RESEARCH ARTICLE

Temporal and inter-farm variability of economic and environmental farm performance: A resilience perspective on potato producing regions in the Netherlands

Wim Paas[1,2]*, Miranda P. M. Meuwissen[2], Martin K. van Ittersum[1], Pytrik Reidsma[1]

1 Plant Production Systems Group, Wageningen University & Research, Wageningen, Netherlands,
2 Business Economics Group, Wageningen University & Research, Wageningen, Netherlands

* wim.paas@wur.nl

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Abstract

In the context of resilience and sustainability of farming systems it is important to study the trade-offs and synergies between economic and environmental variables. In this study, we selected food production, economic and environmental performance indicators of farms in three potato producing regions in the Netherlands: Flevoland, Zeeland and Veenkoloniën. We studied the period 2006 to 2019 using farm accountancy data. We used threshold regressions to determine gradual development and year-to-year variation of those indicators. Subsequently we applied a sparse Partial Least Square (sPLS) regression to study the response of performance, gradual development and year-to-year variation under different conditions regarding weather, market and farm structure. sPLS-model performance was at best moderate. Best model performance was attained for Veenkoloniën, a region with relatively little inter-farm variability and relatively stable economic prices. Model results were very sensitive to the selection of response variables. We found that food production, economic and environmental performance levels and gradual developments were primarily determined by input intensity levels. How these performance levels were determined by input intensity, i.e. positively or negatively, differed per case study. Year-to-year variability was determined by average yearly weather conditions and weather extremes. Overall, we conclude that the method applied to the data we had available mostly provided insights that confirm existing knowledge at case study level. sPLS can be seen as a filter and projector of high-dimensional data that accentuates patterns in the data. In the context of resilience of farms, while using a relatively small dataset, the applicability of our methodology seems limited to a rather homogeneous farm population in a stable economic environment. Researchers intending to apply this method to (arable) farming systems should be well aware of the influence they can have on the results through their selection of response variables.

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Author summary

The sustainability and resilience of farming systems is increasingly challenged by economic and environmental disturbance. It is, therefore, important to empirically assess farming system dynamics under these disturbances and to identify farm characteristics that improve sustainability and resilience. However, quantitative approaches to assess sustainability and resilience simultaneously are scarce. In this paper, we test a multi-variate statistical approach applied to three potato producing regions in the Netherlands under varying market and weather conditions over the period from 2006 till 2019. The performance of statistical models was at best moderate and model results were very sensitive to the selection of response variables. We found that sustainability levels are mainly influenced by input intensity levels. Year-to-year variability was determined by average yearly weather conditions and weather extremes. Farm characteristics that improve resilience could not be identified. Overall, we conclude that the method applied to the data we had available mostly provided insights that confirm existing knowledge at case study level. Researchers intending to apply this method to (arable) farming systems should be well aware of the influence they can have on the results through their selection of response variables.

1. Introduction

In an increasingly variable climatic and socio-economic context, a sustainable and resilient performance of farming systems is challenging [1]. Sustainable performance is important regarding the provision of system functions in the long-term, while resilient performance is important to maintain function performance in the face of disturbances in the short-term [2]. Sustainability and resilience of a farming system is dependent on a balanced performance regarding social, economic and environmental functions [3,4]. However, trade-offs between those functions are common in farming systems [5,6], thus destabilizing the base for sustainability and resilience. One can imagine that these trade-offs only become sharper when faced with disturbances that require an immediate response.

Resilience and sustainability of farming systems are complementary concepts that need to be studied simultaneously in integrated assessments [1,4,7]. Many theoretical and qualitative studies have suggested attributes that increase resilience and sustainability [e.g. 8,9]. For example, diversity is often suggested to increase both. However, few studies have quantitatively studied resilience of farming systems [10], and even fewer address both sustainability *and* resilience indicators. Hence, assessing the performance in terms of both types of indicators, quantitatively, is the focus of this paper.

Existing agro-econometric methods often use production functions to assess resource allocation efficiency and thus assess sustainability. The general notion behind these methods is that increased agronomic and economic efficiency, and thus sustainability, of farming systems can be achieved by increased output efficiency of individual farms. For instance, yield gap analyses that are based on an approach that combines concepts from econometrics and production-ecology [11–13]. Production functions require specific input regarding the shape of functions and are primarily developed for evaluating a single good, e.g. (food) production or economic output. Alternatively, trans-log distance functions could be used that, interestingly, consider multiple response variables simultaneously [14]. Other, purely econometric methods are geared towards assessing the potential for increasing production or economic performance, such as the Just-Pope production function [15] and damage abatement functions [16].

These methods do not include environmental response variables, which makes these less useful for an integrated sustainability study. In addition, these methods usually employed datasets with a limited number of years.

As to resilience, a concept relating to the dynamics of the system, the element of time becomes more important, requiring longitudinal data. There are few studies on the quantitative analysis of resilience in general and in particular studies using longitudinal data are rare [10]. In absence of longitudinal data, cross-sectional data may be used in which the performance or resilience of regions is evaluated relative to one another [e.g. 17–19]. Also model-based methods including future scenarios may be used [20]. Longitudinal data can be used in different ways to study resilience. For instance, to study yield variability in relation to weather conditions and farm characteristics [14,21]. More recently, a framework was introduced that includes multiple variables in combination with resilience concepts such as the recovery time after a shock [22]. In another recent study, longitudinal data was used to study the resilience capacities in terms of robustness, adaptability and transformability for agricultural regions in 11 European countries [23].

In a recent review on quantitative resilience studies, it was noted that environmental indicators are hardly included as response variables [10]. In 2017, a framework was presented that allows to explore covariation of multiple explanatory and response variables over time without the need to pre-define a production function [24]. This provides opportunities to evaluate economic as well as environmental response variables for which no production function can be defined. The proposed framework has been applied to livestock systems [24,25], but to the best of our knowledge not to arable systems. In specialized livestock systems, intermediate activities, such as the growth of grass, are ultimately used to produce one or two outputs, e.g. milk [25] and/or meat. In arable farms, the cultivation of multiple crops are parallel activities with parallel outputs, i.e. the output is usually not concentrated in one or two outputs. As a consequence, variability of output at farm level may play out differently than at crop level [26].

In this paper our overall aim is to study economic and environmental sustainability and resilience simultaneously and quantitatively. To this end, we apply and evaluate the aforementioned framework [24] to arable farming systems, using multivariate (regression) techniques in combination with longitudinal farm accountancy data. We selected three different potato growing regions in the Netherlands as case studies. Employing the method, our specific aim is to identify resilience attributes at farm level, i.e. farm characteristics, that support sustainability and resilience in the context of changes and variability in market and climatic conditions.

2. Methods

2.1. Case studies

In this study, three potato growing regions in the Netherlands are compared. Veenkoloniën (VK) is an agricultural region in the North-East of the Netherlands with sandy and peaty soils. In this region it is common to find a crop rotation with starch potato up to once in two years in combination with mainly sugar beet and cereals. Since about ten years, onion is increasingly cultivated in VK. VK is the largest (starch) potato producing area in the Netherlands and was a case study in the context of the EU Horizon 2020 project SURE-Farm through which this study was funded. Resilience and sustainability in this region were also assessed with participatory and modelling approaches [e.g. 1,7,20,27–30], and this study adds an empirical analysis. For comparative purposes, two other large potato producing areas in the Netherlands were selected as well: Flevoland (FL) in the centre and Zeeland (ZE) in the South-West of the country, respectively. FL and ZE have clayey soils with somewhat wider crop rotations compared to VK, including mainly ware potatoes, sugar beet, cereals and onions (once in three to five years is common). Common additions to crop rotations are carrots in ZE and carrots, vegetables and tulips in FL. Arable farming in VK is less profitable compared to ZE and FL and more prone to the impacts of weather variability and climate change [31]. However, due to the cooperative structure of starch potato cultivation and processing in the area, cultivated area and farm gate prices of starch potato are relatively stable compared to the ware potato prices in ZE and FL.

2.2. Data

We used farm accountancy data collected by Wageningen Economic Research (WEcR) for the Farm Accountancy Data Network (FADN) [32,33]. This data is mainly collected to study economic and environmental performance at farm level, while economic data at crop level is also available. Because of privacy regulations, individual farm data cannot be presented in this study. The data in this study include time series for the period 2006 to 2019 of seven to 14 subsequent years of potato growing arable farms from the three case study regions. The final number of individual farms per region included in the analysis was 15 (FL), 19 (VK) and 17 (ZE) (See also Tables A and B in S1 Text). Weather data was retrieved from the data platform Agri4-Cast [34]. Market data was retrieved from different online sources [35–37].

2.3. Variable selection

2.3.1. Overview. The variable selection in this paper was guided by a resilience framework that was created within the context of the SURE-Farm project [1] (Fig 1). This resilience framework proposes five steps to assess the resilience of farming systems: identification of 1) the farming system, 2) challenges, 3) functions, 4) resilience capacities and 5) resilience attributes. The farming systems are described in the case study section above (Step 1). Explanatory variables related to weather conditions (e.g. precipitation, weather extremes) and market conditions (e.g. fertilizer and land prices) represent challenges that are hypothesized to affect the response variables (Step 2). The response variables are related to functions of farms (Step 3), e.g. food production (for more details see Section 2.3.2). Resilience capacities (e.g. adaptability) are deduced based on the outcomes of this study (Step 4). Explanatory variables related to farm characteristics, e.g. farm area and crop diversity, represent resilience attributes that possibly affect response variables directly, but possibly can also moderate the impact of challenges (Step 5; Fig 1; for more details see Section 2.3.3). Variable selection and links to the resilience framework [1] are elaborated below. All variables and abbreviations of these variables are presented in Table A in S2 Text.

2.3.2. Response variables characterising system functions. For an integrated analysis, we included response variables that cover production, economic and environmental functions at crop, crop rotation and farm level (Table 1). The production at crop level was represented by the average yield of potato (tons/hectare;provided by the data). For the production at crop rotation level we calculated the consumable energy produced (kJ/ha; Eq 1) [38] for the main crops (potatoes, sugar beets, wheat, barley, onions).

$$Crop\ Rotation\ Yield = \sum\nolimits_{C} Energy\ content_{c} * \frac{Total\ yield_{C}}{Area\ of\ maincrops} \tag{1}$$

'Energy content' per main crop *'c'* was in kJ/ton (based on [39]). *'Total yield'* per main crop *'c'* (ton) was provided by the data. '*Area of main crops*' is the sum of area (ha) under cultivation for the main crops. On average, main crops represented more than 85, 91 and 80% of the farm area in FL, ZE and VK. Average operating profit of crops (€/ha) is taken as economic indicator

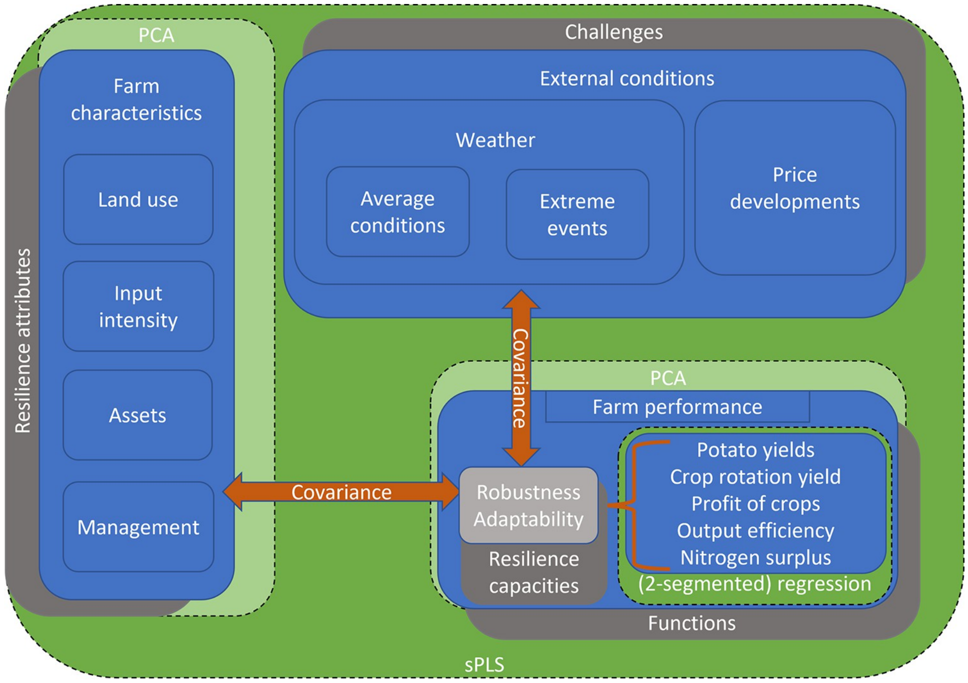

Fig 1. Overview of variables included in the analyses (blue blocks) and their link to the steps in the resilience framework (grey blocks). Green blocks indicate the different analyses that are performed on the data. Orange arrows indicate the type of patterns that are studied in the sPLS regression. PCA: Principle Component Analysis, sPLS: sparse Partial Least Squares.

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at crop rotation level (Eq 2).

$$Profit\ from\ crops = \sum_{C} \frac{Revenue_{C} - Allocated\ Costs_{c}}{Area\ of\ all\ crops} \qquad (2)$$

Table 1. Overview of response variables.

Type of variable	Sub-category	Abbreviation	Unit
Response variables	Output efficiency	OutputEff	€ output / € input
		OutputEff_resi	€ output / € input
		OutputEff_slope	€ / € / year
	Potato yield	Potatoyield	ton / ha
		Potatoyield_resi	ton / ha
		Potatoyield_slope	ton / ha / year
	Crop rotation energy yield	Energyperha	kJ / ha
		Energyperha_resi	kJ / ha
		Energyperha_slope	kJ / ha / year
	Profit crops	ProfitCropsperha	€ / ha
		ProfitCropsperha_resi	€ / ha
		ProfitCropsperha_slope	€ / ha / year
	Nitrogen surplus	Nsurplus	kg / ha
		Nsurplus_resi	kg / ha
		Nsurplus_slope	kg / ha / year

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Where '*Revenue*' per crop '*c*' (Euros) consists of revenue from primary and secondary crop products. '*Allocated costs*' per crop '*c*' include costs for seeding, fertilizer application and crop protection measures in Euros. 'Area of all crops' (ha) represents the sum of all area under crop cultivation. At farm level, all monetary output (revenues; excluding off-farm income) per monetary input (all fixed and variable costs) represents the output efficiency of the farm (€ output/€ input; provided by the data). Having an indicator that expresses efficiency may help to explore possible trade-offs between efficiency and variability that are hypothesized in resilience literature, i.e. more efficient systems are more vulnerable to disturbance [9,40,41]. The nitrogen surplus at farm level is used as an environmental indicator. Nitrogen surplus contributes to expulsion of greenhouse gases, acidification of nearby nature areas and leaching or run-off of N leading to eutrophication of water bodies. Nitrogen surplus is provided by the data. Its calculation is based on a nutrient balance at farm level that considers all nitrogen inputs (mineral fertilizer, external organic nitrogen sources, net manure import, biological nitrogen fixation and atmospheric deposition) minus outputs (animal and crop products) [33,42,43]. Following that calculation, nitrogen surplus includes soil nitrogen stock changes, gaseous emissions, leaching and run-off [42].

High observed levels for potato yield, crop rotation energy yield, profit of crops, output efficiency and low observed levels for nitrogen surplus were seen as positive for sustainability. Slopes and residuals of trendlines were used as additional variables that describe the resilience of farms (Fig 2) [24,25]. Positive slopes for potato yield, crop rotation energy yield, profit of crops and output efficiency, and negative slopes for nitrogen surplus were seen as signs of adaptation towards more sustainability. Small residuals were seen as indicative for farm stability and therefore positive for farm robustness. See also Table A in S2 Text for the response variable abbreviations.

Trendlines were fitted using one- and two-segmented linear regression analyses allowing for an evaluation of structural change in the observed values over time [44]. Linear trendlines can be considered when at least three data points are available. Given the minimal length of the time series data (seven years), only one structural change in trend was considered in between the third from first and third from last observation. To ensure that observed structural changes were not dependent on a single outlier, two additional two-segmented linear regression analyses were performed. In these additional threshold regressions either the last observation of the first segment or the first observation in the second segment was removed. A structural change in trend, and thus a two-segmented model, was accepted and used for further analyses if the p-values of the F-statistics for the optimum breaking point of all three threshold regressions stayed below 0.05. Otherwise a linear regression with one segment was assumed. Regression analyses with structural change tests were performed with the package "strucchange" [44] in the software environment R [45]. We argue that besides the trends themselves, structural changes in trends leading to positive or negative developments can also be seen as indicators for the presence or absence of farm adaptability.

2.3.3. Explanatory variables linking to challenges and resilience attributes. Explanatory variables related to external influences (i.e. challenges) are classified into the following sub-categories: market prices, average weather conditions and extreme weather events. Average market indicators per year include: oil price (€/ 100 litre) [35], fertilizer price (€/kg; NPK12:10:18) [35], land prices (€/ha) [36]) and interest rates (%) [37] (Table B in S2 Text). Average weather conditions included in the analysis are average temperature (degree Celsius), average daily precipitation (mm/day) and average daily precipitation deficit (mm/day) for the whole year, spring (April-June) and summer (July-September) (See S2 Text for more details). To cover the entire growing season of potato from planting (April) until harvesting (September), we deviated from the meteorological definition of spring (1 March– 31 May) and summer (1 June– 31

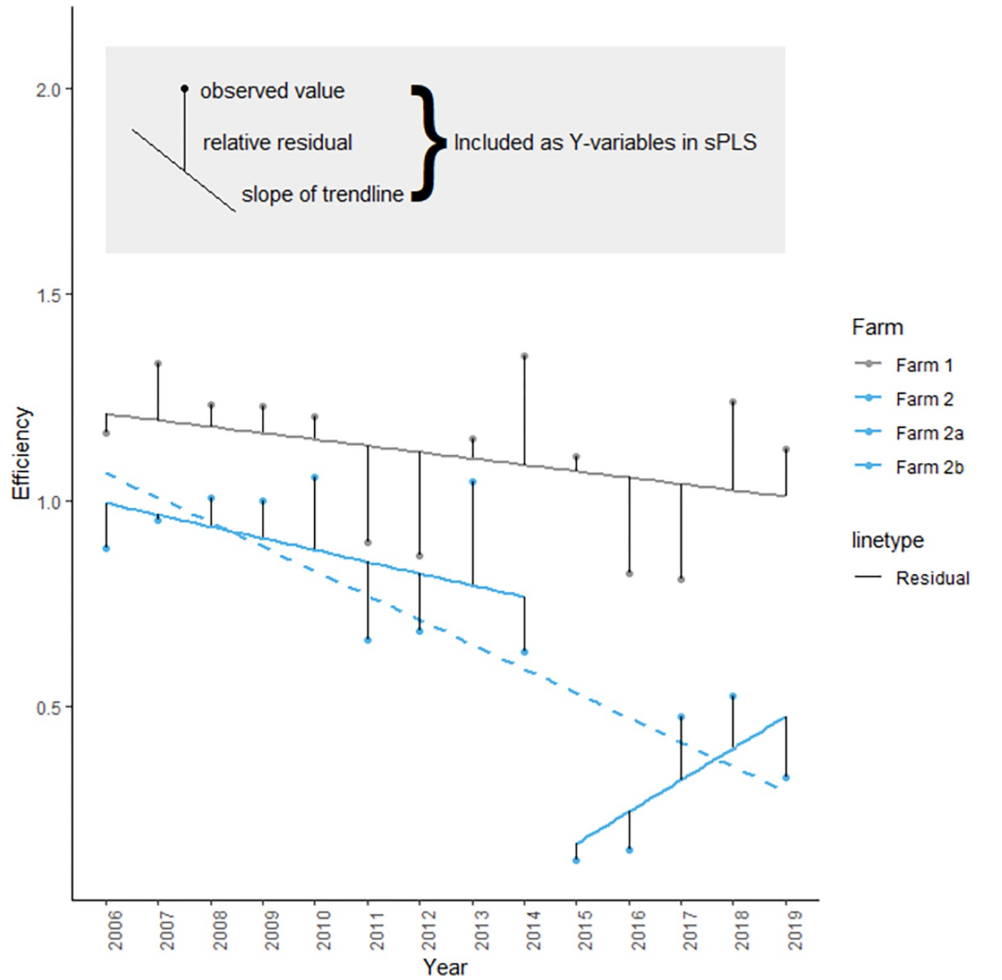

Fig 2. Fitted trend lines for two imaginary farms regarding a unitless efficiency indicator. For the farm with observed values in blue, a two-segmented trendline gives a significant better fit than a single trendline. Three types of Y-variables are eventually included in the analyses: the observed values, residuals and the slope of the trend lines.

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August). Based on the average daily precipitation and temperature, extreme weather events for potato production were calculated using the AgroClimateCalendar (ACC; Table A in S2 Text) [46,47]. Included weather extremes were wet (and warm) conditions, heatwaves, late frosts, warm winters and drought (Tables C and D in S2 Text). Descriptions of the effect of weather extremes are described in Table C in S2 Text. Throughout the observation period, weather extremes were observed in all three case studies.

Explanatory variables related to farm characteristics are divided into the following sub-categories: land use, input intensity, assets and management (Table 2; Fig 1). These sub-categories can be linked to resilience attributes, which are system characteristics that convey general resilience to a farming system [7]. Land use indicators can be used as a proxy for crop diversity, e.g. the share of cereals or potatoes in the crop rotation. Diversity is generally seen as buffer against perturbations and is also considered as a source of renewal after a perturbation [8]. In the case of crop diversity, we see specialization as the inverse of crop diversity, i.e. a large cultivation area dedicated to main crops. Regarding diversity we took the fraction of cereals, the fraction of three main crops (potato, sugar beet and cereals) and the effective number of crops (also known as true diversity index). The indicators under input intensity could be seen as

Table 2. Overview of explanatory variables included in the analysis. Weather conditions and market indicators relate to challenges, while farm characteristics to possible resilience attributes.

Sub-category (1st)	Sub-category (2nd)	Abbreviation	Unit
Weather conditions	Average	Temperature_Spring	degree Celsius
		Precipitation_Spring	mm / day
		Temperature_Summer	degree Celsius
		Precipitation_Summer	mm / day
		Temperature	degree Celsius
		Precipitation	Mm / day
	Extremes*	ExtPrec45_1 (extreme precipitation in 1 day)	#
		ExtPrec60_3 (extreme precipitation in 3 days)	#
		HWave (heat waves)	#
		Frost	#
		WarmWinter	#
		WarmWet	#
		D_Spring (drought in spring)	#
		D_Summer (drought in summer)	#
		WetHumPlant (wet and humid at planting)	#
		WetHumGrow (wet and humid in growing phase)	#
		WetHumHarv (wet and humid at harvesting)	#
Market indicators$		OilPrice	€/ 100 L
		FertilizerPrice	€/ 100 kg
		LandPrice	€/ha
		Interest rate	%
Farm characteristics	Land use	AreaCereals	ha
		AreaMainCrops	ha
		TrueDiversity	#
	Input intensity	Monetary input intensity†	€/cultivated ha
		Labour	AWU / cultivated ha
		Crop protection products (CPP)	€/ cultivated ha
		Nitrogen	€/ cultivated ha
		Phosphate	€/ cultivated ha
		Energy	€/ cultivated ha
		TotalCostsperha‡	€/ cultivated ha
	Management	FarmManagement	# fte managers / ha
		AgeFarmer	Years
		OtherRevenue	€/ cultivated ha
	Assets	Area	ha
		AreaOwned	owned ha / total ha
		OwnCapital	€ own / € total assets
		ModernityBuildings	# (0–100)
		ModernityMachines	# (0–100)
		Depreciation	€ / cultivated ha

†Monetary input at farm level, i.e. all fixed and variable costs.

‡Cultivation costs, i.e. variable costs for crop cultivation.

*See Table C in S2 Text for more information.

$See Table B in S2 Text for more information.

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proxies for the degree to which the system is coupled with local and natural capital. For instance, a low input of crop protection products may suggest a better coupling of farm practices with the environment. From a resilience perspective, high dependence on external inputs (e.g. mineral fertilizer) for a high and stable production in the face of environmental fluctuations (e.g. weather, pests & diseases) may imply a lower degree of autonomy [8]. Certain European crop-livestock systems, for instance, may not be robust enough to withstand a situation in which the import of mineral nitrogen fertilizers is halted [48]. Asset indicators relate mostly to system reserves that can be used in difficult times. Modernity of machines and buildings (actual value/value when new) is linked to the availability of infrastructure for innovation. However, modernity of machines and buildings could also be related to the absence of adaptability and transformability due to sunk costs, i.e. money invested that cannot easily be re-invested [49]. Management indicators, such as the number of full time equivalent (fte) managers per hectare, relate to the degree of experience and attention that is available for agricultural practices. This relates to the potential for learning from past experiences and building human capital, both being important for general resilience [8].

2.4. Detecting the underlying data structure

2.4.1. Principal component analyses. To obtain insight in the underlying data structure, correlation plots were created for response and explanatory variables. In addition, principal component analyses (PCA) were performed separately for the response and explanatory farm variables for each case study area. A multi-level design was included to consider the random effects of individual farms. As a result, farm specific differences will be compensated for, thus reducing the impact of outliers for which multi-variate statistics are sensitive [50]. The first three components of PCA biplots were inspected to detect farms for which all observations were visually separated from the rest of the observations. Those outlying farms were removed from the dataset (only one in FL). PCA biplots were also inspected for the presence of year effects. The presence of a year effect in the PCA-analyses was used as an argument for including random year effects in further analyses. Strongly correlated response variables were removed from further analyses as they can distort the results [51]. We illustrate this potential for distortion by presenting additional model runs with highly correlated response variables.

2.4.2. Sparse Partial Least Squares regression. We used sparse Partial Least Squares regression (sPLS) with year and farms as random effects to study the impact of explanatory variables on the response variables. In sPLS-regressions, explanatory variables (X-variables) are projected on latent variables in such a way that the projected variables can explain as much variation of the response variables (Y-variables) that are also projected on latent variables. Latent variables represent the most dominant patterns in the data. We used sPLS in a regression mode, where the prediction of Y from X results in different identified latent variables than when X would be predicted from Y. This limits the possibility to make inferences on adaptations in X related to observed changes in Y, e.g. changes in inputs as a consequence of a year with low economic performance. Redundancy analysis, in contrast to PLS analysis, only projects X-variables on latent variables, but leaves the Y-variables as they are. Leave-one-out cross-validations were conducted to determine the performance of the sPLS-model. Resulting Q2 -scores were used to determine the number of latent variables (components) in the sPLS-model. Q2-scores express the marginal contribution of components to increase the covariation between the original X- and Y-variables. A component with a Q2-score larger than 0.095 is considered to have a significant contribution [52].

Sparse PLS (sPLS) differs from PLS in that it reduces the model to a pre-defined number of variables that are linked to principal components in the X and Y dimensions. The advantage of sPLS is that interpreting results is becoming easier. A disadvantage is that choosing the number of variables per component introduces arbitrariness. We performed multiple sPLS analyses in which we varied the number of Y-variables (2–5) and X-variables (2–9) per component. To reduce computation time, we initially limited the number of components to two. We selected the best model based on the aggregated Q2-score and explained variance of X- and Y-variables. We also checked the stability of X- and Y-variables selected in the sPLS-models during the cross-validation. In case the second component was contributing significantly, analyses with a third component were considered, for (2–5) Y-variables and (2–9) X-variables. In case the third component contributed significantly, the number of X- and Y-variables to keep was selected using the same criteria as for the first two components. The best model was selected based on the aggregated Q2-score over all components. We also compared the correlation matrix of projected values of continuous explanatory variables and response variables of the sPLS-model with the correlation matrix of the original data. PCA and (s)PLS were performed with the software package "mixOmics" [53] in the software environment R [45]. "mixOmics" does not facilitate the inclusion of interaction terms.

3. Results

3.1. Response variables

3.1.1. General observations. Observed levels of potato yield and profit of crops were highest in FL (Fig 3). The inter-farm variability of potato yields and profit of crops within ZE and FL were much higher than for VK (Fig 3). Observed levels of crop rotation energy yield and nitrogen surplus were lowest in ZE. On average, observed levels of output efficiency were lowest in VK (1.05 €/€) and ZE (1.02 €/€) and highest in FL (1.12 €/€) (Fig 3). In ZE and VK there were multiple outliers regarding nitrogen surpluses of more than 200 kg/ha. In the context of earlier work [54] these values were however not surprising.

The pattern of output efficiency levels from 2006 till 2012 was similar in ZE and FL, with relatively high levels in 2006, 2010 and 2012 (Fig 3). In VK, output efficiency was highest in 2012, which coincided with a high potato yield. Potato yield in all regions was relatively low in the dry year of 2018. Interestingly, output efficiency and profit of crops in FL were relatively high in 2018. Nitrogen surplus levels seemed stable in all case studies. Based on a visual inspection of Fig 3, there were no particular years in which nitrogen surplus was deviating substantially, except for 2018 in VK when it was high, probably because of low yields due to drought.

3.1.2. Structural change. Breaks in trends were mostly detected in VK for the output efficiency between 2011 and 2013 (15 farms) and crop profit in the years 2011 and 2012 (12 farms) (Table A in S3 Text). This corresponds with the increase in output efficiency and profit of crops until 2012 in VK that can be observed in Fig 3. In FL and ZE, breaks in trends were observed for a few farms, mostly in 2012, for potato yield (FL), crop rotation yield (FL, ZE), output efficiency (ZE) and nitrogen surplus (FL, ZE) (Table A in S3 Text).

3.1.3. Yield, profit and output efficiency. Explained variance of the PCA on response variables (levels, residuals and slopes of potato yield, crop rotation yield, profit from crops, output efficiency and nitrogen surplus) per region was between 50–57% over the first three components. Important variables for the first component in all three regions (accounting for 19–29% of variation) were levels of potato yield and crop rotation yield, often accompanied with their residuals, indicating larger absolute variation at higher crop yield levels (Figs A, C, and E in S4 Text). In VK, profit of crops and output efficiency were positively associated with higher crop yields (Fig E in S4 Text). Potato is the largest crop in VK in terms of area and volume, partly explaining the positive

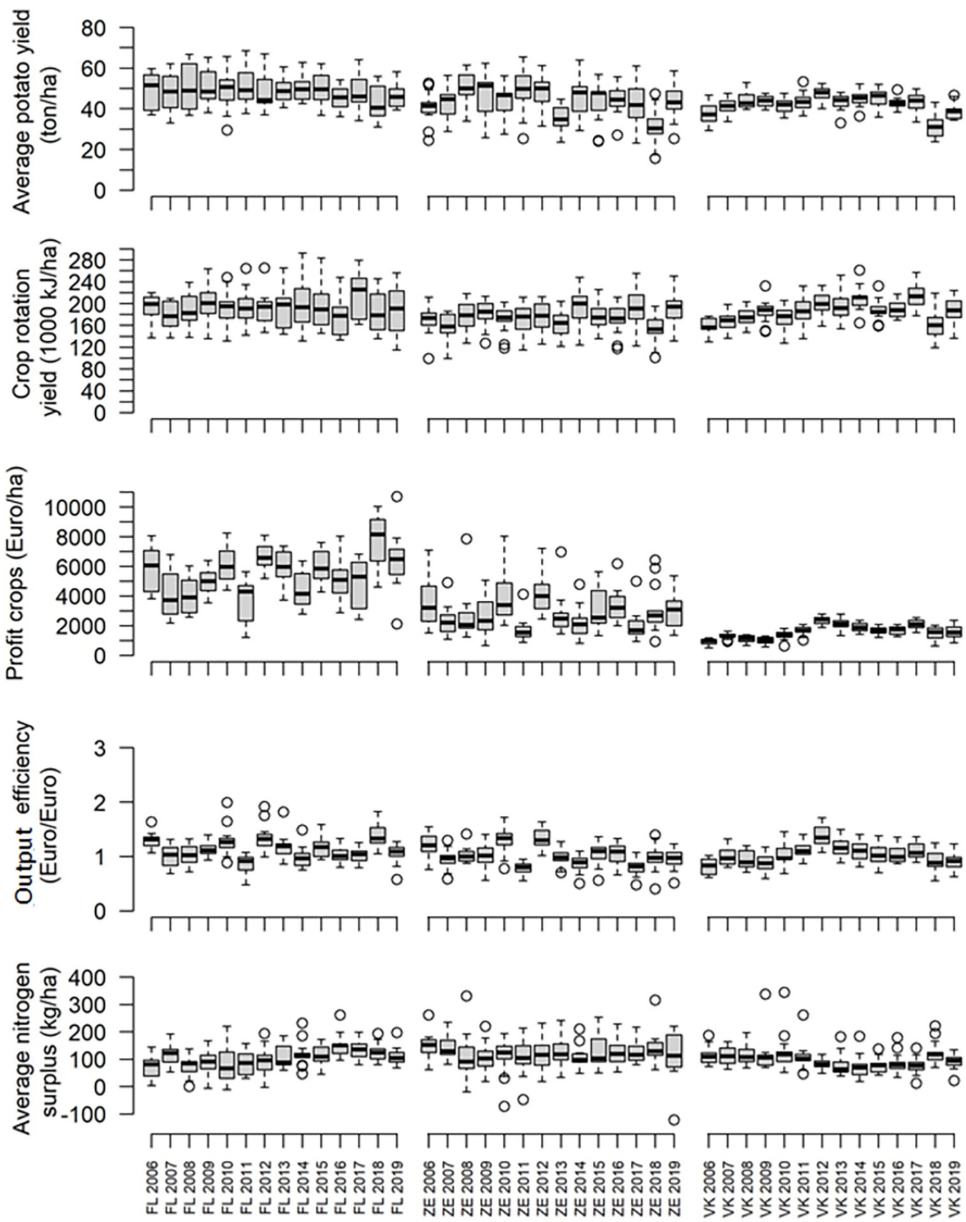

Fig 3. Observed levels of potato yields, crop rotation energy yield, profits from crops, output efficiency and nitrogen surplus for three regions (FL = Flevoland, ZE = Zeeland, VK = Veenkoloniën).

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relation with energy yield and profit. The positive relation between yield and profit could also be attributed to the local cooperative structure. With relatively inelastic prices for starch potato products, the cooperative benefits from larger volumes to be able to pay a good farm gate price to farmers [20] as long as prices of processed products stay relatively inelastic. In FL, residuals of output efficiency and profit of crops and the slope of profit of crops were negatively associated with potato yield and crop rotation energy yield (Fig A in S4 Text). This suggests that farmers in FL somehow can benefit from relatively high prices when yields are relatively low. By contrast, in ZE, level of profit of crops and residuals of profit of crops and output efficiency (second component), had no or very little association with crop yield levels (Fig C in S4 Text).

3.1.4. Synergies and trade-offs with nitrogen surplus. In FL, the second component (17% of variation) was mostly correlated with observed levels and residuals of nitrogen surplus, associated negatively with residuals and level of profit of crops and residuals of output efficiency (Fig A in S4 Text). Overall, this suggested that years with (relatively) high nitrogen surplus coincided with (relatively) low profit of crops and low output efficiency, and vice versa. Farms associated with high levels of nitrogen surplus also showed declining profit of crops (3rd component; 14% of variation; Fig B in S4 Text).

On the first component of ZE and VK, higher crop yield levels and residuals were negatively associated with residuals of nitrogen surplus (Figs C, E in S4 Text). Moreover, in ZE, on the third component (14% of variation), increasing potato yields were associated with farms that had low and decreasing nitrogen surpluses (Fig D in S4 Text). In VK, on the second component (18% of variation), decreasing nitrogen surplus was mostly correlated with increasing output efficiency, potato yield and energy production (Fig E in S4 Text). Residuals of nitrogen surplus were mostly negatively correlated with residuals of profits of crops and output efficiency (third component; 10% of variation; Fig F in S4 Text).

3.1.5. Pre-selection of response variables. Based on the high correlation found between response variables in the PCA and additional correlation analyses (S4 Text), we continued our analyses with crop rotation energy yield, profit of crops and nitrogen surplus (S5 Text). We performed additional analyses with all five response variables and with a different selection of three response variables (i.e. with output efficiency instead of profit of crops). These additional analyses were used to assess the impact of selecting different sets of response variables (S6 Text).

3.2. Explanatory variables

3.2.1. Market indicators. Land prices increased from 2006 till 2008, after which prices stabilized at just above 50,000 €/ha until 2013. From 2013 onwards, land prices increased till over 70,000 €/ha in 2019. Interest rates went up from 3.8% in 2006 to 4.3% in 2007, after which interest rates steadily decreased to negative values in 2019. Interest rates often dropped more than 0.5% per year. Oil prices varied from 64 in 2006 to over 100 €/100 L in 2019 and fluctuated over time with a peak in 2013 and 2014. Fertilizer prices increased from 27.75 €/ 100 kg fertilizer in 2007 to 61.50 €/100 kg in 2009 after which they fluctuated between 41 and 47 €/100 kg. (Fig 4; Table B in S2 Text for absolute values)

3.2.2. Weather conditions. The three case studies were similar in terms of average temperatures per year and per season (spring, summer). With regard to the precipitation deficit, the three case studies had similar values for spring (1.5 +- 0.4–0.5 mm/day precipitation deficit; Fig 5), but for summer, FL had a lower average deficit (0.3 +- 1.0 mm/day) than VK (0.6 +- 0.9 mm/day) and ZE (0.8 +- 1.0 mm/day), which was probably related to the higher precipitation in FL (2.6 +- 0.8 mm/day) than in VK and ZE (both 2.3 +- 0.7 mm/day). No significant trends in temperature, precipitation and precipitation deficit could be detected over the measured period (2006–2019; Table A in S2 Text). Weather extremes occurred regularly (Table D in S2 Text).

3.2.3. Farm characteristics. Explained variance of the PCA on explanatory farm variables per region was between 45–50% over the first three components (Figs I-N in S4 Text). In the PCA's for the three regions, years appeared to be clustered, indicating that years explained part of the variation.

In all case studies, most of the variation (1st component; 22–27% of variation) could be related to many correlated indicators on input intensity in terms of fixed and variable costs (Figs I, K, M in S4 Text). Values of variables related to input intensity did increase over the

Fig 4. Development of relative values of market indicators over time. Absolute values can be found in Table B in S2 Text. Absolute values in 2006 were 44,506 €/ha (land price), 3.8% (interest rate), 64 €/100L (oil price), and 27.35 €/100 kg (fertilizer price).

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years. In particular, cultivation costs increased (Table A in S2 Text). In FL and ZE, the second component was related to the area of main crops and area of cereals (Figs I, K in S4 Text). Area of main crops and cereals seemed to have decreased in the observation period, suggesting decreased specialisation (Figs I, K, M in S4 Text; Fig 6). In FL more specialized farms were associated with less modern machinery, i.e. depreciated machinery (Fig I in S4 Text). In ZE, more specialized farms were associated with higher nitrogen inputs (Fig K in S4 Text). In FL and ZE, the third component was associated with larger farm sizes, lower shares of land

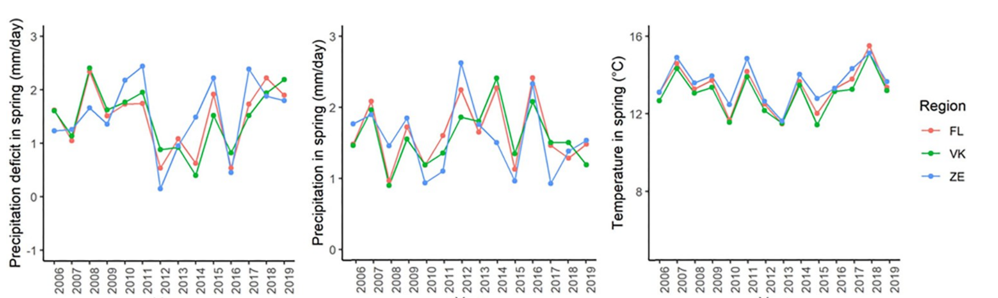

Fig 5. Precipitation deficit, precipitation and temperature in spring in the three case study areas.

https://doi.org/10.1371/journal.pstr.0000046.g005

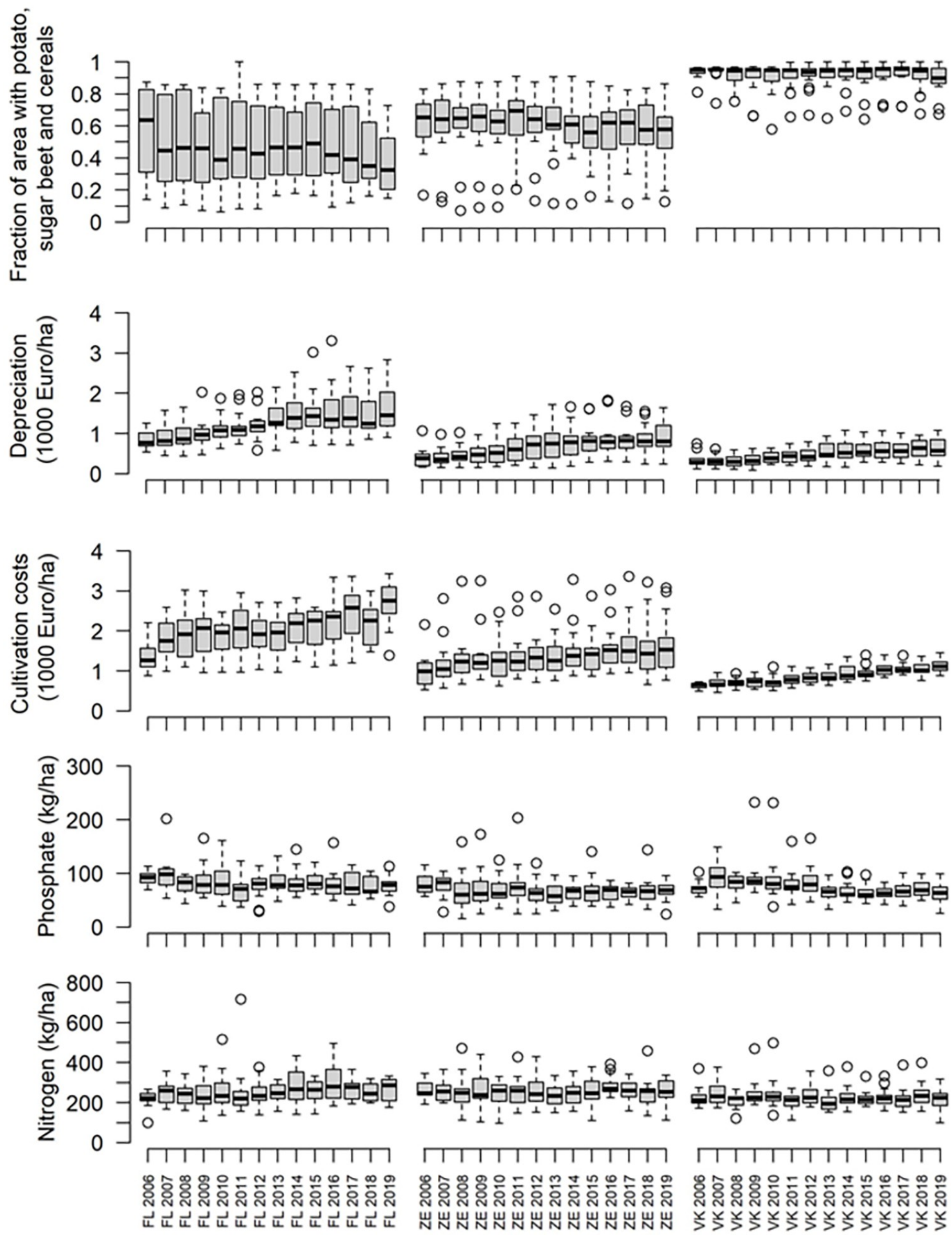

Fig 6. Observed levels of important farm characteristics (explanatory variables) for Flevoland, Zeeland and Veenkoloniën.

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owned, lower number of farm managers per hectare and lower labour input intensity (FL; Fig J in S4 Text) or modernity of buildings (ZE; Fig L in S4 Text).

In VK, the second largest part of the variation was captured by labour input intensity (second component; 12% of variation; Fig M in S4 Text). A third part of the variation could be explained by the number of full time equivalent managers per hectare and the age of the farmer (third component; 10%; Fig N in S4 Text). These indicators seemed unrelated with the indicators describing the degree of intensity.

3.3. Sparse partial least squares regressions

3.3.1. Model performance. On average, across the three case studies, best performing sPLS models included the response variables related to profit of crops, nitrogen surplus and crop rotation energy yield. In all case studies, the predictive power of selected components was at most moderate. The variation in X-variables explained by the X-components was low (Table 3). The explained variation in the Y-variables was higher but still moderate. The best model in VK had three components with a varying number of response variables across components (Table 3). In ZE, sPLS-models performed better when including output efficiency instead of profit of crops (S6 Text). Because the interpretation of sPLS models including either profit of crops or output efficiency is almost identical, we proceed with sPLS models including profit of crops.

3.3.2. System functions affected by challenges and resilience attributes. In all case studies, there was one component associated with weather conditions that covaried with the residuals of nitrogen surplus (FL, VK), profit of crops (FL, ZE) and/or crop rotation energy yield (VK). In FL, nitrogen surplus was affected mostly by drought in spring, or wet conditions later on in the growing period, while profit of crops was positively affected by heatwaves, and generally high temperatures in summer (see 2nd component in Fig 7 and Fig 8; Table C in S5 Text). Interestingly, in contrast to droughts in spring, precipitation deficiency in spring seemed to somewhat improve profits and reduce nitrogen surplus. In ZE, profit of crops was affected negatively by high temperatures, specifically in spring, which was also related to precipitation deficit in that season (S5 Text). Interestingly, farms in ZE seem to benefit from warm winters. The availability of water (precipitation, absence of drought) was correlated to high crop rotation energy yields in VK.

In all case studies, the other component was associated with at least one indicator related to input intensity, the most important being monetary input intensity (all fixed + variable costs of a farm expressed per ha)(ZE, FL; Fig 7; S5 Text), total costs per hectare (ZE, VK), depreciation (FL) and labour (VK). These were negatively correlated with phosphate (VK) and nitrogen (VK, FL) and true diversity (FL). The high intensity in FL in combination with low nitrogen inputs and low diversity, resulted in high and increasing profits, low crop rotation energy yields and a declining nitrogen surplus (Fig 7 and Fig 8). For high-value crops, relatively little money is spent on nutrients. The high intensity in ZE was associated with declining profits from crops, low crop rotation energy yields, and to a lesser extent with low, but increasing nitrogen surpluses. In VK, profit of crops, crop rotation energy yield and to a lesser extent nitrogen surplus were positively linked with phosphate input and low intensity. However, for VK, additional indicators related to economic conditions were associated with lower profit of crops (oil prices, interest rates, land prices), while labour input, farm management and other revenues seemed to compensate for this to a small extent.

Table 3. Number of variables and performance per component of selected sPLS-models with the response variables crop rotation energy yield, nitrogen surplus and profit of crops. All X-variables included.

				Number of variables kept		Variation explained	
Region	**Component**	**Q2-score**	**R2-score**	**X-space**	**Y-space**	**X-space**	**Y-space**
FL	1	**0.113**	0.185	6	4	0.154	0.274
	2	**0.127**	0.133	9	2	0.078	0.210
VK	1	**0.227**	0.351	9	3	0.147	0.298
	2	**0.304**	0.234	9	2	0.096	0.299
	3	**0.170**	0.093	9	5	0.098	0.184
ZE	1	0.073	0.129	2	5	0.175	0.193
	2	0.064	0.186	4	2	0.081	0.164

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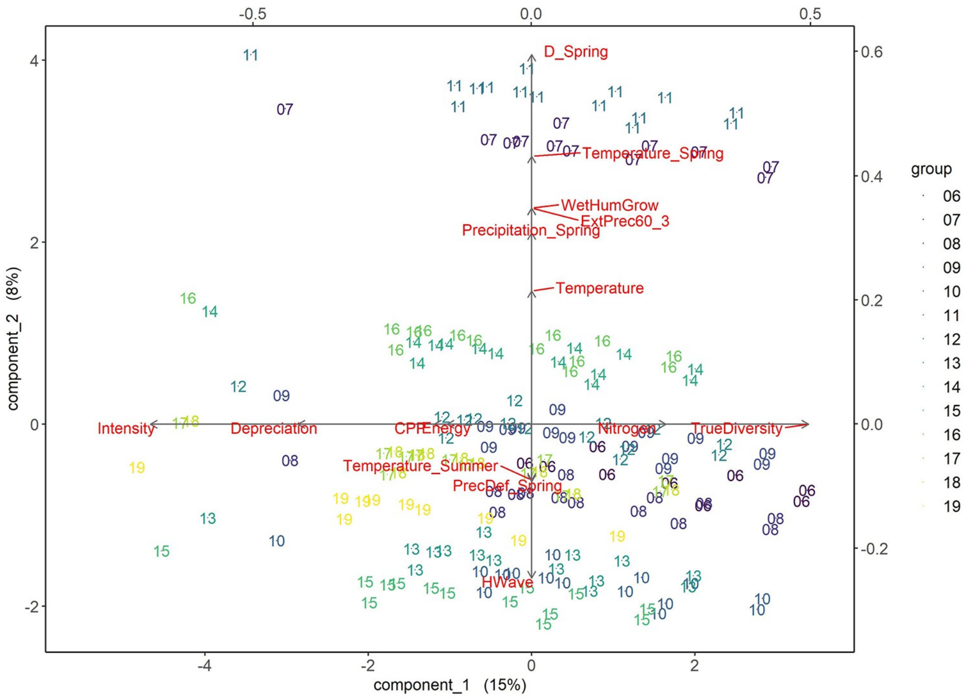

Fig 7. sPLS model results for the first and second X-component in Flevoland. Groups indicate the different years. The left and bottom axis indicate the position of observations in the projected X-space. The top and right axes indicate the correlation of explanatory variables with the first and second component.

https://doi.org/10.1371/journal.pstr.0000046.g007

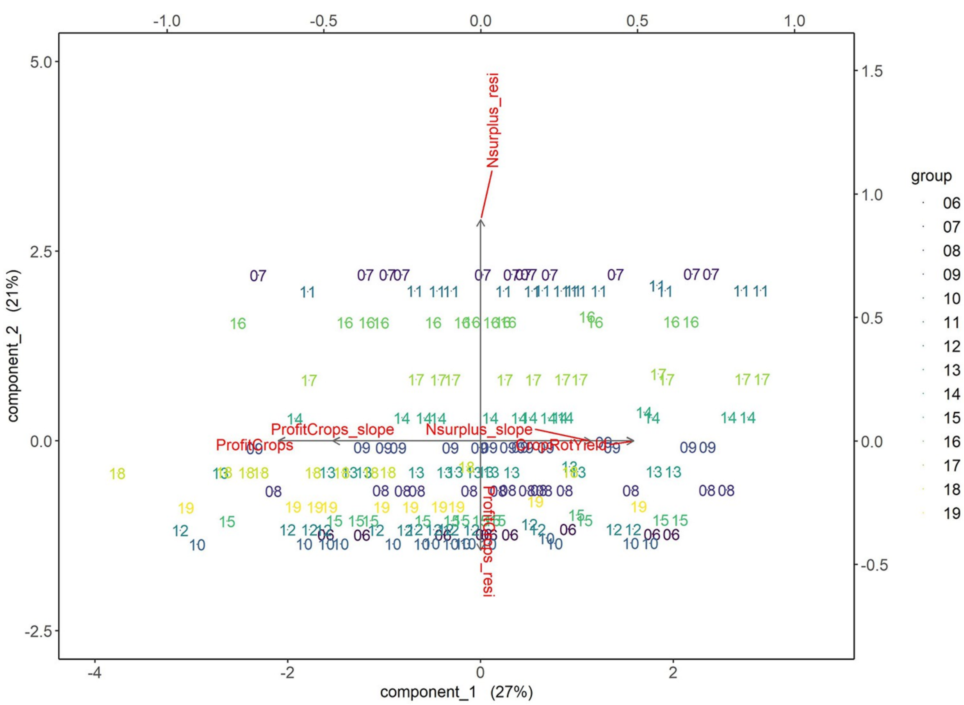

Fig 8. sPLS model results for the first and second Y-component in Flevoland. Groups indicate the different years. The left and bottom axis indicate the position of observations in the projected Y-space. The top and right axes indicate the correlation of response variables with the first and second component.

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In VK, a third component was associated with input indicators of which nitrogen, energy and crop protection products were the most important. These were negatively associated with the share of cereals in the crop rotation. Higher levels of nitrogen and energy input were associated with higher crop energy rotation yield, higher, but over time decreasing, nitrogen surplus and higher and increasing profit of crops. Vice versa, a higher share of cereals in the rotation seemed to reduce nitrogen surpluses.

Interestingly, the strong positive correlation between nitrogen input and nitrogen surplus in the original data of all three case studies (Figs R, S, T in S5 Text), was only included in the final sPLS model in VK. In the sPLS-models with fifteen response variables, the correlation between nitrogen input and surplus was absent in all three case studies (Figs A, B, C in S6 Text).

4. Discussion

4.1. Interpretation of results from a sustainability and resilience perspective

In this paper we aimed to study economic and environmental sustainability and resilience simultaneously and quantitatively. In particular, we aimed to identify resilience attributes at farm level, i.e. farm characteristics, that support sustainability and resilience regarding market and climatic conditions.

4.1.1. Intensity and farm performance levels and trends. Overall, intensity levels played out differently in the three case studies, thus limiting us in generalizing the role of intensity of crop management on economic and environmental farm performance. Higher intensity of farms in terms of euros spent was primarily associated with higher profits from crops in FL and ZE, indicating improved economic sustainability through intensification. In FL, the increased intensity and profit covaried with having additional crops next to the main crops potato, sugar beet and cereals, i.e. diversification. In ZE, this pattern of a relatively positive effect of crop diversity on profit was also visible in the original data, but not included in the final sPLS-model. In FL, a higher intensity level in terms of euros spent, including higher expenditure on crop protection products and energy, was associated with reduced nutrient inputs leading to a declining nitrogen surplus, indicating some gain in the environmental performance. By contrast, in ZE, intensity levels in terms of euros were positively associated with nitrogen input levels, but these were not related to any response variable on nitrogen surplus. In VK, intensity in terms of euros and in terms of nutrients applied were positively related, which positively affected energy yield, profit and nitrogen surplus. Only in VK, input intensity was linked to economic conditions, indicating that increasing production costs are potential direct drivers of intensification that lead to higher yields and profits. Increasing production costs are indeed identified as a major challenge and intensification as an important strategy in VK [7,20,27].

4.1.2. Weather conditions and variability of farm performance. Intensity levels explained levels of farm performance, but not the year-to-year variability (residuals). Instead, weather conditions seemed to explain the year-to-year variability of farm performance.

In FL, farms seemed to benefit from drought in summer. In 2018, when drought in summer was experienced throughout Europe, the clay soils with their high water holding capacity and the opportunity of irrigation may have reduced the impact of drought, while prices were relatively good in this year. In FL and ZE, relatively high temperatures in spring seemed to be associated with the downward fluctuations in profits of crops per ha. In our dataset for FL and ZE, high temperatures in spring coincided often with high yearly temperatures and precipitation deficits.

The results for ZE also suggested that warm winters were actually beneficial for farm economic productivity, rather than being a weather extreme that causes early sprouting of potatoes in storage [46]. A possible explanation could be that warm winters, if extended into spring, lead to early sowing of potato and subsequently can lead to higher yields [55,56]. Yet another explanation could lie in the specific dataset under study: warm winters occurred seven times from 2006 till 2019, while high temperatures in spring and warm winters coincided only twice (2014 en 2019) (Table F in S5 Text). The seemingly positive effect of warm winters could therefore be an artefact, i.e. the coincidental opposite of the observed negative effect of high temperatures in spring. Longer time series would reduce the possibility of having results that could be considered an artefact.

In VK, residuals of crop yield and nitrogen surplus were affected by weather extremes. This suggests that nitrogen supply to fields is adapted to average conditions [54], resulting in nitrogen surplus peaks during or after years in which extreme weather events occurred. With expected increases of heat waves and droughts towards the future, adjusting nitrogen applications to possible lower yields becomes even more important. This finding may also apply to the other two case studies where nitrogen application is also high and correlated with nitrogen surplus, at least in the original dataset (Figs R, S, T in S5 Text). Unfortunately we were not able to verify this based on the final sPLS-models (Figs C, F, I in S5 Text) that seemed to mask the correlation between nitrogen supply and surplus.

4.1.3. Resilience attributes. We did not identify resilience attributes at farm level, i.e. farm characteristics that support farms to cope with trends and variability in market and weather conditions. Instead, farm characteristics (specifically input intensity) seemed important for current levels of system functions (section 4.1.1), while market and weather conditions were having an impact on farm performance trends and variability (section 4.2.2). More empirical analyses seem necessary to understand the role of farm level resilience attributes in coping with market and weather conditions.

4.2. Methodology

4.2.1. General reflections. sPLS can be seen as a projector and filter of high-dimensional data that accentuates certain patterns in the data. In this study sPLS has been used to analyse temporal and inter-farm variability of economic and environmental farm performance in response to challenges regarding market and weather. The method could also be applied to study soils, water bodies or entire ecosystems in response to hazardous pollutants (e.g. from waste-water residues or mine tailings) However, while using sPLS, some patterns may also be overlooked. A general example is the loss of details in sPLS, compared to the PCA analysis. A specific example is the correlation between nitrogen input and nitrogen surplus in the correlation maps of the original (Figs R, S, T in S5 Text) and projected (Figs C, F, I in S5 Text) data: the correlation in the original data structure has disappeared in the projected data. Also the level of detail as provided by the PCA-analyses is not reached. The potential loss of detail in multivariate statistics needs to be considered in other research fields as well. For instance regarding the impact of heavy metals on soil microbiota [see e.g. 57].For our case studies, the models reproduced generally well-known knowledge and experience that could be embedded in an already existing narrative. Including more management specific indicators and following individual farms as was done before could improve model performance and the interpretation of results, but a large part of the variability is likely to remain unexplained [24,25]. At best, this positions the used methods as being explorative (hypothesis forming).

The method simplifies reality by assuming linearity over time and linearity regarding response to explanatory variables. Regarding time, the threshold regression analysis has compensated somewhat for this (see also S5 Text). Regarding explanatory variables such as input intensity levels, it should be noted that these are known to have a non-linear impact on food production and economic productivity. However, due to large differences in input use efficiency among farmers, de facto a linear function may be approaching the data well enough. Interaction effects, for instance of farm characteristics on the impact of weather extremes, could not be studied well. In our case studies, the combination of sPLS (instead of PLS) and random effects improved model performance considerably, but also resulted in a focus on the general impact, rather than a farm specific impact, of weather conditions on farm residuals. In Figs 7 and 8, for instance, farms seem to be impacted in the same extent by weather conditions, i.e. farm characteristics don't seem to influence this. However, it should be noted that weather conditions only explain a small part of variability. Moreover, sPLS (artificially) reduces co-variation between the different model components, compared to PLS as, for instance, was used before [24]. Studying interaction terms in multi-variate ordination techniques, such as PLS and redundancy analyses, are notoriously difficult [58]. A few coarse methods are provided for (visually) assessing interaction effects for data from controlled experiments [58]. Further development of such methods is needed before they can be applied to the datasets used in our analysis, i.e. relatively small, multi-level datasets with continuous and discrete values from an uncontrolled real life context.

4.2.2. sPLS in a sustainability and resilience context. By putting response variables in the context of resilience, a general idea about system's resilience could be obtained. It should be noted that the resilience of an individual farming system should in the end be evaluated in a broader context. For example, lower dependence on externally sourced nitrogen input may be good for reducing the environmental foot print and increasing resilience through increased autonomy. Some reduction in nitrogen input in the Netherlands is not expected to necessarily lead to yield decrease [54,59]. Thus, there seems little risk of externalising environmental pressure to other regions through a decrease in production.

In our analyses, sPLS performed lower in more diverse regions, i.e. in FL and ZE, where farms were more different from one another and where crop prices are more variable compared to VK. This could imply that, when using relatively small datasets, sPLS should be applied to systems with rather uniform farms in a relatively stable economic environment, in order to detect patterns in farm data that is known to usually contain a lot of noise. Interestingly, diversity, in particular in the form of farming system heterogeneity, is considered important in the context of building resilience [7,8,60]. Moreover, stable economic environments are uncommon for most contemporary, intensive farming systems as most are exposed to (fluctuating market prices of) global markets [61–63]. Considering the reflections above, datasets containing more farms over a longer time span are needed to increase the usefulness of our methodology. However, even with large datasets of farms, finding patterns and good explanatory power is not guaranteed [56].

Small residuals were seen as indicative for farm stability and therefore positive for farm resilience regarding robustness. Some argue that stability is not the same as robustness and that more specific indicators are needed [e.g. 22,64]. Interesting in previous work is the use of absolute benchmarks [22], e.g. for minimum wage reflecting economic performance, while our study looks at deviations from the mean or trend without referring to standards. Similarly to economic indicators, yield indicators could be benchmarked against potential yields [e.g. 38] and environmental indicators to existing environmental standards [e.g. 65]. Using standards could put results of our type of work more into perspective of (societal) desired sustainability levels.

4.2.3. Selection of models and response variables influences results. Although sPLS is largely data-driven, the study design has influenced the results. With regard to the selection of components, the acceptable level of the Q2-score is arbitrary [53]. We therefore presented the R2-values as well. Some of the components included the maximum or minimum number of indicators per component as specified a priori, i.e. for the sake of interpretability, arbitrariness was included here as well. Additional analyses suggested that model performance was relatively robust regarding the inclusion of strongly correlated explanatory variables (Table C in S6 Text). In contrast, in the case studies in this paper, strong correlations among response variables lowered model performance (Table A in S6 Text). More specifically, the strong correlation between nitrogen input and nitrogen surplus in the original dataset was disfavoured over correlations of other explanatory variables with response variables related to yield and economic response variables. This "finding" can be seen as an illustration how an abundance of the relatively easy measurable indicators in the economic domain can mask patterns of generally less abundant and more difficult to measure environmental indicators. To avoid neglecting important environmental variables, overrepresentation of economic indicators should be discouraged.

5. Conclusions

Overall, our statistical analyses of farm accountancy data from three regions over a period of 14 years mostly confirmed already existing knowledge. Current levels of farm output and thus sustainability were mainly related to variables associated to farm structure, in particular input intensity-related indicators. Year-to-year variability of farm performance was mainly related to weather conditions and weather extremes. The usefulness of our method to test hypotheses on resilience attributes at farm level seems therefore limited, which may be at least partly due to the dataset.

We aimed to identify resilience attributes at farm level, where resilience attributes are supposed to support farms to cope with trends and variability in market and weather conditions. While our method shows the importance of farm characteristics (specifically input intensity) for current levels of system functions, their importance to cope with challenges remains unclear, because of the much larger effect of the challenges on trends and variability in system functions as compared to farm characteristics. Interactions between challenges and farm characteristics thus need to be further explored with other methods.

The presented methods in this paper can be seen as a way to filter and project high-dimensional data and to accentuate patterns in the data. As such it is a useful way of getting to know the data. In the context of resilience of farms, while using a relatively small dataset, the applicability of our methodology seems limited to a rather homogeneous farm population in a relatively stable economic environment. More comprehensive datasets in terms of number of farms and time span captured should be used to increase the usefulness of our methodology. Researchers intending to apply this method in (arable) farming systems should be well aware of the influence they can have on the results through the selection of response variables. In particular regarding the relative abundance of economic indicators that could mask environmental indicators that are generally more difficult to measure and therefore less abundant.

Supporting information

S1 Text. Number of observations.
(DOCX)

S2 Text. Details on variables.
(DOCX)

S3 Text. Results threshold regression.
(DOCX)

S4 Text. Results PCA.
(DOCX)

S5 Text. Results sPLS-models.
(DOCX)

S6 Text. Additional sPLS-models.
(DOCX)

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Author Contributions

Conceptualization: Wim Paas, Miranda P. M. Meuwissen, Martin K. van Ittersum, Pytrik Reidsma.

Data curation: Wim Paas.

Formal analysis: Wim Paas.

Funding acquisition: Miranda P. M. Meuwissen, Pytrik Reidsma.

Investigation: Wim Paas, Pytrik Reidsma.

Methodology: Wim Paas.

Project administration: Miranda P. M. Meuwissen, Pytrik Reidsma.

Resources: Wim Paas, Miranda P. M. Meuwissen, Pytrik Reidsma.

Software: Wim Paas.

Supervision: Miranda P. M. Meuwissen, Martin K. van Ittersum, Pytrik Reidsma.

Validation: Wim Paas, Pytrik Reidsma.

Visualization: Wim Paas.

Writing – original draft: Wim Paas.

Writing – review & editing: Miranda P. M. Meuwissen, Martin K. van Ittersum, Pytrik Reidsma.

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