"*Fruit basket upset*": spatially explicit crop mixture responses to climatic and economic pressures

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Abstract

Purpose – The choice of crops to produce at a location depends to a large degree on the climate. As the climate changes and food demand evolves, farmers may need to produce a different mix of crops. This study assesses how much cropland may be subject to such upheavals at the global scale, and then focuses on China as a case study to examine how spatial heterogeneity informs different contexts for adaptation within a country.

Design/methodology/approach – A global agricultural economic model is linked to a cropland allocation algorithm to generate maps of cropland distribution under historical and future conditions. The mix of crops at each location is examined to determine whether it is likely to experience a major shift.

Findings – Two-thirds of rainfed cropland and half of irrigated cropland are likely to experience substantial upheaval of some kind.

Originality/value – This analysis helps establish a global context for the local changes that producers might face under future climate and socioeconomic changes. The scale of the challenge means that the agricultural sector needs to prepare for these widespread and diverse upheavals.

Keywords Agricultural diversity, Crop distribution, Land use, Climate change, Adaption planning

Paper type Research paper

1. Introduction

Land use changes are intrinsically linked to human activity and to economic development. They are the outcome of an adaptation process responding to a variety of socioeconomic and agroecological drivers, including climate, that determine the location, magnitude, and direction of change (Foley *et al.*, 2005).When projecting into the future, the movement of temperature gradients and precipitation distributions away from historical patterns is expected to affect the suitability of existing areas for growing key crop commodities (Ceglar *et al.*, 2021; Gao *et al.*, 2021) resulting in the spatial relocation of crop production (Sloat *et al.*,

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2020). Land use will be further influenced by population and economic growth which will modify and increase food demand, requiring more land to be brought into cultivation and altering the mixture of crops across all cropland. These changes will not only affect crop diversity and richness, but they will also reveal how resilient local food systems are in the face of biophysical and socioeconomic shocks (Birthal and Hazrana, 2019).

The spatial reshuffling of crops can also have deep ecological, economic, social and political implications. Some research suggests that agricultural concentration is more likely to lead to conflicts (Vesco *et al.*, 2021). Political and social tensions may be exacerbated by the potential increase in demand for resources in regions already poorly endowed, and where crop production is projected to become more specialized and require higher input use, particularly water (Unfried *et al.*, 2022). Understanding the potential extent and nature of these changes will help prepare producers, and other stakeholders to adapt, seize new opportunities, and deal with challenges.

Due to each region's distinct combination of agroecological features, natural landscapes, as well as the historical practices of agricultural activities, substantial spatial heterogeneity is expected in the way land use changes manifest (Xin *et al.*, 2013). Heterogeneity poses particular challenges because it means that planning for adaptation will require more localized analysis and tailored policy support. For this reason, mapping out land use trajectories under projected socioeconomic and climatic changes, and across different spatial scales, is critical in the design of interventions and policies that can minimize the potential disruption to agricultural production and to people's livelihoods. Such knowledge is also important when planning for future transportation, processing capacity, and the supporting physical infrastructure that goes with, and connects different economic activities (Attavanich *et al.*, 2013), as well as when planning for investments in extension services, and in reorganizing food supply chains.

Reflecting its importance, research on future land use at the global scale has a long history. A stream of the literature has attempted to understand its change dynamics. Several spatial modeling approaches have been used, ranging from regression to integrated assessment models (IAMs) combining biophysical, land use and economic sub-models. However, most of these approaches are concerned primarily with broad patterns in land cover (Mendelsohn *et al.*, 2016; Thiam *et al.*, 2022) while a few studies have explored how crop mixes have already changed in response to specific climate variables like temperature and precipitation change, or how they may change in the future (Cho and McCarl, 2017; Ghahramani *et al.*, 2020; Sloat *et al.*, 2020; Nainggolan *et al.*, 2023). More importantly, existing studies do not always consider how these patterns respond to climate in combination with broad socioeconomic trends, like population or economic growth. Crop yields and prices are often assumed to be fixed, and therefore are not included in studies using regression methods to estimate the impact of climatic, and other variables on crop shares. Among the different approaches to land use modeling, IAMs have the capacity, to varying degrees, to simulate changes in land use patterns, while accounting for socioeconomic drivers of change. However, when IAMs are used to simulate changes in agricultural land use, this is generally performed as a quick steppingstone towards other research objectives like calculating carbon emissions, or climate change mitigation measures (Hasegawa *et al.*, 2017; van der Hilst *et al.*, 2018; Fujimori *et al.*, 2022), or evaluating changes in biodiversity (Leclère *et al.*, 2020).

There is a clear value, then, to understanding the future geographical relocation of crops and the possible change in their global and regional distribution as the result of both climate and socioeconomic changes, simultaneously. Accordingly, the objective of this paper is to estimate potential shifts in cropland patterns between 2005 and 2050. Acknowledging that changes do not happen evenly in terms of magnitude, direction, or across geographies, we first investigate changes at the global scale, and then use China as a case study to examine how spatial heterogeneity may create different contexts for adaptation within a country.

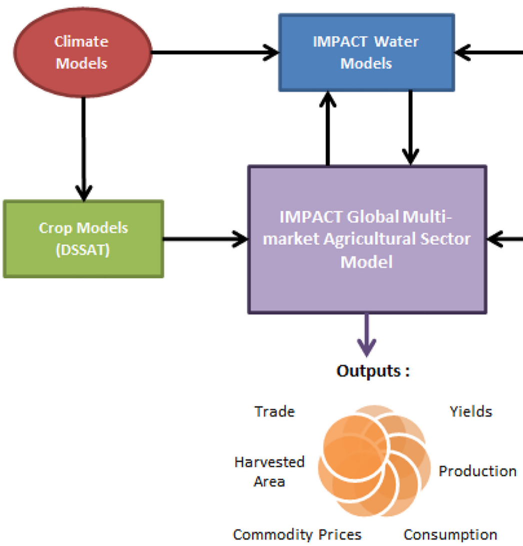
The analysis is based on a newly developed cropland allocation/land use model which estimates the distribution of a set of crops at pixel level by downscaling future global and national projections for cropland expansion to 2050 generated by the IMPACT partial equilibrium model (Robinson *et al.*, 2015). IMPACT simulates how production and supply of agricultural commodities respond to exogenous drivers like climate and population growth to achieve a market equilibrium. As such, its results also indicate the level of change to the structure of the agricultural sector (i.e. crop mixes, area expansion or contraction) required to adapt to climate shocks. Spontaneous adaptation (expressed through changes simulated by the model) is always accompanied by challenges in the form of transaction costs borne by farmers and other stakeholders. The premise underpinning this exercise is that the various levels of projected notable change in the mix of crops, what we call "upheaval", are indicative of the effort, including costs, required for adaptation (whether spontaneous or planned).

2. Materials and methods

The goal of this investigation is to assess how much area will experience a major upheaval in the shares of crops represented and where. We do this by comparing raster maps of individual crop shares between 2005 and 2050. The maps are generated by taking area projections of total cropland from a global economic model and linking them to a crop allocation algorithm to spread that area out to particular locations (pixels).

2.1 Regional-level cropland totals

While at the local level it may appear that the demand for cropland is infinite, global demand for agricultural products restricts the total amount of cropland that can be consistently profitable. Our source for future cultivated area projections is the IMPACT suite of models (Robinson *et al.*, 2015). At its center is a multi-market, partial equilibrium model of the agricultural sector (Figure 1) that spatially disaggregates the world into 320 food production units (FPUs). The FPUs comprise 159 countries (or groupings of countries) with the larger



Source(s): Authors, adapted from Robinson *et al.* (2015)

Figure 1. IMPACT modeling framework

ones further divided into major river basins to facilitate links to hydrological and water resources management models, which are also part of the modeling suite. Agricultural production and demand, as well as trade, are modeled for 62 separate commodities. Crop production from rainfed and irrigated systems have separate supply functions which are built up from area and yield responses to both economic drivers and climate conditions affecting productivity.

In this study, socioeconomic drivers follow the economic and demographic trends of the Intergovernmental Panel on Climate Change (IPCC) middle of the road GDP and population scenario (SSP2) (O'Neill *et al.*, 2014). Projections for gross domestic product, and population are derived from the OECD (Dellink *et al.*, 2017) and from IIASA (IIASA, 2013).

In order to explore some of the uncertainty inherent in climate change projections, the climate drivers for IMPACT are based on five general circulation models (GCMs): GFDL-ESM2M, HadGEM2-ES, IPSL-CM5A, MIROC-ESM-CHEM, and NorESM1-M run under the 8.5 Representative Concentration Pathway (RCP) (Riahi *et al.*, 2011), and processed according to ISIMIP protocols (Muller and Robertson, 2014). Climate is used as an input for process-based crop models to determine yields under the different climate scenarios. In turn, those yields are used to compute shifters and adjust the supply curves to reflect the changes in productivity caused by climate. In our analysis we do not include the effects of CO2 fertilization. Although important steps have been taken to clarify the effects of CO2 especially on global primary production (Chen *et al.*, 2022), its role in shifting cropland distribution is uncertain and likely to be confounded by the interaction with multiple other factors, including locally generated climates and other conditions (Wang *et al.*, 2020).

Central to this investigation are the area simulations from IMPACT for 2005 and 2050. For each FPU, we obtain rainfed and irrigated area projected for five major crops, maize, rice, sorghum, soybeans, and wheat. Together, they account for 50% of the physical cultivated area (36% as rainfed and 14% as irrigated). The other half of cultivated area is placed into a composite "all other crops" category, with the rainfed portion occupying 38% and the remaining 12% being irrigated. The challenge is to convert the twelve FPU-level values (6 rainfed, 6 irrigated) into twelve raster maps showing how much area in each pixel is dedicated to each crop.

2.2 Allocation algorithm

The allocation algorithm assigns portions of crop area to specific locations (in our case, half-degree pixels that are roughly 3,000 square kilometers near the equator) in a way that "adds up" to the appropriate FPU-level totals from IMPACT, while also producing plausible geographic distributions (See Supplementary Information S1). While not a pure optimization approach in a mathematical sense, the algorithm can be thought of as a step-by-step optimization of the location of each crop, since it attempts to generate the most plausible pixel-level distribution of the total cropland areas estimated by IMPACT. We apply our algorithm for both the beginning period of IMPACT simulations (2005), and for the ending period (2050). Changes in cropland use are determined by comparing the allocation results between these two periods.

The allocation begins by trying to assign cropland to the "best" pixels, subject to constraints that promote mixing and limit the degree of concentration. To determine the best locations, we construct "attractiveness indices" for each rainfed and irrigated crop in each pixel. These indices are the weighted sums of four sub-indices, each representing a key influence on land use. The first captures how much time it takes to travel from the potential cropland location to the nearest city (Nelson, 2008). This is a proxy for the complicated effect of distance on the realized crop price; overall, being closer to a city is more attractive than being farther. We do not attempt to predict where new cities may appear in the future, so these values are the same for both the starting and ending periods (2005 and 2050). The second sub-index is the amount of variation in elevation that occurs within the half-degree pixel (Globe Task Team, 1999). This provides an assessment of how flat the pixel is and thus how difficult cultivation might be from a terrain perspective: lower terrain diversity makes the location more attractive. The last two sub-indices depend directly on climate. One is a measure of how similar the climate of the pixel is to the climates that have historically been associated with large scale crop cultivation. The more similar the climate, the easier it should be to apply existing technologies and hence the more attractive for cropland. The fourth and last measure is the potential yield that the crop may be expected to achieve if grown in that pixel with that climate. We use the DSSAT crop modeling framework to simulate the potential yield (Jones *et al.*, 2003; Robertson, 2017; Hoogenboom *et al.*, 2019). The higher the yield, the more attractive the pixel is for that crop.

The algorithm is structured to avoid concentrating each crop in the narrow geographical area that is most "attractive" by allocating a very small amount of land in each step and imposing several constraints. The core of the allocation proceeds by assigning only a small amount of the total FPU cropland area at a time, and rotating which crop is being allocated. Take rainfed maize as an example. The algorithm looks for the pixel that is most attractive for rainfed maize (based on the index) and allocates a small amount of maize area to that pixel: the pixel's maize area is increased and the total maize area remaining to be allocated (from the IMPACT totals) is decreased by the same amount. Then, a second crop, such as wheat, is considered in the same way, and so on until all the crops have been considered, at which point the process repeats until all the necessary cropland has been found. The goal of this iterative procedure is to allow for more than one crop to claim land in the same pixel as well as to make the arbitrary order of the assignment rotation unimportant. We chose to assign no more than 1% of the total amount of area available for cropland at a time; therefore, it would take at least 100 iterations before a pixel can no longer accept cropland.

While this process allows for a mixture of crops within a single pixel, by itself, it will still tend to place crops in the few "best" locations (usually, the highest yielding for each crop). Several constraints discourage excessive concentration. First, no more physical area can be assigned than the size of the pixel itself. We further refine this by setting an upper bound on how much of the pixel is available for cropland. Irrigated crops are allocated first. Irrigated areas are restricted by the amount of area in the pixel thought to be equipped for irrigation, defined by the Global Map of Irrigation Areas (Siebert *et al.*, 2013). Within that equipped area, the fraction available for cultivation is assumed to be capped at 90%. If there is not enough irrigated area available (at the pixel level) to accommodate the total area from IMPACT, the irrigation cap is raised to provide additional area. When even a 100% cap is insufficient, the irrigation area is expanded within pixels already having some area equipped for irrigation. Failing that, an additional fraction of each remaining pixel is made available until enough area is secured. That is, we impose no firm preference about where the new, last resort irrigated area will arise and so it is spread out evenly.

Rainfed cultivation proceeds in a similar manner, but only after all the irrigated areas have been allocated. The area available for rainfed cultivation is the pixel's physical area, minus any water bodies, minus the allocated irrigated areas and plus any unused irrigated area. A cap also applies to the non-irrigation-equipped areas (set at 67%, roughly two-thirds). Again, if the cap proves too restrictive, it is raised until enough area is available. In the extreme case, when IMPACT is indicating a need for more physical area than actually exists, we maximize the available area in the pixels and then reduce the target amount to be allocated to match.

Two more constraints encourage multiple crops within pixels. First, if, after an iteration, the share of an allocated crop exceeds 65% of the area of a specific pixel, then the pixel is considered ineligible for that crop until other crops claim enough area to push that fraction below 65%. The rule is automatically relaxed when the most common crop in the region is the only one left with area to be allocated. The second limitation is that no more than 50% of the available cropland area can be allocated to a single crop within a pixel unless there are no other crops with area left to allocate. The final result of the allocation process is a stack of maps showing how much area for each crop is represented in each pixel.

2.3 Validating cropland allocation

The parameters and constraints described above are intended to enable our allocation algorithm to extend historical patterns of cropland expansion and distribution into the future. To validate the ability of the allocation algorithm to properly reproduce global patterns of cropland, we compare our estimates for the year 2005 to data from three different sources of global land cover data: MODIS (covering 2001–2012) (Friedl *et al.*, 2010; Channan *et al.*, 2014), GLC2000 (targeting 2000) (Bartholomé and Belward, 2005), and Globcover (targeting 2005) (Bicheron *et al.*, 2008).

It is difficult to quantify and accurately locate cropland in the three datasets because it is distributed across "mixed categories", where it coexists with different types of natural vegetation. These categories are broadly defined and provide only a range of area that can be covered by crops. For example, the mosaic vegetation category in Globcover can contain between 20 and 50% of cropland while MODIS cropland/natural vegetation mosaics category can contain between 40 and 60% of small-scale cultivation. Given the high degree of uncertainty, if the model's results indicate the presence of cropland in a pixel that has been classified in the datasets as a category that could contain cropland, we consider that prediction adequately correct. Based on this approach the allocation of cropland appears to be in good agreement with the location of cropland reported by the three datasets. Of the pixels with cropland allocated by our model, 80%, 87%, and 89% of them are also identified as containing cropland by MODIS, GLC2000 and GlobCover, respectively.

2.4 Assessing the amount of upheaval

Within the context of this exercise, if between 2005 and 2050 the proportion of crops grown in a specific pixel are sufficiently different, the interpretation is that farmers will experience upheaval and likely incur costs to adapt to the new climatic circumstances and socioeconomic pressures.

Upheaval, in this context of the mixture of crops, can occur in several ways. The concept we use is based on the relative share of area that each crop occupies with respect to the total cropland area. We are not primarily concerned with whether the total amount of cropland or the total number of crops in the pixel is increasing or decreasing, but rather with changes to the mixture of crops. Of course, if any crop's relative share increases, there is at least one other crop whose share decreases and vice versa (except in the case of the entirety of cropland appearing in a new pixel, or crops disappearing from an old one); so the question becomes what size and types of changes are important.

We consider four fundamental types of outcomes to characterize upheavals. It could happen that the crop mixture in the future is similar to the crop mixture in the past so that the crop mixture is *stable*. It could also be that one or more crops are *burgeoning*. By this, we mean that at least one crop has a large increase in its relative share when moving from the past crop mixture to the future mixture. The opposite case is when one or more crops are *dwindling*, that is, have a large decrease in their relative share. However, the additional shares for the *burgeoning* crops could be built up from small declines in the other crops, so none qualify as *dwindling*. Using the same logic in the other direction, there can be *dwindling* without any crops *burgeoning*. And finally, the two can occur at the same time: *churning*. These latter three situations (when the relative share of at least one crop changes by a large amount) indicate a large upheaval. Producers will need to adjust to an unfamiliar situation which will impose costs on them. These may be learning and investment to take advantage of new opportunities, or they may simply mean that farmers are no longer able to profitably produce what they were accustomed to.

Operationalizing these concepts within our framework requires handling the directly modeled crops separately from the composite "all others" crop. "All others" will mean different things in different places (e.g. millet or palm plantations), but, on average, it represents about half of cropland area. Therefore, changes in "all others" usually represent more upheaval than similarly-sized changes involving any single specific crop. However, since it is a composite, we cannot directly identify any *churning* occurring within "all others". Thus, we are limited to interpreting the share changes for "all others" to *burgeoning*, *dwindling*, or *stability*.

For the simulated crops, assessing upheaval begins by comparing the mix of crops at the beginning and ending time periods (2005 vs 2050). This is done separately for rainfed and irrigated crops. The relative share of each individual crop is determined by dividing the area of the crop by the total amount of the appropriate type of cropland (excluding "all others") in the pixel. If there is no irrigated cropland in the pixel, all irrigated crops are considered to have zero share and similarly for rainfed. We chose a 20-percentage point change as the threshold that indicates a large enough upheaval to qualify as *burgeoning* or *dwindling*. Hence, if all cropland is lost in the future and some crop had at least a 20% share, it will be classified as *dwindling*. In the opposite case, going from no cropland to some cropland, if some crop will have at least a 20% share, it will be classified as *burgeoning*.

As a result of assessing the directly modeled crops and "all others" separately, there are twelve possible combinations, summarized in Table 1 which can be grouped together into the original four overall types of upheaval.

3. Results

We first explore global changes by looking at results for all five GCMs. We then take a closer look into the underlying spatial heterogeneity, both at global scale and for China in particular, focusing on results from the Geophysical Fluid Dynamics Laboratory GCM (GFDL) (Dunne *et al.*, 2013). We chose GFDL because it is one of the leading climate models used in several assessment reports of the IPCC, and because, among the GCMs used in this study, it tends to produce the most conservative results and, therefore, it provides a lower bound of possible crop mix changes in the future. We focus on China because of its climatic conditions that range from tropical to subarctic (Xin *et al.*, 2013) which often result in highly heterogeneous patterns of crop cultivation (Zhou *et al.*, 2017).

3.1 Overall global areas affected by upheaval

Simulation results indicate that large areas across the globe may experience substantial changes in the mix of cultivated crops. Some of this follows directly from IMPACT projections, which show a 16% expansion in rainfed physical cropland area between 2005 and 2050 globally and irrigated physical area growing by 26%. Any new area drawn from previously uncultivated pixels will, by definition, experience a large upheaval. Climate change will alter which locations will be most attractive for each crop, over and above changes induced by diet shifts, trade effects, and cropland expansion.

Under pressure from broad socioeconomic drivers and climate change, large areas of cropland will experience changes in crop shares of more than 20% and thereby experience upheaval by 2050. The global level results are very similar across all the different GCM projections for future climates. Half of total irrigated area exhibits stability in its cropland mix (the bottom/blue segment of the bar graph in Figure 2); the other half splits almost evenly

Upheaval types		Simplified groupings
1	*1+ burgeoning* (share of at least one crop increases >20%) *1+ dwindling* (share of at least one crop decreases >20%) *All others burgeoning* (share of other crop increases >20%)	*Churning (Both major increases and major decreases in the crop shares)*
2	*1+ burgeoning* (share of at least one crop increases >20%) *1+ dwindling* (share of at least one crop decreases >20%) *All others stable* (changes of other crop <20%)	
3	*1+ burgeoning* (share of at least one crop increases >20%) *1+ dwindling* (share of at least one crop decreases >20%) *All others dwindling* (% of other crop decreases >20%)	
4	*1+ burgeoning* (share of at least one crop increases >20%) *0 dwindling* (no crop of which the share decreases >20%) *All others dwindling* (share of other crop decreases >20%)	
5	*0 burgeoning* (no crop of which the share increases >20%) *1+ dwindling* (share of at least one crop decreases >20%) *All others burgeoning* (share of other crop increases >20%)	
6	*1+ burgeoning* (share of at least one crop increases >20%) *0 dwindling* (no crop of which the share decreases >20%) *All others burgeoning* (share of other crop increases >20%)	*Burgeoning* (Major increases in the share of at least one crop)
7	*1+ burgeoning* (share of at least one crop increases >20%) *0 dwindling* (no crop of which the share decreases >20%) *All others stable* (changes of other crop <20%)	
8	*0 burgeoning* (no crop of which the share increases >20%) *0 dwindling* (no crop of which the share decreases >20%) *All others burgeoning* (share of other crop increases >20%)	

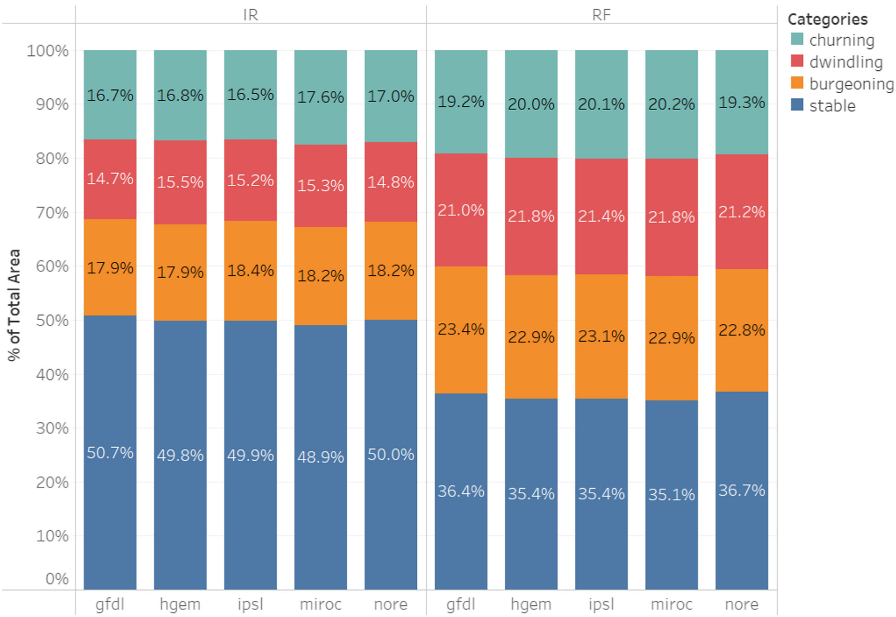
(*continued*)

Table 1.
Types of upheaval related to changes in crop mix

Upheaval types		Simplified groupings
9	*0 burgeoning* (no crop of which the share increases >20%) *1+ dwindling* (share of at least one crop decreases >20%) *All others stable* (changes of other crop <20%)	*Dwindling* (Major decreases in the share of at least one crop)
10	*0 burgeoning* (no crop of which the share increases >20%) *1+ dwindling* (share of at least one crop decreases >20%) *All others dwindling* (share of other crop decreases >20%)	
11	*0 burgeoning* (no crop of which the share increases >20%) *0 dwindling* (no crop of which the share decreases >20%) *All others dwindling* (share of other crop decreases >20%)	
12	*0 burgeoning* (no crop of which the share increases >20%) *0 dwindling* (no crop of which the share decreases >20%) *All others stable* (changes of other crop <20%)	*Stability* (No major increasing nor decreasing shares of any crop)

Source(s): Authors

Table 1.



Note(s): Values based on the average of past and future cropland areas falling into each type
Source(s): Authors; World average, by GCM

Figure 2.
Share of irrigated (left) and rainfed cropland (right) under the four upheaval categories in 2050

between *burgeoning*, *dwindling*, and *churning*. With more cropland in the future, it is not surprising that *burgeoning* (major increase in the share of at least one crop) has a slightly disproportionate share. Rainfed production will be more affected than irrigated across all regions: approximately two-thirds of rainfed areas will experience upheaval. And again, *burgeoning* is the most important type of upheaval observed.

Every region experiences some level of upheaval, and climate change drives most of it. By considering a "no climate change" case (wherein productivity maintains historical patterns), we can assess the amount of upheaval due to non-climate factors. Overall, the share of global rainfed cropland experiencing upheaval from purely socioeconomic factors is 25.8% while climate change pushes that to as much as 64.2%. This is shown in Figure 3, broken out by regions. The effects of socioeconomic trends (as isolated in the no climate change case) appear to be stronger across South Asia and South America. The factors that may cause such shifts range from cropland expansion to diet changes. IMPACT projections show a large change in diet composition for South Asia, especially affecting consumption of cereals and fruits and vegetables (Supplementary Figure S1). The Latin America and Caribbean region shows a smaller effect on diets, but a large increase in harvested area (Supplementary Figures S1 and S2).

3.2 Geographic heterogeneity

Global and regionally aggregated results are useful to highlight major trends, but they hide the finer details of the shifts happening over almost two-thirds of the global production area. To understand this, we map the full set of twelve upheaval categories from Table 1.

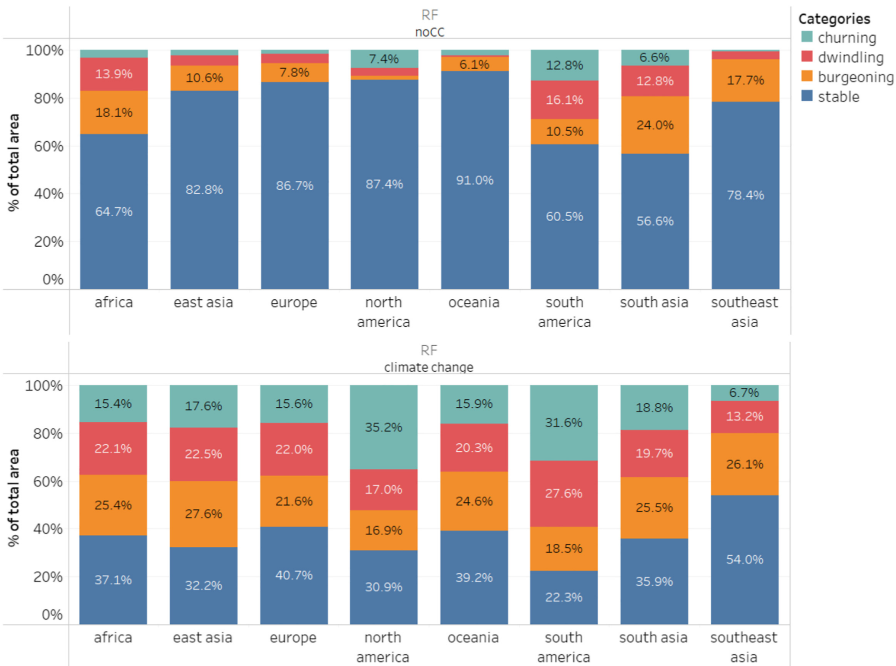


Figure 3.
Share of rainfed cropland under the four categories in 2050, by region

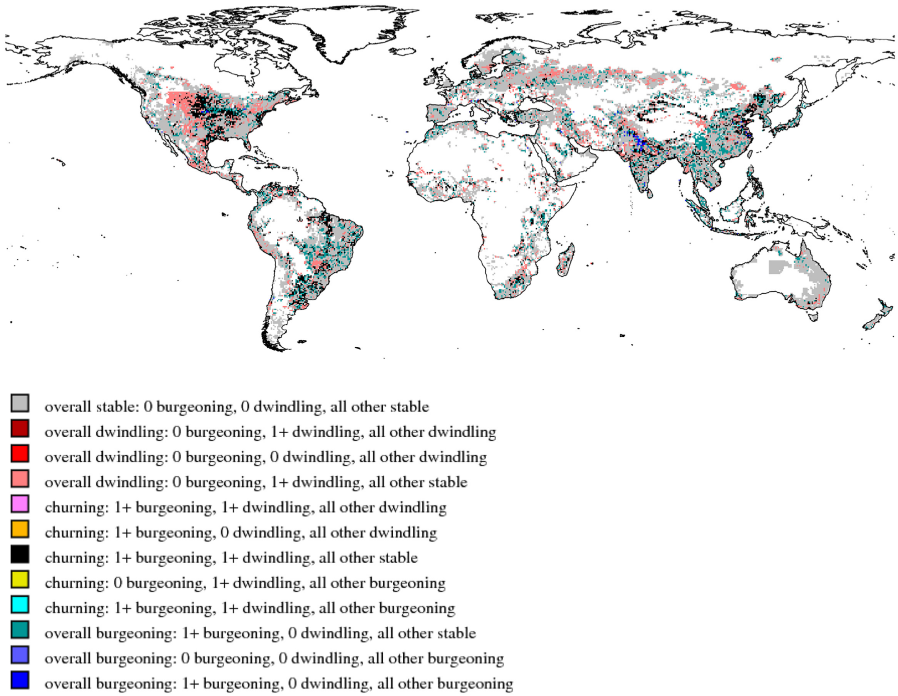
Note(s): Top panel shows share under no CC and bottom panel under climate change. Climate change results show the average effects across all GCMs
Source(s): Authors

Irrigated production systems tend to be focused on specific crops, with the purpose of overcoming water constraints. As a result, they show a limited degree of change in crop composition, compared to rainfed systems. The "all other crops" composite is largely *stable*, except for a few scattered pixels in India and China (Figure 4). The high plains of North America, on the entire latitudinal gradient, show occurrences of *churning* among the five directly modeled crops (black color). A similar geographical north-south arc is visible across the agricultural areas of Argentina and Brazil, in South America. In terms of major geographical movements, we can observe again some *dwindling* in the High Plains of North America and southward movement across Central Asia.

As evidenced by the global totals, rainfed cropland shows a greater variety of upheaval types. The geographic distribution of these types is displayed in Figure 5. Some types show up in widely dispersed locations, especially cases with a simple *burgeoning* or *dwindling* of a single major crop. Others show a higher degree of clustering. One example is West Africa, where the increase in food demand interacts with the variety of crops to show *burgeoning* for "all other crops". Similarly, in Indonesia and Malaysia, the expansion of oil palm falls under "all other crops" in what would otherwise seem to be a stable mix of crops. *Dwindling* of "all other crops" is concentrated in India. Areas exhibiting *churning* of major crops appear to be concentrated in the Indo-Gangetic plain and the Corn Belt of North America (black, Figure 5). Several small pockets of relative *stability* exist on each continent.

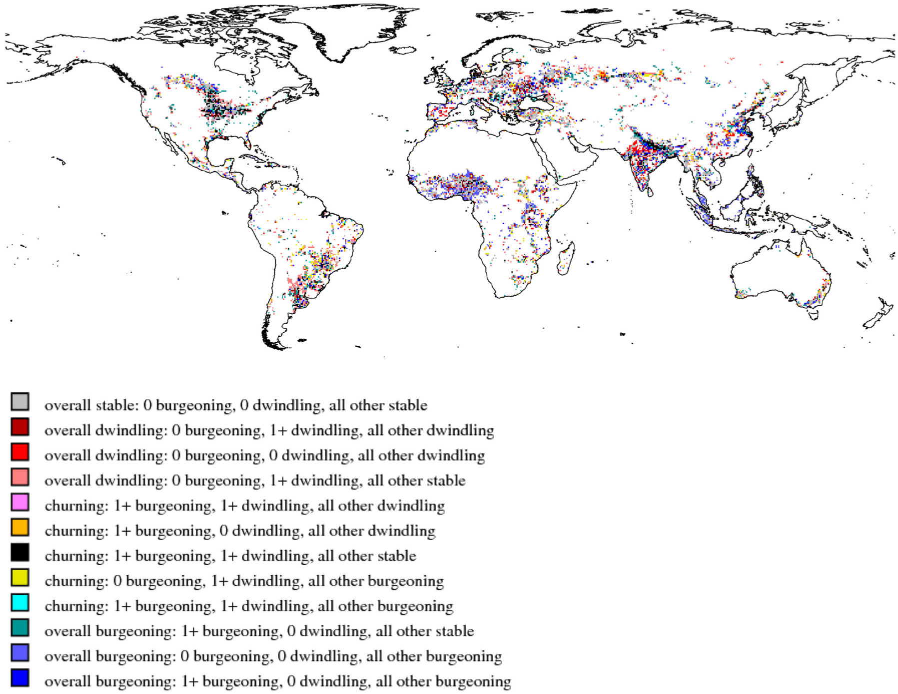
3.3 China case study: sub-national perspective on cropland distribution under future conditions

The global cropland analysis reveals substantial variations in upheaval across and within countries. For example, from Figure 5, West Africa demonstrates a rather uniform increase in



Source(s): Authors

Figure 4. Upheaval types for irrigated cropland: 2005–2050 (GFDL/RCP 8.5)



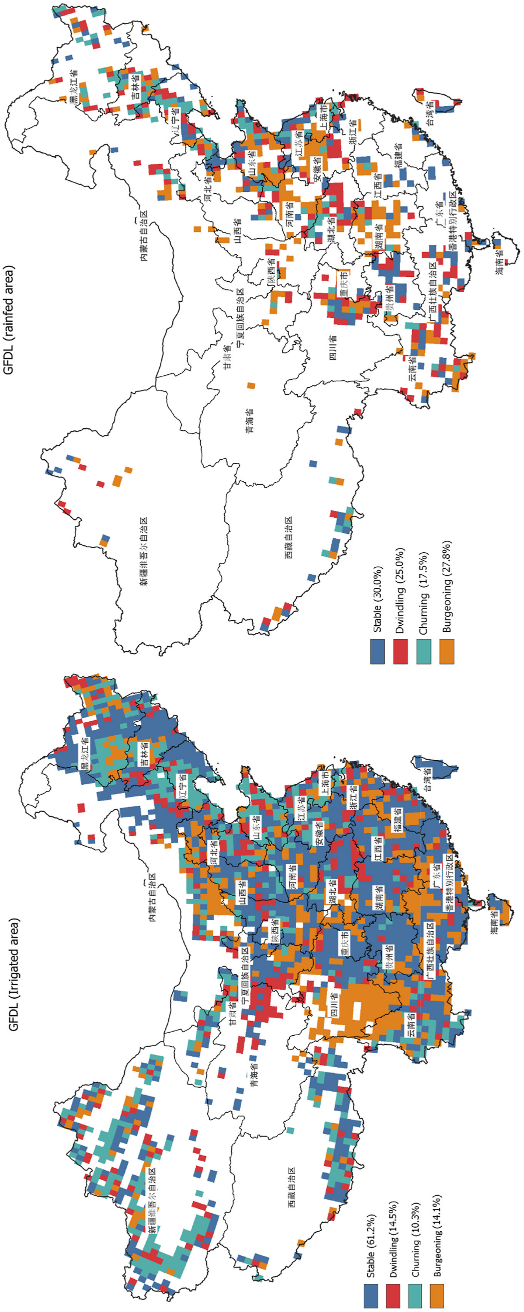
Source(s): Authors

Figure 5.
Upheaval types for rainfed cropland: 2005–2050 (GFDL/RCP 8.5)

the area share for "all other crops", whereas East Asia, especially China, is expected to experience more heterogeneous types of changes in crop mix patterns. Heterogeneity in the spatial distribution of cropland at subnational levels can bring about challenges for the design of agricultural policies aiming at transformational adaptation, since different interventions need to be designed according to local conditions.

In this case study, we follow the same approach used for the global analysis and explore the changing spatial pattern of crop mixtures in China for a particular climate projection (GFDL). We use this climate projection in order to maintain quantitative consistency with the global assessment. Qualitatively, we observe similar geographic patterns for the other GCMs. From 2005 to 2050, the crop mixture on irrigated cropland (Figure 6 left panel) in China is likely to remain stable, except in southwest Sichuan and northern Guangxi where agricultural cultivation is historically characterized by diverse crops, intensive land use, extensive terracing, irrigation, and crop rotation.

Rainfed cropland (Figure 6 right panel) is anticipated to experience substantial upheaval, especially in the major maize production regions in the north. Major increases in the shares of at least one crop (*burgeoning*) are projected for 27.8% of total rainfed cropland, with the bulk expected in northern Anhui, which is predominantly engaged in rice and wheat production. *Dwindling* (major decreases in a crop share) is expected for 25% of total rainfed area, mainly located in the major production areas of Hubei and Jiang-Huai Regions. Interestingly, major upheavals are expected to occur at the border between different crop production regions. For example, *burgeoning* is projected for the mid-lower Yangtze River and middle Huai River Valley, which are at the transition between rice-dominated and wheat-dominated farming



Note(s): Left, irrigated; Right, rainfed
Source(s): Authors

Figure 6.
Upheaval types for cropland in China: 2005–2050 (GFDL/RCP 8.5)

systems or have been historically accustomed to different crop cultivations (Detailed results of all 12 upheaval types are provided in Figure S3 in the Supplementary Information)

4. Discussion and conclusions

Pressure from climate change and from continued growth in population and income are expected to fuel the appetite for more cropland while also changing the composition of the commodities being demanded. Our global modeling exercise shows that these changes will not only drive cropland extensification, but they will also lead to some crop migration and changes in the mix of crops grown in any particular location. The majority of cropland will experience some level of upheaval by 2050 by having at least one crop changing its relative share by 20% or more, compared to 2005. We find that adaptation to climate change is responsible for the largest share of these shifts across all regions of the world. On average, this spontaneous adaptation will entail some combination of crop migration or reshuffling over roughly 50% of global irrigated cropland, and 65% of rainfed cropland.

There is already evidence that changes in climate across the last few decades have altered the distribution of cropland considerably (Reilly *et al.*, 2003; Cho and McCarl, 2017; Leng and Huang, 2017; Wang and Hijmans, 2019; Nainggolan *et al.*, 2023), and that some of the most damaging impacts of warming on major crops (rice, wheat, maize) have been moderated by geographical migration of these crops over time (Sloat *et al.*, 2020). As noted by Nainggolan *et al.* (2023), areas where large changes in crop mix patterns are observed reveal either a large potential for adaptation and/or starting conditions with especially low resilience. Regional differences notwithstanding, the magnitude of the challenge across the next few decades appear dauting and will require massive resource mobilization. Although rapid and deep cuts in greenhouse gas emissions may prevent global warming of 1.5 °C or 2 °C during the 21st century, global surface temperatures are projected to continue increase until at least mid-century (IPCC, 2021). Investments in planned adaptation are therefore crucial to avoid the harsh human and economic toll of climate impacts even over the relatively short term (IPCC, 2022).

Our results suggest that while some producers may not need to substantially change their production system for the time being, the majority will need to. Of those facing large upheaval, some will be able to adapt on their own; others will require some form of support. Even though the model allocates cropland in a way corresponding to spontaneous adaptation, the scale of upheaval revealed is so large that such spontaneity is unlikely to be successful without planned adaptation. Such support will require cooperation between a network of different actors. For example, in China, some radical changes are anticipated to occur across administrative units, highlighting the need for cooperative efforts among local governments.

Support for adaptation needs to take many forms. Farmers often require the assistance of government and international agencies to adopt appropriate farming practices. Transnational agreements and targeted trade policies may at times be necessary to preserve livelihoods as cropland expands and producers switch to new crop mixes. Rural extension services and agricultural training may improve awareness of the potential benefits of change and diversification (Tacconi *et al.*, 2022). Extension offers technical knowledge and skills, as well as access to new planting material, information about new technologies and risk management strategies. Markets are a key source of opportunity (and risk) for farmers. As production patterns shift, value chains (storage, transportation, transformation, and marketing systems) will need to adjust to properly connect producers to markets and to the cities where consumers reside. This change will require not just financial investments, but long-term planning and anticipatory action to overcome the inertia that makes institutions and infrastructure slow to respond to the challenges brought about by climate change (World Bank, 2009).

Recommendations and assistance should be localized, but also responsive to continued research and development. These will refine our understanding of what changes are in store and what kinds of solutions may be more suitable and can be made available in a timely fashion. For instance, while crop-specific breeding programs and research are necessary, a narrow focus of both policies and agricultural research on only few dominant crops may create lock-in conditions which delay and hamper the adoption of new crops and more diversified systems (Meynard *et al.*, 2018; Roesch-McNally *et al.*, 2018).

Agriculture is a major driver of habitat and biodiversity loss. The future expansion of agricultural land, as well as changes in its distribution and the ensuing land cover patterns may have further dire effects on carbon storage, water quality and the overall resilience of natural habitats (Foley *et al.*, 2011; Tilman *et al.*, 2011; Tilman and Clark, 2014; Green *et al.*, 2019; IPBES, 2019). However, it is unclear what the resulting effects may be across all those dimensions as climate change will reshuffle the distribution of cropland, while also reorganizing the future size and pattern of all ecosystems (Peñuelas *et al.*, 2013; Han *et al.*, 2018; García Criado *et al.*, 2020; Rees *et al.*, 2020; Ruiz-Pérez and Vico, 2020). Opportunities and co-benefits from the projected changes should not be discounted. For example, changes in crop mixes may lead to improvements in agricultural biodiversity, with significant potential positive feedback on production systems (Tacconi *et al.*, 2022).

Overall, our results suggest that a successful worldwide effort to adapt to climate change, along with demand pressures from a more crowded and richer planet, would entail a significant redistribution of cropland use patterns and crop mixes. As described above, such a reorganization of crop production is dependent on many political, socio-economic, behavioral, and environmental factors. Our current modeling construct is able to represent and reproduce some of them. Nonetheless, simulating agricultural futures through the IMPACT model and our allocation algorithm requires significant assumptions about producers' and consumers' behavior that drive demand and supply of food products. Both IMPACT simulations and the validation of the cropland allocation algorithm rely on existing global datasets, which come with their own limitations. Still, sensitivity analysis can be conducted to test the robustness of modeling projections; we have done so for future climate conditions by using multiple GCMs, and for the allocation itself by comparing results against three remotely sensed land datasets. Possibly the main limitation of the current approach is the lack of a feedback mechanism whereby the IMPACT economic model can refine its simulations based on the consequences of cropland redistribution. Such a link could enable a more complete investigation of the consequences of policies meant to alter cropping patterns.

This analysis should serve as a starting point for further investigations, to confirm or invalidate its conclusions. We note that our study relies on a partial-equilibrium economic model and a heuristically based allocation algorithm, and that a similar technique could be applied to the results of other global models of cropland distribution (which employ different mechanisms) to examine the consequences of those assumptions on changes in crop mixtures.

References

Attavanich, W., McCarl, B.A., Ahmedov, Z., Fuller, S.W. and Vedenov, D.V. (2013), "Effects of climate change on US grain transport", *Nature Climate Change*, Vol. 3 No. 7, pp. 638-643, doi: 10.1038/nclimate1892.

Bartholomé, E. and Belward, A.S. (2005), "GLC2000: a new approach to global land cover mapping from Earth observation data", *International Journal of Remote Sensing*, Vol. 26 No. 9, pp. 1959-1977, doi: 10.1080/01431160412331291297.

Bicheron, P., Defourny, P., Brockmann, C., Schouten, L., Vancutsem, C., Huc, M., Bontemps, S., Leroy, M., Achard, F., Herold, M., Ranera, F. and Arino, O. (2008), "GLOBCOVER products description and validation report", available at http://due.esrin.esa.int/files/GLOBCOVER_Products_Description_Validation_Report_I2.1.1.pdf

Birthal, P.S. and Hazrana, J. (2019), "Crop diversification and resilience of agriculture to climatic shocks: evidence from India", *Agricultural Systems*, Vol. 173, pp. 345-354, doi: 10.1016/j.agsy.2019.03.005.

Ceglar, A., Toreti, A., Zampieri, M. and Royo, C. (2021), "Global loss of climatically suitable areas for durum wheat growth in the future", *Environmental Research Letters*, Vol. 16 No. 10, 104049, doi: 10.1088/1748-9326/ac2d68.

Channan, S., Collins, K. and Emanuel, W.R. (2014), *Global Mosaics of the Standard MODIS Land Cover Type Data*, University of Maryland and the Pacific Northwest National Laboratory, College Park, MD, Vol. 30.

Chen, C., Riley, W.J., Prentice, I.C. and Keenan, T.F. (2022), "CO2 fertilization of terrestrial photosynthesis inferred from site to global scales", *Proceedings of the National Academy of Sciences*, Vol. 119 No. 10, e2115627119, doi: 10.1073/pnas.2115627119.

Cho, S.J. and McCarl, B.A. (2017), "Climate change influences on crop mix shifts in the United States", *Scientific Reports*, Vol. 7 No. 1, 40845, doi: 10.1038/srep40845.

Dellink, R., Chateau, J., Lanzi, E. and Magné, B. (2017), "Long-term economic growth projections in the shared socioeconomic pathways", *Global Environmental Change*, Vol. 42, pp. 200-214, doi: 10.1016/j.gloenvcha.2015.06.004.

Dunne, J.P., John, J.G., Shevliakova, E., Stouffer, R.J., Krasting, J.P., Malyshev, S.L., Milly, P.C.D., Sentman, L.T., Adcroft, A.J., Cooke, W., Dunne, K.A., Griffies, S.M., Hallberg, R.W., Harrison, M.J., Levy, H., Wittenberg, A.T., Phillips, P.J. and Zadeh, N. (2013), "GFDL's ESM2 global coupled climate-carbon earth system models. Part II: carbon system formulation and baseline simulation characteristics", *Journal of Climate*, Vol. 26 No. 7, pp. 2247-2267, isi: 000316941400007, doi: 10.1175/jcli-d-12-00150.1.

Foley, J.A., DeFries, R., Asner, G.P., Barford, C., Bonan, G., Carpenter, S.R., Chapin, F.S., Coe, M.T., Daily, G.C., Gibbs, H.K., Helkowski, J.H., Holloway, T., Howard, E.A., Kucharik, C.J., Monfreda, C., Patz, J.A., Prentice, I.C., Ramankutty, N. and Snyder, P.K. (2005), "Global consequences of land use", *Science*, Vol. 309 No. 5734, pp. 570-574, isi:000230735200036, doi: 10.1126/science.1111772.

Foley, J.A., Ramankutty, N., Brauman, K.A., Cassidy, E.S., Gerber, J.S., Johnston, M., Mueller, N.D., O'Connell, C., Ray, D.K., West, P.C., Balzer, C., Bennett, E.M., Carpenter, S.R., Hill, J., Monfreda, C., Polasky, S., Rockström, J., Sheehan, J., Siebert, S., Tilman, D. and Zaks, D.P.M. (2011), "Solutions for a cultivated planet", *Nature*, Vol. 478 No. 7369, pp. 337-342, isi:000296021100036, doi: 10.1038/nature10452.

Friedl, M.A., Sulla-Menashe, D., Tan, B., Schneider, A., Ramankutty, N., Sibley, A. and Huang, X. (2010), "MODIS Collection 5 global land cover: algorithm refinements and characterization of new datasets", *Remote Sensing of Environment*, Vol. 114 No. 1, pp. 168-182, doi: 10.1016/j.rse.2009.08.016.

Fujimori, S., Wu, W., Doelman, J., Frank, S., Hristov, J., Kyle, P., Sands, R., van Zeist, W.J., Havlik, P., Domínguez, I.P., Sahoo, A., Stehfest, E., Tabeau, A., Valin, H., van Meijl, H., Hasegawa, T. and Takahashi, K. (2022), "Land-based climate change mitigation measures can affect agricultural markets and food security", *Nature Food*, Vol. 3 No. 2, pp. 110-121, doi: 10.1038/s43016-022-00464-4.

Gao, Y., Zhang, A., Yue, Y., Wang, J. and Su, P. (2021), "Predicting shifts in land suitability for maize cultivation worldwide due to climate change: a modeling approach", *Land*, Vol. 10 No. 3, p. 295, doi: 10.3390/land10030295.

García Criado, M., Myers-Smith, I.H., Bjorkman, A.D., Lehmann, C.E.R. and Stevens, N. (2020), "Woody plant encroachment intensifies under climate change across tundra and savanna biomes", *Global Ecology and Biogeography*, Vol. 29 No. 5, pp. 925-943, doi: 10.1111/geb.13072.

Ghahramani, A., Kingwell, R.S. and Maraseni, T.N. (2020), "Land use change in Australian mixed crop-livestock systems as a transformative climate change adaptation", *Agricultural Systems*, Vol. 180, 102791, doi: 10.1016/j.agsy.2020.102791.

Globe Task Team (1999), *The Global Land One-Kilometer Base Elevation (GLOBE) Digital Elevation Model*, Version 1.0, Boulder, CO, available at: http://www.ngdc.noaa.gov/mgg/topo/globe.html

Green, J.M.H., Croft, S.A., Durán, A.P., Balmford, A.P., Burgess, N.D., Fick, S., Gardner, T.A., Godar, J., Suavet, C., Virah-Sawmy, M., Young, L.E. and West, C.D. (2019), "Linking global drivers of agricultural trade to on-the-ground impacts on biodiversity", *Proceedings of the National Academy of Sciences*, Vol. 116 No. 46, pp. 23202-23208, doi: 10.1073/pnas.1905618116.

Han, Z., Song, W., Deng, X. and Xu, X. (2018), "Grassland ecosystem responses to climate change and human activities within the Three-River Headwaters region of China", *Scientific Reports*, Vol. 8 No. 1, p. 9079, doi: 10.1038/s41598-018-27150-5.

Hasegawa, T., Fujimori, S., Ito, A., Takahashi, K. and Masui, T. (2017), "Global land-use allocation model linked to an integrated assessment model", *Science of The Total Environment*, Vol. 580, pp. 787-796, doi: 10.1016/j.scitotenv.2016.12.025.

Hoogenboom, G., Porter, C.H., Boote, K.J., Shelia, V., Wilkens, P.W., Singh, U., White, J.W., Asseng, S., Lizaso, J.I., Moreno, L.P. and Pavan, W. (2019), "The DSSAT crop modeling ecosystem", *Advances in Crop Modelling for a Sustainable Agriculture*, Burleigh Dodds Science Publishing, pp. 173-216.

IIASA (2013), "'SSP database'. IIASA (international institute for applied systems analysis)", available at: https://secure.iiasa.ac.at/web-apps/ene/SspDb/dsd?Action=htmlpage&page=about

IPBES (2019), *Summary for Policymakers of the Global Assessment Report on Biodiversity and Ecosystem Services of the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services*, in Díaz, S., *et al.* (Eds), IPBES, Bonn.

IPCC (2021), "Summary for policymakers", in Masson-Delmotte, V., Zhai, P., Pirani, A., Connors, S.L., Péan, C., Berger, S., Caud, N., Chen, Y., Goldfarb, L., Gomis, M.I., Huang, M., Leitzell, K., Lonnoy, E., Matthews, J.B.R., Maycock, T.K., Waterfield, T., Yelekçi, O., Yu, R. and Zhou, B. (Eds), *Climate Change 2021: the Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*, Cambridge University Press, Cambridge, and New York, NY.

IPCC (2022), "Summary for policymakers", in Portner, H.-O., Roberts, D.C., Tignor, M.M.B., Poloczanska, E., Mintenbeck, K., Alegría, A., Craig, M., Langsdorf, S., Löschke, S., Möller, V., Okem, A. and Rama, B. (Eds), *Climate Change 2022: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*, Cambdrige University Press, Cambridge and New York, NY.

Jones, J.W., Hoogenboom, G., Porter, C., Boote, K., Batchelor, W., Hunt, L., Wilkens, P., Singh, U., Gijsman, A. and Ritchie, J. (2003), "The DSSAT cropping system model", *European Journal of Agronomy*, Vol. 18 Nos 3-4, pp. 235-265, isi:000180565100003, doi: 10.1016/s1161-0301(02)00107-7.

Leclère, D., Obersteiner, M., Barrett, M., Butchart, S.H.M., Chaudhary, A., De Palma, A., DeClerck, F.A.J., Di Marco, M., Doelman, J.C., Dürauer, M., Freeman, R., Harfoot, M., Hasegawa, T., Hellweg, S., Hilbers, J.P., Hill, S.L.L., Humpenöder, F., Jennings, N., Krisztin, T., Mace, G.M., Ohashi, H., Popp, A., Purvis, A., Schipper, A.M., Tabeau, A., Valin, H., van Meijl, H., van Zeist, W.J., Visconti, P., Alkemade, R., Almond, R., Bunting, G., Burgess, N.D., Cornell, S.E., Di Fulvio, F., Ferrier, S., Fritz, S., Fujimori, S., Grooten, M., Harwood, T., Havlík, P., Herrero, M., Hoskins, A.J., Jung, M., Kram, T., Lotze-Campen, H., Matsui, T., Meyer, C., Nel, D., Newbold, T., Schmidt-Traub, G., Stehfest, E., Strassburg, B.B.N., van Vuuren, D.P., Ware, C., Watson, J.E.M., Wu, W. and Young, L. (2020), "Bending the curve of terrestrial biodiversity needs an integrated strategy", *Nature*, Vol. 585 No. 7826, pp. 551-556, doi: 10.1038/s41586-020-2705-y.

Leng, G. and Huang, M. (2017), "Crop yield response to climate change varies with crop spatial distribution pattern", *Scientific Reports*, Vol. 7 No. 1, p. 1463, doi: 10.1038/s41598-017-01599-2.

Mendelsohn, R., Prentice, I.C., Schmitz, O., Stocker, B., Buchkowski, R. and Dawson, B. (2016), "The ecosystem impacts of severe warming", *American Economic Review*, Vol. 106 No. 5, pp. 612-614, doi: 10.1257/aer.p20161104.

Meynard, J.-M., Charrier, F., Fares, M., Le Bail, M., Magrini, M.B., Charlier, A. and Messéan, A. (2018), "Socio-technical lock-in hinders crop diversification in France", *Agronomy for Sustainable Development*, Vol. 38 No. 5, p. 54, doi: 10.1007/s13593-018-0535-1.

Muller, C. and Robertson, R.D. (2014), "Projecting future crop productivity for global economic modeling", *Agricultural Economics*, Vol. 45 No. 1, pp. 37-50, isi:000329917000004, doi: 10.1111/agec.12088.

Nainggolan, D., Abay, A.T., Christensen, J.H. and Termansen, M. (2023), "The impact of climate change on crop mix shift in the Nordic region", *Scientific Reports*, Vol. 13 No. 1, p. 2962, doi: 10.1038/s41598-023-29249-w.

Nelson, A. (2008), "Estimated travel time to the nearest city of 50,000 or more people in year 2000", Ispra, available at: http://forobs.jrc.ec.europa.eu/products/gam

O'Neill, B.C., Kriegler, E., Riahi, K., Ebi, K.L., Hallegatte, S., Carter, T.R., Mathur, R. and van Vuuren, D.P. (2014), "A new scenario framework for climate change research: the concept of shared socioeconomic pathways", *Climatic Change*, Vol. 122 No. 3, pp. 387-400, isi:000330989300004, doi: 10.1007/s10584-013-0905-2.

Peñuelas, J., Sardans, J., Estiarte, M., Ogaya, R., Carnicer, J., Coll, M., Barbeta, A., Rivas-Ubach, A., Llusià, J., Garbulsky, M., Filella, I. and Jump, A.S. (2013), "Evidence of current impact of climate change on life: a walk from genes to the biosphere", *Global Change Biology*, Vol. 19 No. 8, pp. 2303-2338, doi: 10.1111/gcb.12143.

Rees, W.G., Hofgaard, A., Boudreau, S., Cairns, D.M., Harper, K., Mamet, S., Mathisen, I., Swirad, Z. and Tutubalina, O. (2020), "Is subarctic forest advance able to keep pace with climate change?", *Global Change Biology*, Vol. 26 No. 7, pp. 3965-3977, doi: 10.1111/gcb.15113.

Reilly, J., Tubiello, F., McCarl, B., Abler, D., Darwin, R., Fuglie, K., Hollinger, S., Izaurralde, C., Jagtap, S., Jones, J., Mearns, L., Ojima, D., Paul, E., Paustian, K., Riha, S., Rosenberg, N. and Rosenzweig, C. (2003), "U.S. Agriculture and climate change: new results", *Climatic Change*, Vol. 57 No. 1, pp. 43-67, doi: 10.1023/A:1022103315424.

Riahi, K., Rao, S., Krey, V., Cho, C., Chirkov, V., Fischer, G., Kindermann, G., Nakicenovic, N. and Rafaj, P. (2011), "RCP 8.5-A scenario of comparatively high greenhouse gas emissions", *Climatic Change*, Vol. 109 Nos 1-2, pp. 33-57, isi:000297350200003, doi: 10.1007/s10584-011-0149-y.

Robertson, R. (2017), "Mink: details of a global gridded crop modeling system", Washington D.C, available at: http://ebrary.ifpri.org/cdm/ref/collection/p15738coll2/id/131406

Robinson, S., Mason d'Croz, D., Islam, S., Sulser, T.B., Robertson, R.D., Zhu, T., Gueneau, A., Pitois, G. and Rosegrant, M.W. (2015), *"The international model for policy analysis of agricultural commodities and trade (IMPACT): Model description for version 3"*, IFPRI Discussion Paper 1483, International Food Policy Research Institute (IFPRI), Washington, DC, available at: http://ebrary.ifpri.org/cdm/ref/collection/p15738coll2/id/129825

Roesch-McNally, G.E., Arbuckle, J.G. and Tyndall, J.C. (2018), "Barriers to implementing climate resilient agricultural strategies: the case of crop diversification in the U.S. Corn Belt", *Global Environmental Change*, Vol. 48, pp. 206-215, doi: 10.1016/j.gloenvcha.2017.12.002.

Ruiz-Pérez, G. and Vico, G. (2020), "Effects of temperature and water availability on northern European boreal forests", *Frontiers in Forests and Global Change*, Vol. 3, p. 34, doi: 10.3389/ffgc.2020.00034, available at: https://www.frontiersin.org/article/10.3389/ffgc.2020.00034

Siebert, S., Henrich, V., Frenken, K. and Burke, J. (2013), *Global Map of Irrigation Areas Version 5*, Rheinische Friedrich-Wilhelms-University/Food and Agriculture Organization of the United Nations, Bonn/Rome.

Sloat, L.L., Davis, S.J., Gerber, J.S., Moore, F.C., Ray, D.K., West, P.C. and Mueller, N.D. (2020), "Climate adaptation by crop migration", *Nature Communications*, Vol. 11 No. 1, p. 1243, doi: 10.1038/s41467-020-15076-4.

Tacconi, F., Waha, K., Ojeda, J.J. and Leith, P. (2022), "Drivers and constraints of on-farm diversity. A review", *Agronomy for Sustainable Development*, Vol. 42 No. 1, p. 2, doi: 10.1007/s13593-021-00736-6.

Thiam, S., Salas, E.A.L., Hounguè, N.R., Almoradie, A.D.S., Verleysdonk, S., Adounkpe, J.G. and Komi, K. (2022), "Modelling land use and land cover in the transboundary mono river catchment of Togo and Benin using Markov chain and stakeholder's perspectives", *Sustainability*, Vol. 14 No. 7, p. 4160, doi: 10.3390/su14074160.

Tilman, D. and Clark, M. (2014), "Global diets link environmental sustainability and human health", *Nature*, Vol. 515 No. 7528, pp. 518-522, doi: 10.1038/nature13959.

Tilman, D., Balzer, C., Hill, J. and Befort, B.L. (2011), "Global food demand and the sustainable intensification of agriculture", *Proceedings of the National Academy of Sciences of the United States of America*, Vol. 108 No. 50, pp. 20260-20264, isi:000298034800082, doi: 10.1073/pnas.1116437108.

Unfried, K., Kis-Katos, K. and Poser, T. (2022), "Water scarcity and social conflict", *Journal of Environmental Economics and Management*, Vol. 113, 102633, doi: 10.1016/j.jeem.2022.102633.

van der Hilst, F., Verstegen, J.A., Woltjer, G., Smeets, E.M.W. and Faaij, A.P.C. (2018), "Mapping land use changes resulting from biofuel production and the effect of mitigation measures", *GCB Bioenergy*, Vol. 10 No. 11, pp. 804-824, doi: 10.1111/gcbb.12534.

Vesco, P., Kovacic, M., Mistry, M. and Croicu, M. (2021), "Climate variability, crop and conflict: exploring the impacts of spatial concentration in agricultural production", *Journal of Peace Research*, Vol. 58 No. 1, pp. 98-113, doi: 10.1177/0022343320971020.

Wang, H. and Hijmans, R.J. (2019), "Climate change and geographic shifts in rice production in China", *Environmental Research Communications*, Vol. 1 No. 1, 11008, doi: 10.1088/2515-7620/ab0856.

Wang, S., Zhang, Y., Ju, W., Chen, J.M., Ciais, P., Cescatti, A., Sardans, J., Janssens, I.A., Wu, M., Berry, J.A., Campbell, E., Fernández-Martínez, M., Alkama, R., Sitch, S., Friedlingstein, P., Smith, W.K., Yuan, W., He, W., Lombardozzi, D., Kautz, M., Zhu, D., Lienert, S., Kato, E., Poulter, B., Sanders, T.G.M., Krüger, I., Wang, R., Zeng, N., Tian, H., Vuichard, N., Jain, A.K., Wiltshire, A., Haverd, V., Goll, D.S. and Peñuelas, J. (2020), "Recent global decline of CO2 fertilization effects on vegetation photosynthesis", *Science*, Vol. 370 No. 6522, pp. 1295-1300, doi: 10.1126/science.abb7772.

World Bank (2009), *World Development Report 2010: Development and Climate Change*, World Bank, Washington, DC.

Xin, X., Lin, T., Liu, X., Wan, G. and Zhang, Y. (2013), "The impacts of climate change on the People's Republic of China's grain output", *China Agricultural Economic Review*, Vol. 5 No. 4, pp. 434-458, doi: 10.1108/CAER-03-2013-0049.

Zhou, S., Zhou, W., Lin, G., Cvhen, J. and Jiang, T. (2017), "Adapting to climate change: scenario analysis of grain production in China", *China Agricultural Economic Review*, Vol. 9 No. 4, pp. 643-659, doi: 10.1108/CAER-10-2016-0173.

Supplementary material

The supplementary material for this article can be found online.

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