Agricultural Systems 234 (2026) 104677

Contents lists available at ScienceDirect

Agricultural Systems

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

Research Paper

Diversification and policy options for risk management in arable farming

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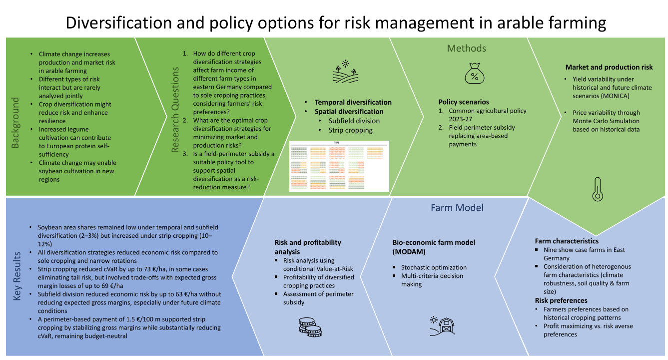
HIGHLIGHTS

- Diversification effects depend on farm type, climate, and risk preferences.
- Sole cropping shows highest tail risk, esp. for large vulnerable farms.
- Smaller field units result in lower risk without gross margin loss despite higher labor demand.
- Strip cropping reduces conditional Value-at-Risk, needing policy support for economic viability.

GRAPHICAL ABSTRACT



ARTICLE INFO

Editor: Carlos Parra-López

Keywords:
Bio-economic farm modeling
Soybean integration
Stochastic optimization
Strip cropping

ABSTRACT

Background: Agricultural production is highly susceptible to weather-related uncertainties, which are expected to increase due to climate change. While most studies address production risks, market risks are often overlooked despite their growing impact on farm income. Crop diversification is a strategy to reduce both production and market risks.
Objectives: This study investigates how temporal and spatial diversification strategies influence farm incomes and risk exposure across different arable farm types in Eastern Germany.
Methods: A stochastic bio-economic farm model (MODAM) was implemented to optimize decision-making. The farm model integrates yield variability from a crop growth model and market volatility through Monte Carlo simulations of crop and fertilizer prices. Nine showcase farms were analyzed under three diversification strategies: temporal diversification, subfield division, and strip cropping, against narrow rotations with sole cropping. All diversification strategies included (among other crops) soybean cultivation. The model assessed two climate scenarios (1990–2020 and 2020–2060) and two policy environments: the CAP 2023 area payment system and a novel premium, paid based on the field perimeter, promoting smaller field units.
Results: Soybean integration into cereal dominated cropping systems was limited under temporal and subfield diversification but increased with strip cropping.
Expected gross margins improved under future climate conditions compared to historical conditions across all strategies.

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https://doi.org/10.1016/j.agsy.2026.104677
Received 5 August 2025; Received in revised form 29 January 2026; Accepted 6 February 2026
Available online 26 February 2026

Diversification consistently reduced economic risk relative to narrow rotations and sole cropping, with subfield division and strip cropping showing the most substantial effects. Strip cropping reduced economic risk but involved higher trade-offs.
Subfield division significantly reduced economic risk without sacrificing gross margins, especially under risk-averse behavioral preferences and future climate scenarios.
A modest perimeter-based payment (1.5 €/100 m length of field edge) replacing area-based premiums helped maintain gross margins under strip cropping while significantly reducing the conditional-Value-at-Risk.
Conclusions: Spatial diversification like subfield division and strip cropping, are effective in mitigating farm income risks under climatic and market uncertainty. Policy instruments such as perimeter-based payments can enhance these effects.

1. Introduction

Agricultural production depends on weather conditions, compelling farmers to adapt to unpredictable risks beyond their immediate control. Many of these production risks are expected to increase under climate change, putting farm incomes and staple food production at risk (Lobell and Di Tommaso, 2025).

Loss of crop pollinators loss (Vasiliev and Greenwood, 2021), alterations in beneficial soil microbes (Singh et al., 2019), increased pest outbreaks (Sharma and Prabhakar, 2014), and increased pathogen load (Garrett et al., 2014) exemplify the biotic stresses of current agriculture. At the same time abiotic stresses such as changes in precipitation and temperature, impact growing conditions, including droughts and floods (Lehner et al., 2006). Extreme, i.e. rare and short-lived climate events are likely to become more frequent and intense (Hasegawa et al., 2021).

As a result, crop yields are expected to decline under climate change in large parts of the world, including some of the most relevant crops such as wheat, rice, maize and soybean (Zhao et al., 2017).

While the majority of studies focus primarily on production risk, studying several risks simultaneously including market risk is often being neglected (Komarek et al., 2020). Only a limited number of studies take market risks into account when investigating climate risk and potential adaptation strategies (Gurgel et al., 2021; Nelson et al., 2014).

Crop diversification is often referred to as one approach to face production and market risk simultaneously and thereby enhance agricultural resilience. By cultivating a variety of crops, farmers can mitigate the impact of adverse weather conditions, pests, and diseases that might disproportionately affect a single crop. Diversification not only helps spread risk but also promotes ecosystem health, reduces vulnerability to market fluctuations, and might enhance overall agricultural sustainability. One ecological benefit often associated with crop diversification, especially the inclusion of catch crops, oilseed rape (Beillouin et al., 2021b) or legumes such as soybeans (Pasley et al., 2021) is a reduction in nitrate leaching.

European countries are currently highly dependent on plant-protein imports. The European Union aimed to reduce the dependency on protein imports by supporting European grown protein plants (European Commission, 2023). So far legume production only makes up a small share (<2%) of European arable land. However, integrating legumes into agricultural systems could reduce the need for nitrogen fertilizer, decrease nitrate leaching (Notz et al., 2023a) and reduce greenhouse gas emissions (Rotundo et al., 2024). Compared to other legumes, soybeans offer higher protein quality and high digestibility. They are therefore highly valuable as livestock feed and for human consumption (Notz et al., 2023b). With changing climatic conditions increasing areas in central Europe might become available for soybean production due to e.g. longer growing periods (Nendel et al., 2023).

The term crop diversification can describe a variety of agricultural practices, including improved genetic diversity within one species, spatial or temporal diversification, agroforestry, landscape diversity (Beillouin et al., 2021a). This study investigates the economic implications regarding risk and income and the ecological effects of three diversification strategies compared to a sole cropping management under historical and future climate conditions. The investigated management strategies include temporal diversification (enhancing crop rotations through the integration of soybeans into cereal-dominated systems) and two approaches to spatial diversification: the division of field blocks into smaller subfields, and the application of a systematic spatial arrangement in which fields are divided into 12-m-wide strips.

These diversification approaches are evaluated within the framework of spatio-temporal crop system design, considering both natural and socioeconomic factors that influence agricultural diversity (Sjulgård et al., 2022). The study's methodology aligns with current research emphasizing the importance of understanding both spatial and temporal changes in crop species diversity at various scales, while addressing the growing need for resilient and sustainable agricultural systems that can adapt to changing climate conditions (Hufnagel et al., 2020; Reckling et al., 2023). Considering market and production risks simultaneously fills the research gap of studies considering multiple climate related risk factors. The bio-economic farm model applied in this study is a multi-criteria decision optimization. The effect of crop diversification on economic risk is considered with respect to different farmers preferences and climate scenarios. The following research questions are being addressed:

1) How do different crop diversification strategies affect the farm incomes of different farm types in eastern Germany compared to sole cropping practices, considering farmers' risk preferences?
2) What are the optimal crop diversification strategies for minimizing market and production risks in arable farms in eastern Germany?
3) Is a field-perimeter subsidy a suitable policy tool to support spatial diversification as a risk-reduction measure?

2. Methods

2.1. Study region and farm types

Nine anonymized showcase farms have been selected all located in the east of Germany within the counties Märkisch Oderland (MOL) and Oder-Spree (LOS). Both counties lie in some of the driest regions of Germany (DWD). Crop production in the area is highly affected by climate change (Kersebaum and Nendel, 2014). The average precipitation in both counties is below the German national average (DWD) with on average 550 mm annual rainfall and a negative water balance. As climate change progresses, heavy precipitation in winter and high temperatures in the summer months are predicted (Czettritz et al., 2023).

Farm characteristics are based on the Integrated Administration and Control System (IACS) dataset (DFBK, 2023). IACS is a national information service tool for agricultural subsidy application. The dataset includes field and farm characteristics as well as the annual cropping patterns. For this study we considered the 442 farms located in the district Oder-Spree (LOS) and the 561 farms in Märkisch-Oderland (MOL). Respectively 212 and 344 of these farms were specialized arable farms. The average farm size for arable farms in the two districts was 237 ha with the biggest farm being above 2500 ha. The farms were separated into three farm size categories (small, medium, and large) based on the official national farm classification (§163 (3) BewG). Farms with a size below 40 ha were counted as small. In order to only include farms with the potential to implement a three-year crop rotation, farms with less than three field blocks were excluded. Farms with 40 ha until 100 ha were defined as medium. All farms with more than 100 ha were categorized as large farms. Based on this classification 93 farms were small (232 farms including farms with less than three field blocks), 73 were medium, and 205 large farms.

For each of the size categories, one farm with a high and one with a low share of climate-robust arable land, but similar characteristics otherwise, was chosen (Table 1 – the title "robust" stands for a high while "vulnerable" stands for a low share of climate robust field blocks). The classification of climate-robust was taken from "Classification of agricultural priority and reserved areas in Brandenburg under consideration of bio-economic climate simulations" (Czettritz et al., 2023). Climate robust in this context refers to areas which are expected to generate relatively stable gross margins even in the least productive years. Across the full farm dataset, the share of climate-robust land per farm ranges from 0% to 100%, with a median of 59% (Table 1). When looking at the classification into robust and vulnerable farms it should be kept in mind that it is based on a modeling approach similar to this study. This previous study comes with its own limitations, e.g. market risk has not been considered. However, the classification of vulnerable and robust farms appears to be appropriated within its limits as we can see a major difference in cVaR between the vulnerable and robust farms, especially for medium and large farms (Table 8).

Due to other factors, such as changes in precipitation, the areas with the highest soil quality index are not necessarily the most robust under future climate conditions (Czettritz et al., 2023). In order to ensure a relatively big variance in climate robustness but comparability in terms of soil quality, farm size and number of fields per farm, the Euclidean distance was estimated to generate a distance matrix for all farms. The matrix quantifies the similarity between each pair of farms. An iterative process was then employed to systematically evaluate all unique pairs, identifying the pair with the smallest distance (indicating maximum similarity in terms of farm size, number of field blocks and soil quality) while simultaneously maximizing the difference in climate robustness.

The average soil index for small farms is 32.65, for medium farms 31.09 and for large farms slightly higher with 35.73. The index goes from 0 to 100 indicating the quality of agricultural soils with 100 being the most productive soils in Germany (Schmitz, 2020). However, the selected farm pairs based on the Euclidean distance are below the average soil index for small and medium farms. Therefore, an additional farm has been selected for each size category which is closest to the mean for all selection criteria, including the climate robustness.

Despite a variety of farm types in the study region, this study is limited to specialized arable farms, making up approximately 61% of farms in Märkisch-Oderland and only 48% of farms in Oder-Spree (DFBK, 2023). Focusing on arable farms leads to an underestimation

Table 1
Summary of showcase farms. Including the farm size [ha], the number of field blocks, average soil index (Schmitz, 2020) and the share of climate robust arable land based on v. Czettritz et al. (2023).

Showcase farm size & climate-robustness	Farm size [ha]	Number of field blocks	Average soil index	Share of robust [%]
Small & robust	15	3	43	99
Small & vulnerable	11	3	42	0
Small & median	13	5	31	57
Medium & vulnerable	48	7	26	0
Medium & median	57	12	29	50
Medium & robust	45	9	26	83
Large & median	891	46	45	64
Large & robust	236	25	31	80
Large & vulnerable	240	19	22	7

of the importance of fodder production. Additional to livestock, the model does not include a biogas power plant. To ensure that the effected crops are cultivated in the resulting cropping patterns, a monetary value has been assigned to silage maize and soybean. However, ensuring energy production and affordable fodder plants might increase the importance of these plants under uncertainty beyond the monetary value represented in the model.

2.2. Crop sequences

Soil type specific crop rotations for the four management scenarios were developed based on empirical data and adapted for each management scenario. Soils were classified in five types ("Landbaugebiete") according to State Office for Rural Development, Agriculture, and Land Consolidation (Hanff and Lau, 2021) where type 1 refers to the most and 5 to the least productive soils (Tables 2 and 3). Cropping patterns vary widely between the five different soil types, identifying the sequences (rotations) separately therefore leads to a better representation of empirical cropping patterns.

For the sole cropping management practice (baseline management practice without diversification strategy) cropping data from the years 2018 to 2021 for the study area was used to determine the most common crop sequences, to best represent the current established practice (IACS 2018–2021). For each soil type, the five most common crop combinations over the four-year period were determined. In a second step for each combination of crops, the most common sequence was determined, and validated by experts to ensure plausibility and consistency. Sequences containing the same crop in three out of four crops have been excluded resulting in three to four crop sequences (hereafter called "rotations") per soil type (Table 1).Crop diversity and the number of viable rotations decline on higher-quality soil. For the diversification strategies, soybeans were integrated into the existing crop rotations on soil types 1–3. Due to the growth conditions, soybean cannot be cultivated on soil types 4 and 5.

Soil type-specific crop rotations were also developed for the strip cropping strategy with two example fields throughout four years (Table 4). Each column represents an image of the field showing the different strips cultivated in one year from above (see Thompson et al., 2025 as an example).

The model enforces strict rotational constraints over time. Once a rotation is chosen, it must be followed in subsequent years. However, fields can be converted to fallow at any point. While the rotational restrictions limit the flexibility compared to real-world farm management, it ensures consistent rotational sequences across the modeled period covering 30 years. Most importantly it allows for the yield data from the crop growth model to account for rotational effects on yield throughout the years and consistent modeling of nitrate leaching and water effects throughout the time series data.

2.3. Production risk

Yield and nitrate leaching levels and variation have been modeled by the crop growth model MONICA ("MOdel of Nitrogen and Carbon dynamics in Agro-ecosystems"). Crop calibrations have been based on previous implementations of the model (Söder et al., 2022; Yu et al., 2025).

The simulations are based on climate data for a 1 km raster with weather data covering the period from 1901 to 2022. The baseline scenario used in this study covers the period from 1990 to 2020. For future climate projections, global climate data from various General Circulation models (ICHEC-EC-EARTH, MOHC-HadGEM2-ES, MPI-M-MPI-ESM-LR) was downscaled by Reginal Climate models (CLMcom-CCLM4–8-17, KNMI-RACMO22E, SMHI-RCA4, MPI-CSC-REMO2009, UHOH-WRF361H). The two future climate scenarios cover the period from 2020 to 2060 under RCP 2.6 and RCP 8.5 with a 1 km resolution. RCP 2.6 represents the low greenhouse emissions in the future, and RCP

Table 2
Most established crop rotations in the case study region (IACS 2018–2021) (left) and temporal diversification including soybean (right). WRA: Winter rapeseed, WW: winter wheat, SM: silage maize, WR: winter rye, WB: winter barley, SB: soybean.

	Most established rotations											Temporal diversification
Year\soil type	1–2				3–4				5			1–3
1	WRA	SM	WW	WW	WRA	SM	WW	WRA	WRA	SM	WR	SM
2	WW	WW	WB	SM	WW	WR	WRA	WB	WR	WR	SM	SB
3	SM	SM	WRA	WB	SM	SM	WW	SM	SM	SM	WR	WW
4	WW	WW	WW	WRA	WW	WR	SM	WR	WR	WR		WRA

Table 3
Strip cropping and crop rotation for soil type 1 to 3 (left) and soil type 4 to 5 (right) throughout a four-year period. Each column can be interpreted as an aerial image of the field showing the stripe arrangement from above. WRA = Winter rapeseed, WW = winter wheat, SB = soybean, SM = silage maize, WR = winter rye.

Strip \ year	1	2	3	4	Strip \ year	1	2	3	4
Strip 1	WRA	WW	SB	WW	**Strip 1**	WRA	WR	SM	WR
Strip 2	WW	WRA	WW	SB	**Strip 2**	WR	WRA	WR	SM
Strip 3	SB	WW	WRA	WW	**Strip 3**	SM	WR	WRA	WR
Strip 4	WW	SB	WW	WRA	**Strip 4**	WR	SM	WR	WRA
Strip 5	SM	WW	SB	WW					
Strip 6	WW	SM	WW	SB					

Table 4
Area weighted mean yield in dry mass under historical (1990–2020) and future (2020–2060) climate conditions. Mean (area weighted average), min-max (minimum and maximum value throughout all fields). Empirical mean: area weighted average based on Hanff and Lau, 2021.

	HANFF	MONICA					
	Empirical t/ha	Historical t/ha			Future t/ha		
	Mean	Mean	Min	Max	Mean	Min	Max
Silage maize	7.71	6.51	2.95	10.99	7.18	2.99	10.84
Soybean*	2.06	2.53	1.37	3.86	3.02	1.78	4.53
Winter barley	4.82	4.88	2.42	6.56	5.24	1.97	7.67
Winter rape	2.83	3.31	1.66	4.12	3.6	1.83	4.37
Winter rye	4.43	3.40	1.57	5.74	3.69	1.65	5.87
Winter wheat	5.04	4.94	2.26	7.11	5.6	2.36	7.74

* Data from a multi-environment field experiments across Brandenburg (Omari et al., 2025).

8.5 is considered as the high-emission scenario where greenhouse gas emission continue to increase throughout the 21st century (IPCC, 2019). Despite the weather and climatic conditions, both models consider detailed soil conditions based on five soil grades (LBG). Management including sowing and harvesting time windows, nitrogen application rates and timing have been fixed based on Czettritz et al., 2023. Soil initial moisture conditions have been set to field capacity for each soil grade. The simulated yield was used as input for the bio-economic model MODAM.

MONICA simulates crop yields based on a wide range of factors, including detailed soil characteristics and weather conditions across multiple climate scenarios. However, it does not account for short-term extreme weather events, such as droughts, heavy rainfall or flooding, which are projected to become more frequent under future climate conditions (Hasegawa et al., 2021). As a result, the model tends to simulate higher yields under future scenarios due to more favorable average temperatures and higher winter precipitation. While MONICA's simulated yields generally align well with empirical data, rye is an exception. For winter rye, the simulations were most pessimistic with an underprediction of 0.78 t/ha under historical conditions, causing a relatively low share of rye production compared to empirical cropping patterns. However, the lower yields could partly be offset by farmers' adapting the variable costs (reducing fertilizers, pesticides and growth regulators) to the lower expected yield level.

2.4. Management strategies

Four management strategies are compared in this study (Fig. 1).
Baseline:

1) **'Sole cropping'** refers to the cultivation of a single crop per year in a simple crop rotation (every year another crop), allowing for the cultivation of only one crop per field block.

Temporal diversification:

2) Enhancement of crop rotations through the integration of soybeans, which aligns with the principle of extending growing seasons and improving soil health through diversified crop sequences (Guinet et al., 2023). However, the field block size stays equal to the 'sole cropping' management strategy, with the cultivation of one crop per field block each year.

Spatial diversification:

3) **Subfields**: Dividing field blocks into smaller subfields contributes to enhanced biodiversity and increased ecosystem services at the landscape level. Changing the number of field units by almost 3 times from 129 to on average 350 field blocks.
4) **Strip cropping**: Application of a systematic spatial arrangement where fields are divided into 12-m-wide strips, following contemporary strip cropping design principles that optimize both agronomic performance and ecological benefits (Juventia et al., 2022). Where 12 m are equal to the working width of widely established machinery, reducing the need for the investment of new technology. The same soil type specific crop rotation, including soybean, is cultivated within all stripes. Through rotating starting crops, the same crop is never cultivated on neighboring strips. The strips are cultivated in an order maximizing the distance to the next strip with the same crop, increasing natural barriers. It is assumed farms divide fields along their longest side to maximize strip length.

The Shannon Evenness Index (SEI) is used to compare the diversification level of each management strategy. SEI is a normalized measure derived from the Shannon Diversity Index taking into account the dis-

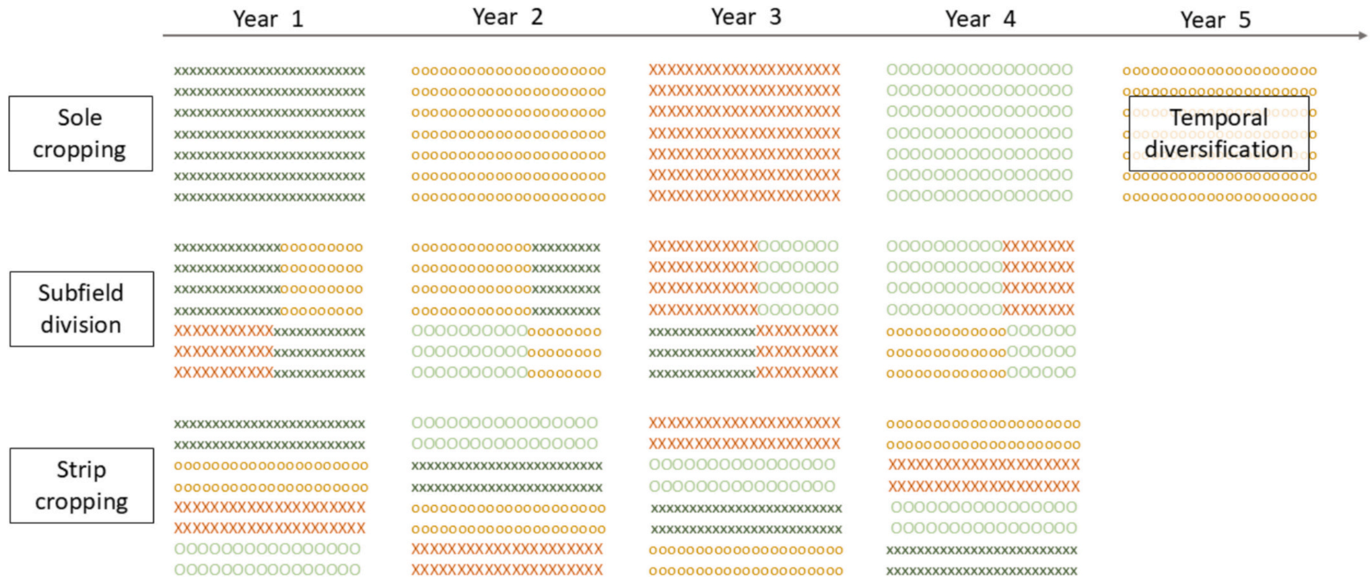

Fig. 1. Overview of the spatial and temporal structure of the four modeled management strategies. Sole cropping and Temporal diversification follow conventional single-crop field use. Subfield division introduces within-field diversification, while strip cropping arranges crops in 12-m strips.

tribution of the different crop types. It is estimated as ($SEI = \frac{H'}{\log(k)}$ where $H' = -\sum p_i log(p_i)$) where p_i is the proportion of total area covered by crop and k is the number of unique crops. The index ranges from 0 one sole crop is cultivated on all fields and 1 evenly distributed of all crops (Payne et al., 2005).

2.5. Costs and prices

Variable costs and labor demand are soil type specific and based on regional data from Hanff and Lau (2021). Soybean cultivation is currently not widely established in the state of Brandenburg. The data set is therefore missing detailed cost data for soybean production. Labor requirements and variable costs of other more commonly cultivated legumes in the region, serve as a proxy for soybeans (See Table 5). The overall wage level is set at 17 euros per hour(Hanff and Lau, 2021). The annual amount of available family labor is set at 2300 h, assuming a 48 h/week, 52 weeks and around 30 holidays and sick leave (Reith, 2018). The MONICA model predicts relatively low rye yields across all scenarios. In order to account for farmers adapting their management practice to the low expected yield, variable costs and labor demand for soil type 1–3 have been adapted to the level of soil type 4 when cultivating rye.

Cultivating smaller units as in the subfield division and strip cropping strategy have a higher labor demand due to scale effects. For these two management practices the labor demand has been increased by 65% based on the average change in labor demand between 40 ha and 1 ha field blocks (KTBL, 2025).

Historical fertilizer and output price series were used to develop price scenarios accounting for market risks over the 30-year time span. Based on 10 years, starting 2010, producer prices for crops and mineral fertilizer (NPK) a Monte Carlo Simulation was used to generate three different price scenarios.

The historical crop price data for winter rapeseed, silage maize and cereals are based on state specific data for Brandenburg collected by the Mecklenburg-Western Pomerania State Office for Agriculture, Food Safety and Fisheries (Landesamt für Landwirtschaft, Lebensmittelsicherheit und Fischerei Mecklenburg-Vorpommern). The data for mineral fertilizer comes from the same data source, however due to data lacks in the state specific dataset, an average value for all eastern German states was used.

Compared to other crops, the soybean market is more fragmented and less transparent (Kezeya et al., 2018). For this reason, access to time-series data for soybeans is more difficult. Price data for soybeans were supplemented based on calculations within the LeguNet project (Kezeya et al., 2023). The calculations are based on data collected by Agrarmarkt Informations-Gesellschaft mbH (AMI).

Based on the empirical timeseries data, a Monte Carlo simulation for each commodity has been transformed with 1000 iterations (times 30 years) each. The resulting median for each commodity was used as the moderate price scenario, while the 40 and 60% quantiles were used as low and high price scenario (Fig. 2). The aim of the price scenarios is not to provide a reliable forecast, but to create coherent price variation scenarios in order to be able to analyze the influence of the various management practices on farm income in the face of price uncertainty.

A Monte Carlo simulation based on historical mineral fertilizer prices from 2010 to 2020 was conducted for urea (N), triple superphosphate (P), and potassium chloride (K), using baseline prices of 0.78 €/dt (N), 1.60 €/dt (P), and 0.73 €/dt (K), and historical volatilities of 19.9% for N, 12.5% for P, and 6.6% for K, based on data collected by the

Table 5
Average variable costs, excluding labor and fertilizer costs [€/ha] and labor demand for sole cropping practices [h/ha] based on Hanff and Lau, 2021.

Crop	Variable cost [€/ha]					Labor demand [h/ha]				
Soil index	1	2	3	4	5	1	2	3	4	5
Silage maize	1041	954	877	792	677	4h32m	4h18m	4h11m	4h00m	4h00m
Soybean	823	752	679	626	577	2h25m	2h21m	2h21m	2h18m	2h14m
W. barley	820	715	627	535	481	2h53m	2h46m	2h42m	2h32m	2h25m
Oilseed rape	958	859	735	615	553	2h56m	2h53m	2h35m	2h25m	2h25m
W. rye	484	484	484	484	417	2h25m	2h25m	2h25m	2h25m	2h18m
W. wheat	865	754	635	542	488	3h07m	2h53m	2h39m	2h28m	2h21m

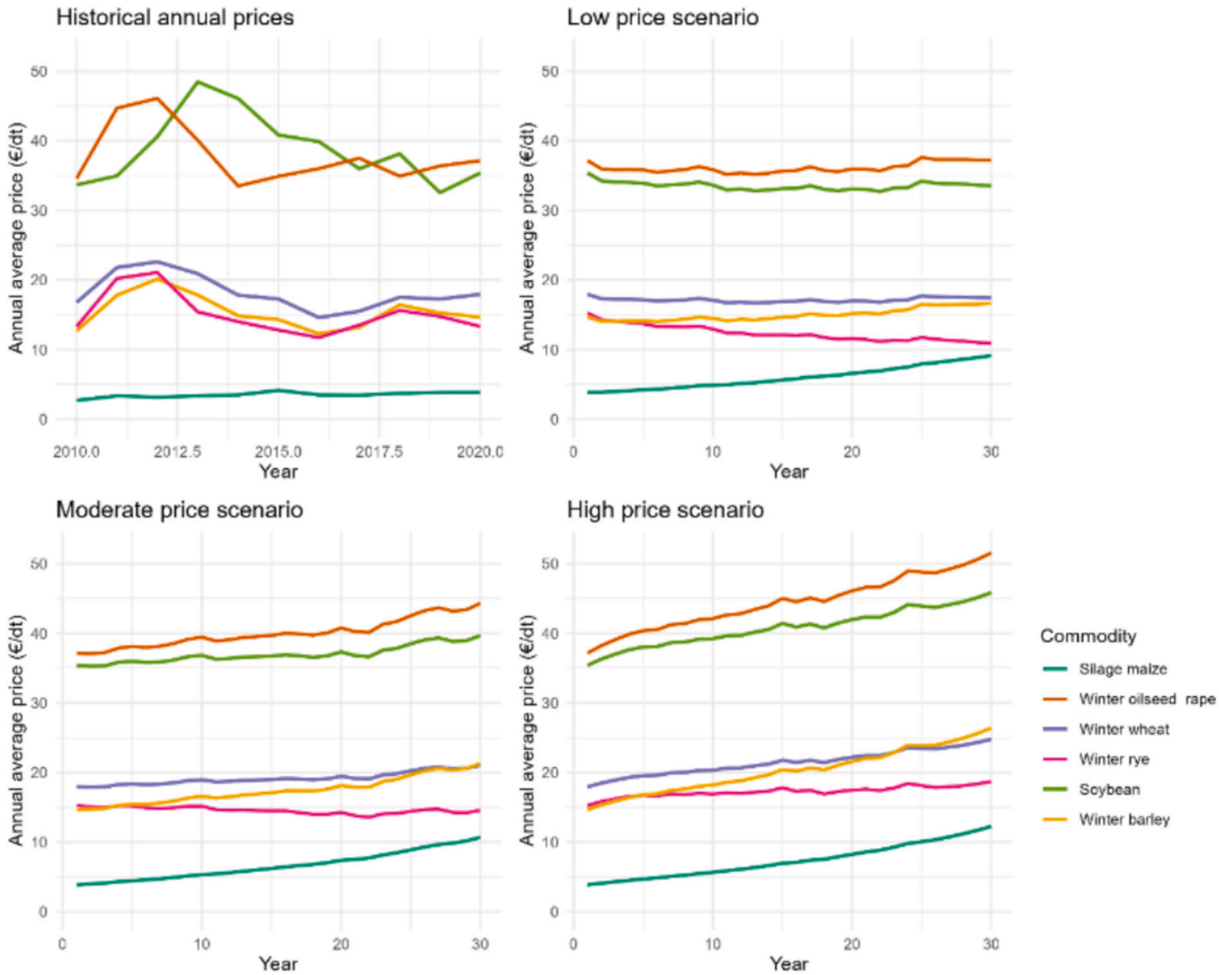

Fig. 2. Historical crop prices (2010–2020) (Landesamt für Landwirtschaft, Lebensmittelsicherheit und Fischerei Mecklenburg-Vorpommern). (top-left). Low, moderate and high crop prices scenarios over 30 years based on Monte Carlo simulations.

Mecklenburg-Western Pomerania State Office for Agriculture, Food Safety and Fisheries. The simulation applied three annual price increase scenarios—low (0.5%), moderate (1%), and high (1.6%). For nitrogen (N), the mean price from 0.84€ (low scenario) to 1.0€ with a maximum value of 1.12€ (moderate) and a high price scenario with the same mean value but a maximum price of up to 1.32€. Phosphorus (P) showed a mean of 0.84€, 1.0€ and 1.12€ for the three scenarios. Potassium (K) average prices range from 0.79€ to 0.84€ and 0.92€ across the scenarios.

For the crop prices the difference in mean between historical and simulated data is smaller due to a smaller trend over time. For soybeans the historical average is equal to 38.80 €/dt the simulations resulted in average values of 33.50€/dt, 37.0€/dt and 40.80€/dt. The price range over all scenarios is equal to 32.70€/dt to 45.60€/dt. Historically the average price of winter barley was 15.40€/dt. The future price scenarios include average prices of 15.0 €/dt, 17.40€/dt and 20.30€/dt. For oilseed rape the 10 year mean is equal to 37.80€/dt and the simulated yield varies from a minimum of 35.20€/dt in the low-price scenario up to 51.50 €/dt in the high-price scenario. For winter wheat the simulated average values of 17.20€/dt, 19.20€/dt and 21.40€/dt lie close to the historical average price of 18.20 €/dt. The historical price average of silage maize is 3.51 €/dt while the price average of the low-price scenario 6.00 €/dt, moderate 6.64 €/dt and high 7.36 €/dt, due to an upwards price trend. The initial Monte Carlo simulation yielded winter rye prices below plausible market levels, likely due to skewed historical data. To preserve model integrity, we adjusted the expected value to align with 3-year average market prices of 14.70 (2018–2021) (Hanff and Lau, 2021).

2.6. Subsidy scenarios

MODAM contains a module with an adaptation of the Common Agricultural Policy (CAP) 2023–27 as applicable in the state of Brandenburg. The module can be switched off in order to run optimization scenarios without any agricultural subsidies. It contains the redistribution payment, relevant parts of the Good Agricultural and Environmental Conditions (GAEC 1–9) and Eco-schemes (ES 1–7) as introduced by the CAP 2023–27. GAEC contain the minimum standards, farms have to follow, in order to receive any premium, while ES contain additional payments based on additional constraints. Some components with a minor impact on crop areas have been excluded based on their irrelevance and data availability within this study. For example, constraints focusing on flower strips or grassland have been excluded since they affect only a small area share.

The CAP module includes the redistribution payment aiming to support small farms with a payment of 69.16 EUR/ha for the first 40 ha of farmland and 41.49 EUR/ha for the next 20 ha. All farms receive redistribution payments regardless of size and cropping practices. GAEC 6 and GAEC 8 have been included as conditions for the 156.56 euros/ha premium. GAEC requires that a minimum of 80% of farmland are cultivated with winter or cover crops and GAEC 8 a minimum of 4% fallow land.

Farms can receive an extra premium for additional fallow land extending the 4% covered by GAEC 8 through Eco-scheme 1a. One percent of extra fallow land is supported by 1300 euros/ha, the next 4% of extra fallow land with 500 euros/ha and one final percent with 300 euros/ha. Finally, Eco-scheme 2 supports diverse crop production with 45 euros/ha if farms cultivate no more than 66% cereals and at least 10% legumes, while cultivating at least main crops with each a share between 10 and 30% of the arable land.

Additionally, to the CAP 2023 subsidy scheme a second subsidy scenario has been developed. The so called ‘field perimeter subsidy’ aims to compensate farmers extra workload by paying ES2 not per ha but field perimeter. When farmers implement field strips, the field perimeter increases and a higher premium can be received. In this study the boarder of each strip is counted to the field perimeter as long as different crops are cultivated on neighboring strips. In a first step the subsidy has been set to 2.50 euros per 100 m. This premium level ensures that public spending does not exceed the theoretical maximum subsidy costs of all showcase farms receiving the 45 euros per hectare premium under ES2. However, most farms did not fulfil the diversification restrictions and did therefore not receive the area subsidy under the CAP23 scenarios. This leads to increased subsidy expenditure when implementing the perimeter subsidy at higher payment levels. As a next step lower premium levels (2.5–1.0 euros per 100 m) have been run individually to investigate the lowest possible premium necessary to avoid the expected gross margins dropping below sole cropping practice.

2.7. Conditional value-at-risk

The Value-at-Risk (VaR) and Conditional Value-at-Risk (cVaR) are two closely related measures of risk. VaR represents a distribution's quantile at a specified threshold, such as the point beyond which 95% of the distribution's outcomes occur. The cVaR indicates the expected loss, particularly focusing on the 5% left tail of the gross margin distribution (Stanislav and Tyrrell Rockafellar, 1999). In this study, both VaR and cVaR refer to absolute measures of loss, representing distance from zero, as opposed to relative VaR, which measures loss relative to the expected value. The VaR can be estimated through a variety of methods. In this study the VaR is estimated using a non-parametric approach based on the simulated gross margins and is therefore not dependent on an underlying predetermined distribution.

In essence, cVaR represents the average of the worst-case outcomes, offering insight into conditions where farmers might face significant challenges due to, for example, adverse climate or market conditions. For instance, if we are interested in the worst 5% cases, cVaR offers the expected loss when the gross margin is below the VaR on the 0.95 level. It is therefore often also referred to as expected tail loss (Sarykalin et al., 2008). The optimization model estimates the cVaR for each of the 30 years separately. We are therefore not optimizing for the worst-case years but the worst outcomes within each year throughout the whole time period. The combination of price variation, climate conditions and cohort running (rotating starting crop) results in a variation of 30 different gross margin values for each chosen cropping pattern each year.

Despite the cVaR having advantages to other risk measures, it does bring its own disadvantages. While cVaR provides a more robust view of tail risk than simple Value-at-Risk, it remains insensitive to higher moments of the distribution. In this study the level has been set to 0.95 based on common practice targeting the most severe 5% of outcomes. In this case that translates to only the worst 2–3 scenarios in each year. It assumes that all losses beyond the threshold are equally relevant and does not consider the values above the threshold, which may oversimplify complex risk preferences in farming contexts.

2.8. MODAM

Multi-Objective Decision Support Tool for Agroecosystem Management (MODAM) is a bio-economic farm model. It generates farm and field specific optimal cropping patterns and corresponding expected economic and ecological indicators. MODAM is a fully dynamic linear program maximization model. The modular structure allows for activating different modules tailored to specific farm structures, facilitating the model's adaptation to various research objectives and regions. The model maximizes the farm income, however multicriteria decision making can be incorporated through the inclusion of different ecosystem services in the objective function (Hosseini-Yekani et al., 2025).

For this study the model has been adapted to a stochastic optimization of expected values under climate, weather and price variation. Decision making has been adapted to allow for risk-adverse behavior by simultaneously maximizing the expected gross margin and minimizing the conditional Value-at-Risk. The model is dynamic, optimizing over a given time period. Due to the stochastic modeling approach, data input requirements significantly increased.

Binary variables have been reduced to a minimum and are only used selectively. They are introduced mainly in the CAP policy module (eligibility for certain premiums yes-no) and for cropping practices limited to sole cropping, where only one rotation per field block is allowed. These discrete decisions are implemented using the Big-M method. While this approach allows to keep the linear structure, it can introduce numerical instability, increase model size and substantially increases running time. The full sole cropping input data set e.g. includes over one million yield values (1,029,420 in total) leading to a running time of several hours. To avoid instability and reduce running time as much as possible the Big-M value is set individually for each farm to the lowest possible value. Additionally, the model has been paralyzed as far as the structure allows it.

The increase in complexity of the model due to the stochastic component is substantially. The structure of MODAM is modular, giving flexibility to include different sets of equations based on the research objectives. Including livestock and biogas as considered in other deterministic MODAM implementations were beyond the scope of this study. The study solely considers arable farming.

Selected core equations of the model are shown below (Eqs. (1)–(10)). Eq. (1) shows the objective function where $NPV(x)$ is the expected net present value of the annual gross margin dependent on the decision variable x (chosen cropping pattern). $cVaR_\theta$ is the expected net present value of the conditional Value-at-Risk of the gross margin under the threshold value θ. Each component of the optimization function is multiplied with a weight γ_i representing farmers preferences. The sum of all weights has to be equal to 1 (Eq. (2)). The model is run twice prior to the final solve, each time optimizing only one of the decision criteria, generating maximum and minimum values of each variable, used to normalize the objective function.

The expected net present value ($NPV(x)$) is equal to the mean gross margin $GMs_{y,scen}$ over the simulated 30-year time span ($|Y|$) and different scenarios (scen), discounted with the discount rate r. The gross margin $GMs(X)_{y,scen}$ in each scenario and year is estimated as the sum of the produced yield ($Pr_{rot,scen}$) times the price ($price_{C,scen}$), minus the costs ($cost_{C,scen}$). While the annual yield depends on climate and weather scenarios, annual prices depend on the price scenarios. In this study we included two climate scenarios, three price scenarios. Additionally, each yield value has been included with cohort runs (changing starting crops for all crop rotations), to avoid a starting crop - weather condition bias. Most rotations include five years. The combination of climate and price scenarios with the cohort runs results in 30 (2x3x5) scenarios for most rotations per year.

The expected net present value of the conditional value at Risk ($cVaR_\theta(x)$) is estimated as the discounted annual average expected loss ($Lo\left(X_{Y,C}\right)_{scen}$) lower than the Value at Risk (VaR_θ) with a probability of θ.

The key constraints of the model are the resource land constraints (Eq. (6)) with a maximum total area of each farm (Al_Y) and the labor restrictions (Eq. (7)). Additionally different crop rotation restrictions are implemented for the four different management strategies.

Objective function

$$Max \ \ \gamma_1 \frac{NPV(X_{Y,C}) - NPV_{min}(X_{Y,C})}{NPV_{max}(X_{Y,C}) - NPV_{min}(X_{Y,C})} - \gamma_2 \frac{cVaR_\theta(X_{Y,C}) - cVaR_{min,\theta}(X_{Y,C})}{cVaR_{max,\theta}(X_{Y,C}) - cVaR_{min,\theta}(X_{Y,C})} \quad (1)$$

s.t.

Weight Normalization

$$\sum_{i=1}^{2} \gamma_i = 1 \quad (2)$$

Net present value

$$NPV(X_{Y,C}) = \frac{1}{|Y|}\sum_{y}\left(\frac{1}{|scen|}\sum_{scen} GMs(X_{Y,C})_{y,scen}\right) exp^{-r(Y-1)}Y \quad (3)$$

Gross Margins

$$GMs(X_{Y,C})_{y,scen} = \sum_{C} X_{Y,C}\left(Pr_{rot,scen}\, price_{C,scen} - cost_{C,scen}\right) \quad (4)$$

Conditional Value at Risk

$$cVaR_\theta(X_{Y,C}) = \frac{1}{|Y|}\sum_{y}\frac{1}{|scen|(1-a)} : \sum_{scen:L_{scen}\geq VaR_\theta} Lo(X_{Y,C})_{scen} \ exp^{-r(Y-1)} \quad (5)$$

Resource constraints
Land constraint

$$\sum_{C} X_{Y,C} \leq Al_Y \quad (6)$$

Labor constraint

$$\sum_{C} X_{Y,C}\, La_{hired} \leq La_{family} \quad (7)$$

This adaptation of MODAM is a multi-criteria optimization. The weight of each criterion (γ_i) has been determined based on empirical data (DFBK). MODAM was run three times including only one of the criterions (i) each time. As a next step a simple model has been used to minimize the positive (n_g) and negative (p_g) deviation between the area of each crop in each MODAM run x_{ig} and the historical cropping pattern x_g by choosing the optimal weight for each criterion (γ_i). Since no soybean has been cultivated in the case study area in 2021, the cultivated area of other legumes has been used as a proxy.

$$\min_{\gamma_i}\sum_{g=1} n_g + p_g \quad (8)$$

subject to

$$\sum_{i=1}^{G} \gamma_i x_{ig} + n_g - p_g = x_g \quad (9)$$

$$\sum_{i=1}^{I} \gamma_i = 1 \quad (10)$$

$$n_g \text{ and } p_g \geq 0 \quad (11)$$

Two sets of preferences have been chosen. The first set representing strictly profit maximizing behavior ($\gamma_{GMmax} = 1, \gamma_{cVaRmin} = 0$) and the second risk averse behavior ($\gamma_{GMmax} = 0.88$, $\gamma_{cVaRmin} = 0.12$). These should be interpreted as approximations rather than precise representations. The cropping patterns used to estimate the weights are shaped by model structure and input data quality. Notably, the model is calibrated under the CAP 2023 framework, whereas the empirical data reflect the previous CAP period. Additionally, the model only allows rotations based on crops included in the dataset, which covers the majority of cultivated area but excludes some minor crops present in real life practice.

2.9. Scenarios

The full model was run multiple times including different input parameters and constraints. Fig. 3 gives a brief overview of the scenarios presented in the result section below. All four management strategies were run separately under historical (1990–2020) and future (2020–2060) climate conditions. Each scenario includes the implementation of the Common Agricultural Policy (CAP) 2023–27. Additional scenarios were included for the strip cropping strategy where Eco scheme 2 is replaced with a perimeter subsidy. The effect of different subsidy levels was investigated by running the final scenario multiple times with different subsidy levels. Between 2.5 €/100 m and 1.0 €/100 m. After running the scenarios with profit maximizing preferences ($\gamma_{GMmax} = 1, \gamma_{cVaRmin} = 0$), all scenarios under future climate conditions were run asecond time under risk averse preferences ($\gamma_{GMmax} = 0.88$, $\gamma_{cVaRmin} = 0.12$).

3. Results

For verification the yield data has been compared with empirical yield data over three years (Hanff and Lau, 2021). The area weighted averages of the simulated data and the area weighted average of the empirical data lie relatively close in both scenarios. For winter barley and winter wheat, the simulated historical means were very close to the empirical value, with a difference below 0.1 t/ha. The future scenarios were on average higher than the historical and the empirical data, for silage maize e.g. the simulated future yield were on average more than 0.7 t/ha higher. For all crops, there were differences between the lowest and the highest yield values, which can be explained by soil quality differences across farms and the 30-year period. Five out of six crops have a larger yield range under historical conditions. Winter barley is the only crop where future conditions show more variability. Since soybeans were grown on only a small area of 500–1000 ha in Brandenburg in 2018–2021, the statewide empirical data does not include soybean production. Therefore a three year average of three field experiments has been included. The mean value of 2.06 t/ha lies slightly below the simulated historical value of 2.53 t/ha.

The results of the farm model show that under historical and future climate conditions strict sole cropping leads to the cultivation of only four crops. In contrast, the temporal diversification and subfield management practices include all six crops from the dataset, although soybean production remains limited, occupying only 2–3% of the cropland in both cases (Table 6). Under climate change a small extra share of arable land is suitable for soybean cultivation. In the strip cropping scenario without additional subsidies, the share of fallow land increases, as the practice is not economically viable across all field blocks, especially under historical climate conditions. Winter barley is excluded from strip cropping rotations, resulting in its omission from cultivation under this strategy. Under historical climate conditions strip cropping appears not to be economically viable on poor soils, leading to no cultivation of winter rye and a high share of fallow land. However, soybean production rises significantly in this scenario compared to the other diversification strategies. When the strip cropping practice is combined with a perimeter subsidy of 1.5 euros per 100 m the share of fallow land under strip cropping decreases slightly under historical conditions and significantly under future weather conditions. This management policy combination shows by far the highest share of legumes.

The 'Shannon Evenness Index' (with ranging from 0 to 1) under future climate conditions and profit maximizing behavior for sole cropping resulted by far in the lowest value with 0.41. Temporal diversification and subfield division result in a similar level with 0.86 and 0.84. Strip cropping shows by far the highest crop evenness with 0.93. Subfield division results in an edge increase of approximately 1.6

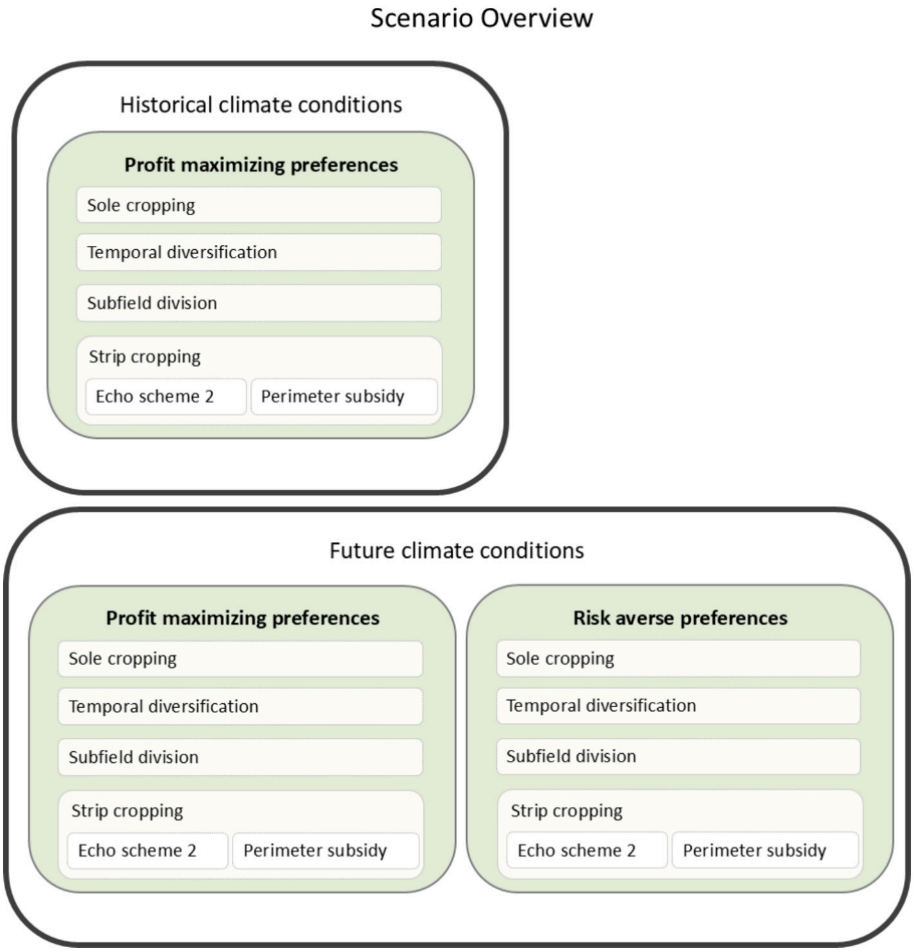

Fig. 3. Overview over all scenarios defined through climate conditions, management strategy, risk preferences and subsidy scheme. All Scenarios include the CAP 23 implementation.

Table 6
Average percentage crop shares over 30 years under historical and future climate conditions and profit maximizing preferences. Perimeter subsidy refers to a subsidy level of 1.5 euro/100 m.

Crop	Sole cropping		Temporal diversification		Subfield division		Strip cropping		Strip cropping & perimeter subsidy	
	Hist.	Fut.	Hist.	Fut.	Hist.	Fut.	Hist.	Fut.	Hist.	Fut.
Fallow	9	8	7	6	8	8	36	24	27	9
Silage maize	22	23	15	16	15	15	11	14	12	17
Soybean	–	–	2	3	2	3	11	10	12	12
Winter barley	–	–	8	7	8	8	–	–	–	–
Winter rapeseed	23	23	23	23	23	23	11	14	12	17
Winter rye	4	4	4	4	4	4	–	8	–	9
Winter wheat	42	42	40	40	40	40	32	30	36	36

times while under strip cropping the field perimeter expanded to nearly 14 times its extent under sole cropping.

All resulting numbers are expressed per hectare, in order to allow for meaningful comparison across farms of different sizes (Table 7).

Large median farms are expected to lose around 95.96€/ha under sole cropping in the worst-case price and climate scenarios. In contrast, under strip cropping, the cVaR drops to −165.24€/ha, which means that even in the worst case, the farm maintains a considerable positive gross margin. In general, a reduction in cVaR, especially values below zero, indicate a lower exposure to economic risk. A cVaR of 0 €/ha means that in the 5% worst-cases a farm does not generate any gross margin but is exactly at the break-even point covering the resulting operating costs.

Under sole cropping median farms have higher gross margins compared to robust and vulnerable farms, however for large farms the robust farm has by far the highest expected gross margin. Under historical climate conditions the classification of vulnerable and robust farms appears to be incoherent, since there is no clear pattern of robust farms showing a lower level of tail risk. That is no unexpected outcome, since the classification targets climate related production risk. Temporal diversification and subfield division generates a similar level of gross margin for all showcase farms compared to sole cropping. Under temporal diversification the cVaR decreases by around 8 €/ha for robust medium farms and by on average 95.96 €/ha for large median farms. For all other farms the effect is minor or the cVaR even increases. Even under profit maximizing preferences, subfield division on the other hand shows a significant drop in left tail risk. For small robust and vulnerable farms e.g. the decrease is over 50 €/ha, for the large robust farm even above 200€/ha decrease, without loses in gross margin despite the 65%

Table 7
Net present value of average per ha gross margin and average annual conditional Value-at-Risk under **historical climate conditions** and profit maximizing behavior ($\gamma_{GMmax} = 1, \gamma_{cVaRmin} = 0$) resulting from the four different management strategies.

Farm size &		Small			Medium			Large		
Characteristic		Robust	Vulnerable	Median	Robust	Vulnerable	Median	Robust	Vulnerable	Median
	NPV [€/ha]:									
Sole cropping	**Gross margin**	251	257	268	221	190	255	229	153	179
	cVaR	0	0	44	101	106	51	291	101	96
Temporal diversification	**Gross margin**	252	259	268	221	190	255	230	153	189
	cVaR	0.00	0	44	92	106	51	379	101	0
Subfield division	**Gross margin**	252	259	268	221	190	254	229	153	179
	cVaR	−53	−52	18	78	93	30	56	96	−4
Strip cropping	**Gross margin**	272	282	281	226	164	234	212	132	183
	cVaR	−147	−151	−172	−218	−49	−201	−169	−167	−165

increase in labor demand. This is achieved through a portfolio effect that spreads the risk across different crops in each field. If conditions in a field block are poorer in individual years, the loss does not effect the full harvest of the field block. The same effect reduces risk under strip cropping, to a much lager extend. The gross margin under strip cropping is higher compared to sole cropping by up to around 21 €/ha for the small robust farm but e.g. the medium vulnerable farm loses around 26 €/ha in expected gross margin. How premium payment plays into the level of gross margin and cVaR is presented in more detail below under future climate conditions.

Under future climate conditions and assuming profit-maximizing preferences, expected gross margins per hectare increase across all farm sizes and management strategies compared to historical conditions. The largest gains are observed for median-sized farms and under diversified practices, particularly subfield division and strip cropping. Changes in tail risk (cVaR) vary by farm characteristics, but in many cases, risk also improves under future climate conditions. The difference in economic risk depends on the farm characteristics, however for a major part improvements can also be observed under future conditions compared to the historical scenarios (Table 8).

Table 8
Net present value of average per ha gross margin and average annual conditional Value-at-Risk **under profit maximizing behavior** ($\gamma_{GMmax} = 1, \gamma_{cVaRmin} = 0$) and percentage difference for **risk averse behavior** ($\gamma_{GMmax} = 0.88, \gamma_{cVaRmin} = 0.12$) under **future climate conditions.**

		Small					
		robust		vulnerable		median	
		Max.	Risk. [Δ]	Max.	Risk. [Δ]	Max.	Risk. [Δ]
Sole cropping	**Gross margin**	295.30	0	305.95	0	322.17	0
	cVaR	−52.50	0	−52.49	0	1.30	−517
Temporal diversification	**Gross margin**	298.75	0	309.44	0	322.92	0
	cVaR	−52.50	0	−52.49	0	−0.47	−1389
Subfield division	**Gross margin**	298.73	0	309.43	0	322.93	−11
	cVaR	−52.50	0	−52.49	0	−17.11	−115
Strip cropping	**Gross margin**	293.63	0	307.65	0	303.90	0
	cVaR	−162.18	−3	−165.46	−4	−190.59	−2

		Medium					
		Robust		Vulnerable		Median	
		Max.	Risk. [Δ]	Max.	Risk. [Δ]	Max.	Risk. [Δ]
Sole cropping	**Gross margin**	264.78	0	236.16	0	309.02	0
	cVaR	54.56	−17	72.57	−14	12.01	−63
Temporal diversification	**Gross margin**	265.91	0	236.20	0	309.33	0
	cVaR	42.53	0	72.59	0	6.25	−117
Subfield division	**Gross margin**	265.94	0	236.21	0	309.34	0
	cVaR	42.51	−38	72.57	−14	6.21	−229
	Gross margin	228.91	0	166.98	−1	166.98	0
Strip cropping	**cVaR**	−206.31	−1	−33.53	−41	−33.53	−5

		Large					
		Robust		Vulnerable		Median	
		Max.	Risk. [Δ]	Max.	Risk. [Δ]	Max.	Risk. [Δ]
	Gross margin	278.83	0	193.44	0	225.34	−1
Sole cropping	**cVaR**	25.08	−19	65.66	−12	61.66	−9
	Gross margin	280.05	−1	193.82	0	242.90	0
Temporal diversification	**cVaR**	17.81	−20	65.85	0	−4.48	0
	Gross margin	280.07	−22	193.85	0	227.48	0
Subfield division	**cVaR**	23.74	−158	65.82	−12	−4.48	0
	Gross margin	221.00	−11	132.60	−1	186.96	−6
Strip cropping	**cVaR**	−176.05	−1	−11.05	−51	−166.13	−4

The classification of vulnerable and climate-robust farms appears to hold better under future climate conditions. Vulnerable farms, do not necessarily have lower expected gross margin than robust farms, but face substantially greater losses under adverse conditions. For instance, the medium vulnerable farm has a cVaR of 72.57 €/ha under sole cropping, compared to only 2.58 €/ha for its robust counterpart.

The effect of the different diversification strategies appears to be relatively similar comparing historical and future scenarios. Strip cropping leads to the biggest decrease in cVaR. For large median farms drops from 61.66 €/ha under sole to–166.13 €/ha under strip cropping. However, the risk reduction costs are relatively high with a decrease in expected gross margin by 38.38€/ha. 'Sole cropping' shows the poorest performance in terms of tail risk but not necessarily the highest expected gross margin. Larger vulnerable farms exhibit particularly high risk under sole cropping (e.g., a cVaR of 65.66 €/ha). 'Temporal diversification' only leads to minor risk reduction, but a small expected gross margin increase. 'Subfield division' shows the best economic performance when looking at the expected gross margin. The risk reduction effect is similar to the effect of temporal diversification through the 'temporal diversification' for most farms. However, for the for the small median farm the cVar drops from 1.30€/ha undersole cropping to −17.11€/ha under subfield division. Strip cropping without an additional subsidy support results in a decrease in gross margin for most farms and the lowest cVaR across all farm types. For medium and large vulnerable farms, the difference in cVaR is over 100 €/ha compared to sole cropping. Making strip cropping the most effective risk reduction tool under profit maximizing behavior.

Under risk averse preferences the decrease in cVaR and the loss in expected gross margin vary between the different farms. Major risk improvement effects mainly farms and management strategies with a high cVaR under profit maximizing behavior. Scenarios with negative cVaR show no or only minor improvement under risk averse preferences. For many scenarios risk reduction can be achieved with only minor losses in the expected gross margin (below 0.5%). However, that trade off between gross margin and cVaR is highly dependent on the scenario. For example, for the large robust farm the gross margin decreases by up to 22%. Subfield division appears to be effective for risk averse farmers, with a major decrease in cVaR with no or smaller losses in expected gross margin.

Strip cropping leads to the biggest decrease in cVaR in all preference and climate scenarios, however without additional subsidy support the expected gross margin is the lower compared to other management strategies.

Table 9 shows the NPV of the average gross margin and cVaR using strip cropping management strategy and the perimeter subsidy with different payment levels under profit maximizing behavior. When the subsidy is set to 2.50 euros, equivalent to the maximum payment under the current CAP diversification subsidy (ES2) we see a major increase in expected gross margins for all farms and as well as a decrease in cVaR. This can be explained by a low adaptation rate of Eco-scheme 2 under all management strategies and therefore lower payments.

For most farms, the expected gross margin under sole cropping (Table 9) can be achieved or exceeded with a subsidy level of 1 €/100 m. For some farms, especially large farms or those in the vulnerable category, a higher subsidy level ($\geq$ 1.5 €/100 m) is necessary to avoid a decrease in expected gross margin. Independent of the subsidy level, the cVaR decreases, showing a reduction in economic risk. Vulnerable farms show the biggest decrease in cVaR across all three sizes. However, for small farms it appears to be also the most profitable.

Table 10 shows the discounted average annual per hectare premium received by each of the farms. For all scenarios in which profit maximizing and risk averse preferences resulted in the same expected premium the number is only shown ones. For subfield division and strip cropping the value varied, they are therefore both included. Across all management scenarios large farms get lower per hectare support due to the redistribution payment aiming to support smaller farms. At the same time for some farms the premium level is lower under temporal diversification as well as subfield division. Indicating that these strategies can reduce subsidy dependency.

The CAP 23 premium payment is highest for all farms under strip cropping and even higher when implementing the perimeter subsidy. The increase without the adapted policy scheme is mainly caused by an increase in fallow land which is subsidized under Eco-scheme 1a. The exact payment and therefore the difference between the final scenario and the other subsidy scenarios is highly dependent on the shapes of the field blocks and the resulting field perimeter when applying the strip cropping. In this study the smaller showcase farms have smaller more fragmented fields resulting in a longer perimeter than the bigger farms and therefore a higher premium payment. ES2 has a very low adaptation rate under all management scenarios. Therefore, the subsidy spendings increase with the perimeter payment under strip cropping. The small risk reduction effect of temporal and subfield division is not tax paid but the opposite, gross margins contain a smaller share of subsidy payment for multiple farms. Only for the strip cropping strategy the premium share increases for all farm types. Preference and policy scenarios.

4. Discussion

Under historical and future conditions and across different scenarios and showcase farms, we found that diversified management strategies outperformed sole cropping in narrow rotations in terms of profitability and risk reduction. Temporal diversification by integrating soybean into the baseline rotations did not reduce risks. For both 'sole cropping' and 'temporal diversification', the model enforces fixed field structures, with one crop allowed per field block. Field blocks can only decrease in size when arable land is left fallow. This simplifies the decision framework of farmers, where adjustments to field configurations are very common. This may be one of the factors explaining the high tail risk and limited risk reduction effect of temporal diversification. Additionally, soybean is the only legume included in this study, making it hard for farmers to

Table 9
Net present value of average per ha gross margin and average annual conditional Value-at-Risk under future climate conditions and profit maximizing behavior ($\gamma_{GMmax} = 1, \gamma_{cVaRmin} = 0$) resulting from the four different management strategy in combination with different levels of perimeter subsidy replacing Ecoschem 2.

Farm size &		Small			Medium			Large		
Characteristics		Robust	Vulnerable	Median	Robust	Vulnerable	Median	Robust	Vulnerable	Median
Subsidy level [€/100 m]	NPV [€/ha]									
0.5	**Gross margin**	210.91	264.88	247.62	151.25	119.77	149.38	113.10	67.89	54.07
	cVaR	−72.17	−114.91	−125.03	−125.18	−100.09	−110.07	−64.18	−60.36	−33.24
1	**Gross margin**	295.03	389.73	357.05	239.61	186.78	226.12	174.03	117.39	92.50
	cVaR	−156.29	−239.77	−234.46	−213.54	−167.10	−186.80	−125.11	−109.86	−71.67
1.5	**Gross margin**	379.15	514.59	466.48	327.97	253.78	302.86	234.97	166.90	130.93
	cVaR	−240.41	−364.62	−343.89	−301.90	−234.11	−263.54	−186.05	−159.37	−110.10
2.5	**Gross margin**	547.39	764.30	685.33	504.70	387.80	456.34	356.84	265.91	207.79
	cVaR	−408.64	−614.33	−562.75	−478.63	−368.13	−417.02	−307.92	−258.38	−186.96

Table 10
Net present value of average per ha premium payment received under future climate conditions and profit maximizing behavior (γ_GMmax = 0.88, γ_cVaRmin = 0.12) as well as risk averse behavior (γ_GMmax = 1, γ_cVaRmin = 0) resulting from the four different management.

		Small			Medium			Large		
		Robust	Vulnerable	Median	Robust	Vulnerable	Median	Robust	Vulnerable	Median
Sole cropping		166.73	160.64	133.66	131.33	134.64	127.48	102.60	102.25	88.13
Temporal		160.65	160.64	133.66	131.33	134.64	127.48	102.60	102.25	112.62
Subfield	Maximizing	160.65	160.64	133.66	131.33	134.64	127.48	102.60	102.25	116.42
	Risk averse			96.42	135.89		131.90	47.45		
Strip cropping	Maximizing	223.83	223.82	223.90	221.54	163.19	217.55	188.26	130.81	130.81
	Risk averse									175.50
Strip cropping & perimeter subsidy		304.88	427.09	380.83	315.33	250.00	276.46	199.74	165.11	119.77

achieve the 10% minimum area share cultivated with legumes in order to be eligible for Eco-scheme 2. Including a variety of legumes might foster adaptation of legume cultivation and improve economic performance and income stability through ES2 payments (Notz et al., 2023a). At the same time the increase in subsidy costs when implementing the perimeter subsidy might actually by smaller when comparing to a scenario with a higher adaption level of ES2.

The ‘subfield division’ strategy is the most flexible of the four, imposing the fewest constraints. It allows multiple crops to be cultivated within a single field block each year, with the model optimizing the share allocated to each. It led to a consistent reduction in cVaR (e.g., >200 €/ha for large robust farms). This risk reduction comes with very low risk reduction costs, shown by the expected gross margin level similar to sole cropping, without an increase in premium payments. In contrast to temporal diversification, labor demand was increased by 65% for spatial diversification strategies (Rezgui et al., 2024). That the gross margin levels did not decrease, shows that the revenue generated was actually higher in the subfield scenarios compared to sole cropping. In practice, the actual impact on labor depends on various factors including field layout, machinery, and distances between parcels, meaning labor effects (and thus economic outcomes) may differ significantly between farms. The implemented increase in labor demand might be too optimistic for some farms and too pessimistic for others, changing the resulting economic effectiveness of the strategy. The high economic performance might be an indicator that the increase was too low and in real life the additional workload might be even higher, reducing the economic benefits of the subfield division and the temporal diversification being more economically viable after all.

Subfield division in our study did not account for improved resource efficiency through the consideration of heterogenous soils within the field blocks. Reducing e.g. fertilizer costs or pesticide dependency might increase the economic performance of the strategy even further. At the same time development of new technologies such as robotics might decrease the additional workload resulting from the division into smaller fields or patches (Grahmann et al., 2024). Integration of soil variation into the design and management of subfields could improve the effectiveness of the optimization, the required data were not available for this study. The optimization based on heterogenous soils might bring agronomic and ecological advantages not captured in the model, such as reduced fertilizer or pesticide use due to e.g. natural field barriers. Resulting input efficiency can also translate into economic benefits. Since these potential benefits have not been considered the results of this study might be underestimating the potential of subfield optimization.

‘Strip cropping’ reduced risks under future and historical conditions, especially for large and vulnerable farms. The risk reduction effect comes from a portfolio effect of harvesting more divers crops each year (Paut et al., 2019). However, in contrast to the subfield division the risk reduction costs are partly covered through a higher level of premium payments. Despite the higher payments compared to the other three strategies, through additional fallow land and ES2, without additional policy support the gross margin level decreases. Strip cropping in Brandenburg has been shown to increase carabid abundance and aphid predation, with no yield penalties (Thompson et al., 2025). Revenues were highest in strip cropping (1450 €/ha) compared to sole cropping (1345 €/ha) and patch cropping (similar to subfield division, 1205 €/ha) without accounting for the costs or subsidies (Thompson et al., 2025). In our study, strip cropping is not economically viable on all fields throughout the years, resulting in a higher share of fallow land. If the additional labor requirement could be reduced by automation and autonomous machines, strip cropping could become the most favorable production system. Al-Amin et al., 2024 found for Indiana, USA that “autonomous strip cropping remained more profitable over a wide range of s/c price ratios, human supervision requirements, and increased field-to-field transition distance”.

The implementation of the field perimeter subsidy as a replacement of the current Eco-scheme 2, improved the economic performance of the strip management strategy already at a premium as low as 1 euro per 100 m field perimeter under future climate conditions. This translates to lower potential policy costs compared to the current Eco-scheme 2. However, due to a low adaption rate of Eco-scheme 2 in the study, premium payments actually increase. This study does not consider the increase in other costs such as bureaucracy costs. Area-based payments are widely established and easily implementable. In this study every strip was treated as an individual field, as long as the neighboring strip is cultivated with a different crop. The perimeter could then be easily identified based on the resulting polygons in the underlying geo data. In practice this geodata is not necessarily available and might result in a major workload in the first implementation year, to determine the exact strips. Additionally, it might be difficult for policy makers to monitor the reported ‘field perimeter’. Determining the rising costs on both sides is difficult and might outweigh the economic benefits to some extent.

It is assumed that crops are cultivated in strips ensuring the biggest possible distance to the next strip with the same crop as shown in Fig. 1. The fields were divided into strips along the longest side maximizing the length of each strip. This does not account for detailed characteristics like hills or field elements such as small ponds, in some cases increasing the number of optimal strips. Additionally, it led to the inclusion of some short strips at the field edge which most likely would be aggregated to the next full strip in real life. The number of strips and the resulting change in field perimeter can only be seen as an approximation. Farmers still have many reservations implementing strip cropping on their fields, especially due to additional labor demand for field operations but also for the administration (Thompson et al., 2024). The model allows individual strips to be turned into fallow land throughout the years. However, it does not allow a mixture of the previous strategies and strip cropping. Implementing a mixture of all strategies with the ideal strategy for each field block might give better outcomes. Since the aim of this study is a comparison of the risk reduction effectiveness, modeling them separately was the best fit approach. The share of soybean production is highest under strip cropping with the implementation of the perimeter subsidy compared to the other management strategies, increasing the benefits of legume production and contributing more to European protein self-sufficiency targets (van Loon et al., 2023). Our study focuses exclusively on economic performance of the different management strategies. However, diversification can also bring ecological benefits. The number of cultivated crops increases from four to six between sole cropping under historical and future climate conditions, increasing biodiversity on the landscape level. The 'subfield division' and especially the 'strip cropping strategy' may contribute to an increase in overall biodiversity and support natural pest suppression (Cuperus et al., 2023).

'Shannon Evenness Index' increases under all diversified management strategies compared to sole cropping, with the highest increase through strip cropping. The configuration heterogeneity through strip cropping might foster biodiversity (Croijmans Luuk et al., 2025) and natural enemy richness (Cuperus et al., 2023). Both spatial diversification strategies result in an increase of field edge, by 1.6 times for subfield division and 14 times under strip cropping, compared to sole cropping. Studies have shown that higher edge density corelates with a lower presence of herbicide-resistant weeds (Garibaldi et al., 2025). The consideration of ecological benefits could further strengthen the argument for the 'strip cropping' strategy and justify the additional costs of a perimeter subsidy scheme.

While our study provides a robust assessment of the economic effects of diversification strategies, the risk preferences implemented in MODAM only showed minor effects (often <0.5% change in GM). For scenarios already with low cVaR, risk-averse preferences had similar levels compared to profit maximizing. Only for some farms eg., for large robust farms, risk aversion cut margins by up to 22%. Future research should consider applying greater emphasis on risk minimization, potentially revealing clearer trade-offs between risk-averse behaviors and profit maximization.

5. Conclusion

This study explored the impact of different crop diversification strategies with soybean on economic performance and risk in eastern German arable farming systems, under historical and future climate conditions. We found that temporal diversification and subfield division strategies resulted in relatively low effects of diversification i.e. low soybean area shares. Under future climate conditions more arable land might be available for soybean production. The area share or soybean cultivation increased most under strip cropping, contributing most to the EU protein self-sufficiency targets. However, strip cropping appears to be not profitable everywhere leading to an increase in fallow land and higher demand for labor.

When comparing historical and future climate conditions, the effect of each diversification strategy appears to be similar, however the level of effectiveness differed. 'Sole cropping' showed the poorest performance in terms of tail risk but not necessarily the highest expected gross margin. Temporal diversification leads to some gains in expected gross margin and no losses, however the reduction in tail loss is limited. Subfield division, significantly reduced risk under historical climate conditions but showed the best economic performance at the expected gross margin. Under risk averse preferences subfield division appears to be quite effective, but strip cropping indicated the highest decrease in conditional Value-at-Risk under both climate scenarios.

Overall, the effectiveness of each diversification strategy is highly dependent on farm characteristics and farmers risk preferences. Temporal diversification alone offers only limited benefits, spatial approaches, especially show a stronger effect on economic tail risk under climate change. Strip cropping demonstrates the greatest effectiveness in risk reduction; however, additional policy support is necessary to offset potential decreases in expected gross margins. A perimeter subsidy can be one policy tool to helping farmers to reduce risk, while keeping a stable income level when introducing strip cropping systems. Considering ecological benefits of more divers cropping systems might further underscore the benefits of such a policy. Future research should account for within-field soil heterogeneity, field-edge yield effects, and ecological co-benefits to more comprehensively assess the value of diversification strategies.

CRediT authorship contribution statement

Hannah Jona V. Czettritz: Writing – original draft, Software, Methodology, Formal analysis, Conceptualization. **Seyed-Ali Hosseini-Yekani:** Software, Methodology, Formal analysis. **Jing Yu:** Writing – review & editing, Data curation. **Moritz Reckling:** Writing – review & editing, Funding acquisition. **Peter Zander:** Writing – review & editing, Methodology, Funding acquisition.

Funding sources

This project was supported by the Leibniz Centre for Agricultural Landscape Research (ZALF) through the integrated priority project: Cropping system diversification to increase the resilience of farming systems (divCROP) 2021–2024 and through Agricultural systems of the future_2: DAKIS2 – Digital knowledge and information processing in agriculture - professional, subproject A;FKZ: 031B1524A.

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 code for the adapted bio-economic farm model is available upon request from the corresponding author. The dataset on climate-robust arable land is publicly available at: https://doi.org/10.4228/zalf-29gf-sj02.

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