

Towards stability of food production and farm income in a variable climate

Article

Published Version

Creative Commons: Attribution 4.0 (CC-BY)

Open Access

Harkness, Caroline, Areal, Francisco J., Semenov, Mikhail A., Senapati, Nimai, Shield, Ian F. and Bishop, Jacob ORCID logoORCID: https://orcid.org/0000-0003-2114-230X (2023) Towards stability of food production and farm income in a variable climate. Ecological Economics, 204 (Part A). 107676. ISSN 0921-8009 doi:

https://doi.org/10.1016/j.ecolecon.2022.107676 Available at https://centaur.reading.ac.uk/108777/

It is advisable to refer to the publisher's version if you intend to cite from the work. See <u>Guidance on citing</u>.

To link to this article DOI: http://dx.doi.org/10.1016/j.ecolecon.2022.107676

Publisher: Elsevier

All outputs in CentAUR are protected by Intellectual Property Rights law, including copyright law. Copyright and IPR is retained by the creators or other copyright holders. Terms and conditions for use of this material are defined in the <u>End User Agreement</u>.

www.reading.ac.uk/centaur



CentAUR

Central Archive at the University of Reading

Reading's research outputs online

Contents lists available at ScienceDirect





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



Towards stability of food production and farm income in a variable climate

Check for updates

Caroline Harkness ^{a,b,*}, Francisco J. Areal ^c, Mikhail A. Semenov ^d, Nimai Senapati ^d, Ian F. Shield ^b, Jacob Bishop ^a

^a School of Agriculture Policy and Development, University of Reading, Earley Gate, Reading RG6 6AH, United Kingdom

^b Sustainable Agricultural Sciences, Rothamsted Research, West Common, Harpenden, Hertfordshire AL5 2JQ, United Kingdom

^c Centre for Rural Economy, School of Natural and Environmental Sciences, Newcastle University, Agriculture Building, King's Road, Newcastle upon Tyne NE1 7RU,

United Kingdom

^d Department of Plant Sciences, Rothamsted Research, West Common, Harpenden, Hertfordshire AL5 2JQ, United Kingdom

ARTICLE INFO

Keywords: Climate variability Sustainable farming practices Stability Yield Diversity Adaptation

ABSTRACT

Stable food production is vital for food security. Stability of farm income is also necessary to ensure the sustainability of food production and to protect livelihoods, in a changing climate. We analyse the relative effects of climate variability, subsidies and farming practices on the stability of food production and farm income. We examine farms in England and Wales between 2005 and 2017, and link farms to climate data at a sub-regional scale. Our results show that variability in temperature and rainfall reduces the stability of farm income and food production. While variability in climate can be largely outside of the farmers control our findings indicate that, under current conditions, farm management can have a larger effect on stability than climate. We identified three key aspects of farm management and policy that improve stability: i) increasing agricultural diversity, ii) increasing the efficiency of agrochemical use and iii) agri-environmental management. These management stability of agriculture whilst reducing negative impacts of farming on the environment. We also found differences in effect size of climate impacts and adaptation options between farm types, emphasising the need for flexible agricultural policies.

1. Introduction

Stable food production is essential for food security (FAO, 2006). Likewise, stability of farm income is necessary to ensure the sustainability of farm businesses that can continue to produce food, and protect livelihoods, in a changing climate. Agriculture is subject to a wide range of risks and uncertainties, including climatic, economic, biotic (pests and disease) and environmental, many of which will intensify with climate change. The capacity of the agricultural system to cope with shocks and maintain stability of food production is vital to attaining the UN Sustainable Development Goals of eradicating hunger and securing food for an increasing global population (Griggs et al., 2013). Examining yield variability and identifying strategies to increase stability of yields is recognised as an important area of research (Porter et al., 2014). Variability of farm income is also considered a key issue faced by farmers and addressed by policy makers (OECD, 2009; Severini et al., 2016), which can, for example, make investment decisions or the ability

to meet loan repayments more difficult. Strategies to increase stability are necessary to ensure the sustainability of farm businesses that can continue to produce food.

Agricultural production is highly dependent upon weather conditions. Climate change and associated increases in weather variability therefore pose many challenges to farmers. Climate variability and extremes (e.g. heat waves, flooding and drought) can severely reduce crop yields (e.g. Deryng et al., 2014; Powell and Reinhard, 2015) and livestock productivity, influencing both the direct health of the animal and feed availability (Kipling et al., 2016). Farm incomes are also impacted by production losses due to adverse weather, in addition to other factors including changes in commodity prices and policy (Reidsma et al., 2009).

Alongside climate impacts, the magnitude and stability of agricultural production and farm income are strongly associated with farm characteristics (e.g. farm type and size), farming practices (e.g. diversity, input intensity) and government subsidies (Harkness et al.,

https://doi.org/10.1016/j.ecolecon.2022.107676

Received 20 May 2021; Received in revised form 4 November 2022; Accepted 8 November 2022 Available online 24 November 2022

0921-8009/© 2022 The Authors. Published by Elsevier B.V. This is an open access article under the CC BY license (http://creativecommons.org/licenses/by/4.0/).

^{*} Corresponding author at: School of Agriculture Policy and Development, University of Reading, Earley Gate, Reading RG6 6AH, United Kingdom.

E-mail addresses: carolineharkness.ac@gmail.com (C. Harkness), Francisco.Areal-Borrego@newcastle.ac.uk (F.J. Areal), mikhail.semenov@rothamsted.ac.uk (M.A. Semenov), nimai.senapati@rothamsted.ac.uk (N. Senapati), ian.shield@rothamsted.ac.uk (I.F. Shield), j.bishop@reading.ac.uk (J. Bishop).

2021; Reidsma et al., 2009). Understanding the effects of these farming practices and subsidies alongside, and in comparison to, the influence of climate could help farms adapt to more variable conditions. To effectively guide adaptation, it is important to understand the relative importance of government policy in comparison to farm-level management practices. However, quantitative assessments on agricultural system dynamics (i.e. changes over time) remain rare at the farm level (Dardonville et al., 2020).

At the farm-level, changes in management can have dramatic impacts on the stability of food production and income. Increased diversity in crop rotations has been found to enhance yield stability in certain crops and reduce the risk of crop failure (Dardonville et al., 2020; Gaudin et al., 2015). Greater use of fertiliser and pesticides is associated with greater yield, however the effect of agrochemicals on the variability of yields is unclear (Dardonville et al., 2020). Management strategies, such as increasing chemical inputs, to enhance food production and its stability may not necessarily have complementary benefits for farm income (profitability), which requires expenditure to be considered. For example, farmers may seek to increase yields, and stability, using chemicals, but this may not always be profitable if any increase in the value of outputs does not exceed the additional money spent on inputs. Reducing input intensity, engaging in government agrienvironment schemes and increasing agricultural diversity, as well as larger farm size have previously been found to increase the stability of income for many farm businesses (El Benni et al., 2012; Enjolras et al., 2014; Harkness et al., 2021; Pacín and Oesterheld, 2014).

To effectively target adaptation, it is necessary to integrate climate, farm characteristics, farming practices and subsidies and assess their relative importance. However, the impacts of these factors are typically examined separately, in different disciplines, and at different spatial scales. The stability of agricultural production is usually assessed via the variability of yield over a given time period (e.g. Ceglar et al., 2016; Reidsma et al., 2009). Few studies have considered the impacts of a range of farming practices, subsidies and climate on the stability of both food production and farm income. Reidsma et al. (2009) found that increasing farm size and output intensity increased crop yield and income stability, while variability in direct payments decreased yield and income stability across regions of Europe. In addition, variability in precipitation decreased yield stability in many crops (Reidsma et al., 2009). In contrast to previous studies, our analysis here also considers the effect of agricultural diversity and agri-environment scheme payments, on the stability of food production and farm income. The production type can also influence the stability of income and food produced (e.g. Chavas et al., 2019; Harkness et al., 2021), therefore we consider differences within and between farm types, which can exhibit very different farm management and characteristics.

The key aim of our research is to examine the relative effect of climate variability in combination with subsidies and farming practices on the temporal stability of food production and farm income, at the farm level. Here, we expand upon our previous work (Harkness et al., 2021) to incorporate the effects of climate variability and additionally examine factors affecting the stability of total food production at the farm level. This provides insight into how policy, and management at the farm-level, can improve the resilience and sustainability of farming in a changing climate. We use a cohort of 929 farms across counties of England and Wales over the period between 2005 and 2017, during which the UK experienced a diverse range of adverse weather conditions including flooding, drought, and heatwaves (e.g. Kendon et al., 2013). We examine the stability of food produced at the farm level using a common unit of calories, which has not been examined previously. This enables us to compare productivity across different crop and livestock products. We examine the stability of farm income using the measure of farm business income, which is in essence the same as net profit and integrates both income and expenditure. Our approach also enables us to evaluate trade-offs between enhancing the stability of food production and of farm income, and where potential adaptations may differ

between farm types.

2. Materials and methods

2.1. Data and study area

We examine data from the Farm Business Survey (FBS) between 2005 and 2017, which is a survey conducted in England and Wales collecting information from approximately 2500 farm businesses annually (Defra, 2020). The FBS records farm level data on financial performance and food production, as well as subsidies received and other farm characteristics, including the county (or unitary authority) location of each farm. Farms are classified in the survey into farm types according to which type of production accounts for more than two-thirds of standard gross margin (SGM). We focus our analysis on the following farm types: cereals (holdings on which cereal and combinable crops account for more than two-thirds of SGM), general cropping (arable crops including field scale vegetables account for more than two-thirds of SGM) and mixed farms; non-specialist holdings in which no other production type accounts for more than two-thirds of SGM, including farms with a mixture of crops and livestock.

Climate variability, and averages, have been calculated using the HadUK-Grid gridded climate observations produced by the Met Office (Hollis et al., 2019). The HadUK-grid dataset includes a wide set of climate variables, including temperature and precipitation, for daily, monthly, seasonal and annual timescales, as well as long term averages and at different spatial resolutions. We average 5 km HadUK-Grid gridded climate observations for each county or unitary authority to provide an estimate of the climate at each farm, and link climatic conditions to farm data at a smaller spatial scale than used in previous studies (e.g. across regions of Europe in Reidsma et al. (2009)). Fig. 1 shows the climate variables (described in section 2.3) for an example 5-year period included in the analysis, which illustrates the spatial differences between the county and unitary authorities (spatial units used in the analysis) in England and Wales.

2.2. Measuring the stability of food production and farm income

We examine the effect of climate variability in combination with subsidies and farming practices on medium-term stability of food production and farm income. We calculate medium-term stability (changes over time) using the standard deviation over a 5-year rolling period, as used in previous studies (Barry et al., 2001; Harkness et al., 2021). This measure indicates the amount of variation or dispersion of farm business income or calories at the individual farm over a 5-year period.

To examine the stability of farm income we use farm business income per hectare (\pounds /ha) which is calculated as the sum of: total output from agriculture, on-farm diversification and subsidies, less all fixed and variable costs, including paid labour and depreciation, and profit or loss from the sale of fixed assets (Harkness et al., 2021). Farm business income is in essence the same as net profit and is the preferred measure of income used by policy makers to examine the impact of policies at the farm level (Department for Environment Food and Rural Affairs et al., 2018).

The Farm Business Survey also records annual food production. To examine the stability of food produced at each farm, we calculate the total calories (kcal/ha) available for direct human consumption. Calories represents a common unit of production (analogous to £/ha for income) and therefore no weighting for different products is required. To calculate calories we use the FAO Food Balance Sheet (FAO, 2021) which derives calories per 100 g for each agricultural commodity. We use these factors to convert the units of food produced in the Farm Business Survey (tonnes (crops), hectolitres (milk), dozen (eggs) and number (livestock)) into calories. Further details on the calculation of calories per food product is provided in the supplementary materials. As this study focuses on the stability of food production, using a consistent

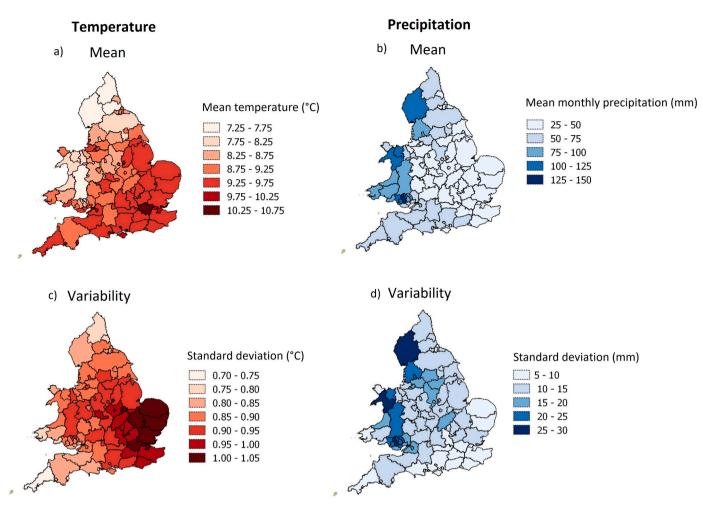


Fig. 1. Spatial distribution of climate variables for an example 5-year period (2009–2013): a) mean temperature b) mean monthly precipitation c) standard deviation of mean temperature d) standard deviation of mean monthly precipitation, during the main growing season (January–June) and across county and unitary authorities of England and Wales.

measure of food production over the period examined allows us to analyse how much total food production has varied for the main food products, as listed in Supplementary Table 1. The stability of calories per hectare has been calculated in the same way as for income; using the standard deviation over a 5-year rolling period.

2.3. The factors affecting farm stability

We use the same methods from Harkness et al. (2021) to calculate the farming practices: farm size, input intensity (cost of chemical inputs per hectare) and agricultural diversification (degree of specialisation in different crop and livestock products). We also examine the effect of subsidies: direct (area-based) payments and agri-environment scheme payments per hectare. We examine three farm types (cereals, general cropping and mixed farms), all received money via the EU common agricultural policy, which provides payments to farmers in two main categories: Pillar 1 provides direct (area based) payments to farmers and market support, namely the Single Payment Scheme (SPS) which was replaced by the Basic Payment Scheme (BPS) in 2015. Pillar 2 pays farmers to implement environmentally friendly actions through voluntary tiered agri-environment schemes, which paid farmers a flat rate for straightforward environmental management across the entire farm landscape, e.g., hedgerow management (Entry Level Stewardship) or followed a more demanding level (Higher level stewardship) requiring more complex and targeted environmental management in return for larger payments. To examine their relative effects on farm stability,

these variables are averaged over the same 5-year rolling period used to derive the dependent variables (standard deviation of farm income and calories). The calculations of independent variables are provided in Table 1.

To examine the effect of climate variability on the stability of food production and farm income, we calculate the standard deviation in temperature and rainfall over a 5-year rolling period. This involves firstly calculating the mean temperature and monthly precipitation for the first 6 months of the year (January – June) in each county to provide an indication of temperature and rainfall in the main growing period (similar to the approach used by Reidsma et al. (2009)). These county level climate conditions are then used to calculate the standard deviation in temperature and precipitation over a rolling 5-year period to examine the effect of climate variability at the farm level. Crops are affected by adverse weather conditions which occur at specific stages of development, however, we wanted to examine how variability in climate conditions can affect total food production at the farm level (across all agricultural products), therefore we measured climate variability across the main part of the growing season for crops in the UK. The stability of performance may also be influenced by average climate conditions (or base temperatures), as well as variability, therefore we include variables capturing the mean temperature and precipitation for each 5-year period, to reduce the risk of confounding these relationships.

The standard deviation is an absolute measure of dispersion, therefore we also control for the level of income and calories produced by

Table 1

Definition and calculations of farming practices, EU subsidy payments and climate variables analysed in the study.

Independent variable	Calculation
Farming practices and subsidies ^a	
Farm size	Area farmed (hectares) = The utilised agricultural area, plus land let in or minus land rented out
Intensity of inputs	The total cost of fertiliser, crop protection and concentrated animal feed (£), per hectare (area farmed) (IRENA indicator 15; European Environment Agency, 2005; Gerrard et al., 2012)
Agricultural specialisation (inverse of diversification)	Herfindahl index $(S) = \sum_{i=1}^{n} (p_i)^2$
	Where <i>n</i> is the total number of farming activities, p_i is the proportion of revenue earned from the <i>i</i> -th farming activity (revenue from farming activity divided by the total farming revenue).
	Can also be written as sum of revenue for each farming activity squared, divided by total revenue for agriculture squared:
	(Wheat ² + barley ² + other cereals ² + oilseed rape ² + peas and beans ² + potatoes ² + sugar beet ² + horticulture ² + other crops ² + by-products and forage ² + milk ² + cattle ² + sheep ² + pigs ² + eggs ² + chickens and other poultry ² + other livestock ² + other agriculture ²) / total agricultural gross revenue ²
Direct payments per hectare	Total direct payments (£) (Primarily the single payment scheme or basic payment scheme), per hectare (area farmed)
Agri-environment payments per hectare Climate variables ^b	Total payments under rural development policy (£; pillar 2), per hectare (area farmed)
Mean temperature (°C)	Mean temperature (°C) for first half of year (Jan to June)
SD of mean temperature (°C)	SD of mean temperature (°C) for first half of year (Jan to June)
Mean monthly precipitation (mm)	Mean monthly rainfall for first half of year (mm) (Jan to June)
SD of mean monthly precipitation (mm)	SD of mean monthly rainfall (mm) for first half of year (mm) (Jan to June)

^a Farming practices and subsidies are averaged over the same rolling five-year time period used to derive the dependent variables.

^b Climate variables (standard deviation (SD) and mean temperature and monthly rainfall) are calculated over the same rolling five-year period.

each farm (using total farm business income and calories per hectare), which may also affect the level of stability.

Summary statistics for the variables used in this study are shown in Table 2. The UK Consumer Price Index is used to deflate all monetary variables, including farm business income, to account for the change in the value of money over time (ONS, 2020).

2.4. Multilevel (two-level linear mixed effect) model

We use a multilevel model to examine the relative effects of climate variability, farming practice and subsidies on the stability of food production and farm income. Multilevel models allow us to account for dependencies within the data: Farms belonging to the same county or unitary authority (level 2) have the same estimated climate and may also have more similar environmental conditions (e.g. soil) than farm in different counties. Farms are also surveyed in the data over multiple years (we consider farms in the survey for a minimum of 5 years) therefore the multilevel model controls for the correlation between observations from the same farm (level 1). This type of model can easily accommodate the unbalanced panel data used in this study (Snijders and Bosker, 1999) and has been used previously to examine the influence of management and climate on farm level performance (Harkness et al., 2021; Reidsma et al., 2007, 2009).

We estimate a varying-intercept Bayesian two-level mixed model with farms nested within counties. The empirical specification of the model is:

$Y_{ijk} \sim ext{Log-normal}ig(u_{ijk}, \sigma_eig)$	
$u_{ijk} = lpha + lpha_{ ext{county}[k]} + lpha_{ ext{farm}[jk]} + \sum eta_p X_{jk}$	
$\alpha \sim \operatorname{Normal}(0, 10)$	
$lpha_{ ext{county}} \sim ext{Normal}ig(0, \sigma_{ ext{county}}ig)$	
$lpha_{ ext{farm}} \sim ext{Normal}ig(0, \sigma_{ ext{farm}}ig)$	(1)
$\beta_{\rm p} \sim {\rm Normal}(0, 10)$	
$\sigma_{\rm e} \sim {\rm HalfCauchy}(10)$	

 $\sigma_{\rm county} \sim {\rm HalfCauchy}(10)$

J

 $\sigma_{\rm farm} \sim {\rm HalfCauchy}(10)$

We fit a log-normal model to account for the non-normal distribution of the dependent variable, Y_{tjk} (the standard deviation of income and calories), in each model and reduce the impact of outliers. In the linear model, α is the mean intercept across all groups, α_{county} is the county level intercept (level 2), α_{farm} is the farm level intercept (level 1). β_p denotes the coefficients for each predictor variable, X_{jk} , which are listed in Table 2. α and β are given a vague (weakly informative) Gaussian prior centred on 0, and the residual variation (σ_e) is given a Half-Cauchy prior (Gelman, 2006; Nalborczyk et al., 2019), thus restricting the range of possible values to positive ones. The same Half-Cauchy prior is specified for the two varying intercepts.¹

In each of the models, predictor variables have been standardised (centred around zero, with a SD of 1) to account for the differences in scale and to examine the relative effect size of each independent variable. Year, t, is also included as a continuous variable to control for the trend in income stability and calories over time, as well as examine the interaction between time and direct payments per hectare, which was significant for mixed farms. Before fitting the models, we checked for outliers and collinearity using pairwise scatterplots. In addition, correlation coefficients between independent variables were all less than the recommended threshold of 0.7 (Dormann et al. (2013).

We fitted a Bayesian multilevel model in the brms package in R (Bürkner, 2017, 2018; R Core Team, 2019). To generate the posterior samples of the parameter estimates brms makes use of the computationally efficient Hamiltonian Monte-Carlo (HMC) Sampler (Neal, 2011) and its extension the no-U-turn Sampler by Hoffman and Gelman (2014) implemented in the Stan software package (Stan Development Team, 2020). Each model was fitted with 4 chains of 10,000 per chain of which 2000 were used for the warm-up. Visual model diagnostics showed adequate mixing of chains for each parameter, with the Rhat value (Gelman and Rubin test statistic; Gelman and Rubin (1992)) less than 1.003, providing strong evidence of convergence. A Bayesian version of the marginal R^2 was obtained using the *bayes_R2* method available in brms (Nalborczyk et al., 2019), with calculations based on Gelman et al. (2019). Due to the temporal nature of the variables we considered the presence of temporal autocorrelation. We inspected the residual variance (σ_e), which showed no significant autocorrelation. For comparison,

¹ We also ran the models using the default priors set in the *brms* package (weakly informative Student-t distributions), which resulted in little change to the model results.

Table 2

Summary statistics of FBS data (2005–2017); values deflated using UK Consumer Price Index (2015 = 100; ONS, 2020).

	Mean (2005–2	2017)		Standard deviation (SD) (2005–2017)				
	All Farms	Cereals	Gen. cropping	Mixed	All Farms	Cereals	Gen. cropping	Mixed
Dependent variables								
SD of Farm Business Income (FBI) per ha (£)	219.57	213.77	271.13	183.97	144.05	116.84	192.72	129.06
SD of calories per ha (kcal)	2,537,320	2,864,774	2,736,539	1,668,707	1,557,537	1,340,314	1,655,014	1,562,107
Independent variables								
Farming practices and subsidies								
Specialisation (Herfindahl index) (0–1)	0.41	0.40	0.37	0.49	0.16	0.14	0.14	0.18
Input intensity per ha (£)	413.59	327.26	399.05	607.44 533.25		137.37	243.86	997.30
Direct payments (SPS/BPS) per ha (£)	237.57	244.15	237.49	223.87	62.36	59.95	57.06	69.42
Agri-environment payments per ha (£)	45.70	48.54	39.81	45.22	50.47	56.62	41.19	43.74
Area farmed (hectares)	234.97	233.52	284.21	192.41	246.33	218.59	358.33	144.99
Climate (Jan-Jun)								
Mean temperature (°C)	8.29	8.31	8.40	8.14	0.66	0.66	0.51	0.74
SD of mean temperature (°C)	0.90	0.91	0.91	0.88	0.21	0.21	0.22	0.19
Mean monthly precipitation (mm)	60.07	58.18	55.95	67.84	16.08	13.79	14.72	18.88
SD of mean monthly precipitation (mm)	15.48	15.27	14.42	16.90	4.53	4.35	3.87	5.09
Control variables								
Farm Business Income (FBI) per ha (£)	390.96	387.20	495.80	301.80	393.09	357.27	460.26	373.88
Calories per ha (kcal)	15,929,805	17,651,252	19,406,013	9,115,433	8,110,153	6,608,759	8,087,139	6,968,904
Number of observations	4529	2357	1044	1128				
Number of farms	929*	512	261	318				
Number of counties/unitary authorities	65	56	38	57				

* Note 162 farms change between farm types during the period, therefore appear in more than one farm type group during the relevant years.

we also estimated the same models using frequentist methods and incorporated a AR(1) residual autocorrelation structure.² The frequentist results are provided in the supplementary materials and show relationships which are consistent with the Bayesian results provided in Section 3.

3. Results

3.1. The effects of farming practices and subsidies on the variability of income

Figs. 2 and 3 show the posterior means, and 95% credible intervals (CIs), of the multilevel models. These figures indicate the relative effect of farming practices, subsidies and climate conditions on the variability (inverse of stability) of food production and farm income, by farm type. The model results are also provided in table A.1 and A.2 in Appendix A. Models use the log of the dependent variable, therefore the exponent of the posterior mean, minus 1 multiplied by 100, provides the percentage change in the variability of income for every increase in the independent variable by one standard deviation, holding all other predictors constant.

3.1.1. Factors affecting the variability of farm income

Farming practices are important factors influencing the variability of farm income per hectare (Fig. 2). Farms which spend more on chemical inputs (fertiliser, pesticide and concentrated animal feed) have more variable income. Increasing input intensity by 1 standard deviation increases the variability of income between 10 and 21% across the 3 farm types, which represents a large increase relative to other factors examined. More specialised cereal and general cropping farms (i.e. those with less diversity of crop and livestock activities) also have more variable income, however, this was not an important factor for mixed farms. For general cropping farms (which are on average the most diverse; Table 2) specialisation has a large relative effect; increasing specialisation by 1 standard deviation increases the variability of income by 13% (95% CI

[7%, 20%]). Larger cereal and mixed farms have more stable incomes. Increasing the area farmed by 1 standard deviation reduces the variability of income by 6% (95% CI [-9%, -3%]) for cereal farms, and for mixed farms the decrease is larger (-11%, (95% CI [-15%, -6%]).

The value of direct payments per hectare is an important factor for cereal farms. An increase in direct payments increases the variability of income by 4% (95% CI [1%, 7%]). While the effect of agri-environment scheme payments differs between farm types. An increase in agrienvironment payments per hectare decreases the variability of income for mixed farms by 6% (95% CI [-10%, -3%]), whereas increases the variability income by 3% for cereal farms, although the lower bound of the credible interval is close to zero (95% CI [0%, 6%]). Subsidies therefore have a smaller relative effect on the variability of income, in comparison to the farming practices examined in this study.

Climatic conditions are also estimated to be an important factor influencing the variability of income. The variability of income for cereal farms are particularly sensitive to changes in both prevailing (mean) temperatures and precipitation and its variability. Larger variability of temperature increases the variability of income for cereal farms by 5% on average, while increasing the variability of precipitation also has the same effect (5% increase). Increasing warmth (mean temperatures) and average precipitation has the opposite effect and are both associated with a decrease in the variability of income of 9%, while holding all other factors constant. Changes in precipitation have a larger effect for mixed farms and are found to be more important than changes in temperature. An increase in mean rainfall reduces the variability of income by 11%, whereas greater variability in precipitation, over a 5year period, increases the variability of income by 7% on average, for mixed farms.

Generally, the relative effects of climatic factors associated with the variability of income were similar in size to the effects of the farming practices examined (Fig. 2). With exception of general cropping farms, where the effect of input intensity and specialisation were found to be more important than the climatic conditions examined (Fig. 2).

3.1.2. Factors affecting the variability of food production

Farming practices examined also affect the stability of food production, however, the relative size of these effects differ between farm types (Fig. 3). For general cropping and mixed farms, increasing input intensity is associated with an average decrease in the variability of

 $^{^2\,}$ At the time of writing, the package used for applying MCMC does not allow for an AR(1) residual autocorrelation structure for unevenly spaced data (longitudinal data with gaps).

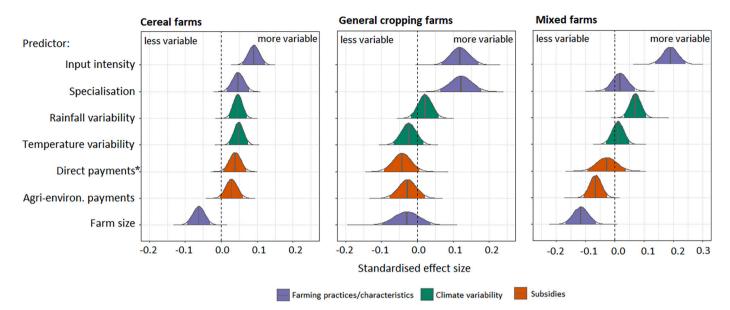


Fig. 2. Posterior distribution of the standardised relative effects of farming practices, subsidies and climate variability on the variability (standard deviation) of farm business income per ha. Shaded areas represent the 95% credible intervals.

*The model also includes an interaction between direct payments and year for mixed farms (refer to Appendix A for the full results).

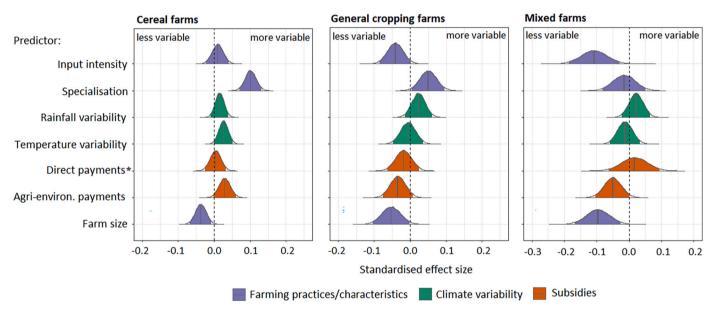


Fig. 3. Posterior distribution of the standardised relative effects of farming practices, subsidies and climate variability on the variability (standard deviation) of calories per ha. Shaded areas represent the 95% credible intervals.

*The model also includes an interaction between direct payments and year for mixed farms (refer to Appendix A for the full results).

calories by 4% and 10% respectively. Spending more on chemical inputs therefore helps improve the stability of food production but increases the variability of farmers income. Increasing specialisation of crop and livestock activities is associated with an increase in the variability of calories for general cropping and cereal farms, however, this was not an important factor for mixed farms. The effect of specialisation is relatively large compared to other factors and is largest for cereal farms. Increasing specialisation by 1 standard deviation increases the variability of calories by 10% for cereal farms (95% CI [7%, 14%]), and by 5% (95% CI [1%, 10%]), for general cropping farms. Larger farms are associated with less variability in calories produced. Increasing the area farmed by 1 standard deviation reduces the variability in calories between 4% and 9% across the 3 farm types.

The value of direct payments is an important factor for mixed farms.

Receiving more direct payments per hectare is associated with an increase in the variability of calories produced by approximately 3% over the period examined, and this effect increases over time. The effect of agri-environment scheme payments on the variability of calories differs between farm types, which is consistent with the effects on farm income. An increase in agri-environment scheme payments per hectare decreases the variability of calories for mixed farms by 5% (95% CI [-10%, 0%]), whereas increases the variability of calories for cereal farms by 3% (95% CI [0%, 6%]), although one bound of the 95% credible interval is close to zero. The relative effects of agri-environment scheme payments are therefore smaller than the farming practices we examined.

Climatic conditions are also estimated to be an important factor influencing the variability of calories, however fewer important effects were found compared to those associated with the variability of income. Changes to both the prevailing (mean) temperature, and variability in temperatures, were important factors affecting the variability of calories for cereal farms; Increasing the temperature variability by 1 standard deviation was associated with an increase in the variability of calories of 3% (95% CI [0%, 5%]). While, increasing warmth (mean temperatures) decreased the variability of calories by 4% (95% CI [-7%, 0%]), while holding all other factors constant. An increase in mean rainfall was also associated with a reduction in the variability of calories produced by mixed farms of 11% (95% CI [-17%, -2%]).

In general, the farming practices employed by farms are therefore associated with a larger relative effect on the stability of calories produced, compared to the effects of more variable climate conditions (Fig. 3). For general cropping farms in particular, farming practices and characteristics were more important than subsidies or climate variability in influencing the variability of calories produced (Fig. 3).

In this study we estimate the relative effects of climate variability using variability in average temperature and monthly precipitation for the main part of the growing season, between January and June. We also estimate models using climate conditions over a 12-month period, using all months in the agricultural season (October to September). Including all months in the analysis does not have a large impact on the results. Results of this sensitivity analysis are available in the supplementary material.

We also examine results using a different calculation of diversity. In the main results we calculate diversity using revenue from different crop and livestock products. We also calculated the equivalent diversity index using the calories produced for each product type per farm (see Table 1). Models using diversity in calories provided very similar results to the models using diversity based on revenues; also showing that specialisation of calories resulted in a large increase in the variability of farm business income and calories.

4. Discussion

Our study provides knowledge on the relative importance of farming practices, subsidies and climate variability on the stability of food production and farm income. Our results highlight the importance of agricultural diversity to increase the stability of both food production and farm incomes. We identified a potential trade-off in the use of agrochemicals between the stability of food production and farm incomes. More efficient use of chemicals may help to increase the stability of income, whilst maintaining outputs. Subsidies paid to farmers through the Common Agricultural Policy have a small effect on the stability compared to farm management. Direct (area based) payments reduce stability of income and food production for certain farm types. Agrienvironment schemes are found to improve stability for mixed farms, whereas the opposite effect is found for cereal farms. Climate conditions also affect both the stability of food production and farm income, however, the importance and relative size of these effects vary between farm type.

4.1. Diversity benefits both the stability of food production and farm income

Our results show that greater agricultural diversity is associated with greater stability of farm income and total calories produced at the farm level. The relative strength of these associations, in comparison to other farming practices and climate conditions, indicates that maintaining and/or increasing agricultural diversity is highly important for the future sustainability of farming systems and food security. More diverse agricultural systems, with a broader range of traits and functions, are associated with a range of benefits which could improve stability of farm performance in a changing climate (Dardonville et al., 2020; Lin, 2011). More diverse agroecological systems, for example with greater crop diversity, have been found to improve pest and disease suppression and soil services (Degani et al., 2019; Lin et al., 2011). In addition, greater

diversity may provide buffering and mitigation to the effects of climate variability and adverse conditions, including drought (Degani et al., 2019; Lawes and Kingwell, 2012) and high temperatures (Gaudin et al., 2015). The income of more diverse farms is also less affected by the price of single commodities on global markets, therefore reducing the potential impact of price downturns (Bradshaw et al., 2004; Pacín and Oesterheld, 2014).

Whilst we examine the effect of agricultural diversity at the farm level, we do not examine functional diversity or composition effect (the diversity of species' niches or functions or the presence of species with certain traits). This could be an important area of research, to identify crop or livestock products which can best support the stability of different farm types.

We also found that farm size is an important factor affecting stability. Larger farms were associated with greater stability of both food production and farm incomes across most farm types. Larger farms may benefit from greater economies of scale (El Benni et al., 2012). Larger farms may also encompass a more diverse range of topography or soils, which could result in different exposure and responses to weather conditions across the farm in similarity to agricultural diversity.

4.2. Increasing inputs results in a potential trade-off between stability of food production and income

Our results show that more intensive farms (those spending more on fertiliser, pesticide and concentrated animal feed) have less stable income. Spending more on increasingly expensive chemical inputs has previously been associated with a reduction in the stability of farm income (Enjolras et al., 2014; Harkness et al., 2021). However, in contrast we find that greater input intensity is also associated with more stability of calories produced at the farm level, for general cropping and mixed farms. The beneficial effect of chemical inputs stabilising food production is largest for mixed farms; mixed farms, on average, spend the largest amount on chemical inputs per ha (Table 1), with mixed farms incurring costs for livestock production. Increased use of concentrated animal feed may protect livestock production from the effects of adverse weather. For general cropping farms, higher input intensity may also help stabilise calories produced by preventing large crop losses (Popp et al., 2013), although the effects are smaller than for mixed farms. It is likely there is a larger and more direct association when feeding an animal (with concentrated animal feed) and the stability of calories produced, compared to the effect of chemical inputs on the stability of crop production. Although to facilitate comparisons between crop types we did not separate input costs into subcategories (e.g., fertiliser, crop protection). Despite the benefits to production, our results indicate that greater input intensity is not economically sustainable for farm businesses, with higher input costs reducing the stability of income. This suggests a potential trade-off in the use of chemical inputs between the stability of food production and farm incomes. Agrochemicals are often used in excess which has limited economic benefit, through declining nutrient use efficiency or pesticide resistance (Roberts, 2008; Varah et al., 2020). Farms in our dataset with particularly high expenditure on inputs are more likely to be experiencing lower efficiency (diminishing returns), resulting in reduced cost effectiveness and the decrease in income stability that we identified. Therefore, while chemicals appear to support production stability (calories produced), by reducing exposure of outputs to environmental conditions, when also considering their cost, greater use of expensive agri-chemicals reduces the stability of income likely due to these excess costs and declining efficiency.

Researchers, farmers and policy makers need to consider how to reduce input-use to increase the stability of farm businesses, but whilst also maintaining food production. Increasing the efficiency of input use is highly important to maintain production but supress costs (Duru et al., 2015). A reduction in the use of chemical inputs is also needed given their associated negative externalities; contamination of the environment and undesirable health effects. Adaptation options include the use

of precision-agriculture technologies to improve the efficiency of farm operations, including better targeted fertiliser and agrochemical applications (Defra, 2017; Gebbers and Adamchuk, 2010), or substitution of chemical inputs with less environmentally harmful ones, including integrated pest management (Barzman et al., 2015). Improved crop rotation and other practices of integrated pest management may offer opportunities to reduce pesticide use without significant losses in crop yields (e.g. Barzman et al., 2015; Lechenet et al., 2017). Greater precision and strategies to adopt a more controlled use of chemicals may therefore offer an important solution to sufficiently support sustainable food production whilst at the same time reducing inputs costs and increasing income stability.

4.3. The effect of subsidies are relatively small and vary between farm type

We find that the value of government subsidies affects both the stability of food production and farm income. Our results indicate a positive association between agri-environment payments and the stability of both farm income and food production, for mixed farms. Agri-environment schemes compensate farmers for engaging in practices to benefit the environment or biodiversity and include options to maintain habitats for wildlife as well as soil management practices, which can help enhance ecosystem services and increase the resilience of the farm landscape (e.g. Degani et al., 2019; Kennedy et al., 2013; Ottoy et al., 2018). Farms receiving larger agri-environment payments may be benefitting from the direct source of income and indirect benefits of ecosystem services to food production. Agri-environment schemes do not seem to have the same stabilising effect for cereal farms. Agrienvironment scheme options may not provide the same benefits for cereal crops, or these farms may engage differently with the scheme.

Our results indicate that direct payments, based on area alone, reduce the stability of income and food production for certain farm types. A guaranteed level of income support from the government has been considered to represent a moral hazard to farmers, who may be more inclined to engage in riskier production, leading to greater variability in farm performance (Enjolras et al., 2014; Harkness et al., 2021; Reidsma et al., 2009). Therefore, this relationship may reflect risk seeking attitudes and the opportunity to take risks, particularly among cereal farms, where an increase in direct payments is found to have a significant effect on increasing the variability of income, however risk attitudes were not examined in this study. Direct payments per hectare are also variable; strengthening of the pound against the Euro between 2009 and 2015 led to a reduction in the pound equivalent, which alongside inflation, has reduced the value of direct payments paid to UK farmers over this period (Harkness et al., 2021).

In general, the effects of subsidies on stability are relatively small in comparison to the farming practices examined. This finding is consistent with previous studies, e.g., Reidsma et al. (2009) where farming practices and characteristics (size, intensity and farm type) are found to be more important factors than subsidies in influencing variability in yields and income at the farm level. Area-based direct payments are not dependent on management, whereas farming practices may have a more direct impact on outputs and ultimately stability. Understanding the mechanisms for the effect of agri-environment scheme payments is difficult due to the variety of environmental options available within the schemes; this initial study is exploratory and the first study to consider the effect of agri-environment scheme payments, however further research to identify which options are associated with greater stability of income and food production, across different farm types and landscapes, could be of interest to farmers and policy makers.

4.4. The effect of climate variability on farm stability differs between farms types

production. For mixed farms, changes in precipitation have a larger effect on the stability of income and are found to be more important than changes in temperature. Reidsma et al. (2009) also found high variability in precipitation has a large effect on agricultural stability across Europe, however, they did not examine the effects between different types of production and examined climate at a larger regional scale. Grass productivity is particularly dependent upon rainfall and limited by more extreme conditions including dry periods in spring and summer (van den Pol-van Dasselaar et al., 2020). Therefore, mixed farms may incur additional costs for feeding livestock during periods of adverse weather leading to greater variability of income. General cropping farms do not appear as sensitive to variability in temperature and precipitation, while the effect of input intensity and specialisation were found to be more important. General cropping farms are, on average, the most diverse farm type (Table 2), which may provide greater resilience to climate variability and adverse weather (Dardonville et al., 2020; Gaudin et al., 2015) and would be an interesting interaction to examine in future research.

Ecological Economics 204 (2023) 107676

An increase in mean temperatures and rainfall are found to be generally associated with greater stability of income and food production. We suggest this is due to crops benefiting from warming, up to their optimum temperature thresholds, over the period of our study. An increase in growing degree days (warmth) has previously been found to increase crop yields and yield stability reflecting greater yields from longer maturing varieties (Butler and Huybers, 2015).

Climate thresholds (cardinal temperatures and rainfall requirements/tolerances) and the timing of sensitive stages differ between crops. Our measures of climate variability were not specific, as we wanted to compare the effects of climate across different agricultural products and farm types. Climate indices specific to single crops (e.g. Harkness et al., 2020) may detect stronger responses for individual crop yields. Our analysis considers changes in county level mean temperatures and rainfall, and their variability, however we do not consider the effects of mean temperatures exceeding optimum thresholds, i.e., under future climates, or the effects of short-term extremes for example heatwaves or heavy rainfall events. The period examined in this study between 2005 and 2017 is not long enough to obtain signals from climate change. Interannual climate variability is driven by a range of different factors and modelling future climate variability is complex. Recent research has found interannual variability (σ) in precipitation is generally expected to increase under global warming, which has implications for the occurrence of droughts and flooding (He and Li, 2019), as well as a projected increase in summer temperature variability and heatwaves (Fischer et al., 2012; Fischer and Schär, 2009). Without adaptation the effects of climate variability could have an increasingly large effect on the stability of future food production and farm incomes, and strategies to reduce this instability should be prioritised.

4.5. Policy and environmental implications

Farmers are facing a more volatile environment, with climate change affecting food production and global food prices. Government policy could be targeted to combat production risks, including those from climate variability, and move towards greater agricultural sustainability.

Policy incentives could encourage the diversification of agricultural production, which is found to be an important factor improving stability. Previous research suggests farmers need more information, training and advice about the options for, and implications of, agricultural diversification (de Roest et al., 2018), to promote understanding, provide ecological expertise and access to different markets. Economic support could also be provided to support any additional start-up and maintenance costs required to diversify production systems.

Recent literature has recognised the challenges for policy makers to support farmers in reducing their chemical use; for example, individual policy instruments (e.g., bans, subsidies and taxes) may not alone be

Climate variability affects both the stability of farm income and food

able to achieve a reduction in pesticides (Lee et al., 2019). Policy makers could encourage the use of precision farming techniques, for example, providing grants or subsidies for machinery and technology which allow for better targeted fertiliser and agrochemical applications. Although it could also be seen as controversial for policy makers to fund precision farming technologies, which may be seen to legitimise chemical-based agriculture (Wolf and Wood, 1997). Lefebvre et al. (2015) argues that there is a clear requirement for public intervention to promote ecological practices in place of agrochemical inputs, e.g., integrated pest management (IPM). A combined suite of incentives, including regulation, incentive-based instruments and information dissemination are most likely to reduce agrochemical use(Lefebvre et al., 2015). Governments must also take an active role in promoting ecological practices in place of agrochemical inputs, not only to farmers but also increasing knowledge and awareness more widely, so that retailers and consumers are aware of the environmental and health consequences of their food choices.

Finally, it is also important that payments for public goods are linked to farmers enhancing or maintaining the environment or biodiversity; and are not solely area based, to ensure payments do not act as a moral hazard (and increase variability). It is difficult to comment on specific options which should be targeted in future schemes due to a lack of data available. However, from our results it is clear that greater emphasis could be given to support agricultural diversification, as well as more precise chemical application. These factors improve the stability of food production and farm incomes and can have complementary benefits for natural ecosystems and environmental goods.

5. Conclusions

Our results highlight the importance of considering both farming practices and climate conditions when examining stability of farm performance at the farm level. While variability in climate can be largely outside of the farmers control our findings indicates that, under current conditions, farm management can have a comparatively large effect on stability which may provide opportunities for farmers, supported by

policy makers, to tackle instability in farm performance. In a changing climate the effects of climate variability could have an increasingly large effect on the stability of future food production and farm incomes, and therefore strategies to address instability should be prioritised. Future climate impacts and adaptation are also likely to vary between farm types, therefore agricultural policy targeting stability should be flexible enough to be tailored to different types of production. The stability of farming is important for future food security, however it is important that changes in farming practices and policy are not at the detriment of the natural environment. The three key aspects of farm management and policy identified to improve stability were: increasing agricultural diversity, increasing the efficiency of agrochemical use and agrienvironmental management, which have also been associated with improving and benefiting natural ecosystems. Therefore, these recommendations may help increase the stability of agriculture whilst also reducing negative impacts of farming on the environment.

Declaration of Competing Interest

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

Data availability

The authors do not have permission to share data.

Acknowledgements

Caroline Harkness acknowledges financial support from the University of Reading and Rothamsted Research, who provided joint funding for this research. Rothamsted Research receives grant-aided support from the Biotechnology and Biological Sciences Research Council (BBSRC) through Designing Future Wheat [BB/P016855/1] and Achieving Sustainable Agricultural Systems [NE/N018125/1] jointly funded with NERC.

Appendix A. Model results tables

Table A.1

Multilevel model results examining the effect of farming practices, subsidies and climate on the variability of farm business income, showing the posterior means, standard deviation (SD) and 95% credible intervals (CI) of each parameter. Parameters that do not have 0 in the 95% credible interval are deemed important and marked with an "*".

	Cereals		General Cropping				Mixed					
Parameter	Posterior mean	SD	95% CI		Posterior mean	SD	95% CI		Posterior mean	SD	95% CI	
σ_{county} (county SD)	0.05*	0.04	0.00	0.13	0.15*	0.06	0.03	0.26	0.09*	0.05	0.01	0.19
σ_{farm} (farm SD)	0.35*	0.02	0.32	0.38	0.44*	0.03	0.39	0.49	0.38*	0.02	0.34	0.42
σ_e (SD of residuals)	0.34*	0.01	0.33	0.35	0.33*	0.01	0.32	0.35	0.35*	0.01	0.34	0.37
α (Intercept)	5.34*	0.04	5.27	5.42	5.39*	0.06	5.26	5.51	4.88*	0.06	4.77	4.99
β (Independent vars):												
Input intensity	0.09*	0.02	0.06	0.12	0.12*	0.03	0.07	0.17	0.19*	0.03	0.14	0.24
Specialisation	0.05*	0.02	0.02	0.08	0.12*	0.03	0.06	0.18	0.02	0.03	-0.03	0.07
Area Farmed	-0.06*	0.02	-0.10	-0.03	-0.03	0.04	-0.10	0.04	-0.12*	0.03	-0.17	-0.06
Direct payments	0.04*	0.02	0.01	0.07	-0.04	0.03	-0.09	0.01	-0.03	0.03	-0.09	0.04
Direct payments x year									0.03*	0.01	0.02	0.04
AES payments	0.03*	0.02	0.00	0.06	-0.03	0.03	-0.08	0.02	-0.07*	0.02	-0.11	-0.03
SD temperature	0.05*	0.01	0.02	0.08	-0.02	0.02	-0.07	0.02	0.01	0.02	-0.03	0.05
SD precipitation	0.05*	0.01	0.02	0.07	0.02	0.02	-0.02	0.06	0.07*	0.02	0.03	0.11
Mean temperature	-0.10*	0.02	-0.14	-0.06	-0.02	0.03	-0.07	0.03	-0.02	0.03	-0.07	0.04
Mean precipitation	-0.09*	0.02	-0.14	-0.05	-0.02	0.04	-0.09	0.06	-0.11*	0.03	-0.17	-0.05
Total Income per ha	0.13*	0.02	0.10	0.16	0.14*	0.02	0.09	0.18	0.11*	0.03	0.06	0.16
Year (t)	-0.02*	0.01	-0.04	-0.01	0.00	0.01	-0.02	0.02	0.04*	0.01	0.02	0.06
Observations (n)	2357				1044				1128			
County (n)	56				38				57			
Farm (n)	512				261				318			
R^2	0.187				0.222				0.519			
WAIC	26,704.05				12,183.29				12,435.64			

Table A.2

Multilevel model results examining the effect of farming practices, subsidies and climate on the variability of calories, showing the posterior means, standard deviation (SD) and 95% credible intervals (CI) of each parameter. Parameters that do not have 0 in the 95% credible interval are deemed important and marked with an "*".

	Cereals	General Cro	pping			Mixed						
Parameter	Posterior mean	SD	95% CI		Posterior me	ean	SD	95% CI	Posterior me	an	SD	95% CI
σ_{county} (county SD)	0.08*	0.03	0.03	0.13	0.08*	0.05	0.01	0.18	0.13*	0.06	0.01	0.26
σ_{farm} (farm SD)	0.31*	0.01	0.28	0.34	0.31*	0.02	0.27	0.36	0.56*	0.03	0.50	0.62
σ_e (SD of residuals)	0.33*	0.01	0.32	0.34	0.34*	0.01	0.33	0.36	0.40*	0.01	0.38	0.42
α (Intercept)	14.65*	0.04	14.58	14.72	14.66*	0.06	14.54	14.76	13.80*	0.07	13.67	13.94
β (Independent vars):												
Input intensity	0.01	0.02	-0.02	0.04	-0.04*	0.02	-0.09	0.00	-0.11*	0.04	-0.19	-0.03
Specialisation	0.10*	0.02	0.07	0.13	0.05*	0.02	0.01	0.10	-0.02	0.03	-0.08	0.05
Area Farmed	-0.04*	0.02	-0.07	-0.01	-0.05*	0.03	-0.11	0.00	-0.10*	0.04	-0.17	-0.03
Direct payments	0.00	0.02	-0.03	0.03	-0.02	0.02	-0.06	0.03	0.02	0.04	-0.06	0.09
Direct payments x year									0.01*	0.01	0.00	0.03
AES payments	0.03*	0.02	0.00	0.06	-0.03	0.02	-0.08	0.01	-0.05*	0.03	-0.10	0.00
SD temperature	0.03*	0.01	0.00	0.05	-0.01	0.02	-0.05	0.04	-0.01	0.02	-0.06	0.03
SD rainfall	0.02	0.01	-0.01	0.04	0.02	0.02	-0.01	0.06	0.02	0.02	-0.02	0.07
Mean temperature	-0.04*	0.02	-0.08	0.00	-0.04	0.02	-0.08	0.01	0.02	0.04	-0.05	0.10
Mean rainfall	0.03	0.02	-0.01	0.07	-0.04	0.03	-0.11	0.03	-0.11*	0.04	-0.19	-0.02
Total Calories per ha	0.17*	0.02	0.13	0.20	0.28*	0.03	0.22	0.33	0.47*	0.04	0.39	0.55
Year (t)	0.02*	0.01	0.01	0.03	0.01	0.01	-0.01	0.03	0.05*	0.01	0.03	0.07
Observations (n)	2357				1044				1128			
County (n)	56				38				57			
Farm (n)	512				261				318			
R^2	0.196				0.227				0.379			
WAIC	71,403.22				31,578.63				33,092.48			

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecolecon.2022.107676.

References

- Barry, P.J., Escalante, C.L., Bard, S.K., 2001. Economic risk and the structural characteristics of farm businesses. Agric. Financ. Rev. 61, 73–86. https://doi.org/ 10.1108/00214760180001117.
- Barzman, M., Bàrberi, P., Birch, A.N.E., Boonekamp, P., Dachbrodt-Saaydeh, S., Graf, B., Hommel, B., Jensen, J.E., Kiss, J., Kudsk, P., Lamichhane, J.R., Messéan, A., Moonen, A.C., Ratnadass, A., Ricci, P., Sarah, J.L., Sattin, M., 2015. Eight principles of integrated pest management. Agron. Sustain. Dev. 35, 1199–1215. https://doi. org/10.1007/s13593-015-0327-9.
- Bradshaw, B., Dolan, H., Smit, B., 2004. Farm-level adaptation to climatic variability and change: crop diversification in the Canadian prairies. Clim. Chang. 67, 119–141. https://doi.org/10.1007/s10584-004-0710-z.
- Bürkner, P.C., 2017. brms: an R package for Bayesian multilevel models using Stan. J. Stat. Softw. 80, 1–28.
- Bürkner, P.C., 2018. Advanced Bayesian multilevel modeling with the R package brms. R J. 10, 395–411. https://doi.org/10.32614/rj-2018-017.
- Butler, E.E., Huybers, P., 2015. Variations in the sensitivity of US maize yield to extreme temperatures by region and growth phase. Environ. Res. Lett. 10 https://doi.org/ 10.1088/1748-9326/10/3/034009.
- Ceglar, A., Toreti, A., Lecerf, R., Van der Velde, M., Dentener, F., 2016. Impact of meteorological drivers on regional inter-annual crop yield variability in France. Agric. For. Meteorol. 216, 58–67. https://doi.org/10.1016/j. agrformet.2015.10.004.
- Chavas, J.P., Cooper, J., Wallander, S., 2019. The impact of input and output decisions on agricultural production risk. J. Agric. Resour. Econ. 44, 513–535. https://doi. org/10.22004/ag.econ.292329.
- Dardonville, M., Urruty, N., Bockstaller, C., Therond, O., 2020. Influence of diversity and intensification level on vulnerability, resilience and robustness of agricultural systems. Agric. Syst. 184 https://doi.org/10.1016/j.agsy.2020.102913.
- de Roest, K., Ferrari, P., Knickel, K., 2018. Specialisation and economies of scale or diversification and economies of scope? Assessing different agricultural development pathways. J. Rural. Stud. 59, 222–231. https://doi.org/10.1016/j. jrurstud.2017.04.013.
- Defra, 2017. Fertiliser usage on farms: Results from the Farm Business Survey England 2015/16.
- Defra, 2020. Farm Business Survey [WWW Document]. URL. https://www.gov.uk/gove rnment/collections/farm-business-survey (accessed 3.20.20).
- Degani, E., Leigh, S.G., Barber, H.M., Jones, H.E., Lukac, M., Sutton, P., Potts, S.G., 2019. Crop rotations in a climate change scenario: short-term effects of crop diversity on resilience and ecosystem service provision under drought. Agric. Ecosyst. Environ. 285, 106625 https://doi.org/10.1016/j.agee.2019.106625.

- Department for Environment Food and Rural Affairs, Department of Agriculture Environment Food and Rural Affairs, Welsh Assembly, The Scottish Government, 2018. Agriculture in the United Kingdom 2017. National Statistics.
- Deryng, D., Conway, D., Ramankutty, N., Price, J., Warren, R., 2014. Global crop yield response to extreme heat stress under multiple climate change futures. Environ. Res. Lett. 9 https://doi.org/10.1088/1748-9326/9/3/034011.
- Dormann, C.F., Elith, J., Bacher, S., Buchmann, C., Carl, G., Carré, G., Marquéz, J.R.G., Gruber, B., Lafourcade, B., Leitão, P.J., Münkemüller, T., Mcclean, C., Osborne, P.E., Reineking, B., Schröder, B., Skidmore, A.K., Zurell, D., Lautenbach, S., 2013. Collinearity: a review of methods to deal with it and a simulation study evaluating their performance. Ecography (Cop.) 36, 27–46. https://doi.org/10.1111/j.1600-0587.2012.07348.x.
- Duru, M., Therond, O., Martin, G., Martin-Clouaire, R., Magne, M.A., Justes, E., Journet, E.P., Aubertot, J.N., Savary, S., Bergez, J.E., Sarthou, J.P., 2015. How to implement biodiversity-based agriculture to enhance ecosystem services: a review. Agron. Sustain. Dev. 35, 1259–1281. https://doi.org/10.1007/s13593-015-0306-1.
- El Benni, N., Finger, R., Mann, S., 2012. Effects of agricultural policy reforms and farm characteristics on income risk in Swiss agriculture. Agric. Financ. Rev. 72, 301–324. https://doi.org/10.1108/00021461211277204.
- Enjolras, G., Capitanio, F., Aubert, M., Adinolfi, F., 2014. Direct payments, crop insurance and the volatility of farm income. Some evidence in France and in Italy. New Medit 13, 31–40.
- European Environment Agency, 2005. Agriculture and Environment in EU-15 The IRENA indicator Report. Copenhagen, Denmark.
- FAO, 2006. Food Security (No. Issue 2).

FAO, 2021. FAO Food Balance Sheet [WWW Document]. FAOSTAT. URL. http://www. fao.org/faostat/en/#data/FBS (accessed 2.26.21).

- Fischer, E.M., Schär, C., 2009. Future changes in daily summer temperature variability: driving processes and role for temperature extremes. Clim. Dyn. 33, 917–935. https://doi.org/10.1007/s00382-008-0473-8.
- Fischer, E.M., Rajczak, J., Schär, C., 2012. Changes in European summer temperature variability revisited. Geophys. Res. Lett. 39, 1–8. https://doi.org/10.1029/ 2012GL052730.

Gaudin, A.C.M., Tolhurst, T.N., Ker, A.P., Janovicek, K., Tortora, C., Martin, R.C., Deen, W., 2015. Increasing crop diversity mitigates weather variations and improves yield stability. PLoS One 10, 1–20. https://doi.org/10.1371/journal.pone.0113261.

Gebbers, R., Adamchuk, V.I., 2010. Precision agriculture and food security. Science 327, 828–831. https://doi.org/10.1126/science.1183899.

Gelman, A., 2006. Prior distributions for variance parameters in hierarchical models. Bayesian Anal. 1, 515–534.

Gelman, A., Rubin, D.B., 1992. Inference from iterative simulation using multiple sequences. Stat. Sci. 7, 457–472. https://doi.org/10.1214/ss/1177011136.

Gelman, A., Goodrich, B., Gabry, J., Vehtari, A., 2019. R-squared for Bayesian regression models. Am. Stat. 73, 307–309. https://doi.org/10.1080/00031305.2018.1549100.

- Gerrard, C.L., Padel, S., Moakes, S., 2012. The use of farm business survey data to compare the environmental performance of organic and conventional farms. Int. J. Agric. Manag. 2, 5–16. https://doi.org/10.5836/ijam/2013-01-02.
- Griggs, D., Stafford-Smith, M., Gaffney, O., Rockström, J., Öhman, M.C., Shyamsundar, P., Steffen, W., Glaser, G., Kanie, N., Noble, I., 2013. Sustainable development goals for people and planet. Nature 495, 305–307. https://doi.org/ 10.1038/495305a.
- Harkness, C., Semenov, M.A., Areal, F., Senapati, N., Trnka, M., Balek, J., Bishop, J., 2020. Adverse weather conditions for UK wheat production under climate change. Agric. For. Meteorol. 282–283, 107862 https://doi.org/10.1016/j. agrformet.2019.107862.
- Harkness, C., Areal, F.J., Semenov, M.A., Senapati, N., Shield, I.F., Bishop, J., 2021. Stability of farm income: the role of agricultural diversity and agri-environment scheme payments. Agric. Syst. 187, 103009 https://doi.org/10.1016/j. agsv.2020.103009.
- He, C., Li, T., 2019. Does global warming amplify interannual climate variability? Clim. Dyn. 52, 2667–2684. https://doi.org/10.1007/s00382-018-4286-0.
- Hoffman, M.D., Gelman, A., 2014. The no-U-turn sampler: adaptively setting path lengths in Hamiltonian Monte Carlo. J. Mach. Learn. Res. 15, 1593–1623.
- Hollis, D., McCarthy, M., Kendon, M., Legg, T., Simpson, I., 2019. HadUK-grid—A new UK dataset of gridded climate observations. Geosci. Data J. 6, 151–159. https://doi. org/10.1002/gdj3.78.
- Kendon, M., Marsh, T., Parry, S., 2013. The 2010-2012 drought in England and Wales. Weather 68, 88–95. https://doi.org/10.1002/wea.2101.
- Kennedy, C.M., Lonsdorf, E., Neel, M.C., Williams, N.M., Ricketts, T.H., Winfree, R., Bommarco, R., Brittain, C., Burley, A.L., Cariveau, D., Carvalheiro, L.G., Chacoff, N. P., Cunningham, S.A., Danforth, B.N., Dudenhöffer, J.H., Elle, E., Gaines, H.R., Garibaldi, L.A., Gratton, C., Holzschuh, A., Isaacs, R., Javorek, S.K., Jha, S., Klein, A. M., Krewenka, K., Mandelik, Y., Mayfield, M.M., Morandin, L., Neame, L.A., Otieno, M., Park, M., Potts, S.G., Rundlöf, M., Saez, A., Steffan-Dewenter, I., Taki, H., Viana, B.F., Westphal, C., Wilson, J.K., Greenleaf, S.S., Kremen, C., 2013. A global quantitative synthesis of local and landscape effects on wild bee pollinators in agroecosystems. Ecol. Lett. 16, 584–599. https://doi.org/10.1111/ele.12082.
- Kipling, R.P., Bannink, A., Bellocchi, G., Dalgaard, T., Fox, N.J., Hutchings, N.J., Kjeldsen, C., Lacetera, N., Sinabell, F., Topp, C.F.E., van Oijen, M., Virkajärvi, P., Scollan, N.D., 2016. Modeling European ruminant production systems: facing the challenges of climate change. Agric. Syst. 147, 24–37. https://doi.org/10.1016/j. agsv.2016.05.007.
- Lawes, R.A., Kingwell, R.S., 2012. A longitudinal examination of business performance indicators for drought-affected farms. Agric. Syst. 106, 94–101. https://doi.org/ 10.1016/j.agsy.2011.10.006.
- Lechenet, M., Dessaint, F., Py, G., Makowski, D., Munier-Jolain, N., 2017. Reducing pesticide use while preserving crop productivity and profitability on arable farms. Nat. Plants 3. https://doi.org/10.1038/nplants.2017.8.
- Lee, R., den Uyl, R., Runhaar, H., 2019. Assessment of policy instruments for pesticide use reduction in Europe; learning from a systematic literature review. Crop Prot. 126, 104929 https://doi.org/10.1016/j.cropro.2019.104929.
- Lefebvre, M., Langrell, S.R.H., Gomez-y-Paloma, S., 2015. Incentives and policies for integrated pest management in Europe: a review. Agron. Sustain. Dev. 35, 27–45. https://doi.org/10.1007/s13593-014-0237-2.
- Lin, B.B., 2011. Resilience in agriculture through crop diversification: adaptive management for environmental change. Bioscience 61, 183–193. https://doi.org/ 10.1525/bio.2011.61.3.4.
- Lin, B.B., Flynn, D.F.B., Bunker, D.E., Uriarte, M., Naeem, S., 2011. The effect of agricultural diversity and crop choice on functional capacity change in grassland conversions. J. Appl. Ecol. 48, 609–618. https://doi.org/10.1111/j.1365-2664.2010.01944.x.
- Nalborczyk, L., Batailler, C., Loevenbruck, H., Vilain, A., Bürkner, P.C., 2019. An introduction to bayesian multilevel models using brms: a case study of gender effects

on vowel variability in standard Indonesian. J. Speech Lang. Hear. Res. 62, 1225–1242. https://doi.org/10.1044/2018_JSLHR-S-18-0006.

- Neal, R.M., 2011. MCMC using hamiltonian dynamics. In: Handbook of Markov Chain Monte Carlo. https://doi.org/10.1201/b10905-6.
- OECD, 2009. Managing risk in agriculture: A holistic approach. In: Managing Risk in Agriculture: A Holistic Approach. https://doi.org/10.1787/9789264075313-en.
- ONS, 2020. Consumer Price Inflation Time Series (MM23) [WWW Document]. URL. htt ps://www.ons.gov.uk/economy/inflationandpriceindices/timeseries/d7bt/mm23 (accessed 3.20.20).
- Ottoy, S., Angileri, V., Gibert, C., Paracchini, M.L., Pointereau, P., Terres, J.M., Van Orshoven, J., Vranken, L., Dicks, L.V., 2018. Impacts of selected ecological focus area options in European farmed landscapes on climate regulation and pollination services: a systematic map protocol. Environ. Evid. 7, 1–10. https://doi.org/ 10.1186/s13750-018-0122-6.
- Pacín, F., Oesterheld, M., 2014. In-farm diversity stabilizes return on capital in argentine agro-ecosystems. Agric. Syst. 124, 51–59. https://doi.org/10.1016/j. agsv.2013.10.008.
- Popp, J., Peto, K., Nagy, J., 2013. Pesticide productivity and food security. A review. Agron. Sustain. Dev. 33, 243–255. https://doi.org/10.1007/s13593-012-0105-x.
- Porter, J.R., Xie, L., Challinor, A.J., Cochrane, K., Howden, S.M., Iqbal, M.M., Lobell, D. B., Travasso, M.I., 2014. Food security and food production systems. In: Field, C.B., Barros, V.R., Dokken, D.J., Mach, K.J., Mastrandrea, M.D. (Eds.), Climate Change 2014 Impacts, Adaptation, and Vulnerability. Part a: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, pp. 485–534. https://doi.org/ 10.1017/CB09781107415379.012.
- Powell, J.P., Reinhard, S., 2015. Measuring the effects of extreme weather events on yields. Weather Clim. Extrem. 12, 69–79. https://doi.org/10.1016/j. wace.2016.02.003.
- R Core Team, 2019. R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna, Austria.
- Reidsma, P., Ewert, F., Oude Lansink, A., 2007. Analysis of farm performance in Europe under different climatic and management conditions to improve understanding of adaptive capacity. Clim. Chang. 84, 403–422. https://doi.org/10.1007/s10584-007-9242-7.
- Reidsma, P., Ewert, F., Oude Lansink, A., Leemans, R., 2009. Vulnerability and adaptation of European farmers: a multi-level analysis of yield and income responses to climate variability. Reg. Environ. Chang. 9, 25–40. https://doi.org/10.1007/ s10113-008-0059-3.
- Roberts, T.L., 2008. Improving nutrient use efficiency. Turkish J. Agric. For. 32, 177–182. https://doi.org/10.3906/tar-0801-9.
- Severini, S., Tantari, A., Di Tommaso, G., 2016. Do CAP direct payments stabilise farm income? Empirical evidences from a constant sample of Italian farms. Agric. Food Econ. 4 https://doi.org/10.1186/s40100-016-0050-0.
- Snijders, T.A.B., Bosker, R.J., 1999. Multilevel Analysis an Introduction to Basic and Advanced Multilevel Modeling. SAGE Publications Ltd, London, UK.
- Stan Development Team, 2020. Stan Reference Manual [WWW Document]. URL. https://mc-stan.org/.
- van den Pol-van Dasselaar, A., Hennessy, D., Isselstein, J., 2020. Grazing of dairy cows in europe-an in-depth analysis based on the perception of grassland experts. Sustain. 12 https://doi.org/10.3390/su12031098.
- Varah, A., Ahodo, K., Coutts, S.R., Hicks, H.L., Comont, D., Crook, L., Hull, R., Neve, P., Childs, D.Z., Freckleton, R.P., Norris, K., 2020. The costs of human-induced evolution in an agricultural system. Nat. Sustain. 3, 63–71. https://doi.org/10.1038/ s41893-019-0450-8.
- Wolf, S.A., Wood, S.D., 1997. Precision farming: environmental legitimation, commodification of information, and industrial coordination. Rural. Sociol. 62, 180–206. https://doi.org/10.1111/j.1549-0831.1997.tb00650.x.