Stabilizing agricultural systems through diversity

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Summary

In the light of climate change, rising demands for agricultural products and the intensification and specialization of agricultural systems, ensuring an adequate and reliable supply of food is fundamental for food security. Maintaining diversity and redundancy has been postulated as one generic principle to increase the resilience of agricultural production and other ecosystem services. For example, if one crop fails due to climate instability and extreme events, others can compensate the losses. Crop diversity might be particularly important if different crops show asynchronous production trends. Furthermore, spatial heterogeneity has been suggested to increase stability at larger scales as production losses in some areas can be buffered by surpluses in undisturbed ones. Besides systematically investigating the mechanisms underlying stability, identifying transformative pathways that foster them is important.

In my thesis, I aim at answering the following questions: (i) How does yield stability differ between nations, regions and farms, and what is the effect of crop diversity on yield stability in relation to agricultural inputs, climate heterogeneity, climate instability and time at the national, regional or farm level? (ii) Is asynchrony between crops a better predictor of production stability than crop diversity? (iii) What is the effect of asynchrony between and within crops on stability and how is it related to crop diversity and space, respectively? (iv) What is the state of the art and what are knowledge gaps in exploring resilience and its multidimensionality in ecological and social-ecological systems with agent-based models and what are potential ways forward?

In the first chapter, I provide the theoretical background for the subsequent analyses. I stress the need to better understand the resilience of social-ecological systems and particularly the stability of agricultural production. Moreover, I introduce diversity and spatial heterogeneity as two prominently discussed resilience mechanisms and describe approaches to assess resilience.

In the second chapter, I combined agriculture and climate data at three levels of organization and spatial extents to investigate yield stability patterns and their relation to crop diversity, fertilizer, irrigation, climate heterogeneity and instability and time of nations globally, regions in Europe and farms in Germany using statistical analyses. Yield stability decreased from the national to the farm level. Several nations and regions substantially contributed to larger-scale stability. Crop diversity was positively associated with yield stability across all three levels of organization. This effect was typically more profound at smaller scales and in variable climates. In addition to crop diversity, climate heterogeneity was an important stabilizing mechanism especially at larger scales. These results confirm the stabilizing effect of crop diversity and spatial heterogeneity, yet their importance depends on the scale and agricultural management.

Building on the findings of the second chapter, I deepened in the third chapter my research on the effect of crop diversity at the national level. In particular, I tested if asynchrony between crops, i.e. between the temporal production patterns of different crops, better predicts agricultural production stability than crop diversity. The stabilizing effect of asynchrony was multiple times higher than the effect of crop diversity, i.e. asynchrony is one important property that can explain why a higher diversity supports the stability of national food production. Therefore, strategies to stabilize agricultural production through crop diversification also need to account for the asynchrony of the crops considered.

The previous chapters suggest that both asynchrony between crops and spatial heterogeneity are important stabilizing mechanisms. In the fourth chapter, I therefore aimed at better understanding the relative importance of asynchrony between and within crops, i.e. between the temporal production patterns of different crops and between the temporal production patterns of different cultivation areas of the same crop. Better understanding their relative importance is important to inform agricultural management decisions, but so far this has been hardly assessed. To address this, I used crop production data to study the effect of asynchrony between and within crops on the stability of agricultural production in regions in Germany and nations in Europe. Both asynchrony between and within crops consistently stabilized agricultural production. Adding crops increased asynchrony between crops, yet this effect levelled off after eight crops in regions in Germany and after four crops in nations in Europe. Combining already ten farms within a region led to high asynchrony within crops, indicating distinct production patters, while this effect was weaker when combining multiple regions within a nation. The results

suggest, that both mechanisms need to be considered in agricultural management strategies that strive for more resilient farming systems.
The analyses in the foregoing chapters focused at different levels of organization, scales and factors potentially influencing agricultural stability. However, these statistical analyses are restricted by data availability and investigate correlative relationships, thus they cannot provide a mechanistic understanding of the actual processes underlying resilience. In this regard, agent-based models (ABM) are a promising tool. Besides their ability to measure different properties and to integrate multiple situations through extensive manipulation in a fully controlled system, they can capture the emergence of system resilience from individual interactions and feedbacks across different levels of organization. In the fifth chapter, I therefore reviewed the state of the art and potential knowledge gaps in exploring resilience and its multidimensionality in ecological and social-ecological systems with ABMs. Next, I derived recommendations for a more effective use of ABMs in resilience research. The review suggests that the potential of ABMs is not utilized in most models as they typically focus on a single dimension of resilience and are mostly limited to one reference state, disturbance type and scale. Moreover, only few studies explicitly test the ability of different mechanisms to support resilience. To solve real-world problems related to the resilience of complex systems, ABMs need to assess multiple stability properties for different situations and under consideration of the mechanisms that are hypothesized to render a system resilient.
In the sixth chapter, I discuss the major conclusions that can be drawn from the previous chapters. Moreover, I showcase the use of simulation models to identify management strategies to enhance asynchrony and thus stability, and the potential of ABMs to identify pathways to implement such strategies.
The results of my thesis confirm the stabilizing effect of crop diversity, yet its importance depends on the scale, agricultural management and climate. Moreover, strategies to stabilize agricultural production through crop diversification also need to account for the asynchrony of the crops considered. As spatial heterogeneity and particularly asynchrony within crops strongly enhances stability, integrated management approaches are needed that simultaneously address multiple resilience mechanisms at different levels of organization, scales and time horizons. For example, the simulation suggests that only increasing the number of crops at both the pixel and landscape level avoids trade-offs between asynchrony between and

within crops. If their potential is better exploited, agent-based models have the capacity to systematically assess resilience and to identify comprehensive pathways towards resilient farming systems.

Zusammenfassung

In Anbetracht des Klimawandels, steigender Nachfrage nach landwirtschaftlichen Produkten und der weitgehenden Intensivierung und Spezialisierung landwirtschaftlicher Systeme ist eine ausreichende und zuverlässige Nahrungsmittelproduktion zentral für die Ernährungssicherheit. Eine hohe Nutzpflanzenvielfalt und räumliche Heterogenität können helfen, die Resilienz bzw. Widerstandsfähigkeit der landwirtschaftlichen Produktion zu stärken. Fällt zum Beispiel die Ernte einer Nutzpflanze aufgrund einer Dürre aus, können andere die Verluste ausgleichen. Außerdem können Produktionsverluste in einigen Gebieten durch Überschüsse in anderen Gebieten kompensiert werden.

In meiner Arbeit habe ich mittels umfassender Landwirtschafts- und Klimadaten und statistischer Analysen untersucht, wie sich insbesondere Nutzpflanzenvielfalt und Klimaheterogenität auf zeitliche Ertragsstabilität auswirken. Zudem habe ich evaluiert, ob asynchrone Produktionstrends unterschiedlicher Nutzpflanzen den stabilisierenden Effekt einer hohen Nutpflanzenvielfalt erklären können. Außerdem habe ich den Effekt asynchroner Produktionstrends unterschiedlicher Nutzpflanzen und von unterschiedlichen Anbaugebieten derselben Nutzpflanze in Bezug auf Produktionsstabilität verglichen und mit einer Computersimulation eruiert, wie diese Mechanismen durch Diversifizierung verändert werden. Zum Schluss habe ich untersucht, wie umfassend die Resilienz ökologischer und sozioökologischer Systeme mittels agentenbasierter Modelle bislang erforscht wurde.

Die Untersuchungen dieser Arbeit zeigen, dass Nutzpflanzenvielfalt die landwirtschaftliche Produktion auf sämtlichen untersuchten Organisationsebenen stabilisiert. Asynchrone Produktionstrends unterschiedlicher Nutzpflanzen können erklären, warum eine höhere Diversität die Produktion stabilisiert. Daneben sind asynchrone Produktionstrends unterschiedlicher Anbaugebiete besonders wichtig. Meine Simulation zeigt, dass nur eine Diversifizierung auf Feld- und Landschaftsebene asynchrone Produktionsmuster zwischen Nutpflanzen und Anbaugebieten gleichzeitig erhöht oder zumindest keine der beiden Mechanismen verringert. Agentenbasierte Modelle bieten die Möglichkeit, Resilienz systematisch zu untersuchen und Wege aufzuzeigen, die zu resilienteren Anbausystemen führen.

Meine Ergebnisse unterstreichen die Notwendigkeit umfassenderer Ansätze um eine resiliente, produktive und nachhaltige landwirtschaftliche Produktion in Zeiten globaler Veränderungsprozesse zu erreichen. Dies beinhaltet insbesondere eine Diversifizierung der Nutzpflanzen auf unterschiedlichen Ebenen unter Berücksichtigung der zeitlichen Produktionstrends sowie eine nachhaltige Nutzung landwirtschaftlicher Betriebsmittel.

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1 Introduction

1.1 Resilience of social-ecological systems

In a world undergoing unprecedented change, understanding the resilience of social-ecological systems, i.e. their ability to absorb change while maintaining functioning and thus persist, is of utmost importance and fundamental to sustain the ecosystem services that humans rely on (Berkes and Folke, 1998; Biggs et al., 2012, 2015; Holling, 1973; Oliver et al., 2015). Resilience has therefore become an increasingly popular concept in science and policy (Donohue et al., 2016). Since agriculture is the most dominant form of land use and essential for human survival, understanding the resilience of agricultural production is particularly important (Campbell et al., 2017). Agriculture is a social-ecological system characterized by the complex interactions between natural processes, which are related to climate and the resources agriculture depends on, and social processes, which are related to the behavior of farmers, markets and consumers. Both kinds of processes act across different spatial and temporal scales, which is distinctive for social-ecological systems (Schlüter et al., 2012).

Shocks, i.e. extreme disturbance events, affecting agricultural production are a threat to food security, in particular if they occur in multiple regions simultaneously (Bailey et al., 2015; Knapp and van der Heijden, 2018; Mehrabi and Ramankutty, 2019). This in turn may lead to regional food shortages, income deficits, price spikes and civil unrest (Bailey et al., 2015; Battisti and Naylor, 2009; Gilbert and Morgan, 2010; Myers et al., 2017; von Uexkull et al., 2016). As agriculture is largely climate-dependent, climate shocks and variation directly affect production stability and possibly erode resilience (Ray et al., 2015). In the light of climate change and rising demands for food, resilient agricultural systems are therefore fundamental to enhance the reliability of agricultural production and thus food security (Knapp and van der Heijden, 2018; Schmidhuber and Tubiello, 2007; Valin et al., 2014).

With a coverage of 12% of the earth's ice-free land surface and increasingly intensified management practices, agriculture substantially contributes to the degradation of natural habitats, the creation of simplified landscapes, soil erosion, depletion of freshwater resources, eutrophication and greenhouse gas emissions

(Bailey et al., 2015; Foley et al., 2005; Ramankutty et al., 2008; Seppelt et al., 2016; West et al., 2014). Accordingly, agriculture plays a major role in the transgression of most planetary boundaries, as well as in the loss of biodiversity and ecosystem services (Beckmann et al., 2019; Campbell et al., 2017; Iverson et al., 2014; Sirami et al., 2019; Steffen et al., 2015; Tscharntke et al., 2015). Moreover, unsustainable agricultural practices undermine the long-term productivity and resilience of agricultural systems (Bailey et al., 2015). Besides the direct degradation of natural resources that agriculture relies upon or the contribution to climate change that potentially undermines agricultural production, the ongoing trend towards monocultures erodes fundamental resilience mechanisms including diversity and heterogeneity from the field to the landscape scale (Lin, 2011; Ortiz-Bobea et al., 2018). Therefore, potential future needs to increase agricultural production due to population growth, altered consumption patterns and rising demands for bioenergy cannot be achieved at the expense of further environmental degradation and the mechanisms underlying the resilience of agricultural production (Bailey et al., 2015; Foley et al., 2011; Rueda and Lambin, 2014).

1.2 Resilience mechanisms: diversity and spatial heterogeneity

In resilience theory, maintaining diversity and redundancy has been postulated as a central principle to increase the resilience of social-ecological systems (Biggs et al., 2012; Kremen and Merenlender, 2018; Mijatović et al., 2013; Weise et al., 2020). One aspect of this principle is related to species diversity, which has been investigated for a long time in ecology. According to the insurance hypothesis, large numbers of species providing the same or similar function imply greater chances that some will maintain functioning even if others fail (Yachi and Loreau, 1999). Likewise, the portfolio effect predicts that stability progressively increases with diversity as the fluctuations of more species are averaged (Doak et al., 1998; Tilman, 1999), i.e. the risk is spread (Weise et al., 2020). Another aspect of this principle relates to spatial heterogeneity (Biggs et al., 2012; Cumming et al., 2016). For example, undisturbed areas can buffer negative effects in disturbed areas. Therefore larger-scale resilience might be higher as local shocks are more likely to be buffered.

Synchrony or asynchrony is another important resilience mechanism, yet related to both species diversity and spatial heterogeneity (Loreau and De Mazancourt, 2008; Mehrabi and Ramankutty, 2019). On the one hand, species that show asynchronous

trends better contribute to temporal stability as they complement each other, also termed ‘response diversity’ in biodiversity research (Elmqvist et al., 2003). On the other hand, different areas better increase larger-scale temporal stability if they are affected asynchronically by disturbances (Mehrabi and Ramankutty, 2019).
In the agricultural context, research has focused on agricultural productivity for a long time, although understanding the stability of crop production and its underlying drivers has gained more attention recently (Knapp and van der Heijden, 2018; Ray et al., 2015). For example, temporal yield stability has been compared between different cropping systems and the synchrony of the production of major crops has been assessed globally (Knapp and van der Heijden, 2018; Mehrabi and Ramankutty, 2019). Moreover, it has been found that climate variability reduces yield stability, while crop diversity and agricultural inputs are enhancing it (Gaudin et al., 2015; Raseduzzaman and Jensen, 2017; Ray et al., 2015; Renard and Tilman, 2019). However, these studies typically focused on one level of organization and a limited number of crops or stability mechanisms. Accordingly, the relationship of different mechanisms and across different levels of organization and scales is poorly understood.

1.3 Assessing resilience

Resilience is a multidimensional concept. On the one hand, it encompasses the three fundamental stability properties recovery, resistance and persistence (Oliver et al., 2015; Standish et al., 2014). Recovery specifies the process of a state variable returning to the values prior to a disturbance and is typically quantified as the time needed until a state variable reaches pre-disturbance levels. Resistance characterizes the limited change of a variable after a disturbance, and persistence is related to the existence of a system as an identifiable unit, described by specific state variables remaining within a certain range. On the other hand, these stability properties can only be applied to specific situations, which are defined by the considered level of organization, state variable, reference state, disturbance, and spatial and temporal scale (Grimm and Wissel, 1997).
In practice, (in)variability is often used as a proxy to assess temporal stability and resilience because a system showing lower variation usually has higher chances that state variables remain within the ranges required for the persistence of a system (Wang and Loreau, 2016). Other stability properties are often difficult to quantify,

for example because unambiguous definitions of a system to determine persistence or of reference states to assess recovery and resistance do not exist (Egli et al., 2019). In the agricultural context, quantitative and data-based studies typically measure the coefficient of variation, its inverse or related metrics to evaluate the temporal (in)stability of yields or production (Gaudin et al., 2015; Knapp and van der Heijden, 2018; Raseduzzaman and Jensen, 2017; Ray et al., 2015; Renard and Tilman, 2019)

Agent-based models complement empirical research, which is, for logistic reasons, limited in coping with these multiple dimensions, and are a promising tool to assess resilience more comprehensively (Egli et al., 2019). Besides their ability to integrate multidimensionality through extensive manipulation of reference states, disturbances and scales in a fully controlled system, agent-based models can capture the emergence of system resilience from individual interactions and feedbacks across different levels of organization and based on different state variables.

Besides their ability to deal with the multidimensionality of resilience, computer simulations and particularly agent-based models can help to identify strategies that increase the resilience of agricultural systems and potential transformative pathways to implement them (Bai et al., 2016; Brown et al., 2016). Therefore, such approaches are promising to support the fundamental transformation that is needed to achieve productive, sustainable and resilient agricultural systems (Bailey et al., 2015; Campbell et al., 2017; Kremen and Merenlender, 2018).

1.4 Objectives and overview

As outlined above, there is a strong need to better understand the mechanisms enhancing the temporal stability and resilience of agricultural systems and to identify pathways to foster them. Accordingly, this thesis aims at investigating the effect of crop diversity, spatial heterogeneity and asynchrony on the temporal stability of agricultural production across multiple levels of organization and scales. To investigate the potential of dynamic modeling approaches beyond data analysis, the thesis reviews the use of agent-based models in exploring resilience and discusses their capacity to support the identification of pathways to strengthen these mechanisms in different contexts.

This thesis consists of four studies. In the first study (Chapter 2), I combined agriculture and climate data at three levels of organization and spatial extents and used statistical analyses:

- To investigate how yield stability differs between individual nations, regions and farms and in relation to all nations, regions and farms.
- To study the effect of crop diversity on yield stability in relation to agricultural inputs, climate heterogeneity, climate instability and time at the national, regional or farm level.

In the second study (Chapter 3), I deepened my research on the effect of crop diversity on the national level and regarding the stability of total agricultural production. In particular, I contrasted the effect of crop diversity and asynchrony between crops, i.e. between the temporal production patterns of different crops:

- To test if crop asynchrony better predicts agricultural production stability than crop diversity.

Drawing from the insights of the two previous studies, I investigated different facets of asynchrony using agricultural data in regions in Germany and nations in Europe (Chapter 4). I aimed at better understanding the relative importance of asynchrony between and within crops, i.e. between the temporal production patterns of different crops and between the temporal production patterns of different cultivation areas of the same crop. The main objectives were:

- To investigate the effect of asynchrony between and within crops on production stability.
- To assess the effect of crop diversity and space on the asynchrony between and within crops, respectively.

The first three studies mainly focused on the determinants of agricultural stability at different levels of organization and scales. However, these statistical analyses were restricted by data availability and focus on correlative relationships, thus they could not provide a mechanistic understanding of the actual processes underlying resilience. Moreover, the analyses were restricted to temporal stability as one aspect to approximate resilience. In Chapter 5, I therefore reviewed the use of agent-based models in resilience research:

- To summarize the state of the art and knowledge gaps in exploring resilience and its multidimensionality in ecological and social-ecological systems with agent-based models.
- To suggest ways forward for a more effective use of agent-based models in resilience research.

In Chapter 6, I finally provide a synthesis of the four studies and showcase potential next steps to identify suitable management strategies and transformative pathways towards stable and resilient agricultural systems.

2 Crop diversity stabilizes agricultural production across scales[1]

2.1 Abstract

Stabilizing agricultural systems enhances the reliability of agricultural production and food security. While crop diversity has been found to stabilize agricultural production, it is unclear whether this holds across different levels of organization and in relation to different agricultural management and climate. We combined data at three levels of organization and spatial extents to investigate yield stability patterns and their relation to crop diversity, fertilizer, irrigation, climate heterogeneity and instability and time of nations globally, regions in Europe and farms in Germany. Yield stability decreased from the national to the farm level. Several nations and regions substantially contributed to larger-scale stability. Crop diversity was positively associated with yield stability across all three levels of organization. This effect was typically more profound at smaller scales and in variable climates. Our results confirm the stabilizing effect of crop diversity, yet its importance depends on the scale, agricultural management and climate.

2.2 Introduction

Stable agricultural systems are fundamental to enhance the reliability of agricultural production and thus food security (Knapp and van der Heijden, 2018), in particular in the light of climate change and rising demands for food (Challinor et al., 2014; Valin et al., 2014). Although understanding the stability of crop production and its underlying drivers has gained more attention recently (Gaudin et al., 2015; Knapp and van der Heijden, 2018; Mehrabi and Ramankutty, 2019; Raseduzzaman and Jensen, 2017; Ray et al., 2015; Renard and Tilman, 2019), their relationship across different levels of organization is poorly understood. For example, stability at the national level is expected to be higher compared to the farm level as it generally increases with scale (Kouadio and Newlands, 2015). Likewise, stability across multiple nations or farms is likely to be higher than the stability of individual nations

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or farms, and different regions differ in their contribution to larger-scale stability (Mehrabi and Ramankutty, 2019).

Resilience theory suggests that crop diversity reduces risks and increases resilience in agricultural systems, i.e. the ability to maintain functioning in the face of disturbance and change (Biggs et al., 2012; Kremen and Merenlender, 2018; Mijatović et al., 2013). If one crop fails due to climate instability and extreme events, others can compensate the losses (Lin, 2011; Raseduzzaman and Jensen, 2017; Yachi and Loreau, 1999). This hypothesis is related to the portfolio effect or insurance hypothesis (Doak et al., 1998; Tilman, 1999; Yachi and Loreau, 1999). Recent studies support theory and found that crop diversity is stabilizing agricultural production (Gaudin et al., 2015; Renard and Tilman, 2019). Agricultural inputs such as fertilizer and irrigation further stabilize yields (Knapp and van der Heijden, 2018; Ray et al., 2015; Renard and Tilman, 2019; Rist et al., 2014), potentially instead of or in addition to crop diversity. During the last decades, dependency on fertilizer and irrigation and the spatial coverage of their application has heavily increased, and hence yielded large production gains (Foley et al., 2011; Tilman et al., 2001). Furthermore, spatial heterogeneity is likely to stabilize agricultural production (Biggs et al., 2012; Kouadio and Newlands, 2015). Given that climate instability and weather are major determinants of yield stability (Ray et al., 2015), climate heterogeneity potentially stabilizes production as it fosters asynchronous production patterns that balance overall production (Mehrabi and Ramankutty, 2019).

Here, we compiled long-term data at three different levels of organization and spatial extents (national-level data at the global extent, regional-level data in Europe, farm-level data in Germany) to analyze patterns of total yield stability in relation to agricultural management and climate. We quantified yield stability at various levels to investigate how yield stability differs between different individual nations, regions and farms and in relation to all nations, regions and farms. We then used linear mixed-effect models to study the effect of crop diversity on yield stability in relation to agricultural inputs, climate heterogeneity, climate instability and time at the national, regional or farm level.

2.3 Materials and Methods

2.3.1 Data sources and treatment

We collected agricultural and climate data across three levels of organization and spatial extents and aggregated them for ten-year time intervals. At the national level we collected global data for five time intervals (1968-1977, 1978-1987, 1988-1997, 1998-2007, 2008-2017) mainly from the FAOSTAT database (Table 2.1). At the regional level, we extracted data for the NUTS 2 regions (where applicable) in Europe for four time intervals (1978-1987, 1988-1997, 1998-2007, 2008-2017). We used agricultural production data from the EUROSTAT database (Table 2.1), while we assigned national data from FAOSTAT to each region within a nation regarding agricultural inputs because higher resolution data was incomplete or not available. At the farm level, we collected data in Germany for two time periods (1998-2007, 2008-2017), largely using the 'Testbetriebsnetz' dataset, a comprehensive assessment of management and socio-economic variables on a large subset of farms across Germany (Table 2.1). Since irrigation is hardly reported in this dataset, we assigned irrigation data reported at the federal state level from EUROSTAT to the respective farms. To describe climate heterogeneity and instability, we used the University of Delaware gridded monthly air temperature and precipitation data at 0.5 degree spatial resolution for all levels of organization (Table 2.1). Details on the underlying data sources can be found in Table 2.1. To exclude nations, regions or farms (further referenced as 'units') where crop cultivation is of very minor relevance, we sorted them by the average cropland area over all reported years in descending order and included units up to a cumulated cropland area of 99.9% of the total cropland area of all units. At the national level, we further excluded Egypt, Guinea, Kenya, Mozambique, North Korea and Zambia due to data quality issues and Ireland, Netherlands, New Zealand because they use much of their fertilizer on pastures (Renard and Tilman, 2019).

2.3.2 Yield stability

To calculate yield stability, several preparation steps were needed. We converted crop-specific production from tons to calories using standardized nutritive factors (Table 2.1). We only included crops, for which nutrient data could be clearly assigned. For each time interval, we only included crops for which time series were complete and where both production and harvested area were reported. This yielded 131 crops globally, 29 crops for Europe and 24 crops for Germany. At the reginal level, this led to the exclusion of the regions in France, Spain and the UK in the most recent time interval (2008-2017). For each unit and year, we then summed calorie production of all crops and divided it by the totally harvested area to obtain overall yields in kilocalories per hectare. To account for stability independent of long-term trends, we time-detrended annual yield data by regressing annual total calorie production on year squared for each time interval and unit (Renard and Tilman, 2019). We calculated *yield stability* as the mean of the non-time-detrended yield divided by the standard deviation of time-detrended yields for each time period following Renard and Tilman (2019) and Mehrabi and Ramankutty (2019). For the German data, we excluded two farms in 2008-2017 as yield stability values were very implausible (>10^{15} compared to a mean value of 10.97 for all other farms). In a next step, we calculated larger-scale yield stability across all nations, regions or farms either with or without the unit. When calculating larger-scale yield stability, we only included the crops grown in the respective unit. For example, if a given region cultivated wheat, maize and potatoes, we calculated European stability (with or without the target region) only with these crops. We then divided yield stability of each unity by the respective large-scale stability to evaluate its performance relative to the larger scale (*relative yield stability*). A value above 1 would indicate that the stability of the unit is higher than the larger-scale stability. Finally, we divided larger-scale stability by the larger-scale stability without the respective unit to test its contribution to larger-scale stability (*yield stability contribution*). A value above 1 would indicate that the unit is positively contributing to larger-scale stability.

2.3.3 Explanatory variables

We used crop diversity, fertilizer, irrigation, temperature and precipitation heterogeneity, temperature and precipitation instability, and time as explanatory variables of yield stability. Regarding crop diversity, we calculated effective diversity as the exponential of the Shannon diversity of the harvested areas of the different crops for each year and unit (Hill, 1973) and calculated mean values for each time interval. To account for land-use intensity, we included fertilizer usage and irrigation. For the national level, we calculated national-level mean nitrogen fertilizer application for each time interval and unit relative to the respective mean cropland area. We used cropland area instead of the sums of the harvested areas of the crops considered as this would potentially overestimate fertilizer application per area because we did not include all crops (see above). For irrigation, we used the mean area equipped for irrigation relative to agricultural land for each time interval and unit. We also used national fertilizer and irrigation data for the regional level as we wanted to cover a large temporal extent regarding agricultural production data (40 years), for which subnational data on agricultural inputs is largely incomplete. For farm-level data in Germany, we used expenditure for fertilizer as a proxy for actual application as the latter has not been reported before 2017. For irrigation, we used federal state level data from EUROSTAT (relative to the total utilized agricultural area) as irrigation is only reported irregularly in the farm-level data. We then calculated mean values of fertilizer and irrigation for each time interval and unit, and standardized fertilizer expenditure by mean total agricultural area (see above). To describe climate heterogeneity and instability, we used gridded monthly temperature (°C) and precipitation (cm) data on 0.5 degree resolution for all levels of organization (Table 2.1). We extracted climate data only within cropland area extent of the year 2000 (aggregated to the same resolution as climate data taking pixel sums) and during the growing season of major crops (Table 2.1). For the aggregated 'cropland mask' we only included pixels that reported more than 1 km^2 of cropland to not overestimate the influence of pixels where agriculture has a very minor relevance. We then aggregated the climate data to the target spatial unit using cropland area-weighted standard deviations and means. We used mean standard deviations for each time interval and unit to describe temperature and precipitation heterogeneity. Since farm locations were only reported at the district level (n = 30) for data security reasons, we calculated the mean of the total harvested area of all crops considered for each time interval and farm to approximate temperature and precipitation heterogeneity at the farm level. Moreover, we calculated temperature and precipitation instability as the negative of the mean temperature and precipitation, respectively, over its standard deviation for each time interval and unit or district for the farm level analysis (Renard and Tilman, 2019).

Our final datasets consisted of 602, 355 and 6384 data points at the national, regional and farm level, respectively, representing 137 nations, 165 regions and 5183 farms. Data for multiple time intervals was available for 97.8%, 74.5% and 23.2% of these nations, regions and farms, respectively.

Table 2.1 Datasets used in this study. Temporal extent reflects the time periods extracted for this study.

Data	Reference	Description	Resolution; temporal extent	Unit	URL
All levels					
Cropland (grid)	(Klein Goldewijk et al., 2017)	Historical cropland distribution	5 arc-min; 2000	km^2	ftp://ftp.pbl.nl/../hyde/hyde3.2/
Growing season	(Sacks et al., 2010)	Crop planting dates	0.5°; NA	Day of year	https://nelson.wisc.edu/sage/data-and-models/crop-calendar-dataset/ArcINFO0-5degree.php
Temperature/ Precipitation	(NOAA/OAR/ESRL/PSD, 2017; Willmott and Matsuura, 2001)	Monthly temperature and precipitation	0.5°; 1968-2017	°C, cm	*UDel_AirT_Precip* data provided by NOAA/OAR/ESRL PSD, Boulder, Colorado, USA: https://www.esrl.noaa.gov/psd/data/gridded/data.UDel_AirT_Precip.html
Crop calories	(FAO, 2001)	Food balance sheets	NA	kcal/100g	http://www.fao.org/docrep/003/x9892e/X9892e05.htm#P8217_125315
National and regional level					
Nitrogen fertilizer	(FAO, 2019)	Fertilizer use in agriculture	National; 1968-2017	t	http://www.fao.org/faostat/en/#data/RFN; http://www.fao.org/faostat/en/#data/RA
Irrigation		Land area equipped for irrigation	National; 1968-2017	% of agri-cultural land	
Cropland (nation)		Cropland	National; 1968-2017	1000 ha	http://www.fao.org/faostat/en/#data/EL

Data	Reference	Description	Resolution; temporal extent	Unit	URL
National level					
Area harvested	(FAO, 2019)	Crop-specific harvested areas	National; 1968-2017	ha	
Production		Crop-specific production	National; 1968-2017	t	http://www.fao.org/faostat/en/#data/QC
Regional level					
Area harvested	(European Comission, 2019)	Crop-specific harvested areas	NUTS2; 1978-2017	1000 ha	
Production		Crop-specific production	NUTS2; 1978-2017	1000 t	https://ec.europa.eu/eurostat/data/database
Farm level					
Area harvested	(BMEL, 2019)	Crop-specific harvested areas	Farm; 1998-2017	ha	https://www.bmel-statistik.de/landwirtschaft/testbetriebsnetz/testbetriebsnetz-landwirtschaft-buchfuehrungsergebnisse/ (farm level data only upon request)
Crop yields		Crop-specific yields	Farm; 1998-2017	dt/ha	
Fertilizer purchase		Expenditure for fertilizers	Farm; 1998-2017	€	
Irrigation		Utilized agricultural area irrigated	State (Germany); 2005, 2007, 2010, 2013, 2016	% of utilized agri-cultural area	https://ec.europa.eu/eurostat/data/database

2.3.4 Statistical analyses

We used the statistical software package R 3.6.1 (R Core Team, 2019) run via RStudio (RStudio Team, 2015) for data analysis. To assess distributional assumptions in the response variable, we used the 'fitdistrplus' package in R (Delignette-Muller and Dutang, 2015). Yield stability was clearly log-normally distributed (a normal distribution had a ΔAIC of +1130.74, +80.31 and + 27531.98 units compared with the log-normal for yield stability at the national, regional and farm level, respectively). To equalize spread and reduce leverage, we square root-transformed fertilizer and irrigation for all levels of organization and log-transformed area harvested at the farm level. We scaled explanatory variables (mean-centered and divided by their standard deviations) to reduce remaining collinearity between main effects (Gelman and Hill, 2006) and to make regression coefficients comparable. At the farm level, we removed time due to its high correlation with temperature and precipitation instability (|Spearman´s rho| < 0.7), and precipitation instability because it inflated variance inflation factors. We then used a linear mixed-effects model using the 'nlme' library in R (Pinheiro et al., 2019) fitting a random intercept for nation, region as a nested effect of nation and farm as a nested effect of district, respectively, for the three levels of organization. We tested the dependence of yield stability on effective crop diversity, fertilizer, irrigation, temperature and precipitation heterogeneity (national and regional level), area harvested (farm level), temperature and precipitation instability and time for all levels of organization. Moreover, we included all pairwise interactions with crop diversity to test whether the effect of crop diversity is lower if agricultural inputs and climate heterogeneity are high, higher if climate instability is high and if it decreased over time. All explanatory variables at all three levels of organization had variance inflation factors below 4, indicating that multicollinearity was successfully removed.

For data security reasons, the farm level data is only available at the Johann Heinrich von Thünen-Institut, Braunschweig, Germany. All other data that support the findings of this study, as well as related codes for data preparation and analyses are openly available on GitHub: https://github.com/legli/AgriculturalStabilityScales

2.4 Results

Generally, nations reached higher yield stabilities than regions and farms (Figures 2.1-2.2). In particular, nations in Central and South America, partially Central and

West Africa, South Asia, Southeast Asia and China showed high stability. In Europe, regions with low stability were mainly found in Spain, Sweden and parts of Eastern Europe. High stability regions were mainly found in the UK, France, Northern Italy and Germany. Average stability of farms was generally higher in districts in Western and Southern Germany, while lowest values were reached in Eastern Germany.

Individual yield stability, i.e. that of a single nation, region or farm, was typically lower compared to the stability over all nations, regions or farms (Figures 2.2, A2). In only 6.3% of all cases, nations reached higher stability compared to global stability. In contrast, 14.6% and 16.3% of the regions and farms reached higher stabilities compared to the stability over all regions and farms, respectively. The difference between individual and larger-scale stability was most profound at the national level. Spatial patterns were similar to actual stability values (Figures. 2.1, A2).

Most nations (71.4%), regions (64.8%) and farms (71.9%) contributed to larger-scale stability (Table 2.2, Figure A3). On average over all time intervals, Brazil, Nigeria, India and China contributed most to global stability, while the United States, Ukraine and Russia contributed least. Regions in the United Kingdom, Northern France, Germany and Italy, and Finland contributed most to European stability. On average, farms hardly contributed to larger-scale stability (average contribution for farms contributing to larger-scale stability was 1.001).

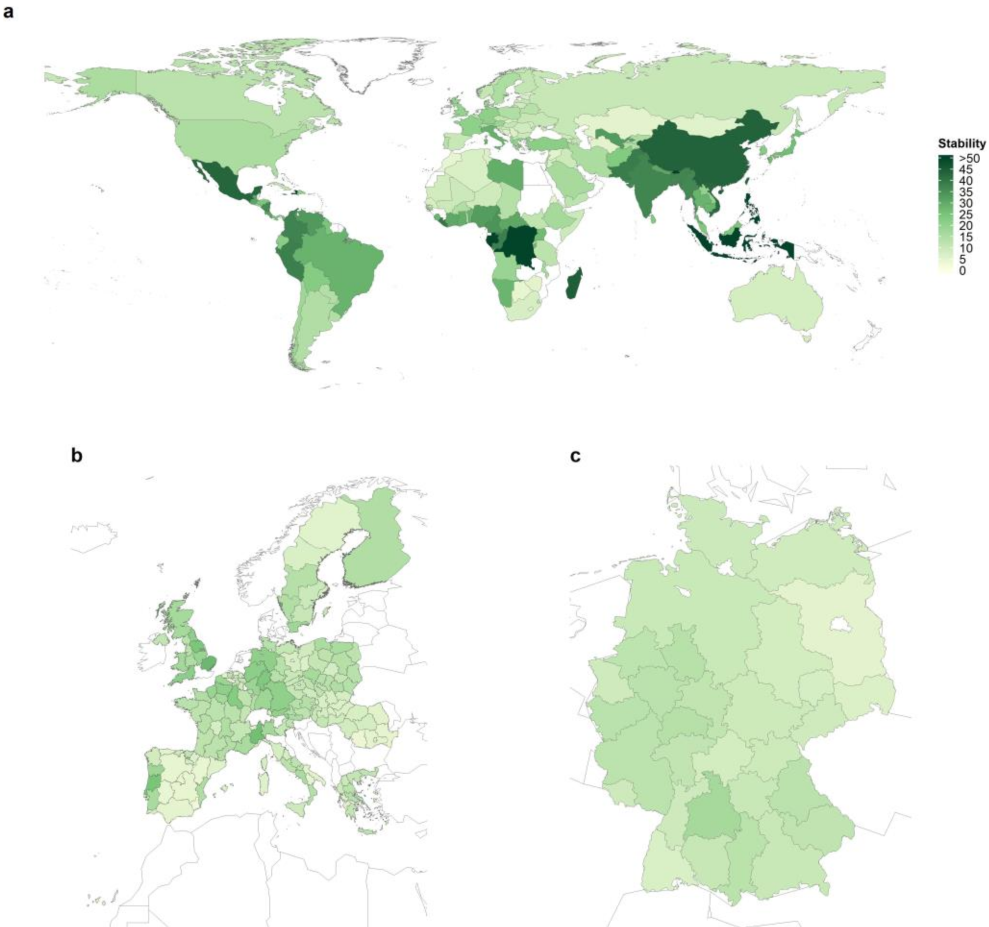

Figure 2.1 Yield stability for nations (a), regions in the European Union (b) and farms in Germany (c). Values are averaged over all time periods (n = 137 for the national, n = 165 for the regional and n = 5183 for the farm level). Farm values are aggregated to the district level (mean values of the underlying farms), assuming that they are representative for the respective district. Units excluded from the analyses are shown in white.

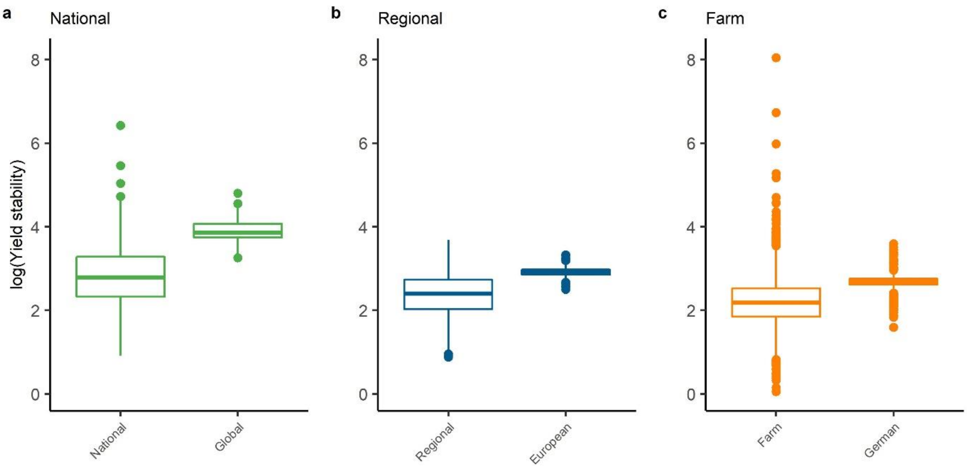

Figure 2.2 Whisker plots for yield stability of nations (a), regions (b) and farms (c) compared to larger-scale yield stability over all nations ('Global'), regions ('European') and farms ('German') for all time periods (n = 602 for the national, n = 355 for the regional and n = 6384 for the farm level). Yield stability was log-transformed. Larger-scale stability was calculated as the stability over all nations, regions or farms (only including the crops grown in the respective unit).

Table 2.2 Yield stability contribution of nations and regions that increased or decreased global or European stability by more than 5%, on average over all time intervals. Yield stability contribution was calculated as the larger-scale stability over all nations or regions divided by the larger-scale stability without the respective nation or region (only including the crops grown in the respective unit).

Country	**Yield stability contribution**	**Region (Counry)**	**Yield stability contribution**
China	1.15	Piemnte (Italy)	1.07
India	1.12	Scotland (UK)	1.05
Brazil	1.07	…	…
Indonesia	1.05	…	…
…	…	…	…
…	…	Castile-Leon (Spain)	0.95
Russia	0.94	Andaluisa (Spain)	0.94
United States	0.9	Castille-La-Mancha (Spain)	0.87

Crop diversity was positively and significantly associated with yield stability across all levels of organization (Figures 2.3, A1; Table A1). Fertilizer also showed a positive association at all levels, but was insignificant at the national level. Precipitation heterogeneity showed a strong and significant positive relationship with yield stability at the national and regional level, while area harvested (used as a proxy for climate heterogeneity) was positively associated with yield stability at the farm level. Temperature instability was negatively associated with yield stability at all levels of organization, but was insignificant at the regional level. The same applied for precipitation instability at the national and regional level. At the national level, precipitation heterogeneity had the highest positive effect size, while at the regional and farm level this applied for fertilizer and crop diversity, respectively. Time was negatively associated with yield stability at the farm level.

At the national level, the positive association of crop diversity with yield stability was highest if irrigation was low and if precipitation instability was high (Figure 2.4). At the regional level, this association was highest if irrigation was high (Figure 2.5). At the farm level, the positive relationship of diversity was most profound in farms with high irrigation, low area harvested and high temperature instability (Figure 2.6).

The explanatory power of the models was 0.34 (R2 marginal) and 0.58 (R2 conditional) for the national, 0.36 and 0.62 for the regional and 0.1 and 0.48 for the farm level, respectively.

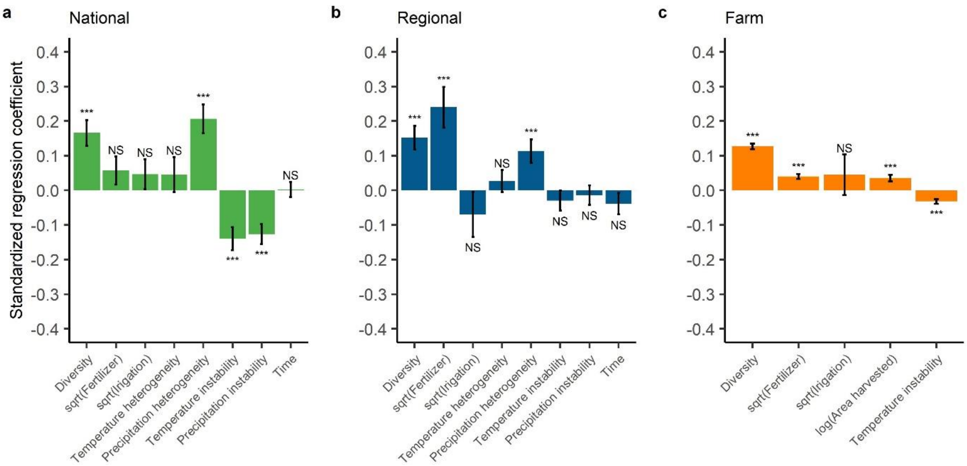

Figure 2.3 Determinants of yield stability at the national (a), regional (b) and farm level (c). Regression coefficients (± SE) are shown for fixed effects included in the linear mixed-effects

models at the national (n = 602), regional (n = 355) and farm level (n = 6384). Yield stability and area harvested were log-transformed, irrigation and fertilizer were square-root-transformed. Each explanatory variable was standardized to zero mean and one standard deviation across all nations, regions or farms and time intervals. *$P < 0.05$;**$P < 0.01$; ***$P < 0.001$; *NS* = not significant.

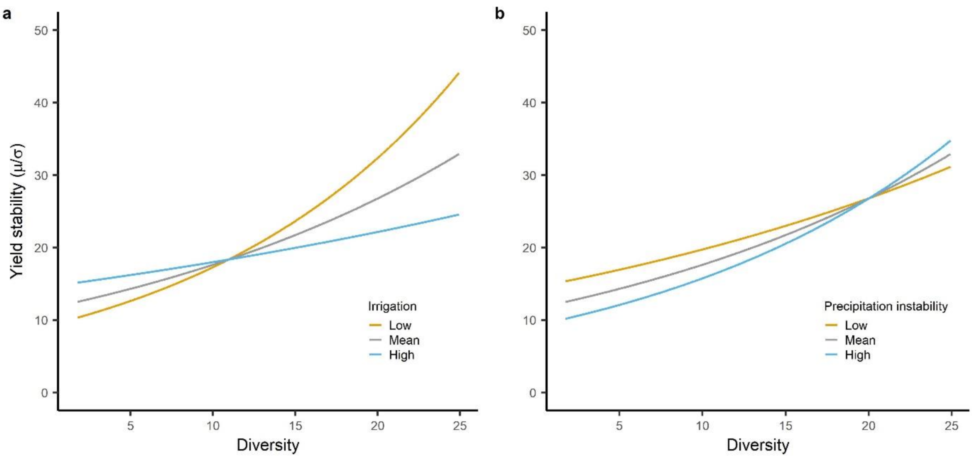

Figure 2.4 Effect of crop diversity in combination with irrigation (a) and precipitation instability (b) on yield stability at the national level (n = 602). Predicted values for yield stability were back-transformed from log-transformation. Predictions were calculated using the observed range of the focal explanatory variable, while keeping all the other variables at their mean values. Only interactions with p-values < 0.1 are shown.

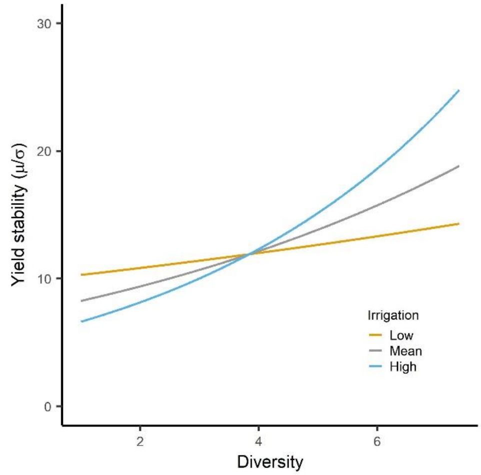

Figure 2.5 Effect of crop diversity in combination with irrigation on yield stability at the regional level ($n = 355$). Predicted values for yield stability were back-transformed from log-transformation. Predictions were calculated using the observed range of the focal explanatory variable, while keeping all the other variables at their mean values. Only interactions with p-values < 0.1 are shown.

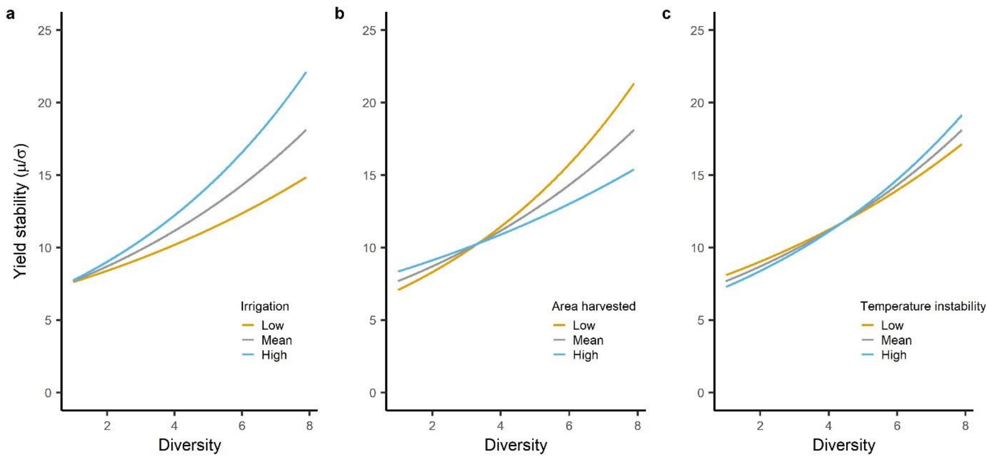

Figure 2.6 Effect of crop diversity in combination with irrigation (a), area harvested (b) and temperature instability (c) on yield stability at the farm level ($n = 6384$). Predicted values for yield stability were back-transformed from log-transformation. Predictions were calculated using the observed range of the focal explanatory variable, while keeping all the other variables at their mean values. Only interactions with p-values < 0.1 are shown.

2.5 Discussion

Our results suggest that yield stability generally increases at larger scales. On the one hand, mean national-level stability was 84% and 105% higher compared to the regional and farm level, respectively, although these differences might be partially explained by different sets of crops considered. On the other hand, stability over all nations, regions or farms was on average 2.3, 1.5 or 1.4 times higher compared to individual stability. The benefits of scale are most likely related to increasing spatial heterogeneity and better opportunities to buffer local disturbances (Allred et al., 2014; Biggs et al., 2012; Marchand et al., 2016). The importance of scale in stabilizing yields has certain implications for recent discussions on the regionalization of food systems (Opitz et al., 2016). They indicate that limiting the spatial scale of the production might increase the vulnerability to disturbances, hence trade is a potentially important resilience mechanism (Marchand et al., 2016). Additionally, market access has been found to enhance food security (Sibhatu and Qaim, 2018). However, agricultural management can potentially reduce the dependency on trade to stabilize production. Moreover, reshaping regional food systems bears a great potential to promote more holistic agricultural approaches (see below) and to promote food security even in the Global North (Hendrickson, 2015; Opitz et al., 2016). Consequently, fostering food system resilience requires a combination of ecological and socio-economic approaches at multiple levels and scales (Hendrickson, 2015).

We identified several nations and regions that substantially contribute to larger-scale stability. For example, China, India, Brazil and Indonesia increased global stability by more than 5% each on average. In contrast, Russia and the United States substantially decreased global yield stability. Regarding the United States, this is most likely related to a high specialization on certain crops that contribute substantially to global production (Ortiz-Bobea et al., 2018). Indeed, production of maize, soybean and, to some extent, wheat in the Midwest have been found to increase the variance of the global production of these crops (Mehrabi and Ramankutty, 2019). From a global perspective, strategies to improve stability in areas that decrease global stability are of high priority. Farms only had a marginal influence on larger-scale stability as it is unlikely that individual farms have an effect on the combined stability of thousands of farms across Germany.

Our results suggest that crop diversity is a key mechanism to increase yield stability across all levels of organization. At the farm level, it even had by far the largest positive effects of all explanatory variables considered. We found evidence that the positive effect of crop diversity on yield stability was higher in variable climates, supporting resilience theory (Biggs et al., 2012; Yachi and Loreau, 1999). Moreover, at the national level this effect was highest when irrigation was low, highlighting its relevance in the absence of technological means to address yield stability. However, this effect was inverse at the regional and farm level, suggesting that combined efforts are needed to increase yield stability. At the farm level, the positive association of crop diversity was highest in small farms. Additionally, the absolute effect of crop diversity increased from national to farm level (Figures 2.4-2.6, grey line). These findings suggest that crop diversity is particularly relevant at smaller scales. To our knowledge, this is the first study that investigated the effect of crop diversity at different scales using a large and comprehensive sample size. Thus, it provides a valuable extension to previous findings at the national (Renard and Tilman, 2019) and local scale (Gaudin et al., 2015).

Except for irrigation at the regional level, agricultural inputs were positively associated with yield stability. In contrast to findings of Renard and Tilman (2019) however, they were insignificant at the national level, probably due to additional variables and interactions included here. Fertilizer had the strongest positive association at the regional level, suggesting that agricultural inputs are not only relevant to close yields gaps (Mueller et al., 2012), but also to increase their stability (Knapp and van der Heijden, 2018; Renard and Tilman, 2019). However, this dependency on agricultural inputs has serious implications for biodiversity and ultimately human well-being (Beckmann et al., 2019; Loos et al., 2014; Tscharntke et al., 2012; West et al., 2014), and associated specialization may also increase climatic sensitivity of agriculture (Ortiz-Bobea et al., 2018). Furthermore, the resources needed are limited and both nitrogen fertilizer and irrigation already reached a peak-year (Seppelt et al., 2014). Accordingly, more integrated approaches to tackle the multiple challenges agricultural landscapes face today such as crop diversification, renewable inputs and other agroecological principles are needed (Gurr et al., 2016; Kremen and Merenlender, 2018). For example, more diverse cropping systems, beyond just organic agriculture, could potentially achieve higher production than today (Knapp and van der Heijden, 2018; Seufert et al., 2012), thus providing a viable option to feed the world more sustainably (Muller et al., 2017) and to conserve biodiversity and ecosystem services (Iverson et al., 2014; Sirami et al., 2019; Tscharntke et al., 2015).

Precipitation heterogeneity was positively associated with yield stability, most likely because it leads to asynchronous or contrasting production patters between and within crops (Mehrabi and Ramankutty, 2019; Suweis et al., 2015). For example, some areas in a certain year experience production losses due to bad conditions, while others experience favorable conditions that compensate them. As the relative effect of precipitation heterogeneity was highest at the national level, the relevance of this mechanism might increase with scale, i.e. opposite to the effect of crop diversity. Therefore, understanding the linkages of scale and the performance of different stabilizing mechanisms is a promising avenue for future research.

We found that climate instability substantially decreased yield stability, in particular at the national level. Thus, expected increases in climate instability in the light of climate change may not only lead to yield losses but also to lower temporal stability of yields (Challinor et al., 2014; Liang et al., 2017). In the European and German context, climate seems to play a minor role, i.e. effect sizes were comparable or even lower than the effect sizes of crop diversity and agricultural inputs. European agriculture benefits from a comparably stable climate and is largely intensified (Václavík et al., 2013). Accordingly, until now climate instability can be buffered by agricultural management. This has also been observed for agricultural productivity in the United States (Liang et al., 2017).

The study presented here includes two major limitations. First, data quality at all levels of organization is limited. For example, several datasets had to be rescaled due to different spatial resolutions and many units were excluded due to data gaps. Nevertheless, the consistency of certain patterns across different levels of organization and the alignment with previous findings and theory increase their reliability. Second, the explanatory power of the fixed effects included in our statistical models (R2 marginal = 0.10-0.36) indicates that important drivers of yield stability are missing, potentially related to pesticide use, capital stock, market access and land-use history, for which temporal and spatial data coverage is yet limited.

This study opens new avenues for future research. Future assessments could include different crop varieties and functional traits as they most likely play a fundamental role for resilience (Ficiciyan et al., 2018). Further studies could include other aspects of resilience, disturbances and agricultural diversity (Cottrell et al., 2019; Egli et al., 2019; Letourneau et al., 2011; Lin, 2011). Moreover, the processes driving agricultural specialization, for example economic globalization, and their consequences need to be mechanistically investigated (Lambin and Meyfroidt, 2011; Magliocca et al., 2013).

2.6 Conclusion

Our study suggests that crop diversity consistently increases yield stability across different levels of organization and that this effect is higher in variable climate and at smaller scales. In contrast, precipitation heterogeneity is particularly stabilizing yields at larger scales. Our results also show that agricultural inputs mainly have a stabilizing effect, while climate instability reduces stability. These findings emphasize the need for integrated land-use planning including diversification of farming systems from the farm to the national level and sustainable usage of agricultural inputs, also given the environmental and socio-economic risks of primarily focusing on technological measures.

Acknowledgements

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3 National food production stabilized by crop asynchrony[2]

3.1 Introduction

Recently, Renard and Tilman (2019) reported that crop diversity stabilizes national food production. They analyzed the dependence of national caloric yield stability over 176 crops on effective crop diversity, climatic instability, agricultural management, warfare and time. Effective crop diversity was calculated as the exponential value of the Shannon diversity index of crop harvested areas. We here suggest that two additional aspects should be considered in the discussion on the diversity-stability nexus. First, besides yield stability, the stability of overall production is also a relevant aspect of food security. Second, actual benefits of crop diversity are not related to harvested areas *per se* but to the temporal production patterns of the cultivated crops (Mehrabi and Ramankutty, 2019). We hypothesize that planting multiple crops stabilizes agricultural production only if they experience asynchronous production trends, e.g. due to distinct responses to climatic, economic and political shocks (Lesk et al., 2016; Suweis et al., 2015). Here, we use statistical models to test if crop asynchrony even better predicts agricultural production stability than crop diversity.

3.2 Materials and Methods

We largely used the same datasets as Renard and Tilman (2019) (Tables A2, A3) and derived the same explanatory variables used in their analysis, including effective crop species diversity (FAO, 2019), irrigation (FAO, 2019), nitrogen use intensity (FAO, 2019), warfare (Marshall, 2016), temperature and precipitation instability (Klein Goldewijk et al., 2017; Sacks et al., 2010; Willmott and Matsuura, 2001) for five ten-year intervals between 1961-2010 (see Appendix 7.2.1 for details) to predict the stability of total caloric production (FAO, 2019, 2001). We additionally calculated synchrony between crop-specific calorie production (Loreau and De Mazancourt, 2008; Mehrabi and Ramankutty, 2019), an index bounded between zero and one,

[2] Under review as: Egli, L., Schröter, M., Scherber, C., Tscharntke, T., Seppelt, R. National food production stabilized by crop asynchrony. Nature. (11. August 2020)

where one indicates full synchrony. Asynchrony was then calculated by subtracting synchrony from 1 so that higher values indicate higher asynchrony. We used total production instead of yield stability as the response variable because this offers additional insights to food security and because this can be directly related to asynchrony (see Appendix 7.2.1 for details). Moreover, total production incorporates the effects of changes in cropland area resulting from farmers' planning decisions and global market dynamics.

First, we investigated the relationship between effective crop species diversity and crop asynchrony and tested if this relationship changed over time as crop homogenization occurred during the last decades (Khoury et al., 2014). We used a linear mixed-effects model with random slopes for diversity, and random intercepts for time intervals to predict crop asynchrony. Second, we investigated how crop diversity, crop asynchrony or both affect caloric production stability. For this, we constructed the main linear regression model used in Renard & Tilman (2019) using production stability as response variable (see Appendix 7.2.1 for details). We then ran two additional regression models, one where we replaced crop diversity by crop asynchrony and one where we added crop asynchrony.

3.3 Results

Crop diversity and crop asynchrony were correlated (|Spearman´s rho| = 0.49, $P < 0.05$; Figure 3.1a). However, the positive effect of crop diversity on asynchrony decreased over time (Figure 3.1a), indicated by a better performance of a linear mixed-effects model including time interval (AIC = -340.22) compared to a linear model including crop diversity only (AIC = -336.88). The positive effect of crop asynchrony on caloric production stability was more than three times the effect of crop diversity (Figure 3.1b; Table A4). Other predictors showed similar trends, although the effect of nitrogen use intensity, time and precipitation instability was stronger in the diversity model, while the effect of irrigation was lower and insignificant. Moreover, the explanatory power of the model increased from $R2$ = 0.28 in the crop diversity model to $R2$ = 0.60 in the asynchrony model (Table A4). In the model including both predictors, the stabilizing effect of crop asynchrony was even stronger and the effect of crop diversity turned negative (Figures 3.1b, A4), but explanatory power only increased by 0.01 (Table A4). Although crop diversity and asynchrony were correlated, multicollinearity was not an issue in the combined model (variance inflation factors below 2). Given that crop asynchrony was a strong predictor of caloric production stability, we further explored their relationship in the most recent time interval (2001-2010). Highest national crop asynchronies were mainly observed in South and Southeast Asia, China, Central America and parts of Africa (Figure 3.2). These countries typically showed high production stability and all countries with high asynchrony achieved at least medium stability. Highly stable countries with low to medium asynchrony were mainly found in North and South America (Figure 3.2). The 29 countries with low asynchrony and stability, for example Russia, Argentina and Australia contributed to more than 11% of the total crop caloric production.

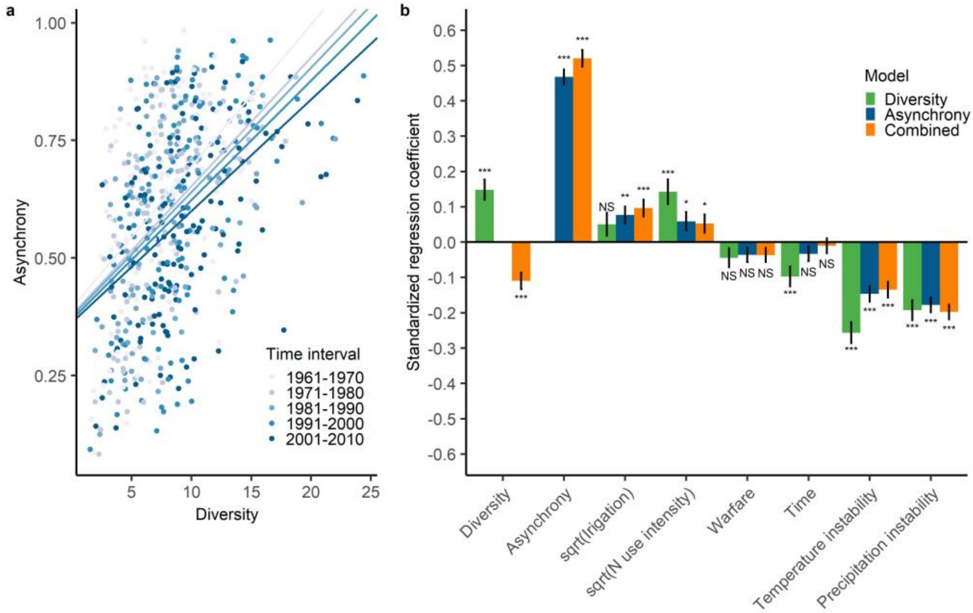

Figure 3.1 Crop asynchrony as a function of crop diversity (a) and determinants of national caloric production stability (b). Crop asynchrony as a function of crop diversity using a linear mixed-effects model with random slopes for diversity, and random intercepts for time intervals. Dots show national data colored by time interval (n = 590). Regression coefficients (± SE) for all variables in the linear regression models including crop diversity (green), crop asynchrony (blue) and both (orange) (n = 590). Caloric production stability was log-transformed, irrigation and nitrogen use intensity were square-root-transformed. Each

predictor variable was standardized to zero mean and one standard deviation across all nations and time intervals. *$P < 0.05$;**$P < 0.01$; ***$P < 0.001$; *NS* = not significant.

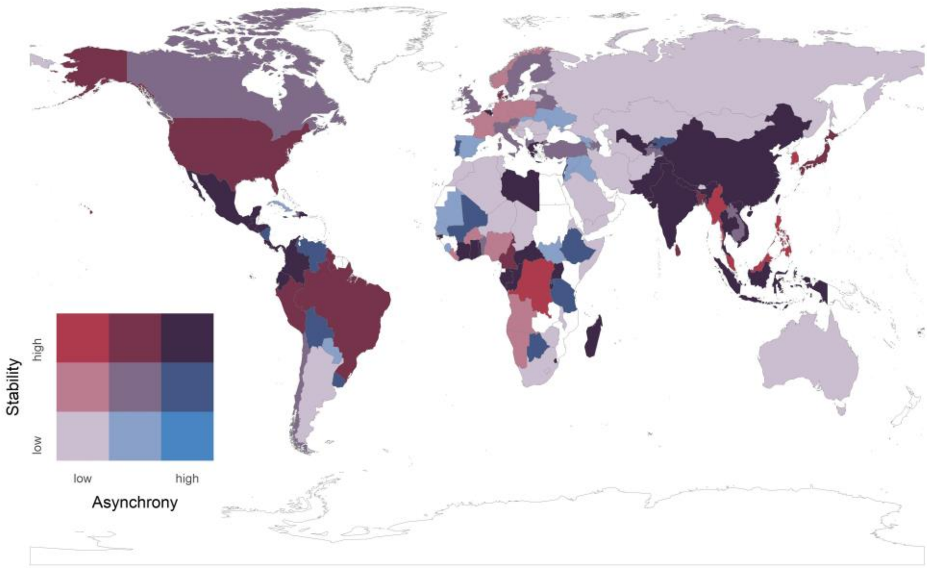

Figure 3.2 National crop asynchrony and caloric production stability worldwide. Crop asynchrony and caloric production stability are shown for the 2001-2010 interval and grouped by tertiles ($n = 136$). Countries excluded from the analysis are shown in white.

3.4 Discussion and Conclusion

Our analysis provides an important extension to the results presented by Renard & Tilman (2019). We found that the relationship of crop diversity and crop asynchrony decreased over time, which is a potential consequence of increasing homogeneity of global food supplies (Khoury et al., 2014). Most importantly, we identified that asynchrony is one important crop property (or trait) that can explain why a higher diversity supports stability of national food production. Crop diversity as such provides only limited insights into the mechanism underlying stability. Benefits of crop diversity depend on the actual production patterns of the cultivated crops. Therefore, strategies to stabilize agricultural production through crop diversification also need to account for the asynchrony of the crops considered.

The results from the crop diversity model are largely similar to the findings of Renard and Tilman (2019) because the different response variables (caloric yield vs. production stability) were highly correlated (|Spearman´s rho| = 0.84, $P < 0.05$). However, the effect of irrigation was less stabilizing for production compared to yield stability and the opposite was true for nitrogen use intensity. Moreover, overall production stability significantly decreased over time, which has serious implications for food security.
Asynchrony emerges from distinct responses of crops to climatic, economic and political shocks (Lesk et al., 2016; Suweis et al., 2015). While there is increasing knowledge about the underlying drivers of overall production losses (Cottrell et al., 2019), little is known about the effects on individual crops in various environmental and socio-economic contexts, in particular regarding their temporal variance (Knapp and van der Heijden, 2018; Mehrabi and Ramankutty, 2019) at the farm level, where management decisions are made. Moreover, growing crops in different seasons is additionally expected to increase asynchrony, which should be further investigated. Likewise, we need to better understand the conditions under which asynchrony is needed for and beneficial to stability. Spain, for example, experienced medium asynchrony but low stability in 2001-2010, while the opposite was true for Germany. In countries with low crop asynchrony and stability, planting additional crops with different responses to climatic and market disturbances may be a viable option to increase stability and thus food security (Knapp and van der Heijden, 2018), in particular in the light of climate change and rising perturbations in global markets (Suweis et al., 2015). On the national level, this is especially relevant for countries facing severe food insecurity such as Malawi. For countries such as Russia and Argentina, which recently experienced low asynchrony and stability, but contributed to more than 5% of the global crop calories, increasing crop asynchrony is an important aspect to consider from a global perspective. Growing trade and dietary changes might further lead to crop homogenization (Khoury et al., 2014; Mehrabi and Ramankutty, 2019) and thus pose risks on the stability of national and global food production.

Acknowledgements

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4 Disentangling the effects of asynchrony between and within crops on the stability of agricultural production[3]

4.1 Abstract

Asynchrony between the temporal production patterns of different crops ('asynchrony between crops') and between the temporal production patterns of different cultivation areas of the same crop ('asynchrony within crops') have been proposed as important mechanisms to buffer climate variability and other disturbances and thus to stabilize agricultural production. Better understanding their relative importance is important for agricultural management, but so far this has been hardly assessed. We used crop production data to investigate the effect of asynchrony between and within crops on temporal production stability and their relationship to crop diversity and space, respectively, in regions in Germany and nations in Europe. We found that both asynchrony between and within crops consistently stabilized agricultural production. Adding crops increased asynchrony between crops, yet this effect levelled off when exceeding eight crops in regions in Germany and when exceeding four crops in nations in Europe. Combining already ten farms led to high asynchrony within crops in regions, indicating distinct production patters. Combining multiple regions within a nation also increased asynchrony within crops, but values remained relatively low, indicating that regions in European countries show similar temporal production patterns. Our results stress the need to consider both mechanisms to foster resilient farming systems in the light of climate change, rising demands for agricultural products and the intensification and specialization of agricultural systems.

4.2 Introduction

Climate variation and other disturbances are important determinants of the variability of agricultural production (Cottrell et al., 2019; Ray et al., 2015; Renard and Tilman, 2019; Suweis et al., 2015). Therefore, buffering variation and

[3] In preparation: Egli, L., Seppelt, R. Disentangling the effects of asynchrony between and within crops on the stability of agricultural production.

disturbances is fundamental to enhance the reliability of agricultural production and thus food security (Knapp and van der Heijden, 2018; Schmidhuber and Tubiello, 2007). Understanding the mechanisms stabilizing agricultural production has gained more attention recently (Gaudin et al., 2015; Knapp and van der Heijden, 2018; Mehrabi and Ramankutty, 2019; Raseduzzaman and Jensen, 2017; Ray et al., 2015; Renard and Tilman, 2019). Asynchrony between the temporal production patterns of different crops (‘asynchrony between crops’) and between the temporal production patterns of different cultivation areas of the same crop (‘asynchrony within crops’) have been suggested as key factors to stabilize agricultural production (Mehrabi and Ramankutty 2019; Chapter 3).

Asynchrony between crops mainly emerges from distinct temporal production patterns of different crops (Mehrabi and Ramankutty, 2019). Increasing crop diversity stabilizes agricultural production if they experience asynchronous production trends, e.g. due to distinct responses to climatic, economic and political shocks (Lesk et al., 2016; Suweis et al., 2015); the same stabilizing mechanism due to ‘response diversity’ of different species of the same guild is discussed in biodiversity research (Elmqvist et al., 2003). Therefore, asynchrony is one important property that can explain why a higher diversity supports the stability of national food production (Chapter 3).

Asynchrony within crops is mainly related to space and more importantly to spatial heterogeneity (Kouadio and Newlands, 2015). For example, different cultivation areas of the same crop experience different climatic conditions. If these conditions lead to asynchronous temporal production patterns, e.g. to a production surplus in one place and a loss in the other, the two places stabilize each other (Mehrabi and Ramankutty, 2019). Therefore, larger areas with high spatial heterogeneity can better buffer local shocks, e.g. related to climate or weather events, political changes and mismanagement (Cottrell et al., 2019; Suweis et al., 2015). In particular, spatial climate heterogeneity has been found to increase production stability (Chapter 2).

The relevance of different stabilizing mechanisms additionally differs across different levels of organization and scales. For example, it has been found that the stabilizing effect of crop diversity is particularly high in smaller farms, while spatial climate heterogeneity is more important at the national level (Chapter 2). Therefore, a better understanding of the effect of different stability mechanisms across different spatial scales is needed to advance resilience research (Cumming et al., 2016).

While the effect of asynchrony between and within crops has been recently assessed individually, their relative importance to stabilize agricultural production has been hardly assessed. However, this is important to inform agricultural management strategies that seek to foster the stability of agricultural systems. In this study we aim at addressing the effect of asynchrony between and within crops on the temporal stability of agricultural production in regions in Germany and nations in Europe, i.e. at different levels of organization. Moreover, we assessed their relationship to crop diversity and space, respectively.

4.3 Materials and Methods

4.3.1 Methodological summary and data availability

We used crop production data to study the effect of asynchrony between and within crops on the stability of agricultural production in regions in Germany and nations in Europe, i.e. at different levels of organization. For each region in Germany we derived asynchrony between the total crop-specific temporal production patterns, and the asynchrony between the temporal production patterns of the same crop in different farms in two time periods (1998-2007, 2008-2017). For each considered nation in Europe, we calculated asynchrony between crops and between the temporal production patterns of the same crop in different regions within this nation in four time periods (1978-1987, 1988-1997, 1998-2007, 2008-2017). For both nations and regions, we assessed the effect of crop diversity and space on asynchrony between and within crops, respectively.

We used the statistical software package R 3.6.1 (R Core Team, 2019) run via RStudio (RStudio Team, 2015) for analyses. For data protection reasons, the farm level data is only available at the Johann Heinrich von Thünen-Institut, Braunschweig, Germany. All other data that support the findings of this study (Table 4.1), as well as related codes for data preparation and analyses are openly available on GitHub: https://github.com/legli/Asynchrony.

Table 4.1 Datasets used in this study. Temporal extent reflects the time periods extracted for this study.

Data	**Reference**	**Description**	**Resolution; temporal extent**	**Unit**	**URL**
Germany					
Area harvested	(BMEL, 2019)	Crop-specific harvested areas	Farm; 1998-2017	ha	https://www.bmel-statistik.de/landwirtschaft/testbetriebsnetz/testbetriebsnetz-landwirtschaft-buchfuehrungsergebnisse/ (farm level data only upon request)
Crop yields		Crop-specific yields	Farm; 1998-2017	dt/ha	
Crop calories	(FAO, 2001)	Food balance sheets	NA	kcal/100g	http://www.fao.org/docrep/003/x9892e/X9892e05.htm#P8217_125315
Europe					
Area harvested	(European Comission, 2019)	Crop-specific harvested areas	NUTS2; 1978-2017	1000 ha	
Production		Crop-specific production	NUTS2; 1978-2017	1000 t	https://ec.europa.eu/eurostat/data/database
Crop calories	(FAO, 2001)	Food balance sheets	NA	kcal/100g	http://www.fao.org/docrep/003/x9892e/X9892e05.htm#P8217_125315

4.3.2 Methodological details

We collected German and European agricultural data for different time periods. In Germany, we collected data in Germany for two time periods (1998-2007, 2008-2017), using the 'Testbetriebsnetz' dataset, a comprehensive assessment of management and socio-economic variables on a large subset of farms across Germany (Table 4.1). For the European data, we extracted data for the NUTS 2 regions (where applicable) for four time intervals (1978-1987, 1988-1997, 1998-2007, 2008-2017) using agricultural production data from the EUROSTAT database (Table 4.1). To exclude farms or regions where crop cultivation is of very minor relevance, we sorted them by the average cropland area over all reported years in descending order and divided it by the total cropland area of all farms or regions and calculated the cumulative sum. We only included farms or regions up to of 99.9% of the cumulative sum.

To calculate production stability, several preparation steps were needed. We converted crop-specific production from tons to calories using standardized nutritive factors (Table 4.1). We focused on 12 major crops (Table 4.2). For each time interval, we only included crops for which time series were complete and where both production and harvested area were reported. For each year, we then summed calorie production of all crops across all farms within each district ('Regierungsbezirk') (German data) or across all regions within each nation (European data) to obtain overall production in kilocalories. To account for stability independent of long-term trends, we time-detrended annual production data by regressing annual total calorie production on year squared for each time interval (Renard and Tilman, 2019). We calculated production stability as the mean of the non-time-detrended production divided by the standard deviation of time-detrended production for each time period following Renard and Tilman (2019) and Mehrabi and Ramankutty (2019). Likewise, we calculated time-detrended production for each crop. We then derived synchrony between crops during the ten years following Loreau and De Mazancourt (2008) and Mehrabi and Ramankutty (2019) with the 'codyn' package (version 2.0.3) in R (Hallett et al., 2016), which we then subtracted from 1 to receive asynchrony (Chapter 3). Next, we calculated crop-specific asynchrony between the time-detrended production in farms or regions where a given crop was reported. We averaged these values over all crops using

harvested area-weighted means to estimate asynchrony within crops of regions in Germany and nations in Europe.
Based on the derived metrics, we tested the dependence of production stability on asynchrony between and within crops. Therefore, we fitted a linear mixed-effects model using the 'nlme' library in R (Pinheiro et al., 2019) including a random intercept for region for the German data and for nation for the European data.
Next, we investigated the effect of the number of crops on asynchrony between crops, and of the number of farms (Germany) or regions (Europe) on asynchrony within crops. Within each region or nation we started with the most abundant crop and then iteratively added crops with decreasing abundance. For each number of crops we derived asynchrony between crops for each region or nation as described above. Likewise, within each region or nation, we iteratively added farms or regions, starting with the one with the highest total harvested area, and derived asynchrony within crops as described above.

Table 4.2 Crops included in the different analyses (G = Germany, E = Europe).

Crop	Analysis
Barley	G, E
Maize	G, E
Millet	E
Potato	G, E
Rapeseed	G, E
Rice	E
Rye	G, E
Sorghum	E
Soybean	G, E
Sugar beet	G, E
Sunflower	G, E
Wheat	G, E

4.4 Results

Both in Germany and Europe, asynchrony between and within crops were positively associated with stability (Figure 4.1; Table 4.3). The effect of asynchrony within crops was stronger, yet insignificant in Europe.

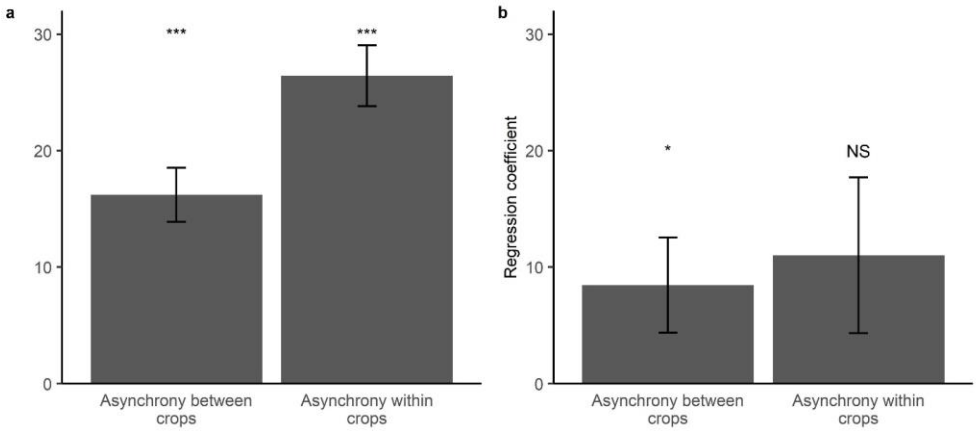

Figure 4.1 Observed effect of asynchrony between and within crops in regions in Germany (a) and nations in Europe (b) on production stability. Regression coefficients (± SE) are shown for fixed effects included in the linear mixed-effects models for Germany (*n* = 60) and Europe (*n* = 44) and indicate the change of production stability by one unit of change in asynchrony between and within crops (R2m = 0.76, R2c = 0.82; R2m = 0.16, R2c = 0.34). *P < 0.05;**P < 0.01; ***P < 0.001; *NS* = not significant.

Table 4.3 Determinants of stability for regions in Germany (*n* = 60) and nations in Europe (*n* = 44). Regression coefficients are shown for fixed effects included in the linear mixed-effects models and indicate the change of production stability by one unit of change in asynchrony between and within crops.

	Germany			**Europe**		
Variable	**Estimate (SE)**	**T**	**p-value**	**Estimate (SE)**	**T**	**p-value**
(Intercept)	-13.49 (2.14)	-6.31	<0.0001	6.19 (2.68)	2.31	0.03
Asynchrony between crops	16.2 (2.33)	6.95	<0.0001	8.47 (4.09)	2.07	0.05
Asynchrony within crops	26.43 (2.6)	10.16	<0.0001	11.02 (6.69)	1.65	0.11
R2 marginal	0.76	-	-	0.16	-	-
R2 conditional	0.82	-	-	0.34	-	-
AIC	284.87	-	-	282.67	-	-

Increasing the number of cultivated crops increased asynchrony between crops (Figure 4.2a, b). However, when exceeding eight crops the effect leveled off and then slightly decreased in regions in Germany. In nations in Europe it leveled off when exceeding four crops but then increased again after eight crops. Already when considering only a few farms within a region, high asynchrony within crops was achieved and maximum values were achieved with around 100 farms or more (Figure 4.2c). Considering multiple regions within a nation also increased asynchrony within crops, but mean values remained below 0.4 and the effect leveled off after approximately ten regions (Figure 4.2d).

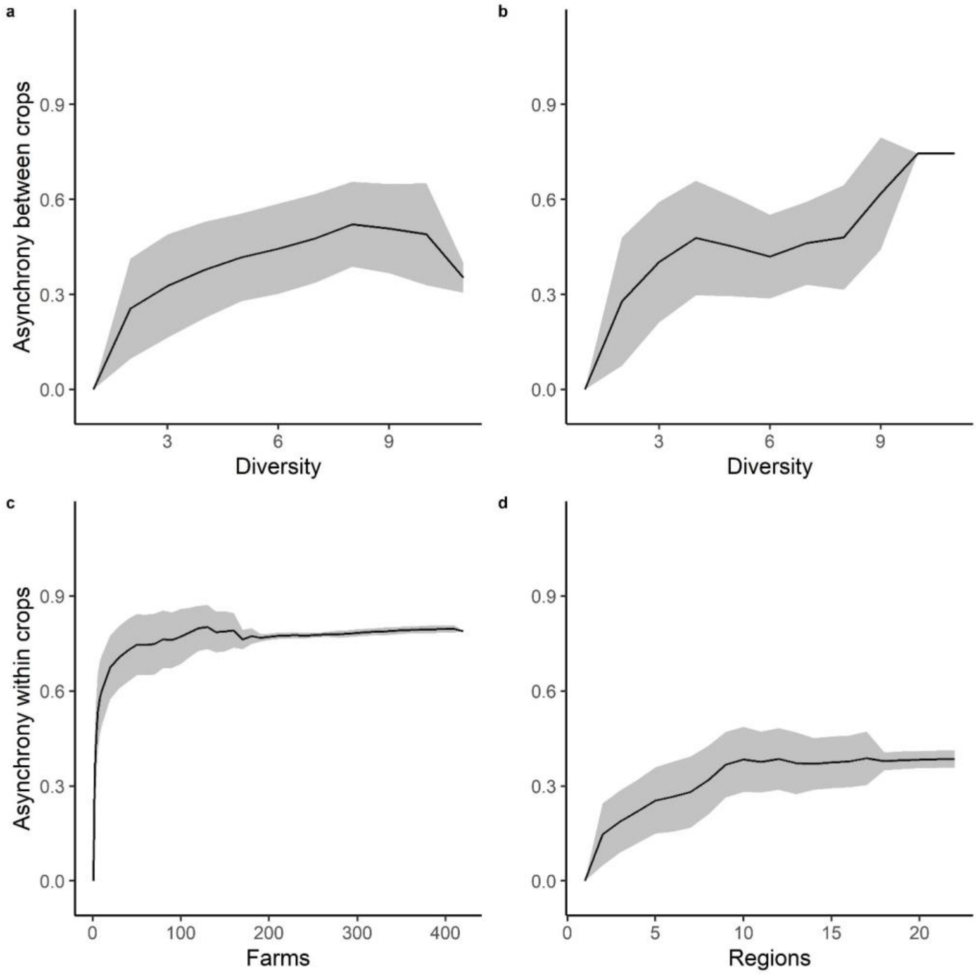

Figure 4.2 Effects of adding crops (a, b) and farms (c) or regions (d) on asynchrony between and within crops, respectively, in regions in Germany (a, c) and nations in Europe (b, d). Lines show mean values over all regions or countries. Shaded areas show standard deviations.

4.5 Discussion

Our results suggest that both asynchrony between and within crops are important mechanisms to stabilize agricultural production. However, in regions in Germany, the effect of asynchrony within crops was more than 60% higher, while it was insignificant in nations in Europe. To our knowledge, this is the first study that systematically compares their relative importance. Accordingly, this study specifies why climate heterogeneity stabilizes agricultural production (Chapter 2) and compares the effect of asynchrony within crops to the effect of asynchrony between crops, which has been previously studied individually (Mehrabi and Ramankutty, 2019; Chapter 3). In contrast to Mehrabi and Ramankutty (2019), it additionally relates these mechanisms to production stability at different levels of organization.

We found that the effect of asynchrony between crops was substantially weaker than the effect of asynchrony within crops in Germany. This suggests that some crops react similarly to climate and other disturbances and thus experience comparable production trends. While crop diversity increases asynchrony between crops, this effect levels off or even turns slightly negative when exceeding eight crops in regions and four crops in nations. Likewise, it has been found that also when much more crops are considered, crop diversity and asynchrony are only partially correlated and that the effect stagnates at some point (Chapter 3). Therefore, strategies to stabilize agricultural production also need to account for the asynchrony between crops. Nevertheless, planting crops with similar production patterns enhances redundancy, which in turns contributes to the resilience of food systems (Biggs et al., 2012; Garnett et al., 2020; Hendrickson, 2015; Lin, 2011).

The effect of asynchrony within crops was more than 60% higher than the effect of asynchrony between crops in regions in Germany. This is because already few farms within a region can achieve a high asynchrony within crops. However, in Europe it was insignificant, potentially because regions in Europe often face similar conditions and are largely intensified (Václavík et al., 2013). Therefore, asynchrony between regions within a country was relatively low and leveled off when exceeding approximately ten regions, which probably also explains the lower explanatory power of the respective regression model. Nevertheless, stability generally increases from smaller (e.g. farm level) to larger levels of organization (e.g. national level), in particular if spatial heterogeneity is high (Biggs et al. 2012; Allred et al. 2014;

Kouadio and Newlands 2015; Chapter 2). This effect could be even stronger if areas beyond national boundaries would be included as their climate is more independent, thus contributing to stability at a larger scale (Mehrabi and Ramankutty, 2019). Consequently, we can hypothesize trade to be another relevant stability mechanism as it increases the spatial production base and decreases the vulnerability to local disturbances (Marchand et al., 2016). Contrasting the importance of local vs. larger-scale mechanisms for the stability of agricultural production is an important avenue for future research, also in the light of recent discourses on the resilience of globalized vs. regionalized food systems (Garnett et al., 2020; Hendrickson, 2015).

Regional agricultural census data only provide limited insights into the effects of agricultural management. Therefore other tools such as computer simulations need to be developed to investigate management approaches that increase asynchrony between and within crops simultaneously and avoid potential trade-offs. While crop diversification typically increases asynchrony between crops, asynchrony within crops needs to be addressed by altering landscape configuration, e.g. by increasing the spatial fragmentation of crop distribution (Lin, 2011). Besides their potential stabilizing effects, related measures could also benefit overall productivity, biodiversity and ecosystem services more generally (Kremen and Merenlender, 2018; Li et al., 2020; Seppelt et al., 2020, 2016).

Adapting measures to buffer climate variability, climate change and other disturbances requires actions at multiple levels of organization (Hendrickson, 2015; Ziervogel and Ericksen, 2010). Besides institutional and political context, farm level responses are essential in this regard (Reidsma et al., 2010). Therefore, approaches incorporating farmer characteristics, including agent-based models (An, 2012; DeAngelis and Grimm, 2014), are essential to better understand land-use system dynamics (Brown et al., 2014) and the conditions favoring asynchronous production. Further studies could incorporate other aspects of asynchrony and its underlying drivers, for example related to growing crops in multiple seasons, as well as different farm and disturbance types (Reidsma et al. 2010; Cottrell et al. 2019; Chapter 3). Uncovering a wide range of mechanisms working at different levels of organization, scales and time horizons will be needed to identify comprehensive pathways towards productive and resilient farming systems (Battisti and Naylor, 2009; Lesk et al., 2016; Valin et al., 2014; Weise et al., 2020).

4.6 Conclusion

Our study suggests that both asynchrony between and within crops are important mechanisms to stabilize agricultural production at different levels of organization. Increasing the number of crops enhances asynchrony between crops, but this effects levels off at some point due to redundancy, while cultivating crops in few distinct farms already drastically increases asynchrony within crops. Our findings add valuable insights to recent discussions on resilience mechanisms and emphasize the need for integrated management approaches from the farm to the landscape level to foster resilient farming systems in the light climate change, rising demands for agricultural products and the intensification and specialization of agricultural systems.

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5 Exploring resilience with agent-based models: state of the art, knowledge gaps and recommendations for coping with multidimensionality[4]

5.1 Abstract

Anthropogenic pressures increasingly alter natural systems. Therefore, understanding the resilience of agent-based complex systems such as ecosystems, i.e. their ability to absorb these pressures and sustain their functioning and services, is a major challenge. However, the mechanisms underlying resilience are still poorly understood. A main reason for this is the multidimensionality of both resilience, embracing the three fundamental stability properties recovery, resistance and persistence, and of the specific situations for which stability properties can be assessed. Agent-based models (ABM) complement empirical research, which is, for logistic reasons, limited in coping with these multiple dimensions. Besides their ability to integrate multidimensionality through extensive manipulation in a fully controlled system, ABMs can capture the emergence of system resilience from individual interactions and feedbacks across different levels of organization. To assess the extent to which this potential of ABMs has already been exploited, we reviewed the state of the art in exploring resilience and its multidimensionality in ecological and social-ecological systems with ABMs. We found that the potential of ABMs is not utilized in most models as they typically focus on a single dimension of resilience by using variability as a proxy for persistence, and are limited to one reference state, disturbance type and scale. Moreover, only few studies explicitly test the ability of different mechanisms to support resilience. To overcome these limitations, we recommend to simultaneously assess multiple stability properties for different situations and under consideration of the mechanisms that are hypothesized to render a system resilient. This will help us to better exploit the potential of ABMs to understand and quantify resilience mechanisms, and hence

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support solving real-world problems related to the resilience of agent-based complex systems.

5.2 Introduction

In a world undergoing unprecedented change, understanding the resilience of agent-based complex systems, i.e. their ability to absorb change while maintaining functioning and thus persist, is of utmost importance (Biggs et al., 2012, 2015; Holling, 1973). Resilience has therefore become an increasingly popular concept in ecology, socio-ecology and other environmental sciences, as well as in many international bodies and conventions such as the Convention on Biological Diversity (CBD), the Organisation for Economic Co-operation and Development (OECD) and Wetlands International (Donohue et al., 2016). Increasing the capacity of agent-based complex systems (Grimm et al., 2005) to sustain their functioning and services under disturbances and ongoing change is of prime interest (Biggs et al., 2012; Oliver et al., 2015).

However, putting resilience into practice is challenging. Inconsistent terminology keeps hampering communication and understanding among theoreticians, empiricists and policy-makers (Baggio et al., 2015; Brand and Jax, 2007; Donohue et al., 2016; Grimm and Wissel, 1997; Pimm, 1984). In particular, the meaning of the term ‘resilience‘ differs widely between social and natural sciences. In social-ecological research, ‘resilience’ is primarily an integrated and holistic approach within sustainability science, which emphasizes social-ecological feedbacks, change as inherent element of social-ecological systems, and the capacity of such systems to adapt (Biggs et al., 2015). Quantification of resilience has so far not been a major issue, which might be one of the reasons why putting resilience into practice is still difficult.

In contrast, in ecology ‘resilience’ originally referred to the recovery of certain state variables to pre-disturbance levels (Pimm, 1984). More recently, ecologists use ‘resilience’ as a multidimensional umbrella for the specific stability properties, or dimensions, recovery and resistance (Oliver et al., 2015; Standish et al. 2014), which are quantifiable (Table 5.1). Indeed, a few experimental studies quantified resilience by measuring its multiple dimensions (Donohue et al., 2016; Hillebrand et al., 2018). Biodiversity research, in particular, is focusing on the (in)variability of state variables as a proxy for ‘stability’ (Wang and Loreau, 2016) because a system showing lower variation usually has higher chances that state variables remain within the ranges required for the persistence of a system. In this interpretation, resilience, defined as the ability to function and persist despite disturbances and change, is the consequence of recovery and resistance, which in turn may be determined by mechanisms such as adaptive capacity or learning, which are also discussed in social-ecological research. In addition to the multidimensionality of resilience, assessments of its properties also depend on the levels of organization, state variables, reference states, types of disturbance and scales considered (Biggs et al., 2012; Carpenter et al., 2001; Grimm and Wissel, 1997). Consequently, in ecology a reductionist interpretation of resilience prevails as resilience research often ends up in more or less unrelated assessments of specific properties in specific ecological situations (Grimm and Wissel, 1997).

To move on in resilience research, the holistic and reductionist interpretation of resilience need to be reconciled. Although the old management slogan 'If you can't measure it, you can't manage it' might represent a too narrow 'command-and-control' notion of management, we argue that some quantification of resilience is needed to assess the state of a system in response to changes or actions, and to uncover the major resilience mechanisms. Therefore, we would ideally perform controlled experiments within entire systems and simultaneously measure recovery, resistance, and persistence, as well as (in)variability. To learn about the mechanisms underlying resilience, we would implement possible mechanisms, such as those listed by Biggs et al. (2012, 2015) or Desjardins et al., (2015), and measure the different dimensions of resilience for different levels of organization, state variables, reference states, types of disturbances, and spatial and temporal scales (Grimm and Wissel, 1997). However, except for artificial systems in ecology such as micro- and mesocosms or extremely simplified settings such as in behavioral economics, this is hardly possible.

Consequently, modeling plays an important role for understanding agent-based complex systems as it complements empirical research. Ecology in particular has a long tradition in modeling because ecological systems are complex, large, and often develop too slowly to be understood via short-term studies. Modeling also plays an increasing role in social sciences (Edmonds and Meyer, 2017; Epstein, 2006; Gilbert and Troitzsch, 2005; Tesfatsion, 2006). If a model captures multiple patterns describing the system in reality, it can be used to systematically explore resilience mechanisms. Model predictions then can be tested in targeted surveys or experiments, so that models informed by observations, and observations motivated by model predictions, are truly integrated. Accordingly, modeling could facilitate the consideration of the multidimensionality of resilience and thereby foster the integration of the holistic and reductionist approaches to resilience.

Agent-based models (ABM) play a particularly important, but certainly not exclusive, role in this context because decision-making agents, for example humans, individuals of other species, or institutions, are the building blocks of agent-based complex systems such as ecological systems, land-use systems, cities, or financial markets. ABMs have been widely used to understand observed system-level patterns mechanistically because these patterns emerge from individual variation, local individual interactions and adaptive behavior (An, 2012; DeAngelis and Grimm, 2014; Matthews and Gilbert, 2007). In social-ecological systems (SES), which are characterized by feedbacks between ecological and social processes (Biggs et al., 2015; Ostrom, 2009; Parker et al., 2008), ABMs are often used to better understand resource use and its consequences for humans and ecosystems (e.g. Rammer and Seidl, 2015; Schlüter et al., 2009; Walker and Janssen, 2002).

ABMs have a great potential but their development, testing and analysis is challenging, and the corresponding methods and strategies are complex. The corresponding methodology developed slowly but also significantly over the last two decades (Grimm et al., 2010, 2005; Grimm and Berger, 2016a; Heppenstall et al., 2012; O'Sullivan and Perry, 2013; Robinson et al., 2007; Tesfatsion, 2006), but the common practice of model analysis in terms of sensitivity, uncertainty, understanding of emergence, and robustness is still quite limited (Schulze et al., 2017).

Facing the high relevance of resilience research and the potential of ABMs to advance this field by integrating holistic and reductionist approaches to resilience, an overview on how resilience, and in particular its multidimensionality is operationalized in ABMs is needed. Therefore, we aimed to summarize the state of the art, identify possible knowledge gaps, and suggest ways forward for a more effective use of ABMs for resilience research. We first provide relevant definitions and concepts and then conduct a review of ABMs assessing resilience. Based on this we formulate general recommendations that might help developing and analyzing ABMs in a way that delivers more comprehensive insights into resilience.

Table 5.1 Definitions, assessment, implications and examples of the stability properties related to resilience.

Stability property	**Definition/assessment**	**Implications**	**Example**
Recovery	Process of a state variable returning to the values prior to a disturbance. / Time needed until the state variable reaches pre-disturbance levels (dashed arrow Figure 5.1).	Measuring recovery for different variables may lead to different conclusions.	Abundance after disturbance through a pesticide might recover quickly, but age and size structure might take much longer to return to pre-disturbance levels (Galic et al., 2017; Martin et al., 2014).
Resistance	The change of a state variable after a disturbance ('amplitude', solid arrow Figure 5.1).	Just referring to the amplitude is merely descriptive.	
	Comparison of amplitude with and without mechanisms that are assumed to affect resistance.	Better understanding why resistance emerges.	Productivity of a low diversity system might be more affected by species loss (Figure 5.1 B) compared to a diverse system (Figure 5.1 A).
	Buffer mechanisms: Require observing the variable of interest and a variable that measures buffer capacity.	If a buffer works, the variable of interest is hardly affected by a disturbance, but the buffering capacity is reduced. One disturbance might be buffered well but reduces buffer capacity for another disturbance.	Size structure of *Daphnia magna* populations buffered against pesticides that mainly affected small individuals and against predators focusing on larger ones. Combination of both disturbances leads to

Stability property	Definition/assessment	Implications	Example
			extinction (Gergs et al., 2013).
Persistence	Existence of a system through time as an identifiable unit, described by specific state variables remaining within a certain range (shaded area Figure 5.1).	Cannot only be directly assessed if a system definition exists and functional and/or if structural criteria for quantifying when a system has lost its identity are available (Jax et al., 1998).	Savannas are characterized by both a tree cover of not more than 20% and a scattered distribution of trees (Calabrese et al., 2010).
Variability / invariability	Change of a state variable over time (Arnoldi et al., 2016). Often used as a proxy for persistence because it is assumed that a system showing lower variation has higher chances that state variables remain within the ranges required for the persistence of a system.	Continuous variation might increase resilience as it supports reconfiguration in response to disturbance (Holling and Gunderson, 2002).	

5.3 The multiple dimensions of resilience

In ecology, the multidimensionality of resilience or stability has been acknowledged for a long time (Grimm and Wissel, 1997; Pimm, 1984), although the term 'multidimensionality' has become more popular only recently (e.g. Donohue et al., 2016). Recent reviews on resilience in ecology agree that resilience per se is not quantifiable, but only its different dimensions, or components: recovery, resistance, and variability (Oliver et al., 2015; Standish et al., 2014; Figure 5.1; Table 5.1). More generally, also the persistence of systems can, at least in microcosms or models, be quantified in terms of population persistence (e.g. Drake and Lodge, 2004), or characteristic patterns in organization or spatial structure (Cumming and Collier,

2005; Jax et al., 1998). Since these different stability properties are not always correlated (Dey and Joshi, 2013; Tung et al., 2016), just looking at one of them only gives limited insights into the emergence of resilience.
A second level of multidimensionality that is also increasingly acknowledged lies in the fact that recovery, resistance, persistence and variability can only be applied to specific situations, which are defined by the considered level of organization, state variable, reference state, disturbance, and spatial and temporal scale (Grimm and Wissel, 1997; they originally referred to 'ecological situation', but here we use the more generic term 'specific situation'). The assessment of the stability properties does not only depend on the system of interest itself and its mechanisms, but also on how we observe it. Different state variables and levels of organization (e.g. individual agents vs. communities) may react differently to disturbances (Figure 5.1 A, B vs. E, F). Likewise, the way we define the reference state determines how close a variable returns to its 'normal' state after a disturbance. For example, comparing the state variable against a dynamic reference (temporal development of the state variable without disturbance) may indicate slower recovery and larger amplitude (Figure 5.1 C, D) than when compared to a static reference (Figure 5.1 A, B). Virtually all stability properties, in particular variability and persistence, will depend on the spatial and temporal scales considered (Cumming et al., 2016). For example, in metapopulations the local existence of populations does not inform about regional persistence (Hanski and Gilpin, 1991). Disturbances of populations by toxicants or predators may affect different size classes so that consequences for resilience are not captured by only considering total abundance (Gergs et al., 2013). In mesocosm experiments addressing the response of aquatic invertebrate communities to a pulse exposure of an insecticide, species composition changed strongly while two ecosystem functions (primary production and respiration) hardly changed (Radchuk et al., 2016). In all these cases a multidimensional view, considering several state variables, levels of organization or disturbance type, provided insight into the internal organization of the system and, hence, its resilience mechanisms.

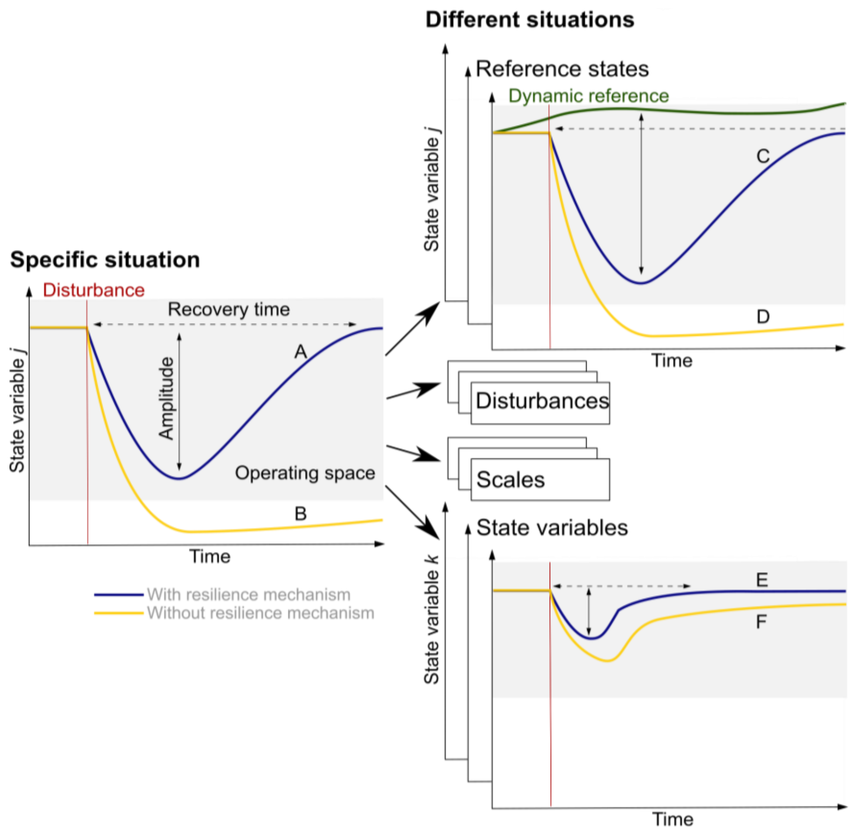

Figure 5.1 Schematic illustration of the three stability properties recovery, resistance, and persistence assessed across the different dimensions of specific situations. A multidimensional view is needed to learn more about the mechanisms underlying resilience, i.e. the stability properties need to be assessed for different state variables, levels of organization, disturbances, and spatial and temporal scales. Curves show the response of a state variable to a disturbance (red line) in a system with (purple) and without (orange) a resilience mechanism. The dashed arrow indicates recovery time, the solid arrow the amplitude, which might indicate resistance. The operating space (shaded area) defines a desired range, within which a state variable should remain that a system persists. The green curve indicates a dynamic reference, i.e. the temporal development of the state variable without disturbance. The different dynamics A-E are referred to in the main text.

5.4 Literature review

5.4.1 Methods

We conducted a Web of Science Topic Search (TS) using the search term TS = (‘individual* based* model*’ OR ‘agent* based* model*’) AND resilience*. Our search yielded 118 articles (3 July 2017). We excluded 29 paper because no ABM or results were presented or because the ABM was not used to study resilience. Since we were only interested in model applications to ecological and social-ecological systems, we excluded articles investigating systems related to economy (*n*=10), technology and human safety (*n*=10), sociology (*n*=3), medicine (*n*=2) or other systems (*n*=3). We additionally included four articles that were reviewed in Parrott et al. (2012) and An et al. (2014), but did not appear in our topic search. We evaluated the retained 65 articles with respect to the modeled system, their operationalization of multidimensionality of resilience and the representation of resilience mechanisms. Methodological details and the definitions underlying our evaluation, and detailed results can be found in Appendix 7.3.

5.4.2 Results

5.4.2.1 Stability properties

The reviewed models, mainly investigating social-ecological systems (Figure 5.2a), usually studied specific stability properties in isolation. Only 15 studies included one (*n*=13) or two (*n*=2) stability properties in addition to variability (Figure 5.2b). Of all reviewed articles, 94% measured the variability of one (*n*=18) or more state variables (*n*=43), while the other three stability properties where typically quantified with only one state variable. Recovery was measured in eight studies and persistence in nine studies, while resistance was hardly quantified (*n*=4).

5.4.2.2 Specific situations

Of the 65 studies, 46 addressed multiple dimensions of specific situations. Out of these, 38 studies used different state variables corresponding to different levels of organization (Figure 5.2c). Around half of the studies defined static (n = 9, e.g. value of a state variable prior to a disturbance; Figure 5.1 A, B) or dynamic reference states (n = 27, e.g. baseline scenario; Figure 5.1 C, D), of which two included more than one reference state. While the majority of the reviewed studies explicitly modeled disturbances (Figure 5.2d), only ten studies included more than one disturbance. Press disturbances, altering the system permanently, were investigated in 13 studies.

Most studies included a pulse disturbance which either occurred once (n = 10) or multiple times (n = 24). Of all reviewed articles, ten assessed resilience at more than one spatial scale and 13 focused on more than one temporal scale.

5.4.2.3 Resilience mechanisms

While the assessment of stability properties could be related to resilience mechanisms in 56 articles, they were explicitly communicated in only 40 articles. About one quarter of the studies investigated potential resilience mechanisms directly, e.g. by contrasting system behavior with and without a proposed mechanism.

5.4.3 Discussion

Our literature review shows that most existing models focus on a single dimension of resilience; i.e. they use variability as a proxy for persistence or resilience, and are limited to one reference state, disturbance type and scale. Less than one fourth of the reviewed studies varied more than two dimensions of specific situations, and only 15 studies assessed multiple stability properties. Moreover, relatively few studies explicitly test the ability of different resilience mechanisms to support resilience. Accordingly, the potential of ABMs for rigorous manipulation of relevant interactions and feedbacks across the dimensions of specific situations, and the subsequent assessment of different stability properties to identify resilience mechanisms has been exploited to a limited degree. This confirms previous findings, e.g. regarding the lack of incorporation of alternative theories of human decision-making (Groeneveld et al., 2017) or the limited analysis of ABMs developed for social-ecological systems (Schulze et al., 2017).

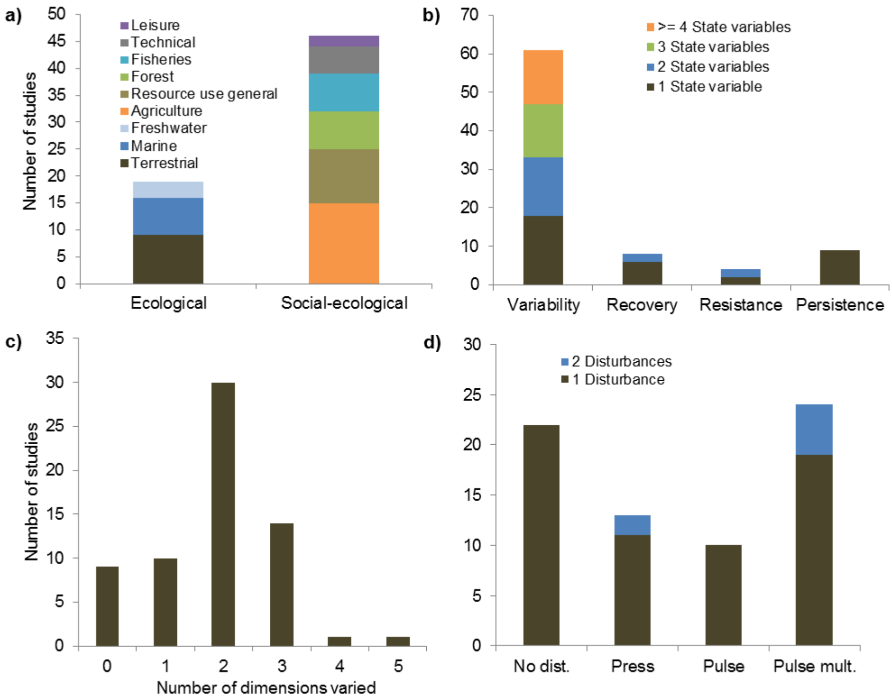

Figure 5.2 (a) Overview of the systems investigated in the 65 reviewed articles. (b) The number of studies measuring the stability properties variability, recovery, resistance and persistence. (c) The number of dimensions of specific situations varied in each study. (d) The number of studies investigating no disturbance, press, pulse or multiple pulse disturbances.

5.5 Discussion and recommendations

Using the concept of resilience to guide the sustainable management of complex ecological and social-ecological systems is attractive and has been called for by international organizations. However, there are two main challenges. First, resilience is a multidimensional concept necessitating the measurement of several stability properties for different state variables, reference states, disturbance types and spatial-temporal scales (Carpenter et al., 2001; Grimm and Wissel, 1997). Second, measurements of several stability properties is prohibitively costly in empirical and experimental conditions. In this context, ABMs provide a solution by allowing for an extensive exploration of the multidimensionality underlying resilience at relatively low costs.

Despite the suitability of ABMs to study resilience, agent-based modeling is not a panacea to resilience research and has to overcome several challenges. ABMs have been criticized for their high complexity and uncertainty, and the consequent lack of predictive power, validation and verification (Bankes, 2002; Grimm and Railsback, 2005; Lempert, 2002; Matthews and Gilbert, 2007; Parker et al., 2003). ABMs and models in general cannot capture the full complexity of real agent-based systems. Therefore, reality checks with targeted empirical research and observations, narratives of events and mechanisms that are not captured in data sets, and 'expert judgements' can be critical (Millington et al., 2012; Topping et al., 2015). Moreover, tools and approaches have been developed to increase rigor and comprehensiveness of agent-based modeling (Grimm et al., 2005), as well as to improve modeling practice to better inform decision-making (Grimm et al., 2014; Schmolke et al., 2010).

Our review demonstrates that ABMs studying most dimensions of resilience and specific situations have been developed, which provides insight into the resilience of the modeled systems as well as the mechanisms underlying it. However, our review also indicates that most of these dimensions have been studied in isolation. Therefore and based on the overall progress that has been made in agent-based modeling over the last 20 years, or so (An, 2012; Epstein, 2006; Farmer and Foley, 2009; Grimm and Berger, 2016a, 2016b; Matthews and Gilbert, 2007), we here make three recommendations to advance ABM as a tool for resilience research in ecology and socio-ecology (Table 5.2). These are heuristics rather than specific methods or techniques, but we nevertheless hope that they help broaden the scope of future studies.

First, we recommend quantifying two or more stability properties simultaneously. The fact that resilience cannot be addressed with a single metric needs to be better addressed in ABMs because the different stability properties are not necessarily correlated (Dey and Joshi, 2013; Hillebrand et al., 2018; Tung et al., 2016), and measuring only one stability property can mislead the management actions. For example, Naghibi and Lence (2012) found that the impact of high flow events due to river management on salmon population during the spawning period materialized much earlier regarding recovery than regarding resistance. Therefore, just looking at resistance would underestimate the long-term impacts of high flow events, e.g. as a result of opening a floodgate.

Regarding variability, instead of only looking at the change of a variable over time, the coefficient of variation can be better compared among studies as it is independent of the magnitude and allows for a closer integration of modeling and empirical research, where this metric is commonly used (Donohue et al., 2016). On a related note, we encourage modelers to address resistance in their resilience assessments, which is often measured in empirical and experimental studies, albeit mostly in laboratories and simplified, small systems. Only combined efforts and the use of identical stability properties by empiricists and modelers will truly advance our understanding of resilience and its application. Moreover, we suggest to not only look at the change of the state variable, but also at the behavior of the underlying buffer mechanisms, which has been hardly done in the reviewed studies. These buffers may typically respond slowly, but changes can lead to nonlinear changes or regime shifts once a certain threshold is exceeded (Biggs et al., 2012).

Regarding persistence, a system definition is required. For a population this is straightforward in principle because extinction clearly defines how long a population persisted. For real populations however, quasi-extinction may be more relevant (Holmes et al., 2007) because it is usually impossible to show that a population really went extinct, so that detection thresholds need to be defined. Also for communities and ecosystems, the definition of such thresholds is required. The arbitrariness of such thresholds can be reduced by their systematic variation, while looking for abrupt changes in characteristics, functions, or services of a system. For semi-arid savannas, for example, 20% tree cover is a generally accepted threshold because higher values indicate bush encroachment due to overgrazing, which will lead to the loss of the service 'rangeland' (Jeltsch et al., 1997).

Second, we propose to assess stability properties from different perspectives, i.e. under different specific situations. This is important for both an improved understanding of resilience, and the reconciliation of different management and policy objectives (Donohue et al., 2016). Our review revealed that most models only consider a few specific situations. Once a model of adequate complexity exists and has proven to be structurally realistic (Grimm and Railsback, 2012; Wiegand et al., 2003), many specific situations can be assessed, which will provide more comprehensive insights into resilience. For example, a static reference state may be appropriate for a pulse disturbance, but including a press disturbance requires a dynamic reference. Moreover, several state variables describing different levels of organization often respond differently to changes and may require different reference states. For example, Cordonnier et al. (2008) applied a management perspective to assess the protective ability of managed forests stands against avalanches and rock falls, by measuring how long several threat-specific state variables stayed within favorable reference states. They found that only relatively low thinning intensities protect against both threats, i.e. multiple dimensions needs to be observed to guide proper management. Similarly, only a systematic combination of various disturbances, potentially acting on different scales, allows to disentangle multiplicative, synergistic and antagonistic effects (Belarde and Railsback, 2016). Likewise, varying the spatial scale, in particular the size, of the modeled system is a simple but often rewarding exercise, which is often ignored. Exploring variability, recovery, or persistence for different system sizes can lead to surprises because certain mechanisms may unfold only at larger scales, or break down at smaller ones (Cumming et al., 2016).

Third, we advocate for starting model-based resilience analysis with hypotheses about underlying resilience mechanisms and how one could quantify their effects. Many resilience mechanisms have been proposed, but if, how and when they render a system resilient remains often unclear (Biggs et al., 2012; Desjardins et al., 2015), for instance, regarding the role of biodiversity for the resilience of complex systems (Cardinale et al., 2012). Since many of the assumed mechanisms, such as learning and adaption, are related to individual variation, interactions, decision-making and feedbacks, ABMs offer a promising tool to uncover them. To this end, we manipulate, or even deactivate a given mechanism, such as recolonization, social influence on land-use practices, or learning, and explore how the different dimensions of resilience change, across different situations. Ten Broeke et al. (2017), for example, found that adaption through inheritance of specific traits (harvesting and moving rates) could prevent the collapse of a stylized common-pool resource system.

A stronger focus on resilience mechanisms can, in principle, reconcile the reductionist and holistic interpretations of resilience to some degree: adaptive capacity, for example, would no longer only reflect a way of thinking or dealing with agent-based complex systems, but we could quantify the effects of adaptive capacity on resilience (measured by the three stability properties) and compare it with other possible resilience mechanisms.

Table 5.2 Main recommendations to advance agent-based modeling as a tool for resilience research in ecology and socio-ecology.

Aspect	Recommendations
Stability properties	• Quantify multiple stability properties simultaneously because they are not necessarily correlated • Consider to measure variability as coefficient of variation (ratio of standard deviation to mean) for better comparison among studies and closer integration of empirical research • Measure the behavior of the underlying buffer mechanisms as their changes can lead to nonlinear changes or regime shifts • Define systems to assess persistence, e.g. by systematically identify thresholds to measure quasi-extinction
Specific situations	• Assess stability properties for different situations to foster a more comprehensive understanding of resilience • Assess the stability properties for several state variables describing different levels of organizations to account for potentially different conclusions about resilience • Use a dynamic reference state for press disturbances to account for long-term changes • Systematically combine various disturbances with different strengths and acting on different scales to disentangle multiplicative, synergistic and antagonistic effects • Explore stability properties for different temporal and spatial scales because certain mechanisms may unfold only at larger scales, or break down at smaller ones
Resilience mechanisms	• Identify potential resilience mechanisms • Explicitly test and manipulate mechanisms to see if, how, and under what conditions they render a system resilient

5.6 Conclusion

In conclusion, we found that the reviewed studies typically focus on a single dimension of resilience by using variability as a proxy for persistence, and are limited to one reference state, disturbance type and scale. Moreover, only few studies explicitly test the ability of different mechanisms to support resilience. Therefore, we suggest that it is time to move on from focusing on a single attribute of resilience to reveal the multidimensionality of resilience, especially given that ABMs provide a unique opportunity for doing so backed up by increasing computational power. In particular, we propose using ABMs to systematically assess multiple stability properties for different situations, while explicitly testing the effect of potential resilience mechanisms. The recommendations presented here will hopefully promote a more systematic and comprehensive exploration of the multiple dimensions of resilience in ABMs. Such advancement will foster the understanding of the mechanisms determining resilience, which is fundamental to safeguard ecosystem services and to ultimately ensure sustainability.

Acknowledgements

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6 Discussion and outlook

6.1 Main results

The first major aim of this thesis was to analyze the stability of agricultural production across various levels of organization and scales and its relationship to crop diversity, spatial heterogeneity and asynchrony between and within crops (Table 6.1). Stability has multiple dimensions and hence proxies, but for theses analyses I focused on temporal stability, i.e. the temporal invariability of yields and total production. The related analyses were based on extensive agricultural datasets, climate data and statistical analyses. Acknowledging that data analysis only examines correlative relationships of current or past situations, the second aim was to review the state of the art and potential knowledge gaps in exploring resilience and its multidimensionality in ecological and social-ecological systems with agent-based models (ABM) and to derive recommendations for a more effective use of ABMs in resilience research.

Scale is an important dimension when assessing the stability of agricultural production. First, stability differs across scales. The second chapter shows that national-level stability is more than 80% higher compared to regional and farm level stability. Moreover, stability over all nations, regions or farms was typically higher than individual stability. Second, the importance of different stability mechanism varies with scales. For example, the absolute effect of one unit increase in crop diversity was higher at the farm and regional level than at the national level and the effect of diversity was strongest in small farms. Furthermore, at the national level, spatial heterogeneity of precipitation reached the highest effect size, indicating that this mechanism is particularly important at larger scales. Third, scale also has implications for the management of stability mechanisms. Chapter 4 suggests that combining multiple farms or regions strongly increases asynchrony within crops. This effect could be even stronger if cultivated areas beyond national boundaries would be included as their climate is more independent, thus contributing to stability on a larger scale (Mehrabi and Ramankutty, 2019). Trade might be another relevant stability mechanism as it increases the spatial production base and decreases the vulnerability to local disturbances (Marchand et al., 2016). Therefore, the importance of scale merits further attention in recent discourses on the resilience of globalized vs. regionalized food systems (Garnett et al., 2020; Hendrickson, 2015; Marchand et al., 2016; Opitz et al., 2016). While my results confirm the widely believed stabilizing effect of considering larger spatial scales, quantitative assessments were rare, and I could show that stability mechanisms are also scale-dependent. In contrast to scale, effects of diversity and heterogeneity on stability are harder to predict intuitively.

This thesis suggests that crop diversity is a key mechanism to increase yield stability across different levels of organization. At the farm level, it even had the largest positive effects of all explanatory variables considered. At the national and farm level, there is evidence that the positive effect of crop diversity on yield stability was higher in variable climates, supporting resilience theory (Biggs et al., 2012; Yachi and Loreau, 1999). Moreover, at the national level this effect was highest when irrigation was low, highlighting its relevance in the absence of technological means to address yield stability. However, this effect was inverse at the regional and farm level, suggesting that combined efforts are needed to increase yield stability. Chapter 3 shows that crop diversity as such provides only limited insights into the mechanisms underlying stability and that asynchrony is one important crop property that can explain why a higher diversity supports stability of national food production. This finding is confirmed in Chapter 4 that shows that crop diversity increases asynchrony between crops, but only to a certain degree. Therefore, strategies to stabilize agricultural production through crop diversification also need to account for the asynchrony of the crops considered and with respect to different environmental und socio-economic processes (Cottrell et al., 2019; Lesk et al., 2016; Suweis et al., 2015).

Chapter 2 indicates that spatial heterogeneity is an important stability mechanism, in particular at larger scales. More specifically, it shows that precipitation heterogeneity was positively associated with yield stability, most likely because it leads to asynchronous or contrasting production patters within crops (Mehrabi and Ramankutty, 2019; Suweis et al., 2015). This hypothesis is confirmed in Chapter 4, i.e. asynchrony within crops had a strong positive effect on stability at the regional and national level. The stronger effect of asynchrony within crops compared to asynchrony between crops at the regional level is related to the fact that already few farms within a region can achieve a high spatial asynchrony within crops. This finding also needs to be acknowledged in agricultural management. While crop diversification typically increases asynchrony between crops, asynchrony within crops needs to be addressed by altering landscape configuration, e.g. by increasing the spatial fragmentation of crop distribution (Lin, 2011). Besides their potential stabilizing effects, related measures could also benefit overall productivity, biodiversity and ecosystem services more generally (Kremen and Merenlender, 2018; Li et al., 2020; Seppelt et al., 2020, 2016)

Besides the stability mechanisms related to diversity and redundancy, agricultural inputs were mostly positively associated with yield stability. Fertilizer, for example, had the strongest positive association at the regional level, suggesting that agricultural inputs are not only relevant to close yields gaps (Mueller et al., 2012), but also to increase their stability (Knapp and van der Heijden, 2018; Renard and Tilman, 2019). However, this dependency on agricultural inputs has serious implications for biodiversity and ultimately human well-being (Beckmann et al., 2019; Loos et al., 2014; Tscharntke et al., 2012; West et al., 2014), and associated specialization may also increase climatic sensitivity of agriculture (Ortiz-Bobea et al., 2018). Furthermore, the resources needed are limited and both nitrogen fertilizer and irrigation already reached a peak-year (Seppelt et al., 2014). Accordingly, more integrated approaches to tackle the multiple challenges agricultural landscapes face today such as crop diversification, renewable inputs and other agroecological principles are needed (Gurr et al., 2016; Kremen and Merenlender, 2018).

I found that climate instability substantially decreased yield and production stability, in particular at the national level (Chapters 2 and 3). Thus, expected increases in climate instability in the light of climate change may not only lead to yield losses but also to lower temporal stability of yields (Challinor et al., 2014; Liang et al., 2017). In the European and German context, climate seems to play a minor role, i.e. effect sizes were comparable or even lower than the effect sizes of crop diversity and agricultural inputs. European agriculture benefits from a comparably stable climate and is largely intensified (Václavík et al., 2013). Accordingly, until now climate instability can be buffered by agricultural management. However, this might change in the future, thus strategies to lower the vulnerability to climate variation and shocks are crucial for the stability of agricultural production and food security (Lesk et al., 2016). Chapter 4 suggest that planting additional crops that react differently to climatic disturbances and potentially increasing the spatial heterogeneity of crop distribution is a promising avenue in this context.

Agricultural production and associated stability can be measured differently. For Chapter 2, I used average yields per hectare, while in Chapters 3 and 4, I focused on total production. Yield is a more standardized metric as it is independent of areal changes. Besides yields, total production and its stability is also a relevant aspect of food security. Moreover, the link between production-based crop asynchrony and total production stability is clearer than the relationship of yield-based crop asynchrony and overall yield stability. This is because less abundant crops have an equal weight if asynchrony between crops is based on yields, but their actual contribution to stability is limited.

Chapter 5 argues to assess different stability properties, situations and mechanisms. While the previous chapters covered different spatial scales, variables and mechanisms, I only focused on the temporal stability of agricultural yields and production. However, assessing other stability properties in agricultural datasets is challenging because clear definitions of reference states are difficult. Nevertheless, statistical tools have been used to measure other facets of stability, for example, to detect food production shocks based on outliers (Cottrell et al., 2019). Generally however, statistical approaches only offer limited insights to causalities and mechanisms.

Besides their capacity to provide a mechanistic understanding of certain processes, agent-based models can incorporate different stability properties and situations through extensive manipulation in a fully controlled system. However, Chapter 5 points out that the potential of ABMs is not utilized in most models as they typically focus on a single dimension of resilience and are mostly limited to one reference state, disturbance type and scale. Moreover, only few studies explicitly test the ability of different mechanisms to support resilience. To advance ABM as a tool for resilience research in ecology and socio-ecology, two or more stability properties should be quantified simultaneously because different stability properties are not necessarily correlated (Dey and Joshi, 2013; Hillebrand et al., 2018; Tung et al., 2016), and measuring only one stability property can mislead management actions. Furthermore, stability properties should be assessed from different perspectives, i.e. under different specific situations. This is important for both an improved understanding of resilience, and the reconciliation of different management and policy objectives (Donohue et al., 2016). Finally, model-based resilience analyses should start with hypotheses about underlying resilience mechanism and how one could quantify their effects. Many resilience mechanisms have been proposed, but if, how and when they render a system resilient remains often unclear (Biggs et al., 2012; Desjardins et al., 2015).

Table 6.1 Synthesis of the investigated effects related to diversity on the stability of agricultural production and related chapters in this thesis (brackets indicate that the effect was not significant). Note that at the farm level, spatial heterogeneity was approximated with the total area harvested.

	National	Regional	Farm	Chapter(s)
Crop diversity	+	+	+	2, 3
Spatial heterogeneity	+	+	+	2
Asynchrony between crops	+	+		3, 4
Asynchrony within crops	(+)	+		4

6.2 Limitations

The statistical analyses in Chapters 2 to 4 face four major limitations. First, data quality at all levels of organization is limited. Besides qualitative and methodological differences in the agricultural databases (Dunmore and Karlsson, 2008), several datasets had to be rescaled due to different spatial resolutions and many units were excluded due to data gaps, which could affect my conclusions (Verburg et al., 2011). Nevertheless, the consistency of certain patterns across different levels of organization and the alignment with previous findings and theory increases their reliability.

The second limitation is related to data availability. In particular, consistent datasets at the subnational level covering a large spatial and temporal extent and including an adequate number of crops are missing. Therefore, the analyses across different levels of organization covered different extents (world, Europe and Germany), while fixed system boundaries would be important to allow a more systematic and rigorous comparisons. Recent efforts to compile gridded harvested area and production data globally and for multiple decades could support a more systematic

assessment of the relationships investigated, for example at different grain sizes, once they are available for additional crops (Meyer et al., 2015; Ray et al., 2012).
Third, the explanatory power of several statistical models applied here was limited. For example, the farm level model in Chapter 2 achieved a marginal R2 of only 0.1. This indicates that important drivers of stability are missing, potentially related to pesticide use, capital stock, market access and land-use history, for which temporal and spatial data coverage is yet limited. Moreover, other disturbances besides climatic variability are important in the agricultural context, for example in relation to political changes and mismanagement (Cottrell et al., 2019; Suweis et al., 2015).
The fourth limitation relates to the fact that linear models are mainly suited to assess associations between variables but not to identify causal relationships. Besides other statistical approaches better addressing causal inference (Pearl, 2009), agent-based models can provide a mechanistic understanding of the actual processes underlying resilience. As discussed above, they can also better deal with the multidimensionality of resilience.
Despite the suitability of ABMs to study resilience, agent-based modeling is not a panacea to resilience research and has to overcome several challenges. ABMs have been criticized for their high complexity and uncertainty, and the consequent lack of predictive power, validation and verification (Bankes, 2002; Grimm and Railsback, 2005; Lempert, 2002; Matthews and Gilbert, 2007; Parker et al., 2003).

6.3 Perspectives

In this thesis, I investigated the effect of crop diversity, spatial climate heterogeneity, and asynchrony between and within crops at different scales using a large and comprehensive database. In contrast to earlier studies, it more systematically confirms the importance of crop diversity and spatial heterogeneity to stabilize agricultural production. Moreover, agent-based models have been identified as a promising tool to address the multidimensionality of resilience. However, uncovering a wide range of additional mechanisms working at different levels of organization, scales and time horizons will be needed to identify comprehensive pathways towards productive and resilient farming systems (Battisti and Naylor, 2009; Lesk et al., 2016; Valin et al., 2014; Weise et al., 2020). Moreover, besides stability, adequate production and productivity are fundamental to food security.

Therefore, factors affecting both stability and productivity and potential trade-offs need to be simultaneously studied in future (Bailey et al., 2015; Brown et al., 2016).
As diversity is central to resilience, the processes driving agricultural specialization, for example economic globalization, and their consequences need to be mechanistically investigated (Lambin and Meyfroidt, 2011; Magliocca et al., 2013). Besides the diversity of different crops, future assessments could include different crop varieties and functional traits as they most likely play a fundamental role for resilience (Ficiciyan et al., 2018).
Further studies could incorporate other aspects of asynchrony and its underlying drivers, for example related to growing crops in multiple seasons, different farm and disturbance types (Cottrell et al., 2019; Loreau and De Mazancourt, 2008; Reidsma et al., 2010; Chapter 3). While there is increasing knowledge about the underlying drivers of overall production losses (Cottrell et al., 2019), little is known about the effects on individual crops in various environmental and socio-economic contexts, in particular regarding their temporal variance at farm level, where management decisions are made (Knapp and van der Heijden, 2018; Mehrabi and Ramankutty, 2019).
Additional resilience mechanisms, for example related to function, adaption and structure and also with respect to the multiple actors engaged in agricultural production should be incorporated in future studies (Biggs et al., 2012; Weise et al., 2020). Moreover, different stability properties should be considered, e.g. regarding the recovery of different agricultural systems after shocks. Furthermore, practical and innovative approaches to achieve resilience of food systems across the entire supply chain and their upscaling potential needs to be investigated (Hendrickson, 2015; Nature Food, 2020). For example, regionalized food distribution networks that increase redundancy, diversity and adaptive capacity, as well as food democracy and sovereignty, e.g. through direct links of consumers and producers, and agroecological approaches could be promising alternatives to the concentrated and consolidated global food system and to simultaneously achieve resilience, productivity and environmental sustainability (Bailey et al., 2015; Garnett et al., 2020; Hendrickson, 2015; Kremen and Merenlender, 2018; Nature Food, 2020; Opitz et al., 2016; Schipanski et al., 2016).
While agent-based models are a promising tool for resilience research, future ABMs need to assess multiple stability properties for different situations and under

consideration of the mechanisms that are hypothesized to render a system resilient. Moreover, reality checks with targeted empirical research and observations, narratives of events and mechanisms that are not captured in data sets, and 'expert judgements' can be critical (Millington et al., 2012; Topping et al., 2015). Tools and approaches that have been developed to increase rigor and comprehensiveness of agent-based modeling, as well as to improve modeling practice to better inform decision-making need to be further operationalized (Grimm et al., 2014, 2005; Schmolke et al., 2010).

In the following, two directions of future research are illustrated. First, I show how a simulation approach could help to identify management strategies that account for asynchrony between and within crops. Second, I showcase the use of agent-based models to find transformative pathways towards resilient farming systems.

6.3.1 Managing asynchrony

In Chapter 4, both asynchrony between and within crops have been identified as important mechanisms to stabilize agricultural production. In a next step, management approaches to increase asynchrony between and within crops simultaneously need to be investigated and potential trade-offs need to be identified. While crop diversification typically increases asynchrony between crops, asynchrony within crops needs to be addressed by altering landscape configuration, e.g. by increasing the spatial fragmentation of crop distribution (Lin, 2011).

To illustrate the potential effect of crop diversification and distribution here, I developed a model that simulates a stylized landscape. I initialized the landscape with varying size (5x5, 9x9 and 33x33 pixels) and number of crops (1 to 14), which I allocated with equal area shares according to one of three management strategies. In the specialized landscape the crops were cultivated in coherent larger patches, while in the fragmented landscape, the crops were distributed randomly, yet still only one crop was cultivated per pixel. In the diversified landscape, all crops were cultivated in each pixel. I kept the crop distribution for each run (10 years) constant while I changed annual temperature and precipitation stochastically. Based on the actual crop distribution and climate, I calculated crop-specific annual suitability values using crop-specific climate response functions to approximate production (Zabel et al., 2014). Based on this, I calculated asynchrony between and within crops and averaged the values over ten repetitions for each configuration. Methodological details are described in Appendix 7.4.1.

Independent of landscape size and management, crop diversity consistently increased asynchrony between crops, although the effect stagnated or even decreased when exceeding ten crops (Figure 6.1). This finding is similar to the observations in Chapters 3 and 4, i.e. that crop diversity supports asynchrony between crops only up to a certain degree due to redundancy regarding the response to climate. In contrast, increasing crop diversity negatively affected asynchrony within crops unless management was diversified or fragmented in large landscapes. The major reason for this is that multiple crops that are only grown in monoculture in a limited area can hardly buffer local climatic shocks. These findings indicate that only a combination of crop and landscape diversification avoids trade-offs between the two stabilizing mechanisms. Therefore, approaches and frameworks to increase agricultural stability need to account for diversification from the field to the landscape scale (Lin, 2011; Wanger et al., 2020)

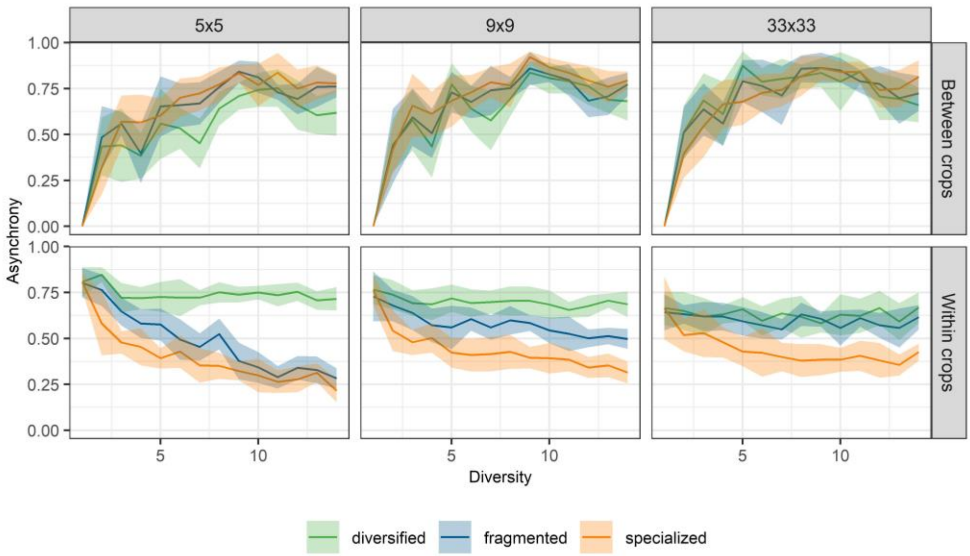

Figure 6.1 Simulated effect of increasing crop diversity in stylized landscapes of varying size and under different management strategies (diversified, fragmented, specialized) on asynchrony between and within crops. For each simulation, crop distribution was fixed, while temperature and precipitation were randomly updated each year based on a

predefined range and following a gradient. Lines show mean values over all ten repetitions and shades show standard deviations.

6.3.2 Agent-based models to identify transformative pathways towards resilient farming systems

Besides environmental factors, land-use decisions heavily depend on institutional settings, economic constraints and incentives, farmers' characteristics and attitudes (Bartkowski and Bartke, 2018; Magliocca and Ellis, 2016; van Vliet et al., 2015). For example, participation of European farmers in biodiversity policies is not only driven by economic interests but by also individual attitudes (Siebert et al., 2006). Given the importance of individual behavior, explicitly incorporating farmer characteristics is essential to better understand land-use system dynamics (Brown et al., 2014).

In a globalized world, local land use is increasingly driven by interactions between distant places (Liu et al., 2013; Meyfroidt et al., 2013). Free trade between regions, for example, is expected to lead to an optimal and efficient distribution of land use, thus maximizes overall production (Brown et al., 2014). However, this fundamentally alters local agricultural land-use patterns and spatially separates sites of production and consumption (Anderson, 2010; Cumming et al., 2014). As discussed in Chapter 2, trade can help to buffer local shocks, but can also reduce crop diversity, i.e. an important stability mechanism, through specialization on the crops with the best local conditions.

Factors fostering the stability of agricultural systems have been investigated in depth in this thesis, but the emergence of stable agricultural systems, in particular in the context of distant processes, is poorly understood. As outlined in Chapter 5, agent-based models (ABM) are a promising tool to systematically assess resilience and its multidimensionality, hence they can account for the complexity of local to global scale, and ecological and socio-economic interactions (Brown et al., 2014; Meyfroidt et al., 2013). Since ABMs attempt to model system-level behavior from individual characteristics, interactions and feedbacks, e.g. between human and nature, they are a promising tool in this context and have been widely used to study land-use change and transformations mechanistically (An, 2012; Brown et al., 2016, 2014; DeAngelis and Grimm, 2014; Magliocca et al., 2013; Magliocca and Ellis, 2016; Matthews and

Gilbert, 2007). As a follow-up of this thesis, ABMs could be used to identify pathways that foster diversification and thus the resilience of agricultural systems (Kremen and Merenlender, 2018).

To showcase the use of ABMs in this context, I here developed a simple stylized ABM to study the emergence of land use in response to local and distant drivers, including the potential to grow different crops, trade and farmers' focus on different crops and their ability to compete. The potential for each of the four crops is maximal in one of the four corners of the landscape and decreases linearly with distance from that corner. Farmers and farms are not modeled explicitly but implicitly by distinguishing five types of farmer utilizing the patch's crop-specific potentials: 'specializers' which, on a given patch, grow one of four possible crops (maize, wheat, rice and soybean) in monoculture, and 'diversifiers' which grow all four crops simultaneously. The farmer types compete for land, which is driven by farmer type-specific attributes and utility that depend on the actual production under current conditions and crop-specific demands. Climate is either stable or variable which directly affects the crop-specific potential based on response functions for the four crops (Zabel et al., 2014). Moreover, if trade is allowed, the potential to grow wheat, rice and soybean is reduced to represent that other (not explicitly modeled) regions have better opportunities to grow certain crops. A detailed model description following the ODD (Overview, Design concepts, Details) protocol for describing agent-based models is available in Appendix 7.4.2 (Grimm et al., 2010, 2006; Railsback and Grimm, 2019).

In the baseline settings, i.e. no climate variability and trade, the 'diversifier' is most abundant, especially in marginal regions, where the potential for the different crop is limited, while 'specializer' are only found were the potential of their target crop is high (Figure 6.2). If trade is allowed, the farmer type that specializes on maize dominates the landscape. Only in the regions, where the potential to grow maize is lower, the diversifier can persist. Climate variability increases the success of the diversifier as this type can better deal with disturbances that affect different crops differently.

While this model is only used for illustration, it already shows that relatively simple and stylized models can be used to simulate general land-use patterns. A similar yet more complex model has been used to investigate the outcome of different scenarios and behavioral variations and their accordance with land-use visions in Europe

(Brown et al., 2016). They also found that trade reduces small-scale diversity, but behavioral effects can counteract this process. Accordingly, such models can capture processes at different levels of organization and their interactions and potential trade-offs. Therefore, they can provide valuable insights on potential leverage points and policies for sustainability transformations (Abson et al., 2017; Bai et al., 2016).

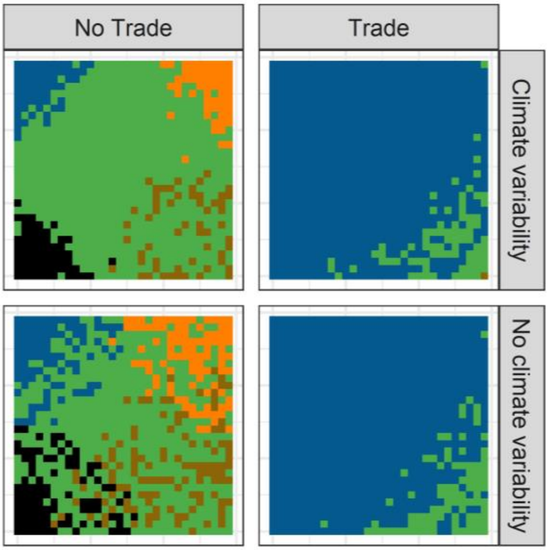

Figure 6.2 Land-use patterns emerging from different scenarios with or without climate variability and trade, respectively (blue = maize specializer, orange = wheat specializer, black = rice specializer, brown = soybean specializer, green = diversifier). The respective agent-based model is described in Appendix 7.4.2.

6.4 Conclusion

Nothing less than a fundamental transformation of agricultural systems is needed to achieve resilient, productive and sustainable landscapes that work for people and nature. This thesis contributes to the first of these goals. It demonstrates that crop diversity and in particular asynchronous temporal production patterns between crops increase the temporal stability of agricultural production across different levels of organization. Spatial heterogeneity and the asynchrony between the temporal production patterns of different cultivation areas of the same crop are also shown to be important stabilizing mechanisms. The simulation suggests that only increasing the number of crops at both the local and landscape scale avoids trade-offs between asynchrony between and within crops. My findings emphasize the need for integrated management approaches including diversification from the farm to the landscape scale and accounting for asynchrony and sustainable usage of agricultural inputs to foster resilient farming systems in the light of climate change, rising demands for agricultural products and the intensification and specialization of agricultural systems. If their potential is better exploited, agent-based models provide an opportunity to identify resilient farming systems and pathways to achieve them.

Future work could simultaneously assess aspects related to resilience, productivity and sustainability to identify potential synergies and trade-offs. Moreover, further studies could include other aspects of resilience, disturbances and agricultural diversity, as well as innovative agricultural approaches. Related research will help to address one of the great challenges humanity faces today, i.e. to fundamentally and urgently transform agricultural systems.

7 Appendices

7.1 Appendix of Chapter 2

Table A1 Determinants of yield stability at the national, regional and farm level. Regression coefficients are shown for fixed effects included in the linear mixed-effects models at the national (n = 602), regional (n = 355) and farm level (n = 6384). Yield stability and area harvested were log-transformed, irrigation and nitrogen use intensity were square-root-transformed. Each explanatory variable was standardized to zero mean and one standard deviation across all nations, regions or farms and time intervals.

	National level			Regional level			Farm level		
Variable	**Estimate (SE)**	**T**	**p-value**	**Estimate (SE)**	**T**	**p-value**	**Estimate (SE)**	**T**	**p-value**
(Intercept)	2.82 (0.04)	74.61	<0.001	2.36 (0.06)	36.85	<0.001	2.2 (0.04)	52.37	<0.001
Diversity	0.17 (0.04)	4.41	<0.001	0.15 (0.03)	4.43	<0.001	0.13 (0.01)	15.93	<0.001
sqrt(Fertilizer)	0.06 (0.04)	1.4	0.16	0.24 (0.06)	4.07	<0.001	0.04 (0.01)	5.42	<0.001
sqrt(Irigation)	0.05 (0.04)	1.06	0.29	-0.07 (0.06)	-1.07	0.29	0.04 (0.06)	0.76	0.45
Temperature heterogeneity	0.04 (0.05)	0.89	0.37	0.03 (0.03)	0.83	0.41	-	-	-
Precipitation heterogeneity	0.21 (0.04)	4.96	<0.001	0.11 (0.03)	3.35	0	-	-	-
log(Area harvested)	-	-	-	-	-	-	0.04 (0.01)	3.63	0
Temperature instability	-0.14 (0.03)	-4.19	<0.001	-0.03 (0.03)	-1.03	0.31	-0.03 (0.01)	-4.71	<0.001
Precipitation instability	-0.13 (0.03)	-4.41	<0.001	-0.01 (0.03)	-0.49	0.62	-	-	-
Time	0 (0.02)	0.1	0.92	-0.04 (0.03)	-1.25	0.21	-	-	-
Diversity:sqrt(Fertilizer)	0.01 (0.04)	0.39	0.7	-0.01 (0.04)	-0.22	0.82	0.01 (0.01)	1.46	0.14
Diversity:sqrt(Irigation)	-0.08 (0.04)	-2.07	0.04	0.09 (0.04)	2.37	0.02	0.03 (0.01)	4.37	<0.001
Diversity:Temperature heterogeneity	-0.02 (0.03)	-0.71	0.48	-0.04 (0.03)	-1.29	0.2	-	-	-
Diversity:Precipitation heterogeneity	-0.05 (0.04)	-1.4	0.16	0.03 (0.03)	1.09	0.28	-	-	-
Diversity:log(Area harvested)	-	-	-	-	-	-	-0.04 (0.01)	-6.49	<0.001
Diversity:Temperature instability	-0.02 (0.03)	-0.62	0.54	0.03 (0.03)	1.29	0.2	0.02 (0.01)	2.54	0.01
Diversity:Precipitation instability	0.04 (0.02)	1.85	0.07	-0.03 (0.02)	-1.16	0.25	-	-	-

	National level			Regional level			Farm level		
Variable	**Estimate (SE)**	**T**	**p-value**	**Estimate (SE)**	**T**	**p-value**	**Estimate (SE)**	**T**	**p-value**
Diversity:Time	0.01 (0.02)	0.28	0.78	-0.02 (0.03)	-0.66	0.51	-	-	-
R2 marginal	0.34	-	-	0.36	-	-	0.1	-	-
R2 conditional	0.58	-	-	0.62	-	-	0.48	-	-
AIC	1002.53	-	-	377.35	-	-	8674.43	-	-

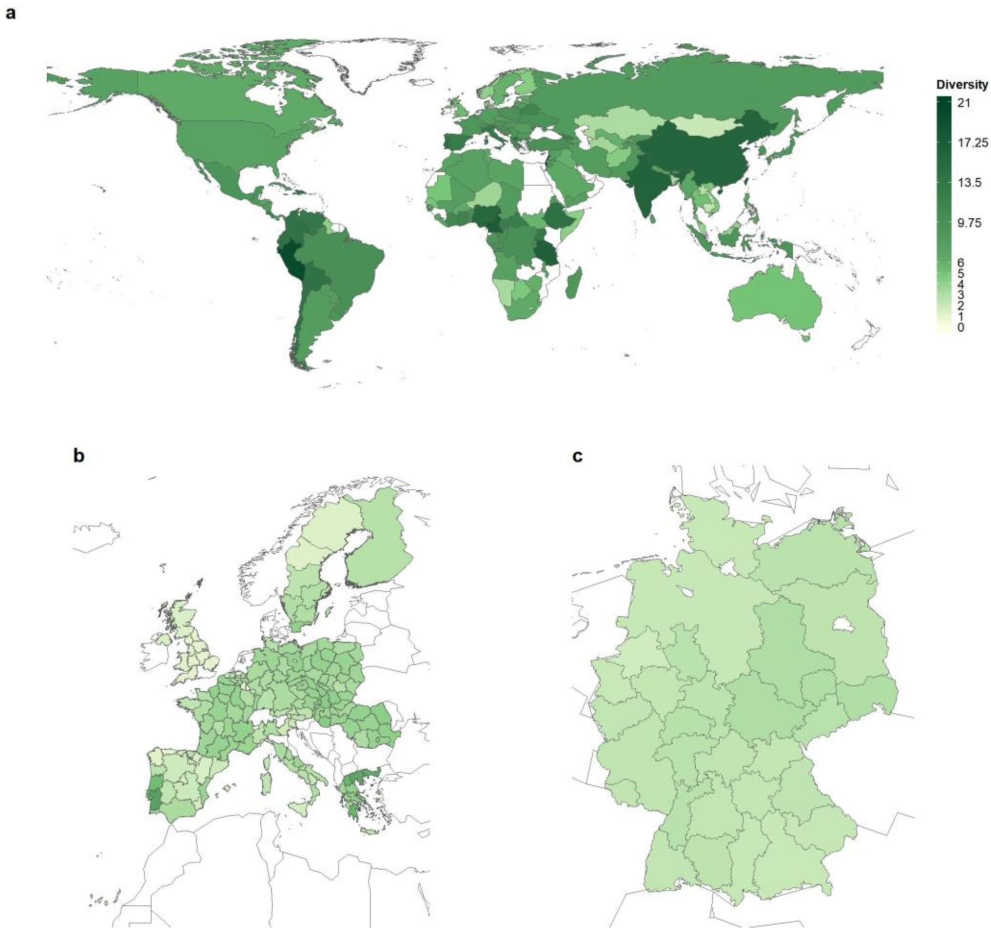

Figure A1 Effective crop diversity for nations (a), regions in the European Union (b) and farms in Germany (c). Effective crop diversity was calculated as the exponential of the Shannon diversity. Values are averaged over all time periods (n = 137 for the national, n = 165 for the regional and n = 5183 for the farm level). Farm values are aggregated to the district level (mean values of the underlying farms), assuming that they are representative for the respective district. Units excluded from the analyses are shown in white.

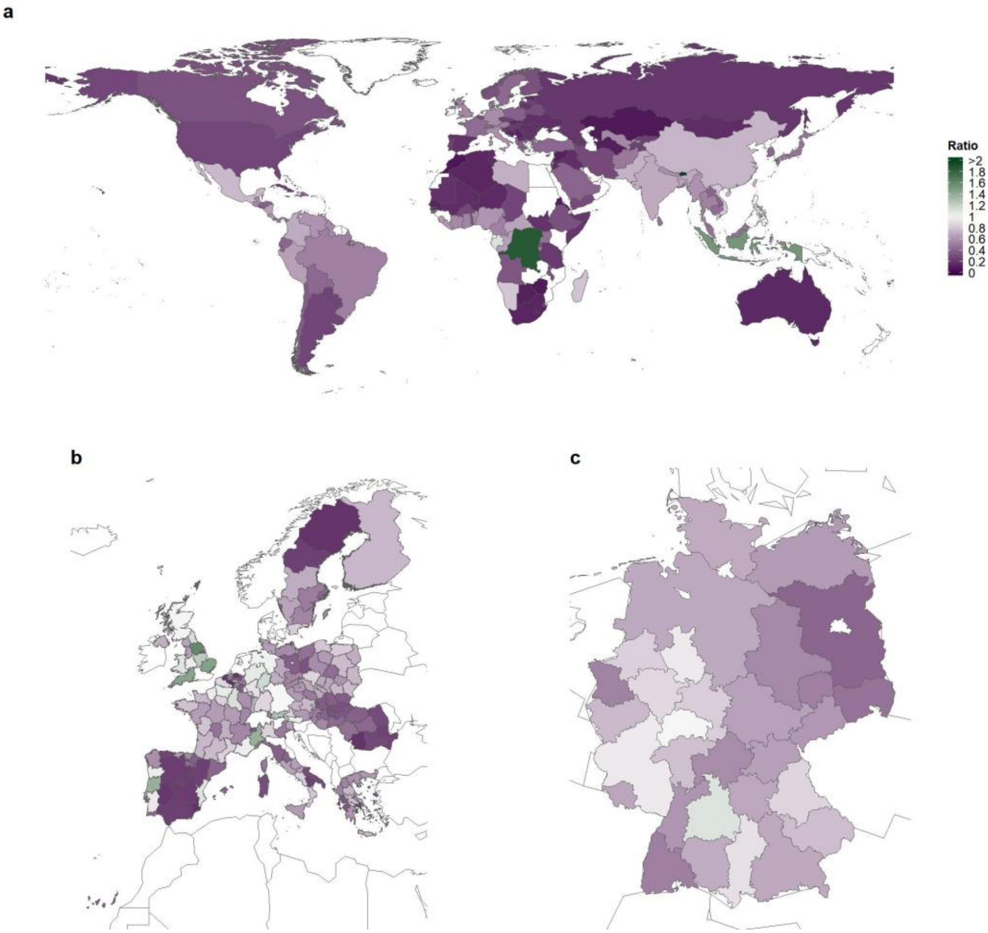

Figure A2 Relative yield stability for nations (a), regions in the European Union (b) and farms in Germany (c). Relative yield stability was calculated as the stability of each nation, region or farm divided by the respective larger-scale stability over all nations, regions or farms. Green colors show units that reached higher individual stability compared to larger-scale stability, purple colors show units that reached lower individual stability compared to larger-scale stability. Values are averaged over all time periods (n = 137 for the national, n = 165 for the regional and n = 5183 for the farm level). Farm values are aggregated to the district level (mean values of the underlying farms), assuming that they are representative for the respective district. Units excluded from the analyses are shown in white.

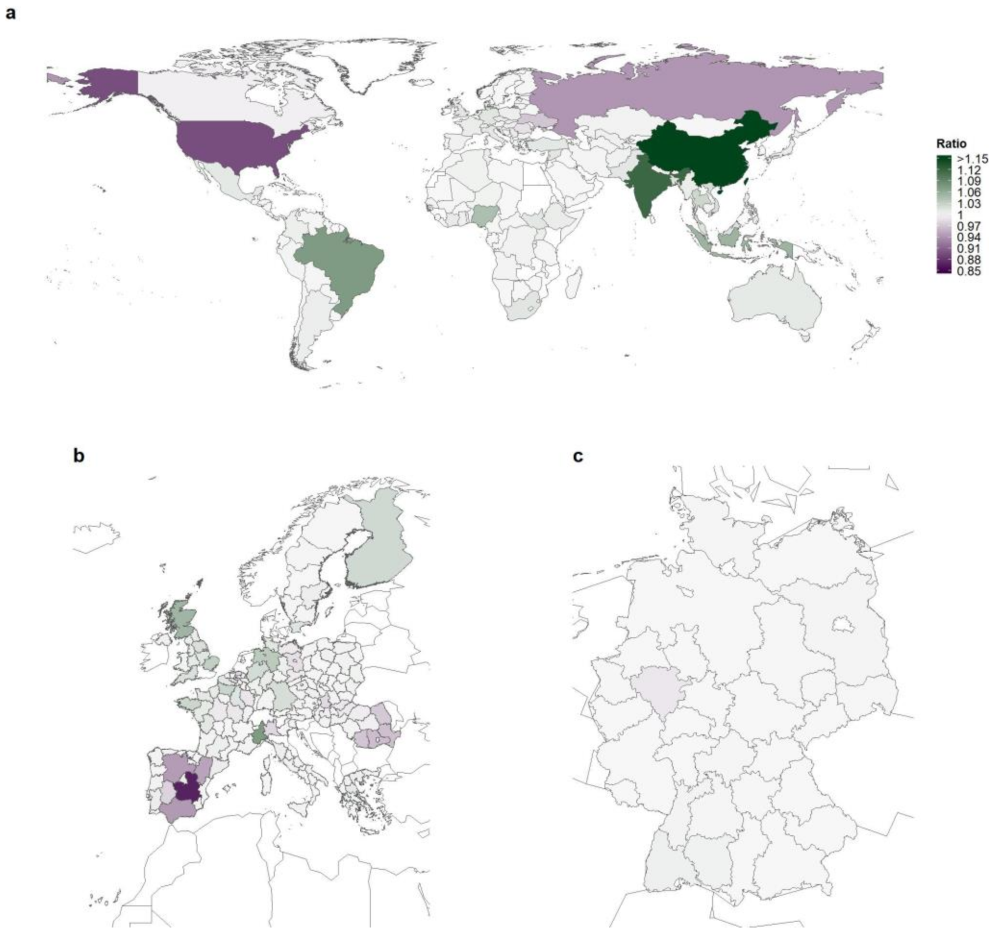

Figure A3 Yield stability contribution of nations (a), regions in the European Union (b) and farms in Germany (c). Yield stability contribution was calculated as the larger-scale stability over all nations, regions or farms divided by the larger-scale stability without the respective nation, region or farm (only including the crops grown in the respective unit). Green colors show units increasing larger-scale stability, purple colors show units decreasing larger-scale stability. Values are averaged over all time periods (n = 137 for the national, n = 165 for the regional and n = 5183 for the farm level). Farm values are aggregated to the district level (mean values of the underlying farms), assuming that they are representative for the respective district. Units excluded from the analyses are shown in white.

7.2 Appendix of Chapter 3

7.2.1 Supplementary methods

We compiled various datasets to reconstruct the main model used in Renard and Tilman (2019), using national caloric production stability instead of yield stability as a response and effective crop species diversity, temperature and precipitation instability, irrigation, nitrogen fertilizer, warfare and time intervals (1961-1970, 1971-1980, 1981-1990, 1991-2000, 2001-2010) as predictors. Besides crop diversity, we additionally included crop asynchrony as a predictor. We focused on production instead of yields for two reasons. First, because from a food security perspective the stability of the overall production is also relevant. Second, the link between production based crop asynchrony and total production stability is clearer than the relationship of yield based crop asynchrony and overall yield stability. This is because crop abundance is irrelevant in the yield based asynchrony calculation, while less abundant crops typically have a lower influence on overall yield stability, which divides total production overall crops by total harvested areas.

We calculated all metrics analogously to Renard and Tilman (2019), but used partially different datasets and data treatment strategies. We used different datasets for climate and crop-specific calories (Table A2). In total, we included 131 crops, for which nutrient data could be clearly assigned (Table A3). We then also time-detrended production data by regressing annual total calorie production on year squared for each time interval and country. For each country and time interval, we only included crops for which time series were complete. To not overestimate inputs per hectare in the reduced crop dataset, we divided total nitrogen use by the total cropland area instead of the sums of the harvested areas of the crops considered, and used the area equipped for irrigation as a proportion of the total agricultural area. We extracted monthly temperature and precipitation data only within the cropland area extent of the year 2000 (aggregated to the same resolution as climate data taking pixel sums) and during the growing season of major crops. During the extraction, we only included pixels that reported more than 1 km^2 of cropland to not overestimate the influence of pixels where agriculture has a very minor relevance. We then aggregated the climate data to each country using cropland area-weighted means. Following Renard and Tilman (2019), we excluded Egypt, Guinea, Ireland, Kenya, Mozambique, Netherlands, New Zealand, North Korea and Zambia from

our analyses. Further, we only included countries with a cumulated mean cropland area of up to 99.9% of the global cropland area to exclude countries where agriculture has a very minor relevance. To calculate asynchrony between crops, we first calculated synchrony of time-detrended crop-specific calorie production per time interval and country following the methodology described in Loreau and De Mazancourt (2008) and Mehrabi and Ramankutty (2019) and subtracted it from one. Synchrony basically relates the total temporal variance between crops to the variance within crops. Our final dataset consisted of 590 complete data points, including 136 countries.
We used the statistical software package R 3.6.1 (R Core Team, 2019) for data analysis. We applied a linear mixed-effects model with random slopes for crop diversity, and random intercepts for time intervals to predict crop asynchrony using the 'lme4' package (version 1.1-21) (Bates et al., 2015) in R. We assessed its performance in relation to a linear model including diversity only using AIC (Akaike´s information criterion). We used the 'codyn' package (version 2.0.3) (Hallett et al., 2016) to calculate crop asynchrony (1 – synchrony). We then used linear regression to test the dependence of national caloric production stability on effective crop diversity, crop asynchrony, or both, as well as temperature and precipitation instability, irrigation, nitrogen fertilizer, warfare and time intervals. We applied the same transformations as Renard and Tilman (2019) to directly compare the results of both analyses. To better compare regression coefficients, we standardized each predictor to zero mean and one standard deviation. All predictors in all three models had variance inflation factors below two, indicating that multicollinearity was not an issue. The order of crop diversity and asynchrony in the combined model did not change our conclusion, i.e. F values for crop asynchrony (F (1, 589) = 650.41, P < 0.05; F (1, 589) = 738.94, P < 0.05) were always higher than for crop diversity (F (1, 589) = 99.06, P < 0.05; F (1, 589) = 10.53, P < 0.05) as shown by analysis of variance. All R codes as well as the associated datasets are provided in a public repository on GitHub: https://github.com/legli/AgriculturalStability.

Table A2 Data sources underlying the analyses.

Data	Reference	Description	URL
Agricultural			
Area harvested	(FAO, 2019)	Crops	http://www.fao.org/faostat/en/#data/QC
Crop production	(FAO, 2019)	Crops	http://www.fao.org/faostat/en/#data/QC
Crop calories	(FAO, 2001)	Food balance sheets	http://www.fao.org/docrep/003/x9892e/X9892e05.htm#P8217_125315
Cropland (country)	(FAO, 2019)	Land use	http://www.fao.org/faostat/en/#data/EL
Cropland (5 arc-min grid)	(Klein Goldewijk et al., 2017)	Historical cropland distribution for the year 2000	ftp://ftp.pbl.nl/../hyde/hyde3.2/
Growing season	(Sacks et al., 2010)	Crop planting dates	https://nelson.wisc.edu/sage/data-and-models/crop-calendar-dataset/ArcINFO0-5degree.php
Environmental			
Temperature / Precipitation	(Willmott and Matsuura, 2001)	Monthly temperature (°C) and precipitation (cm)	*UDel_AirT_Precip* data provided by NOAA/OAR/ESRL PSD, Boulder, Colorado, USA: https://www.esrl.noaa.gov/psd/
Management			
Nitrogen fertilizer	(FAO, 2019)	Fertilizers by nutrient; Fertilizers archive	http://www.fao.org/faostat/en/#data/RFN; http://www.fao.org/faostat/en/#data/RA
Irrigation	(FAO, 2019)	Land use	http://www.fao.org/faostat/en/#data/EL
Socio-economic			
Warfare	(Marshall, 2016)	Armed conflicts and intervention (ACI)	http://systemicpeace.org/inscrdata.html

Table A3 Crops considered in the analyses.

Almonds, with shell	Chillies and peppers, green	Linseed	Pulses, nes
Anise, badian, fennel, coriander	Cinnamon (canella)	Lupins	Pumpkins, squash and gourds
Apples	Cloves	Maize	Quinces
Apricots	Cocoa, beans	Mangoes, mangosteens, guavas	Quinoa
Areca nuts	Coconuts	Maté	Rapeseed
Artichokes	Coffee, green	Melons, other (inc.cantaloupes)	Raspberries
Asparagus	Cow peas, dry	Melonseed	Rice, paddy
Avocados	Cranberries	Millet	Roots and tubers, nes
Bambara beans	Cucumbers and gherkins	Mustard seed	Rye
Bananas	Currants	Nutmeg, mace and cardamoms	Seed cotton
Barley	Dates	Nuts, nes	Sesame seed
Beans, dry	Eggplants (aubergines)	Oats	Sorghum
Beans, green	Figs	Oil palm fruit	Soybeans
Berries nes	Fonio	Oilseeds nes	Spices, nes
Blueberries	Fruit, citrus nes	Okra	Spinach
Brazil nuts, with shell	Fruit, fresh nes	Olives	Strawberries
Broad beans, horse beans, dry	Fruit, pome nes	Onions, dry	String beans
Buckwheat	Fruit, stone nes	Onions, shallots, green	Sugar beet
Cabbages and other brassicas	Fruit, tropical fresh nes	Oranges	Sugar cane
Canary seed	Garlic	Papayas	Sugar crops, nes
Carobs	Ginger	Peaches and nectarines	Sunflower seed
Carrots and turnips	Gooseberries	Pears	Sweet potatoes
Cashew nuts, with shell	Grapefruit (inc. pomelos)	Peas, dry	Tangerines, mandarins, clementines, satsumas
Cashewapple	Grapes	Peas, green	Taro (cocoyam)
Cassava	Groundnuts, with shell	Pepper (piper spp.)	Tea

Cassava leaves	Hazelnuts, with shell	Persimmons	Tomatoes
Cauliflowers and broccoli	Karite nuts (sheanuts)	Pigeon peas	Triticale
Cereals, nes	Kiwi fruit	Pineapples	Vegetables, fresh nes
Cherries	Kola nuts	Pistachios	Vetches
Cherries, sour	Leeks, other alliaceous vegetables	Plantains and others	Walnuts, with shell
Chestnut	Lemons and limes	Plums and sloes	Watermelons
Chick peas	Lentils	Poppy seed	Wheat
Chicory roots	Lettuce and chicory	Potatoes	

Table A4 Determinants of national caloric production stability. Linear regression models include crop diversity (diversity model), crop asynchrony (asynchrony model) or both (combined model) (n = 590). Caloric production stability was log-transformed, irrigation and nitrogen use intensity were square-root-transformed. Predictor variables were standardized to zero mean and one standard deviation.

	Diversity model			**Asynchrony model**			**Combined model**		
	Estimate (SE)	***T***	***P* -value**	**Estimate (SE)**	***T***	***P*-value**	**Estimate (SE)**	***T***	***P*-value**
(Intercept)	2.6 (0.03)	97.96	<0.0001	2.6 (0.02)	131.39	<0.0001	2.6 (0.02)	133.7	<0.0001
Diversity	0.15 (0.03)	5.28	<0.0001	-	-	-	-0.11 (0.02)	-4.65	<0.0001
Asynchrony	-	-	-	0.47 (0.02)	22.7	<0.0001	0.52 (0.02)	22.43	<0.0001
sqrt(Irigation)	0.05 (0.03)	1.56	0.12	0.08 (0.02)	3.22	0.001	0.1 (0.02)	4.04	<0.0001
sqrt(N use intensity)	0.14 (0.03)	4.09	<0.0001	0.06 (0.03)	2.24	0.03	0.05 (0.03)	2.02	0.04
Warfare	-0.04 (0.03)	-1.65	0.1	-0.04 (0.02)	-1.82	0.07	-0.04 (0.02)	-1.86	0.06
Time	-0.1 (0.03)	-3.5	0	-0.03 (0.02)	-1.6	0.11	-0.01 (0.02)	-0.5	0.62
Temperature instability	-0.26 (0.03)	-8.68	<0.0001	-0.15 (0.02)	-6.49	<0.0001	-0.13 (0.02)	-6.02	<0.0001
Precipitation instability	-0.19 (0.03)	-6.8	<0.0001	-0.18 (0.02)	-8.61	<0.0001	-0.2 (0.02)	-9.52	<0.0001
AIC		1166.13			819.67			800.10	
R2		0.28			0.60			0.61	

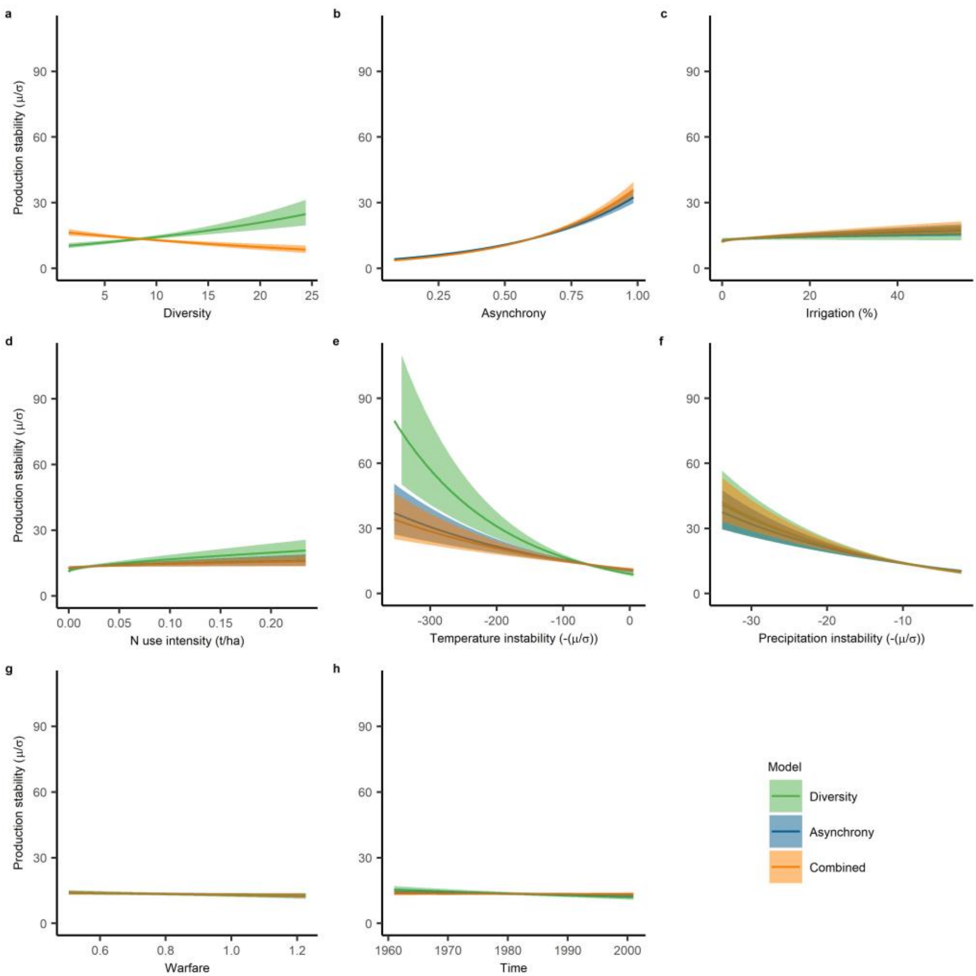

Figure A4 Main determinants of national caloric production stability. Results are shown for the linear regression models including crop diversity (green), crop asynchrony (blue) and both (orange) (n = 590). Irrigation and nitrogen use intensity were back-transformed from square-root-transformation, predicted values were back-transformed from log-transformation. Predictions were calculated using the observed range of the focal predictor, while keeping all the other predictors at their mean values. Shaded areas represent 95% confidence intervals.

7.3 Appendix of Chapter 5

7.3.1 Review methods and definitions

While we included some additional articles (see main text), we did not attempt a full 'snow ball search', i.e. checking the reference lists of all articles found for further relevant publications. The list of all evaluated and excluded paper is provided in the Supplementary material. For the purpose of this review we define scenarios as various instances of the same model used to assess system's response to targeted changes (e.g. contrasting policies, structural and procedural changes, and targeted parameter changes). We disregarded scenarios only varying disturbances, to clearly distinguish scenarios and disturbances. Regarding disturbance, we differentiate pulse disturbances following Pickett and White (1985, p. 7), multiple pulse and press disturbances. A pulse disturbance has a beginning and an end, is short relative to the typical time scale of change of the system considered, and has consequences beyond its duration. Multiple pulse disturbances overlap with 'disturbance regimes' (e.g. continuous vs. rotational grazing), which are characterized by the frequency and spatial extent of disturbances in a certain region (Turner, 2010). Contrastingly, a press disturbance permanently changes system drivers or structure. For all disturbance types, we only considered physical changes, while socio-economic changes (e.g. price shocks, policy changes) were considered in scenarios.

7.3.2 Supplementary results

7.3.2.1 Stability properties

If excluding variability, only two studies investigated more than one stability property. Naghibi and Lence (2012), for example, assessed different properties of fish population size; population variability, the time until the initial population recovered after a high flow event, and the population differences between the disturbed and undisturbed state (amplitude, which may indicate resistance). Recovery was quantified mostly via return time to pre-disturbance conditions, except for Balbo et al. (2014), who quantified the maximum amplitude allowing for recovery of hunter-gatherer populations under climatic changes. Resistance was measured as the amplitude between a disturbed and non-disturbed state (Naghibi and Lence, 2012), as the reaction time relative to the appearance of a disturbance (Dressler et al., 2016), as the deviance from a baseline scenario under different mechanisms potentially enhancing resistance (Rasch et al., 2016; Smith, 2014), or as economic buffer capacity (Rasch et al., 2016). Persistence was typically determined by the rate or probability of extinction of the population of interest in the entire system, except Cordonnier et al. (2008), who measured the time spend within favorable ranges of different state variables ('permanence'), and Johnson (2009), who interpreted changes in characteristic length scales as range shifts.

7.3.2.2 Specific situations

In total, 30 studies varied two dimensions of specific situations, typically the level of organization and state variable (*n*=24). Only 14 studies varied three dimensions, of which all, except two, included level of organization and state variable. Four and five dimensions were varied in one study each. Johnson (2009) used different window sizes to assess natural length scales of complex systems (landscape level) and species composition (community level) across two different disturbances (patch clearing and species invasion). Cordonnier et al. (2008) defined different reference states for three different state variables on different levels of organization, which were used to assess the response of forests to two different disturbances (random and gap thinning) acting on different spatial extents.

In 74% of the studies, at least two state variables were quantified. Most studies considered demographic (e.g. population size, sex ratio), ecological (e.g. diversity, plant cover, biomass) and economic (e.g. income, yield) variables. In total, 38 studies assessed more than one level of organization. Fujii et al. (2009), for example, investigated the resilience of subtropical forests on three different levels. They measured diameter at breast height (individual level), species diversity and composition (community level), and biomass (ecosystem functioning).

Reference states were not defined in almost half of the studies (*n*=29). Eight studies defined static reference states (e.g. landscape configuration before a disturbance), one study included static and dynamic states, while the remaining 27 studies compared the simulations against a dynamic reference (e.g. baseline scenario). Only two studies included more than one reference state; Cordonnier et al. (2008) defined favorable value ranges of three indicators in addition to a dynamic baseline scenario, while Jenkins et al. (2017) compared eight experiments of insurance schemes and technical protection measures to reduce flood damage under future climatic conditions against the respective experiments under current climate (baseline).

Of the reviewed studies, 43 explicitly modeled disturbances, but only ten studies included more than one disturbance (nine studies included two and one study three). For example, Rammer and Seidl (2015) studied the impacts of multiple forest thinning, a single clear cut and global warming on timber production. Press disturbances, altering the system permanently, were investigated in 13 studies, such as climatic changes (Balbo et al., 2014; Janssen, 2010; Jiang et al., 2012; Perez et al., 2016; Rammer and Seidl, 2015; Rebaudo and Dangles, 2015; Reed et al., 2011; Smith, 2014), the exclusion of fish (Doropoulos et al., 2016; Mumby et al., 2016), invasion of a new species (Johnson, 2009), and exposure to chemicals and salt (Bi and Liu, 2017; Gabsi et al., 2014). Most studies assessed multiple pulse disturbances, e.g. multiple natural disasters (Charnley et al., 2017; Jenkins et al., 2017; Naghibi and Lence, 2012; Vincenzi et al., 2008; Vogt et al., 2014), climatic shocks (Dieguez Cameroni et al., 2014; Rogers et al., 2012), clearing or thinning (Cordonnier et al., 2008; Fujii and Kubota, 2011; Johnson, 2009; Kubicek et al., 2012; Rammer and Seidl, 2015; Soussana and Lafarge, 1998; Wakeford et al., 2008; Wild and Winkler, 2008), and fishing events (Kubicek and Reuter, 2016; Lindkvist and Norberg, 2014; Morrison and Allen, 2017; Piou et al., 2015; Schlüter and Pahl-Wostl, 2007; Vergnon et al., 2008).

Of the reviewed articles, only ten assessed resilience at more than one spatial scale. Of these studies, five varied the spatial extent of disturbances, for example, Kubicek et al. (2012) studied the effects of different diameters of a mechanistic disturbance on a coral reef community. Four studies applied the same model to different study sites (Dressler et al., 2016; Fujii et al., 2009; León and March, 2014; Vincenzi et al., 2008). In contrast, Ye et al. (2013) tested the effect of the configuration and number of habitat patches on population dynamics in fragmented landscapes. Johnson (2009) used different window sizes to assess natural length scales of complex systems.

Temporal scales were varied in 13 studies, of which eleven tested various durations of disturbances. Kanarek et al. (2008), for example, introduced a climatic disturbance leading to resource degradation for one, five or ten years to study its effects on foraging behaviour of geese. In contrast, Balbo et al. (2014) used precipitation models on different temporal scales to investigate scale-dependent disappearance of hunter-gatherers, and Christie and Knowles (2015) tested if different time scales affect their conclusions regarding the resilience of habitat corridors. Three studies combined both spatial and temporal scales. Wild and Winkler (2008), for example, systematically varied the proportion and interval of krummholz removal to study its coexistence with grassland.

7.3.2.3 Resilience mechanisms

Resilience mechanisms could be identified in 56 articles, but were explicitly communicated in only 40 articles. Only about one quarter of the studies investigated potential resilience mechanisms directly. Bohensky (2014), for example, found that learning improved the success of water management strategies under variable water availability. Decelles et al. (2015) showed the importance of geographical connectivity for successful transportation of larvae transport. Schlüter et al. (2009) and Schlüter and Pahl-Wostl (2007) found that the use of multiple ecosystem services (response diversity) increased the economic and ecological performance of a river ecosystem providing fish and irrigation for agriculture. ten Broeke et al. (2017) revealed that adaption through inheritance of specific traits (harvesting and moving rates) could prevent the collapse of a common-pool resource system.

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7.4 Appendix of Chapter 6

Chapter 7.4.1 provides a narrative description of the simulation model introduced in Chapter 6.3.1. Chapter 7.4.1 provides a detailed description of the agent-based model showcased in Chapter 6.3.2 following the ODD protocol.

7.4.1 Managing asynchrony: model description

I simulated different management strategies in a stylized landscape to simulate the effect of climate on crop-specific suitability as a proxy for production and thus to derive aggregated measures of asynchrony between and within crops. For the simulations, I used the statistical software package R 3.6.1 (R Core Team, 2019) run via RStudio (RStudio Team, 2015).

First I initialized the landscape with 5x5, 9x9 or 33x33 pixels. Then, I allocated 1 to 14 crops with equal area shares according to one of three management strategies: specialized, fragmented and diversified. To create the specialized and fragmented landscape, I used the 'nlm_mdp' function in the 'NLMR' package with a roughness of 0 and 1, respectively. I then allocated the given number of crops with equal weights using the 'util_classify' function in the 'landscapetools' package. For the diversified landscape, I allocated each crop equally to each pixel. I kept the crop distribution constant while I simulated annual temperature and precipitation for ten years with fixed mean values (24°C and 7500mm). Each year I randomly sampled temperature and precipitation deviation from a uniform distribution with a maximum value of 10°C and 5500mm, respectively. To simulate climate gradients, I used the 'nlm_mdp' function with a roughness of 0 and transformed the resulting range (0-1) to the actual temperature and precipitation range (mean ± deviation).

For each pixel and allocated crop I computed annual temperature and precipitation related suitability using general crop-specific climate response functions that associate a suitability index from 0 (not suitable) to 1 (highly suitable) to each temperature or precipitation value (Zabel et al., 2014). I selected the minimum of the two resulting suitability values per crop as natural suitability is restricted, i.e. lower values of one factor cannot be compensated by the other one. I used suitability as a proxy for production. I then calculated the total annual production of all pixels for each crop to derive synchrony between crops following Loreau and De Mazancourt, (2008) and Mehrabi and Ramankutty (2019) with the 'codyn' package (version 2.0.3) in R (Hallett et al., 2016), which I then subtracted from 1 to receive asynchrony

(Chapter 3). Next, I calculated crop-specific asynchrony between all pixels where a given crop was cultivated and averaged it over all crops (no weighting was needed because crop shares were similar) to estimate asynchrony within crops.

For each combination of landscape size, number of crops and management strategy (n = 126), I repeated the simulation for 10 times and calculated mean and standard deviation of asynchrony between and within crops.

7.4.2 Agent-based model: ODD protocol

7.4.2.1 Purpose and patterns

The model is designed to investigate how agricultural land use depends on the potential to grow different crops (related to landscape characteristics and climate variability), trade and farmers' focus on different crops and their ability to compete. The model is considered realistic enough for its purpose if general patterns in the context of globalization and resilience theory are mimicked. Free trade between regions is expected to lead to a distribution of crops where they can be grown most efficiently while diversified systems are expected to be more successful in the face of climate variability. The model's design is motivated by the model CRAFTY (Competition for Resources between Agent Functional Types) (Murray-Rust et al., 2014). In contrast to CRAFTY, my model only represents land-use change within croplands used by farmer types that can cultivate different crops.

7.4.2.2 Entities, state variables and scales

The model has two entities, patches and the environment. Square units of land referred to as patches are the basic entity of the model. The state variables characterizing each patch are: (1) its *coordinates*, (2) the *potentials* to grow four possible crops (maize, wheat, rice and soybean); they are set initially and can be modulated by climate conditions and trade, and (3) the *farmer type* that is currently cultivating this patch, which is 0 if abandoned (Table A5).

Farmers and farms are not modeled explicitly but implicitly by distinguishing five types of farmer utilizing the patch's crop-specific potentials: specializers which, on a given patch, grow one of four possible crops in monoculture, and diversifiers which grow all four crops simultaneously. Farmer types are distinguished by the following variables (which are implemented as patch variables); the first two of them are parameters of a function describing how production depends on the potential (Cobb-Douglas function; see Appendix 7.4.2.7 below):

Potential sensitivity. This variable modulates, as an exponent to *crop_potential*, the farmer types' production (see equation D1 below). It reflects the specialization and hence dependency, for example in terms of equipment on a specific crop. Specializers have a sensitivity of 1 for one crop and 0 for all others because they do not grow them, while diversifiers have a sensitivity of 0.25 for all four crops. Hence, production of diversifiers is less sensitive to low potential of each crop than that of the corresponding specializers.

Production optimal. This variable modulates, as a factor, the farmer-type specific production (see equation D1 below). Specializers have a value of 1 for their crop, so they can fully exploit the given crop's potential while diversifiers have a value of 0.25 for all four crops so that they can maximally utilize 25% of the actual potential because they grow multiple crops at once.

Abandonment threshold. This threshold represents the minimum utility a farmer type is willing to accept. Specializers have a value of 0 but diversifiers a value of 0.2 because they are less specialized and therefore need to invest more for growing a resource so that at some point the utility of a patch is no longer worth it.

Competition threshold. Of the farmer types chosen to compete with the current farmer type using a patch, one is chosen with a probability relative to its utility. It will then take over if its utility is larger than that of the resident farmer type plus the *competition threshold*. Specializers have a value of 0.2 while diversifiers a value of 0, assuming that they have less resources to compete. Table A6 provides an overview of the farmer types' variables.

The environment is characterized by *crop-specific demands* and *climate conditions*. Demands are relative to the total number of patches. If the region is independent, all crops are demanded equally, while under trade, the demand is highest for the crop with the best growing conditions (0.7).

The model world consists of 30x30 patches. The region is characterized by climate conditions (mean and variability) and crop-specific potentials. If the region is independent the potential for each of the four crops is maximal (=1) in one of the four corners and decreases linearly with distance from that corner. If the region is connected to other regions by trade (not explicitly modeled), the potentials of three crops are reduced to 20% of the original potential; this setting assumes that other regions exist that have better opportunities to grow these three crops.

Spatial resolution is not explicitly defined, but should be small enough that the assumption that a patch is dominated by one crop is plausible (e.g. 1 km^2 in areas with large scale farming). A time step represents one year. Simulations are run for 50 years.

Table A5 State variables of patches.

State variable	Description	Range	Initial value
xcor, ycor	x and y coordinates specifying patch position	0-29	
crop_potential_landscape	List of baseline potential for each of the four crops (without climate effects)	0-1	Gradient from each corner
crop_potential	List of current potential for each crop based on baseline potentials and current climate	0-1	crop_potential_ landscape
farmer_type	Farmer type currently cultivating this patch	specializer on maize (1), specializer on wheat (2), specializer on rice (3), specializer on soybean (4), diversifier (5), not cultivated (0)	0

Table A6 Variables specifying the farmer types. Note that these variables are represented as a patch variable in the model.

State variable	Description	Values
potential_sensitivities	The importance of crop-specific potentials for a farmer type to successfully	[1 0 0 0], [0 1 0 0], [0 0 1 0], [0 0 0 1], [0.25 0.25 0.25 0.25] for farmer types 1-5 (values in

State variable	Description	Values
	utilize a patch (determines production)	list are for maize, wheat, rice and soybean)
production_optimal	Maximum crop-specific production a farmer type can achieve under optimal conditions (determines production)	[1 0 0 0], [0 1 0 0], [0 0 1 0], [0 0 0 1], [0.25 0.25 0.25 0.25] for farmer types 1-5 (values in list are for maize, wheat, rice and soybean)
abandonment_threshold	Minimum utility a farmer type is willing to accept	0 for specializers, 0.2 for diversifiers
competition_threshold	Ability to keep a patch if other farmer types try to take over this cell	0.2 for specializers, 0 for diversifiers

7.4.2.3 Process overview and scheduling

In each time step, the following submodels are executed in the given order. Details on the submodels are given below (Appendix 7.4.2.7).

Abandon: Based on the actual production and the unmet demand for each crop, utility is determined in each patch. If it falls below the abandonment threshold of the farmer type, the patch is abandoned.

Compete: For each patch, potential farmer types competing for this patch are sampled. Then the utility of each potential farmer type is calculated and one farmer type is randomly selected relative to its utility. If the focal patch is empty, the selected farmer type takes over this cell. If the patch is occupied, the selected farmer type competes with the current farmer type. If its utility is larger than the utility plus the competition threshold of the existing farmer type, the patch is taken over.

Simulate climate: Actual climate is determined based on the given mean and standard deviation; crop-specific potentials of patches are updated accordingly.

Harvest: The production of each patch is calculated based on the occupying farmer type and actual potentials.

Update supply: The total crop-specific production is calculated and subtracted from the respective demand levels to calculate the unmet demand.

7.4.2.4 Design concepts

Basic principles: Farmer types are the main entity of the model. They represent generalized forms of behavior (Arneth et al., 2014; Murray-Rust et al., 2014). Changes of farmer types and thus land use on a patch are driven by their state

variables, given potentials and levels of unmet demands that determine utilities and hence abandonment and competition among farmer types. Competitive expansion is a general mechanism to simulate competition (Magliocca and Ellis, 2016).
Emergence: Land uses emerge based on the success of different farm types.
Adaption: Unsuccessful farmer types leave and more successful ones take over.
Objectives: Farmer types aim for patch-specific utilities higher than the abandonment threshold. If this target is not reached, the patch is abandoned.
Learning: Not included.
Prediction: Not included.
Sensing: Farmer types sense the baseline potential of each targeted patch.
Interaction: Interaction between farmer types that compete for the same patch.
Stochasticity: Climate is simulated randomly within a given range. The farmer type targeting a cell is determined by probabilities.
Collectives: Not included.
Observation: Spatial explicit land-use change

7.4.2.5 *Initialization*

Crop-specific potentials are initialized based on current settings. Two landscape types exist. In both types maize has highest potential in the upper left (=1 in the first landscape), wheat in the upper right, rice in the lower left and soybean in the lower right corner of each region. The potential is linearly decreasing to 0 at maximum distance from the respective corner. In the second landscape type (trade), the potentials of wheat, rice and soybean are reduced to 20% of the values of the first landscape type. Further, total crop-specific production (0), demand and unmet demands are initialized.

7.4.2.6 *Input data*

NA

7.4.2.7 *Submodels*

The descriptions contain codes (e.g. A1) that link the described process with the model code. Names of the submodels, variables and parameters are identical in the description and the code. Submodels are executed in the given order. All model parameters are listed in Table A7.

Abandon

First, for each patch *utility* of the farmer type *f* currently cultivating a patch is calculated as:

$$utility_f = \frac{\sum_i^4 production_{f,i} \times unmet\_demand_i}{utility_{max}} \text{ (A1)}$$

where $production_{f,i}$ is the production of crop i of farm type f based on equation D1, $unmet\_demand_i$ is the unmet demand of crop i as calculated in S2, $utility_{max}$ is the maximum utility over all farm types under *optimal production*. The numerator of the formula is based on the CRAFTY model.

If the utility falls below the abandonment threshold the patch is abandoned and all state variables are adapted accordingly (A2).

Rationale: If a farmer type can contribute a lot to currently unmet demand its utility is higher than if demand is already largely supplied. This reflects basic microeconomic theory of supply and demand. Different farmer types differ in their minimum utility a farmer type is willing to accept. For example, production costs of diversified farmer types might be higher because more manual labor is needed so that minimum utility (indirectly reflecting actual income) needs to be higher.

Compete

For each patch, the probability that a farmer type targets this patch is 0.5 (B1). Then the potential production of each farmer types is calculated according to equation D1 and utility according to equation A1. Then one of the farmer types targeting this patch is randomly selected with a probability relative to its utility (B2). If the patch is empty or the utility of this farmer type is larger than the utility plus the competition threshold of the existing farmer type, the patch is taken over (B3) and all variables are updated accordingly (B4).

Rationale: Farmers have imperfect knowledge to find land that can be cultivated. Competitive expansion of farmer types with higher utilities reflects basic economic theory on comparative advantage (Magliocca and Ellis, 2016). Competition thresholds may differ between farmer types as they have different abilities to keep their land (e.g. better networks, contracts or potentials). Specializer for example, typically have higher capital stocks and savings, so they can better secure land, even if current utility is low.

Simulate climate

Updates current climate and the corresponding patch-specific potentials for each of the four crops under these conditions. Actual climate values are sampled from a normal distribution with predefined mean values (list_mean_climate) and standard deviations (list_deviation_climate) for each region (C1). Minimum and maximum climate values are restricted to the mean ± standard deviation. The crop-specific potentials for these values are then red from the respective list representing crop-specific response function to temperature (list_climateSuitability) (C2). This list is red from the input file 'cropClimateResponse.csv', which was based on empirical data and represents crop-specific suitability for different temperatures (Zabel et al., 2014). Potentials of each patch are then updated accordingly, if the climate based potentials are lower than the baseline potentials (C3). Otherwise, they are kept to their baseline values (crop_potential_landscape), which represent optimal conditions (C4).

Rationale: Climate directly affects the suitability to grow different crops. The respective response functions differ between crops as they have different requirements and abilities to deal with climate variability. These functions are implemented for maize, wheat, rice and soybean and are based on empirical data of crop-specific responses to temperature (Zabel et al., 2014).

Harvest

Given actual climate conditions, possible production for each crop and farmer type in each patch is calculated. The formula to calculate production is based on the CRAFTY model, where a Cobb-Douglas production function is used to combine optimal production levels with dependence on each potential. Patch specific production of crop i of the cultivating farmer type f is calculated as:

$$production_{f,i} = production\_optimal_{f,i} \times potential_i^{potential\_sensitivity_{f,i}} \quad \text{(D1)}$$

where $production\_optimal_{f,i}$ represents the maximum production of crop i by farm type f under optimal conditions (i.e. maximum potential), $potential_i$ represents the current potential of the patch for crop i, $potential\_sensitivity_{f,i}$ represents the dependence of farm type f on the potential of crop i.

Rationale: Functions of this form are commonly used to represent land-use productivity (Murray-Rust et al., 2014). To not overestimate production abilities, optimal production needs to be defined. In this model, optimal production abilities and potential sensitivities are identical, so that under full dependency the entire potential for a crop can be leveraged. Farmer types differ in these parameters. For example, a specializer only wants to grow a specific crop if the potential for this crop is high, i.e. the dependency is high.

Update supply

Total crop-specific production is summed over all patches (E1). Then unmet demand for each crop is calculated as the difference between demand and supply (E2). Rationale: These overall values are needed to calculate utilities for each farmer type (see above).

Table A7 Parameter values.

Parameter	Description	Range	Value baseline
time_steps	Duration of the simulation	1-100	50
Trade?	Determines the landscape type. Either all 4 crops have high suitability (at each corner) or only one	true, false	false
abandonment_treshold	Minimum utility a farmer type is willing to accept for each patch	0 - 1	0 for farmer types 1-4, 0.2 for farmer type 5
competitiveness_threshold	Ability of a farmer type to keep the land if other farmer types try to take over this cell	0 - 1	0.2 for farmer types 1-4, 0 for farmer type 5
mean_climate	Mean temperature (°C)	0 – 40	20
deviation_climate	Standard deviation of temperature (°C)	0 – 20	0
demand_proportion	Demand for the for croups relative to the number of patches	0.25 for all crops	0.25 for all crops

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