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Impact assessment of climate change at farm level: A methodological approach based on integrated biophysical and economic models

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Abstract: The dominant agricultural sector in Slovakia is crop production, with the majority of arable land dedicated to cultivating cereals (57%), followed by fodder crops (20%) and industrial crops (19%). Slovakia has technical and biophysical potential for expanding biomass production. However, it is crucial to identify optimal production practices, alternative costs, and environmental outputs. Farms become more vulnerable to the worldwide threat posed by climate change. Based on research, farmers can effectively mitigate the adverse effects of climate change by making necessary adjustments to their current farming techniques. Thus, by using an advanced tool like integrated farm models, farmers can evaluate and manage a range of risks related to their activities. This paper aims to present the application of integrated modelling frameworks at the farm level and propose a framework for studying the consequences of climate change through a scenario-based approach at the farm level. Integrated assessments provide new insights that complement those derived from more detailed assessments. Based on the model developed, the results of two research questions are provided. Since, from the viewpoint of the farmer, risk and unpredictability associated with lower yields are frequently the main causes of lower income, spatially explicit integrated modelling is applied, enabling economic optimisation of crop production on a selected farm with a focus on maximising net returns while considering biophysical parameters. The modelling results depict the distribution of selected crops on arable land and the most suitable management practices for crop production in terms of nitrogen application and irrigation utilisation. Additionally, we develop an integrated model proposing the estimation of the risk of yield variability and nitrogen emissions for three climate change scenarios for the simulated period of 2020–2100 on the model farm. In response to the problems posed by climate change, this integrated approach can assist evidence-based decision-making and sustainable agriculture practices.

Keywords: climate change scenarios; crop production management; farm model; integrated modelling framework

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Environmentally friendly agricultural systems are increasingly emphasised, particularly in light of the impact of intensive agricultural practices on the environment: organic farming, precision farming, integrated farm management, regenerative agriculture, sustainable intensification, and agroecological approaches encompass a wide range of techniques, albeit significantly overlapping in philosophy and approaches. Their common goal is to enhance environmental management by increasing biodiversity, regenerating damaged soil, and protecting it. Nevertheless, since these systems are frequently linked to lower yields, there may be a conflict with the pressing need to boost food production in order to satisfy the demands of an expanding population (Durham and Mizik 2021).

Over the past century, farming systems across Europe have undergone significant transformation due to mechanisation, intensification, and specialisation (Jepsen et al. 2015). Large increases in productivity and labour efficiency were made possible by the introduction of technology such as chemical fertilisers, improved varieties, and irrigation, along with increased access to mechanisation (Matson et al. 1997). However, this also resulted in a greater dependence on external, frequently non-renewable resources (Pretty 2008). These advancements led to the emergence of highly specialised agricultural systems, which are frequently found in concentrated agricultural landscapes that may be susceptible to the negative consequences of climate change (Olesen and Bindi 2002).

Growing concerns about the environmental consequences of agricultural activities, as well as the need to increase productivity, require the development of monitoring and evaluation tools regarding the ecological-economic performance of agricultural enterprises. This is particularly relevant in the context of the trade-off between climate impacts and farm economic performance, as the adverse effects of global warming become increasingly apparent. Measuring ecological performance in terms of greenhouse gas emissions is crucial because it can provide policymakers and farm managers with reliable information to propose measures to reduce greenhouse gas emissions while improving economic performance (Stetter and Sauer 2022).

The extent to which a system is affected by climate change depends on its exposure to climate change, its sensitivity and its adaptation potential. Sensitivity is the extent to which a system is impacted, either negatively or favourably, by climate-related stimuli, whereas exposure is the type and extent to which a system is exposed to climatic fluctuations. The ability of a system to respond appropriately to current or upcoming changes and impacts brought on by climate change is known as adaptation potential. Therefore, in order to deal with the negative effects of climate change, it is necessary to not only understand how vulnerable and exposed farming systems are but also to quantitatively quantify the impacts of climate change and provide suitable adaptation strategies (Groot et al. 2016).

To assess compromises and complementarities among all key components of agricultural systems and to determine the costs and benefits of environmentally friendly practices that are also economically viable, an interdisciplinary approach is needed (Roberts et al. 2023). Given the enormous environmental impact of conventional agricultural production, one of the main challenges is achieving a balance between large-scale food production to meet the growing needs of society and the preservation of resilient agroecosystems (Bullock et al. 2017; Kazemi et al. 2018; Skaf et al. 2019). A modern approach to food security and sustainable agriculture should encompass an interdisciplinary perspective that includes economic, biophysical, social, and environmental aspects (Skaf et al. 2019).

Environmental, climatic, and economic strategies implemented in agriculture are linked to soil, its condition, quality, management, and use. Soil is a natural and the largest carbon reservoir and water accumulator. Soil degradation releases carbon in the form of emissions (Song et al. 2022). Proper management of agricultural production can contribute to carbon sequestration in the soil.

Managing the agricultural land itself does not cause greenhouse gas emissions, but improper agricultural practices, such as excessive use of nitrogen fertilisers, can lead to significant greenhouse gas emissions from agricultural soil; on the other hand, soil and its management have the greatest impact on risk reduction, emission reduction, and CO_2 sequestration, making a significant and financially effective contribution to the transition towards carbon neutrality (OECD 2014; Lal et al. 2015). The benefits and impacts of carbon neutrality will be far-reaching and sustainable in terms of economic development, technological progress, and a healthy environment (Koondhar et al. 2021).

Challenging the global issue of climate change creates risks in physical systems, ecosystems, economy and society; therefore, assessing climate risks across domains and in a manner meaningful to decision-makers is a major scientific challenge (Adger et al. 2018). The ongoing climate change increasingly threatens the agricultural sector as well by jeopardising ecosystem

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resilience and global food security. Although yields of all crops have increased in recent decades, this growth is primarily attributed to advances in plant genetics, the introduction of new crops, and soil management practices (FAO 2017). However, it is challenging to differentiate the direct impact of changing temperatures and precipitation on crop productivity, considering additional contributing factors such as the spatial distribution of agricultural land, economic conditions of land use, and soil fertility (Termorshuizen and Opdam 2009). In terms of research on natural aspects, the main emphasis is on creating crop models for dynamic simulation of crop growth and the impact of climate change on crop growth (Hasegawa et al. 2022).

Bioeconomic modelling represents a tool for assessing ex-post or ex-ante the impact of political and technological changes on agriculture, the economy, and the environment (Janssen and Van Ittersum 2007). A bioeconomic model is defined as a model that links farm decisions on resource management with current and alternative production options, describing input-output relationships and related externalities (Dreschler and Watzold 2001; Rashford et al. 2008).

Models that integrate bio-physical indicators with profitability indicators allow the analysis and evaluation of the consequences of various management decisions in agriculture. Integrated modelling enables the examination of decision-making processes for farmers at various levels, ranging from the farm level to the national scale.

The main goal of the study is to present the application of integrated modelling frameworks at farm levels and to propose a framework for studying the consequences of climate change through a scenario-based approach at the farm level.

MATERIAL AND METHODS

To develop a farm-level integrated modelling framework enabling economic optimisation of crop production on the farm level with respect to crop management with a focus on maximising net returns after considering environmental parameters, farm data from Rišňovce were used. Rišňovce is a village located in the Nitra Region of Slovakia, situated in the western part of the country.

The model farm was characterised by soil conditions that are generally suitable for agricultural activities. The region has a mix of different soil types, including chernozem, cambisols, fluvisols, and phaeozems. Basic data involved five crops (alfa, spring barley, rapeseed, maize, and wheat), and five soil types / land covers represented by sondes (SA50, SA160, SA 163, SA164, SA165). Figure 1 represents the model farm and soil types for all sondes. Averaged economic data (per crop) were derived from farm financial reports (price, variable and fixed cost, labour, subsidies) for the period 2010–2020.

To create an integrated model estimating the risk of yield variability and nitrogen emissions for three climate change scenarios for the simulated period 2020–2100 [for RCP (Representative Concentration Pathways) scenarios RCP 2.6, RCP 4.5, RCP 8.5].

RCP 2.6 aims to limit global temperature rise to well below 2 °C above pre-industrial levels, with efforts to keep the increase below 1.5 °C. RCP 4.5 represents a scenario where greenhouse gas emissions peak around 2040. RCP 8.5, on the other hand, is a high emissions scenario where greenhouse gas concentrations continue to rise throughout the 21st century, leading to significant warming and climate impacts (Moss et al. 2010).

Data from the model farm Rišňovce (economic data) were used, employing climate simulations through the DAISY model provided by the partner institution VÚPOP (Soil Science and Conservation Research Institute), National Agricultural and Food Center (NPPC). DAISY represents a one-dimensional model of agroecosystems, simulating crop growth and development, soil water dynamics, thermal regime, organic matter balance, and nitrogen dynamics in agricultural soils. The managerial model enables the development of complex management scenarios. The model recognises two types of activities, direct action and conditional decision. A direct action is a simple activity such as plowing, sowing or harvesting. A conditional decision regulates the execution of activities such as fertilisation, irrigation or harvesting (Takáč and Šiška 2011).

The model outputs take the form of crop production and indicators representing nutrient and water balances in crops and soil, as well as nutrient, water, and temperature stress on crops during their development (Takáč and Šiška 2011).

As for the crop production management, there were irrigation managements: rainfed/irrigated (rfmgt/irmgt) and five variants of nitrogen fertiliser load (zero 2_N0, low 3_NN, medium 4_NS, high 5_NH, unlimited 6_NA). Biophysical crop responses were simulated based on climate input from five sondes using DAISY simulations for the period 1965–2020 (averages).

Farm-level integrated modelling. Integrated modelling combines several types of models into a bottom-up optimisation model. The framework integrates

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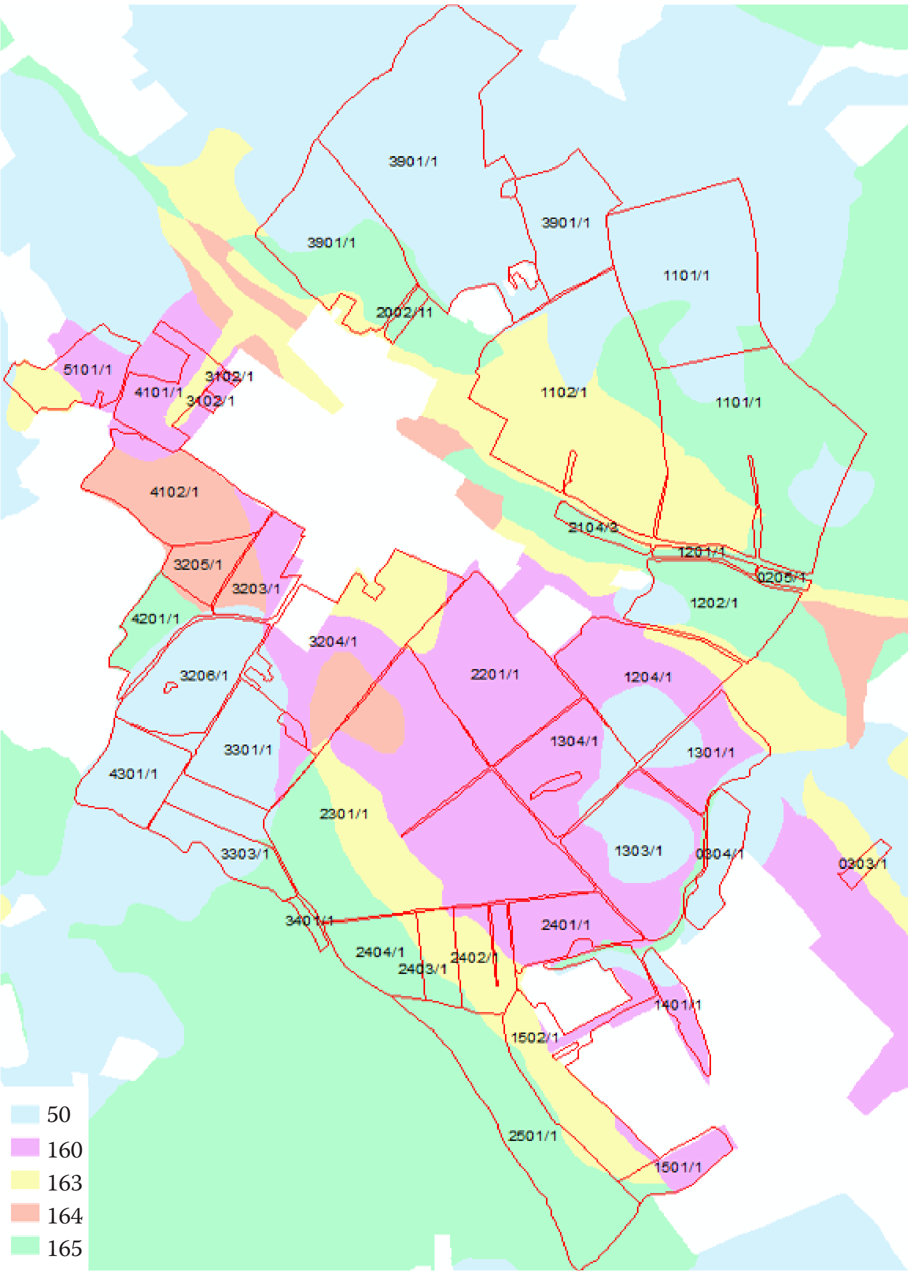

Figure 1. Rišňovce farm with identification of sonda/land cover

Description of land cover type: 50 clayey brown earth, 160 sandy brown earth, 163 sandy-loam chernozem, 164 loam-sandy chernozem,165 clayey chernozem

Source: Author's own map based on LPIS (2022)

agronomic information and biophysical models into a regional land-use optimisation model from the bottom up, considering the heterogeneity of alternative costs for selecting agricultural production and environmental outcomes (Mitter et al. 2015).

The linar programming (LP) optimisation model for the farm takes the form:

$$\pi_{s,m} = \Sigma_r(YLD_{s,c,m} \times price) - (L_c + VC_c + FerC_{c,m} + IrrC_{c,m}) \quad (1)$$

$$\max\pi = \Sigma_{s,m}(\pi_{s,m} \times x_{s,m}) \quad (2)$$

$$s.t. = \Sigma_s(a_{a,m} \times x_{r,m}) \leq b_s \quad (3)$$

$$\Sigma_m M_{s,c,m} \times \theta_{s,m} \leq b_{s,c} \quad (4)$$

$$\Sigma_c b_{s,c} \leq \Sigma_m(\theta_{s,m}\, \Sigma_c M_{s,c,m}) \quad (5)$$

where: π – net returns; YLD – hectare yield of the crop in dry matter; L – labour costs; VC – variable costs; $FerC$ – fertiliser costs; $IrrC$ – irrigation costs; indices s, c, m – sonde, crops, and crop management, respectively; objective function is subject to spatial constraints (b) available for sonde s; A – Leontief production func-

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tion, the technological matrix for transforming inputs into crop products; θ – decision variables; M – matrix of crop mixes observed at farm.

In LP form, the model includes a convex combination of observed crop mixes. Non-linear program accounts with calibration to averages of observed crop shares and crop management reality of farm.

To process all models, the GAMS base module software was used with the CPLEX solver installed (license S220627|0002AO-WIN).

RESULTS

Farm integrated modelling. Average crop yields are higher when farms adopt more intensive farming techniques, such as increased nitrogen loads and irrigation. This is a crucial factor, especially when farmers must face the consequences of changing climate and its impact on crop production systems. Adapting farming practices on land can ensure a positive relationship between agriculture and ecology (Bhusal et al. 2022).

By utilising an LP model for the integration of biophysical and economic data in agriculture, farmers can make data-driven decisions regarding crop selection and production management, ultimately aiming to maximise profitability while considering factors like land availability and soil type variations.

The LP model enables the optimisation of crop production to select net returns, maximising production choices with respect to management and subject to land endowment by soil type. Crop responses simulated by the DAISY model provide data on yields and environmental parameters for different crop management options (nitrogen application and irrigation). The model farm incorporated a convex mixture of observed crop mixes. The optimal approach, where net returns equal EUR 817 651 while adhering to the best crop production management option, was obtained by using the LP model for maximising net returns. Table 1 provides the report on the distribution of optimal management production choices with respect to irrigation management and nitrogen fertiliser load based on the results of the LP model. Given the model results, on soil type 50 (SA50), a combination of high nitrogen input with irrigation for alfalfa and maize (189.46 ha) and non-limited nitrogen input with irrigation for spring barley, rapeseed, and wheat (220.47 ha) appeared to be the optimal management production option.

Accordingly, Table 1 provides crop mix for each soil type as the observed crop mix yielding the highest net returns. It represents the report on the crop production choice for each crop on each soil type. Thus, given soil type 50, clayey brown earth (SA50), alfalfa should be grown on 30.1 ha and maintained with a high nitrogen fertiliser load and irrigation (NV_irmgt); on the other hand, maize should be grown on 159.36 ha and managed similarly. Based on the LP model results, spring barley (18.11 ha), rapeseed (34.67 ha), and wheat (167.69 ha) should all be irrigated and fertilised with an unlimited nitrogen load (NA_irmgt). For sandy brown earth (SA160), 14 ha of alfalfa was optimally managed with a medium nitrogen load with irrigation, while 69.21 ha of maize was managed as a high nitrogen fertiliser load without irrigation, thus rainfed. Sandy-loam chernozem (SA163) in optimal solution 79.82 ha was managed with low nitrogen fertilisers load and irrigation, and 122.02 ha was managed with unlimited

Table 1. Linear programing model, net returns maximizing crop production choices – crop, management, land allocation (in ha)

Sonde	Crop management					Land allocation				
	5_NV_rfmgt	3_NN_irmgt	4_NS_irmgt	5_NV_irmgt	6_NA_irmgt	ALFA	BARS	MAIZ	RAPE	WHEW
SA50	–	–	–	189.46	220.47	30.10	18.11	159.36	34.67	167.69
SA160	69.21	–	14.00	–	230.55	14.00	24.10	69.21	134.16	72.29
SA163	–	79.82	–	–	122.02	10.62	18.08	36.83	69.20	67.11
SA164	–	–	–	–	65.51	–	10.43	–	25.13	29.95
SA165	–	–	–	–	264.08	7.55	0.87	124.39	72.48	58.79

Crop production management: 5_NV_rfmgt - high nitrogen fertilizers load, rainfed management; 3_NN_irmgt – low nitrogen fertilizers load, irrigated management; 4_NS_irmgt - low nitrogen fertilzers load, irrigated management; 5_NV_irmgt- high nitrogen fertilizers load, irrigated management; 6_NA_irmgt – unlimited nitrogen fertilizers load, irrigated management; Crop mix: ALFA – alfaalfa, BARS – spring barley, RAPE – rapeseed, MAIZ – maize, WHEW – wheat.

Source: Authors' own data processing of the model farm PD Rišňovce based on simulated data from the DAISY model

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nitrogen fertilisers load and irrigation. Loam-sandy chernozem (SA164) and clayey chernozem (SA165) were optimally managed as crop management with unlimited nitrogen fertiliser load and irrigation.

To account for the efficiency of water use, the environmental indicator water use efficiency (WUEF) was assessed, pointing out the amount of produced grain dry matter or dry matter from harvested biomass per unit of water consumed (transpiration + evaporation from the soil), in case of rainfed/irrigated management. Table 2 represents the *WUEF* for crop production choices – crop selection, management, and land allocation – that maximize net returns, as an extension of the LP model

Based on Table 2, the type of soil (Figure 1) had a large effect on *WUEF,* which is clearly indicated by having higher *WUEF* for irrigated scenarios, sandy soils (SA160) would be able to produce sufficient yields even aligning with the rainfed management. Yields would be triggered by higher application of nitrogen. However, a rainfed or irrigated scenario depends on the specific environmental conditions, water availability, and crop requirements.

An indicator showing the amount of nitrogen (kg/ha) consumed by the crop for the formation of harvested biomass during the growing season is the so-called nitrogen harvest (*Nharvest*). The *Nharvest* (Table 3) was an important indicator in determining crop yields because it was positively associated with grain yield. The relationship between this indicator and crop grain yield depends on crop genotypes and soil and crop management practices used (Fageria 2014). The most important practices that can improve *Nharvest* were, among others, using adequate nitrogen loads,

Table 2. Linear programming model, *WUEF* for net returns maximizing crop production choices – crop, management, land allocation (kg/ha)

Sonda	*WUEF*				
	5_NV_rfmgt	3_NN_irmgt	4_NS_irmgt	5_NV_irmgt	6_NA_irmgt
SA50	74.17	45.64	59.57	74.12	83.56
SA160	68.84	57.62	66.15	68.84	69.19
SA163	77.67	58.39	66.25	80.12	84.25
SA164	76.40	57.99	72.35	80.83	82.03
SA165	74.53	47.47	61.27	75.01	83.88

Crop production management: 5_NV_rfmgt – high nitrogen fertilizers load, rainfed management; 3_NN_irmgt – low nitrogen fertilizers load, irrigated management; 4_NS_irmgt – low nitrogen fertilizers load, irrigated management; 5_NV_irmgt- high nitrogen fertilizers load, irrigated management; 6_NA_irmgt – unlimited nitrogen fertilizers load, irrigated management; *WUEF* – water use efficiency

Source: Authors' own data processing of the model farm Rišňovce based on simulated data from the DAISY model

Table 3. Linear programming model, *Nharvest* for net returns maximizing crop production choices – crop, management, land allocation (kg/ha)

Sonda	*Nharvest*				
	5_NV_rfmgt	3_NN_irmgt	4_NS_irmgt	5_NV_irmgt	6_NA_irmgt
SA50	583.45	378.98	491.95	632.74	894.76
SA160	411.04	278.92	354.07	411.04	441.97
SA163	629.75	413.71	514.33	655.38	845.13
SA164	567.63	370.20	483.80	602.43	715.30
SA165	592.95	395.24	507.62	642.31	899.47

Crop production management: 5_NV_rfmgt high nitrogen fertilizers load, rainfed management; 3_NN_irmgt – low nitrogen fertilizers load, irrigated management; 4_NS_irmgt – low nitrogen fertilizers load, irrigated management; 5_NV_irmgt – high nitrogen fertilizers load, irrigated management; 6_NA_irmgt – unlimited nitrogen fertilizers load, irrigated management; *Nharvest* – nitrogen harvest

Source: Authors' own data processing of the model farm Rišňovce based on simulated data from the DAISY model

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planting nitrogen-efficient crops, and using appropriate crop mixes.

The non-linear programing (NLP) model enabled the optimisation of crop production to select net returns, maximising production choices with respect to observed reality on the farm. For the model farm, the NLP model was calibrated to averages of observed crop shares. The objective value of net returns, as determined by the calibrated model, was EUR 464 119. The results of the calibrated model are shown in Table 4, which also shows how the land was allocated among the crops. The farm's observed crop management was described as rainfed management and the use of high-nitrogen fertilisers (NV_rfmgt).

When comparing the optimal solution for the LP and the NLP model, the distribution of land among crops changed. The LP model allows for the variety of crop managements respecting the biophysical responses of crops leading to net return maximisation. On the other hand, the NLP model represents the calibration of the model to observed farm reality. It is important to note two points here: *i*) the farm currently operates without irrigation, thus is entirely rainfed; and *ii*) unlimited nitrogen fertilisers represents environmental bias as well as legislative bias.

The model in the LP, as well as the NLP form, assumes that prices remained constant. This assumption allows it to focus on optimising crop management practices and assessing the environmental impacts, particularly regarding crop yield variability and nitrogen consumption.

Integrated model for estimating the risk of crop yield variability and nitrogen emissions. The creation of a proposal for an integrated model framework focused on modelling risks related to climate change scenarios was aimed at estimating the risks associated with the variability of crop yields and nitrogen emissions due to changing climate.

Table 5 represents the correlation analysis of selected biophysical data: *YLD* (crop yield of grain or dry biomass yield), *NYLD* (nitrogen content in the dry matter of grain), *NS* (number of days during the growing season with nitrogen stress), *WS* (number of days during the growing season with water stress), *N_F* (total amount of nitrogen as NO_3 and NH_4 fertiliser applied during the growing season), *N_H* (total amount of nitrogen consumed by crops for biomass formation during the growing season), *N_R* [total amount of nitrogen (kg/ha) consumed by crops for post-harvest residue biomass formation during the growing season], *N_Fixation* (total amount of nitrogen fixed by crops during the growing season), *N_Leak* (total amount of leached nitrogen from the soil during the growing season). Nitrogen indicators enabled us to measure and evaluate environmental impacts effectively. It is obvious that crop yield was most affected by nitrogen consumption and therefore was also affected by nitrogen stress and water stress. When crops do not receive an adequate amount of nitrogen, they may experience nitrogen stress, leading to reduced yields, and lower-quality produce. Nitrogen stress and water stress were interconnected factors affecting crop yield. Water stress occurs when crops do not receive enough water for optimal growth and development. The combined effects of nitrogen stress and water stress can significantly limit the productivity and health of crops, ultimately affecting their overall yield.

Figure 2 illustrates changes in hectare yields based on data simulated by the DAISY model for the historical period 1965–1990 and the historical period 1991–2020. Responses of individual crops are monitored for six management scenarios: 1_00: no nitrogen application (manure application), 2_N0: no nitrogen application, 3_NN: low nitrogen input, 4_NS: medium nitrogen input, 5_NV: high nitrogen input, 6_NA: unlimited nitrogen

Table 4. Non-linear programing model, calibrated crop production choices crop, management, land allocation (in ha)

Sonda	Crop management	Land allocation				
	5_NV_rfmgt	ALFA	BARS	MAIZ	RAPE	WHEW
SA50	409.93	34.03	35.95	173.65	84.29	82.01
SA160	313.76	16.41	73.74	77.30	74.35	71.97
SA163	201.84	7.18	38.21	64.99	42.85	48.62
SA164	65.51	–	16.38	13.08	16.38	19.67
SA165	264.08	4.89	33.12	121.18	47.14	57.75

Crop production management: 5_NV_rfmgt – high nitrogen fertilizers load, rainfed management; crop mix: ALFA – alfaalfa, BARS – spring barley, RAPE – rapeseed, MAIZ – maize, WHEW – wheat

Source: Authors' own data processing of the model farm PD Rišňovce based on simulated data from the DAISY model

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Table 5. Correlation matrix of bio-physical data characterizing the crop response to changing management practices under altered climate scenarios

Pearson's *r*	*YLD*	*NYLD*	*NS*	*WS*	*N_F*	*N_H*	*N_R*	*N_Fixation*	*N_Leak*
YLD	–	0.81	–0.55	–0.35	0.55	0.79	0.44	0.22	0.18
NYLD	0.81	–	–0.53	–0.32	0.68	0.91	0.57	0.26	0.23
NS	–0.55	–0.53	–	–0.21	–0.40	–0.48	–0.24	–0.26	–0.15
WS	–0.35	–0.32	–0.21	–	–0.14	–0.29	–0.17	–0.17	0.05
N_F	0.55	0.68	–0.40	–0.14	–	0.75	0.76	–0.25	0.20
N_H	0.79	0.91	–0.48	–0.29	0.75	–	0.47	0.12	0.20
N_R	0.44	0.57	–0.24	–0.17	0.76	0.47	–	–0.22	0.22
N_Fixation	0.22	0.26	–0.26	–0.17	–0.25	0.12	–0.22	–	–0.08
N_Leak	0.18	0.23	–0.15	0.05	0.20	0.20	0.22	–0.08	–
NH4_Volat	0.04	–0.07	0.02	–0.01	0.04	–0.10	0.15	–0.06	0.18
Denit	0.18	0.30	–0.01	–0.36	0.21	0.20	0.20	0.26	–0.08

YLD – dry biomass yield; *NYLD* – nitrogen in YLD; *NS* – nitrogen stress; *WS* – water stress; *N_F* – amount of nitrogen applied; *N_H* – amount of nitrogen consumed by crops; *N_R* – amount of nitrogen consumed by crops for post-harvest residue biomass formation; *N_Fixation* – nitrogen fixed; *N_Leak* – nitrogen leakage; *NH4_Volat* – NH_4 volatilization; *Denit*– denitrification

Source: Authors' own data processing of the model farm PD Rišňovce based on simulated data from the DAISY model

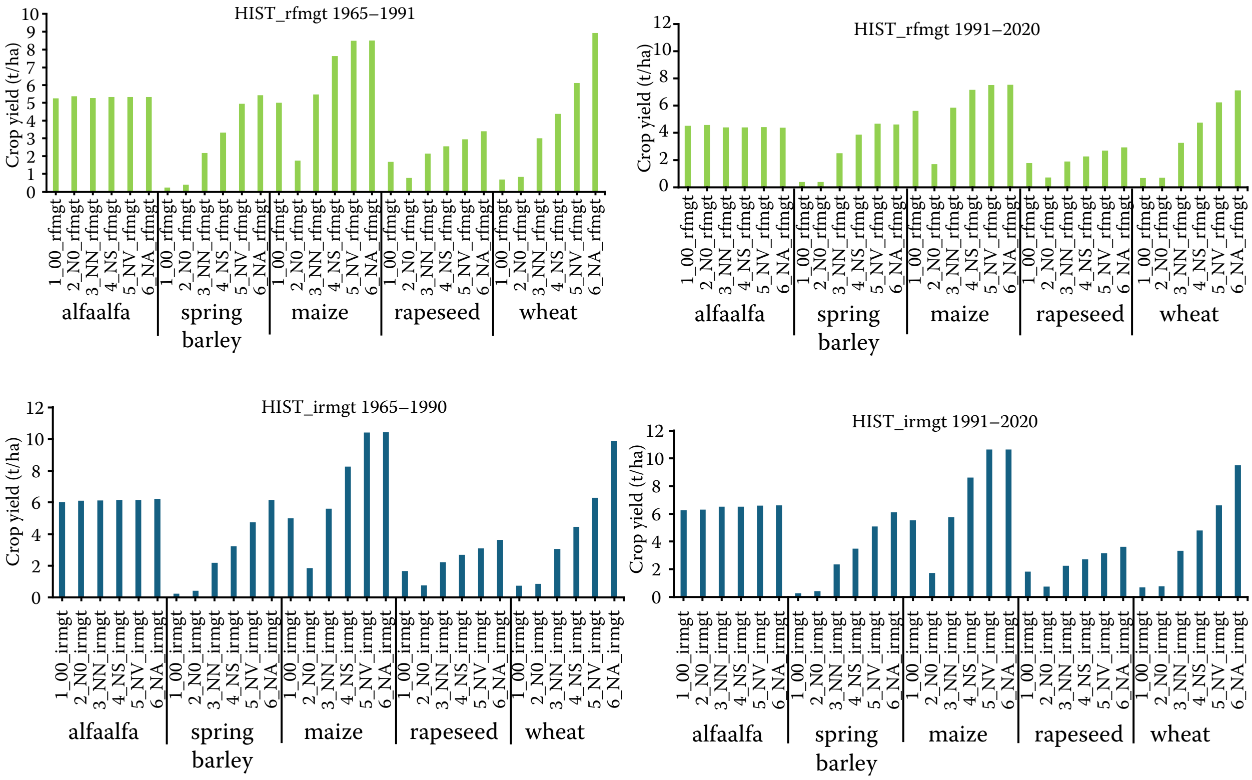

Figure 2. Simulated variability of crop yields on the model farm between two periods (1965–1990 and 1991–2020) for 6 management scenarios

Crop production management: 1_00_rfmgt – no nitrogen application (manure application) rainfed, 2_N0_rfmgt – no nitrogen application rainfed, 3_NN_rfmgt – low nitrogen input rainfed, 4_NS_rfmgt – medium nitrogen input rainfed, 5_NV_rfmgt – high nitrogen input rainfed, 6_NA_rfmgt – unlimited nitrogen input rainfed; 1_00_irmgt – no nitrogen application (manure application) irrigated, 2_N0_irmgt – no nitrogen application irrigated, 3_NN_irmgt – low nitrogen input irrigated, 4_NS_irmgt – medium nitrogen input irrigated, 5_NV_irmgt – high nitrogen input irrigated, 6_NA_irmgt – unlimited nitrogen input irrigated

Source: Author's own processing based on crop yield simulations by the DAISY model (NPPC, VUPOP)

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input. Each scenario was simulated as rainfed (rfmgt) and with irrigation (irmgt). It was possible to observe a decline in yields of individual crops (especially barley, maize, and rapeseed) between the periods 1965–1990 and 1991–2020. It was also apparent that irrigation-based management strategies resulted in better hectare yields, particularly for maize.

Figure 3 represents simulations of crop yield variability for the climate change scenario RCP 4.5. The selected RCP scenario projected a peak in greenhouse gas emissions around 2040, highlighting the importance of considering expected changes in precipitation patterns as a result of increased emissions (Moss et al. 2010). From Figure 3, it is evident that a decrease in yields can be anticipated, especially for crops sensitive to water availability, such as maize.

On the other hand, based on simulated responses, it was clear that irrigation application leads to a significant increase in yields, particularly for economically significant crops like maize and wheat.

Based on the integration of simulated biophysical data on crop yields, nitrogen, and water balance with economic data, it was possible to derive an integrated model for estimating the risk of crop variability and nitrogen emission under climate change.

Figure 4 represents a proposition of the integrated risk estimation model, showing the model inputs (I) and outputs (O) for the sample farm. The ultimate model outcome would represent optimal production choice under the changing climate on the farm level.

DAISY simulated biophysical data. Information obtained from simulations of the physical and biological processes affecting crop growth, water use, and nitrogen availability can shed light on the interactions between elements in agricultural systems. The proposed model took into account the relationship between crop yields, nitrogen levels, and water balance. Understand-

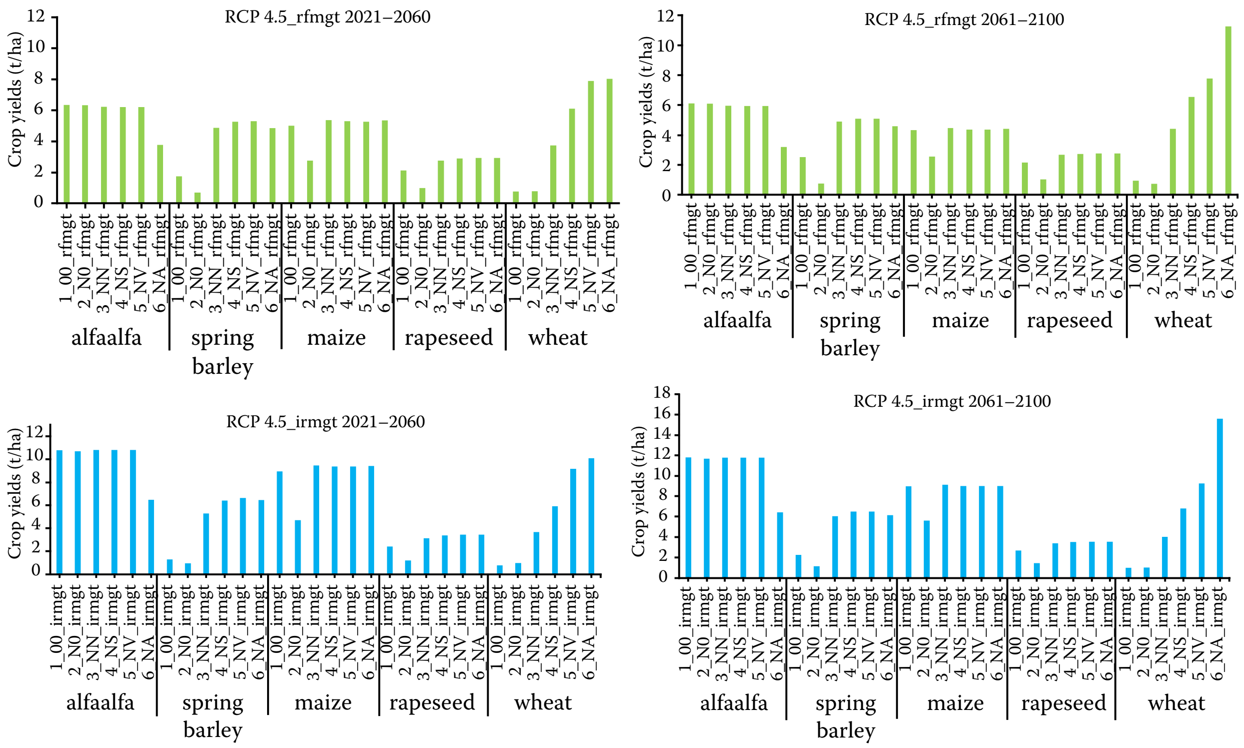

Figure 3. Simulated variability of crop yields on the model farm between two periods (2021–2060 and 2060–2100) for the climate change scenario RCP 4.5, considering 6 management scenarios

Crop production management: 1_00_rfmgt – no nitrogen application (manure application) rainfed, 2_N0_rfmgt – no nitrogen application rainfed, 3_NN_rfmgt – low nitrogen input rainfed, 4_NS_rfmgt – medium nitrogen input rainfed, 5_NV_rfmgt – high nitrogen input rainfed, 6_NA_rfmgt – unlimited nitrogen input rainfed; 1_00_irmgt – no nitrogen application (manure application) irrigated, 2_N0_irmgt – no nitrogen application irrigated, 3_NN_irmgt – low nitrogen input irrigated, 4_NS_irmgt – medium nitrogen input irrigated, 5_NV_irmgt – high nitrogen input irrigated, 6_NA_irmgt – unlimited nitrogen input irrigated

Source: Author's own processing based on crop yield simulations by the DAISY model (NPPC, VUPOP)

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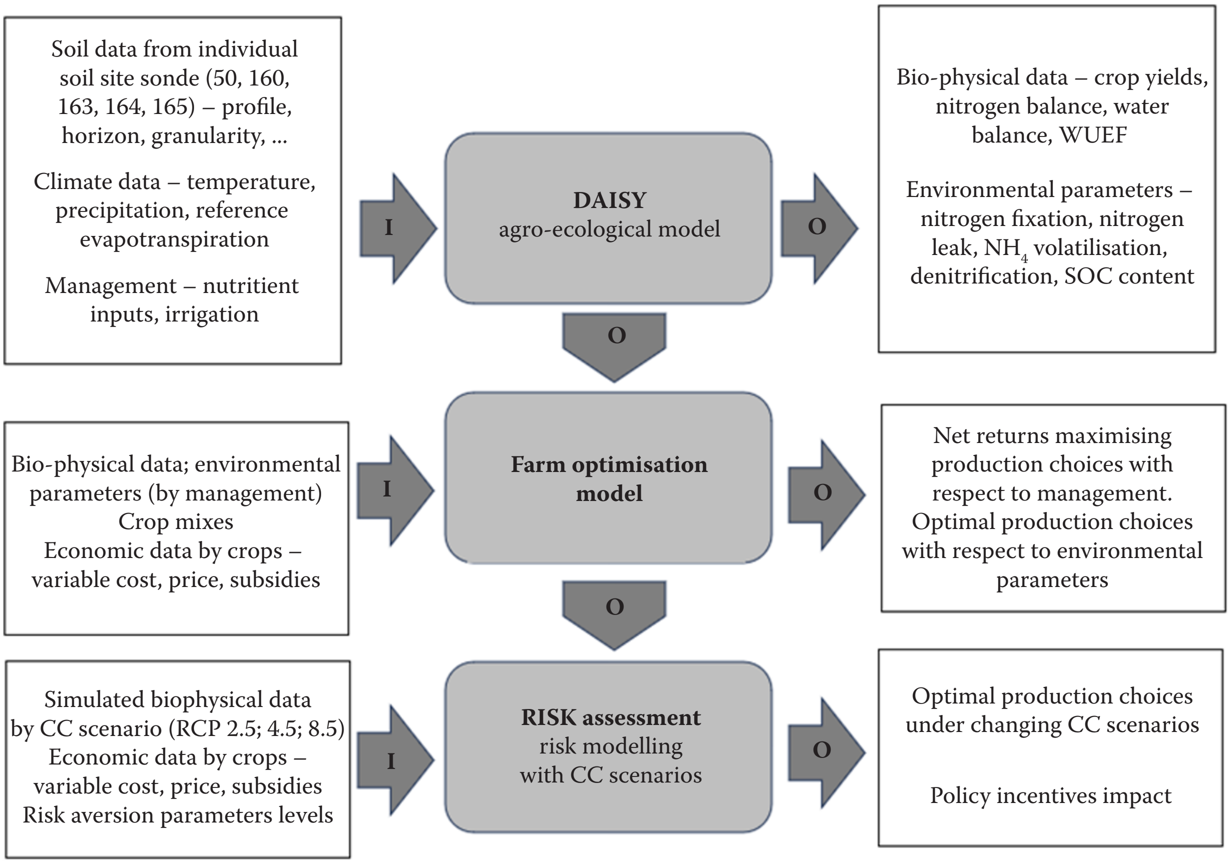

Figure 4. Description of the integrated risk estimation model

I – model input; O – model output; CC – climate change; SOC – soil organic carbon; WUEF – water use efficiency
Source: Author's own processing

ing these dynamics is crucial for assessing agricultural productivity and sustainability.

Farm optimisation model. The model incorporates economic data, including market pricing, variable costs, and economic indicators. This makes it possible to take economic considerations into account when evaluating the effects of crop variability and nitrogen emissions.

Risk assessment. The likelihood and magnitude of crop yield variations under changing climatic circumstances can be predicted using an integrated risk estimation model. Farmers and policymakers can use this information to help in planning and decision-making. The model may bring some insight into the risks of nitrogen pollution and the effects of agricultural practices on the environment by examining nitrogen levels and emission patterns within agricultural systems.

An integrated risk estimation model for agriculture is a sophisticated tool that helps assess and manage various risks that farmers may face in their operations. The proposed model incorporates data from multiple sources, such as weather patterns, soil quality, market conditions, and crop health, to provide a comprehensive analysis of potential risks. Model in this form can help farmers make informed decisions related to crop selection, resource allocation, pest control, and more. Ultimately, an integrated risk estimation model aims to enhance the overall resilience and sustainability of agricultural practices.

DISCUSSION

Crop simulation model results are used in bio-economic farm models to evaluate how climate change and technological advancements affect crop yields. Climate change is expected to boost crop yields in North-West Europe, according to crop simulation models. They do not, however, consider the conse-

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quences of catastrophic occurrences like droughts and protracted wet weather. The anticipated benefits of climate change on crops may be offset by the increased frequency of such extreme events and the anticipated extra harm from pests and illnesses (Paas et al. 2016). Under the condition of land endowment by soil type, the LP and NLP models allow for the optimisation of crop production to choose net returns, maximising production decisions with regard to management. The DAISY model's simulation of crop responses provides the information needed to determine yields and environmental parameters for various crop management strategies (such as irrigation and nitrogen application). Alternative approaches, such as crop growth simulation models, provide a speedier and less expensive means of examining how agricultural land management practices affect crop yields and the environment. When creating agricultural land management strategies, modelling can yield findings that are somewhat dependable as long as the models are tested and calibrated using trustworthy field data (Santhi et al. 2006; Zhao et al. 2016; Choruma et al. 2019). Crop models, for instance, have been used to improve management techniques like water and fertiliser application at the farm and plot levels (Khan and Walker 2015). Effective responsiveness and adaptation are necessary to deal with the negative consequences of climate change and maintain agricultural productivity. Given the abundance of existing adaptation strategies, both researchers and farming communities have acknowledged this (Olesen et al. 2011). Based on Steidl et al. (2015), changes in crop species or dates of sowing and harvesting are examples of short-term adaptation, whereas long-term adaptation calls for structural adjustments to the farming system, new water-saving land management strategies, and improved irrigation use efficiency (or the breeding of new crop varieties, which is outside the scope of farms).

Considering the allocation of land for different crops when using the combined biophysical and economic data enables us to respect the agronomic requirements of crop production management while maximising profit. According to the presented farm-integrated model for the historical period, depending on the soil type, the optimal crop management scenario appeared to be higher nitrogen fertilisers load and irrigation in order to maximise net returns. Crop yields were significantly impacted by the frequency of irrigation and the rate at which nitrogen is applied. Grain yields were generally lower in non-irrigated areas without nitrogen treatment, and they tended to rise with increased nitrogen application frequency and rate (Cui et al. 2021; Jia et al. 2021).

This follows earlier results Bullová et al. (2020), who stated that the optimal way of cultivation must correspond with agronomic requirements and is influenced by the production area determined by soil type. In a previous study (Svetlanská et al. 2017), the authors emphasised the importance of production selection, stating that high nitrogen input and irrigation represent a conventional way of managing crop production, which can lead to environmental pressures in terms of water resource depletion and soil degradation. Investments in improved technology can motivate farmers to transition to lower-input, sustainable management of crop production that still ensures a high economic return on crop production. Similarly, Mitter et al. (2015) concluded that environmental degradation caused by crop cultivation can be reduced by adjusting management practices and increased incentives from policymakers in the form of support for sustainable land use management. The environmental impact of crop cultivation can be reduced by adjusting management practices and increased incentives from policymakers. In contrast to intensive farming, the innovative methods and new approaches toward sustainable farming system enhance the agricultural productivity, and quality of life of farmers (Frank et al. 2014).

With the global threat caused by climate change, farms are becoming vulnerable. By proposing an integrated modelling framework for assessing the optimal crop management decisions under different climate change scenarios on the farm level, we are able to identify solutions which would lead to profit maximisation but also yield protecting decisions in terms of nitrogen input application and use of irrigation. This is in line with other research findings claiming that advancing climate change risk assessment is essential for more informed decisions reducing negative climate change impacts (Zscheischler et al. 2018; Simpson et al. 2021). One way of modelling such risk is to use the mean-variance approach (Markowitz 1952, 1987). For example, Roche and McQuinn (2004) used mean-variance portfolio optimisation to investigate optimal land allocation decisions taking into consideration agricultural policy change, and Barkley et al. (2010) applied it to optimise the selection of wheat varieties in a specific region. The empirical evidence of Delfiyan et al. (2021) revealed that farmers can manage the negative impact of climate change effectively by adapting their current farming practices. Thus, farmers can assess and manage a variety of risks associated with their operations

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with the use of an advanced tool as a risk estimate model. The model explorations confirmed that a sudden lack of irrigation water will cause a shock and raise the demand for an adapted crop sequence, as mentioned by Schuler et al. (2020). Both models in this study demonstrated that there is potential for adaptation: switching the crops cultivated could result in better outcomes on the 'profit' and 'soil organic matter balance' metrics while requiring less effort than irrigated scenarios. This research revealed that the crops chosen for a rainfed scenario were primarily wheat, barley, and sunflower, when maximising profits was the primary goal. Rapeseed, soybean, maize, or sorghum were added in different amounts to wheat and barley in FarmDESIGN's outcomes, where other goals (labour, soil organic matter balance) were just as significant as operational profit. However, operating profitability under rainfed conditions will be significantly lower than in a future scenario with irrigation, given the crops and the associated assumptions and limits we applied. Alternative methods or revenue streams must be implemented in order to close this disparity.

CONCLUSION

This scientific contribution aimed to demonstrate the use of an integrated model combining biophysical and economic data at the farm level and to suggest a framework for scenario-based research on the effects of climate change at the farm level. Guidelines, models, and frameworks that were developed to facilitate the process of planning adaptation are examples of methods and tools for adapting to climate change. The first research objective involved creating a farm-explicit integrated model for the identification of optimal crop management practices respecting different soil types at the farm. The integrated model combined agronomic information and biophysical models into land-use optimisation model in a bottom-up system, considering the heterogeneity of alternative costs in the selection of agricultural management practices (management choice). Models in LP and NLP forms revealed that the distribution of land among crops enabled a range of crop management strategies that maximise net return while considering the biophysical reactions of the crops. Higher nitrogen fertiliser load and irrigation appear to be the ideal crop management scenarios, depending on the soil type, according to the farm-integrated model for the historical period. It should be highlighted that the model farm should consider investing in irrigation since it did not already use irrigation. The importance of considering market dynamics in future research should be recognised. Environmental policies and climate change may influence agricultural prices. As we refine our model, incorporating variable price scenarios could provide a more comprehensive understanding of the economic impacts at both the farm and regional levels.

As a part of the second research objective, an integrated model for estimating the risk of crop yield variability and nitrogen emissions was proposed. The proposed framework involved DAISY simulated biophysical data, farm optimisation model and risk assessment. The framework had the potential to bring some insight into the risks of nitrogen pollution induced by climate change under different RCP scenarios and the effects of agricultural practices on the environment by examining nitrogen levels and emission patterns within agricultural systems.

Through the integration of biophysical and economic data, this proposed model offers a comprehensive approach to assessing the risks associated with crop variability, nitrogen emissions, and their interactions in the context of a changing climate. This integrated model can support evidence-based decision-making and sustainable agricultural practices in response to the challenges posed by climate change.

The suggested framework will be expanded into a risk assessment model at the farm level, which will serve as the foundation for an upgrade on the regional level, in order to guide future research.

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