

From local to global and from global to local: Designing the protocol to model agriculture and climate resilience

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ABSTRACT

Agriculture is an essential factor in the climate-food-biodiversity nexus, affecting climate resilience and, ultimately, whether we achieve the global Sustainable Development Goals. This study aimed to investigate the local-global interaction by integrating sustainability indicators with three modelling methods to address agriculture and climate resilience. The novelty of this research lies in its innovative methodology, which employs locally sourced indicators to integrate with climate and crop growth models (DSSAT, local biophysics), fed into large-scale equilibrium models (MAGNET, global economics) and Life-Cycle Assessment tools (LCA, environmental feedback). This enables precise mapping and analyzing regions that are most and least vulnerable to climate change, which is crucial for informing policymakers. Additionally, the novel methodology has incorporated focus groups to design a set of indicators that are compatible with typological input data for the modelling protocol.

Our methodology quantified the impact of heat, drought, CO₂, and extreme weather conditions on local yield changes. This approach uniquely combined regional-level data with five types of indicators: farming practices, water, climate/soil, biodiversity, and economics. Focus groups were instrumental in the process of gathering, selecting, and fine-tuning indicators, identifying gaps, and areas where policies should be tailored and targeted.

This innovative work represents a significant step forward for evidence-based policy-making and allows us to emphasize the role of “local-to-global” feedback in scaling up models. It demonstrates how localized climate extremes can disproportionately influence the stability of global wheat production. It is important to highlight that biodiversity indicators are significantly missing from the large-scale modelling of the climate-food-biodiversity nexus.

1. Introduction

Agriculture has many connections – technical, economic, environmental and agronomic – to climate resilience. According to Holling (Holling, 1973), climate resilience is the ability of local actors that is needed to recover from compound events (CE), including unforeseen global shocks. In this study, we brought together, for the first time, three modelling methods for addressing agriculture and climate resilience,

while starting from a participatory process in an international setting to envision 2030 policy-making. In light of the increasing demands for reporting in the realms of policy planning, implementation, evaluation, and impact assessment, the academic debate highlights the need for evolution in existing monitoring and data collection systems to encompass new policy topics such as climate resilience, soil health, and more nuance on fertilizer and pesticide use (Bassi et al., 2011). Thus, modellers are confronted with the assumption that no individual

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indicator can provide sufficient information for policymakers (Barnes and Thomson, 2014). Further, demand for new measurement and evaluation requirements is limited by the typology of input data in models and imperfect compatibility with CE-related indicators. The CE-related indicators for agriculture, to be useful in policy-making, need representability in the global models, and some extent of specificity for the crop at the local scale (winter wheat in this study). Interpreting CE-related indicators in agriculture at the global and local scales together is a significant challenge (Hölscher et al., 2022; Matlock et al., 2018; McDermid et al., 2017; Rega et al., 2019).

Achieving climate resilience requires farmers to adapt their practices to a changing climate CE (European Commission and EU Climate Adaptation Strategy, 2021) and reduce agricultural emissions and sequester carbon in soils. Using assessment tools for the many phenomena involved in climate resilience in agriculture, which range from the global to the local, is a complex field that needs to assess CE-related indicators. Furthermore, the literature emphasizes climate resilience as dependency on farms performing well in terms of robustness, adaptability and transformability (Darnhofer, 2014), as well as the role of policy in promoting climate-resilient farms (Ansah et al., 2019; Buitenhuis et al., 2020). Studies have also examined huge efforts, in the context of climate resilience, to come up with coherent policy indicators (Beitnes et al., 2022), soil indicators (Janků et al., 2022), various disease indicators (Rocklöv et al., 2023) and efforts in measuring the relevance of agricultural research indicators (Pelucha et al., 2021).

In this paper, we present a study conducted under the European project ECOREADY. The project sets out to establish a network of local-scale living labs, tendered internationally, to study how agriculture can become more resilient to CEs in the era of global challenges. To prepare for this, we focus on three questions: How can available models inform policies for mitigating CEs and increasing climate resilience in global agriculture on a local scale? How can we forecast climate mitigation and increased climate resilience with suitable indicators, using winter wheat in the Central Bohemia Region (CBR) as a test case? What lessons have we learned from using indicators in global assessment tools such as models?

The novelty of this paper responds to the shortcomings in the traditional global assessments, that is reliant on broad-brush indicators, which are often insufficient in capturing the nuanced local realities of wheat production. This research presents a groundbreaking methodology, demonstrating how locally sourced indicators can effectively inform wheat yield trends across both global and local scales. This granular understanding facilitates the coupling of three models in view of precisely mapping and analyzing regions that are most and least vulnerable to climate change, a crucial advancement for global food security. Such detailed methodology enables policymakers to recognize existing indicator gaps to inform models on the one hand, and strategically tailor and target policy measures on adaptation and investment on the other hand. In sum, we introduce a novel indicator-based methodology for upscaling models, illustrating how localized climate extremes can disproportionately influence the stability of global wheat production.

This paper aims to (a) survey global models and assess how well are suited for policy-making with regard to climate resilience in agriculture; (b) understand how the indicators relevant and meaningful for policy-making have been taken up by Intermediate Modelling of climate and crop growth, Computable General Equilibrium model tools and Life-Cycle Assessment tools; (c) suggest what knowledge is currently missing for CE-related indicators in agriculture; and (d) design the protocol to model agriculture and climate resilience by combining the different modelling tools while starting from identical indicators and describing various climate resilience trends. This aim was to prepare a methodology for local policy-making design under living labs, focusing on CE and agriculture under global challenges.

1.1. Indicators

Indicators are inputs used in assessment tools that represent values measured quantitatively or felt qualitatively (Meadows, 1998). Indicators are similar to parameters, which provide information about the state of the environment, but indicators have a broader significance beyond the current understanding of parameter values (OECD, 1999; Vereijken, 1992). In EU statistics, indicators are derived from quantitative measurements at the macro scale of nations (Oenema et al., 2011). Indicator monitoring is also an extensive area that includes many indicators prepared for specific scenario studies (Hölscher et al., 2022; Rega et al., 2019; Kelly et al., 2018; Šálek et al., 2018; Verkerk et al., 2018). Indicator monitoring is a precondition of policy-making (Bassi et al., 2011), as effective policy-making starts with well-defined, measurable indicators. The utilization of indicators helps translate policy objectives into specific, measurable, achievable, relevant, and time-bound targets. The meaningful indicator-based approach not only enhances the clarity of policy intentions but also allows for systematic evaluation and adaptation of policies based on their performance against established benchmarks (Bassi et al., 2011).

Specifically, indicators at the local scale are required for assessments of climate-resilient farms. This will rely on indicators that take into account CEs, such as risks, shocks, including droughts, floods and temperature extremes, while indicating the presence or absence of farming practices to mitigate CEs. According to Latruffe et al. (Latruffe et al., 2016), indicators are „statistical constructs which support decision-making by revealing trends in data“. To support decision-making, indicators must be quantitative and directly linked to the drivers that policymakers identify from the global to the local-scale agriculture. There is a vast field of climate-related indicator assessments (Dabkiene et al., 2021; Dornik et al., 2024; Nelson et al., 2010). Agrobiodiversity is an indicator that plays a crucial role in enhancing climate resilience in agriculture and the adaptability of cropping and farming systems to climate change (Jackson et al., 2013; Štefanić et al., 2020). This includes improving the ability of agricultural systems to withstand and recover from climate CEs, such as droughts, floods, and pest outbreaks (Mijatović et al., 2013). Another indicator is associated with farming practices. Policies note that farming practices can have an impact on climate resilience (Bhatnagar et al., 2024) and biodiversity (European Commission and EU Climate Adaptation Strategy, 2021). When practices are based on the management of diverse agroecosystems, such as crop rotations, intercropping, no till, changed times of sowing and climate-proof crop varieties, they can contribute to climate resilience by leveraging the accumulated knowledge of local communities in dealing with variable climatic conditions (Rega et al., 2019; Mariel et al., 2021) while not decreasing agricultural output (Rega et al., 2019). On the other hand, intensive farming practices have adversely affected biodiversity (Pe'er et al., 2014; Raven and Wagner, 2021). EU policies target climate resilience as part of the Climate Adaptation Strategy (European Commission and EU Climate Adaptation Strategy, 2021), and as part of the objectives of agriculture at large, as postulated in the EU Farm-to-Fork Strategy (European Commission, 2020), referring to the past policies (EU White paper on Adapting to Climate Change in 2009 and Biodiversity Strategy to 2020 and 2010). Then there is the new CAP to deliver on the Farm-to-Fork Strategy. It is a contextual driver setting out the policy vision relevant to agriculture, requiring that fertilizer use is reduced and that 25 % of the agricultural area be under organic management in 2030. While the global-scale indicators for climate resilience (such as yields) are well understood and documented, there is a lack of evidence for locally sourced indicators (e. g. soil biodiversity, plant biodiversity, crop varieties, arthropod and insect occurrence) that are closely linked with climate CEs.

1.2. Focus groups

Mitigating CEs and increasing climate resilience in agriculture on a

local scale, while facing global challenges, is a broad area of research based on CE-related indicators. Hamilton et al. (Hamilton et al., 2020) showed that in participatory processes, indicators are interpreted by actors according to their attitudes toward different scenarios about “where we might be heading”. Participatory processes employ various actors to establish networks, communicate iteratively and gather information. This aspect is pronounced in the international setting. The participatory processes lay the foundation for focus groups to be conducted within a specific time and space. Focus groups are an approach commonly used in social sciences (Orvik et al., 2013; Reed, 2008), and are also utilized in agricultural research (European Commission, 2020; Jones et al., 2014; Steinke et al., 2022). They are designed to gather human-oriented information (Morgan, 1996). Focus groups provide a way of soliciting information about the robust conditionalities, limits, values and potentials of farming practices. They also take into account the preparedness of actors to adapt established farming techniques, tools, etc. to achieve more climate-resilient farms.

1.3. Modelling tools

In approaching our four-fold objective, in outlining the key indicators relating to CEs and pertinent to the year 2030, we worked with several modelling teams from around Europe. This helped us represent, for the first time, various assessment tools for agriculture modelling and work towards a reduction in their uncertainties. All the models simulated land system assessment, but each model has its unique focus. MAGNET model, for example, has a greater focus on macro-economic picture, Life Cycle Assessment (LCA) focuses on product-based modelling, while Intermediate Modelling applies climatic data assessment combined with a crop model. To advance the modelling for the test case, we built two opposing requirements into the models. The models need to be complex enough to account for relevant indicators depending on the drivers of change in the test case. But, there is also a need for the models to be frugal, so that they can simulate and assess manifold living-lab situations in the future, similar or not to the test case. The assessment tools that we apply in this study are shown in Fig. 1.

Intermediate modelling tools. Among the assessment tools used in this study is the Intermediate dynamic crop model. This agronomic model condenses assumptions about biological processes interacting with the environment through mathematical equations, including crop phenology simulation and statistical models (Potopová et al., 2021a, 2021b, 2023a). Crop models combine weather, soil, genetic, and management components to simulate yield, resource use, and outputs of nutrients and chemicals to surrounding water, air, and ecological

systems. Although various model-based decision-support tools have been developed since the 1980s to support decision-making for agricultural planning, crop management and crop phenology models have contributed little to practical agriculture (van Ittersum and Donatelli, 2003). Yet, growing interest among farmers has focused research on tuning crop models to improve the economic viability of agriculture by reducing certain inputs (e.g., chemicals, water, etc.). In our study, the crop model simulates the main processes that determine crop growth and development due to changing climate and agricultural management for winter wheat. Our tool is derived from the most common Intermediate dynamic crop models used for winter wheat, such as APEX (Donatelli et al., 2010), CROPSYST (Stöckle et al., 2003; Hoogenboom et al., 2003), FASSET (Berntsen et al., 2003), HERMES (Kersebaum et al., 2001), STICS (Brisson et al., 1998) and WOFOST (Boogaard et al., 1998). Therefore, the study takes into account weed, pest, and disease pressures and predicts performance under a range of inputs and practices that represent coexistence with highly controlled, intensive production technologies and new wheat varieties. Intermediate crop dynamic simulation models are a key tool in assessing the impact of future climate change. Compared to other models, we restrict ourselves to DSSAT (Decision Support System for Agrotechnology Transfer, <http://dssat.net/>) as an advanced crop model. Additionally, to model compound events (CEs), the Intermediate statistical regression models were used (Fig. 1). The model encompasses data on integration indices pertinent to CEs, e.g. risk of winterkill–blackfrost, drought and heat events, heat stress during flowering and drought grain filling while assessing the linkages to food security (Potopová et al., 2021a, 2021b).

Computable General Equilibrium model (MAGNET). MAGNET has been one of the most used tools for assessing the impact of economic policies (<https://www.magnet-model.eu/>). In contrast to Partial Equilibrium models, which focus on selected markets, CGE models simulate equilibrium in all markets of the economy, making them suitable for analysing the welfare impacts of policies. Compared to the input-output models, CGE models allow for substitution in production technology and provide endogenous price responses. The emergence of CGE models was triggered by converting the Walrasian general equilibrium structure to real economic data. The first CGE models were comparative static models with applications in the area of public finance and international trade. A large expansion of CGE models occurred in the 1990s when they were used to analyse the impacts of economic integration, trade and agricultural policies. Recently, CGE models have become more specialized and are increasingly used in studies on possible trade-offs with other global challenges such as climate resilience and biodiversity. The comparatively static models have been mostly replaced by dynamic CGE

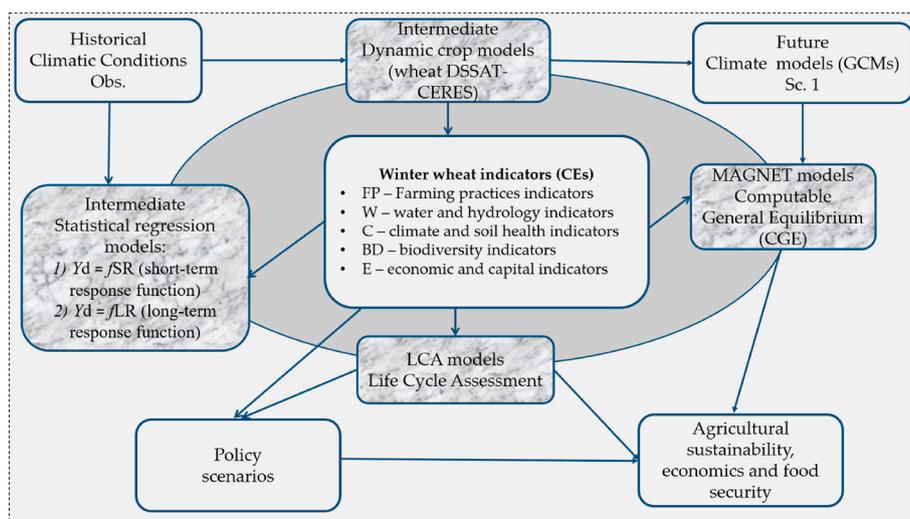


Fig. 1. Schematic links of Intermediate crop models, Magnet and LCA models.

models with recursively dynamic or forward-looking specifications. CGE models have found an important application in food security analysis because they enable the measurement of indicators covering various food security dimensions (van Meijl et al., 2020a, 2020b). In the last decade, CGE models have established importantly in the field of long-term projections based on foresight studies, such as those of the Shared Socioeconomic Pathways (Riahi et al., 2017; van der Mensbrugghe, 2015), i.e. the scenarios of possible socioeconomic futures to explore the implications of climate change. They comprise several different narratives of the world’s future with quantified drivers of population, economic activity, urbanisation, and income inequality (O’Neill et al., 2017). CGE models are used to implement an array of indicators to clarify the scenarios or alternative foresight scenarios to provide long-term projections of economic development (van Meijl et al., 2020a, 2020b; Doelman et al., 2019; van Dijk and Meijerink, 2014). Although the gains in the reduction of GHG emissions from the food system are notable (between 9 % in Philippidis et al. (2021) and 29 % in Springmann et al. (2018)) there are important trade-offs with nutrition, inclusiveness, sustainability and growth (IFAD, 2021; Kuiper and Cui, 2021).

Life Cycle Assessment (LCA). LCA is a tool to assess the environmental aspects and potential impacts associated with a product’s life cycle, from raw material extraction through production, use and disposal (ISO, 2006). From an initial focus on accounting for the physical flows in a product’s life cycle, these methods gradually evolved to account for environmental impact potentials, such as climate change and resource scarcity. In furthering LCA methodology development, standardization and harmonization, life cycle thinking has been widely used as a decision support tool by policymakers as it fulfils three fundamental policy needs, i.e. life cycle data that is reproducible, verifiable and comparable. The European Union has made efforts to implement a life cycle-oriented approach in policies, although mandatory requirements related to these approaches are relatively limited (Boschiero et al., 2023). LCA features a combination of characteristics that enable addressing questions that no other assessment tool can. LCA is based on considering the complete life cycle of a product (avoiding burden-shifting between stages in the supply chain), covering a wide array of indicators associated with, e.g., global warming potential, water- and land use) to identify potential trade-offs, and a quantitative approach that is rooted in natural science (Niero et al., 2015).

2. Data and methods

2.1. Designing the methodology

Our study was primarily defined by the entirely novel utilization of three modelling tools, brought together for the first time. The novel methodology used in the study was set up as the process of developing and finetuning a protocol for modelling the sustainability indicators along the gradient from local to global and from global to local. The methodology was anchored in the assessment of indicators that convey information relevant to policy-making. The methodology itself is the main novelty of this study, as we sought to support policy-making associated with mitigating the impact of climate compound events (CEs) and enhancing climate resilience in global agriculture with reference to a local scale. Wheat production in Central Bohemia was taken as a test case. This protocol is intended to support the ongoing development of the Horizon EcoReady project and facilitate the evolution of data from living labs throughout the various bioclimatic zones in the EU. Each of the living labs, which have been tendered globally, will soon examine the policy-making aspects of a specific food product at the local level, and their findings will need to be interpreted on a global scale.

The overview of the methodology is shown in Fig. 2. Three streams of modelling were brought together, based on work on sustainability indicators, to understand how to forecast climate CEs and increase climate

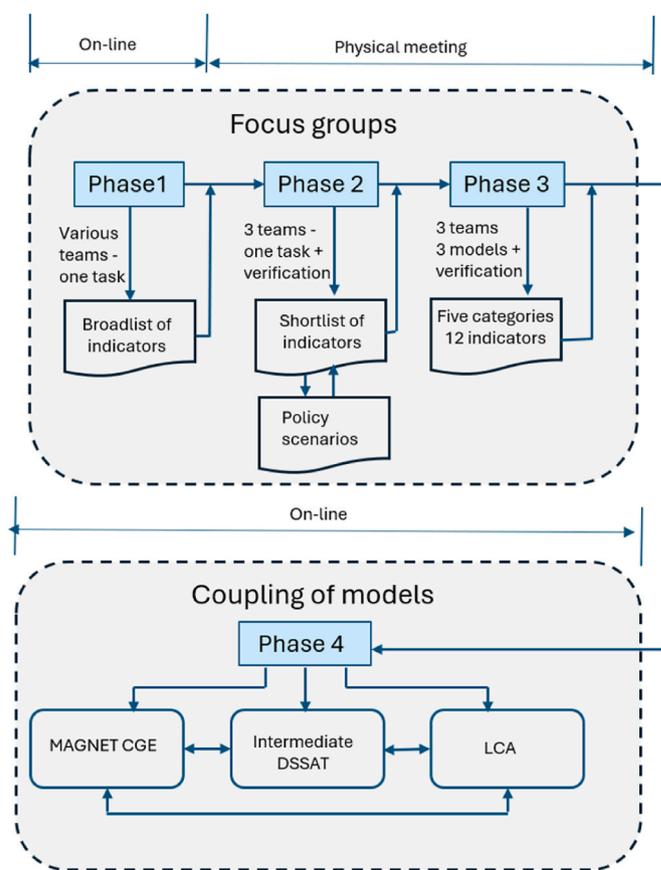


Fig. 2. Scheme of the proposed methodology involving the design of the set of indicators through focus groups, and applying the indicators through the coupling of models.

resilience. Our protocol makes a unique contribution to the policy-making field by involving focus groups (online and physical) in the international setting to assess indicators vis-à-vis policy scenarios. The focus groups aimed to learn about the adequacy of indicators and their compatibility with the typology of input data of the modelling tools. Qualitative and quantitative data were assessed. The qualitative data came from the focus group processes, while the quantitative data were collected from the three modelling groups. We evaluated the modelling strengths and weaknesses with regard to the adequacy of indicators to be used as model inputs.

2.2. Unfolding phase 1 to phase 4

The CE-related indicators for the testing of the protocol were compiled during several phases of the data gathering process. Scientists and stakeholders were invited to participate in this process based on their expertise with data for policy-making associated with climate resilience, food security, yields and environmental impacts relevant to wheat production in Central Bohemia. The preliminary Phase 1 unfolded over a few months. It consisted of a structured online process that involved focus groups in learning about indicators for policy-making and then proceeded to compiling CE-related indicators (March to November 2023). Subsequently, focus groups met physically during a multi-day format in the Hague (9th–11th November 2023). The meeting employed the focus groups to assess the preliminary indicators (Phase 2). Also, the focus groups convened here physically around the three modelling tools (Phase 3) to identify potential issues with data availability with regard to these indicators to be used under each modelling approach. Finally, in the aftermath of the physical meeting of focus groups, we rolled out Phase 4. This phase consisted of the interactive

online procedure involving all three modelling groups and the facilitator of the earlier phases. During Phase 4, the indicators distilled from Phase 3 were put through the coupling process involving three streams of modelling and then the collaborative fine-tuning to find out the robustness of the protocol and the relevancy of the outputs for policy-making.

Throughout Phase 1 to Phase 4, we did not aspire to assess any single policy, nor individual scientific paradigm, such as regional self-sufficiency in the narrow sense that Kaufman et al. (Kaufmann et al., 2022) promote. However, we made efforts to understand the environmental impacts alongside the macroeconomics of winter wheat production in the region. While the modelling of the yield indicator is a veritable arena of research, in this international study, we focused on the preparations of policy-making associated with sustainability and climate resilience rather than just yields.

2.3. Study area and test case

The Central Bohemian Region (CBR) has an area of 10,928 km². The number of municipalities and population make it the largest region of the Czech Republic. It has developed agricultural production which profits from excellent natural conditions in the northeastern part. It is great at growing wheat, barley, beet, and in parts close to towns, fruits and vegetables. The food industry is one of the key industries in the region. The agricultural area under organic farming accounts for 4.7 % (whereas the nationwide average is 17.8 %). The average area of one organic farm is 71 ha. The area of arable land is 9300 ha (Czech Statistical Office, 2022). This ratio, favouring arable land when compared to other regions, makes growing cereals an important commodity for the future. The tiny share of organic management in CBR is precisely because the region is the leader in conventional commodity output. Yet, there is a large extension of uplands in the southwest of CBR, where farming is already low intensity and may be potentially converted to organic without compromising wheat output. The rapidly changing agroclimatic conditions pose a significant challenge to farmers (Trnka et al., 2011; Pinke et al., 2022).

Winter wheat (*Triticum aestivum*) is an important commodity in CBR. Winter wheat flowers in June. It suits deeper, loamy and clayey soils with a neutral to slightly acidic soil reaction and sufficient nutrient supply. The conditions for growing wheat are particularly good in areas with average spring and summer temperatures of 14–17 °C and low rainfall of 250–350 mm (Kubát, 2002; Zimolka and Cultivation, 2005). According to the Food and Agriculture Organization (Alexandratos and Bruinsma, 2012), the global annual demand for cereals is projected to grow from approximately 2.1 Gt in 2005/2007 to 3.0 Gt by 2050 (including maize, rice, sorghum, and millet, in addition to wheat itself). Sustainability of wheat production is directly influenced by water scarcity (Trnka et al., 2019). Previous studies have demonstrated that global wheat production strongly depends on water availability during and before the crop-specific and typically unirrigated growing season (Zampieri et al., 2017). Between 1985 and 2007, drought effects on global wheat production doubled compared to those in 1964–1984 (Lesk et al., 2016).

2.4. Phase 2 and phase 3: focus groups on indicators

The focus groups included a diversity of international experts (n = 35) that represented the respective modelling fields (Intermediate modelling, MAGNET, LCA), agricultural science, ecology, biology and economics. We also monitored the geographic affiliation of experts to ensure that boundaries were set on the countries in the EU. The focus groups were conducted initially in an online manner (Phase 1) and were conducted physically over three days (Phase 2 and Phase 3).

Our approach was designed to go beyond previous studies showing that participatory processes in the international setting are effective in two aspects. One is the potential of focus groups to pinpoint policies that

address specific environmental problems (Reed, 2008). Second is that externally, participants are easier to communicate with, even when focusing on complex technical indicators, and they allow exchanges about internal ecological assessments that are more precise (Schwartz et al., 2022). The difference in both these aspects is the innovative focus of the approach. Therefore, focus groups are a useful tool for working on complex technical subjects in a semi-structured way (Reed, 2008). By jointly discussing the subject in an international setting, participants can consider and react to arguments presented by others, which facilitates the examination of group dynamics and the formation of opinions. Our major consideration was to include conflicts between different actors and/or groups. Conflict has revolved around the pursuit of less compatible goals, as this is inherent in visions of sustainability transitions in agriculture (Skrimizea et al., 2020). To navigate conflict, we emphasized: a) setting clear goals and scope of exercise; b) acknowledging uncertainty; c) ensuring transparency and inclusion; d) applying criteria that also guard the overall technical-competence profile, and expressly introducing the necessary skill requirements in the composition of the focus groups (Soriano et al., 2023). The evaluation in focus groups had to include conflicts between different actors and/or groups. Conflict has revolved around the pursuit of less compatible goals of policy-making (or different views on how to achieve a common goal, as this is inherent in agricultural policy-making (Tanneberger et al., 2017)).

Phase 2 – Focus groups on the delineation of CE-related indicators consisted of three teams of 8–9 experts. Each team comprised of an agricultural scientist, ecologist, economist, and modelling experts for Intermediate Modelling, MAGNET, and LCA. The objective was to compile a list of indicators that are relevant for monitoring climate resilience, including issues related to soil health, water quality, farming practices and biodiversity associated with wheat cultivation in CBR. The international teams built on a large list of indicators from Phase 1. The Phase 2 and Phase 3 rolled out within the focus group meeting that gathered physically over three days in the Hague. Phase 2 employed the focus groups to distil the list of indicators based on specific drivers affecting wheat cultivation in the region. The verification process was integrated through an iterative assessment of the indicator list subsequently within all three teams. Based on these indicators, the focus groups formulated a policy scenario summing up how the sector will evolve by 2030. The policy scenarios were not required to consider the formal climate science typology. Rather, these scenarios were the mere tools to distil the indicator list, thus emphasizing the data that are needed for policy-making. The teams worked in a semistructured manner with the support of a facilitator. The outcome was the list of CE-related indicators built into three policy scenarios.

Phase 3 – Focus group continued to work in Phase 3 on the models' ability to take up the selected indicators. In this phase, the focus groups were reformatted around the three modelling groups. Each group convened to arrange the CE-related indicators into five domains: FP – Farming practices indicators; W – water and hydrology indicators; C – climate and soil health indicators; BD – biodiversity indicators; E – economic and capital indicators. The indicators arranged in the five domains are shown in Table 1. For each of these indicators, the researchers conducted a preliminary analysis of each assessment tool (Intermediate modelling, MAGNET, LCA), to determine whether the tool was capable of taking up the indicator, whether data were available for the indicator at the local level for CBR, and whether the global scale of the models can be utilized for the local scale of the test case in CBR. Then, a shortlist of 12 indicators (yellow highlight in Table 1) relevant to CE was created based on the most important and probable drivers. The indicators' shortlist was put forward as inputs to modelling.

2.5. Phase 4: modelling methods

Schematic links of Intermediate crop models, MAGNET and LCA models are portrayed in Fig. 1. Furthermore, Fig. 2 shows the basic

Table 1
Broadlist of CE-related indicators in five domains.

	Indicators		Intermediate dynamic crop model	Intermediate statistical model	MAGNET	LCA	Data availability	Bridge between indicators and models
FP - Farming Practices								
FP	share of farms that apply minimum of three crops at the farm	%	-	-	-	via yield change	Y	gap
FP, W	use of pesticides	kg year ⁻¹ per country	+	-	+	+	Y	LCA yes, MAGNET working on it
W	use of fertilizer	kg ha ⁻¹	+	-	+	+	Y	Well covered in LCA, MAGNET yes
FP	share of areas under organic management	%	-	-	via yield change	+/-	Y	gap
W - Water Conservation								
C, W	soil moisture at above field capacity	%	+	+	via yield change	-	Y, Exn	MAGNET yes, LCA no
C, W	water balance	mm	+	+	via yield change	-	Y, Exn	MAGNET yes, LCA no
W	volume of water consumption (rain, irrigated etc)	tonne, m3	-	+	+	+	Y, Exn	yes
W	ground water level	cm	-	-	-	-	Y	gap
W	soil water content	%	+	-	-	-	Y, Exn	gap
W	gross nitrogen balance	tonne, kg ha ⁻¹	+	+	via yield change	via yield change	Y	Yes
BD - Biodiversity								
BD	occurrence of endangered species sensitive to intensive farming	number	-	-	-	-	Y	gap
BD	no. of arthropods and insects per unit	number, kg m ⁻²	-	-	-	-	(no) patchy	gap
BD	resistant species of weeds and pathogens	number	-	-	-	-	Y	gap
BD	occurrence of invasive species of weeds, pathogens	number	-	-	-	-	Y	gap
BD	share of farmland covered by landscape features	%	-	-	-	-	Y	gap
C - Climate and Soil Health								
C	soil organic carbon content	%	-	-	via yield change	+	Y	LCA needed for emission modelling, MAGNET yes
C	precipitation	mm	+	+	via yield change	+	yes	MAGNET yes, LCA as input for emission modelling
C	tropical days and heat stress during flowering	number	+	+	via yield change	via yield change	Y, Exn	MAGNET yes, LCA no
C	sunshine hours, global solar radiation	hours	+	+	via yield change	via yield change	yes	gap
C	snow cover	cm	+	+	via yield change	via yield change	Y, Exn	gap
C	late spring frosts	days	-	+	via yield change	via yield change	Y, Exn	Expert judgment on how inputs are changing
C	CO2 atmosphere concentration	ppm	+	-	+	via yield change	Y	gap
C	soil erosion	tonne ha ⁻¹ year ⁻¹	-	-	via yield change	+	Y	gap
E - Economic and Capital								
E	yield	tonne ha ⁻¹	+	+	+	+	Y	yes
E	capital stock at farm level	euros year ⁻¹	-	-	+	-	Y	MAGNET yes, LCA no
E	investment	euros year ⁻¹	-	-	+	-	Y	MAGNET yes, LCA no
E	turn over	euros year ⁻¹	-	-	+	-	Y	MAGNET yes, LCA no

Note: + the model ability to incorporate the indicator as input; - the model unable to incorporate the indicator; Y - data available; Exn -Expert judgment needed; Yellow code – the indicators that can be processed by the involved models.

workflow for the modelling components that iterated the assessment of several indicators from Table 1 as model inputs. The modelling assumptions were the same for all these components in the application of the 2050 scenario. Here, we applied the formal climate science scenario.

2.5.1. Intermediate Modelling

We conducted quantification with regard to compound events of soil-climate-water extremes that relate to the growing season of winter

wheat. The CERES wheat model has been used from the DSSAT family of models, as a complex model used to integrate indicators relating to crops (winter wheat), soil, climate, and management for making appropriate decisions under various climatic conditions. Our approach was to quantify responses to compound events of climate change and variability impacts on yield. For simulating crop growth and development, we used as inputs: daily and monthly weather datasets of precipitation (mm day⁻¹), daily mean of maximum (Tmax, °C) and minimum

temperature (T_{min} , °C) for two periods, and global solar radiation ($MJ\ m^{-2}\ day^{-1}$). The 2021–2050 scenario (Sc. 1) was compared to the observed period 1991–2020 (Obs.). To assess the compound events of soil-climate–water extremes on winter wheat growth, we calculated several parameters for each district of Central Bohemia (CBR) and the Czech Republic. For the growing season of winter wheat, we quantified the number of days in heat waves, the number of extremely hot days (Heat stress), the number of frost days (Frost stress), and the number of days with low soil moisture up to 40 cm (AWR, drought stress) for Obs. and Sc. 1. Heat waves are defined as at least three consecutive days with T_{max} of at least 30 °C, with at least one day reaching 35 °C, and T_{min} not dropping below 20 °C. Frost days are the number of days with T_{min} below 0 °C during GS. Drought stress is the number of days with low soil humidity in a depth of 40 cm when the relative content of plant-available water (AWR) drops below 30 %. Heat stress is the number of days with T_{max} above 35 °C during the growing season. The study produced maps with a resolution of 500 m for CBR and the Czech Republic, which provide information on future climate change. With regard to Agroclimatic Scenarios Quantification, to simulate future CEs in winter wheat production, the sixth phase of the Coupled Model Inter-comparison Project was used, focusing on two Shared Socioeconomic Pathways – SSP1-2 (used as a sustainable development pathway for the future agricultural system), and SSP2-4.5 (which projects a middle pathway with some degradation of environmental systems but some improvements in resource and energy use). Furthermore, we used Statistical regression model relating to climate data. Following the methodology of Meitner et al. (Meitner et al., 2023), the CMIP6 multi-model ensemble of the median value of CEs was used under the median of SSPs. This ensemble of simulations represents a future for winter wheat production where development trends are not extreme in any of the dimensions but follow middle-of-the-road pathways. From the model ensemble, we assessed the most likely future climate development and the range within which this development can take place. Including these projections in crop models can help assess possible impacts and explore management strategies to adapt to climate change in winter wheat production, as shown in Fig. 1.

2.5.2. MAGNET CGE

The study used a global model called Modular Applied GeNeral Equilibrium Tool (MAGNET) to simulate the effects of climate-related yield shocks on the wheat sector of the Czech Republic's economy. MAGNET is a recursive and dynamic, multi-regional, multi-commodity CGE (computable general equilibrium) model that covers the global economy (Woltjer et al., 2014). As with other CGE models, MAGNET explicitly represents the economic linkages across the different sectors of each regional economy. It is built upon the Global Trade Analysis Project (GTAP) model (Hertel et al., 1997) and has been widely used for policy analysis in the area of the food-climate-energy nexus field (Doelman et al., 2019; Kuiper and van den Bos Verma, 2021; Gatto et al., 2023; van Meijl et al., 2024). The MAGNET model is built in a modular way and expands upon the GTAP model through the addition of a number of policy-relevant modules. Currently, MAGNET uses version 11.B of the GTAP database, which covers 160 regions, 65 sectors and 8 production factors. The original GTAP database was further disaggregated to include additional agricultural and bioeconomy sectors. As a result, the complete MAGNET database contains a total of 129 sectors and 154 commodities. The MAGNET database contains several types of input data: i) data from the GTAP database organized in form of the Social Accounting Matrix, providing comprehensive information on production, gross bilateral trade flows, transport costs and trade protection data for 160 countries for the benchmark year 2017. In addition, several other satellite data is added to the MAGNET database such as data for detailed modelling of bioeconomy, biofuel and renewable sectors, food waste data, nutrition data, Green House Gas emissions, pesticide and fertilizer use, SDG indicators data and several other. For the recent applications of MAGNET model and databases, see Doelman et al. (Doelman et al.,

2019), Kuiper et al. (Kuiper and van den Bos Verma, 2021), Gatto et al. (Gatto et al., 2023), de Lange et al. (de Lange et al., 2024), Yin et al. (Jin et al., 2024), and Bartelings et al. (Bartelings et al., 2024).

To reduce computational time, the MAGNET regions were aggregated into blocks. These blocks included the most relevant countries, with a specific focus on the EU member states, including the Czech Republic. There are 37 regions in the aggregated version. The production sectors were aggregated into 87 activities, with 18 belonging to the primary agricultural sector (see Fig. 3).

Production technology used in the model is a multi-nested CES production function that respects different substitutability among production factors and other inputs. For primary agricultural sectors including wheat, the production technology is represented using a production structure as shown in Fig. 4. In this structure, land can be substituted with fertilizer and other production factors; however, other material inputs are modelled as a fixed proportion of the output (Leontief production function). Next to defining substitution possibility in the mix of inputs, the production technology in MAGNET also includes parameters of technological change (productivities), which allow for a shift in the production function to achieve higher or lower output under constant inputs. In the particular test case, an exogenously imposed yield shock in the wheat sector is translated in MAGNET as a factor-augmenting technical change in land. This means that the model can achieve a higher output of wheat under constant land input. As a CGE model, this external shock is further transmitted from the wheat production sector to the other primary agricultural sectors, the rest of the economy and the rest of the world.

2.5.3. Life-Cycle Assessment

To evaluate the environmental impacts related to winter wheat production in Central Bohemia Region (Czech Republic), we employ principles of the Life Cycle Assessment (LCA) methodology in this study. We are conducting the LCA only for those parameters that have an interaction with the other models/tools used in this paper (Fig. 5). In this way, we utilise the LCA in a breakthrough way. Two scenarios are evaluated, one based on observed data in the period 1990–2020 (Obs. - baseline) and one based on an exponential statistical regression model for the period 2021–2050 (Sc. 1).

Goal and scope definition. The functional unit is a quantity description of the function or service for which the assessment is performed (Niero et al., 2015). The functional unit of this study is 1 tonne of winter wheat grain grown in Central Bohemia region of Czech Republic. The functional unit is the basis for determining the reference flow. The reference flow is the amount of product required to fulfil the function unit, considering product losses throughout the supply chain. The system boundaries indicate which stages and activities of a product's life cycle are included in the assessment. In this study a cradle to farm-gate assessment is performed, meaning we consider activities up to it leaves the farm. The modelled wheat indicator includes typical inputs such as seed, fertilizers, pesticides, diesel and water, as well as crop yield as the main output.

The life cycle inventory. LCA studies aim to determine the environmental impact of a product, including agricultural commodities. An LCA always depends on assumptions and scenarios and assesses the real world in a global model (Brentrup et al., 2004). In this study, we assess impacts related to fertiliser production and application and water use. Peatland oxidation, land use and land use change are considered for inclusion, but literature and preliminary calculations show an almost negligible impact (PAS, 2012; Tanneberger et al., 2017). Data on wheat yield and fertilizer use has been retrieved from the Intermediate exponential statistical regression model (Tables 4 and 5). The yield of the co-product has been considered based on a sustainable removable fraction of 30 % (Searle et al., 2017). Neither system expansion nor subdivision was possible, therefore economic allocation has been applied to partition all upstream emissions between the main product (wheat grain) and co-product (mainly wheat straw). Emissions related to

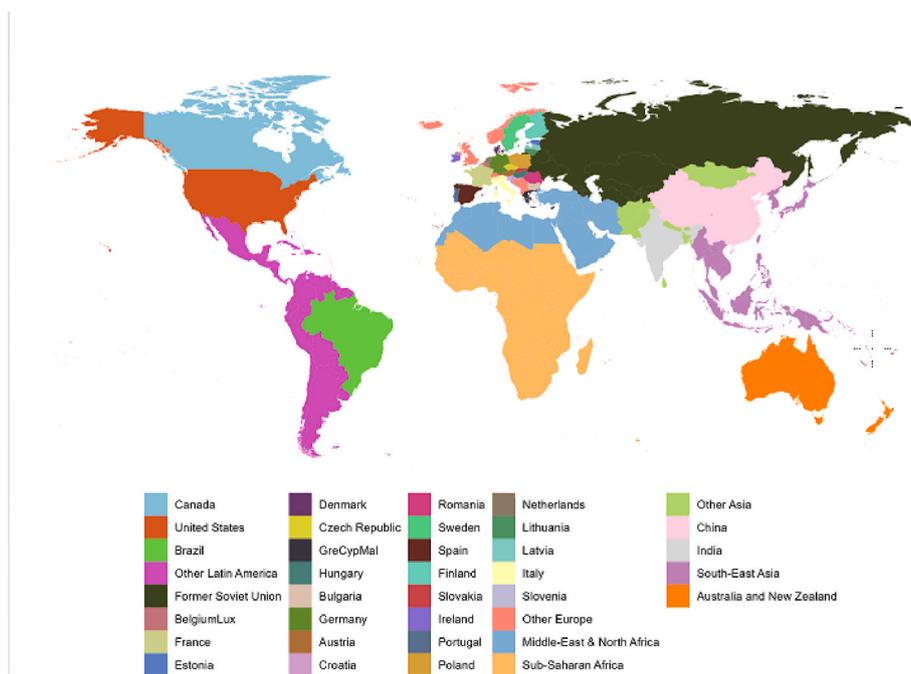


Fig. 3. Regional aggregation in MAGNET.

CROPS: pdr wht grain veg fruit nuts roots pulses oils sug oagr crops
 red = elasticities (range)
 (% of cost structure, range)

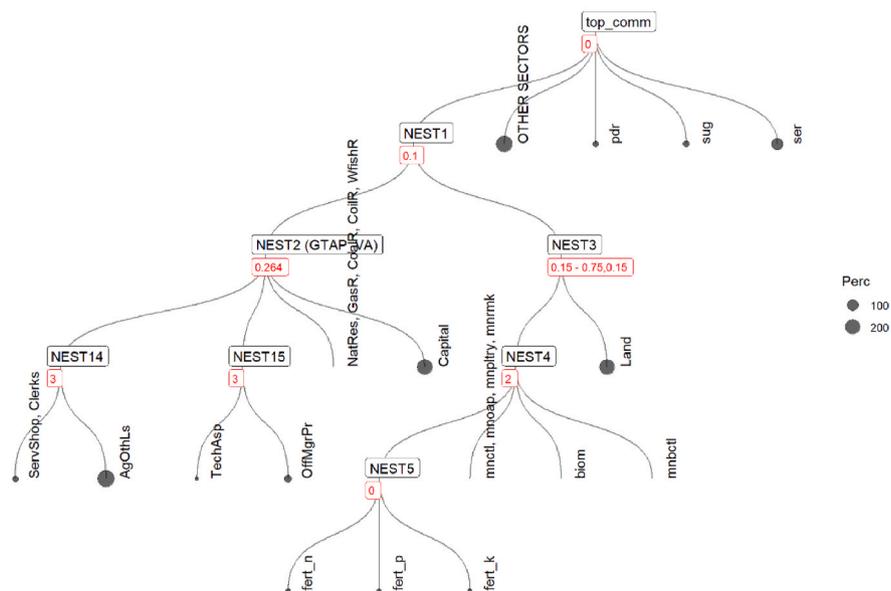


Fig. 4. Nested production structure of crop sectors in MAGNET.

the use of fertilizers have been calculated according to IPCC Tier 1, for ammonia, carbon dioxide from lime, urea- and urea-compounds, nitrous oxide from direct and indirect and nitrate (IPCC, 2020). Phosphorus emissions have been calculated according to the guidance in the product environmental footprint (European Commission, 2021). Blue and green water use was derived from Mekonnen and Hoekstra (Mekonnen and Hoekstra, 2010). Agri-footprint 6.0 (economic allocation) was used as a background database (Blonk Sustainability Tools, 2023). The allocation method used in this database is consistent with the allocation method applied in the foreground system. SimaPro 9.5 was used for modelling.

Impact assessment. The life cycle impact assessment (LCIA) method translates all emissions and resource extractions compiled in the LCI,

into environmental impacts. In this study, we have used the impact assessment method ReCiPe 2016.

3. Results

3.1. Delineation of indicators

The indicators were obtained by analyzing the scenarios formulated by each focus group, composed of international experts and focusing on the test case region. The following policy scenarios were developed. SCENARIO I – Agricultural sustainability brings effect to climate resilience: Farmers are more aware of the effect of farming practices on

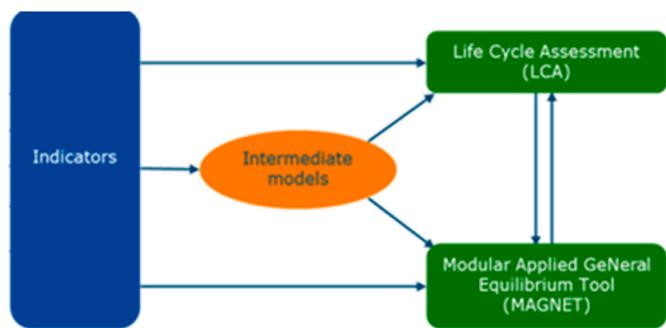


Fig. 5. LCA uses outputs from Intermediate modelling, while there is interaction between outputs of LCA and MAGNET.

biodiversity issues and soil organic carbon content. To achieve these goals, precision agriculture, integrated pest management techniques, crop rotations and organic agriculture are implemented. Although EU policy makes efforts to drive change in farming practices, capital availability influences farmer behaviour in positive or negative ways. SCENARIO II – Prominent adaptation measures in agriculture: Farmers implement changed timing and practices of field operation, fertilisation regimes, crop protection, soil water conservation practices and climate-proof crop varieties. Relating to the projected warmer and drier climate, environmental regulations for soil erosion are revised, and subsidy schemes to support crop insurance are systematically applied at the country level as part of adaptation planning in local-scale agriculture. SCENARIO III – Soil water depletion and soil measures. Climate changes, compounded by agricultural practices, lead to water and soil organic matter depletion. The farming practices and plot configurations have further depleted the ability to generate nutrients via soil microbiota. An intervention to reverse this trend included the creation of local water reservoirs for storage and use in times of drought. Farm plots will include trees and hedgerows to cut wind erosion and improve water retention. Farming practices, including crop rotations and intercropping, would be incorporated to improve soil biology.

In Phase 1, each focus group assessed, for their scenario, the indicators required (shown in Table 2). Further requirements in terms of farming practices, capital and policy have also been assessed (shown in Table 3).

3.2. Intermediate modelling through statistical regression models and dynamic crop model

We have developed an Intermediate modelling tool to assess changes in the winter wheat yield at field and regional levels in the Czech Republic. The tool integrates statistical regression models, the dynamic crop model DSSAT-CERES with experimental fields, and CMIP6 multi-model ensemble climate models as tools for predicting the yield under current and future climatic scenarios. An Intermediate modelling scheme allows for a direct interpretation of the spatial parameter variability and usage in crop yield assessments (Fig. 6) with climate projections (Figs. 7–8). Firstly, the four statistical regression models assessed the percentage changes in yield (Sc1) (Tables 4 and 5). Intermediate modelling forecasts, through these models, future yield changes based on the current system. The analysis of fluctuations in crop yields

Table 2
Indicator requirements stemming from policy scenarios.

	Scenario I	Scenario II	Scenario III
Biodiversity indicators	Y	N	Y
Climate and soil indicators	Y	Y	Y

Note: Y – Required, N – Not immediately mentioned, Bold font – unanimous opinion. Source: Focus groups Ecoready.

Table 3
Farming practices, capital and policy circumstances required by policy scenarios.

	Scenario I	Scenario II	Scenario III
Farming practices required	Precision agriculture Pest management	Changed timing and practices of field operation Fertilisation regimes	Local water reservoirs Installing trees and hedgerows
Crop rotations	Crop rotations Organic agriculture	Crop protection Soil water conservation Climate-proof crop varieties	Crop rotations Intercropping
Adaptation significant	Y	YY	Y
Farm advisory and training required	Y	Y	N
Capital availability significance	Y	N	N
Coherent policies	YY	YY	N

Note: Y – Required, YY – prominent significance, N – Not immediately mentioned, Bold font – unanimous opinion. Source: Focus groups Ecoready.

Table 4
Application of Intermediate statistical regression models to estimate changes in the winter wheat yield in Central Bohemia Region.

ISRM	Observed yield, tha ⁻¹ Obs.	Changed yield, % Sc. I	R ²	p-value
LRYd	5.16 [3.91–6.70]	–11.0	0.595	0.026
ExRYd		+10.7	0.599	0.002
LogR Yd		+5.7	0.415	0.039
PolynRYd		+10.8	0.601	0.001

Note: LRYd – linear model, ExRYd – Exponential model, LogR Yd –Logarithmic model, PolynRYd – polynomial model.

Table 5
Application of Intermediate statistical regression models to estimate changes in fertiliser use.

ISRM	Obs.	Sc. I	R ²	p-value
	Total fertiliser use, kgha ⁻¹	%		
LRFu	131.38 [89.93–171.93]	+5.6	0.595	0.001
ExRFu		+6.9	0.599	0.001
LogR Fu		+2.9	0.415	0.002
PolynRFu		+4.2	0.601	0.000
	Nitrogen (N, kgha ⁻¹)	%		
LRFu	98.71 [62.09–129.76]	+4.2	0.920	0.002
ExRFu		+5.3	0.864	0.001
LogR Fu		+2.3	0.874	0.002
PolynRFu		+2.3	0.940	0.000
	Phosphorous (P, kgha ⁻¹)	%		
LRFu	19.41 [13.16–26.79]	+5.6	0.500	0.001
ExRFu		+6.9	0.456	0.001
LogR Fu		+9.5	0.651	0.001
PolynRFu		+10.4	0.759	0.000
	Potassium (K, kgha ⁻¹)	%		
LRFu	13.26 [9.16–17.57]	+6.9	0.500	0.003
ExRFu		+8.1	0.456	0.003
LogR Fu		+10.3	0.651	0.001
PolynRFu		+16.7	0.759	0.000

Note: LRYd – linear model, ExRYd – Exponential model, LogR Yd –Logarithmic model, PolynRYd – polynomial model.

over time was based on several components: (1) the average yield change due to management and other non-climatic factors, was considered (2) agro-meteorological conditions (i.e. drought, heat and frost stress indicators), during the growing season from one year to the next were taken into account, (3) the yield response to drought and heat

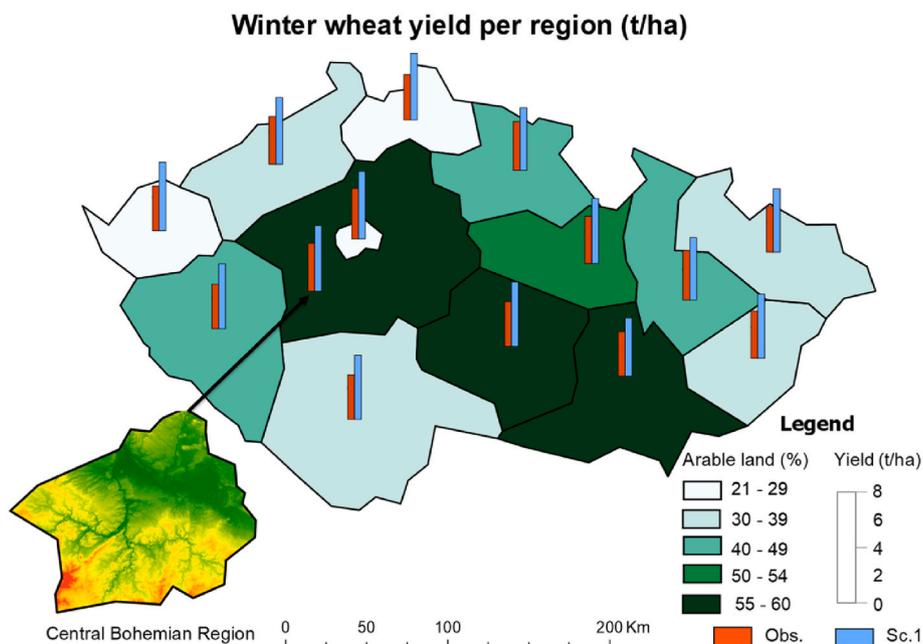


Fig. 6. Observed (2000–2020) and forecasted winter wheat yield ($t\ ha^{-1}$) for the 2021–2050 period (Sc.1) by the polynomial regression model. The map represents the share of arable land as a percentage of the region’s total area, and harvest per hectare bars for the observation (Obs.) and the future (Sc.1) periods. The regions were classified according to the proportion of arable land with lighter colours for smaller and darker colours for larger areas. The data were taken from the Land Cover Explorer Application portal (ESRI, 2022).

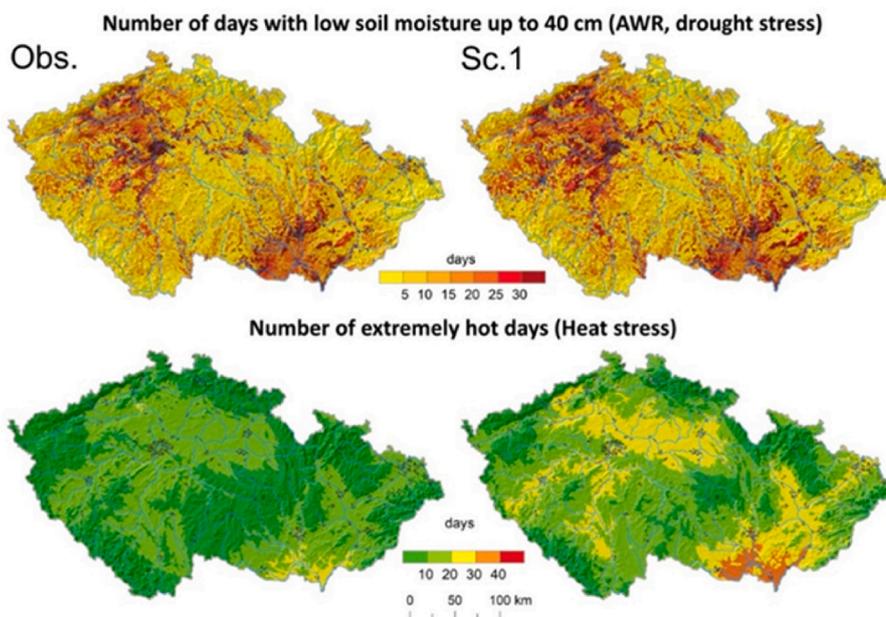


Fig. 7. Maps of drought and heat stress indicators during the winter wheat growing season for future scenarios, 2021–2050 (Sc.1) compared to the observed period 1991–2020 (Obs) at the country level.

stress conditions was examined, and (4) the residual error, which refers to the yield fluctuations caused by random factors, was analyzed (Potopová et al., 2015). During the historical period, the median yield of 13 regions ranged from 5.20 to 5.80 tha^{-1} (Fig. 6). However, the observed yield in the CBR region ranges from 3.91 to 6.70 tha^{-1} . The anticipated cropping pattern over the next 20 years (Sc1), three regression models project an increase (5.7–10.8 %) in winter wheat yield in CBR. From the results obtained, several features stand out: Firstly, CBR will be more exposed to compound events (Drought, Heat, and Frost stress), thus being more exposed to high crop losses per

hectare compared to the historical period. Secondly, cultivation regions in moderately warm and cold climate zones will become more suitable. This corresponds to the projection maps for Drought and Heat stress (Fig. 6). Lastly, in areas with the highest share of arable land, such as CBR, Sc1 projects an increase in the yield but also an increase in the frequency of extreme climate events, which could become even more adverse for cultivation of wheat in the future.

Secondly, a crop modelling approach was used to suggest new strategies for adapting and mitigating the consequences of adverse climate events. The approach involved selecting new wheat varieties that are

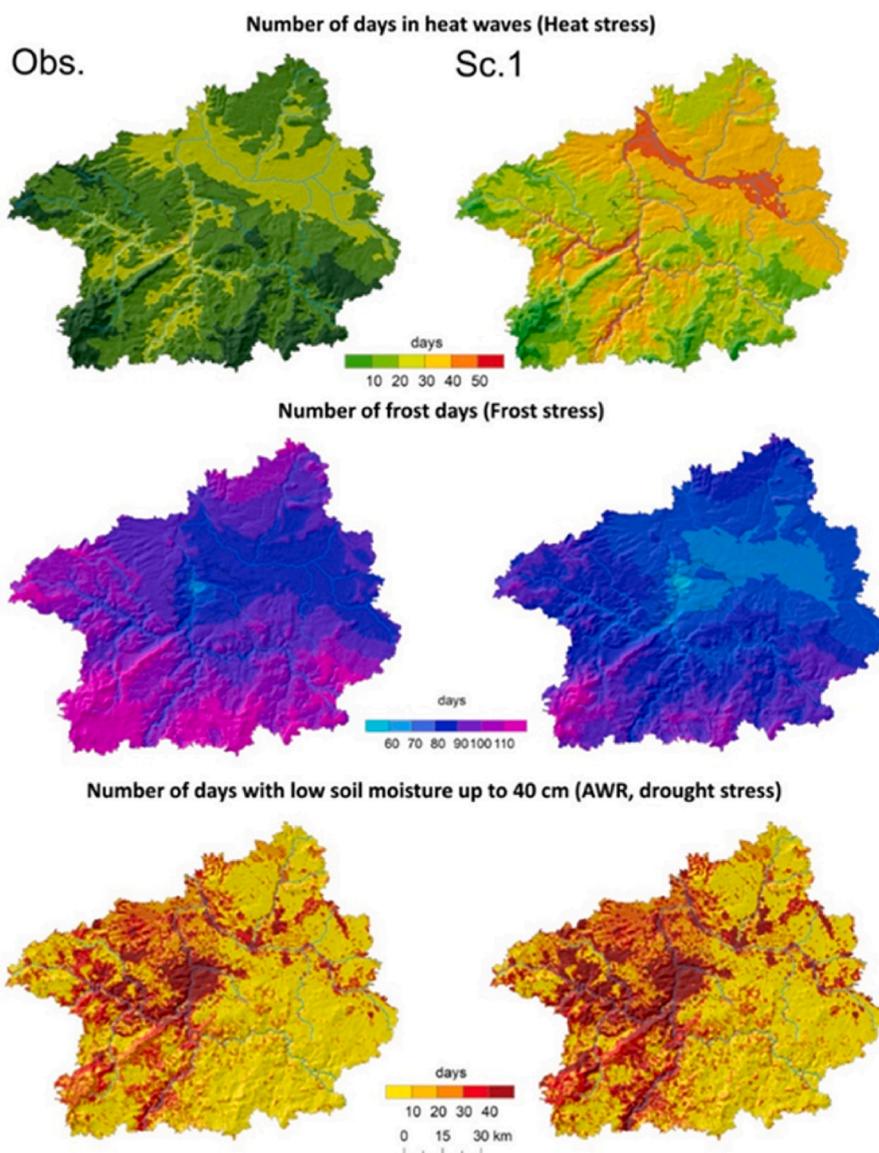


Fig. 8. Maps of heat, frost, and drought stress indicators during the winter wheat growing season for future scenarios, 2021–2050 (Sc.1) compared to the observed period 1991–2020 (Obs.) at the regional level.

resistant to such events. As input data in the crop model, we used a long-term field experiment dataset of two tested perspective varieties (Sultan and Samanta winter wheat varieties) under climate change conditions. The dynamic crop model DSSAT-CERES simulates the soil-plant-atmosphere system and provides yield production output that is directly linked to the crop growth and development of winter wheat attributes at the field (Table 6). It should be considered that the simulated yield values exceed those of the statistical regression model because the crop model took into account two well-adapted and

promising wheat varieties. The yield effects of technological change and the impact of several perturbed environment variables, such as temperature, precipitation, solar radiation, CO₂ and nitrogen (Table 5) were also included in the crop model. The results of Sc. 1 showed that an increase in temperature, precipitation, and CO₂ can lead to an increase in winter wheat production. This is because a milder winter can benefit the Sultan and Samanta wheat varieties cultivated in CBR.

Table 6
Simulation yield (tha⁻¹) by the dynamic crop model DSSAT-CERES (soil-crop-atmosphere system).

DSSAT, CERES model	Observed yield, tha ⁻¹ Obs.	Predicted yield, tha ⁻¹ Sc.1	R ²	RMSE (t ha ⁻¹)
Sultan variety	9.68* [6.87–9.68]	11.25	0.881	+0.59
Samanta variety	8.58* [6.72–10.47]	8.81	0.781	-0.04

RMSE* = root mean square error.

3.3. MAGNET CGE

A two-stage process was applied to simulate the impact of the climate-related yield shock. First, a baseline scenario was constructed, which provides the business-as-usual case of the economy in the medium-run future (year 2030). In this medium-run baseline, we implemented a climate-related shock provided by the Intermediate Dynamic crop model -DSSAT-CERES. Specifically, we applied a 13 % increase in land productivity nationally, which represents an increase of median yields from 9.13 to 10.39 tha⁻¹ (see Table 6). The results (shown in Table 7) are grouped into the main indicator domains. MAGNET being an economy-wide model, is guided by economic mechanisms in terms of

Table 7
Impact of climate-related yield shock on selected indicators.

Domain/Indicator	Sector	
	Wheat	Agri-food
Economy		
Production volume	+9.27 %	+0.24 %
Exports	+13.45 %	+1.08 %
Imports	-5.05 %	+0.00 %
Market price	-2.08 %	-0.02 %
Environment		
Water use	-0.05 %	+0.00 %
Land use	-1.34 %	-0.11 %
Fertilizer application	+7.96 %	+2.12 %
GHG emissions	+8.17 %	+2.03 %
Food security		
Caloric availability	+0.11 %	+0.01 %
Self-sufficiency	+8.24 %	+0.27 %
Food affordability	-	+3.49 %

Source: MAGNET results. All results are presented as percentage changes as resulting from the comparative static analysis of the productivity shock in MAGNET based on the 2030 baseline results.

the impact of the yield shock. It is found that a positive yield shock would bring higher wheat output (+9 %) and reduce market prices of wheat (-2 %). Note that this result is driven by the interplay of demand and supply. On the supply side, increased land productivity enables to achieve higher production volume with the same amount of input. On the demand side, since domestic wheat consumption is rather stable, excess supply is immediately transmitted to foreign markets, underlying the competitive advantage of Czech wheat in international trade. These positive results are also reflected in the increase in production (+0.24 %) and exports (+1 %) for the aggregate agri-food industry. The generally positive economic results of the climate-related yield shock have both environmental and food security consequences. From the environmental point of view, increased productivity helps in reducing the demand for land and water, alleviating the agricultural footprint. On the other hand, the higher wheat output also requires greater use of fertilizer (+7.96 %), which is related to potentially negative impacts on health and soil quality. Nonetheless, the quantified increase in fertilizer use is in line with the estimates from the Intermediate statistical model. Similarly, due to the increased use of fossil-based inputs, also GHG emissions would also increase proportionally. From the food security point of view, the results are positive for the food availability component (higher wheat production), food access (food affordability increases as wheat prices fall) and also resilience (self-sufficiency of wheat would be improved).

3.4. Life-Cycle Assessment

In Table 8, the characterized LCA results for 1 tonne of winter wheat grain are presented for both the baseline (Obs.) as well as Scenario 1 (Sc. 1). The baseline wheat model was created based on the observed data from the Intermediate statistical regression model as presented in Tables 4 and 5. In this study, we only focus on those parameters that are linked between the models applied in this study. The main parameters taken into account are the yield, water use and fertiliser production and application. We present the results only for those impact categories that are expressly sensitive to the input parameters. The following impact

Table 8
characterized results for 1 tonne of winter wheat grain for the baseline (Obs.) and scenario 1 (Sc.1).

Impact category	CF _m	Unit	baseline	scenario 1
Climate change	Global Warming Potential (GWP)	kg CO ₂ -eq to air	322.22	302.61
Freshwater eutrophication	Freshwater Eutrophication Potential (FEP)	kg P-eq to freshwater	0.48	0.46
Terrestrial acidification	Terrestrial acidification potential (TAP)	Kg SO ₂ -eq to air	4.33	4.11
Land use	Agricultural land occupation potential (LOP)	m ² x yr annual cropland-eq	1.80	1.66
Water consumption	Water consumption potential (WCP)	m ³ water-eq consumed	0.38	0.36

categories are selected: climate change, freshwater eutrophication, terrestrial acidification, land use and water consumption. These main parameters were adapted based on the exponential statistical regression model in Tables 4 and 5, which led to the LCA output for Sc.1. Compared to the baseline scenario (Obs.), lower values are observed for all impact categories under study in Sc.1. The increase in the yield is higher than the increase in fertilizers being used, this results in a lower impact per weight unit for the product under study.

4. Discussion

4.1. Key findings

The proposed methodology took as a starting point the recognition that global sustainability assessments typically use broad-brush data that may lack crucial indicators needed to capture the complex local realities of wheat production. In our research, the key findings include.

- 1) We offer a novel methodology to demonstrate how locally sourced indicators can effectively be employed in the coupling of Intermediate DSSAT (local biophysics), MAGNET (global economics), and LCA (environmental feedback) models to reveal wheat yield trends at both global and local scales;
- 2) This detailed, localized understanding of the role that indicators play in assessments that are essential for precise mapping and analysis of areas most and least susceptible to climate change. This is vital for evidence-based policy-making;
- 3) The study has found that the mechanistic pathways from indicators based on local biophysics can be bridged with the locally sourced indicators relevant to the global scale. This enables us to emphasize the role of “local-to-global” feedback in upscaling models, illustrating how localized climate extremes can disproportionately control the stability of global wheat production, and thus should be the priority for policy-making;
- 4) The focus groups are an excellent way to organize and optimise modelling that uses heterogeneous methods to achieve a common goal. These participatory processes in the international setting have proven to be effective in conducting indicator assessments related to sustainability, with the aim of informing policymakers about indicator gaps, as well as the highlighting the strategic areas for tailoring and targeting policy measures.

4.2. Coupling of intermediate DSSAT, MAGNET and LCA models

Our work advances integrated sustainability assessments by coupling biophysical and economic models across scales. Using the Intermediate DSSAT crop model to simulate local yield indicators under diverse climate and management scenarios, we linked these as outputs to the global MAGNET computable general equilibrium (CGE) model. This integration quantified regional market dynamics (e.g., including food prices, trade, land-use change, and macroeconomic impacts) driven by localized climate effects. Environmental consequences were further captured through Life Cycle Assessment (LCA), evaluating system-wide emissions, resource use, and land conversion. This novel methodology applied principles of the LCA methodology to assess the impacts related to the interlinked parameters in the climate and crop growth models.

The data used stems from the Intermediate models, which predict the future crop yield and fertilizer use based on statistical regression models.

This multi-model approach aligns with established AgMIP protocols (Nelson et al. (2014) and emerging resilience frameworks. Potopová et al. (2023b), for example, integrate the Environmental Policy Integrated Climate model (EPIC (Williams et al., 1989)), the animal-level simulation model (RUMINANT (Herrero et al., 2013)), and the economic model (Global Biosphere Management Model, GLOBIOM (Havlík et al., 2014)) to project climate-induced fodder shortages disrupting Czech livestock systems. Similarly, regional applications of DSSAT for optimizing winter oilseed rape, tomato, and bell sweet pepper production (Potopová et al., 2025) alongside global DSSAT-MAGNET linkages (van Meijl et al., 2018) demonstrate how bridging scales resolves limitations of siloed models. Furthermore, this multi-model approach is akin to the coupling of economic models with LCA (Beaussier et al., 2019, 2022).

These efforts mirror scale-integration approaches such as Jägermeyr et al. (2021), who coupled gridded crop models (GGCMI) with economic tools (MAGPIE) to resolve spatial mismatches in climate impact assessments. As emphasized by van Meijl et al. (van Meijl et al., 2018) and Ahmed et al. (2017), such integrations are essential to capture both agro-ecological constraints and market adaptations. The long-term food security projections can reveal if the food security situation is expected to remain stable in the longer horizon (Willett et al., 2019). While projections of food supply show usually a stable trend, the evolution of agri-food trade balances and nutrient import dependency varies significantly and reveals which countries can worsen or improve their food security position in the future. Thus, our work delivers a novel protocol using locally sourced indicators to not only integrate DSSAT (local biophysics), MAGNET (global economics), and LCA (environmental feedback), but also go beyond the previous approaches so as to formalize recursive climate-agriculture interactions.

4.3. Importance of modelling the indicators relevant for policy-making

Indicators provide a means to monitor progress towards policy objectives, allowing for necessary adjustments throughout the implementation process (OECD, 1999; Kelly et al., 2018). Indicators help assess the effectiveness of implemented policies, grounding modifications in empirical data and observed outcomes (OECD, 1999; Kelly et al., 2018). Common Agricultural Policy (CAP) encompasses support measures that require precise tailoring and targeting to ensure sustainability outcomes on the ground. Our research went beyond the previous policy assessments that found the CAP measures to be less effective (Röder et al., 2024). The proposed novel protocol involved an array of actors in finetuning the indicator framework across five domains (FP – Farming practices indicators; W – water and hydrology indicators; C – climate and soil health indicators; BD – biodiversity indicators; E – economic and capital indicators). Sourcing indicators across these domains fosters a thorough and localized understanding that is essential for accurately mapping and evaluating agricultural areas that are most and least vulnerable to climate change. This understanding informs evidence-based policy-making. As we approach the new CAP 2025–2035, there is a pressing need to monitor policy performance thus far (Röder et al., 2024). With specific information at hand, policymakers will identify indicator gaps and strategically tailor policy measures for adaptation and investment, targeting the most strategic agricultural areas.

Furthermore, we found that indicators play a crucial role in facilitating actor engagement throughout the modelling process. This fosters a sense of ownership among various actors with relevance for policy-making. It ensures that the indicators used for model input data are pertinent and beneficial from multiple perspectives, enhancing their overall relevance and applicability.

4.4. Local-global feedback

Our protocol formalizes the modelling synergy to navigate the “local-to-global” feedback loop, following Antle et al.’s (Antle et al., 2015) integrated assessment paradigm. The local-to-global feedback is clarified by quantifying the contributions of heat, drought, CO₂, and extreme events to local yield changes. This dual-scale design—akin to Folberth et al.’s (Folberth et al., 2016) EPIC-IIASA model coupling for Central Europe—addresses critical gaps in modelling indicators for climate resilience policies. Unlike other studies, which mainly focus on the global wheat yield indicator, this work uniquely integrates regional-level yield data from a wheat-producing nation, with a modelling effort involving five distinct indicator categories. This novel protocol thus quantifies how local climate shocks propagate through global markets to reshape policies and thus inform policy-making as well as farm decisions. The protocol does so by capturing the cascading land/resource impacts, while resolving critical scale-disconnect gaps in indicators for resilience policies. It ensures that climate impacts on local production inform global trade/policy responses, while economic signals (e.g., price shocks) may recursively influence real-time analytics for evidence-based policy-making and on-farm decisions.

4.5. Limitations of research

While it was possible to distil five categories of indicators relevant to climate resilience in agriculture, such that could support all three types of models that may inform policy-making, this study had to acknowledge the limitations of this modelling methodology. Heterogeneity of typological input data in the three models is, to an extent, an obstacle in proceeding to apply the model-upscaling protocol for indicators relevant to climate resilience. To apply the proposed protocol, the MAGNET CGE model has to be coupled with Intermediate modelling for crops and climate that has the capability of processing locally-sourced indicators. Furthermore, although the MAGNET CGE is a very powerful tool to model food security at the global level, it cannot capture impacts on the regional level. Thus, the proposed methodology assumes that a positive climate-driven yield shock applies uniformly across all regions in the Czech Republic. Furthermore, MAGNET CGE needs to be coupled with LCA to be able to elaborate on information on biodiversity. In general, among the five categories of indicators, the category of biodiversity indicators is the least integrated in the input typologies of the three models, while LCA is by now the more advanced in covering this area in more detail. Thus, the integration with LCA should be deepened in future research. It is also advised to keep connecting LCA and Intermediate modelling tools to strengthen the links of the global assessments with climate and crop growth models. This research would deepen our understanding of the environmental elements that influence sustainability transitions in agriculture.

Furthermore, a limitation of our methodology is that as models incorporating environmental and sustainability indicators become more sophisticated, the challenge of accurately capturing the complexities of local-global feedback grows. These complexities are inherently tied with uncertainty. Consequently, our proposed methodology is partially constrained by how we integrate uncertainty across these models and into policy-making. This primarily involves quantifying uncertainties, such as those related to focus-group feedback, which entails ways to measure the imprecision associated with expert judgments and data. Future research could address this limitation by building comprehensive uncertainty frameworks that address the uncertainty associated with using indicators across various types of input data in our models.

5. Conclusions

To conclude, most global assessments relating to Sustainable Development Goals use coarse-resolution data (e.g., national-level data) and thus oversimplify local variability. By illustrating how localized

trends diverge from global averages, this study offers new insights and enables mapping and analyzing regions where wheat yields are most and least sensitive to climate change, ultimately impacting global food security. The proposed methodology is innovative in its potential to help policymakers in identifying strategic zones for adaptation or investment, especially considering the new CAP 2027–2035. While existing studies typically focus on the global wheat yield indicators and evaluate trends in response to climate change, this study stands out by uniquely integrating regional-level yield data from a wheat-producing country with the help of five categories of indicators. Based on these indicators, we were able to introduce a novel protocol that couples three models to demonstrate how local climate extremes (heat, drought, CO₂, and extreme weather conditions) disproportionately shape global production volatility. The five categories of sustainability indicators, which extend beyond the traditional yield measurement to characterize climate resilience, are uniquely integrated into three models through typological input data. This integration of sustainability indicators into the models, facilitated through extended focus groups (both online and physical meetings), forms the core of the proposed methodology, offering a valuable contribution to the fields of modelling the environmental and sustainability indicators. Consequently, our research enhances policy monitoring tools, empowering policymakers to make evidence-based decisions that move beyond mere assumptions or political agendas. Furthermore, by diligently monitoring the proposed indicators, policymakers can better anticipate and address emerging challenges.

Intermediate modelling, which involves using climate and crop growth models, can capture climate CEs that occur simultaneously during the crop cycle and can greatly affect agricultural production and food security. Computable General Equilibrium models, such as MAGNET, are important tools that can provide insights into possible future trajectories for food systems. These models are to be inserted in assessments that capture potential trade-offs between various dimensions of sustainability at the macroeconomic level. It is recommended to further continue linking Life Cycle Assessment and Intermediate modelling tools through coupling with climate and crop growth models to gain a better understanding of the environmental factors that shape sustainability transitions in agriculture.

Through this study, we have identified sustainability indicators as inputs for global models, which can help us understand many aspects of climate resilience, including yield and food security. The current lack of indicators to comprehend the impact of agriculture on biodiversity is concerning, especially in light of the EU's Biodiversity Strategy. In order to monitor the effectiveness of agricultural policies and tailor and target policy support measures, it is necessary to have robust models, regulations, and institutions to ensure accurate forecasting. However, it is crucial to continue to make efforts and develop reliable data sets that are specifically relevant for the EU Biodiversity Strategy, so it is possible to monitor biodiversity indicators that demonstrate the complex interrelationships between biodiversity, climate resilience and farming.

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CRedit authorship contribution statement

Vera Potopova: Writing – review & editing, Writing – original draft, Supervision, Methodology, Formal analysis, Conceptualization. **Jana Poláková:** Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Conceptualization. **Zuzana Smeets Kristkova:** Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Conceptualization. **Jeroen Weststrate:** Writing – review & editing, Writing – original draft, Formal analysis,

Conceptualization. **Willem-Jan van Zeist:** Formal analysis. **Annabel Oosterwijk:** Formal analysis. **Michaela Kolárová:** Formal analysis. **Marcos Dominguez Viera:** Formal analysis. **Pavel Zahradníček:** Investigation. **Petr Štěpánek:** Investigation. **Nils Bunnefeld:** Writing – review & editing, Supervision. **Markus Dettenhofer:** Methodology, Conceptualization. **Ioannis Manikas:** Funding acquisition.

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Declaration of competing interest

The authors declare the absence of any financial or personal relationships that could potentially influence the work reported in this article.

Data availability

Data will be made available on request.

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