Aalto-yliopisto
Aalto-universitetet
Aalto University

Master's Programme in Water and Environmental Engineering

Agricultural input contributions to global crop yields

Aino Ahvo

Master's Thesis
2022

Aalto-yliopisto
Aalto-universitetet
Aalto University

Author Aino Ahvo	
Title of thesis Agricultural input contributions to global crop yields	
Programme Water and Environmental Engineering	
Thesis supervisor Prof. Matti Kummu	
Thesis advisor(s) Dr Matias Heino and Dr Vilma Sandström	
Date 28.04.2022 **Number of pages** 51 + 5	**Language** English

Abstract

Food production today is more global than ever. Food trade ensures adequate and diverse food even in areas with low self-sufficiency. Foodstuffs are being traded across the world, but so are agricultural inputs such as fertilizers, machinery, and pesticides. Shocks and disturbances in the trade flows of agricultural inputs, caused by e.g. conflict, may be devastating to the food production and yields of otherwise self-sufficient countries. This aspect of food security and resilience requires more attention. In this study, we modelled the effects of agricultural input shocks using global spatial data on crop yields, fertilizers, machinery and pesticides with random forest, a machine learning algorithm. We show that the most drastic yield losses are caused by shocks in one or multiple fertilizers. Areas with the highest crop yields suffer the most from all agricultural input shocks, while low-yielding areas are seldom affected. Yield losses in these high-yielding 'breadbasket' areas of the world would be detrimental to global food security. Our study provides important information in high spatial definition to be used in future discussions on food security and resilience.

Keywords food security, agricultural input, random forest, fertilizers

Aalto-yliopisto
Aalto-universitetet
Aalto University

Tekijä Aino Ahvo	
Työn nimi Maatalouden tuotantopanosten vaikutus maailman viljelykasvisatoihin	
Koulutusohjelma Water and Environmental Engineering	
Vastuuopettaja/valvoja Prof. Matti Kummu	
Työn ohjaaja(t) TT Matias Heino ja FT Vilma Sandström	
Päivämäärä 28.04.2022 **Sivumäärä** 51 + 5	**Kieli** englanti

Tiivistelmä

Ruoan tuotanto on kansainvälisempää kuin koskaan. Tuonti ja vienti mahdollistavat sen, että ruokaa on saatavilla ja se on monipuolista myös niillä alueilla, joilla omavaraisuusaste on alhainen. Maailman ympäri kuljetetaan ruoan lisäksi myös ruoantuotantoon tarvittavia lannoitteita, torjunta-aineita, koneita ja laitteita. Katkot ja häiriöt maatalouden tuotantopanosten tuontikuljetuksissa voivat olla vahingollisia sellaisten alueiden ruoantuotannolle ja sadoille, jotka ovat muuten omavaraisia. Tähän ruokaturvan ja sen häiriönsietokyvyn ulottuvuuteen on syytä kiinnittää enemmän huomiota. Tässä tutkimuksessa rakensimme random forest -koneoppimismallin selvittääksemme maatalouden tuotantopanosten tuontikatkosten vaikutuksia satoihin käyttäen viljelysatoja, lannoitteita, maatalouskoneita ja torjunta-aineita koskevia maailmanlaajuisia paikkatietoaineistoja. Tulokset osoittavat, että katkokset yhdessä tai useammassa lannoitteessa aiheuttavat suurimmat satomenetykset. Alueet, joilla sadot ovat suurimpia, kärsivät eniten tuotantopanosten katkoista, kun taas matalasatoisilla alueilla vaikutuksia ei juuri näy. Satomenetykset näissä maailman ”vilja-aitoissa” runtelisivat koko maailman ruokaturvaa. Tutkimuksemme antaa lisää tietoa keskusteluun ruokaturvasta ja sen kestävyydestä ja häiriönsietokyvystä.

Avainsanat ruokaturva, maatalouden tuotantopanos, random forest, lannoitteet

Contents

Preface

I want to thank Professor Matti Kummu for giving me the opportunity to work in the Water and Development Research Group (WDRG) on an interesting topic. Thank you for your guidance and indulging me in my passion for data visualization. I also want to warmly thank my advisors Dr Matias Heino and Dr Vilma Sandström for their support, help and technical expertise. I want to thank all WDRG and especially Dr Daniel Chrisendo for great discussions following the presentation of my work. Maa- ja vesitekniikan tuki ry (MVTT) is acknowledged for their financial contribution to this study.

Thank you to my sister and various friends for listening to my dippa troubles with patience, and special thanks to Samu for important ALE-related comments. I want to thank my Mum for spellchecking and everything else. Lastly, I want to thank all the engineers in my life; especially my Dad, who can fix anything, and Vaari, the OG engineer who graduated exactly 70 years ago and continues to inspire us all with his wit and intellect.

Porvoo, 29 April 2022, at 1 am
Aino Ahvo

Abbreviations

ALE	accumulated local effects
FAO	Food and Agriculture Organization of the United Nations
ha	hectare; 10,000 m^2
K	potassium
LOESS	locally estimated scatterplot smoothing
mtry	number of parameters to split nodes in the random forest algorithm
N	nitrogen
NSE	Nash-Sutcliffe model efficiency
ntree	number of trees grown in the random forest algorithm
OOB	Out-of-Bag, data left out in the bootstrapping process of random forest
P	phosphorus
RMSE	root mean square error

1 Introduction

Food is a basic human right (UN, 1948). For this right to be ensured, food security needs to be improved globally and locally. According to the definition of FAO, the Food and Agricultural Organization of the United Nations, food security is achieved when “food is available, accessible, nutritious, and its supply is stable” (FAO et al., 2015). Climate change and climate extremes, economic slowdowns and conflicts are recognized as the biggest threats to and disruptors of global food security (FAO et al., 2021). The capability to respond and adapt to potential disruptions in any of the aspects of food security mentioned above is called resilience (Seekell et al., 2017). Many studies and policy changes to improve resilience have been launched in recent years.

There are two ways to increase resilience related to national and regional food security: increasing food production and increasing trade (Fader et al., 2013). Historically, increased food imports have improved food availability in countries more than increased self-sufficiency (Porkka et al., 2013). Interest in self-sufficiency has, however, grown in recent years (Clapp, 2017) due to e.g. the food crisis of 2007–2008 and more recently the COVID-19 pandemic (Falkendal et al., 2021). Since today’s global food trade network is interconnected and complex, disturbances in some of the nodes can quickly expand to a global scale as e.g. increased food prices (Puma et al., 2015). The trade of food that enhances food security and resilience locally and regionally could reduce resilience on the global scale (Kummu et al., 2020; Seekell et al., 2017).

Global agricultural trade is not only composed of food stuffs, but also agricultural inputs that are used to produce the food (e.g. Lehikoinen et al., 2021). While some countries might be self-sufficient enough in their food system to handle disturbances or shocks in the food trade flows, the efficiency of their food production and yield might be influenced by the trade flows of imported agricultural inputs. The resilience of different countries’ food systems therefore relies on both aspects (Marchand et al., 2016).

The global agricultural trade system can be disturbed by e.g. natural disasters, trade price fluctuations, export bans, global pandemics and geopolitical tensions (FAO, 2015; Heslin et al., 2020; Puma et al., 2015). These can all cause sudden changes or shocks in the flows of food and agricultural inputs, when trade routes are disconnected on purpose, by a crisis, or by a natural disaster. One of the identified causes of the 2007–2008 food crisis was the high price of P fertilizers (up to 800% increase in price), oil and energy. The high price of fertilizers led to failing crops for developing world farmers, food-related unrest in many countries and export bans of food and inputs, as well as increasing government subsidies for fertilizers to combat the price increase (Chowdhury et al., 2017; Cordell and White, 2011; Vidal, 2008). The COVID-19 pandemic lockdowns saw interruptions in shipping and transport logistics and e.g. fertilizer retail store closures due to movement restrictions, exposing the fragility of supply chains of food and agricultural inputs (Amjath-Babu et al., 2020; Garnett et al., 2020). Post-Brexit UK has seen shortages in petroleum and supermarket food, stemming from logistical problems caused by immigration and movement restrictions. These problems have also affected agricultural inputs (Harris, 2021). The container ship Evergiven blocked one of the busiest trade routes on the globe for several days in March 2021. The Suez Canal is an important transport route for many agricultural inputs and their raw materials, including 30% of the world's potassium fertilizers (Sainsbury, 2021). Maritime chokepoints around the world present risks of potential trade route shocks.

The global effects of agricultural input shocks have been studied widely in economic trade models (Beckman et al., 2020; Haile et al., 2016; Kalkuhl et al., 2016; O'Hara et al., 2015) that concentrate on the market price fluctuations of crop inputs. In most of these studies, the actual agricultural input volumes decrease only a few percent even after doubled prices. The "shocks" are thus mild, as are their effects on yield. In a global data-based article Mueller et al. (2012), while not studying agricultural input shocks directly, identify areas of fertilizer overuse where food security could be maintained with considerably less nutrients. These areas are likely to be resilient to shocks in agricultural inputs.

Recent national-level studies examine the agricultural input aspect of food system resilience in more detail. Jansik et al. (2021) report the status of Finnish agricultural input resilience, based on information gathered from stakeholder interviews. All pesticides and most modern seeds are currently imported to Finland, as is energy (electricity and oil). All these inputs have limited replaceability in the event of a shock, but vulnerability is reduced by involving multiple suppliers (countries, vendors) for all inputs. Similarly, Lehikoinen et al. (2021) study the most important Finnish trade relationships connected to food security. They find that Finland relies most on imports for energy, but for other inputs like fertilizers and machinery it is a net exporter, which increases resilience. Both Jansik et al. (2021) and Lehikoinen et al. (2021) highlight Finland's dependency on Russian oil and ammonia. Political instabilities in the region could affect Finnish food production, as shown by planned preparations for the effects of sanctions against Russia during the war in Ukraine (ProAgria, 2022). Nanda et al. (2019) study food security resilience in the face of phosphorus scarcity in India using a qualitative framework based on stakeholder engagement and literature. They find that the most influential factor in India's low phosphorus resilience is the dependence on phosphorus imports, followed by a large proportion of small farms, farmers' low purchasing power and poor soil fertility levels. Targeting these areas with policy changes would improve resilience considerably. Barbieri et al. (2021) study global phosphorus resilience by examining different countries' soil phosphorus reserves, phosphate rock reserves and phosphorus exports. They find that countries with an economy highly dependent on phosphorus rich exports, but low phosphorus soil or rock reserves are most vulnerable to global shocks in phosphorus. Argentina and Indonesia are examples of such vulnerable countries.

These studies highlight the effect of agricultural inputs and their trade on the resilience of different countries, and recognize the risks of agricultural input shocks for global food security (Kalkuhl et al., 2016; Marchand et al., 2016). To our knowledge, however, no studies have been conducted on the effects of agricultural input shocks on crop yields on a global scale. Inspired by previous national-scale agricultural resilience and input shock studies mostly based on expert estimates (Jansik et al., 2021; Nanda et al., 2019), we wanted to take a data-driven approach to find out how shocks in agricultural inputs would affect different global crop yields. We aimed to study whether there are areas and/or crops that are especially vulnerable to shocks in agricultural inputs and what the most important inputs in these vulnerable areas might be. Identifying at-risk areas and crops could benefit further studies on national and global food security in the face of future global change.

2 Background

Agricultural food production today is a complex sum of many factors. Different kinds of crops require different physical, chemical, biological and anthropological interventions to produce adequate yields. Geography, climate and soil composition determine the baseline for agricultural production, but with man-made agricultural inputs, crop yields can be increased. Indeed, modern population growth in the 20th century was possible only after the invention of nitrogen fertilizer manufacture. Food production and yields increased even more dramatically after the Green Revolution, which began in the 1950's and 60's when modern agricultural inputs and practices were introduced. These include synthetic fertilizers, pesticides, improved high yield variety seeds, mechanization of farming, and improved irrigation practices (Evenson and Gollin, 2003; Pingali, 2012).

Despite agrotechnological inventions increasing yields around the globe, environmental conditions and climate still determine the highest achievable yields and much of the spatial and temporal differences between yields. According to Lobell and Field (2007), approximately 30% of yield variability may be explained by climatic characteristics, and Ray et al. (2015) show that 32–39% of global interannual yield variability in maize, rice, wheat and soybean is explained by climate. The effectiveness of different agricultural inputs is not independent from climate either: modern seed varieties and fertilizers work best with large rainfall or irrigation, where increases in yield are 40%, but in hardier or more marginalized environments the yield growth can be only 10% (Pingali, 2012). The effects of agricultural inputs on yield are not always straightforward or universal, and many laboratory, field and statistical analyses have studied their relationships over the years.

2.1 Fertilizers

When crops grow, they assimilate carbon and nutrients into their plant tissue. When a crop is harvested, these nutrients are removed from the ecosystem. Many years of harvesting from the same field will deplete its nutrient reserves if the soil is not well managed or conserved. Nutrients need to be replenished in the soil, either through biological nitrogen fixation with suitable plants, or by adding manure or commercial nutrients. In historical small-scale farming, where animal agriculture was practiced together with farming, manure was easily available to improve nutrient balance in the fields. Today, crop farming and manure production are often separated by geography as well as farm specialization, so farms rely heavily on commercial nitrogen, phosphorus, and potassium fertilizer products (Robertson and Vitousek, 2009). Commercial fertilizer use is more precise and less laborious because the nutrient content per volume is constant and high. For the same amount of nutrients, much more organic fertilizer, such as manure or crop residues is needed than mineral fertilizers.

Globally it is recognized that increased synthetic and mineral fertilizer use in the Green Revolution over the years led to increased yields (Conant et al., 2013). McArthur and McCord (2017) found that yields increased linearly with fertilizer use from 1961 to 2000 when studying countries individually.

The most important nutrients supplied by fertilizers are nitrogen (N), phosphorus (P) and potassium (K). Nitrogen is a vital part of any cell structure in amino acids and proteins. In plants, nitrogen is also important in chlorophyll and photosynthesis. Nitrogen can be synthetized with the Haber-Bosch method, discovered in 1909. Phosphorus is an important component of many organic molecules in plants and animals. Phosphorus fertilizer is manufactured from phosphate rock, a finite natural resource. Depending on the author, phosphorus reserves are estimated to be exhausted in the next 50–100 years (Cordell et al., 2009). Potassium is essential in maintaining the correct osmotic balance in plants and other organisms, as well as functioning in several enzymes. The correct osmotic balance helps plants transport nutrients and is vital in protecting the plant from harsh environmental conditions as well as diseases and pests. Adequate K fertilization also helps plants to assimilate more N fertilizer (Johnston, 2003).

The share of commercial, mineral, inorganic or synthetic fertilizers of total agricultural fertilization varies according to the study source and year. For nitrogen, the inorganic share is estimated to be between 44% and 55.6% in 2000 (Liu et al., 2010; Sheldrick et al., 2002; Smil, 1999; Zhang et al., 2021). For phosphorus, the inorganic share is between 40% and 64.2% (Liu et al., 2008; Lun et al., 2018; Sheldrick et al., 2002). The only global estimate of the share of inorganic potassium is from Sheldrick et al. (2002), 15%, but Liu et al. (2017) estimate that 43.5% of potassium nutrients in 2010 came from inorganic fertilizers in China, the largest fertilizer user of the globe.

The consumption and share of inorganic fertilizers also vary between regions (Figure 1). In Africa and South America, the use of inorganic commercial fertilizers is much more limited than in the rest of the world. Asia uses over 60% of the world's mineral nitrogen fertilizers (Liu et al., 2010). This major share of the global mineral nitrogen fertilizer reserves is still only half of the total nitrogen input in Asia; the rest of the nitrogen comes from manure and biological fixation.

The exact percentages of inorganic fertilizer use are hard to estimate, but the consensus is that commercial fertilizers are a vital part of today's agriculture. They are highly necessary to maintain the food production volumes required for today's world population. Erisman et al. (2008) estimate that 44% of the world population in 2000 was sustained by synthetic nitrogen fertilizers.

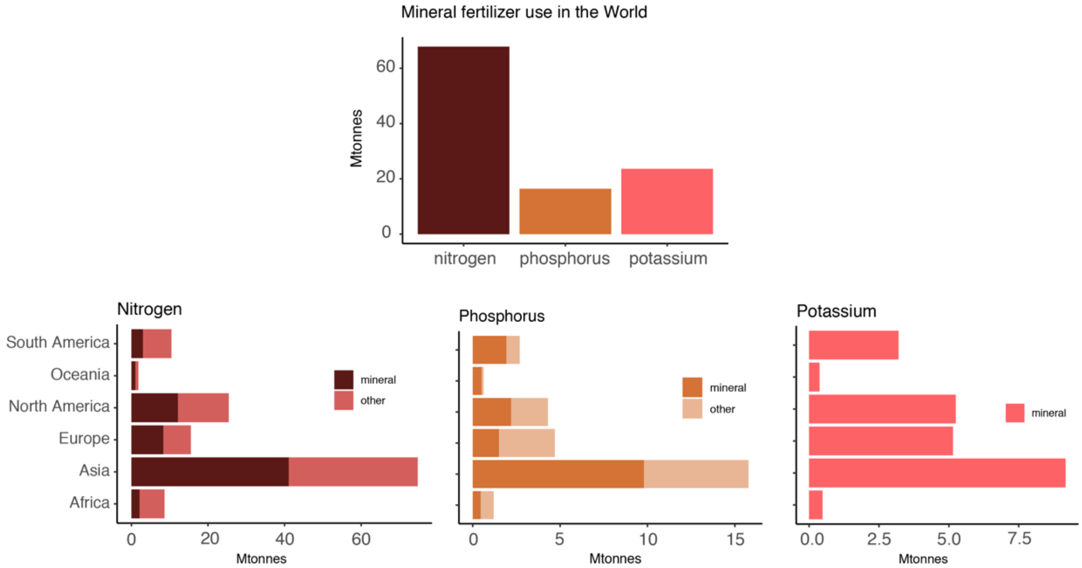


Figure 1: Fertilizer consumption in different continents in 2000. Nitrogen from (Liu et al., 2010), phosphorus from (Lun et al., 2018), and potassium from FAOSTAT (FAO, 2021b). No data was available for non-mineral potassium fertilizer use.

Even though the increase in yields during the Green Revolution was made possible by the use of mineral and synthetic fertilizers, the exact relationships between fertilizers and yields are more difficult to study and they depend on environmental and other factors. Mueller et al. (2017) summarize many nitrogen input vs. yield models and find them all to start with a small or zero intercept, and at low nitrogen input rates yields increase rapidly, but the effect plateaus at higher input rates. After a certain threshold (different for each crop and dependent on climate conditions), adding more nitrogen fertilizer does not increase yield as effectively or does not increase it at all. A similar relationship type is estimated for phosphorus as well as phosphorus and nitrogen interplay (Frank et al., 1990). Summarizing many decades of fertilizer studies, Stewart et al. (2005) conclude that the average share of yield achieved with fertilizers ranges from about 40% to 60% in the USA and England, with higher values in the tropics.

Timing of fertilizer input is also crucial and can affect nutrient use efficiency i.e. assimilation into the crop (Sinclair and Rufty, 2012). The different major nutrients also need to be in balance with each other for best possible results to be achieved.

Many farmers with access to fertilizers and means to purchase them use more fertilizers than theoretically necessary to “be safe”, which contributes to global nutrient pollution from leaching farmlands. Ju et al. (2009) show that in China, nitrogen input is largely excessive, with no changes to yield even if nitrogen input decreased by 50%. Many studies agree that there are great regional and geographical differences in nitrogen use efficiency (e.g.

Mueller et al., 2017; Vitousek et al., 2009), driven by country-specific policies and management practices (Wuepper et al., 2020). Globally, nitrogen input practices and fertilizer need are often out of sync (Cassman et al., 2002); developed countries are able to fertilize an already nutritious soil, whilst in the developing countries the fertilizers added might not be enough to replenish the soil nutrient reserves after harvest. Poorly managed crop fertilization does not increase the crop yield with the full potential of the fertilizers but increases environmental pollution through nutrient leaching and runoff. According to Lassaletta et al. (2014), more than half of the nitrogen input to crops (including organic and inorganic nitrogen) is not assimilated to the crops but lost to the environment.

2.2 Machinery

Machinery and farm mechanization was an important part of the Green Revolution, freeing human and animal labour from all parts of agriculture: crop establishment, harvesting, weeding, application of fertilizers and pesticides, but also from post-harvest operations, storage and further processing. According to Mrema et al. (2014), machinery has several benefits in increasing crop production: the cultivated area can be expanded and the correct timing of agricultural operations is easier. Furthermore, tractors can be used not only in crop production directly, but also in e.g. infrastructure improvement and transportation, indirectly helping to maximize production.

Studies directly linking agricultural machinery and yield are scarce, contradictory, and the effects of machinery are often hard to separate from those of fertilizers. In the developing countries, increase in machinery coincides and correlates with increased cereal yields from 1960 to 2000 (Sims et al., 2016), but the regression is not significant according to McArthur and McCord (2017). In China, 11.8% of the agricultural output or yield growth between 1965 and 1989 has been attributed to farm power or machinery (following fertilizers 21.9%, research 19.8% and institutional change 13.8%) (Mrema et al., 2014). Verma (2006) summarizes many Indian studies on yield increases and mechanization: farms owning or hiring tractors had 12–32% higher yields than traditional manual labour farms. In addition, they show that yields of wheat, rice, sugarcane and potato increase significantly in farms after tractor purchase. Verma (2006) notes, however, that in many studies the yield increases could be attributed to better fertilization and irrigation, which usually accompany more mechanized farms. Singh (2006) used multiple linear regression to study the impacts of fertilizers, irrigation and farm power on yield in Indian farms: they conclude that irrigation contributes most to yield, followed by farm power and then fertilizers (standardized regression coefficients 42%, 32% and 26% respectively).

The studies of the effects of machinery and mechanization on yield have focused on the transition from human and animal power to machines, mostly during the Green Revolution. In developed countries, precision agriculture is highly mechanized, and larger yields rely more and more on agricultural technology (Jansik et al., 2021). Agricultural machinery is highly dependent on skilled experts and specific spare parts for its repair, which in turn are dependent on trade flow functionality. More studies are needed on the degree of precision agriculture and its effect on yield.

2.3 Pesticides

FAO defines pesticides as substances used for "repelling, destroying or controlling any pest, or regulating plant growth". The term "pest" includes insects, plant pathogens, weeds, fungi, molluscs and rodents among others. According to estimates by FAO (2021d), these pests decrease global crop yields between 20% and 40% each year.

The Green Revolution increases in yield are in part explained by the use of pesticides (Cooper and Dobson, 2007). Pesticides have allowed for food production to expand to areas unsuitable without pest control and for some crops to be planted earlier in otherwise suboptimal conditions, lengthening the growing period and increasing yields. In addition to quantity increasing, the quality of crops has also improved in part due to pesticides. Pesticide use has freed manpower from manual and mechanical weeding and other intensive crop management. Pesticide use has enabled farmers to modify production systems and to increase crop productivity without sustaining the higher losses likely to occur from an increased susceptibility to the damaging effect of pests (Oerke et al., 2012).

Webster et al. (1999) calculate a 160% to 185% increase in yield due to pesticide use, and Zhang et al. (2015) show a statistically significant positive effect of pesticides on rice, cotton and maize production in China. The same study also finds that pesticides are heavily overused for these crops. Globally, pesticide use rates vary depending on crop and climate, but also depending on e.g. farm size. Many studies identify risk-averse behaviour in pesticide use: farmers are prepared to spray more pesticides to be safe (Jørgensen et al., 2019). This seems to be the case at least in developed countries; Ghimire and Woodward (2013) found evidence of over-use of pesticides at high GDP per capita levels but under-use in low GDP per capita level countries.

Approximately 3 million tonnes of pesticides were used in 2000 globally. There are geographic differences in pesticide use: Asia uses as much pesticides as the other continents combined (Figure 2) (FAO, 2021c). China, USA, Brazil and Argentina are the biggest users in absolute tonnes (Maggi et al., 2019). Global use has been growing steadily through the years.

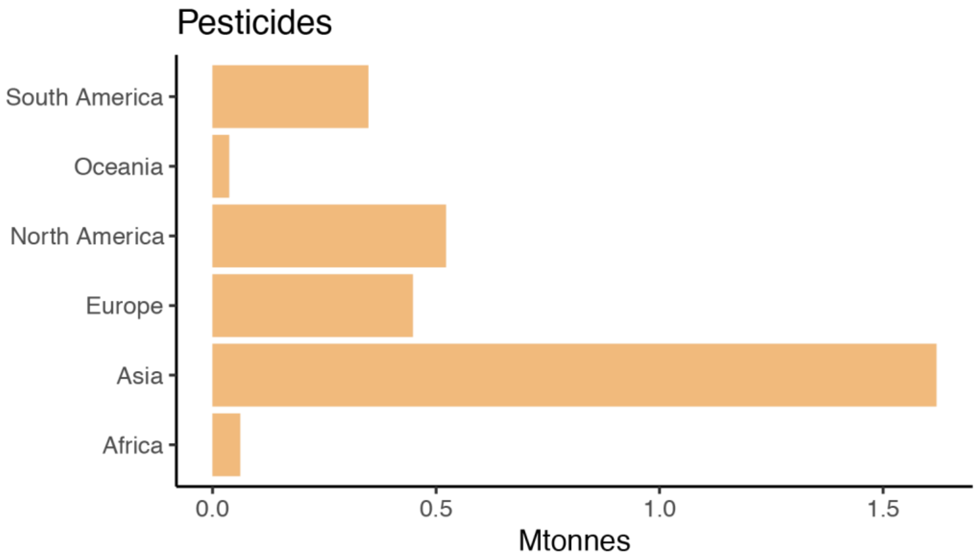


Figure 2: Pesticide use in different continents of the world. Data from FAO (2021c).

3 Material and methods

Global spatial data on crop yields and agricultural inputs was used to construct models with a machine learning method. Effects of climate were addressed by modelling yields and agricultural inputs in different climate bins.

3.1 Data

Agricultural input and climate bin data was available for 12 crops, that were thus selected for analysis: barley, cassava, groundnut, maize, millet, potato, rice, sorghum, soybean, sugarbeet, sugarcane and wheat.

Yield data (tonnes/ha) was sourced from Monfreda et al. (2008). It represents the average yield between 1997 and 2003, thus minimizing the effect of interannual yield variability. For production calculations, harvested area (ha) from the same dataset was used (Table 1).

Fertilizer grid data was acquired from the EarthStat website by request. Only the mineral part of fertilizer application in Mueller et al. (2012) was used, as it is affected by trade. Atmospheric deposition or manure-based fertilization was not taken into account in this analysis.

For machinery use, World Bank data from FAO (2021a) was aggregated across multiple years to an average for each country and transformed into a raster. If the World Bank data source did not have machinery data for a particular country, the average of the continent was used. In the case of Sub-Saharan Africa, the continent average was missing from the original data and was calculated as an average of those Sub-Saharan countries for which data was available. The machinery data is not crop-specific, but rather a proxy measure of the degree of agricultural mechanization used in the area.

Pesticide data from Maggi et al. (2019) consists of application rate data of the 20 most used pesticides for each crop class. Crop-specific pesticide data was available for wheat, maize, rice and soybean. For the eight other crops, the aggregate class Other was used, as classified by Maggi et al. (2019). The pesticide data was given as high and low estimates, but for our analysis, a mean estimate was calculated from these. Furthermore, the 20 different pesticide application rates were rescaled by giving the highest application rate of each pesticide the value 1. The 20 rescaled pesticide grids were then summed together. This way we were able to decrease the amount of pesticide variables to just one, while retaining the significance of each individual pesticide. Straight-forward summing of individual pesticides would have masked the active ingredients that are only needed in smaller quantities.

We included a statistic for irrigation in our model, as irrigated crops have higher yields (Lobell et al., 2009). According to Wang et al. (2021), global irrigated wheat yields are 34% larger than rainfed yields, and irrigated maize yields are 22% larger than rainfed yields. They also discovered geographic and climatic differences in the effect of irrigation on yield: the largest effects of irrigation on yield increase are found in drier areas like the US Great Plains, Southern Europe and Northern China. Irrigation also enhances the effect of fertilization: the same fertilizer input produces higher yields on irrigated crops than on non-irrigated, based on empirical studies by e.g. Di Paolo and Rinaldi (2008) as well as yield modelling results by Mueller et al. (2012). Even in a situation of agricultural input shocks, the infrastructure for irrigation would remain unchanged and could potentially alleviate the effects of decreased inputs. Irrigated and rainfed harvested area was sourced from Portmann et al. (2010), and for our analysis it was transformed to the share of harvested area under irrigation (%).

Table 1: Spatial datasets used as input for the model.

name	*unit*	*timeframe*	*notes*	*reference*
Yield	kg/ha	2000 – Average of census data between 1997–2003	Crop-specific	Monfreda et al. (2008)
Precipitation and temperature	mm, °C	Historical climate data 1970–2000 averaged	Crop-specific, calculations modified from (Mueller et al., 2012)	WorldClim data from Fick and Hijmans (2017)
Machinery	Tractors/ 100 km^2	1995–2005	not crop-specific	FAO (2021a)
Fertilizer application rate	kg/ha	2000*	Crop-specific, mineral fertilizer only	Mueller et al. (2012)
Pesticide application rate	kg/ha	estimation for year 2015	Crop-specific for maize, rice, soybean and wheat, aggregate classes for others	Maggi et al. (2019)
Share of harvested area under irrigation	%	annual irrigation averages around the year 2000	Crop-specific	MIRCA2000 data from Portmann et al. (2010)

* From Mueller et al. (2012): "Data represents the year 2000 largely as a collection of data from 1999, 2000. Data for some countries is as old as 1994 or as recent as 2001."

3.2 Methods

3.2.1 Climate bins

To control for the yield variation caused by climate, we divided each crop into climate zones or bins according to temperature and precipitation in order to study the variation in yield caused only by the agricultural inputs. For example, crops in Finland are compared to crops in similar climate bins in Canada, Russia and China to capture the relationships between inputs and yield in their respective climates. The climate bin method has been used successfully before in global agricultural production analyses (Johnston et al., 2011; Licker et al., 2010; Mueller et al., 2012). In our study, the climate bin method is differs from earlier methods with respect to data analysis and research questions were different: Johnston et al. (2011) and Licker et al. (2010) use growing degree days (GDD) and the soil moisture index to construct the climate bins, while Mueller et al. (2012) use GDD and precipitation and divide the bins by equal harvested area. All earlier climate bin methods discarded the bottom 5% of observations with the lowest harvested area, but our study did not. Earlier methods have generated 100 climate bins, we used 25 to have more datapoints in each climate bin.

In this study, to create climate bins with equal amounts of datapoints, WorldClim weighted mean temperature and total precipitation 5 arcmin grid data were used (Fick and Hijmans (2017), Table 1). For each crop area, temperature and precipitation were divided into 5 quantiles to group the crop area into 25 different climate zones (see example in Figure 3).

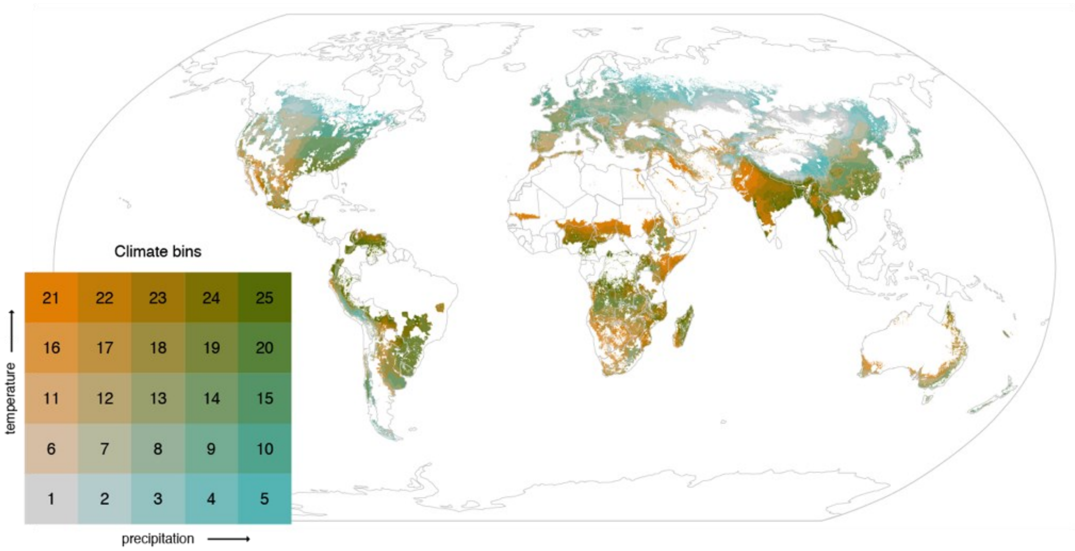


Figure 3: Calculated climate bins for wheat. Each climate bin represents an area with similar temperature and precipitation characteristics.

3.2.2 Random forest regression

Following division into climate bins, preliminary examination of the agricultural input data revealed that the relationship between that data and with crop yields was not linear, and that the different inputs correlated together (e.g areas with high fertilizer input also have high pesticide input). A machine learning approach was thus selected, as it can handle non-linear relationships and predictor interactions and is able to process many different types of datasets with minimal intervention (Leng and Hall, 2020).

Random forest (Breiman, 2001) is a machine learning algorithm based on classification and regression trees (Breiman et al., 2017) with some special modifications. Firstly, the tree is constructed with bootstrapped data, i.e. a random subset of the data with resampling. Within each node of the tree, a defined number of randomly selected parameters is used to split the node so that the weighted variance is minimized. Hundreds or even thousands of trees are constructed like this, making them uncorrelated and preventing overfitting (i.e. fitting the model too well to the training data without learning any general relationships). The final output of the random forest regression is the average of all the output values of the individual uncorrelated trees in the forest. Random forest can be adjusted with different hyperparameter values (Probst et al., 2019). A larger number of trees grown (*ntree*) improves the accuracy of the random forest but increases the required computing power. The number of parameters used to split the node (*mtry*) is usually set to p/3 in case of regression, where p is the number of variables in the model. The third hyperparameter value is *nodesize* which is the minimum number of observations remaining in the tree's terminal (leaf) node. The default value for regression trees is 5. Smaller *nodesize* values lead to deeper trees, because more nodes are needed to reach the small terminal nodes. The random forest default values have been shown to produce good results (Fernández-Delgado et al., 2014).

As random forest is essentially a black box model, some specialized analyses are needed to distinguish the effect of different parameters on the forest result. For our model, we used accumulated local effects or ALE plots to analyze model behaviour (Apley and Zhu, 2020; Zhao and Hastie, 2021). In ALE, different variable effects are separated from their combined effects by calculating differences in model predictions when changing the parameter at certain intervals. The ALE score is the parameter effect in relation to the average of the model.

In the past, random forest has been used for yield predictions with smaller scale climate, irrigation and satellite data (Chlingaryan et al., 2018; Everingham et al., 2016; Fukuda et al., 2013; Johnson et al., 2016; Newlands et al., 2014). It has also been used in agricultural modelling to help select the important variables for constructing another type of model (Tulbure et al., 2012).

Jeong et al. (2016) study the random forest algorithm in global yield predictions in comparison with multiple linear regression. They find that in global wheat yield prediction as well as smaller scale maize and potato yield prediction, random forests outperform multiple linear regression in prediction accuracy. However, Jeong et al. (2016) uses mostly meteorological and geophysical variables and only one agricultural input (nitrogen). In predicting yield variability in time and space, Feng et al. (2018) and Leng and Hall (2020) also find that random forest performs better than regression or process-based models, but they only use climate data. To our knowledge, no random forest analyses have been done with only global, trade-dependent agricultural input data.

With the modelling method selected and data pre-processed, the random forest models for each of the 12 crops and their 25 climate bins were constructed. The agricultural input and yield data were assigned into their respective climate bins and transformed into dataframes, where each row consisted of a 5 arcmin grid cell and all its agricultural input and yield data.

Random forest regression was performed with R package randomforest (Liaw and Wiener, 2002) on each climate bin individually. To minimize overfitting and spatial autocorrelation, the data in each climate bin was divided into 60 arcmin grids, that were randomly assigned to training and testing data (75% and 25%, respectively).

The training data was used to construct the forest with hyperparameter values mtry = 2, ntree = 1000 and nodesize = 5. Default hyperparameter values were used for all forests for all crops, as preliminary testing with hyperparameter tuning showed little or no improvement to model performances.

Model performance was visualized and measured by comparing the model predictions of the testing data to the known original yields, and root mean square error (RMSE) and Nash-Sutcliffe model efficiency (NSE) values were calculated. RMSE-scores of the different crop models are relative to the average yields, which can vary considerably between crops. Another way to examine model performance in a more standardized manner is the Nash-Sutcliffe model efficiency score, which varies between $-\infty$ and 1, 1 describing a perfect model and values ≤ 0 describing a model that has the same predictability as a mean value. Values between 0 and 1 indicate an acceptable performance (Moriasi et al., 2007).

In addition, the random forest algorithm performs similar validation by using the Out-of-Bag (OOB) data, i.e. data that is left out by the algorithm when bootstrapping the data for different trees in the random forest. The OOB and test data validation processes can be used to investigate the possible overfitting of the model. If the OOB validation scores are significantly better than the test data validation scores, the model may be overfitted to the original training data. Yield modelling with machine learning does not yet have established metrics for evaluating models, but we are using the same methods as Jeong et al. (2016).

The constructed forest was then used to predict different agricultural input shock scenario effects on crop yield. The scenarios tested were individual input shocks (N-rate shock, P-rate shock, K-rate shock, machinery shock, pesticide shock), shock to all fertilizers, and shock to all inputs. Three degrees of shock severity were used for each scenario: 25%, 50% and 75% decreases in scenario inputs.

For each bin, forest construction and scenario prediction were iterated 50 times with results saved from each iteration. We were thus able to calculate prediction variances between iterations, improving the estimation of model stability (Leng and Hall, 2020).

All analyses and calculations were performed using R software version 4.0.4 (R Core Team, 2021) using R Studio. The code is available in github: https://github.com/ahvoa/shock_pub

4 Results

4.1 Model evaluation

We evaluated the random forest models by comparing the trained model with the test data. Figure 4 presents the root mean square errors (RMSE) of each climate bin for wheat, calculated with the OOB method (leaving out data when constructing the model with training data) and manually comparing with the test data. The RMSE-scores are not significantly different in the training and the testing data.

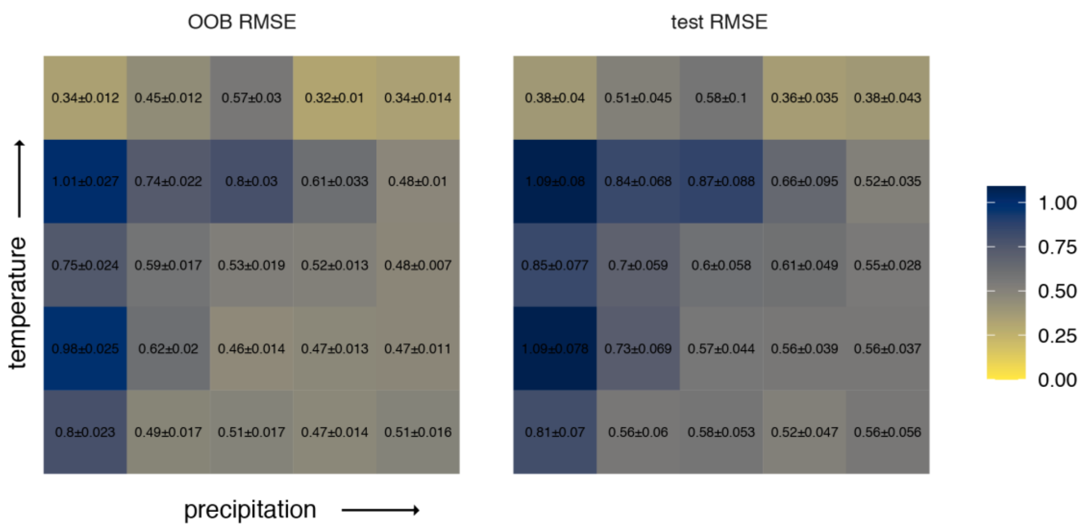


Figure 4: Wheat model RMSE (root mean square error) scores calculated while training the model (OOB RMSE) and with the test data (test RMSE). A lower score denotes less error and thus a better model.

Because RMSE-scores are calculated relative to the average yield of crops, a more objective indicator of model performance, NSE, was calculated. For most of the crops and climate bins, the NSE-scores are above 0.65 (Figure 5), indicating that the models have good (NSE > 0.65) or very good (NSE > 0.75) simulation results and predicting power (Moriasi et al., 2007). The scores for sugarbeet seem to be especially high, while cassava and groundnut climate bins 1–4 have very poor scores. Scenario predictions from these poorly scored climate bins were examined with caution.

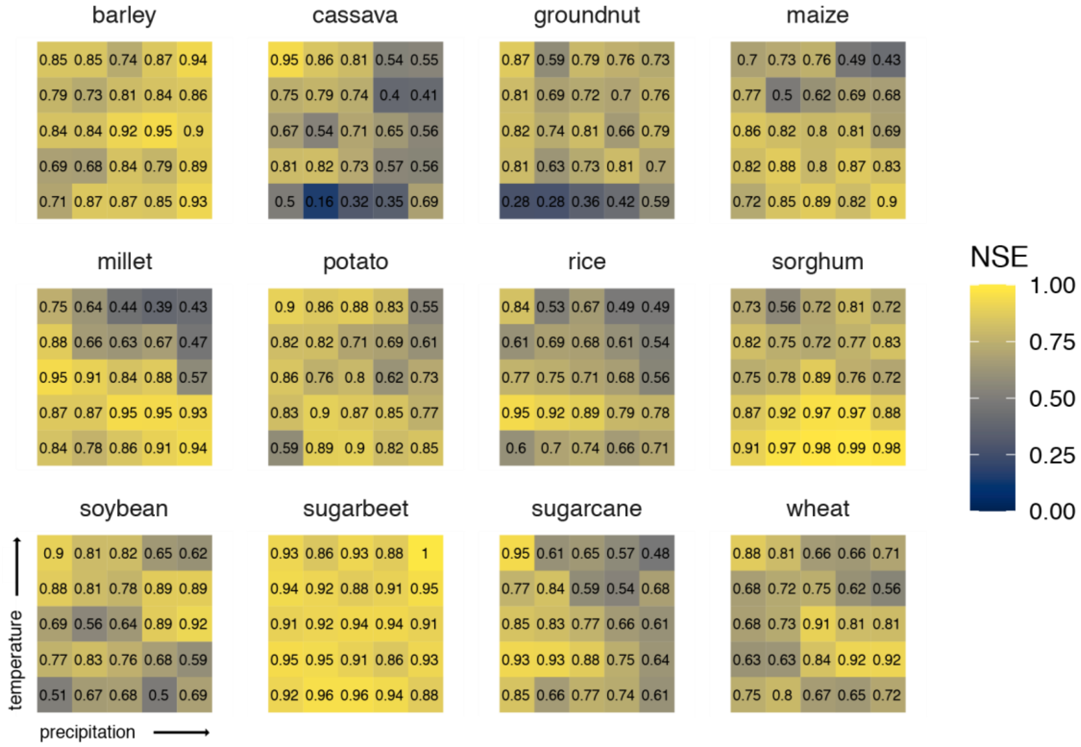


Figure 5: NSE (Nash-Sutcliffe model efficiency) scores for all crops. A score above 0.5 denotes a satisfactory model, above 0.65 a good model and above 0.75 a very good model.

Model validation was further studied by plotting observed and modelled yields from the testing dataset that was left out when constructing the model (Figure 6). Visual inspection reveals that in many models, the linear regression line of the observed vs. modelled yield follows the 1:1 red line quite well. The deviations suggest that lower yields are predicted to be slightly higher than their observed values, whilst higher yields are slightly lower in the prediction than observed.

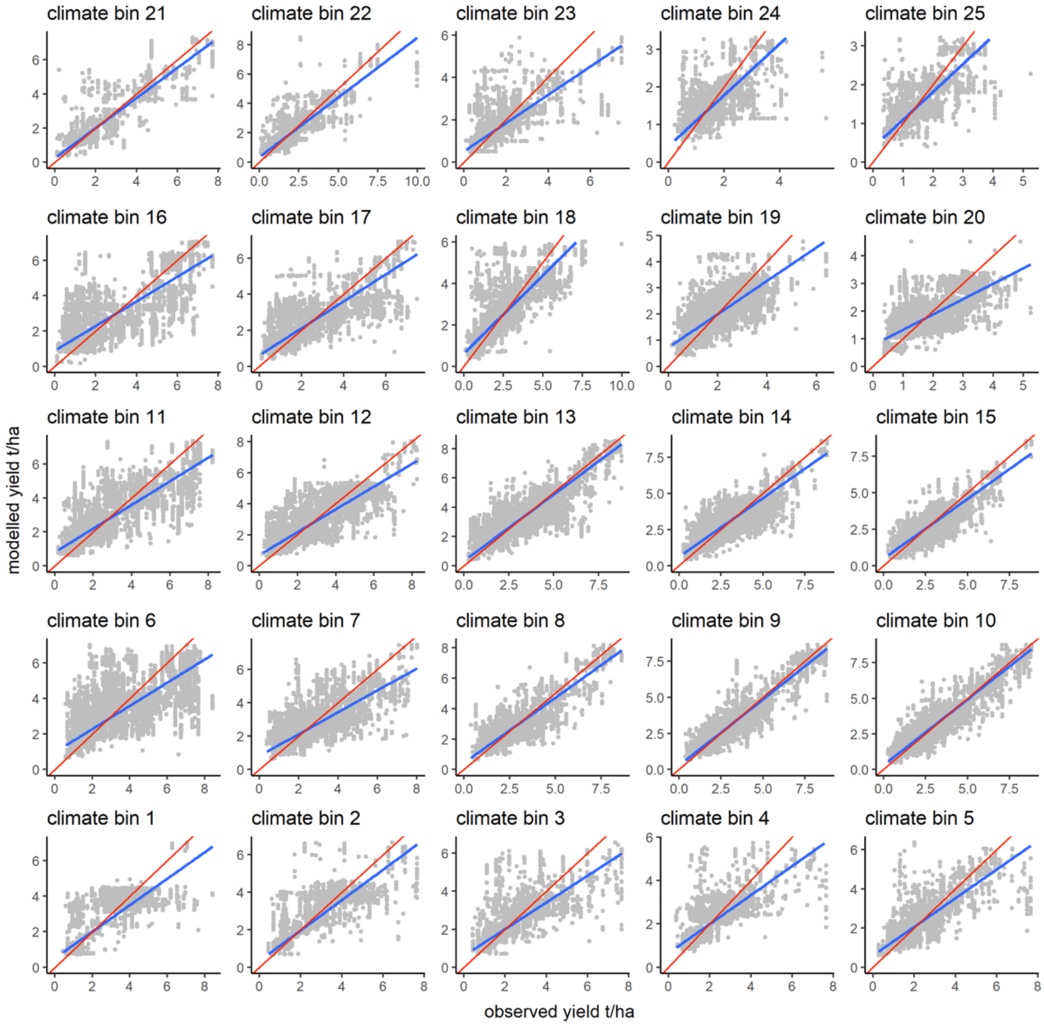


Figure 6: Wheat validation scatterplots comparing the observed (x-axis) and modelled (y-axis) yields from the test dataset. The red diagonal line denotes the 1:1-line where modelled yields would be identical to original yields. The blue line represents linear regression between the observed and modelled yields.

4.2 Model behaviour

Model behaviours, i.e. the relationships of each parameter to yield, were studied using accumulated local effects (ALE) plots. The differences between model iterations in each bin were inspected visually (Figure 7). The plots show what the effect of each parameter with different input rates is compared to the average prediction. For example, for a machinery rate above 500 tractors/km2, the predicted yield is 1 kg/ha higher than the average prediction. There is some deviation in ALE-scores between different iterations of the model, especially for fertilizers and machinery. This group of ALE plots is very representative of the other crops and climate bins: usually the ALE-scores of pesticides and irrigation are very limited and they have little deviation between iterations. Fertilizers and machinery have more variability in their effects on the model. For this particular wheat climate bin 10, the high N-rate, K-rate and machinery have a positive effect on the yield. In the agricultural input shock scenarios, it could be expected that these inputs are also critical.

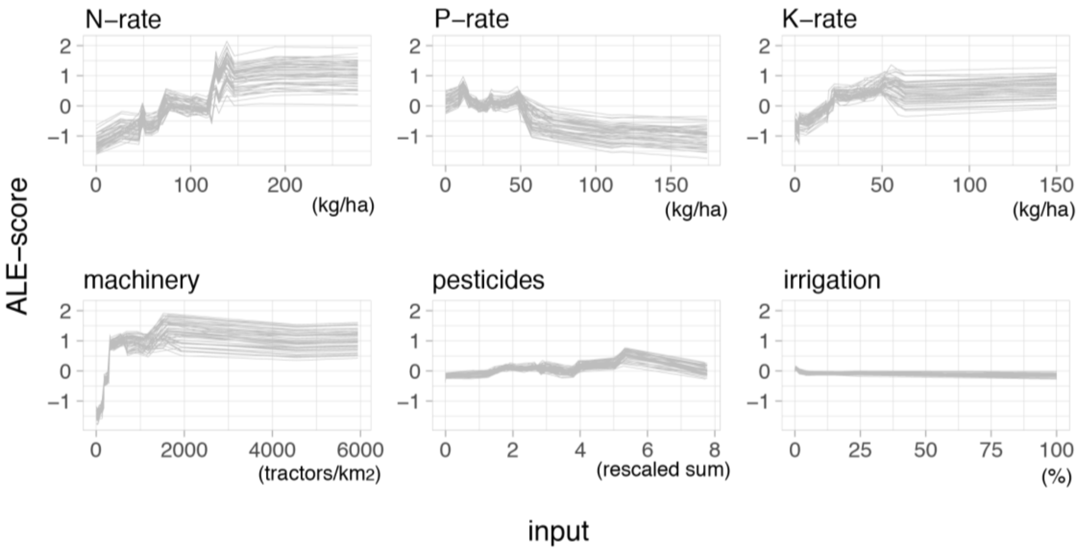


Figure 7: ALE-plot (Accumulated Local Effects) for wheat climate bin 10. Each grey line represents the ALE-results of one model iteration.

The iteration ALE-plots from each wheat climate were summarized into one climate bin ALE-score line with LOESS (locally estimated scatterplot smoothing, Cleveland and Devlin (1988)) and the results for the whole crop is presented (Figure 8). For N-rate, P-rate and irrigation, the ALE-plots in each climate bin are quite similar. For the other inputs the effects of the parameter rate on yield differ more between climate bins. Figure 8 plots also reveal that the agricultural input rates are not distributed equally between climate bins; some bins do not have the highest input rates.

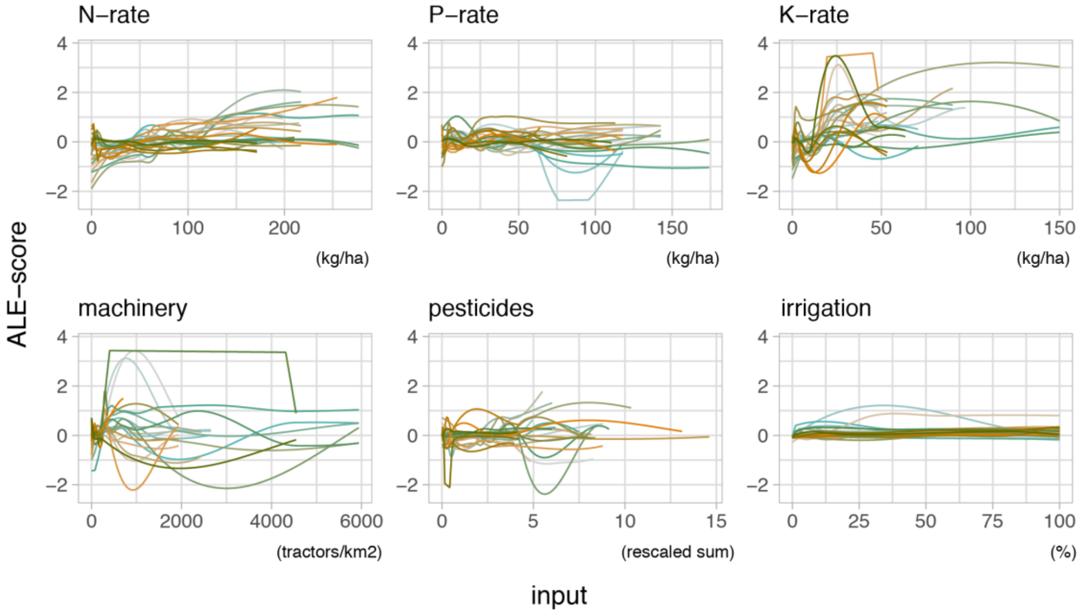


Figure 8: LOESS-smoothed ALE-scores for each climatebin for wheat. The colours represent each climate bin as in Figure 3.

4.3 Scenarios

The random forest models constructed from agricultural input and yield data were used to predict yield changes in agricultural input shock scenarios for each climate bin individually. Figure 9 presents the results for all different shock scenarios for wheat bin 10. The results here, and the typical result from most scenarios in all crops and climate bins, were that after a shock in agricultural inputs, the areas with the highest original yields suffered the most. In the N-rate shock scenario, when the original yield is high (x-axis), the shock yield is smaller (y-axis). If the original yield is smaller, the shock yield stays the same or may even increase: the points are on the red line or above it. Additionally, larger input shock scenarios decrease the yields more: 75% input shock plots have the lowest shock yields.

Some shock scenarios do not seem to decrease the yields very much. In Figure 9, only shocks in the N-rate, K-rate and machinery show declines in yields, as well as a fertilizer shock and a shock in all inputs. N-rate, K-rate and machinery were also shown to be influential for this model in the ALE-plots in Figure 7 Similar responses are seen in all crops, with the significant shock scenarios varying between crops and climate bins.

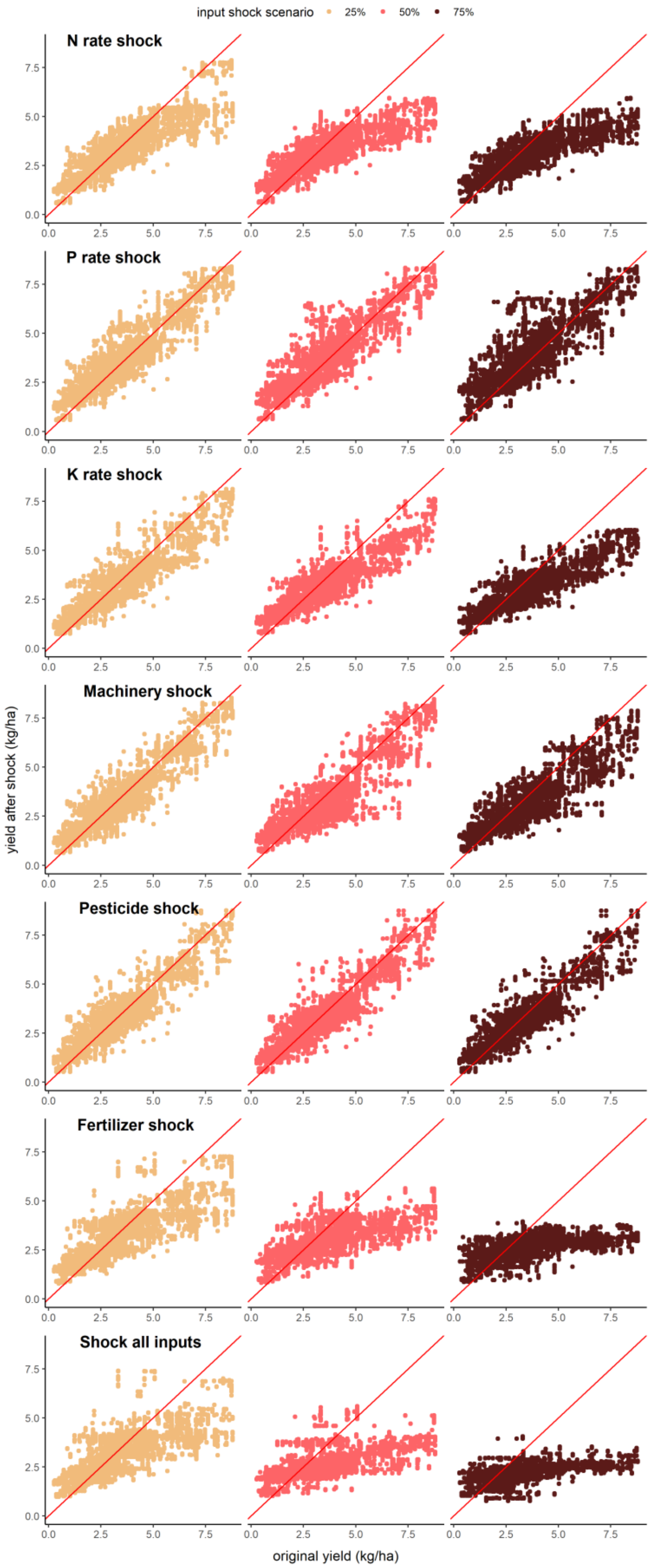


Figure 9: Wheat bin 10 scatterplots for each of the studied shock scenarios. The red diagonal line denotes the 1:1-line where scenario-yields would be identical to original yields. Points below the red line indicate that the agricultural input shock decreased yield.

When exploring the 50% N-input scenario (Fig. 10) we found that yield decreases were induced in e.g. Central Europe, the eastern parts of North America and some locations in Southern Africa, China and India. On the other hand, a shock in all inputs simultaneously decreases yield more and in more locations, as seen in Fig. 11. The areas affected are larger and the yield decreases deeper than in a single input shock scenario.

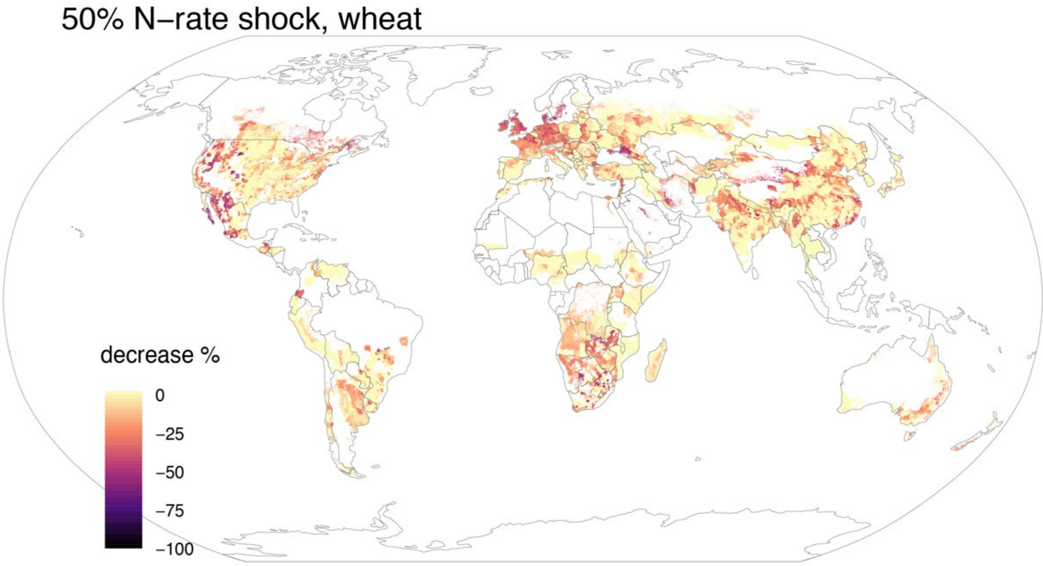


Figure 10: Yield decrease of wheat after a 50% shock in N-input. The map only highlights the yield decreases and omits yield increases.

No one geographical area has large declines in all crops, but in some areas yields decreases can be seen for a few different crops (Figure 11). The yields of barley, maize, potato and wheat all decrease heavily in Western United States. Barley, maize, millet, potato, sorghum and soybean yields all decrease in Northern Argentina. Barley, maize, potato, wheat and to some extent sugarbeet also see large yield decreases in Central Europe: France, Germany and the UK.

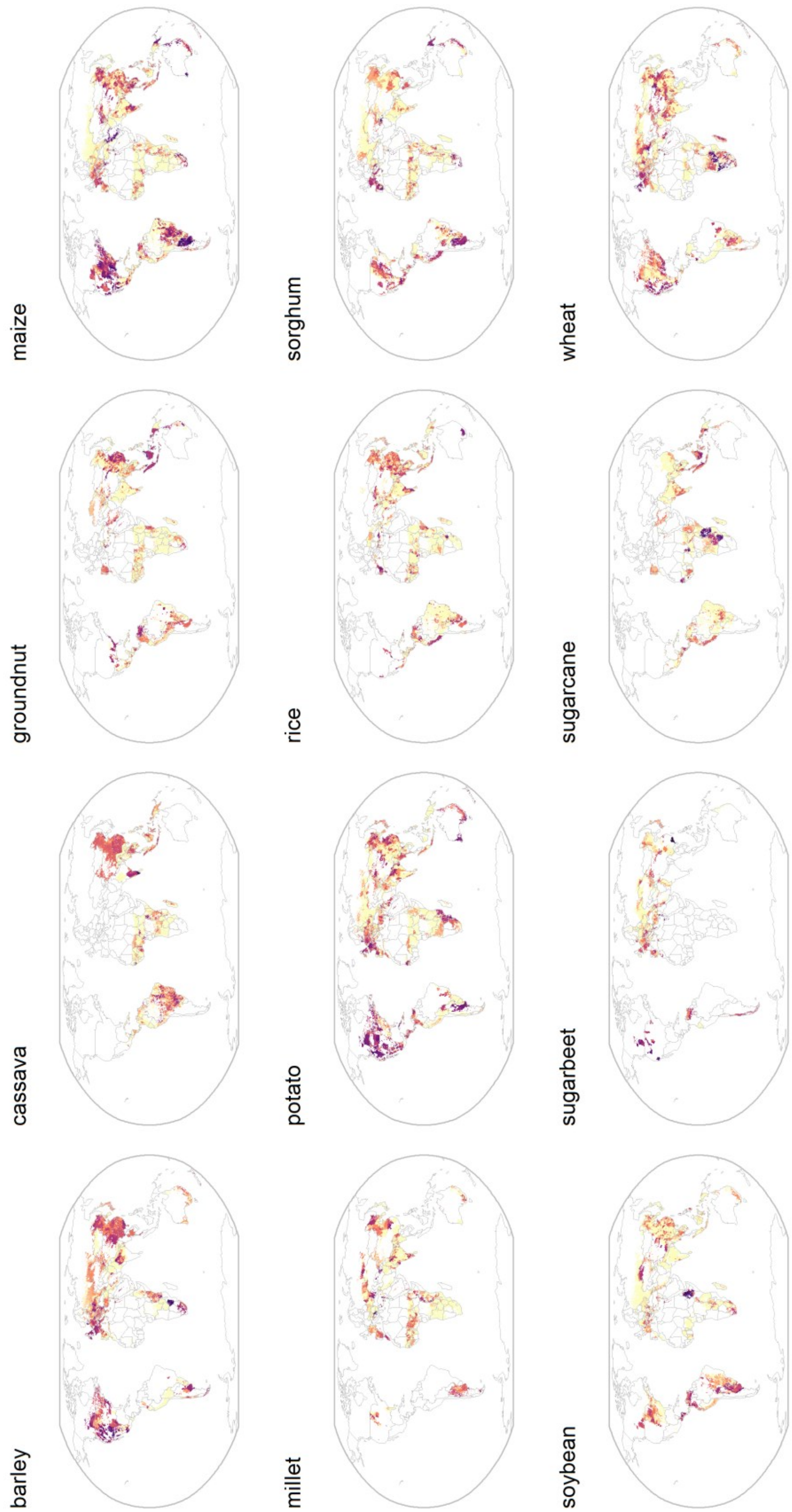


Figure 11: Yield decreases in all crops after a 50% shock in all inputs. The maps only highlight the yield decreases and omit yield increases.

To study the results more in relation to each climate bin, scenario results of all climate bins of a crop were aggregated, focusing on yield decreases (Figure 12). Crop-wide it is confirmed again that a higher shock degree causes more yield decline. There are differences between the climate bins in the shocks they are susceptible to; climate bins 9–13 seem to respond heavily to N shock. Most climate bins experience yield decrease in a larger area when all inputs have a shock and in many climate bins the fertilizer shock effect is the same as the effect of a shock in all inputs. There are some climate bins, such as 21–25, that do not see a huge yield decrease area share with any shock type. A P-rate shock or a pesticide shock seems to have little effect in some of the climate bins of wheat, even at 75%.

While Figure 12 shows how the area of the yield decrease changed with different shocks, Figure 13 shows how deep the yield decrease is in each climate bin. The depth of the yield decline does not change as drastically as the area of decline in the previous figure. The average yield declines are around -25% of the original yield, and a little more for the fertilizer shock scenario and the all input shock scenario.

However, for some climate bins, the agricultural input shock does not increase the area of yield decline, but rather the depth: instead of decreasing the yield in more cells, the shock induces deeper yield decreases. An example in the wheat crop is climate bin 1, where the area of yield decline does not increase between shocks or shock degrees (Figure 12), but the depth of the yield decline increases for a 75% fertilizer shock and a shock all (Figure 13).

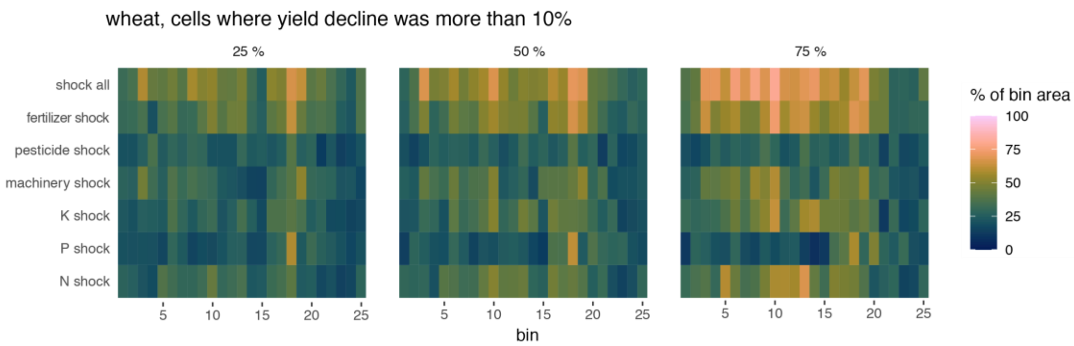


Figure 12: Wheat shock tile plots. Each tile represents the share of the respective climate bin's cells where yield decline after the shock was greater than 10% from the original yield.

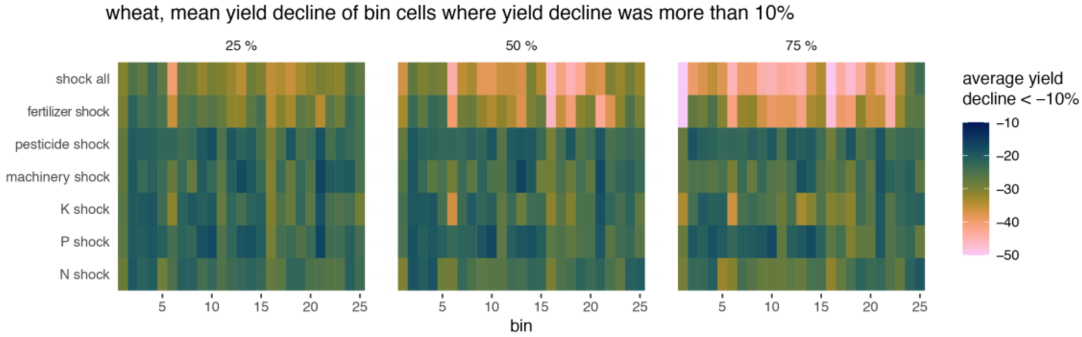


Figure 13: Mean yield decline of bin cells where yield decline was more than 10%. The colour of the tile reflects the average yield decline of all the cells where decline was greater than 10% of the original yield (note the different colour scale). Tile plots for other studied crops can be found in the Supplementary Material.

There are similarities and differences between the crops and their climate bins in their yield decrease responses to the different shock scenarios (see Supplementary Fig. A 1). For many crops, the shock in pesticide inputs has little effect on yield decrease. For most crops, shock yield decreases are similar with a shock in all fertilizers and a shock in all inputs, emphasizing the importance of fertilizers.

Over all 12 crops, there is no trend detected in the shock-induced yield decline related to the climate bin variables. In individual crops, some clustering of heavily affected bins can be seen (Supplementary Fig. A 2–A 3), but in general agricultural input shock effects are not concentrated in particular climate types.

To better study the differences between crops and to compare our results to existing literature, scenario results were converted from yields to production volumes. Shock scenario effects on production were calculated by multiplying all shock yields (t/ha) with their harvested area (ha) and comparing to the original production (Figure 14). These calculations did not focus on the yield decreases but included all predicted shock yields. The different shock percentages have a different effect on the production decrease, which does not necessarily reflect the rate of increase in the shock: for wheat, a 25% shock in all inputs decreases production by 15%, but a 50% shock decreases production by 20%.

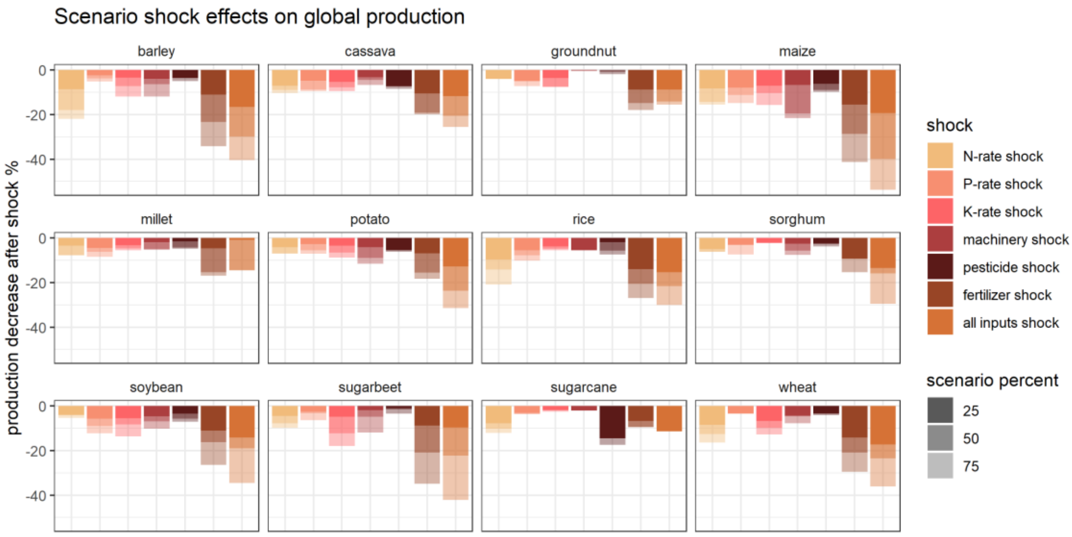


Figure 14: The effects of the different shock scenarios on global production (production = yield * harvested area). The different shades indicate the effect of different shock percentages.

The crop most affected in global production by a shock in all agricultural inputs is maize, where production declines over 50% with a 75% shock in all agricultural inputs. The largest yield decreases by shocks in individual agricultural inputs occur in barley, rice and wheat, by N-rate, and in maize, by machinery. Soybean and sugarbeet production are affected by shocks in K-rate. Despite not showing significant effects on yields in previous figures, pesticides seem to have a substantial effect on e.g. sugarcane production on the global scale.

In addition to studying the differences in shock scenario productions between different crops, country-specific production changes were studied after the shock scenario “50% shock in all inputs” (Fig. 15). All the studied crops were included in these calculations.

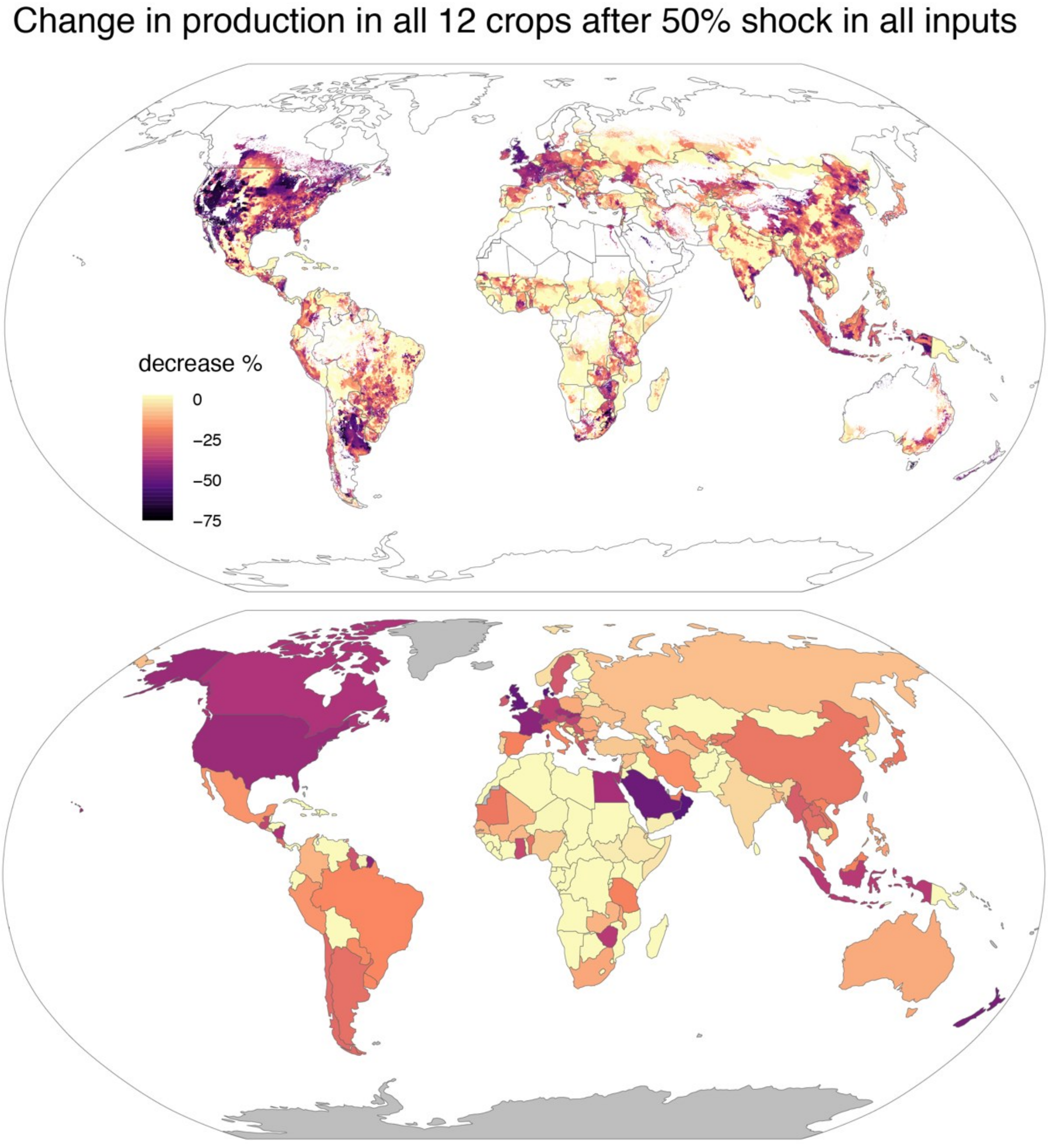


Figure 15: Change in total production over 12 analyzed crops, a) on grid cell level and b) by country. Same colour scale for both maps.

The countries with the largest relative decreases in production are Denmark, Oman, the United Kingdom, New Zealand, and Saudi Arabia, with declines greater than 50%. Of the five current top producers of the studied 12 crops (Brazil, China, India, Thailand, and the United States), United States has the largest decline in production, -42%. The largest absolute decline occurs in the United States, where production declines by 200 million tonnes, followed by China with a 140 million-tonne decline. Many countries in Africa and e.g. Finland and the Baltics suffer very little.

5 Discussion

Random forest models were built with agricultural input and yield data. The models were then used to predict yield changes in 21 different agricultural input shock scenarios. We used spatially gridded datasets, which allowed us to model the effects in high resolution and identify sub-national differences. The scenario results demonstrate that agricultural input shocks are especially devastating to high-yield areas in Northern America and Western Europe. The input use in these areas is also typically high. In lower-yielding and low-input areas, the yields stayed the same or could even increase. By focusing on the yield decreases we were able to highlight the areas where agricultural inputs are most crucial.

Studying model behaviour using ALE-plots revealed that there are similarities and differences between climate bins and crops in the way each agricultural input affects yield. The results from the shock scenarios clarified this even more: most crops and climate bins had decreased yields after shocks in one or more fertilizers, but there were some instances affected by neither. Because a shock in agricultural inputs affects high-yielding areas more, the decreases in these "bread-basket" areas influence global food production and food security. This study demonstrates the importance of the agricultural input aspect in food system resilience both nationally and globally.

5.1 Models

Most of the random forest models for crops and climate bins had NSE scores above 0.65 (Figure 5), indicating good or very good model performance (Moriasi et al., 2007). Sugarbeet models, in particular, had high NSE scores in all climate bins. These high NSE values are similar to the results in Jeong et al. (2016) for global wheat yield predictions with random forest. There was variation between climate bins and crops with some performing better than others. Analyzing the performances with respect to the temperature and precipitation quantiles (Figure 5), it seems there are some extreme bins where the NSE-score is low, for example the lowest temperature quantile of cassava and groundnut, and the highest temperature and precipitation bins of millet. It is possible that in these climate bins the input data is not diverse enough to produce good models, or that climate or other factors play a more important role than the agricultural inputs we studied. The model validation scatterplots (Figure 6) confirm the well-performing models. The fact that some models predicted higher yields to be lower than observed yields is important to keep in mind when analyzing the scenario results.

The RMSE scores between training and testing datasets were similar (Figure 4), which usually indicates that the model does not overfit. Comparing to Jeong et al. (2016), their calculated RMSE for globally predicted wheat yields is 0.32 t/ha, 11.9% of the average yield. Our wheat climate bin RMSEs varied from 14% to 40% of the average yields. Better RMSE scores in Jeong et al. (2016) may be due to a larger number of mostly climate based variables, but Jeong et al. (2016) also note that the good results may be a product of spatial autocorrelation between datapoints in similar political units; this could also be the case in our study with sugarbeet. Observations are never completely independent in geographic data due to e.g. cultural and governance practices being similar in geographically close areas. Ferraciolli et al. (2019) shows that spatial autocorrelation increases overfitting in a yield model for sugarcane and that it underestimates the error of the model. They counteract the problem by splitting the data into k-means clusters and assigning clusters randomly to training and testing data. Similarly to Ferraciolli et al. (2019), we attempted to minimize overfitting and spatial autocorrelation by dividing the training and testing data into grids to keep adjacent cells in different groups to make sure that the model predictions were truly based on relationships in the data. The division was also altered for each iteration of the model, and the final result is the median of all the different iterations.

All statistically built models are only as good as their data, and similarly the random forest models presented here rely on the data they were constructed with. Most of the input data and yield data are from the same time period, with averages around the year 2000. The pesticide data is from 2015 according to Maggi et al. (2019), but the underlying data used to model the pesticide rates in their article ranges from 1994 to 2016. Climate data used for defining the climate bins are averages from 1970–2000. Our models describe the relationships between yields and agricultural inputs around the year 2000, but we assume that the relationships between the inputs and yield have remained quite similar and changes are slow, and that the results are therefore applicable also to the current situation. Because data is aggregated across many years, yield variability between years is muted in the averaging process. Our models and scenarios represent relationships and changes in the averages, but in reality, interannual variability in yields could alleviate or exacerbate the changes seen in the models and scenarios.

Apart from temporal accuracy, spatial accuracy is also a limitation in the models. Despite being in the same resolution, the data rasters might not always align with complete accuracy, creating some datapoints with unreasonable agricultural input and yield compilations. We believe these instances to be rare enough not to affect the model functionality, as random forest is quite robust to outliers (Breiman, 2001). Yet another aspect that could have affected model performances are the details of the model input data: for a wheat climate bin with 28,000 observations, there are only 30 unique values for N-rate or P-rate. Many of the fertilizer rates are known only at subnational/county level. For machinery, we used country-level data or, in some cases, continental averages. The low level of detail in the data could increase spatial autocorrelation. More detailed data would improve the accuracy and prediction power of our model.

The ALE-plots show that different model iterations behave quite similarly (Figure 7). The greatest differences between iterations are seen with the highest agricultural input values. The plots reveal interesting patterns in the models, some expected and others unexpected. Fertilizers were expected to have a great impact on the yield, and this is confirmed by the majority of ALE-plots (Figure 8). Many yield relationships follow the typical form described by Mueller et al. (2017) for nitrogen, (high slope at low rates, plateau at higher rates), but some unusual bell shapes are also found for some climate bins, where medium fertilizer rate corresponds to highest effect on yield. This might be an indication that areas with medium mineral fertilizer input and highest yields are using more manure-based or organic fertilizers to increase the yield.

Machinery also often has a Mueller-type ALE-plot response, where at smaller machinery rates even a small increase has a large effect on yield, but at the highest machinery rates the effect on yield stay the same. This is to be expected, as moving from human- or animal-powered land modification to agricultural machinery has been shown to increase the productivity of farms (e.g. Mrema et al., 2014).

Irrigation or the irrigated share of the harvested area was expected to have a greater effect on yield, based on previous literature (e.g. Lobell et al., 2009; Wang et al., 2021). Even in the hot and dry climate bins the ALE plots do not show a large effect of irrigation on yield compared to the other inputs. Somewhat unexpectedly, pesticides also have low ALE scores throughout most of the crops and climate bins compared to the other agricultural inputs, despite having the most detailed data (Figure 7 and Figure 8). Both irrigation and pesticide use may be masked by the other inputs; their effect may be larger on their own but compared to fertilizers and machinery it is minimal.

5.2 Scenarios

The scenario yields predicted by the random forest models are presented in Figs. 9–13 and the Supplementary Material. Random forest regression predicts the shock scenario yields by “selecting” observations in the same climate bin where input use is similar to scenario use. Decreased scenario shock yields indicate that in the climate bin, original yields were only attainable with original input values. Increased yields after scenario shocks mean that in the same climate bin, similar or better yields are possible with less commercial agricultural inputs.

We found that for all the studied shock scenarios, the largest yield decreases were observed for high yields, whilst lower yields tended not to be affected negatively by the shocks. As seen in the Figure 6 scatterplots, a very small part of this effect could be attributable to model performance. The increase in low yields and the variation between areas of low yields and low rates of commercial agricultural inputs might be due to using more manure-based fertilization, using more efficient agricultural practices or to better soil quality.

In contrast, high yields are very dependent on commercial agricultural inputs and are therefore negatively affected by agricultural input shocks. The variation of high yields can be explained by variation in agricultural input use. The scenario predictions thus identify areas of high yields that need commercial trade-dependent agricultural inputs to sustain their original high values. The original high yields are only possible in their respective climate bins with a specific higher agricultural input intensity. The scenario shocks are also larger in absolute values for the higher input and higher yielding areas.

Because shock scenario yield decreases are focused on high yields, the areas most affected by shocks in agricultural inputs are the high-yielding areas or "breadbaskets" of the globe (Figure 11 maps, and Figure 15 country map): Northern America, Central Europe, Argentina and parts of China. The large yield reductions also affect the total global production of the crops (Figure 14): even though many smaller yields were not negatively affected by the agricultural input shocks, as seen in Figure 9 scatterplots, global production overall decreases due to the decreasing yields of the world's high-yielding breadbasket areas. In addition to creating problems for local food security, shocks in agricultural inputs could affect the global food trade if large yield decreases fall on important global food exporters and trade nodes (Puma et al., 2015). More research is needed to fully understand the interconnected effects of agricultural input shocks on the global food trade.

The highest agricultural input values do not always correlate with the highest yields. In Fig. 16 the N-rate for the highest original yields is ca. 150–200 kg/ha, while the highest N-rate of 300 kg/ha produced original yields of 2.5 t/ha (darkest black points, indicated with green). The deepest yield decreases are seen in the highest original yields. Their original high yields were possible with a certain optimum combination of fertilizers, other inputs and agricultural qualities. The highest N-rate and the low original yield connected to it indicate overuse of the fertilizer with regard to the other agricultural management factors. The full potential of high N-input is not achieved because best results require high fertilization coupled with adequate water supply and soil modification using machinery. Other fertilizers also need to be in sync, both temporally and stoichiometrically, with the N-fertilizer to produce maximum yields.

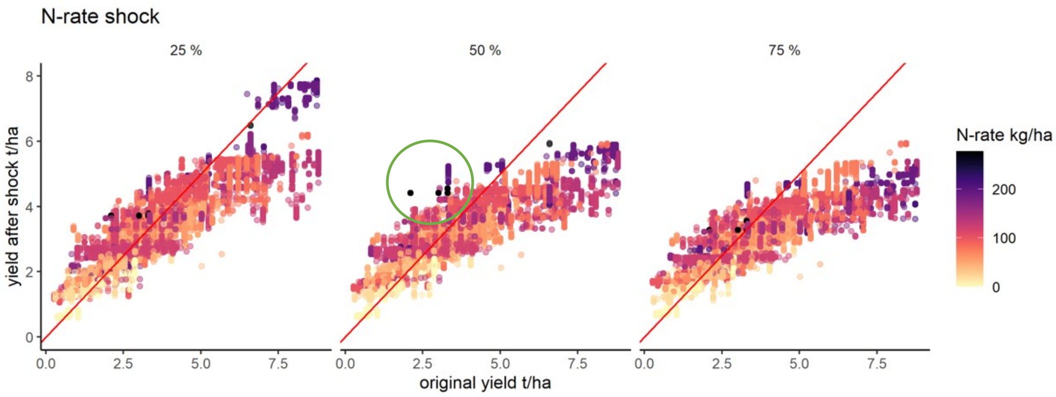


Figure 16: Wheat bin 10 fertilizer shock. The green circle demonstrates the grid cells with the highest N-rates that nonetheless have a relatively low original yield (2.5t/ha) and subsequently do not suffer large yield decreases after shocks in N-input.

5.3 Soil nutrients could affect shock scenarios

Overusing fertilizers is not uncommon. For example, Sattari et al. (2012) and references therein describe situations where years and decades of phosphorus fertilizer overuse results in a residual phosphorus pool in the soil large enough to support good yields without external phosphorus input. Does our model consider this situation?

The random forest models presented here do not directly address residual nutrients in the soil, but areas with overuse of fertilizers are not predicted to suffer yield decreases from the shock since there are locations in the same climate bin where the yields are the same or better with less nutrients (as seen in Figure 16 above). Better yields are achieved with less inputs that are better balanced and correctly managed or due to better soil, and thus the model predicts similar or even increased yields for areas where fertilizers are overused.

Overuse of fertilizers is a large source of water pollution, and many studies and government programmes aim to reduce it (HELCOM, 2013). The use of fertilizers is spatially imbalanced: both over- and underuse occurs. In China for example, previous research indicates fertilizer overuse and subsequent fertilizer surplus in the soil, especially for phosphorus (Lun et al., 2018; MacDonald et al., 2011). It is shown in many studies (e.g. Mueller et al., 2012; Wuepper et al., 2020) that China could reduce its fertilizer inputs without affecting yield. West et al. (2014) find that "~50% of the excess nitrogen and phosphorus is concentrated in only 24% and 21% of the world's cropland area, respectively, and that China, India, and the United States together account for ~64% to 66% of excess nitrogen and phosphorus". West et al. (2014) also calculate that between 14% to 29% of nitrogen and between 13% to 22% of phosphorus could be reduced without affecting current yields, targeted to excessive users. Our shock scenarios indicate yield decreases in high-yielding areas of China, India and the United States (Fig. 11), but only after shocks largely exceeding the reductions proposed by West et al. (2014). Therefore, our results do not contradict previous studies on excess fertilizers; the shock scenarios are a greater reduction in agricultural inputs than the overuse seems to be.

In some parts of the globe, not enough fertilizers are used. MacDonald et al. (2011) study global agricultural phosphorus balances in 2000 and identify areas of deficit where the phosphorus input from inorganic or organic fertilizers is not equal to the amount harvested, meaning that soil phosphorus reserves are being depleted. One of the highly deficit areas is Argentina. The Lun et al. (2018) study demonstrates similar results on the country level for phosphorus, and Liu et al. (2010) also calculate nitrogen deficit soils for Argentina. In our scenarios, Argentinian yields of maize, potato, sorghum and soybean were found to be sensitive to shocks in fertilizer input with significant yield decreases after shock scenarios. Due to nutrient deficient soils the true effects of agricultural input shocks might be even worse than calculated in our analysis. P deficiency was also found for Eastern Europe and Russia, but our analyses did not predict yield decreases in these areas due to their low original yields.

A more detailed analysis of soil nutrient budgets combined with the results from our analysis could reveal more information on vulnerable areas. The use of soil residual nutrient data could enhance the estimation of yield decrease since the nutrient reserves in the soil could either alleviate or exacerbate the effects of input shocks.

5.4 Study limitations

In addition to soil nutrient balances, other datasets could improve the agricultural input models, scenario predictions and subsequently analyses on food security and vulnerability, especially for lower yields. Agricultural field slope or soil type are demonstrated not to be significant parameters in yield models according to Mueller et al. (2012). Data on non-commercial fertilizers and nutrient use is available and was considered for our analysis to study whether higher manure use would protect from fertilizer shocks, but ultimately the data was left out. As regards to non-mineral and non-commercial fertilizers, it is difficult to estimate e.g. whether the manure is self-supplied or transported from elsewhere and thus susceptible to trade disturbances or not.

Other agricultural inputs considered in food security analyses include energy and imported seeds. Energy used in agriculture in the form of oil is included in our analysis indirectly through machinery, but energy is also used in post-harvest processing of crops, affecting the eventual quality and quantity of yield. According to Jansik et al. (2021), animal husbandry and greenhouse crops are more energy-intensive and energy-dependent forms of agriculture than field crops.

High-yielding seed varieties are an important factor at least in the developed countries. The shocks could be crucial, depending on crop and climate conditions: in Finland approx. 70% of sugarbeet crops are grown from imported seeds modified for Finnish climate conditions, according to Jansik et al. (2021). They estimate large decreases in sugarbeet yields due to seed import shocks, based on Finnish expert interviews. A potato seed import shock is estimated to cause a 10% decrease in yield on the first year, and a more severe one if the shock was prolonged. A small part of the shock could be alleviated by own seed production. Including the use of imported seeds in agricultural input shock analyses would provide important information with regard to food security. Unfortunately, no globally comprehensive data was available to be included in our analysis.

While more variables like governance, GDP etc. might have improved the model's accuracy, we deliberately wanted to mask the effects of non-input related factors for the purposes of the scenarios. This way the shock scenario yield estimates are based on all yields of the climate bin and not just on cells with similar governance or GDP, to allow for a more diverse overview.

5.5 Comparison to other agricultural input shock studies

Mueller et al. (2012) use global spatial data and models to calculate yield gaps for major crops. They also model areas where reductions in fertilizers would be possible without yield decreases for the major cereals: wheat, rice and maize. The methods and result units are different from our analysis, but some visual comparisons between maps could be made. The major areas that could not withstand reductions in fertilizers according to Mueller et al. (2012) are Eastern Europe, Central Africa, and South America. In our analysis, these same areas were not particularly susceptible to fertilizer shock scenarios, because of their low original yields, except for Argentinian croplands. Their model is based on slightly different global yield data and is constructed from both the global data and previous models of input yield relationships. In their model, lower yields are more affected by agricultural input than in our models. A more detailed analysis of their results and more than visual comparison could reveal more similarities or differences in the results.

Jansik et al. (2021) use expert interviews to investigate the effects of agricultural input shocks on Finnish agriculture. In their estimate, a total shock in the input of farm chemicals, fertilizers and pesticides could reduce yields by 10–40% (crops not specified). In our scenarios, a 75% shock in all inputs reduced the yields of Finnish wheat, barley and potato by a maximum of 40%. Jansik et al. (2021) also conclude that the effects of pesticide shocks would be severe: grain yields could decrease by 30%, potato yields by 50% or more. In our study, pesticide shocks had a low effect globally, but in our Finnish

75% pesticide shock scenarios, barley, potato and wheat yields decreased moderately: 15%, 30% and 25%, respectively.

Haile et al. (2016) use an economic trade model to predict the effects of phosphate price increase and find that even if the international price of P doubled, the global crop yield decreases only by 1–7% in wheat, maize, rice and soybean. The decrease in actual fertilizer input was not discussed in the model. O'Hara et al. (2015) also study the effects of a phosphate fertilizer price shock using economic models. In their study, the phosphate fertilizer price increases by 200%, but the global use of phosphate fertilizers declines by only 3%. They find decreases in production to be only a few percent globally, from 0% to 14% in the largest producers. In India, the phosphate price increase leads to phosphate and potash application rates changing by -11% and -26%, respectively. For maize, this means a 14% reduction in production. In our somewhat comparable shock scenarios, a 25% P-rate shock and a 25% fertilizer shock, maize production in India decreased by 3% and by 12%, respectively.

Beckman et al. (2020) model the food security impacts of EU's Green Deal and Farm to Fork strategies on a global level. These EU strategies aim to reduce pesticides by 50% and fertilizers by 20%, as well as land use (by 10%) and antimicrobial use in livestock (by 50%). If all countries decreased the mentioned agricultural inputs, agricultural production would decrease in some places as being too costly, while increasing in other places where farming is more profitable due to changes caused by adopting the strategy. The study predicts wheat production changes of -33%, +3% and -33% for China, the United States and the EU, respectively. This can be compared to our shock scenario of a 25% shock to all inputs, which resulted in -25%, 0% and -7% production changes in the respective countries.

5.6 Shock alleviating factors

Economic models like those presented in Beckman et al. (2020); Haile et al. (2016) and O'Hara et al. (2015) allow for reaction to world events and crop management changes in response to them, whereas in our model, yields for all cells are predicted individually and independently from neighbouring cells. The economic models assume alleviating factors to price increase shocks or scenarios: governments of developed countries can subsidize farmers to buy farm chemicals; the world market and grain prices shift the production locations of different crops. Individual farmers can increase or decrease their farming acreage to adjust to new input levels, and they can also substitute chemicals with machinery and labour or adjust their farming practices with investments (Beckman et al., 2020; Haile et al., 2016).

Compared to the phosphorus price shock scenarios (Haile et al., 2016; O'Hara et al., 2015), our input shock scenarios are more drastic. Especially the all input shock scenario in our study represents a more war-like or severe pandemic situation, a worst-case scenario. Our study also assumes that the agricultural input shock occurs at a critical time point in crop management or that the shock is prolonged and exhausts the buffering capacity countries or individual farms might have. The stakeholder interview study by Jansik et al. (2021) concludes that, on average, Finnish farmers have 10-15% of their yearly fertilizers and pesticides in storage.

Farm chemicals and other agricultural inputs in national or personal reserves could alleviate the trade shocks, but otherwise means to substitute the missing agricultural inputs are scarce. Some pesticides can be replaced by mechanical weeding or adjusting crop management timing (Jørgensen et al., 2019). In high-precision agriculture in the developed countries, machinery is nigh impossible to be replaced by manpower or even animal power without huge yield losses (Jansik et al., 2021). Supplementing fertilizers with organic nutrients from manure and crop residues is possible up to a certain degree. In a time of agricultural input shock, manure etc. could become a commodity to be traded and become scarce on their own.

Many previous studies have focused on P due to its finite reserves, but our analysis shows that for some areas, other inputs and their shortages may be just as important as regards yield. The summarizing tile plots in Figs. Figure 12 andFigure 13 and the Supplementary Material do not reveal any one agricultural input as being the most influential in shock yield decreases across all climate bins and crops. Globally, 50% of fertilizers are of commercial origin and susceptible to trade shocks. The most severe yield decreases are related to shocks in fertilizers. To increase food security and resilience in the face of global trade network uncertainties, areas with a high degree of commercial fertilizer use should seek to replace them with more sustainable and local bio-based fertilizers, especially in the case of finite phosphorus reserves. The adverse effects of overusing fertilizers, like eutrophication, could also be mitigated by more sustainable and circular fertilizer use.

Our analysis describes the yields and agricultural inputs in the year 2000, and the shock scenario effects on the relationships of that time point. In the future as the changing climate will change global yields (Wheeler and Von Braun, 2013), it can also modify agricultural input requirements, e.g. more pest damage means increased pesticide application (Rosenzweig et al., 2001). Thus some inputs might be more crucial for future yields. The growing global population and the goals to provide food security for all will also increase the need of agricultural inputs. The dwindling commercial phosphorus resources, expected to be depleted in 50 to 100 years (Cordell et al., 2009) will force the agricultural sector to find new, sustainable ways of increasing and maintaining high yields. All in all, agricultural inputs and their availability should be taken into account now and in the future when a more resilient and sustainable global food system is constructed.

6 Conclusions

To our knowledge, this work is the first attempt at constructing a model and scenarios to study trade-dependent agricultural input shocks and their effects on global yields with high spatial definition. Previous studies have focused on price increases and economic effects, and yields and crop production have been treated as national aggregates and without a precise spatial dimension.

The random forest models presented in this study had a predicting power of 60–80% on average, indicating good performance. The models were used to predict yield changes in the face of agricultural input shocks. The relationships between agricultural inputs and crop yields are complex, as are the effects of different input shocks. The largest yield decreases were observed for high-yielding areas of each crop, where the specific high agricultural input rates are in balance to produce maximum yields. These high-yielding areas are important not only for regional food security, but also for global food production.

With more precise agricultural input data and additional supporting environmental data, the effects of agricultural input shocks could be understood even better. Our results highlight the fragility and interconnectedness of the food-related trade system. The results can serve to evaluate regional food security more comprehensively, and together with other information help identify at-risk areas.

References

Amjath-Babu, T.S., Krupnik, T.J., Thilsted, S.H. and McDonald, A.J. 2020. Key indicators for monitoring food system disruptions caused by the COVID-19 pandemic: Insights from Bangladesh towards effective response. Food security 12(4), 761-768.

Apley, D.W. and Zhu, J. 2020. Visualizing the effects of predictor variables in black box supervised learning models. Journal of the Royal Statistical Society: Series B (Statistical Methodology) 82(4), 1059-1086.

Barbieri, P., MacDonald, G.K., Bernard de Raymond, A. and Nesme, T. 2021. Food system resilience to phosphorus shortages on a telecoupled planet. Nature Sustainability, 1-9.

Beckman, J., Ivanic, M., Jelliffe, J.L., Baquedano, F.G. and Scott, S.G. 2020. Economic and Food Security Impacts of Agricultural Input Reduction Under the European Union Green Deal's Farm to Fork and Biodiversity Strategies. USDA Economic Research Service (Economic Brief Number 30).

Breiman, L. 2001. Random forests. Machine Learning 45(1), 5-32.

Breiman, L., Friedman, J.H., Olshen, R.A. and Stone, C.J. 2017. Classification and regression trees, Routledge.

Cassman, K.G., Dobermann, A. and Walters, D.T. 2002. Agroecosystems, nitrogen-use efficiency, and nitrogen management. AMBIO: A Journal of the Human Environment 31(2), 132-140.

Chlingaryan, A., Sukkarieh, S. and Whelan, B. 2018. Machine learning approaches for crop yield prediction and nitrogen status estimation in precision agriculture: A review. Computers and Electronics in Agriculture 151, 61-69.

Chowdhury, R.B., Moore, G.A., Weatherley, A.J. and Arora, M. 2017. Key sustainability challenges for the global phosphorus resource, their implications for global food security, and options for mitigation. Journal of Cleaner Production 140, 945-963.

Clapp, J. 2017. Food self-sufficiency: Making sense of it, and when it makes sense. Food Policy 66, 88-96.

Cleveland, W.S. and Devlin, S.J. 1988. Locally weighted regression: an approach to regression analysis by local fitting. Journal of the American statistical association 83(403), 596-610.

Conant, R.T., Berdanier, A.B. and Grace, P.R. 2013. Patterns and trends in nitrogen use and nitrogen recovery efficiency in world agriculture. Global Biogeochemical Cycles 27(2), 558-566.

Cooper, J. and Dobson, H. 2007. The benefits of pesticides to mankind and the environment. Crop Protection 26(9), 1337-1348.

Cordell, D., Drangert, J.-O. and White, S. 2009. The story of phosphorus: global food security and food for thought. Global Environmental Change 19(2), 292-305.

Cordell, D. and White, S. 2011. Peak phosphorus: clarifying the key issues of a vigorous debate about long-term phosphorus security. Sustainability 3(10), 2027-2049.

Di Paolo, E. and Rinaldi, M. 2008. Yield response of corn to irrigation and nitrogen fertilization in a Mediterranean environment. Field Crops Research 105(3), 202-210.

Erisman, J.W., Sutton, M.A., Galloway, J., Klimont, Z. and Winiwarter, W. 2008. How a century of ammonia synthesis changed the world. Nature Geoscience 1(10), 636-639.
Evenson, R.E. and Gollin, D. 2003. Assessing the impact of the Green Revolution, 1960 to 2000. Science 300(5620), 758-762.
Everingham, Y., Sexton, J., Skocaj, D. and Inman-Bamber, G. 2016. Accurate prediction of sugarcane yield using a random forest algorithm. Agronomy for Sustainable Development 36(2), 27.
Fader, M., Gerten, D., Krause, M., Lucht, W. and Cramer, W. 2013. Spatial decoupling of agricultural production and consumption: quantifying dependences of countries on food imports due to domestic land and water constraints. Environmental Research Letters 8(1), 014046.
Falkendal, T., Otto, C., Schewe, J., Jägermeyr, J., Konar, M., Kummu, M., Watkins, B. and Puma, M.J. 2021. Grain export restrictions during COVID-19 risk food insecurity in many low-and middle-income countries. Nature Food 2(1), 11-14.
FAO 2015. The impact of natural hazards and disasters on agriculture and food security and nutrition: A call for action to build resilient livelihoods, Food and Agriculture Organization of the United Nations.
FAO 2021a. Agricultural Machinery, tractors, https://data.worldbank.org/indicator/AG.AGR.TRAC.NO, date accessed: [24 March 2021].
FAO 2021b. Fertilizers by Nutrient, Food and Agriculture Organization of the United Nations, https://www.fao.org/faostat/en/#data/RFN/, date accessed: [22 November 2021].
FAO 2021c. Pesticides Use, Food and Agriculture Organization of the United Nations, https://www.fao.org/faostat/en/#data/RP, date accessed: [22 November 2021].
FAO 2021d. Q&A on Pests and Pesticide Management, https://www.fao.org/news/story/en/item/1398779/icode/, date accessed: [13 December 2021].
FAO, IFAD, UNICEF, WFP and WHO 2021. The State of Food Security and Nutrition in the World 2021. Transforming food systems for food security, improved nutrition and affordable healthy diets for all., FAO, Rome, Italy.
FAO, IFAD and WFP 2015. State of Food Insecurity in the World 2015. Meeting the 2015 international hunger targets: taking stock of uneven progress, Food and Agriculture Organization of the United Nations, Rome.
Feng, P., Wang, B., Li Liu, D., Xing, H., Ji, F., Macadam, I., Ruan, H. and Yu, Q. 2018. Impacts of rainfall extremes on wheat yield in semi-arid cropping systems in eastern Australia. Climatic Change 147(3), 555-569.
Fernández-Delgado, M., Cernadas, E., Barro, S. and Amorim, D. 2014. Do we need hundreds of classifiers to solve real world classification problems? The Journal of Machine Learning Research 15(1), 3133-3181.
Ferraciolli, M.A., Bocca, F.F. and Rodrigues, L.H.A. 2019. Neglecting spatial autocorrelation causes underestimation of the error of sugarcane yield models. Computers and Electronics in Agriculture 161, 233-240.
Fick, S.E. and Hijmans, R.J. 2017. WorldClim 2: new 1-km spatial resolution climate surfaces for global land areas. International Journal of Climatology 37(12), 4302-4315.
Frank, M.D., Beattie, B.R. and Embleton, M.E. 1990. A comparison of alternative crop response models. American Journal of Agricultural Economics 72(3), 597-603.

Fukuda, S., Spreer, W., Yasunaga, E., Yuge, K., Sardsud, V. and Müller, J. 2013. Random Forests modelling for the estimation of mango (Mangifera indica L. cv. Chok Anan) fruit yields under different irrigation regimes. Agricultural Water Management 116, 142-150.

Garnett, P., Doherty, B. and Heron, T. 2020. Vulnerability of the United Kingdom's food supply chains exposed by COVID-19. Nature Food 1(6), 315-318.

Ghimire, N. and Woodward, R.T. 2013. Under-and over-use of pesticides: An international analysis. Ecological Economics 89, 73-81.

Haile, M.G., Kalkuhl, M. and von Braun, J. 2016. Worldwide acreage and yield response to international price change and volatility: a dynamic panel data analysis for wheat, rice, corn, and soybeans, *in:* Food price volatility and its implications for food security and policy, pp. 139-165, Springer.

Harris, L. 2021. Brexit farm inputs shortages and delays persist, Farmers Weekly, https://www.fwi.co.uk/business/markets-and-trends/input-prices/brexit-farm-inputs-shortages-and-delays-persist, date accessed: [3 August 2021].

HELCOM 2013. HELCOM Copenhagen Ministerial Declaration Taking Further Action to Implement the Baltic Sea Action Plan - Reaching Good Environmental Status for a healthy Baltic Sea, Copenhagen, Denmark.

Heslin, A., Puma, M.J., Marchand, P., Carr, J.A., Dell'Angelo, J., D'Odorico, P., Gephart, J.A., Kummu, M., Porkka, M. and Rulli, M.C. 2020. Simulating the cascading effects of an extreme agricultural production shock: global implications of a contemporary US dust bowl event. Frontiers in Sustainable Food Systems 4, 26.

Jansik, C., Huuskonen, H., Karhapää, M., Keskitalo, M., Leppälä, J., Niemi, J., Niskanen, O., Perttilä, S. and Rinne, M. 2021. Maatalouden tuotantopanosten saatavuuden riskit: Kriiseihin varautuminen ruokahuollon turvaamisessa, Luonnonvarakeskus.

Jeong, J.H., Resop, J.P., Mueller, N.D., Fleisher, D.H., Yun, K., Butler, E.E., Timlin, D.J., Shim, K.-M., Gerber, J.S. and Reddy, V.R. 2016. Random forests for global and regional crop yield predictions. PLoS One 11(6), e0156571.

Johnson, M.D., Hsieh, W.W., Cannon, A.J., Davidson, A. and Bédard, F. 2016. Crop yield forecasting on the Canadian Prairies by remotely sensed vegetation indices and machine learning methods. Agricultural and Forest Meteorology 218, 74-84.

Johnston, A.E. 2003. Understanding Potassium and It's Use in Agriculture, European Fertilizer Manufacturers' Association, Brussels.

Johnston, M., Licker, R., Foley, J., Holloway, T., Mueller, N.D., Barford, C. and Kucharik, C. 2011. Closing the gap: global potential for increasing biofuel production through agricultural intensification. Environmental Research Letters 6(3), 034028.

Jørgensen, L.N., Kudsk, P. and Ørum, J.E. 2019. Links between pesticide use pattern and crop production in Denmark with special reference to winter wheat. Crop Protection 119, 147-157.

Ju, X.-T., Xing, G.-X., Chen, X.-P., Zhang, S.-L., Zhang, L.-J., Liu, X.-J., Cui, Z.-L., Yin, B., Christie, P. and Zhu, Z.-L. 2009. Reducing environmental risk by improving N management in intensive Chinese agricultural systems. Proceedings of the National Academy of Sciences 106(9), 3041-3046.

Kalkuhl, M., Von Braun, J. and Torero, M. 2016. Food price volatility and its implications for food security and policy, Springer Nature.

Kummu, M., Kinnunen, P., Lehikoinen, E., Porkka, M., Queiroz, C., Röös, E., Troell, M. and Weil, C. 2020. Interplay of trade and food system resilience: Gains

on supply diversity over time at the cost of trade independency. Global Food Security 24, 100360.
Lassaletta, L., Billen, G., Grizzetti, B., Anglade, J. and Garnier, J. 2014. 50 year trends in nitrogen use efficiency of world cropping systems: the relationship between yield and nitrogen input to cropland. Environmental Research Letters 9(10), 105011.
Lehikoinen, E., Kinnunen, P., Piipponen, J., Heslin, A., Puma, M.J. and Kummu, M. 2021. Importance of trade dependencies for agricultural inputs: a case study of Finland. Environmental Research Communications 3(6), 061003.
Leng, G. and Hall, J.W. 2020. Predicting spatial and temporal variability in crop yields: an inter-comparison of machine learning, regression and process-based models. Environmental Research Letters 15(4), 044027.
Liaw, A. and Wiener, M. 2002. Classification and regression by randomForest. R news 2(3), 18-22.
Licker, R., Johnston, M., Foley, J.A., Barford, C., Kucharik, C.J., Monfreda, C. and Ramankutty, N. 2010. Mind the gap: how do climate and agricultural management explain the 'yield gap' of croplands around the world? Global Ecology and Biogeography 19(6), 769-782.
Liu, J., You, L., Amini, M., Obersteiner, M., Herrero, M., Zehnder, A.J.B. and Yang, H. 2010. A high-resolution assessment on global nitrogen flows in cropland. Proceedings of the National Academy of Sciences 107(17), 8035-8040.
Liu, Y., Villalba, G., Ayres, R.U. and Schroder, H. 2008. Global phosphorus flows and environmental impacts from a consumption perspective. Journal of Industrial Ecology 12(2), 229-247.
Liu, Y., Yang, J., He, W., Ma, J., Gao, Q., Lei, Q., He, P., Wu, H., Ullah, S. and Yang, F. 2017. Provincial potassium balance of farmland in China between 1980 and 2010. Nutrient Cycling in Agroecosystems 107(2), 247-264.
Lobell, D.B., Cassman, K.G. and Field, C.B. 2009. Crop yield gaps: their importance, magnitudes, and causes. Annual Review of Environment and Resources 34, 179-204.
Lobell, D.B. and Field, C.B. 2007. Global scale climate–crop yield relationships and the impacts of recent warming. Environmental Research Letters 2(1), 014002.
Lun, F., Liu, J., Ciais, P., Nesme, T., Chang, J., Wang, R., Goll, D., Sardans, J., Peñuelas, J. and Obersteiner, M. 2018. Global and regional phosphorus budgets in agricultural systems and their implications for phosphorus-use efficiency. Earth System Science Data 10(1), 1-18.
MacDonald, G.K., Bennett, E.M., Potter, P.A. and Ramankutty, N. 2011. Agronomic phosphorus imbalances across the world's croplands. Proceedings of the National Academy of Sciences 108(7), 3086-3091.
Maggi, F., Tang, F.H.M., la Cecilia, D. and McBratney, A. 2019. PEST-CHEMGRIDS, global gridded maps of the top 20 crop-specific pesticide application rates from 2015 to 2025. Scientific Data 6(1), 1-20.
Marchand, P., Carr, J.A., Dell'Angelo, J., Fader, M., Gephart, J.A., Kummu, M., Magliocca, N.R., Porkka, M., Puma, M.J. and Ratajczak, Z. 2016. Reserves and trade jointly determine exposure to food supply shocks. Environmental Research Letters 11(9), 095009.
McArthur, J.W. and McCord, G.C. 2017. Fertilizing growth: Agricultural inputs and their effects in economic development. Journal of Development Economics 127, 133-152.

Monfreda, C., Ramankutty, N. and Foley, J.A. 2008. Farming the planet: 2. Geographic distribution of crop areas, yields, physiological types, and net primary production in the year 2000. Global Biogeochemical Cycles 22(1).
Moriasi, D.N., Arnold, J.G., Van Liew, M.W., Bingner, R.L., Harmel, R.D. and Veith, T.L. 2007. Model evaluation guidelines for systematic quantification of accuracy in watershed simulations. Transactions of the ASABE 50(3), 885-900.
Mrema, G., Soni, P. and Rolle, R.S. 2014. A regional strategy for sustainable agricultural mechanization: sustainable mechanization across agri-food chains in Asia and the Pacific region. RAP Publication (2014/24).
Mueller, N.D., Gerber, J.S., Johnston, M., Ray, D.K., Ramankutty, N. and Foley, J.A. 2012. Closing yield gaps through nutrient and water management. Nature 490(7419), 254-257.
Mueller, N.D., Lassaletta, L., Runck, B.C., Billen, G., Garnier, J. and Gerber, J.S. 2017. Declining spatial efficiency of global cropland nitrogen allocation. Global Biogeochemical Cycles 31(2), 245-257.
Nanda, M., Cordell, D. and Kansal, A. 2019. Assessing national vulnerability to phosphorus scarcity to build food system resilience: the case of India. Journal of Environmental Management 240, 511-517.
Newlands, N.K., Zamar, D.S., Kouadio, L.A., Zhang, Y., Chipanshi, A., Potgieter, A., Toure, S. and Hill, H.S.J. 2014. An integrated, probabilistic model for improved seasonal forecasting of agricultural crop yield under environmental uncertainty. Frontiers in Environmental Science 2, 17.
O'Hara, J.K., Mulik, K. and Gurian-Sherman, D. 2015. Agricultural production impacts of higher phosphate fertilizer prices. Journal of International Agricultural Trade and Development 9(2), 233-253.
Oerke, E.C., Dehne, H.W., Schönbeck, F. and Weber, A. 2012. Crop production and crop protection: estimated losses in major food and cash crops, Elsevier.
Pingali, P.L. 2012. Green revolution: impacts, limits, and the path ahead. Proceedings of the National Academy of Sciences 109(31), 12302-12308.
Porkka, M., Kummu, M., Siebert, S. and Varis, O. 2013. From food insufficiency towards trade dependency: a historical analysis of global food availability. PloS one 8(12), e82714.
Portmann, F.T., Siebert, S. and Döll, P. 2010. MIRCA2000—Global monthly irrigated and rainfed crop areas around the year 2000: A new high-resolution data set for agricultural and hydrological modeling. Global Biogeochemical Cycles 24(1).
ProAgria 2022. Kevään kylvöihin viljaa ja valkuaiskasveja - jos taloudellisesti mahdollista, Pro Agria, https://www.proagria.fi/ajankohtaista/kevaan-kylvoihin-viljaa-ja-valkuaiskasveja-jos-taloudellisesti-mahdollista-17894, date accessed: [19 March 2022].
Probst, P., Wright, M.N. and Boulesteix, A.L. 2019. Hyperparameters and tuning strategies for random forest. Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery 9(3), e1301.
Puma, M.J., Bose, S., Chon, S.Y. and Cook, B.I. 2015. Assessing the evolving fragility of the global food system. Environmental Research Letters 10(2), 024007.
R Core Team 2021. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria.
Ray, D.K., Gerber, J.S., MacDonald, G.K. and West, P.C. 2015. Climate variation explains a third of global crop yield variability. Nature Communications 6(1), 1-9.

Robertson, G.P. and Vitousek, P.M. 2009. Nitrogen in agriculture: balancing the cost of an essential resource. Annual Review of Environment and Resources 34, 97-125.

Rosenzweig, C., Iglesius, A., Yang, X.-B., Epstein, P.R. and Chivian, E. 2001. Climate change and extreme weather events - Implications for food production, plant diseases, and pests.

Sainsbury, P. 2021. Suez Canal choked by giant container ship disrupting a key food and fertiliser trade route, Materials Risk. Commodity market insights & expertise, http://materials-risk.com/suez-canal-choked-by-giant-container-ship-disrupting-a-key-food-and-fertiliser-trade-route/, date accessed: [11 October 2021].

Sattari, S.Z., Bouwman, A.F., Giller, K.E. and van Ittersum, M.K. 2012. Residual soil phosphorus as the missing piece in the global phosphorus crisis puzzle. Proceedings of the National Academy of Sciences 109(16), 6348-6353.

Seekell, D.A., Carr, J., Dell'Angelo, J., D'Odorico, P., Fader, M., Gephart, J.A., Kummu, M., Magliocca, N., Porkka, M., Puma, M.J., Ratajczak, Z., Rulli, M.C., Suweis, S. and Tavoni, A. 2017. Resilience in the global food system. Environmental Research Letters 12(2), 10; 11-10.

Sheldrick, W.F., Syers, J.K. and Lingard, J. 2002. A conceptual model for conducting nutrient audits at national, regional, and global scales. Nutrient Cycling in Agroecosystems 62(1), 61-72.

Sims, B.G., Hilmi, M. and Kienzle, J. 2016. Agricultural mechanization: a key input for sub-Saharan Africa smallholders. Integrated Crop Management eng 23.

Sinclair, T.R. and Rufty, T.W. 2012. Nitrogen and water resources commonly limit crop yield increases, not necessarily plant genetics. Global Food Security 1(2), 94-98.

Singh, G. 2006. Estimation of a mechanisation index and its impact on production and economic factors—A case study in India. Biosystems engineering 93(1), 99-106.

Smil, V. 1999. Nitrogen in crop production: An account of global flows. Global Biogeochemical Cycles 13(2), 647-662.

Stewart, W.M., Dibb, D.W., Johnston, A.E. and Smyth, T.J. 2005. The contribution of commercial fertilizer nutrients to food production. Agronomy Journal 97(1), 1-6.

Tulbure, M.G., Wimberly, M.C., Boe, A. and Owens, V.N. 2012. Climatic and genetic controls of yields of switchgrass, a model bioenergy species. Agriculture, Ecosystems & Environment 146(1), 121-129.

UN 1948. Universal declaration of human rights. UN General Assembly 302(2), 14-25.

Verma, S. 2006. Impact of agricultural mechanization on production, productivity, cropping intensity income generation and employment of labour. Status of Farm Mechanization in India 2006, 133-153.

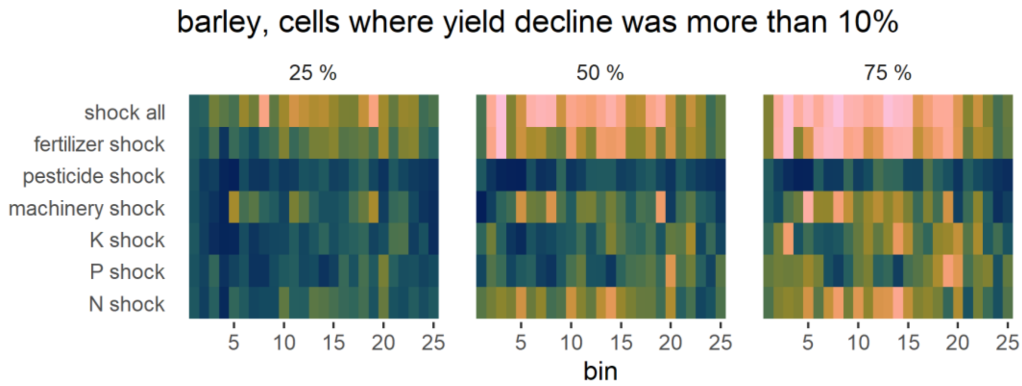
Vidal, J. 2008. Soaring fertiliser prices threaten world's poorest farmers, The Guardian (online edition), https://www.theguardian.com/environment/2008/aug/12/biofuels.food, date accessed: [14 November 2021].

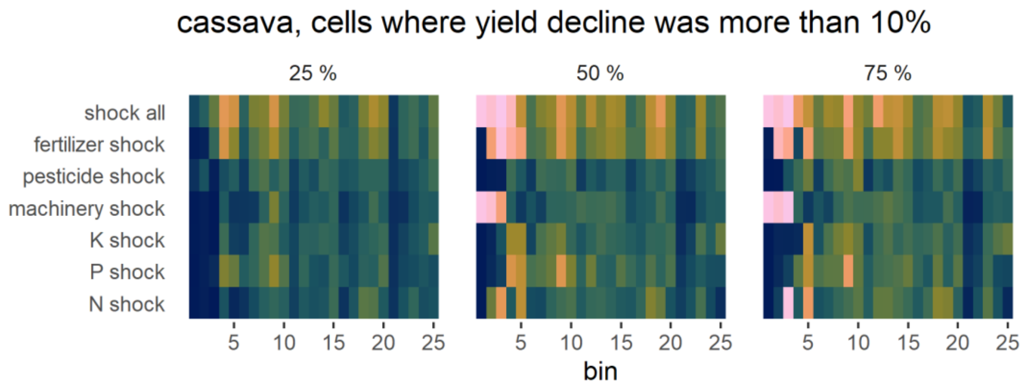
Vitousek, P.M., Naylor, R., Crews, T., David, M.B., Drinkwater, L.E., Holland, E., Johnes, P.J., Katzenberger, J., Martinelli, L.A. and Matson, P.A. 2009. Nutrient imbalances in agricultural development. Science 324(5934), 1519-1520.

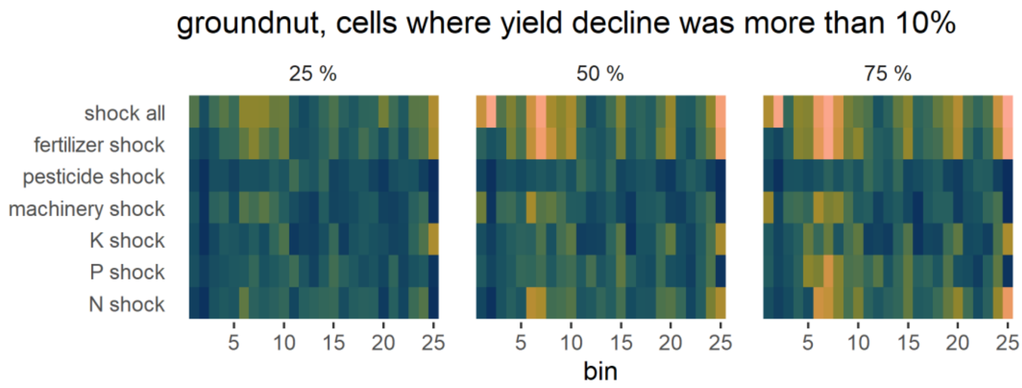
Wang, X., Müller, C., Elliot, J., Mueller, N.D., Ciais, P., Jägermeyr, J., Gerber, J., Dumas, P., Wang, C. and Yang, H. 2021. Global irrigation contribution to wheat and maize yield. Nature Communications 12(1), 1-8.
Webster, J.P.G., Bowles, R.G. and Williams, N.T. 1999. Estimating the economic benefits of alternative pesticide usage scenarios: wheat production in the United Kingdom. Crop Protection 18(2), 83-89.
West, P.C., Gerber, J.S., Engstrom, P.M., Mueller, N.D., Brauman, K.A., Carlson, K.M., Cassidy, E.S., Johnston, M., MacDonald, G.K. and Ray, D.K. 2014. Leverage points for improving global food security and the environment. Science 345(6194), 325-328.
Wheeler, T. and Von Braun, J. 2013. Climate change impacts on global food security. Science 341(6145), 508-513.
Wuepper, D., Le Clech, S., Zilberman, D., Mueller, N. and Finger, R. 2020. Countries influence the trade-off between crop yields and nitrogen pollution. Nature Food 1(11), 713-719.
Zhang, C., Guanming, S., Jian, S. and Hu, R.-f. 2015. Productivity effect and overuse of pesticide in crop production in China. Journal of Integrative Agriculture 14(9), 1903-1910.
Zhang, X., Zou, T., Lassaletta, L., Mueller, N.D., Tubiello, F.N., Lisk, M.D., Lu, C., Conant, R.T., Dorich, C.D. and Gerber, J. 2021. Quantification of global and national nitrogen budgets for crop production. Nature Food, 1-12.
Zhao, Q. and Hastie, T. 2021. Causal interpretations of black-box models. Journal of Business & Economic Statistics 39(1), 272-281.

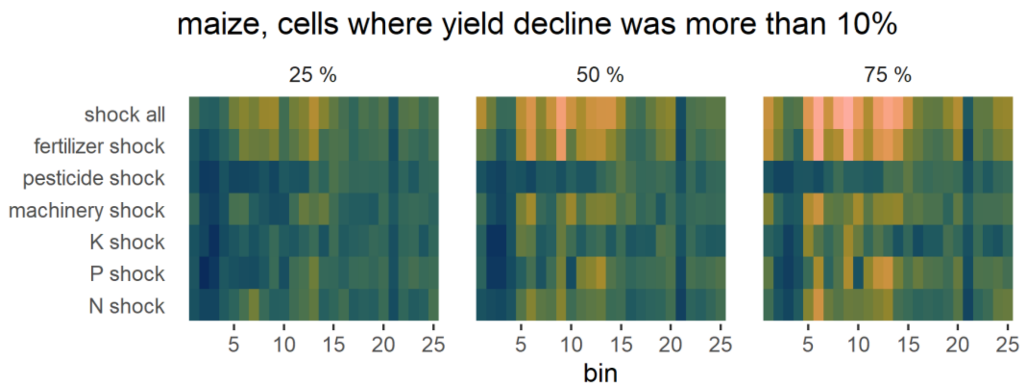
A. Supplementary Material

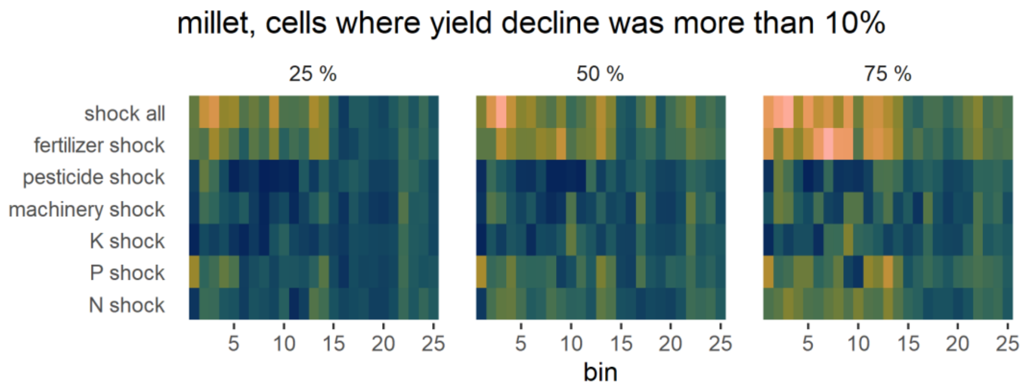
Fig. A 1: tile plots for all studied crops, representing the share of climate bin cells where yield decline was more than 10% of the original yield. Barley has the largest area of decreased yield with the biggest shock scenarios. The variation is also strong, with a 25% shock showing a much smaller yield decrease area than a 75% shock. In barley, there is also considerable variation between the different climate bins and scenarios. Maize, rice and wheat do not see such drastic yield decrease variation between the 25%, 50% and 75% scenarios. The variation between climate bins and scenarios is also smaller, with many areas predicting a ~50% share of yield decrease. For soybean, the average share of bin area where yield decrease was more than -10% is smaller than for the above-mentioned crops, around 30%. Some climate bins in potato and barley are most affected by machinery shocks. Machinery also seems to be an important factor in the yield of cassava, indicating for bins 1–3 that 100% of their area experienced yield decline. However, the NSE scores for these climate bins of cassava were very poor (Figure 5), so these yield decline results may not be very reliable.

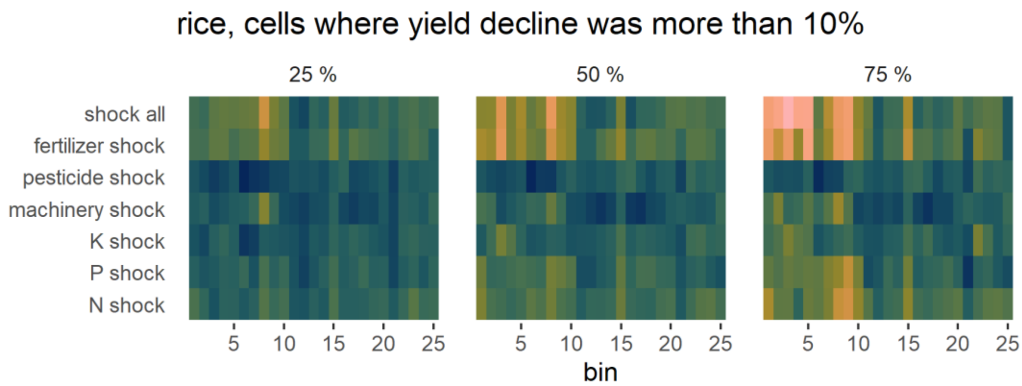




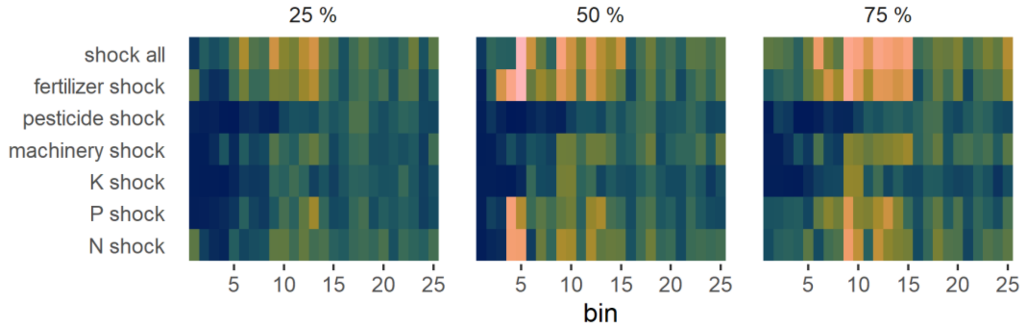

groundnut, cells where yield decline was more than 10%
25 %
50 %
75 %
shock all
fertilizer shock
pesticide shock
machinery shock
K shock
P shock
N shock
5 10 15 20 25
bin


maize, cells where yield decline was more than 10%
25 %
50 %
75 %
shock all
fertilizer shock
pesticide shock
machinery shock
K shock
P shock
N shock
5 10 15 20 25
bin

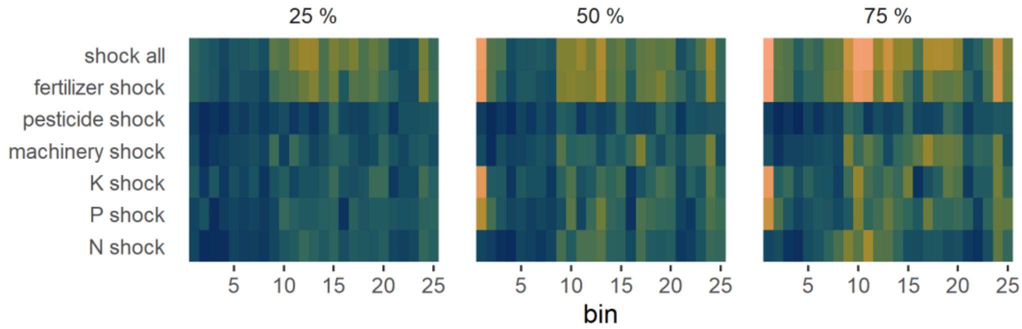

millet, cells where yield decline was more than 10%
25 %
50 %
75 %
shock all
fertilizer shock
pesticide shock
machinery shock
K shock
P shock
N shock
5 10 15 20 25
bin


rice, cells where yield decline was more than 10%
25 %
50 %
75 %
shock all
fertilizer shock
pesticide shock
machinery shock
K shock
P shock
N shock
5 10 15 20 25
bin

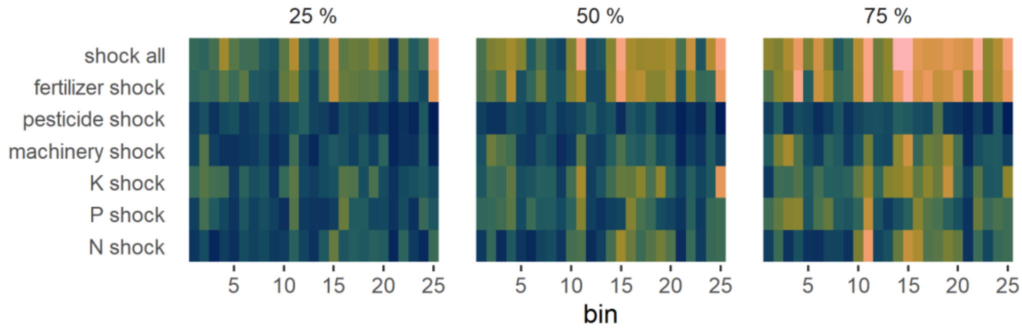
sorghum, cells where yield decline was more than 10%



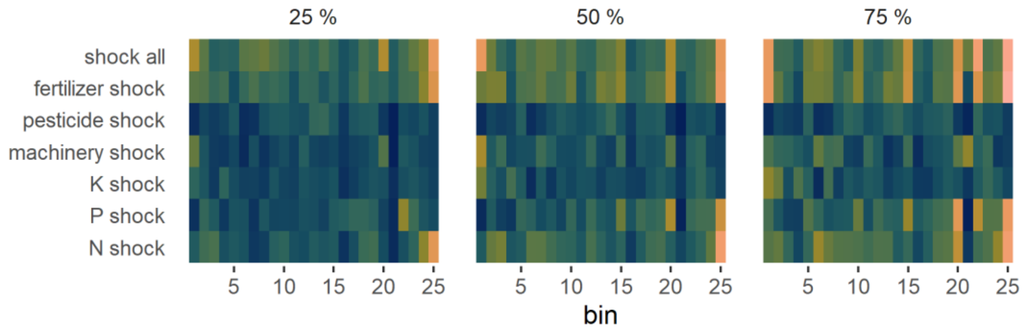
soybean, cells where yield decline was more than 10%

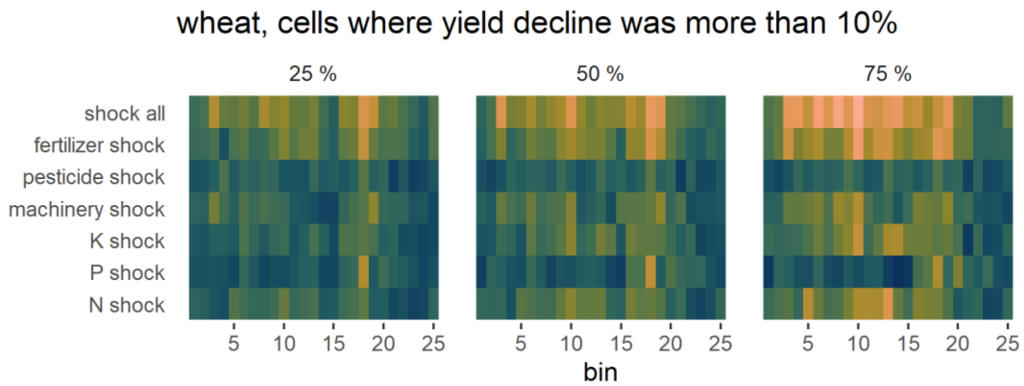


sugarbeet, cells where yield decline was more than 10%



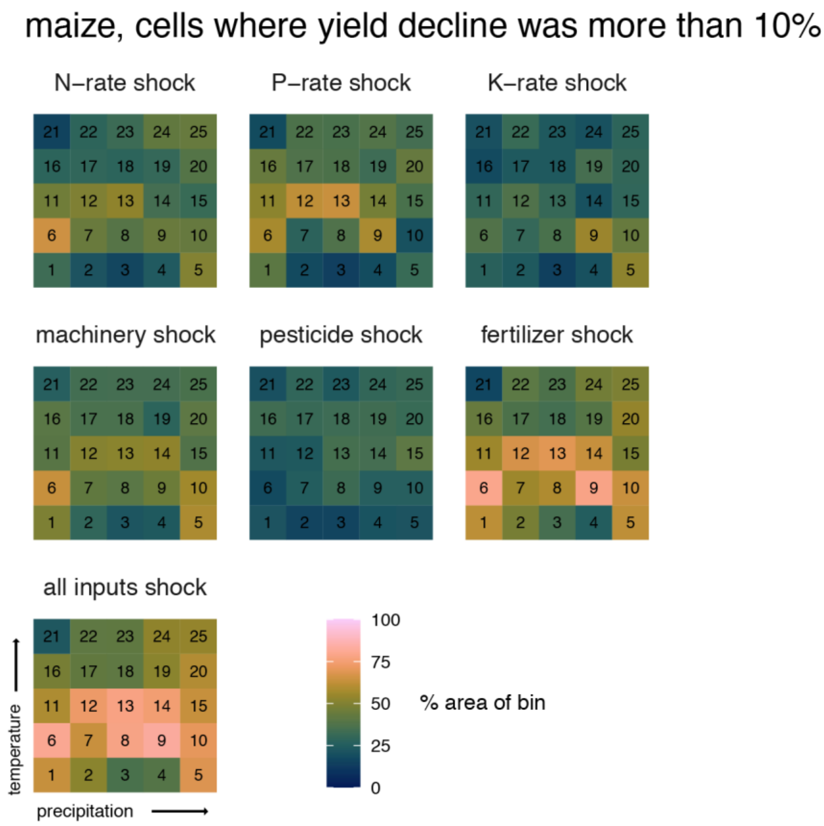
sugarcane, cells where yield decline was more than 10%



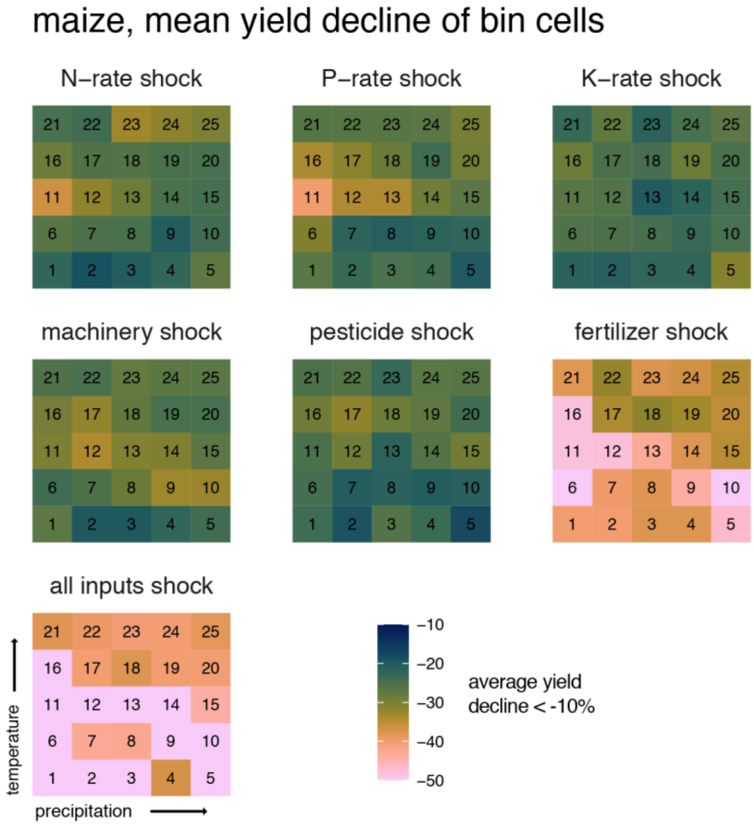


A 1: Tile plots showing the percentage of bin area where shock yield was at least 10% lower than the original yield. Colour legend is the same as in Fig. A 2.

Figs. A 2 and A 3: maize tile plots for one shock percentage (75%) arranged to highlight the effect of climate bins. For example, climate bins 8, 9, 12, 13, and 14 share relatively close temperature and precipitation conditions and are also most heavily affected by the shock in all inputs.



A 2: Maize, percentage of bin area where the shock yield was at least 10% lower than the original yield.



A 3: Maize, mean shock yield decline in cells where the shock yield was at least 10% lower than the original yield.