 \\ \sigma_1 & \sigma_1 & \sigma_1 + \sigma_2 & \sigma^2_{Pea-IC} \end{bmatrix} \tag{3}$$

where σ^2_i is the strip or error variance of treatment i, σ_1 is the covariance due to replicate or block effects, respectively, and σ_2 allows to model the confounded effect of interspecific competition and strip or plot effect, respectively. Treatment-specific variances were assumed ($\sigma^2_{Oat\_SC}$ to σ^2_{Pea-IC}) as variances e.g. for yield of pea sown in full density in SC and yield of pea sown in reduced density in IC cannot be assumed as equal.

In summary, the current study extended the common RCBD model in four points: First, the model accounted for the repeated measures structure within strips by fitting strip and error effects. Second, it accounts for block effects. Third, the model allows fitting heterogeneous treatment-specific variances. Finally, the fitted model allows that the covariance between error effects within a replicate or block is not constant by fitting a separate covariance between oat and pea in IC. This separate covariance (σ_2) can be interpreted as a confounded effect of interspecific competition, strip and replicate (or plot and block) effects. The variance-covariance structures were fitted using the restricted maximum likelihood method (Patterson and Thomson 1971).

Model assumptions were checked graphically via residual plots (Figs. S1-S3). Data for yield, shoot and weed dry matter were transformed logarithmically prior to analysis to fulfil model assumptions. Treatment means were compared using Tukey's test and a letter display was derived (Piepho 2004). Means were back-transformed for presentation purpose only. They were denoted as medians and the standard errors were back-transformed using the delta method.

Land equivalent ratio

The treatment means were further used to calculate the land equivalent ratio (LER) and the partial LER

Table 2 Descriptive statistics of soil variables for the experiments in Germany in 2018 and 2019

Year	Soil variables	n	Mean	SD	Min	Max	CV (%)[a]
2018	ECa (mS m^{-1})	40	26.8	4.29	18.5	34.0	16.0
	Water (Vol-%)	40	20.4	1.12	18.8	24.1	5.5
	Clay (%)	40	32.4	5.03	20.4	41.1	15.5
	Corg (%)	40	0.71	0.23	0.35	1.13	32.4
	Ct (%)	40	0.75	0.24	0.38	1.23	32.0
	Nt (%)	40	0.08	0.03	0.03	0.13	37.5
	Nmin (kg ha^{-1})	40	11.5	5.17	5.59	25.2	45.0
2019	ECa (mS m^{-1})	90	20.7	5.95	13.3	30.3	28.7
	Water (Vol-%)	30	19.0	1.06	17.6	22.0	5.6
	Clay (%)	30	28.9	12.6	15.2	53.5	43.6
	Corg (%)	30	0.74	0.15	0.42	0.95	20.3
	Ct (%)	30	0.79	0.16	0.47	1.03	20.3
	Nt (%)	30	0.08	0.01	0.05	0.11	12.5
	Nmin (kg ha^{-1})	30	16.1	5.7	8.6	34.5	35.4

[a]CV = coefficient of variation (SD × 100 / Mean)

Table 3 Descriptive statistics of soil variables for the experiment in Sweden in 2019

Soil variables	n	Mean	SD	Min	Max	CV (%)[a]
ECa (mS m^{-1})	150	14.7	2.37	11.2	24.0	16.1
Water (Vol-%)	150	8.90	3.55	4.2	26.5	39.9
Clay (%)	25	6.69	0.92	5.0	7.9	13.8
SOM (%)	25	2.49	0.27	2.1	3.2	10.8
Ct (%)	150	1.89	0.42	1.20	3.18	22.2
Nt (%)	150	0.16	0.04	0.09	0.26	25.0
Nmin (kg ha^{-1})	25	32.9	7.62	20.7	46.5	23.2
AL-P (mg kg^{-1})	25	21.0	4.4	13.4	28.2	21.0
pH	25	6.92	0.64	6.15	8.18	9.2

[a]CV = coefficient of variation (SD × 100 / Mean)

(pLER) to compare yield (and likewise shoot dry matter) produced in IC and SC defined according to Mead and Willey (1980) as:

$$\begin{aligned} pLER_{Oat} &= Yield_{Oat-IC}/Yield_{Oat-SC} \\ pLER_{Pea} &= Yield_{Pea-IC}/Yield_{Pea-SC} \\ LER &= pLER_{Oat} + pLER_{Pea} \end{aligned}$$

where Oat-IC and Oat-SC and Pea-IC and Pea-SC are yields of oat and pea in IC and SC, respectively.

In our case, differences in mean yield with their corresponding standard errors were estimated on the log-transformed scale. These differences of means between SC and IC from the same crop (oat, pea) on the transformed scale correspond to ratios on the original scale. Thus, back-transformed differences between means of SC and IC of the same crop can be interpreted as pLER. The LER was finally calculated as the sum of estimated pLER of oat and pea. Note that pLER and LER were not calculated per block and subsequently analysed, because the response variable yield was assumed to be log-normal distributed. Thus, the ratio of two yield values is neither normal nor log-normal distributed. Additionally, the 95% confidence limits for pLER values were calculated and back-transformed. The pLER values outside the 95% confidence limits were considered as significantly different. This significance test was done for 0.6 for pea and 0.4 for oat in the additive design in Germany and for both crops with 0.5 for the replacement design in Sweden, respectively. The values 0.6 (0.75 / 1.25) and 0.4 (0.5 / 1.25) result from the proportion of pea and oat sown in the additive IC design with a total density of 1.25, where absolute sowing densities of pea and oat were 0.75 and 0.5 compared with the sowing density of the respective sole crops. LER is not a parameter in our model, therefore, a test of LER against 1 was not possible. LER can be included in a different model, e.g. in the PROC NLMIXED procedure in SAS. Unfortunately, our experimental design cannot be parameterized in PROC NLMIXED, therefore, estimated LER values and tests would differ.

Coefficient of variation

As an indicator for yield stability, coefficients of variation (CV) for yield were calculated for each treatment by:

$$CV_i = \sqrt{e^{s_i^2} - 1} \tag{4}$$

Table 4 Median values of grain yield of sole crops (Oat-SC, Pea-SC), the single intercrops (Oat-IC, Pea-IC) and the total intercrop (IC) for the experiments in Germany in 2018 and 2019, and in Sweden in 2019, respectively

Treatment	Grain yield (kg ha^{-1})		
	Germany 2018	Germany 2019	Sweden 2019
Oat-SC	5077^a (±109)	4605^a (±107)	3950^a (±91)
Oat-IC	3835^c (±72)	3345^b (±139)	3359^a (±202)
Pea-SC	3217^d (±153)	2785^c (±169)	1125^b (±317)
Pea-IC	775^e (±52)	1271^d (±89)	183^c (±42)
IC	4610^b (±89)	4616^a (±165)	3542^a (±206)

Medians within one column sharing an identical letter are not significantly different from each other ($p < 0.05$). Values in brackets represent the standard error

where CV_i is the coefficient of variation of treatment i and s_i^2 is the estimated variance of treatment i on the log-transformed scale (Lewontin 1966). Note that in our case there are two variances, one for strip effects and one for the error. We therefore used the variance of the mean to calculate CV, as this variance accounts for both variances. For presentation purpose and to make CV values comparable with commonly used CV values, we afterwards multiplied the CV with the square root of the number of blocks. The rationale is that this factor relates between standard deviation and standard error in models with only error variance. The multiplication is therefore an *ad-hoc* approximation that equally affects the absolute values of all CV. Note that the CV only depends on the variance on the log-transformed scale, therefore, the comparison of models assuming homogeneous and heterogeneous variances for strip and error effects on the log-scale correspond to a test whether the CV of different treatments on the original scale were similar or not. For this comparison, the variance-covariance structure R (3) was fitted by assuming the same variance for (i) all four cropping systems ($\sigma^2_{Oat-SC} = \sigma^2_{Pea-SC} = \sigma^2_{Oat-IC} = \sigma^2_{Pea-IC}$), (ii) cropping systems with oat ($\sigma^2_{Oat-SC} = \sigma^2_{Oat-IC}$) or (iii) cropping systems with pea ($\sigma^2_{Pea-SC} = \sigma^2_{Pea-IC}$). These different models were compared based on the Akaike information criterion (AIC), which allows evaluating the fit of models with different covariance structures (Wolfinger 1993). Smaller AIC values indicated better model fit. Models with a difference in AIC smaller than two were considered as equally well fitting. The test for

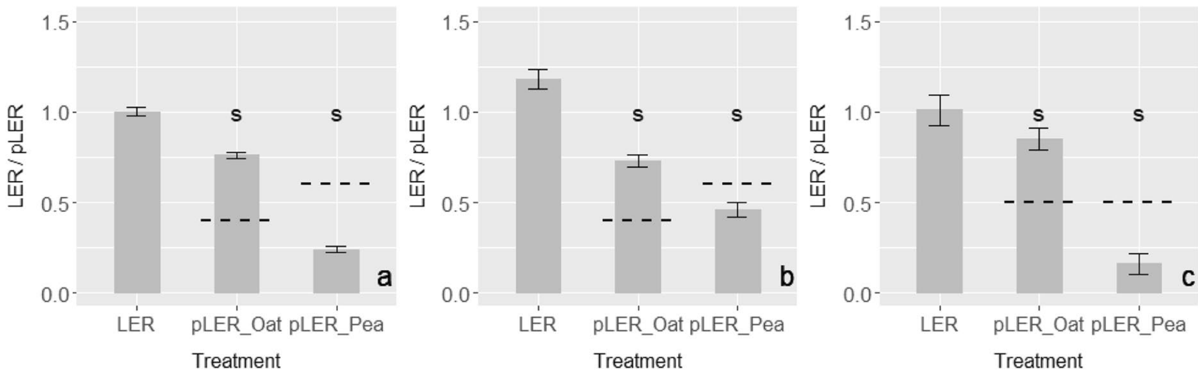

Fig. 4 Land equivalent ratio (LER) and partial LER (pLER) of oat and pea for the experiments in Germany in 2018 (**a**) and 2019 (**b**) with the additive IC design, and in Sweden in 2019 (**c**) with the replacement IC design, respectively. The 95% confidence intervals of pLER values (Table S1) were used to test for significant differences from 0.6 for pea and 0.4 for oat (dashed lines) in the additive IC design in Germany and 0.5 for both crops (dashed lines) in the replacement design in Sweden (s = significant), respectively. A test for LER against 1 was not possible with our statistical model. Error bars represent the standard error

differences in CV was not affected by multiplication made afterwards.

In addition to the comparison of CV of individual treatments, we also estimated the CV for each cropping system, i.e. the two SCs combined (CV_{SC})and IC (CV_{IC})as follows (Kish and Hess 1959):

$$CV_{SC} = \sqrt{e^{(s^2_{Oat-SC}+s^2_{Pea-SC})/2} - 1} \tag{5}$$

$$CV_{IC} = \sqrt{e^{(s^2_{Oat-IC}+s^2_{Pea-IC})} - 1} \tag{6}$$

CV_{SC} can be interpreted as the CV that would result from growing each SC on one half of the field. Note that for the estimation of CV_{IC}, the covariance between oat and pea in IC fitted within the model was ignored. Thus, the CV of IC across crops is approximate. A significance test between CV_{SC} and CV_{IC} was not possible with our statistical model as these are not parameters in our model. The significance test can be included in a different model, e.g. in the PROC NLMIXED procedure in SAS. Unfortunately, our experimental design cannot be parameterized in PROC NLMIXED, therefore, estimated values of CV_{SC} and CV_{IC} and tests would differ.

Regression analysis with soil variables

The statistical model was extended by treatment-specific regressions with the measured soil variables (Tables 2 and 3). The aim was to test if soil variables influence pea and oat grown as SC or IC differently. A multiple regression approach with the all subset method, but less than three soil variables was used. The best fitting model was selected based on the lowest AIC. The latter requires that the maximum likelihood method was used for calculating AIC. Seven soil variables were included for the experiments in Germany (Table 2) and nine soil variables for the experiment in Sweden (Table 3). For soil variables not measured in every plot, data imputation was performed prior to analysis assuming an AR1 × AR1 spatial model. The final estimated and observed values of soil variables used for the regression analysis are shown as heatmaps in Figs. S4-S6. The spatial variation in observed yields of all treatments and block-wise calculated pLERs and LER are given in Figs. S7-S9.

Results

Variability in soil characteristics

The measured soil physical and chemical characteristics showed variations within the experimental fields (Tables 2 and 3). The two experimental fields at the German site showed very similar mean values for each of the measured soil variables (Table 2). Differences were apparent in the variability within the fields. In 2018, the highest CV was found for Nmin (45%) followed by similar CVs for Nt, Corg, and Ct (32–38%). The CV for clay (44%) was the highest in

2019 followed by Nmin (35%) and ECa (29%). Ct and Corg showed very similar CVs around 20%.

At the Swedish site, soil water was the variable with the highest CV (40%) followed by Nt, Nmin, Ct and AL-P between 21 and 25% (Table 3). The CVs for ECa, clay, SOM, and pH were comparably lower (9–16%).

Grain yield

Similar differences amongst treatments were found for grain yields in all three experiments (Table 4). The highest grain yields were found in Oat-SC and the total intercrop (IC), which differed significantly only in Germany in 2018. IC yielded 91, 100, and 90% of the total grain yield measured in Oat-SC with a substantial proportion of Oat in IC with 83, 72, and 95% for 2018 and 2019 in Germany and the Swedish site, respectively. Pea was in general more productive at the German site both in SC and IC.

The land equivalent ratio (LER) was 1.18 in Germany in 2019 and close to 1.0 in the other two experiments (Fig. 4). The partial LERs (pLER) also expressed the high contribution of oat in LER being significantly higher than 0.4 with 0.73 and 0.76 at the German sites in the additive IC design and 0.85 (significantly higher than 0.5) at the Swedish site in IC with replacement design. The $pLER_{Pea}$ was comparably lower, and particularly low at the Swedish site. In the additive IC design in Germany, $pLER_{Pea}$ was quite low in 2018 with 0.24, while in 2019 $pLER_{Pea}$ was 0.46, but still significantly lower than 0.6. LER values calculated per block showed considerable within-field variations between 0.7 and 1.5 for Germany in 2018 (Fig. S7) and 0.9 and 1.5 in 2019 (Fig. S8), and 0.5 and 2.5 for the experiment in Sweden (Fig. S9).

The CV was considerably lower for oat (12–43%) compared with pea (30–199%) and in general, lower at the German site compared to the Swedish site (Fig. 5a, c, e). The difference between single sole crops and intercrops showed similar values only being significantly higher for Pea-IC in Germany in 2018 and Oat-IC in Germany in 2019. The CV of Pea-IC and Oat-IC were considerably larger in the replacement design in Sweden compared with the additive IC design in the experiments in Germany. The comparison of CV for grain yield between the total intercrop (IC) and the combined sole crops showed, however, only minor absolute differences between 2 and 5% with a lower CV in IC for two year x site combinations and higher CV in IC in Germany in 2019 (Fig. 5b, d, f). The combined sole crop yield is an estimate of the yield variation that would result if a field would be divided in two equal areas each used for the cultivation of oat and pea SCs. The CV of IC was very close, in Germany in 2019 even slightly lower, to Oat-IC and in all cases considerably lower than the CV of Pea-SC (Fig. 5).

Shoot dry matter

Differences in shoot dry matter between crops and cropping systems followed in principal the same pattern as previously shown for grain yield with higher values for oat than for pea, and a significant contribution of Oat-IC in the intercrop (Table 5). The LER for shoot dry matter was slightly higher in all experiments compared with LER for grain yield (Fig. 4).

Weed dry matter

The differences in weed dry matter showed the same order for all three site x year combinations (Fig. 6). The highest weed dry matter was consistently found in Pea-SC, where it was fourteen times (Sweden) or higher than in Oat-SC. Intercropping drastically reduced weed dry matter compared to Pea-SC, although it was significantly higher than in Oat-SC. In the additive ICs in Germany, the reduction in weed dry matter was similar for both years with 92 and 90% compared with SC-Pea for 2018 and 2019, respectively, while in the replacement design at the Swedish site the reduction was lower with 82%.

Regression analysis with soil variables

Regressions were performed for grain yield, shoot and weed dry matter of oat and pea grown either in SC or IC with all possible combinations of up to two soil variables and models were compared based on AIC. Models with certain covariables had in all cases lower AICs than the baseline model (i.e. without covariable) (Table S2).

For the German site in 2018, the regression model which includes both water content and Corg had the lowest AIC value for grain yield and shoot dry matter (Table S2). A significant positive response to Corg was found for oat in both SC and IC (Table 6). Pea had a significant positive response to water content for grain yield when grown as IC, but not for shoot dry matter,

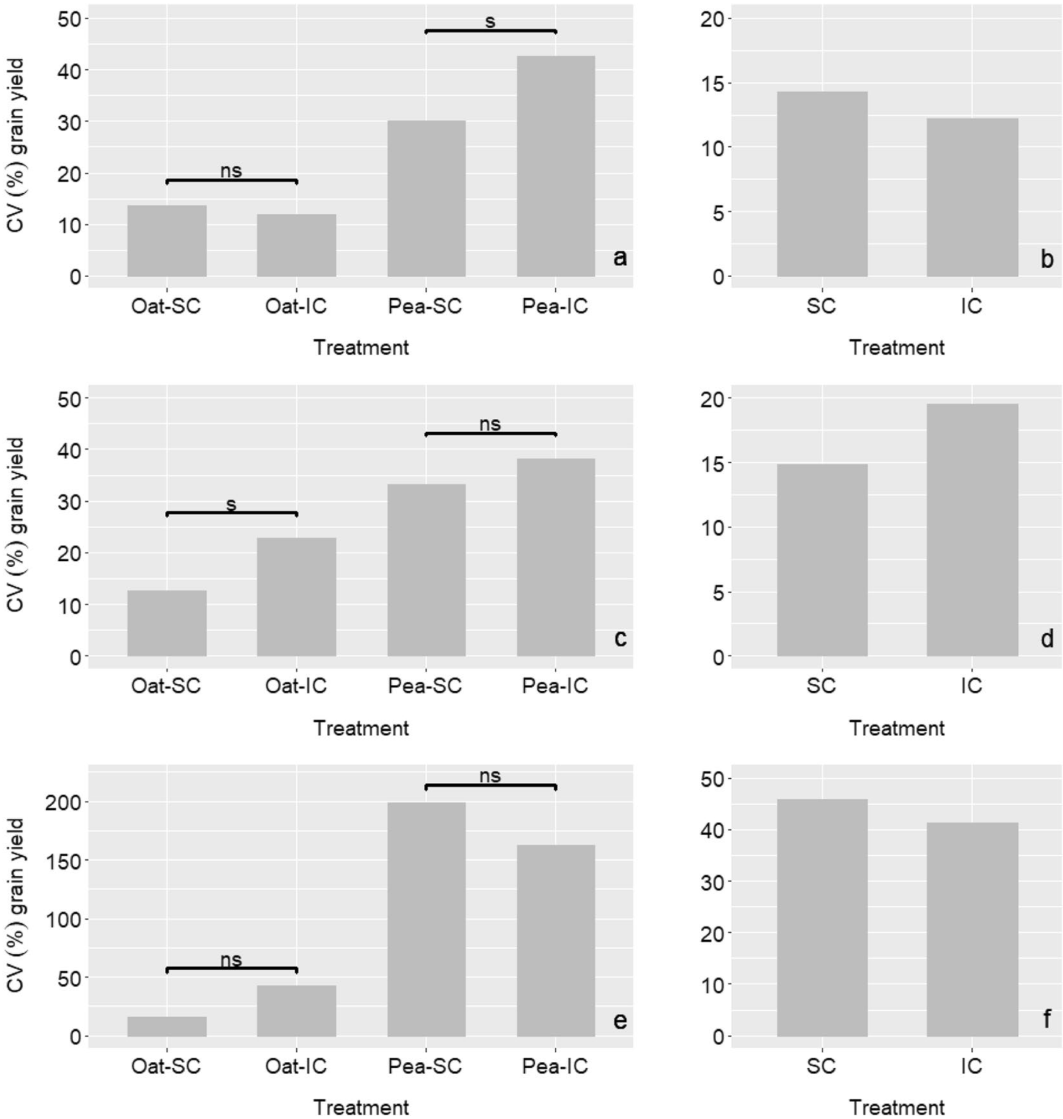

Fig. 5 Coefficient of variation (CV, %) for grain yield of sole crops (Oat-SC, Pea-SC) and each single intercrop (Oat-IC, Pea-IC) (**a**, **c**, **e**), and for the total grain yield of the combined sole crops (SC, Eq. (5)) and the intercrop (IC, Eq. (6)) (**b**, **d**, **f**), respectively, for the experiments in Germany in 2018 (**a**, **b**) and 2019 (**c**, **d**) and in Sweden in 2019 (**e**, **f**). Significance based on difference in AIC values larger than 2 (s = significant, ns = non-significant). Note that a significance test between the CV of SC and IC was not possible with our statistical model

while in general no response was found for Pea-SC (Table 6). Oat showed a slight positive response to water in SC. Regression analysis for weed dry matter did not show a substantial improvement in AIC, i.e. no relation to soil variables was found (Table S2).

For 2019, the lowest AIC was found for the combination of ECa and Nt for grain yield and shoot dry matter (Table S2). For oat in SC and IC both target crop variables were significantly related to an increase in ECa with an additional positive response of only Oat-SC to Nt, while no effect was found in general for pea (Table 7). Weed dry matter was not significantly related to any soil covariable (Table S2).

For the Swedish site, the regression model for grain yield and shoot dry matter with the lowest AIC included both ECa and water content (Table S2). The

Table 5 Median values of shoot dry matter of sole crops (Oat-SC, Pea-SC), the single intercrops (Oat-IC, Pea-IC) and the total intercrop (IC), and LER and pLER for the experiments in Germany in 2018 and 2019 with the additive IC design, and in Sweden in 2019 with the replacement IC design, respectively

Treatment	Germany 2018	Germany 2019	Sweden 2019
	Shoot dry matter (kg ha^{-1})		
Oat-SC	9859^a (±295)	9294^b (±158)	7525^a (±169)
Oat-IC	7696^b (±217)	7363^c (±229)	6279^a (±360)
Pea-SC	7989^b (±327)	7142^c (±207)	2877^b (±588)
Pea-IC	2071^c (±87)	2905^d (±153)	623^c (±102)
IC	9767^a (±234)	10,269^a (±276)	6902^a (±375)
		LER / pLER	
LER	1.04 (±0.021)	1.20 (±0.035)	1.05 (±0.079)
pLER$_{Oat}$	0.78^s (±0.018)	0.79^s (±0.026)	0.83^s (±0.055)
pLER$_{Pea}$	0.26^s (±0.012)	0.41^s (±0.024)	0.22^s (±0.057)

For shoot dry matter, medians within one column sharing an identical letter are not significantly different from each other ($p < 0.05$). The 95% confidence intervals of pLER values (Table S1) were used to test for significant differences from 0.6 for pea and 0.4 for oat in the additive IC design in Germany and 0.5 for both crops in the replacement IC design in Sweden (s = significant), respectively. A test for LER against 1 was not possible with our statistical model. Values in brackets represent the standard error

ECa had a significantly positive effect on grain yield and the shoot dry matter of Oat-SC (Table 8). On the contrary, the yield of pea in IC showed a strong decrease with increasing ECa and on the other hand a strong positive response to water content. The best regression model for weed dry matter included Nt and Ct and showed a significant response in Pea-SC with a minor decrease with Ct and a considerable positive response to Nt.

Discussion

The present study is to our knowledge the first investigation of within-field yield variability in cereal-grain legume IC compared to SC. Our results showed that the response of crop performance (yield and shoot dry matter) to within-field variability in soil conditions was mostly species-specific with a positive response of oat to availability of nutrients and of pea to water availability. In addition, there was an indication of complementarity in IC for nutrient uptake and competition for water. Yield stability (indicated by CV) was consistently higher for IC compared with Pea-SC, but not Oat-SC. The comparison of yield stability in IC with the combined SCs did only indicate minor differences, which could not be tested for significance with our statistical model. In the experiment with the highest LER, the CV of both IC-Oat (significantly) and IC-Pea (not significant) were larger than their SC equivalents. For the CV of the total IC, however, the results indicated a lower CV than each of the two crops in IC. We interpret this as a result of within-field variation in inter-specific interactions in line with the EPF principle (Jensen et al. 2015), that consequently increases variability in yield of component crops in IC, which might decrease the CV of the total IC.

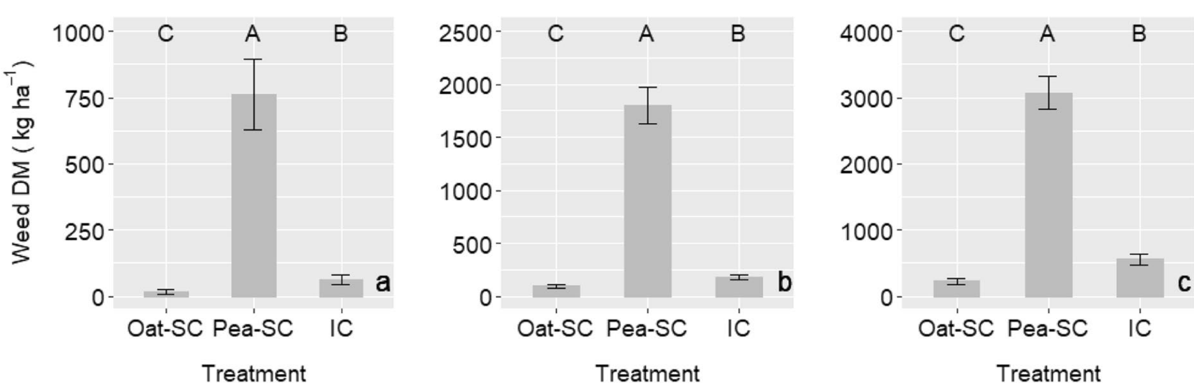

Fig. 6 Median values of weed dry matter (DM) of sole crops (Oat-SC, Pea-SC) and the intercrop (IC) for the experiments in Germany in 2018 (**a**) and 2019 (**b**), and in Sweden in 2019 (**c**). Within each single figure, bars headed by an identical letter are not significantly different from each other ($p < 0.05$). Error bars represent the standard error

Table 6 Results of the regression analysis for grain yield and shoot dry matter in Germany in 2018 for sole crops (Oat-SC, Pea-SC) and intercrops (Oat-IC, Pea-IC)

Target variable	Covariable	Treatment	Parameter estimate	Standard error	*p*-value
Grain yield	Water content	Oat-SC	0.04	0.02	0.0596
		Oat-IC	0.027	0.016	0.1021
		Pea-SC	0.003	0.047	0.9479
		Pea-IC	0.137	0.065	0.0417
	Corg	Oat-SC	0.248	0.085	0.0072
		Oat-IC	0.226	0.08	0.0083
		Pea-SC	-0.012	0.206	0.9530
		Pea-IC	0.214	0.319	0.5062
Shoot dry matter	Water content	Oat-SC	0.041	0.022	0.0697
		Oat-IC	0.019	0.017	0.2836
		Pea-SC	0.024	0.033	0.4750
		Pea-IC	-0.004	0.049	0.9423
	Corg	Oat-SC	0.364	0.092	0.0006
		Oat-IC	0.4	0.08	0.0001
		Pea-SC	0.213	0.139	0.1376
		Pea-IC	0.017	0.229	0.9402

p-value for a test of the ratio against one. The regression models with the lowest AIC included water content and Corg (Table S2)

Crop productivity

At the Swedish site pea showed considerably lower yield and shoot dry matter, both for SC and IC, compared with the German site. These differences were not found for oat. The lower water availability (lower water content measured before the experiment and lower precipitation during April and July) and water holding capacity of the sandy soil indicate that water limitations were the primary reason to explain the

Table 7 Results of the regression analysis for grain yield and shoot dry matter in Germany in 2019 for sole crops (Oat-SC, Pea-SC) and intercrops (Oat-IC, Pea-IC)

Target variable	Covariable	Treatment	Parameter estimate	Standard error	*p*-value
Grain yield	ECa	Oat-SC	0.012	0.003	0.0004
		Oat-IC	0.017	0.005	0.0033
		Pea-SC	-0.012	0.012	0.3219
		Pea-IC	-0.001	0.014	0.9701
	Nt	Oat-SC	3.148	1.335	0.0269
		Oat-IC	1.569	2.407	0.5230
		Pea-SC	-1.107	5.123	0.8307
		Pea-IC	4.99	7.251	0.4980
Shoot dry matter	ECa	Oat-SC	0.077	0.027	0.0101
		Oat-IC	0.095	0.044	0.0450
		Pea-SC	-0.075	0.051	0.1571
		Pea-IC	0.057	0.11	0.6098
	Nt	Oat-SC	46.972	12.882	0.0015
		Oat-IC	15.231	21.356	0.4864
		Pea-SC	33.647	21.818	0.1367
		Pea-IC	66.626	54.335	0.2322

p-value for a test of the ratio against one. The models with the lowest AIC included ECa and Nt (Table S2)

Table 8 Results of the regression analysis for grain yield, shoot and weed dry matter in Sweden in 2019 for sole crops (Oat-SC, Pea-SC) and intercrops (Oat-IC, Pea-IC)

Target variable	Covariable	Treatment	Parameter estimate	Standard error	*p*-value
Grain yield	ECa	Oat-SC	0.545	0.193	0.0072
		Oat-IC	0.205	0.3	0.4981
		Pea-SC	2.235	1.72	0.2003
		Pea-IC	-3.067	1.158	0.0114
	Water content	Oat-SC	-0.254	0.177	0.1586
		Oat-IC	0.009	0.245	0.9722
		Pea-SC	0.013	0.972	0.9892
		Pea-IC	4.048	0.89	< 0.0001
Shoot dry matter	ECa	Oat-SC	0.425	0.186	0.0272
		Oat-IC	0.112	0.314	0.7231
		Pea-SC	1.507	0.985	0.1330
		Pea-IC	-1.514	0.84	0.0809
	Water content	Oat-SC	-0.047	0.17	0.7846
		Oat-IC	0.05	0.258	0.8461
		Pea-SC	0.028	0.557	0.9608
		Pea-IC	2.325	0.642	0.0010
Weed dry matter	Ct	Oat-SC	0.128	0.918	0.8901
		Pea-SC	-1.802	0.413	< 0.0001
		IC	-0.022	1.014	0.9826
	Nt	Oat-SC	1.641	9.704	0.8664
		Pea-SC	24.91	5.006	< 0.0001
		IC	3.804	10.941	0.7296

p-value for a test of the ratio against one. The models with the lowest AIC included ECa and water content for grain yield and shoot dry matter, and Ct and Nt for weed dry matter (Table S2)

lower productivity of pea at the Swedish site (Jamieson et al. 1984). The average LER values showed a per area advantage in yield and shoot dry matter only for the German site in 2019 (LER close to unity in the other two experiments), which was achieved through a higher pLER of pea compared to the other two experiments. A higher pea density in the additive design in Germany increases in general the competitiveness of pea (Yu et al. 2016), however, the lower pLER of pea in Germany in 2018, indicates that more abundant and evenly distributed rainfall was a major reason for the higher competitiveness of pea in Germany in 2019. A higher water availability might have reduced water competition by oat in IC as Pea-SC had a similar yield in both years in Germany. Similar results were found for a faba bean – wheat IC grown in a dry year in Denmark, where faba bean and pea yielded very low in IC, however, LER values were close to 1 reflecting the high compensatory growth of the cereal (Sears et al. 2021). This was also shown consistently in our study with a $pLER_{Oat}$ between 0.73 and 0.85. Previous studies show that the pLER of cereals increases with the quantity of N fertilizer applied (e.g. Jensen 1996, Yu et al. 2016). In our study, N fertilizer was only moderately applied to a level of around 70 kg N ha^{-1} (Nmin + fertilizer N). Consequently, N fertilization was probably not the only reason for the high competitiveness of oat. LERs around unity with a high $pLER_{Oat}$ indicate that complementarity between oat and pea was not efficient, and oat was the dominant crop – e.g. in water and N acquisition – and compensated strongly for the competition exerted on pea (Justes et al. 2021).

Yield stability

Besides a potential increase in the productivity of IC, a higher yield stability under contrasting environmental conditions might be an argument for growing crops in IC. Yield stability in cereal-legume IC compared to their SCs has been investigated on spatial (comparison across sites) and temporal scales (across years for the same location) (Raseduzzaman and Jensen 2017; Weih et al. 2021). These results have been inconclusive, which can at least partly be attributed to different statistical approaches (Weih et al. 2021). In our study, we analyzed yield stability within a field, an important aspect on large farmers´ fields. Our results showed that yield stability in IC was higher than in SC-Pea and similar to Oat-SC. This is comparable to previous findings in cereal-legume IC (Raseduzzaman and Jensen 2017) and the general found higher CV of legume SCs compared with cereal SCs (e.g. Watson et al. 2017). A higher yield stability was shown for replacement designs compared with additive designs of cereal-legume ICs (Raseduzzaman and Jensen 2017). Our comparison of the CV between IC and the SCs did not show any difference between the additive IC design in the German experiments and the replacement design at the Swedish site. This might be explained by the high contribution of oat to grain yield and shoot dry matter of IC in our study, which lowered the CV of IC irrespective of IC design.

It may be relevant in grain legume production, that IC can increase yield stability compared to pea sole cropping. However, it may be more interesting to know if IC can increase yield stability compared to both sole crops that are considered for IC. This is why we compared the CV of IC with the combined CV of the SCs, i.e. testing if IC would lead to higher overall stability than if the two crops were grown as SCs on equal proportions of the same land. This comparison did not indicate a higher yield stability in IC. Slightly lower CV in IC were found for the two experiments with an LER around 1.0 and a higher CV in IC for the experiment in Germany in 2019 with the highest LER. In the first case, the pLER of oat was very high in these experiments reflecting a yield-stabilizing effect of oat, which had a lower CV. In the second case, the CV of both oat (significant) and pea (non-significant) were higher in IC compared with their SC equivalents, which might be the consequence of the different competitive abilities of pea and oat in response to the within-field variations in soil conditions. As such, our findings of a higher CV of IC considering the CV of each IC component crop would actually be an expected result of the EPF principle. The common assumption of a higher yield stability in IC is most probably related to not differentiating between the component crops in IC. Calculating the CV based on the total yield in IC can result in balancing between the two crops and result in a lower CV (Weih et al. 2021). In our study, we estimated heterogeneous variances for each crop also in IC and our comparison with the combined SCs can be seen in analogy to the LER, for which crop-specific yields are compared and then summed instead of dividing the total yield in IC with the average yield of both SCs. We assume that this comparison gives practically meaningful results because oat and pea are not comparable from qualitative and economic perspectives and there are production aims, e.g. producing a high legume yield in IC. For the interpretation of results, it is important to know the yield achieved for each component crop in IC and its stability. The alternative calculation of the CV for the total grain yield of IC also showed only minor differences between IC and the combined SCs, not indicating a higher yield stability of IC (Fig. S10).

Weed dry matter

The high productivity of oat was also reflected in the lowest weed dry matter in Oat-SC being just slightly lower than in IC, and both being substantially more competitive against weeds than Pea-SC. These results reflect the commonly found weed suppression in cereal-legume IC being in many cases almost or equally strong as the more competitive sole crop (Hauggaard-Nielsen et al. 2001; Gu et al. 2021). In comparison with SC-Pea, weed dry matter in IC was reduced by 92 and 90% at the German site in 2018 and 2019, and by 82% in the Swedish trial, respectively. This might indicate an increased weed suppression in the additive IC design in Germany compared with the replacement design at the Swedish site as shown in a meta-analysis by Gu et al. (2021). Whereas, an experimental study by Corre-Hellou et al. (2011) did not show any significant difference between additive and replacement designs of pea and barley on weed suppression in IC. The large dry matter proportion of Oat, being the stronger competitor against weeds, in IC across all sites was most probably the most important determinant for the substantially lower weed dry matter in IC compared with SC-Pea.

Effects of spatial variability in soil characteristics on crop performance

The aim of the regression analysis was to detect soil characteristics that might indicate possible reasons for differences found between crops and cropping systems. For example, if differences in the response are found for crops, but not between SC and IC, this might be an indication that the impact of interspecific interactions in IC were of minor importance for crop performance. In general, the interpretation of significance in multiple regression tests should be taken with care given the influence of multiple testing. A more conservative approach would be the use of the Bonferroni-adjustment in case of multiple testing. In this case, the nominal Type I error would be divided by the number of tests performed. In our case, the number of tests for the best fitting models was either 4 or 8 tests for each trait. We analyzed eleven traits, which resulted in 82 tests (54 in Tables 6, 7, 8 and 28 in Tables S3, S4) and a comparison-wise error rate around 0.0006. There are several alternatives to adjust for multiple testing. To simplify presentation, we used a comparison-wise nominal error rate of 0.05 (Carmer and Walker 1982).

The regression analysis showed that Corg had a positive effect on grain yield of oat irrespective of the cropping system in Germany in 2018. While water content had a slight positive effect on the grain yield of Oat-SC and Pea-IC. This might be an indication that oat was a stronger competitor for water than pea as it showed a relieve both for Oat-SC, where it competes with the same species, as in Pea-IC competing with oat. Thus, the high $pLER_{Oat}$ and the LER of unity were a result of oat growth being enhanced by more available nutrients exerting strong competition for water, which was not alleviated by any complementary use of water by e.g. different root distributions. Interestingly, the positive response of Pea-IC was not found for shoot dry matter, which might be related to the higher drought sensitivity of pea during grain filling.

Grain yield and shoot dry matter of oat showed a positive response in SC and IC to ECa in the experiment in Germany in 2019, while a positive effect to Nt was only found for Oat-SC. In this case, no response to ECa and Nt was found for pea. This might indicate that the higher LER was the result of a complementary use of N as Oat-IC did not respond to an increase in Nt given more available soil N as pea has access to an additional N source through symbiotic N_2 fixation. Given the more abundant and evenly-distributed rainfall during this season, an influence of water limitations is less likely. ECa was highly correlated with clay (0.96***, Table S5), for which the same differences were found in combination with Ct (highly correlated with Nt, 0.91***, Table S5) resulting in the second-best regression model (Table S3).

For the Swedish site, ECa only affected positively grain yield and shoot dry matter of oat in SC, while an opposite effect was found for Pea-IC, which in addition, showed an increase with water content. The second-best model for grain yield only included water and for shoot dry matter pH and AL-P (Table S4). In both models, a significant response to these soil variables was only found for pea. ECa and water were highly correlated (0.91***) with each other and both with other soil variables (Table S6). In particular, the correlation between water content and soil variables related to nutrient availability (e.g. SOM, AL-P, and pH) complicates the interpretation. Given the low water content measured in the beginning of the experiment, the sandy soil texture and low rainfall, water limitation was most likely affecting pea. Yield in SC-Pea was also much lower compared to the German sites. The highest $pLER_{Oat}$ and the lowest $pLER_{Pea}$ was found in this experiment, which indicates that water competition was the primary reason for the low LER around 1. On the other hand, this experiment clearly showed the high compensation potential of oat.

Effects of spatial variability in soil characteristics on weed dry matter

The only considerable improvement in model fit was found for weed dry matter at the Swedish site. Significant effects were found on weed dry matter of SC-Pea with a significant negative effect of Ct, while the effect of Nt was positive. Both variables were highly correlated (Table S6). The sum of the two products of the estimated slope with their mean value resulted in a positive response of weed dry matter, which might indicate that a higher nutrient availability increased the competitive ability of weeds against SC-Pea. In our study, we could not differentiate between the effects of soil variables on crop and weed growth and the effect they exert on each other. As crop and weed dry matter are response variables, a bi-variate analysis would be required, which is very complex given the variance covariance structures already included in our statistical model. The integration of a bare plot in each block would be an alternative option to quantify weed suppression by comparing the bare plot (only weeds) with the plots planted with SCs and IC (Corre-Hellou et al. 2011). This would also enable a regression analysis with soil covariables on weed dry matter only. This might allow a deeper analysis or at least interpretation of the individual effects of soil characteristics and crop competition on weed dry matter.

Future research on combined ecological and technical precision farming in IC

The agronomic management of intercropping systems comprises many factors, such as sowing density, cultivar selection and N fertilization, which will affect the final productivity and yield proportion of the IC components. In cereal-legume IC, a high productivity is generally expected if N availability is low and water supply is sufficient stimulating complementary N use and reducing the negative impacts of water limitations on the legume crop (Justes et al. 2021). A recent meta-analysis showed that under low to moderate N fertilizer rates, competitive balance between cereals and legumes can be modified by the sowing ratio (Yu et al. 2016). At high N rates, sowing the legume earlier than the cereal showed a positive effect on pLER of the legume. Our experiments showed that besides N fertilizer application, within-field heterogeneity in soil characteristics related to nutrient availability (Corg, clay) also created a competitive advantage for the cereal. The negative effect of water availability on the legume crop was also evident in two of our experiments. Our study adds another dimension to the agronomic management as soil characteristics have not been included in the analysis of cereal-legume ICs. For example, our study suggests that for site-specific management within the field, varying the sowing ratio might be an option to increase the competitiveness of the legume at sites with a higher nutrient availability, if water supply is sufficient.

In future experiments, a higher temporal and spatial resolution of measurements of crops and soil variables e.g. by using remote sensing technologies would strongly help to gain more insight into the inter-specific growth dynamics in IC within a field. Samplings in particular during the establishment of the crops and during sensitive growth stages, e.g. flowering of the legumes, would be important. These samplings should be aligned with analysis of water and nitrogen availability to gain more insight into the dynamics of inter-specific interactions. This data can also be used in crop growth models, which might further help to disentangle effects of correlated soil variables and enable in the future to guide the application of precision farming in intercropping systems (Tilman 2020).

The experimental design with parallel strips and repeated measures per strip is quite easy to establish and thus highly suitable for on-farm experiments. However, the repeated data structure implies two random factors (strip and plot) to be estimated, which complicates variance-covariance matrices. The statistical analysis developed in this study can be used for such type of experiment. Note that the repeated data structure reduced the number of true replicates compared to a design with equal size without repeated data. One such alternative design is the RCBD with three plots (i.e. one unit including both SCs and IC) per block. The latter, when technically possible, allows to use the PROC NLMIXED procedure in SAS for analysis as the three plots per block are randomized. While the procedure only uses maximum likelihood estimation, it offers an easy option to estimate and compare for significance the LER against 1 and the differences between CV of different crop-by-cropping system combinations.

Conclusion

By this thorough investigation of within-field spatial variations in both soil characteristics and crop performance, we have demonstrated that different soil variables influenced the two studied crops (oat and pea) differently. This finding indicates that IC enables the Ecological Precision Farming principle, since contrasting responses to soil variations between two crops is expected to enhance the complementarity and compensation mechanisms in IC. However, our study did not provide evidence for a higher yield stability in IC compared to the combined SCs. The lower yield stability of IC coinciding with the highest LER rather questions if an increase in yield stability can be expected when interspecific interactions between crops in IC vary according to within-field soil variations. The experimental design in this study and the developed statistical analysis can contribute to further research about spatial variations in interspecific interactions in IC, which will improve the understanding of plant-plant and plant-soil interactions and can generate recommendations for the practical management of intercrops depending on a certain production aim.

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Author contributions All authors contributed to the study conception and design. Data collection was performed in the German trials by Sebastian Munz and Julian Zachmann, and by Iman Raj Chongtham and Nawa Raj Dhamala in the trials in Sweden. Statistical analysis was conducted by Jens Hartung and Sebastian Munz. The first draft of the manuscript was written by Sebastian Munz and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript. Funding acquisition by Sebastian Munz and Erik Steen Jensen.

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Data availability The datasets generated during this study and the SAS code for the statistical analysis are available from the corresponding author upon reasonable request.

Declarations

Conflict of interest The authors declare having no conflict of interest.

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