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What is the importance of crop diversity for national nutrient supply?

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Abstract

About a quarter of the world's population suffers from micronutrient deficiencies. That reinforces the view that not only hunger but also malnutrition needs to be assessed in nutritional science. Crop Diversity is considered to have a positive effect on different food security dimensions. As one of the four dimensions, food availability (i.e. supply), is mainly made up by production and trade. Diversification respectively specialisation strategies are shown to effect both- production and trade. Here I show, by including trade and production on national scale how crop diversity influences the supply of nutrients. A new approach based on three analysis steps combines current scientific concepts. (1) First, three contrasting diversity metrics of crops produced within a country are calculated: richness, inverse Simpson index and asynchrony. (2) Second, to assess how many of the national required nutrients can be achieved through the national supply of nutrients, FAO balance sheets are combined with the USDA food composition database. (3) Third, I use linear and linear mixed effect models to quantify the link between the resulting fulfilled nutritional supply and crop diversity. By assessing 57 countries worldwide in five decades (1961-2010), I found that the status in terms of nationally achieved nutrient requirements increased for all regions except Sub-Saharan Africa. I find that crop diversity does not contribute markedly to achieve a better nutrient supply for respective populations. I argue that this does not exclude it's relevance to other food security dimensions and suggest further analysis, for which the present analysis can be seen as model approach.

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II. Terms and Acronyms

Terms

fulfilled requirements	the percentage of the population, that could be nourished by the national food supply (with equal distribution) per nutrient
full basket	the percentage of the population, that could be fully nourished by the national food supply (with equal distribution); oversupply of one nutrient does not compensate for a lack of supply of others
minimal model	model excluding those predictors, that are highly correlated and those that have no have significant effect on the response variable. Diversity variables are kept regardless of their effect size
self-sufficient food basket	the share of the population, that could be nourished (with equal distribution) by the domestically produced food supply per nutrient
self-sufficient full basket	the share of the population, that could be fully nourished by the national food supply (with equal distribution) which is produced domestically; oversupply of one nutrient does not compensate for a lack of supply of others

Acronyms

AI	Adequate Intake
AIC	Akaike Information Criteria
AR	Average Requirement
DRVs	Dietry Reference Values
EFSA	European Food Safety Authority
FAO	Food and Agriculture Organization of the United Nations
FAOSTAT	Statistics Division of the Food and Agriculture Organization of the United Nations
FBS	Food Balance Sheets
ICC	Intraclass Correlation Coefficient
LPI	Level of Phytate Intake
OECD	Organisation for Economic Co-Operation and Development
PAL	Physical Activity Level
SCF	Scientific Committee for Food
SDGs	UN Sustainable Development Goals
UN	United Nations
USDA	U.S. Department of Agriculture
VIF	Variance Inflation Factor
WDI	World Development Indicators
WTO	World Trade Organization

1. Introduction

Almost 690 million people, which is 8.9 percent of the global population were undernourished in 2019 and two billion people, which is 25.9 percent of the global population suffered from micro nutrient deficits (FAO, IFAD, UNICEF, WFP and WHO, 2020). Diet quality, described by FAO, IFAD, UNICEF, WFP and WHO (2020) "compromises four key aspects: variety/diversity, adequacy, moderation and overall balance." The general increase in crop yields since the 1960s (Ramankutty et al., 2018; Massawe et al., 2016) enhanced the perspective that not only hunger, but malnutrition is a big threat to human well being as it especially affects the health of more vulnerable people, like children, the elderly or pregnant women.

Food production systems underlie spatiotemporal dynamics, thus different diversification strategies coexist and vary widely among agroecosystems and climates (Beillouin et al., 2020). Consequently, the scale of the analysis heavily influences the results. For example agricultural concepts, such as intercropping or agroforestry, are mostly observed on field level. Cropping failures due to political, climatic or economic shocks occur locally, but they influence supply and access to food on global scale, as the global market prices might rise. Crop asynchrony, that is when local production trends differ from global production trends can decrease the overall risk, as local production failures can be compensated by the global market (Mehrabi and Ramankutty, 2019). Additionally high crop diversity is often considered to be an indicator of food security (Massawe et al., 2016, e.g.). Species-specific crop failures due to e.g. climatic shocks or pests contribute less to overall yield in a highly diverse cropping system. Crop diversity itself can have different meanings, based on either genetic, taxonomic or functional traits. While genetic variety is of great importance for biodiversity, there is a lack of sufficient data. However, concerning food security issues analysing diversity of crops on species or family level and aggregating on crop groups yields sufficient information.

Publications that examine the link between crop diversification and food security are scarce. Many of them are on field, landscape, or household (Sibhatu et al., 2015) level. But especially in recent years that topic is receiving more attention (Nicholson et al., 2020; Renard and Tilman, 2019, e.g.). Research concerning crop diversity and food security issues can be categorized differently, focusing either on: household, (sub-) national or global level; thematically, which implies the different dimensions of the food security definition or structural, focusing either the supplier or the consumers perspective.

Regarding crop diversity, there is no consensus how to define it. Thus, it is important to differentiate between various metrics and definitions. Counting the number of different crops or crop groups, called richness, is a common assessment, but if used it is often supplemented by additional evenness analysis (Khoury et al., 2014, e.g.). Biodiversity indices incorporate both richness and the evenness of the crop abundance, also called relative abundance. Therefore varieties of the Shannon-Wiener and the Simpson Diversity index are often used. Those indices consider that some nations might have a big crop richness, but very small effective diversity, due to few dominant species. In return, there are countries with lower richness, but due to bigger evenness of their crop abundance, they have a higher effective diversity. The Shannon diversity index is comparatively sensitive to small changes in richness thus focusing the scarce species. The Simpson diversity index in contrast emphasises the evenness, thus emphasising on dominant crops. Regarding food security, it might be obvious, that common and often dominant species contribute most to feeding the world and therefore their crop diversity would be assessed best through the evenness itself or evenness-focused indices like the Simpson index. But especially regarding nutritional supply it should not be neglected, that in particular rarer agricultural commodities deliver essential micro nutrients. Millet, for example, whose acreage declined significantly between 1961 and 2013, contains four times more iron than the widely grown rice (Defries et al., 2015).

The green revolution, a series of agricultural modernizations beginning in the 1960s, developed unequally across the world and across crops. This leads until today to high inputs and thus outputs especially of the main staple crops: rice, maize and wheat and some others, so that only 20 plant species compromise 90% of the world‘s calories (Massawe et al., 2016). Taking data from 1961 to 2009, a general inventory of the changing global crop abundance, richness and composition was performed by Khoury et al. (2014). Similar to other scientists,(Aguiar et al., 2020; Nicholson et al., 2020, e.g.) they found that the national diversity of different crop commodities increased, whereas the global diversity decreased, resulting from "Westernization transition in preference of energy-dense foods [...] over traditional crops" (Khoury et al., 2014). Nevertheless, crop diversity on national level differs within regions and countries with increases, decreases and no-changes coexist (Martin et al., 2019; Nelson et al., 2016). Some countries concentrated on export and thus specified their crop production, others diversified their commodity chain in order to cover their own needs. The synchrony of global and local production (and vice versa production failure) with data on maize, rice, soy and wheat from 1961- 2008 was analyzed by Mehrabi and Ramankutty (2019). They found "that the degree of synchrony between crop-growing locations has played an important role in regulating the stability and variation in global crop production" (Mehrabi and Ramankutty, 2019). In a further step they analyzed the historical synchrony within crops. Therefore they quantified the degree of synchronization in global crop production with all crops combined and converted them to calories. They found that the four observed crops did not consistently compensated each other, which can be interpreted as crop diversity does not reduce food security risks on global scale. This study concentrated on the global food supply, in contrast to Renard and Tilman (2019), who focus on the national availability of aliments. Renard and Tilman (2019) aimed to identify different stabilizers of national year-to-year yields of 176 different crop species in 91 countries. They converted the combined crop yields in caloric and in economic yields to get comparable and understandable outputs. Evaluating many regression coefficients, crop diversity, the share of irrigated land and the intensity of fertilizer use were found to have the most positive effect on the year-to-year crop yield stability, with crop diversity as the main driver. They used the Shannon diversity index to measure both the crop diversity and the crop group diversity. Directly referring to Renard and Tilman (2019), Egli et al. (2020) published a further analysis with a similar study design evaluating stabilizing effects of crop asynchrony compared with stabilizing effects of crop diversity. Therefore, they reverse-engineered the study of Renard and Tilman (2019) with small differences. They applied data on crop production instead of crop yields, as they assumed it to be a better indicator for food security. Using different models with crop diversity and asynchronous production trends either combined or separated, they found crop asynchrony and crop diversity highly correlated. They conclude that asynchrony "is an even better predictor of agricultural production stability than is crop diversity". (Egli et al., 2020)

The paper "Global relationships between crop diversity and nutritional stability", authored by Nicholson et al. (2020) is not peer reviewed yet. Nonetheless, it fills some of the knowledge gaps, by focusing on the nutritional stability, using crop composition data between 1961 and 2016. To include global trade, they created two food supply scenarios: in one they evaluated the sole national production and in the other one they evaluated the production plus imports. First, they created bipartite crop-nutrient networks. The robustness of the national nutritional supply was then modeled through the loss of single crops. Results show that even though crop diversity has increased, mainly through expanded imports, nutritional stability did not change or even declined in most parts of the world, except Asia. These findings are especially interesting, as they contradict the common understanding, that a greater crop diversity leads automatically to a greater supply of nutrients. The study concludes that they have emphasized on the "physical availability" part of food security and that this does not fully reflect the topic of food security. Remans et al. (2014) calculated the diversity of both the produced and the supplied nutritional outcome on national level. Therefore, they used three different metrics: the Shannon entropy diversity metric, a functional diversity metric, which is based on the nutritional composition and amount of each food item present and the percentage of energy not coming from staple crops. They found that "for low-income countries the diversity of agricultural goods produced in a country is a strong predictor for food supply diversity; for middle- and high-income countries national income and trade are better predictors." In this study they accounted for nutritional diversity in general, but the nutritional diversity metric does not scale to the individual nutrients and their respective requirements.

Kummu et al. (2020) assessed food production, food supply and independences on food imports on national level. They showed that "food supply diversity [which does not directly indicate crop diversity] increased significantly for most of the world's population at the cost of an elevated dependency upon food imports". To measure their food supply and food diversity index, Kummu et al. (2020) used the Shannon diversity index, inspired by the earlier analysis of Remans et al. (2014). As Kummu et al. (2020) discussed in their study, they concentrated on trade related resilience, whereas Seekell et al. (2017) assessed a country's resilience by different socio-economic, biophysical and production diversity factors. Resulting that Kummu et al. (2020) and Seekell et al. (2017) getting partly contrasting results concerning the state of food security in some regions. To estimate the socio-economic access to food, Seekell et al. (2017) calculated an index based on the income of the poorest quintile relative to the food prices.

While a lot of papers (Renard and Tilman, 2019; Mehrabi and Ramankutty, 2019; Seekell et al., 2017, e.g.) do not pay sufficient attention to the utility dimension of food security, which can be explicitly measured in nutrient supply, other works (Khoury et al., 2014; Nicholson et al., 2020; Kummu et al., 2020, e.g.) cover that at least in basic components such as: calories, protein, fat and weight. Nicholson et al. (2020) is reaching the finest nutritional scale by creating a functional relationship between crop diversity and nutritional stability. Global trade influences the supply of food within a country and therefore on one hand can possibly stabilize food security and on the other hand due to a strong dependency a country is more exposed to price shocks, trade wars and synchronized crop failures. This issue is mostly assessed through the number of imports or indirectly via overall national food supply data, for example provided by the Food and Agriculture Organization of the United Nations (FAO) in so called Food Balance Sheets (FBS) (Nicholson et al., 2020; Kummu et al., 2020; Khoury et al., 2014, e.g.). Socio-economic variables, which depict the ability of the population within a country to buy and thus consume food are sparely assessed. In conclusion, recent studies mostly indicate that crop diversity improves aspects of food security, although to date there is still no approach to analyze the impact of crop diversity on overall food security, demonstrating how complex the field of food security is.

Here I show a link of crop diversity facets and food security facets. One objective is to develop more sophisticated methods for assessing food security, using a new metric for national nutritional supply. Four main questions will be answered: 1. How has the national nutrient supply changed since the 1960's, and what regional patterns can be observed? 2. How did trade patterns evolve and to what degree do they influence the national nutrient supply? 3. What is the importance of crop diversity for the national nutrient supply? 4. Which diversity factor respectively which diversity strategy is most suitable to assess the diversity - food security nexus? Therefore, I use complementary ecological metrics of crop diversity on global level to cover both the relevance of scarce crops for specific micro nutrients and the overall importance of common crops to feed the world population.

2. Data and Methods

2.1. Data

Here I present the key databases and data sets used in the analysis. As most variables were provided by the FAO, their database Statistics Division of the Food and Agriculture Organization of the United Nations (FAOSTAT) is shortly described. The nutritional conversion factors and the dietary reference values are already processed data and fundamental to the methodology of this analysis.

A.0 provides a short description, the download date and the source for all data used in the analysis.

2.1.1. FAOSTAT

Yearly data on the agricultural production, food composition (i.e. food supply), fertilizer use, area equipped for irrigation, area of agricultural land and livestock production per country is provided by the FAOSTAT (see Table A.0). Data for maximally 245 countries depending on the considered domain, from 1961 until today is available. Statistics are primarily gathered from questionnaires submitted mostly voluntarily by member countries and from national publications (FAO, 2021). To complete data sets, they use information from international publications and reports "issued by boards and associations" (FAO, 2021). The FAO checks all data sets for consistency and quality by comparing different sources and filling gaps, when required. The general supply of food, also called food composition, is derived by FAO FBS, which provide production, trade and utilization data on 98 food commodities. Here crop but also animal commodities are included. These data is widely used in nutritional science (Wood et al., 2018). FBS include data on production, import and export quantity; variations in stock and "other uses". "Other uses" refer to data on Food-items not used for human diets, such as meat for pet food or oil for soap production. The Item "Agriculture" provided by FAOSTAT contains the total area used for agricultural production, including "Land under permanent meadows and pastures", "Land under temporary crops" and some others. Some uncertainties about the accuracy of the submitted data exist. For example it is found that the cropland area provided by FAOSTAT differs from calculated measurements through remote sensing (Liu et al., 2018). In most countries the FAO cropland data tends to be smaller than the calculated cropland area from remote sensing products (Liu et al., 2018). Nonetheless, the FAOSTAT database provides the most common, comprehensive and harmonized data set available for global agricultural analysis.

2.1.2. Nutritional Conversion Factors

The U.S. Department of Agriculture (USDA) provide nutritional values of different commodities in a food composition database (USDA, 2021). Wood et al., 2018 assigned to every FAO-specific commodity different USDA-specific commodities, following the approach of Smith et al., 2016. They excluded beverages, spices and some other components. To allow for reproducibility they have been publishing the translation table ("USDA_Nutrients.xlsx", see Table A.0) which I used for calculating the nutritional supply per year and country.

2.1.3. Dietry Reference Values

The European Food Safety Authority (EFSA) provides Dietry Reference Values (DRVs) for healthy populations. DRVs vary depending on life-stage and sex. These include reference values for different ages and special requirements for lactating and pregnant women. It was assumed that every infant is breastfed for the first six months and thus, does not have own nutritional requirements. Some limitations for global purpose need to be clarified. As nutrient and energy requirements were calculated by using reference weights from Scientific Committee for Food (SCF) reports in 1993 and 2000 a limited number of (EU) states is represented in this data. To simplify my analysis these weights were assumed to be valid for the whole world. One has to acknowledge the implicit bias, that the average European is taller and heavier, thus requiring bigger amounts of nutritious intake than the average world population (WorldData.info, 2021). Energy requirements differ for different Physical Activity Level (PAL). Similarly zinc requirements differ for different Level of Phytate Intake (LPI). In this analysis the same PAL and LPI for each country, year and sex/life-stage group was assumed and noted within 03_fullfilled_demand.R (available at: `https://github.com/AnnikaErtel/CropDiversity_NutritionalSupply`). The EFSA provides different statistical values for different purposes. I used the Average Requirement (AR), which is "the level of (nutrient) intake that is adequate for half of the people in a population group, given a normal distribution of requirement" (EFSA, 2010). Whenever the AR is not provided I took the Adequate Intake (AI), following the recommendations of the EFSA. The AI is "the average observed daily level of intake by a population group (or groups) of apparently healthy people that is assumed to be adequate" (EFSA, 2010).

2.1.4. Other Variables

To account for the purchasing power of the population within each country the GDP per capita (current US$) is included in the analysis. Values were available via the World Bank World Development Indicators (WDI) databank. I reused the year-to-year temporal instability of the mean growing-season precipitation and temperature directly from the data Egli et al., 2020 provided. Oriented on the approach of Renard and Tilman, 2019 I used the warfare variable, which is the number of armed conflicts per nation for the respective decade. As the diversity measurement richness is likely to be strongly correlated with the absolute assessed size, the agricultural area is tested as predicting variable. Crop diversity is calculated from the crops planted within a country, whereas the degree of livestock intensity might influence the diversity heavily, as on one hand feed is mainly produced from few crops and on the other hand countries could rather specialize their agriculture on livestock, than on crops.

2.2. Methods

All calculations were carried out with the open source programming language *"R"* (Version 3.6.3). It is made for statistical purposes and is made up of different packages (R Core Team, 2020). A.10 provide the current version of *"R"* and all packages directly and indirectly used in this analysis. The scripts itself can be downloaded from the open Github repository: `https://github.com/AnnikaErtel/CropDiversity_NutritionalSupply`.

2.2.1. Study design

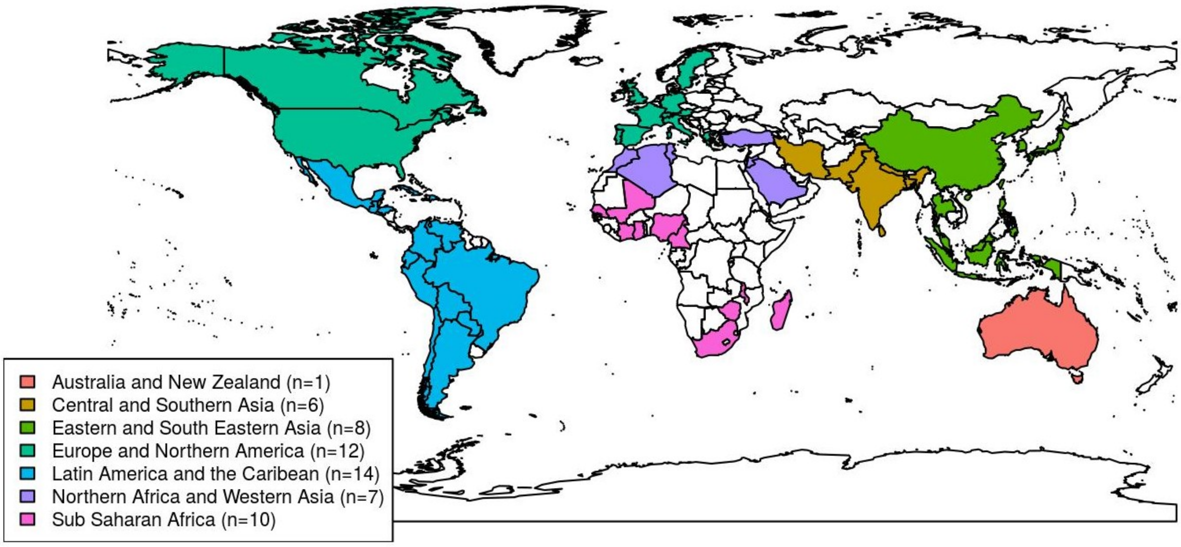

Figure 1: **Map of evaluated countries.** Countries (n=57) are classified in target regions as defined for the United Nations (UN) Sustainable Development Goals.

In order to assess different climatic, demographic, political and infrastructural situations I evaluated a large temporal and spatial heterogeneity (see 01_country_selection_&_split.R) Following the approach of Renard and Tilman, 2019 the 100 most populous nations (as of 2010) were preselected, while countries whose borders have changed in the time frame (1961-2010) of the analysis were omitted. In their global analyses Egli et al., 2020 and Renard and Tilman, 2019 excluded countries, because of poor quality of the FAO data. Countries with high estimated rather than directly communicated values were excluded as well as other nations because of uncertainties concerning fertilizer use and Egypt as it had 100% of the cropland area equipped for irrigation for the complete time series. Additional to the nations Renard and Tilman, 2019 excluded, I excluded those for which the time series for any of the variables was incomplete, resulting in a final data set of 57 countries within a 50-year period that began in 1961 and ended in 2010. I divided the time series into 5 decades for each variable, using the mean of the annually resolved data. To assess regional differences in the analysis I referred to the regional grouping the UN uses to define the sustainable development goals for the whole world. Figure 2 shows the selection and grouping of countries used.

2.2.2. Diversity Metrics

For calculating the different diversity metrics I used the agricultural data set derived by the FAO including information on "Area Harvested", "Production" and "Yield". See 05_diversity.R for the complete calculation. I used production instead of the harvested area, as it was more frequently reported and had fewer missing values. Furthermore in the context of food security, production contains more directly interpretable information than harvested area or yield. The commodity "Mushrooms and truffles" was excluded from the diversity analysis as it is no plant but funghi.

Spatial Diversity Metrics I calculated the number of crops cultivated, i.e. the richness R, and the inverse Simpson diversity index of crops cultivated (1). Both measures were calculated for each nation and year.

$$inverse - Simpson - index = \frac{1}{\sum_{i=1}^{R} p_i^2} \tag{1}$$

In (1) p_i is the proportion of crop i in the total production. Higher values of the inverse Simpson index imply higher diversity and lower values imply lower diversity.

Temporal Diversity Metrics I calculated Asynchrony as measurement for temporal diversity, by subtracting the synchrony metric developed by Loreau and Mazancourt, 2008 from one (see (2)). Due to an increase in harvested area and yield over time, due to agricultural expansion and intensification, the production data was time-detrended. On this account, following Egli et al., 2020 a linear regression between annual production and the year squared was computed for each decade and country. The resulting residuals measure the deviation from the long-term average, thus displaying temporal diversity. The asynchrony per country and decade was then calculated by

$$Asynchrony = 1 - \left(\frac{\sigma\left(x_T\right)^2}{\left(\sum_i \sigma_{x_i}\right)^2} \right) \tag{2}$$

It compares the variance σ^2 of the aggregated species abundance x_T, here the residuals of the time detrended production, with the sum of the variances $\sum \sigma^2$ of the individual species x_i. The index is standardized between 0 and 1 and higher values indicate more asynchronous, thus more diverse agriculture and vice versa.

2.2.3. Nutritional Status

Nutritional Supply To calculate the national fulfilled requirements, I first calculated the general availability (i.e. supply) of nutrients in each country. See 02_nutritional_supply.R for full calculation. Therefore, I combined the FAO FBS and the USDA Food Composition database following the approach of Wood et al., 2018. Consequently, I used the nutrient translation table "USDA_Nutrients.xlsx" provided by Wood et al., 2018. By multiplying each food component by a refuse fraction, the analysis included only the edible amounts of each commodity. These were multiplied by the concentration of nutrients in each product, evaluating eight nutrients: protein, energy, zinc, calcium, iron, vitamin B12, folate and vitamin A. The total food supply per country, year and nutrient, from here on called *total nutritional supply* is then defined as:

$$\begin{aligned} total\ nutritional\ supply = \sum_{i}^{N} production_i + imports_i + changes\ in\ stocks_i \\ -exports_i - waste_i - other\ uses_i \\ -conversion\ to\ seed_i - conversion\ to\ feed_i \end{aligned} \tag{3}$$

Nutritional Demand I calculated the nutritional demand of the total population within each country. See 03_nutritional_demand.R for full calculation. The number of people per age class and sex was provided by the World Bank Health Nutrition and Population Statistics database. The population data of the World Bank had no information about pregnant and lactating women, so I used the "Birth rate, crude (per 1,000 people)", from the same database to approximate the number of pregnant and lactating women in each year. I assumed the childbearing age to be between 15 and 49 and that each of these women breastfeeds for six months after nine months of pregnancy. For the total national nutritional demand I multiplied the sex and life stage specific AR, respectively AI (see 2.1.3), provided by the EFSA, by the population statistics for each country, year and nutrient:

$$nutritional\ demand = AR\ or\ AI_{lifestage,\ sex} * Population \tag{4}$$

Full basket First I calculated the percentage of people that can theoretically meet their nutritional needs through their respective national supply (i.e. fulfilled requirements) for each country, year and nutrient from the aforementioned data products
(see 04_fulfilled_nutritional_demand.R):

$$fulfilled\ nutritional\ demand = \frac{total\ nutritional\ supply}{nutritional\ demand} \tag{5}$$

For the purpose of assessing an overall adequate supply status of nutrients, I introduced the variable full basket. It is the percentage of the population that can theoretically be fully nourished by the national food supply. Therefore, for each country and each year the minimum value of the fulfilled nutritional demand of all nutrients was set as the full basket variable. This reduced eight values (i.e. one for each nutrient) to one full basket value for each year and country. In this context an oversupply of one nutrient does not compensate for a lack of supply of others.

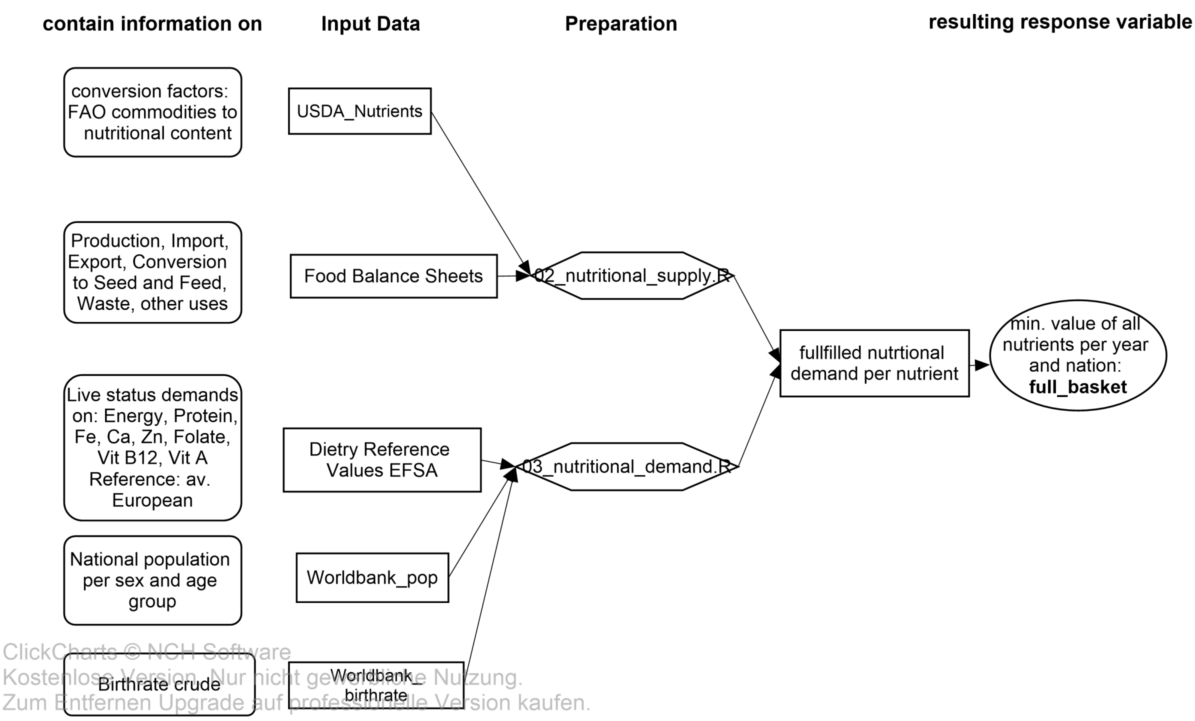

Figure 2: **Flowchart of full basket calculation:** General overview, including input information and used scripts. Information on data sources can be found in A.0. A more general workflow for the present study is shown in A.1. All scripts are available at: `https://github.com/AnnikaErtel/CropDiversity_NutritionalSupply`. I used the free software: ClickCharts NCH Software for visualisation.

Self-sufficient full basket In order to depict the nutritional independence respectively the remoteness from the world market I estimated the share of the fulfilled requirements that is produced self-sufficiently. For calculation see 04_fulfilled_nutritional_demand.R. On this account, the amount of each required nutrient, which was nationally produced and available for human consumption was calculated. This was divided then by the fulfilled requirements per year, country and nutrient.

$$\frac{\frac{production - exports - other\ uses - conversion\_to\_seed - conversion\_to\_feed}{nutritional\ demand}}{fulfilled\ nutritional\ demand} = self\text{-}sufficient\ food\ basket \tag{6}$$

Values close to 1 indicate that nearly all of the fulfilled requirements are produced domestically and few is imported. Decreasing values indicate decreasing self sufficiency. As the elements "feed" and "seed" include imported and domestically produced nutrients the self-sufficient food basket (and self-sufficient full basket) tends to underestimate the actual degree of self sufficiency especially for feed importing countries, thus explaining negative values. The calculation of the self-sufficient full basket variable for each country and year was done analogous to the calculation of the full basket. I set the minimum value of all nutrients of the self-sufficient food basket to the final value of the variable self-sufficient full basket. Again, this reduced eight values (i.e. one for each nutrient) to one full basket value for each year and country.

2.2.4. Models and Statistical Analyses

In order to disentangle which factors influence the percentage of the population, that could be nourished by the national food supply and in which relative importance these factors stand to each other, I tested different models. I used full basket (see 2.2.3 for calculation) as response variable and tested for linear and linear mixed effect models as well as for different compositions of predictor variables.
For each diversity metric I calculated each version of the model separately. By that means I show which diversity strategy might best improve or which diversity metrics might best represent the impact on the fulfilled nutritional status. Despite the changed diversity predictor, all other variables and in some cases additionally their interactions kept the same for each version.
Additionally to simple linear models I tested linear mixed effect models with random intercepts for each of the seven regions (see Tab.: A.4 for direct comparison). This approach is based on the logical hypothesis that there are different interrelationships, i.e. nested effects of regions. To underpin this thinking, a null model with the nested region effect as only predictor was carried out. The resulting Intraclass Correlation Coefficient (ICC) of 0.56 (see in 07_analysis_new.R) indicates that 56% of the variability of is explained by regional effects.

All variables calculated and gathered were expected to have an influence either on the response variable full basket or on the diversity variables. I give an overview about the expected direction of influence and the mechanisms those variables indicate in table A.2. I performed some general transformations of the variables to better meet the statistical assumptions for respective modeling. Because variables of this analysis have various ranges and units, I standardized each, to have zero mean and unique variances. To achieve nearly normally distributed residuals some variables were transformed (log: full basket, gdp per capita, agricultura area, temperature instability; log1p: livestock; square-root: N_use, irrigation, precipitation instability, squared: self sufficient food basket). The residuals of each variable from the model including all variables are plotted in A.6, respectively in A.7 for the residuals of each variable from the minimal model. Following recommendations (e.g.: Faraway, 2006; Knapp, 2019) I used the maximum likelihood instead of the restricted maximum likelihood approach. This is necessary for comparing different models.

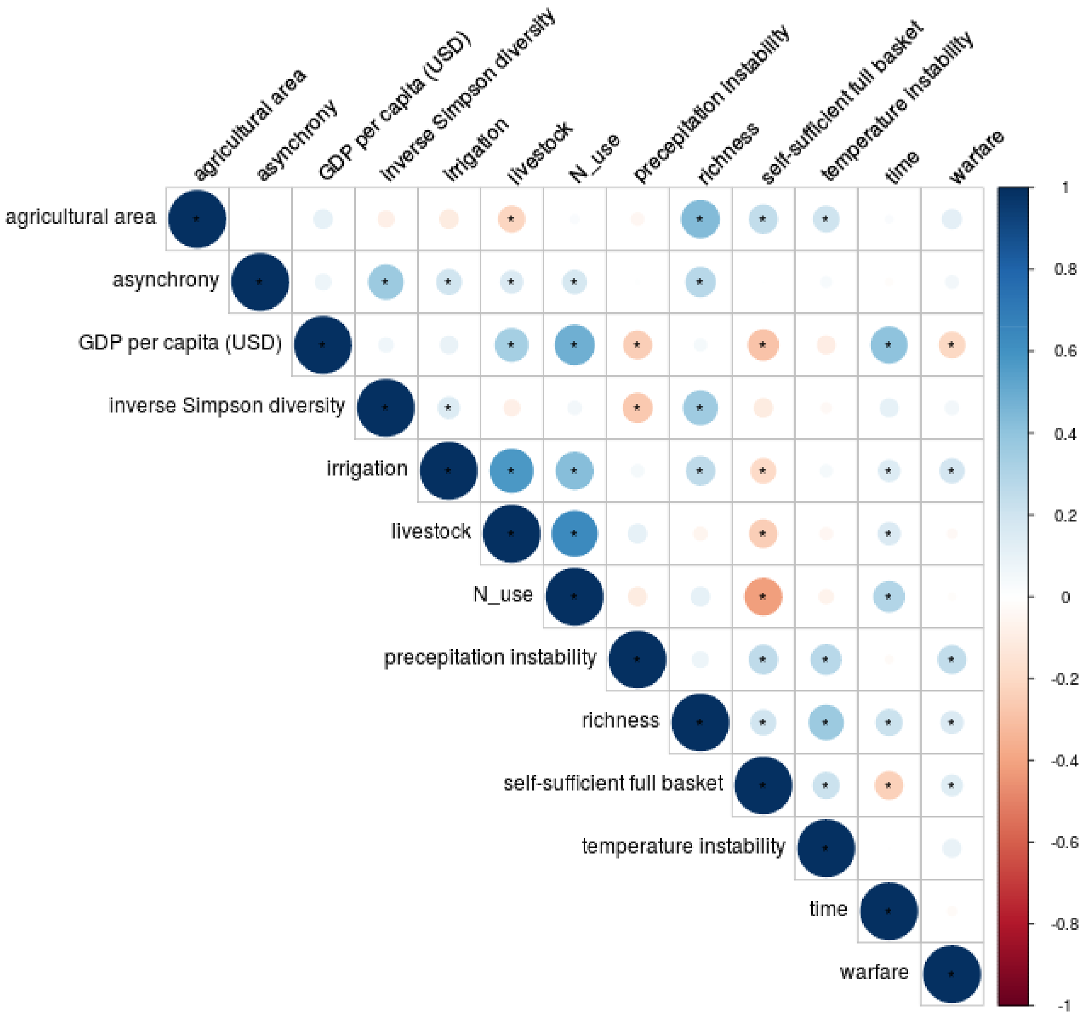

Figure 3: **Correlation matrix,** showing positive correlations between variables in blue and negative correlations in red. The stronger the correlation, the more intense are the colours. Correlations with p <0.05 are marked by *. Fig.: A.3 shows matrix of associated R^2 values. I used the R package corrplot for calculation and visualisation (Wei and Simko, 2021)

For clarity I focused on versions of the minimal model for interpretation. Figure 3 shows the correlation of the individual predictors with each other. Variables revealing strong correlation are more likely to depict the same process and are thus not used in the minimal models (see Fig.:6 & A.2). The variable self-sufficient full basket is highly correlated with most of the variables and can not be replaced by one other variable, it rather summarizes different single effects and is thus kept as a predictor in the final minimal model. The intensity of fertilizer use and the area equipped for irrigation, both indicators for mechanisation and investment in agriculture (see A.2) show high positive correlations. As they are likely to decrease the explanatory power of the underlying process, I only used the stronger indicator "irrigation" in the minimal models (see A.5). Variables not showing a significant influence on the response variable full basket, are further excluded from the minimal models. In conclusion minimal models are models excluding those predictors, that are highly correlated and those that have no have significant effect on the response variable. Diversity variables are kept regardless of their effect size, as their are the variables of main interest.
To compare the quality of each model, I used different criterion. The Akaike Information Criteria (AIC) and the Variance Inflation Factor (VIF), as well as the coefficient of determination R^2 for each model is reported. The lower the AIC, the better performs a model. VIFs are given for all predictors and although one can not trace back which predictors are causing multicollinearity, lower the VIFs indicate less multicollinearity. Although there is an ongoing discussion about reasonable thresholds of the VIF (O'brien, 2007), VIFs below two respectively below four for all predictors are considered to indicate that multicollinearity is not a problematic issue in the tested model (Pennsylvania-State-University, 2018). For mixed effect models marginal R^2 are associated only with the fixed effects, whereas the conditional R^2 include fixed and random effects. A comparison between the Richness-model including all predictors and the minimal Richness-model is shown in table A.5. Table A.4 exemplifies a comparison, using Richness as diversity predictor, of a linear model and the same model with additional nested effect of regions. Table A.5 shows a comparison between the richness mixed effect model including all predictors and the minimal richness based model. Table A.8 shows the comparison between the three distinct diversity metrics within the minimal mixed effect model.

3. Results

3.1. Status of Food Security

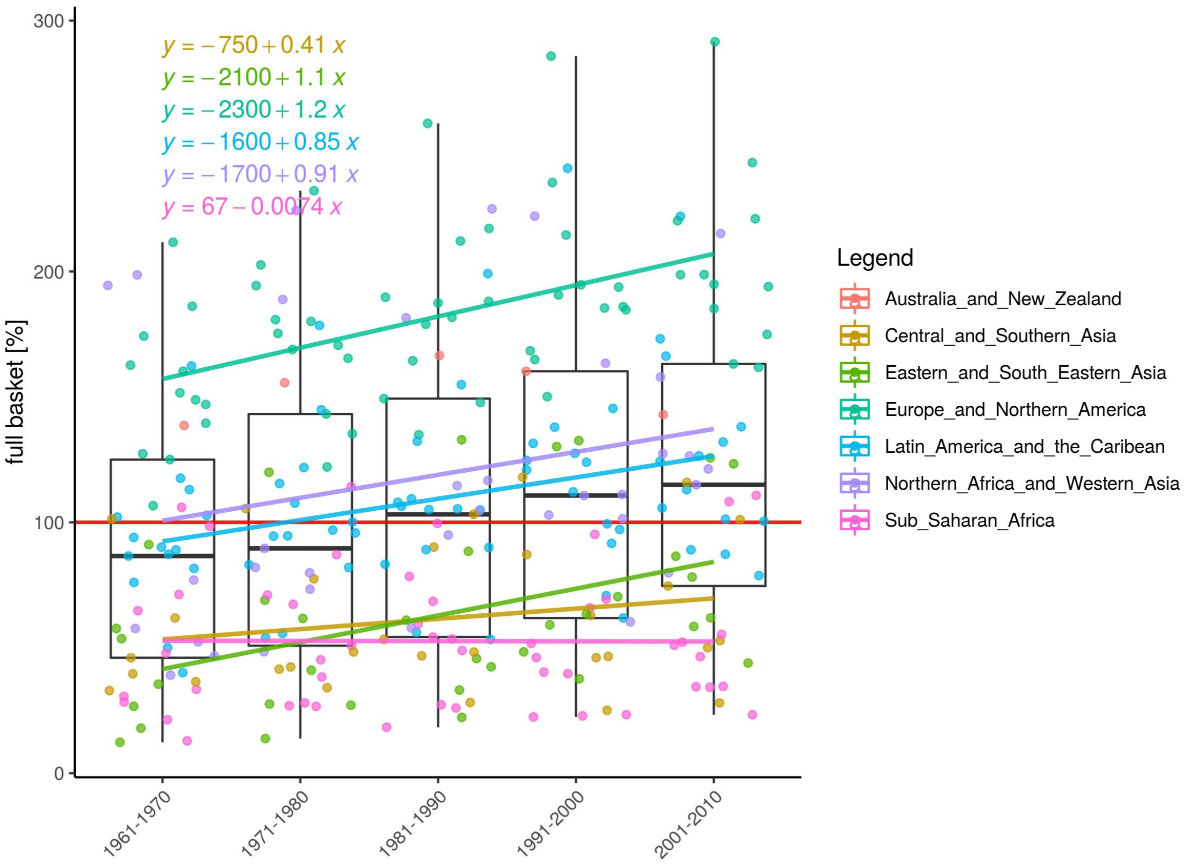

Figure 4: **full basket per decade and region.** Boxplots display the global *(n= 57 countries)* median (black horizontal line) full basket status per decade, the 25th and 75th percentile (lower and upper hinges) and the whiskers indicating 1.5* Inter Quartile Range from each hinge. The Points *(n=285)* depict the percentage of the population that can theoretically be fully nourished by the national food supply (full basket) for each decade in 1961-2010. Coloured lines indicate the observed linear trend for each region between 1961 and 2010. Equations are for the linear trends. Latter value depict the intensity and direction of the correlation. No linear trend is shown for Australia and new Zealand since there are too few data available *(n=5)*. Red horizontal line marks 100%: points above express that there is theoretically sufficient national nutritional supply to feed the population. This graphic was created with the R package ggplot2 (Wickham, 2016).

General fulfilled requirements of nutrients per nation, relative to their population (i.e. full basket, see 2.2.3 for calculation) increased globally by an average of 31% from 1961 to 2010. Since the 1980s the global nutritional supply exceeds the demand for more than half of the assessed nations. The lowest full basket values were observed for China and Nigeria in the 1960’s, whereas the highest full basket value was observed for the United States in

2000's. Europe and Northern America was the region with the best food supply for the entire time period, followed by the region Northern Africa and Western Asia and the region Latin America and the Caribbean. This order stayed the same until 2010. The region Eastern and South Eastern Asia showed the lowest full basket in 1961-1970. The regions Sub-Saharan Africa and Central and Southern Asia revealed a higher full basket with very similar values for the same decade. However, over the studied time period a strong increase was observed for Eastern and South Eastern Asia. Whereas Sub-Saharan Africa (slope = -0.0074) shows almost no change in the full basket, both regions Europe and Northern America (slope = 1.2) as well as Eastern and South Eastern Asia (slope = 1.1) show relatively strong increase. Consequently Eastern and South Eastern Asia exceeding both regions: Sub-Saharan Africa and Central and Southern Asia in the 70's or 80's respectively. Resulting from the strong increase of the region Europe and Northern America relative to the quasi no change of Sub-Saharan Africa, the range between highest and lowest full basket value was highest in 2001-2010 (Fig. 3). Despite partly positive trends, in 2001-2010 the amount of national available nutrients was still too little to nourish the whole population in most countries of Asia and Sub-Saharan Africa (see Fig.: 4).

3.2. Self-Sufficiency

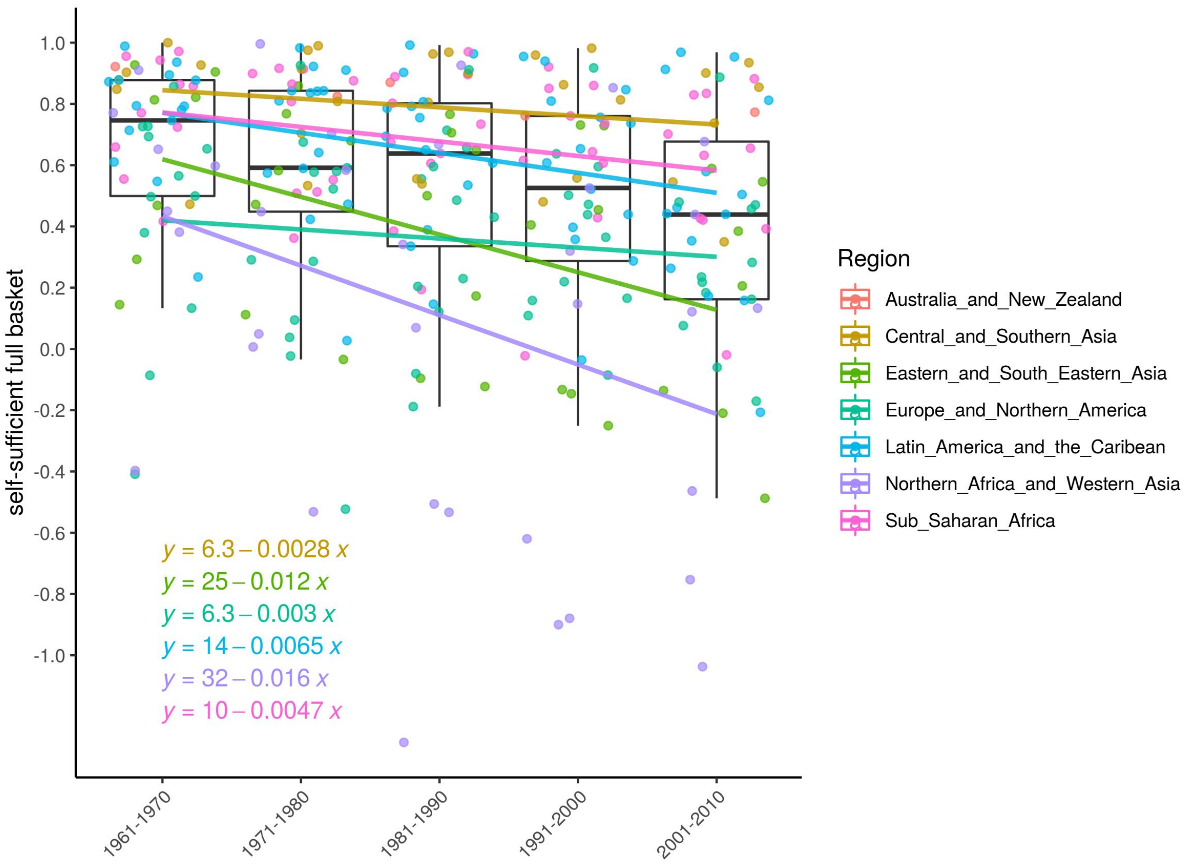

Figure 5: **self-sufficient full basket per decade and region.** Boxplots display the global *(n= 57 countries)* median (black horizontal line) self-sufficient full basket status per decade, the 25th and 75th percentile (lower and upper hinges) and the whiskers indicating 1.5* Inter Quartile Range from each hinge. Points *(n=285)* showing the lowest share of the fulfilled national nutritional demand per nutrient, that is produced within a country (i.e. self-sufficient food basket, see 2.2.3 for calculation). The higher the values, the more of the achieved food basket is produced self-sufficiently. Coloured lines indicate the observed linear trend for each region between 1961 and 2010. Equations are for linear trends. Latter value depict the intensity and direction of the correlation. No linear trend is shown for Australia and new Zealand, since there are too few data available *(n=5)*. This graphic was created with the R package ggplot2 (Wickham, 2016).

Points (n = *285*) close to 1 indicate that for these nations nearly all of the fulfilled requirements are produced locally and few is imported. Decreasing values indicate decreasing self sufficiency. As the elements "feed" and "seed" include imported and domestically produced nutrients the self-sufficient food basket tends to underestimate the actual degree of self sufficiency especially for feed importing countries, thus explaining negative values. For most countries the trend for share of the achieved food basket, which is produced self-sufficiently is strongly positive. More than half of the countries produced at least 50% of the required self-sufficiently over the entire time period" Nonetheless, self-sufficiency decreased over the studied time period, a trend that is evident for each region (Fig. 5). Different magnitudes of change between regions can be observed. This results in an increase of variation of self sufficiency in each decade on global scale. The two regions Northern Africa and Western Asia as well as Eastern and South Eastern Asia are showing the strongest decrease in the lowest share of the fulfilled national nutritional demand per nutrient, that is produced domestically (i.e. self-sufficient food basket, see 2.2.3 for calculation). Some countries of the region Northern Africa and Western Asia (e.g.: Saudi Arabia and Jordan) display strong negative values for the whole time period (see Fig.: 5).

3.3. Determinants of national fulfilled requirements

Effect sizes of the model including all variables, with richness as diversity indicator and the model containing only the variables that show significant effects do not differ widely (see A.5). The ICC of 0.30 for the Richness respectively 0.31 for the inverse Simpson Diversity and Asynchrony minimal model (see A.8) show that 30% and 31% respectively of the total variance can be explained by region-specific effects. The VIF in all minimal models is <2.2. Considering the determinants of coefficients R^2 (Conditional & Marginal) and the AIC, the Richness minimal model performs best (see A.8).

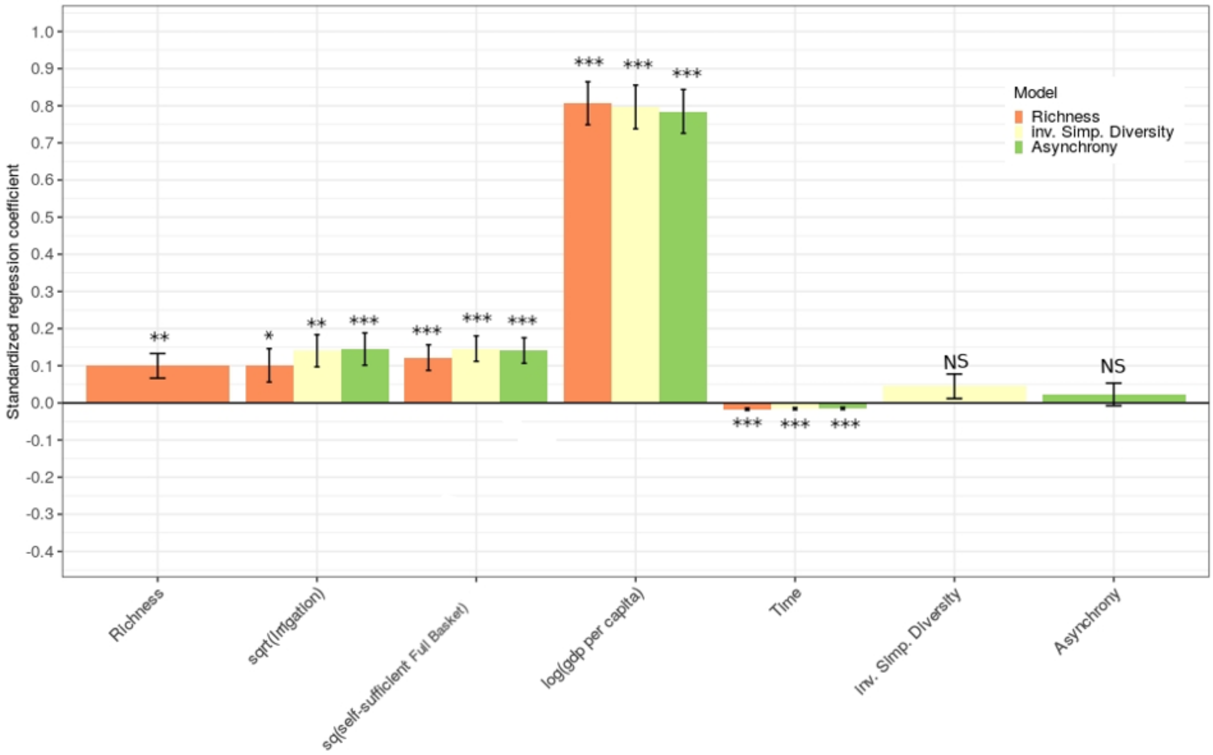

Figure 6: **Determinants of national fulfilled requirements** (resp. full basket) Regression coefficients for all predictors in the minimal model. One model for each diversity metric, including Richness (orange), inverse Simpson Diversity (yellow) and Asynchrony (green) (n = 285). Irrigation was square- root transformed, gdp per capita was log transformed and the self-sufficient full basket was squared. *p <0.05; **p <0.01; ***p <0.001; NS, not significant. See A.8 for a summary of the models. This graphic was created with the R package ggplot2 (Wickham, 2016).

Figure 6 shows the minimal model for each different diversity metric. Predictors, which I expected to contribute negatively to the fulfilled requirements (see A.2) show no significance and are thus not part of the minimal model (see 2.2.4). GDP per capita has by far the strongest effect on the response variable in all models (Richness: r = 0.81; inverse Simpson Diversity: r = 0.80; Asynchrony: r = 0.78). Irrigation (Richness: r = 0.1, inverse Simpson

Diversity: r = 0.14, Asynchrony: r = 0.14) and self-sufficient full basket (Richness: r= 0.12, inverse Simpson Diversity: r = 0.15, Asynchrony: r = 0.14) show positive effects of similar magnitude. Effect sizes for different models, depending which diversity metrics was used, do not differ greatly (see A.8). Nonetheless, the Richness model shows less effect of Irrigation and self-sufficient full basket, whereas gdp per capita has a greater effect compared to the other models. Looking at the effects of diversity on the full basket, different results emerge. Whereas inverse Simpson Diversity and Asynchrony both show no significance, Richness has the same regression coefficient as irrigation (r = 0.1) and almost the same as self-sufficient full basket (r = 0.12), in the Richness model.

4. Discussion

This study shows that the national supply of nutrients has markedly improved globally since the 1960s, but also uncovers large regional differences and increasing inequality (see Fig.: 4). Unsurprisingly, the financial status of citizens, which is here depicted in GDP per capita, has a large effect on the nutritional supply (see Fig.: 6). Trade patterns assessed via the share of self sufficiently produced and available nutrients show the increasing globalisation of food production (see Fig.: 5). The hypothesis that diversity contributes markedly to the absolute national nutritional supply must be rejected based on the results of the present analysis. Nonetheless, my findings highlight the importance of the simplest diversity metric Richness compared to the inverse Simpson Diversity and the Asynchrony metric. However, the fact that most other indicators, such as temperature or precipitation instability show no significant effect on the nutritional supply is surprising (see A.4).

Country classification

Scientific assessment of food security is done typically within the recent socio-economic status of regions, for example as they are classified by the worldbank or directly along a monetary gradient (Miller et al., 2016; Barry et al., 2019, e.g.:). In the present analysis I used geographical regions based on the classification the UN uses for the UN Sustainable Development Goals (SDGs), rather than development indices. This was done for several reasons: I used data reaching back to 1961 and the socio-economic status changed for many countries in the given time period, thus explaining why assessing via recent classifications is inappropriate. Furthermore classifications, for example from the world bank were not complete before 1989 and definitions changed ever since (World-Bank-Group, 2019), so that a dynamic assessment, with a consistent methodology was not possible. GDP per capita can neither be seen as indicator for human well being (Constanza et al., 2014; Ward et al., 2016, e.g.:) nor as a indicator for overall food security. I used it nonetheless, to assess the change in socioeconomic situation, as it is exists for large temporal and spatial scale. My results show that at least it is highly correlated with the availability of nutrients on national scale (see Fig.: 6, see also Fig.: 7). However, the large explanatory power of my model, which attributes to the single monetary predictor variable GDP per capita, suggest that a division along a monetary gradient could have further disentangled the underlying processes. This argumentation is supported by other scientists, finding partly different results concerning the evolution of food security (Porkka et al., 2013) and the importance of crop diversity (Aguiar et al., 2020) for regions divided along a monetary gradient.

In the present study I assessed only 57 countries. Within all regions, except the region Australia and New Zealand, I assessed at least six (Central and Southern Asia) and up to 14 (Latin America and the Caribbean) countries per region. Some world regions, especially large parts of Africa and the post-soviet states are heavily underrepresented. This limited number of samples have different implicit problems: Regional differences in which factors influence national nutrient supply and to what extent cannot be disentangled in separate models, due to missing statistical power. Figure 4 visualises the need for a special assessment of regional patterns of the full basket variable, as expected differences between the nutrition status of regions are depicted in the full basket variable. Furthermore as already described above, the large explanatory power of GDP per capita and as well the differences in the shape of regional trends of full basket (see Fig.: 4) suggest more complex analyses.

Nutritional supply is not equal to food security

> *Food security exists when all people, at all times, have physical and economic access to sufficient safe and nutritious food that meets their dietary needs and food preferences for an active and healthy life.* - World-Food-Summit, 1996

It is important to mention, that the present approach is not intended to depict over all food security nor overall food quality.
Food security, as described above compromises four dimensions: *availability of food, access to food, utilisation of food* and the *stability* of the aforementioned dimensions over time (FAO, 2008). This study focuses on the first dimension *availability*, by evaluating the extent to which the national supply of nutrients meets the requirements of the population.
But even if there is theoretically enough food available on national scale, *access* to diverse food may be limited either due to infrastructural distribution issues or due to poverty (Miller et al., 2016). Since I have only assessed the national scale, I cannot represent how great the inequality is within a population, thus I can not scale down how many people really suffer from micro or macro nutrient deficits.
Food utilisation describes how many of the nutrients available at the individual level are metabolised and thus contribute to meeting nutritional needs. The preparation and storage of food heavily influences nutrient contents of food and bioavailability on individual scale (Reddy and Love, 1999; EFSA, 2010). This has to be assessed on household or individual level and cannot be captured in the current approach. Furthermore the bioavailability of some nutrients differ depending on the rest of the diet. Zinc absorption for example is heavily influenced by so called inhibitors, more precisely phytate. Phytate intakes are strongly linked to the amount of staples (e.g.: cereals, corn, rice and related products) consumed (Lönnerdal, 2000). This varies widely for different cultures and times and also for the affiliation of individuals to an income class. Food systems clearly changed since the 1960's: simliar to crop acreage on national scale (Khoury et al., 2014), diets have been diversified on individual scale, but homogenized globally (Vermeulen et al., 2020). This is widely due to the availability of cheap ultra processed foods and beverages (Barry et al., 2019; Vermeulen et al., 2020). And it goes hand in hand with a generally improved situation of nutrient supply in most regions (see Fig.: 4, see also "*Change in nutrient supply*"). The required intake

of energy depends on the level of daily physical activity, which reveals another dimension of data gaps - this time at the expense of physically hard-working people. It is likely that their requirements are underestimated by taking averages as a reference. These people used to be considered rather low-income earners. Today, however with physical facilitations at work, transportation and even leisure through newer and cheaper technologies, this assumption is no longer true (Barry et al., 2019). Due to large regional, temporal, income and work related specific differences a differentiation of diets and physical activity was not possible in the present study. Therefore I assumed medium levels of phytate intakes and physical activity globally (see script: 03_nutritional_demand.R). In nutritional science there is the talk of "the double burden of malnutrition, which is the coexistence of under-nutrition [...] and overweight, obesity, and diet-related noncommunicable diseases" (Barry et al., 2019). This phenomenon affects low- and middle-income countries, where there are regional and temporal differences, with either the wealthier or poorer populations more likely to suffer from obesity and related diseases (Barry et al., 2019). But increasing numbers of overweight people and diet-related noncommunicable diseases remains a problem as well in high income countries (Chooi et al., 2019). It is important to state, that the present analysis only assessed the minimum requirements and that food security in terms of adequate nutrition (i.e.: no over or under nutrition), needs a more nuanced approach. Nontheless, with assessing special requirements for each age and sex, additionally to assessing special requirements for pregnant and breastfeeding women the present study is able to account for different metabolism rates for specific life-stage groups for each time period.
The fourth dimension *stability* needs to hold for each of the fore mentioned dimensions to achieve over all food security. The nexus of stability of food supply and crop diversity is already assessed elsewhere, with remarkable and already mentioned insights (see *Introduction*) (Egli et al., 2020; Renard and Tilman, 2019). Direct comparisons of results are not possible as the underlying statistics of the different approaches differ fundamentally.

Change in nutrient supply: observed regional patterns since the 1960's

The need for assessing food security, which scale down to crucial nutrients instead of solely caloric security is ubiquitous in nutritional science (Sibhatu et al., 2015; Kummu et al., 2020; Seekell et al., 2017, e.g.:), but to date assessments are still scarce. Thus, the new metric "full basket" developed here to to tackle this issue adds an important dimension to scientific discussions in the field of nutritional science. It measures how many people can be fully nourished by the national supply of nutrients. It contains country-specific nutritional requirements, with special mention here of the individual requirements of all age and life groups (i.e. sex), pregnant and as well breastfeeding women. By comparing these requirements with the total supply derived from the FBS the metric takes into account trade patterns and thus provides a more realistic approach to assessing the actual nutritional status of countries, compared to other studies (Egli et al., 2020, Renard and Tilman, 2019, Kummu et al., 2020 e.g.:). All calculations were performed with eight different nutrients (energy, protein, zinc, calcium, iron, vitamin B12, folic acid and vitamin A) and thus provide a high resolution in the assessment of nutrients that are crucial for a healthy human diet. The idea of reducing these nutrients to one response variable by counting only those nutrient statuses that meet across all nutrients, compresses the results and focuses on a complete healthy diet. In that way the metric can be used in various contexts and scales. From a global perspective, the improved food security situation in terms of calories is consensus, both in policy organisations and in academia (Ramankutty et al., 2018, FAO, IFAD, UNICEF, WFP and WHO, 2020, e.g.:).

In line with Schmidhuber et al., 2018 my findings using the new developed full basket metric report additional to the improved caloric supply, an improved nutritional security situation in terms of micro and macro nutrient supply. Increasing inequality in food supply between regions occurs from different magnitude of improvements within different regions. This is widely known and depicted in different indicators and approaches (FAO, 2014). My findings which highlight the nutritional perspective, confirm these developments. Sub-Saharan Africa is of special concern, as its food security is highly vulnerable and climate change and a growing population influence both food supply and food demands in opposite directions (Bernstein, 2008). I observed almost no change of the nutritional supply status in Sub-Saharan Africa in 1961-2010 and the lowest fulfilled nutritional status in most recent years (see Fig.: 4). Evidence for this was found before, for example in Akachi and Canning, 2010, where they assessed trends in body height and child mortality in Sub-Saharan Africa, both seen as indicators for the quality of child nutrition. Other indicators, like the rising number of stunted children in Sub-Saharan Africa (FAO, IFAD, UNICEF, WFP and WHO, 2020) reveal equally an unchanged or even worsened food security situation. It is worth to specially mention the result, that the region Eastern and Southeastern Asia managed to achieve a better nutritional status than the two regions Sub-Saharan Africa and Central and Southern Asia, although it was worse than both aforementioned regions in the 1960's (see Fig.: 4). Its overall economic growth and improvement in living conditions draw much attention and was early described as the "East Asian miracle" (World Bank Group, 1993). The improved nutritional status (see Fig. 4) in the region Eastern and South Eastern Asia was accompanied with fast raising gdp per capita (van Kees Donge et al., 2012, see also Fig.: 7).

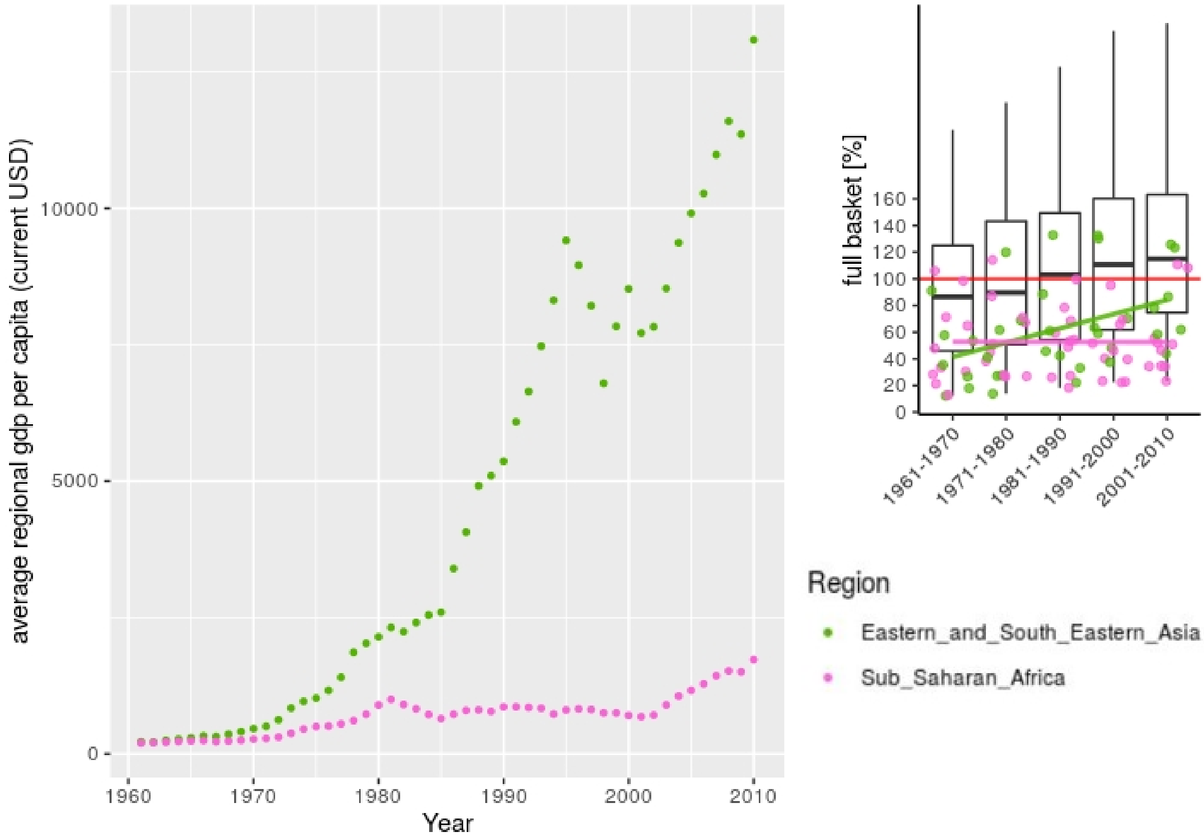

Figure 7: **Average GDP per capita and full basket in Eastern and Southeastern Asia as well as in Sub-Sahara Africa from 1961-2010.** ***Left:*** Average GDP per capita for all countries in the region Eastern and Southeastern Asia and the region Sub-Saharan Africa, which were assessed in the present study. Mind: For Mali and Indonesia no GDP per capita is reported before 1967, so they are only assessed afterwards. ***Right:*** Full Basket for all assessed countries in the region Eastern and Southeastern Asia and the region Sub-Saharan Africa. Red horizontal line marks 100%: above there is theoretically sufficient national nutritional supply to feed the population. Black boxplots display the global assessment. This graphic was created with the R package ggplot2 (Wickham, 2016).

Figure 7 shows the development of the average GDP per capita in the assessed nations for East and Southeast Asia and for Sub-Saharan Africa on the left. The right plot shows the associated development of the full basket- which depicts nutrient availability. In comparison, one can clearly see that from the '80s onwards, GDP per capita in East and Southeast Asia increases much faster than in Sub-Saharan Africa. This is also the time where the East and Southeast Asian full basket exceeds the Sub-Saharan African one. The use of GDP per capita in the present study was thereby already discussed in *Country classification*.

Trade Patterns: development and their influence on nutrient supply

I calculated the share of the *fulfilled demand (i.e.:* $\frac{supply}{demand}$*)* per country and nutrient, which was produced self sufficiently. Or in other words: the national proportion of each nutrient available for human consumption, which stayed within the country, thus was neither imported nor exported. I found that within all regions the share for the lowest fulfilled nutritional demand, which was produced self sufficiently decreased (see Fig.: 5). This can be interpreted as increasing trade and thus increasing globalisation. Increasing globalisation of food supply has already been mapped in many ways (Kinnunen et al., 2020, e.g.:), with this study confirming the discussion on the nutritional science basis. Porkka et al., 2013 on the other hand, assessed self-sufficiency in food according to the extent to which the need for kcal/capita/day was met by domestic production. This is substantively different to the present approach. Porkka et al., 2013 did not take into account a countries ability to produce the actual supply domestically (incl. trade, changes in stocks, excl. conversion to feed & seed, other uses and waste). I show how much of the fulfilled requirements (i.e.: $\frac{supply}{demand}$) is produced domestically, regardless of the extent to which actual demands are met, thus assessing the actual supply. Advantage of this is, that this metric is uncorrelated with the actual full basket (see script 07_analysis_new.R) and thus can be used to model the determinants of the fulfilled nutritional demand (see Fig.: 6). At first sight Porkka et al., 2013 and I get contrasting results considering the development of self sufficiency. They conclude with mostly stable self sufficiency situations between 1965 and 2005, whereas I show decreasing trends in self sufficiency (see Fig.: 5). This originates from the fact that my variable self-sufficient full basket depicts trade patterns independent from the overall nutritional status, the variable in Porkka et al., 2013 shows higher dependence on the actual nutrition situation, in particular in the context of absolute trade (in-)dependency.

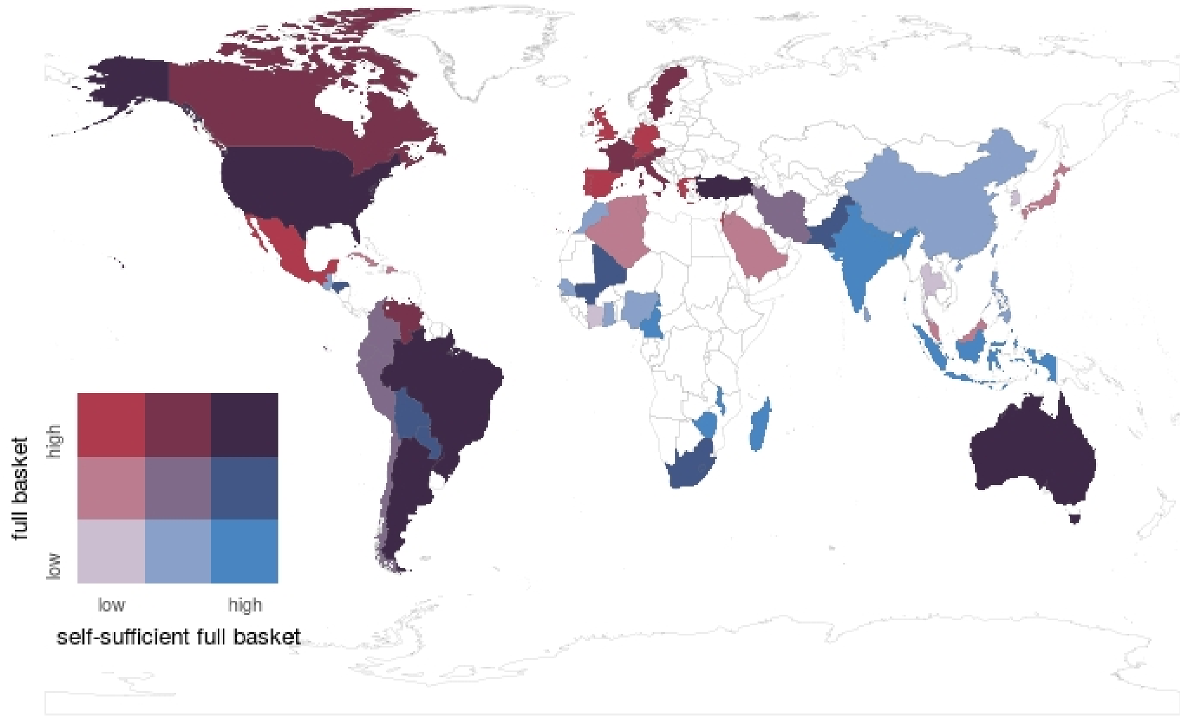

Figure 8: **Bivariate Map: Georaphical distribution of fulfilled and the fulfilled self-sufficently produced nutrient requirements in 2001-2010.** Countries tending to reddish colors achieved high full baskets (i.e. fulfilled nutrient demands), but low self sufficiently produced food baskets. Blueish colors indicate a high proportion of the full basket (no matter to what extent it actually meets the demands) that is domestically produced and simultaneous low full baskets. Countries in dark purple colors have high values, while light purple colors have low values in both full basket and self-sufficient full basket. Mind that assignment of countries to colors is relative to the other countries. This graphic was created with the R package ggplot2 (Wickham, 2016). The underlying script and map was provided by Egli et al., 2020 (see `https://github.com/legli/AgriculturalStability`).

Figure 8 shows the geographical distribution of the and the self-sufficient full basket in the most recent decade (2001-2010). This figure illustrates what is already shown in figure 4 and figure 5 for 2001-2010. It clearly depicts the harsh gradient of the food security situation between countries belonging to the Global North and countries belonging to the Global South. Despite its common assignment to the global South, South America and Arabic Countries achieve widely a medium to high fulfilled supply. But simultaneously my analysis shows a less clearer division between countries, having high or low shares of self-sufficiently produced nutrients. Countries as well of the Global North (e.g.: USA, Australia) and the Global South (e.g.: India, Madagaskar) had high extents of self sufficiency and vice versa had other countries of the Global North (e.g.: Germany, Spain) and the Global South (e.g.: Thailand, Cote d'ivoire) low extents of self sufficiency. This shows that the relationship is not clear-cut and needs to be looked at more closely. The extent to which traded commodities contribute to the national available nutrients is mainly controlled from respective trading policies. In respect of food supply, there are contrasting attitudes whether or not increasing trade (i.e. imports and exports of agricultural products) at the expense of self-sufficiency improves overall food security. Generally spoken, a countries policy could either support or impede imports and/or exports in direct or indirect (e.g.: logistics, finance) food related business sectors (Zongo, 2021). Some see tools such as subsidies or tariffs mainly as distortions, others as way to secure food supply. Increased trade can have positive influence on food availability, due to a redistribution of commodities or resources (Brooks, 2015; Carr et al., 2016), but it can also marginalise trading agents, which do not have the financial means to keep up with the world market (Lawrence, 2017). Trading agents here, refer to those governments, companies or individual producers, which directly or indirectly either sell or buy food at the global market and are thus exposed to price shocks, trade wars and synchronized crop failures. Globalisation-critical scholars state that increasing trade at the cost of self-sufficiency rises the risk for small-scale producers and peasants as well as nations to be dependent on Transnational Corporations (Lawrence, 2017). My analysis shows that increasing levels of self-sufficiency are positively related to increasing fulfilled requirements (see Fig.: 6). Although only food availability on national scale is assessed here (not food security in general), my results indicate that self-sufficiency at least on national scale is an important piece to provide enough nutrients to nourish a population. This partly contrasts basic recommendations, made by supranational organisations, such as the Organisation for Economic Co-Operation and Development (OECD) or the World Trade Organization (WTO), which in most cases support the idea of reducing trade barriers (Brooks, 2015), thus increasing trade.

Suitability of models

As discussed in *Country classification* I expect regional effects, but due to the limited data I did not run separate models for each region. If there is a large regional heterogeneity some processes or factors could be hidden, over- or underestimated, especially in simple linear models. To account for the effects, due to similar processes within regions I run linear mixed effect models with random intercepts for regions (see A.5). In that way it is possible to compare the variances between regions, thus accounting for regional differences without losing the information about which part of the variance all regions have in common (Harrison et al., 2018). It is mostly recommended to fit linear mixed effect models and allow slope and intercept variances to vary (Harrison et al., 2018; Knapp, 2019). In context of the present study that means that random intercepts and forced slopes are an unrealistic assumption, as the full basket values are most likely not only regionally but also timely correlated. However, I decided not to additionally test for random slopes, as this requires a lot more data (Harrison et al., 2018). Further an unbalanced number of observations within the regions is another issue in the use of mixed effect models. This occurs with the region Australia and New Zealand, which contains only Australia, thus having only 5 data points. Nonetheless, due to the adopted regions for the SDGs I counted it separately (see *Country classification*). However, this issue is more important in using random slopes, rather than random intercept models (Harrison et al., 2018). Ideally the distribution of the residuals would be normal. Linear mixed effect models are shown to be relatively robust to violations of this assumption (Schielzeth et al., 2020), nonetheless I transformed some variables to normalize the distributions. Figure A.7, shows the distribution of the residuals from the minimal richness model after transformation. Another basic assumption of linear mixed effect models is a normal distribution of the response variable (Knapp, 2019; Schielzeth et al., 2020, e.g.:). As the full basket variable follows rather a skewed left distribution (see A.9) I propose testing a generalized mixed effect model additionally. Generally the suitability of the analysis has markedly improved by implementing linear mixed effect models, with random intercepts. In further analysis increasing the number of observed countries could allow for other, more robust modeling methods.

Richness: The only diversity metric depicting diversity - food security nexus?

By using three different and complementary diversity indicators (richness, inverse Simpson diversity and asynchrony) different aspects of crop diversity should be depicted. Richness is the simplest diversity metric and often considered to be not sufficient to really depict diversity patterns. Therefore additional assessment is crucial. The inverse Simpson diversity metric depicts the probability that two crops randomly selected from a sample are not the same. And thus especially weighs the abundance of crops. These contrasting ecological metrics of crop diversity on global level cover both the relevance of scarce crops for specific micro nutrients and the overall importance of common crops to feed the world population.
Asynchrony, as I assessed it, is bigger when aggregated crop production trends differ from the summed crop-specific production trends. I used the metric to cover the temporal facets of crop diversity. Richness is the only diversity factor which shows significance in all analysed models. Furthermore it even shows similar effect sizes compared to the indicators for agrotechnicial investments (i.e.: irrigation) and the trade indicating variable (i.e.: self-sufficient food basket) (see Fig.: 6, A.8, A.5). It is questionable if this statistical strength, compared to the other diversity indicators is due to its specific diversity related content. I suggest it rather sums up the correlations of other indicators which influence a countries richness. Variables which all correlate positively with richness, but not with inverse Simpson diversity and asynchrony are: agricultural area, warfare and temperature instability (see Fig.: 3).
Contrary to inverse Simpson diversity and asynchrony, richness does not inherently include

a factor for the agricultural area. In ecology, richness is considered to be highly sensitive to the spatial scale (Rahbek, 2005) - here to the absolute agricultural area per country. Agricultural systems clearly differ from natural systems, but this relation still holds. As agricultural area increases, there is a greater likelihood that there will be more producers, more diverse climatic or soil conditions and thus more different crops in absolute terms. Furthermore, temperature instability correlates as well positively with richness. The exclusion of this variable thus contributes to the significance of richness. Additionally to the positive correlation with richness, temperature instability and agricultural area correlate positively with each other (see Fig.: 3). However, since this correlation (temperature instability vs. agricultural area) only has a very small R^2 (see A.3), the correlation is negligible in terms of content. This indicates that the correlation is not due to the general relationship of agricultural area and temperature instability but due to the selection of assessed countries. Countries having the highest values for temperature instability in the present analysis (from high to lower: Peru, Ecuador, China, Nepal, Bolivia, ...) are shown to be mountainous regions and with exception of China they are all relatively small. Mountainous regions are more likely to have extreme weather events and as well small farm sizes (Mazzocchi and Sali, 2016). This could explain why temperature instability is correlated with richness but not (due to small R^2) with agricultural area. As this does not explain, why temperature instability does not correlate with inverse Simpson diversity and asynchrony, further investigations need to be done. The country selection is further clearly biased in context of the warfare aspects. Countries whose borders have changed in the time frame of the analysis (1961-2010) were omitted. Armed conflicts are often a reason for political instability, which often bring changing borders, as countries split or reunite. With the framework of the present analysis countries that experienced such conflicts are not assessed. Due to this a qualified statement of the impact of warfare on crop diversity is not possible. Despite their correlation with richness, I excluded the variables for absolute agricultural area, temperature instability and warfare, among others, from the models described in more detail for methodical reasons (see section 2.2.4).

5. Conclusion

Although most indicators are shown to have no significant influence in the model, this study accounts for a wide range of possible impact dimensions. The effect of biophysical impacts (temperature and precipitation instability), agrotechnological investments (Nitrogen use, Irrigation), Socio-economic and political indicators (warfare, gdp per capita) as well as trade patterns (self sufficient food basket) were assessed. Additionally to account for a possible effect on the hypothesis building crop diversity variables, the share of livestock production in agricultural area and the absolute agricultural area were assessed. With this approach I

answered the questions posed in the *Introduction*.
The food supply situation in terms of the fulfilled national nutrient requirements improved markedly in most regions. Sub-Saharan Africa shows almost no improvement, while South and Southeast Asia shows a rapid improvement, accompanied by a general economic growth, accelerating in the 1980's. The assessment of the share in the fulfilled nutrient demand, which is produced self sufficiently shows increasing globalisation of food supply. My models indicate, that high self sufficiency contributes to a better nutrient supply on national scale. Nonetheless, this relation is not clear cut as countries having low self sufficiency and high full baskets and vice versa, coexist. Contrary to expectations crop diversity does not show to have a positive influence on the fulfilled nutrient requirements. Therefore I calculated different diversity metrics. As I didn't find a clear relationship I can not clearly depict the suitability of each metric to assess the diversity-food security nexus.
The present study can function as a model for further analyses and can be conducted at different scales and food security dimensions. The structure of the study allows to also reuse only parts of it in different contexts and scales. One could specially mention the R script 03_nutritional_demand.R, as it provides further information for the reuse in regional contexts. In subsequent analysis I suggest assessing the stability aspect of food supply, as it could yield more insights concerning the importance of crop diversity in food security.

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A. Appendix

Filename	Description	Downloaded	Source
Production_Crops_E_All_Data.csv	Crop specific area, yield, production	16.01.21	http://www.fao.org/faostat/en/#data/QC
FAOSTAT_fertilizer.csv	Fetilizer application: kg N_use Intensity per ha Cropland 1961-2020	16.04.21	http://www.fao.org/faostat/en/#data/RA
Area_equ_Irrigation.csv	Share in agricultural land equipped for irrigation	16.04.21	http://www.fao.org/faostat/en/#data/EL
FAO_Livestock.csv	livestock per agricultural land area in livestock units	29.05.21	http://www.fao.org/faostat /en/#data/EK
FAO_Agriculture.csv	agricultural land (incl. crops & livestock)	29.05.21	www.fao.org/faostat /en/#data/RL
FoodBalanceSheets Historic_E_All_Data.csv	food composition 1961-2013	16.02.21	http://www.fao.org/faostat/en/#data/FBSH
USDA_Nutrients.xlsx	matches FAO commodities with nutritional values provided by the USDA	21.09.20	https://knb.ecoinformatics.org/view/doi:10.5063/F1542KR1
DRVs_[Pop_Group].xlsx	Dietry Reference Values for each [Pop_Group]:"Adults", "Children_and_adolescents", "Infants", "Lactating_women", "Pregnant_women"	11.03.21	https://efsa.gitlab.io/multimedia/drvs/index.htm
Worldbank_Pop.csv	Population by age and sex	11.03.21	https://databank.worldbank.org/source/health-nutrition-and-population-statistics
Birth_rate.csv	Birthrate crude by 1000 women	11.03.21	https://databank.worldbank.org/source/world-development-indicators

GDP_per_capita_USD.csv	GDP (current US$) 1960-2010	29.05.21	https://databank.worldbank.org/source/world-development-indicators
FAO_pop_2010.csv	Population Data of 2010	22.04.21	http://www.fao.org/faostat/en/#data/OA
warefare.xls	Number of armed conflicts	16.04.21	http://systemicpeace.org/inscrdata.html
egli_climate_ national.csv	National Tempearature and Precepitation (stability)	16.01.21	https://github.com/legli/AgriculturalStability/tree/master/datasetsDerived

Table A.0: **Summary of data used in the analysis**, with: filename, a short description of the dataset, the download date and the weblink to the source

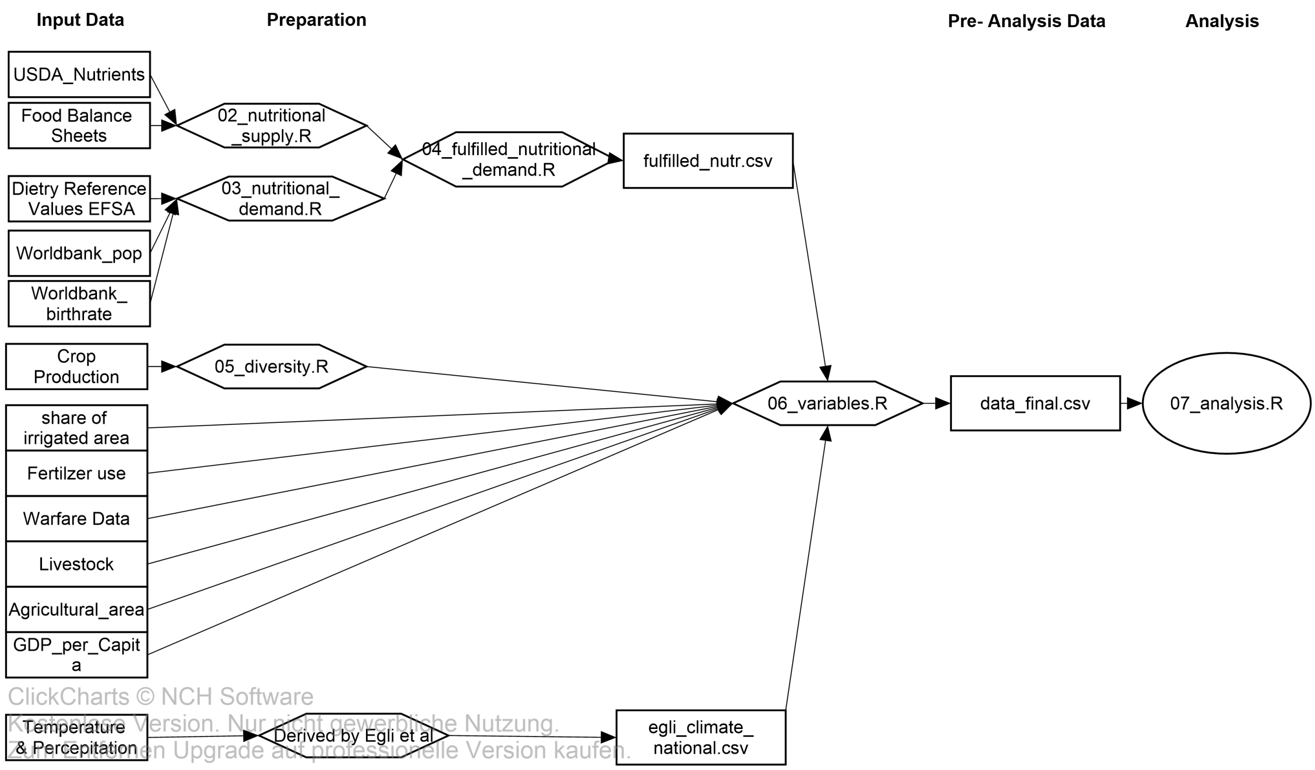

Figure A.1: **Overview about general workflow and used scripts.** All scripts are available at: `https://github.com/AnnikaErtel/CropDiversity_NutritionalSupply`. I used the free software: ClickCharts NCH Software for visualisation.

Type of Variable	Name of Variable	Description	Indicator for	expected effect
response	full_basket	share in population, that can theoretically be fully nourished by national food supply	food security	
predictor	richness	number of crops	change in absolute variety of crops	↑
predictor	inverse Simpson	probability that two randomly chosen individuals belong to different species (McCune and Grace 2002)	change in crop abundance	↑
predictor	asynchrony	asynchronous production trends between crops (Ramankutty, 2019)	temporal diversity	↑
predictor	N_use	kg of Nitrogen use per ha of total cropland area	mechanisation / investment in agriculture	↑
predictor	Irrigation	share in agricultural land equipped for irrigation	mechanisation / investment in agriculture	↑
predictor	temperature_instability	year-to-year instability(sd) of temperature	climatic instability	↓
predictor	precipitation_instability	year-to-year instability (sd) of growing-season precipitation	climatic instability	↓
predictor	warfare	number of armed conflicts	political instability	↓
predictor	self_sufficiant_full_basket	percentage of the achieved nutritional full food basket that is produced self-sufficiently	independence from/ restricted access to world market	↓↑
predictor	agricultural_area	agricultural area in absolute ha	size of agricultural area	←
predictor	livestock	amount of livestock in livestock units (LSU) per agricultural land area	share in livestock production in agriculture	←
predictor	gdp_per_capita	GDP divided by midyear population in current US Dollars	purchase power of the population to buy food	↑

Figure A.2: **Table of all variables and their expected influence on the response variable,** $\uparrow$ indicate expected positive, $\downarrow$ indicate expected negative and $\leftarrow$ no expected influence on the response variable. Those are included in the analysis due to their expected influence on hypothesis building diversity variables. $\uparrow\downarrow$ indicate, that expected influence on the response variable is not clear.

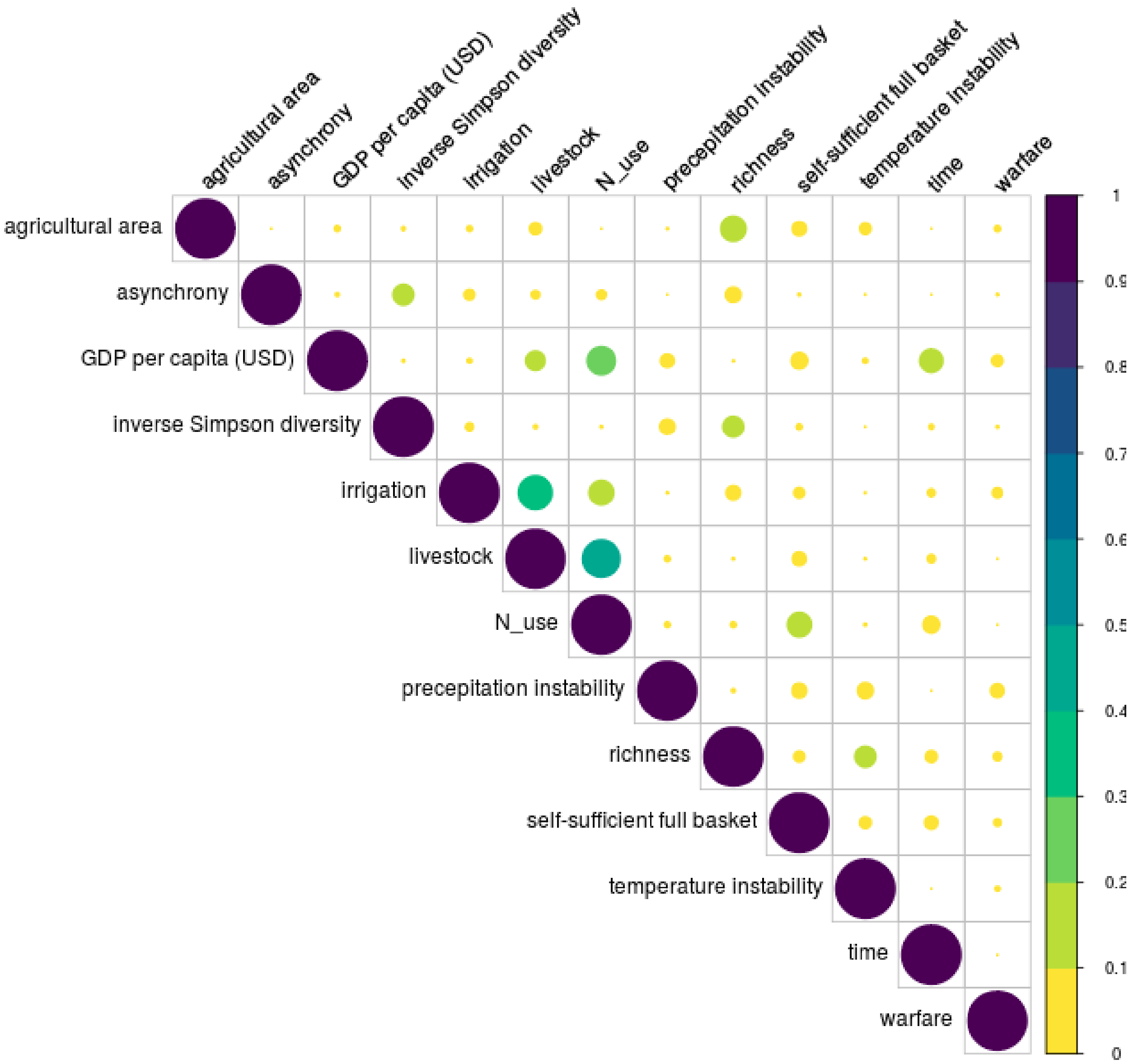

Figure A.3: R^2**-matrix of correlations,** showing R^2 values of all associated correlations depicted in Fig.: 3. I used the R package corrplot for calculation and visualisation (Wei and Simko, 2021)

Response variable: full_basket

	with random effect		without random effect	
Predictors	*Estimates*	*p*	*Estimates*	*p*
(Intercept)	33.80	**<0.001**	42.76	**<0.001**
richness	0.10	**0.003**	0.13	**0.001**
irrigation	0.10	**0.024**	-0.00	0.923
self_sufficient_full_basket	0.12	**<0.001**	0.15	**<0.001**
GDP.per.capita	0.81	**<0.001**	0.97	**<0.001**
time	-0.02	**<0.001**	-0.02	**<0.001**
ICC	0.31			
N	7 Region			
Observations	285		285	
Marginal R^2 / Conditional R^2	0.596 / 0.723		0.684 / 0.678	
AIC	429.903		493.449	

Figure A.4: **Model comparison of the minimal richness model with and without random intercepts for regions** The mixed effect model including random intercepts for 7 regional groups, shows lower AIC and higher Conditional R^2 compared to the adjusted R^2 values in the model without random intercepts, thus performing better. The **VIF** for all predictors in the model without random intercepts is <2.0 and <2.2 for all predictors in the model including random intercepts, indicating higher, but still low probabilities of multicolinearity in the second model. Models are calculated using base R (R Core Team, 2020) the lme4 package (Bates et al., 2015).

Response Variable: full_basket

	full model		minimal model	
Predictors	*Estimates*	*p*	*Estimates*	*p*
(Intercept)	31.67	**<0.001**	33.80	**<0.001**
richness	0.11	**0.005**	0.10	**0.003**
irrigation	0.12	**0.015**	0.10	**0.024**
N_use	-0.10	0.066		
precepitation.instability	-0.07	0.100		
temperature.instability	0.01	0.857		
warfare	-0.05	0.117		
self_sufficient.full.basket	0.12	**0.001**	0.12	**<0.001**
livestock	0.01	0.836		
GDP.per.capita	0.82	**<0.001**	0.81	**<0.001**
time	-0.02	**<0.001**	-0.02	**<0.001**
ICC	0.30		0.31	
N	7 Region		7 Region	
Observations	285		285	
Marginal R^2 / Conditional R^2	0.614 / 0.730		0.596 / 0.723	
AIC	428.687		429.903	

Figure A.5: **Model comparison of the richness model including all predictors and the richness minimal model,** including only those predictors which show significant correlation. The AIC and both R^2 indicators showed slightly worse results in the minimal model. Marginal R^2 are only associated with the fixed effects, whereas the Conditional R^2 include fixed and random effects. The **VIFs** dropped from <2.7 for all predictors in the full model to <2.2 for all predictors in the minimal model, indicating that multicolinearity espeacially in the minimal model is a minor problem. The ICC of 0.30 for the Richness respectively 0.31 for the inverse Simpson Diversity and Asynchrony model show that 30% respectively 31% of the total variance can be explained by the belonging to a special region. Models are calculated using the lme4 package (Bates et al., 2015).

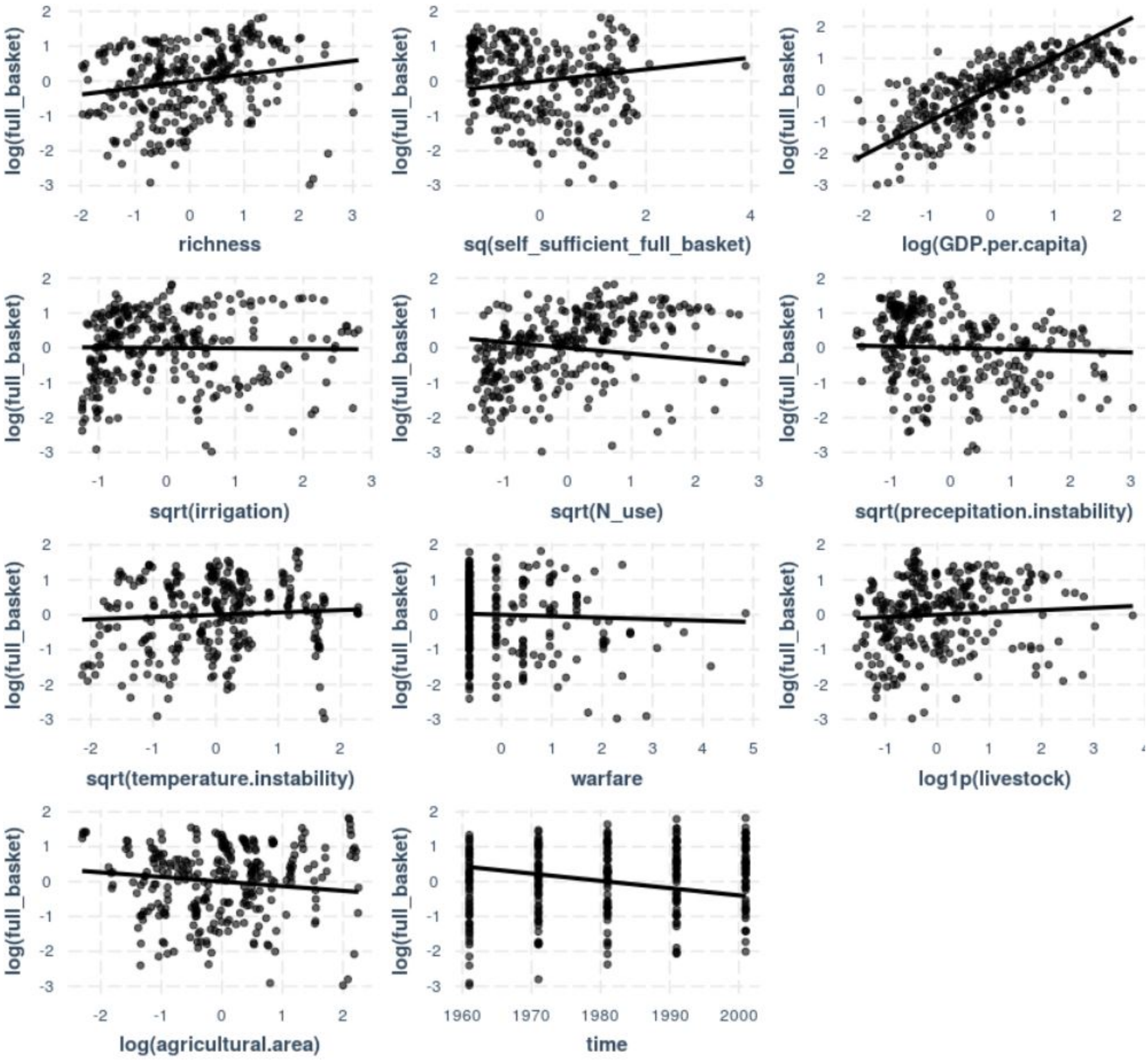

Figure A.6: **Residuals of each predictor from the richness full model.** I standardized the variables to have zero as mean and unique variances. Data was transformed (log() = natural logarithm(x) , log1p = natural logarithm(1+x), sqrt(x) = square-root(x), sq(x) = squared(x)), to achieve nearly normal distribution of the predictor's residuals from the model. For visualisation I used the R package jtools (Long, 2020).

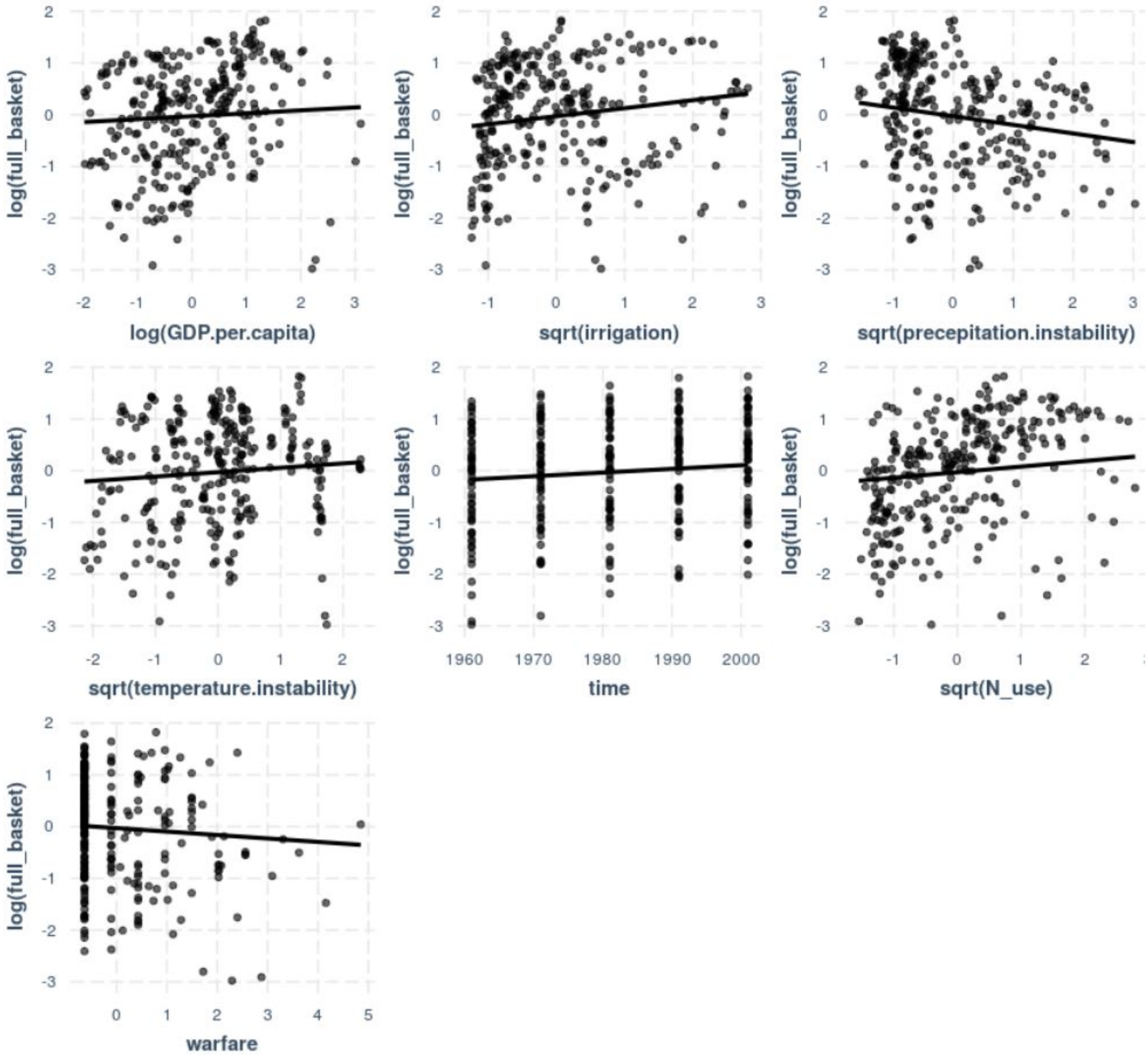

Figure A.7: **Residuals of each predictor from the minimal model.**I standardized the variables to have zero as mean and unique variances. Data was transformed (log() = natural logarithm(x) , log1p = natural logarithm(1+x), sqrt(x) = square-root(x), sq(x) = squared(x)) to achieve nearly normal distribution of the predictor's residuals from the model. For visualisation I used the R package jtools (Long, 2020).

linear mixed effect model with response variable: full_basket

	Richness		inverse Simpson		Asynchrony	
Predictors	*Estimates*	*p*	*Estimates*	*p*	*Estimates*	*p*
(Intercept)	33.80	**<0.001**	30.91	**<0.001**	29.64	**<0.001**
richness	0.10	**0.003**				
irrigation	0.10	**0.024**	0.14	**0.001**	0.14	**0.001**
self_sufficient.full.basket	0.12	**<0.001**	0.15	**<0.001**	0.14	**<0.001**
GDP.per.capita	0.81	**<0.001**	0.80	**<0.001**	0.78	**<0.001**
time	-0.02	**<0.001**	-0.02	**<0.001**	-0.01	**<0.001**
inverse.Simpson.diversity			0.04	0.176		
asynchrony					0.02	0.455
ICC	0.31		0.33		0.33	
N	7 Region		7 Region		7 Region	
Observations	285		285		285	
Marginal R^2 / Conditional R^2	0.596 / 0.723		0.569 / 0.711		0.562 / 0.708	
AIC	429.903		436.962		438.228	

Figure A.8: **Model comparison of minimal model with different diversity metrics.** The Richness model performs best, with the lowest AIC and highest R^2. The **VIF** for all predictors in all models are <2.2, indicating that multicolinerarity is a minor issue. Richness is the only diversity metrics showing a significant regression coefficient. Models are calculated using the lme4 package (Bates et al., 2015).

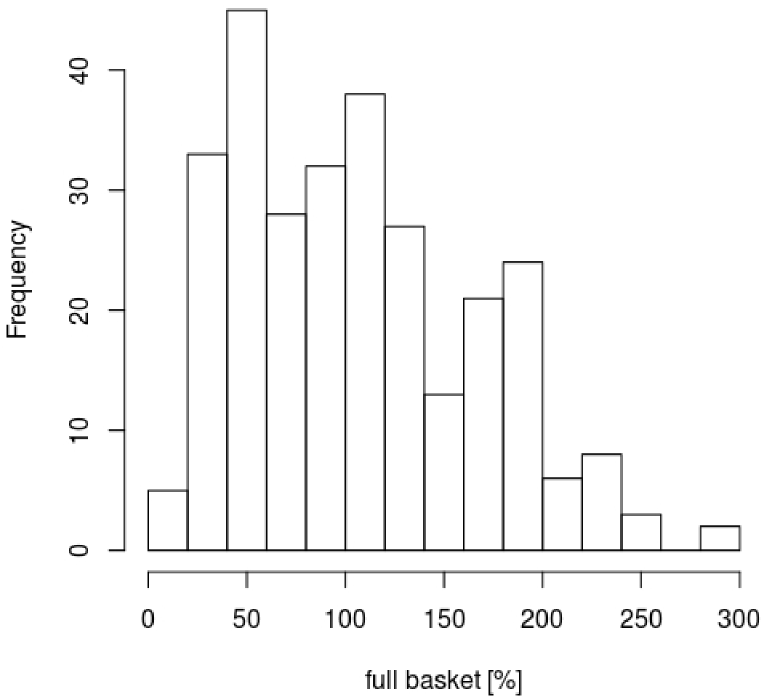

Figure A.9: **Distribution of full basket:** shows a skewed left distribution.

```
R version 3.6.3 (2020-02-29)
Platform: x86_64-pc-linux-gnu (64-bit)
Running under: Ubuntu 16.04.7 LTS

Matrix products: default
BLAS:   /usr/lib/openblas-base/libblas.so.3
LAPACK: /usr/lib/libopenblasp-r0.2.18.so

locale:
 [1] LC_CTYPE=en_US.UTF-8       LC_NUMERIC=C
LC_TIME=en_US.UTF-8        LC_COLLATE=en_US.UTF-8
 [5] LC_MONETARY=en_US.UTF-8    LC_MESSAGES=en_US.UTF-8
LC_PAPER=en_US.UTF-8       LC_NAME=C
 [9] LC_ADDRESS=C               LC_TELEPHONE=C
LC_MEASUREMENT=en_US.UTF-8 LC_IDENTIFICATION=C

attached base packages:
[1] stats     graphics  grDevices utils     datasets  methods   base

other attached packages:
 [1] jsonlite_1.7.2         yaml_2.2.1             knitr_1.33
devtools_2.4.2
 [5] usethis_2.0.1          rgdal_1.5-23           forcats_0.5.1
dplyr_1.0.6
 [9] purrr_0.3.4            tidyr_1.1.3            tibble_3.1.2
tidyverse_1.3.1
[13] stringr_1.4.0          countrycode_1.2.0      colorRamps_2.3
corrplot_0.89
[17] multipanelfigure_2.1.2 magrittr_2.0.1         formattable_0.2.1
broom_0.7.6
[21] cowplot_1.1.1          ggpubr_0.4.0           ggplot2_3.3.3
lmtest_0.9-36
[25] zoo_1.8-9              lme4_1.1-27            Matrix_1.3-4
readr_1.4.0
[29] sp_1.4-5

loaded via a namespace (and not attached):
 [1] assertive.base_0.0-9       minqa_1.2.4
colorspace_2.0-1           ggsignif_0.6.1
 [5] ellipsis_0.3.2             rio_0.5.10
rprojroot_2.0.2            fs_1.5.0
 [9] rstudioapi_0.13            remotes_2.4.0              fansi_0.5.0
lubridate_1.7.10
[13] xml2_1.3.2                 codetools_0.2-18           splines_3.6.3
cachem_1.0.5
[17] pkgload_1.2.1              nloptr_1.2.2.2             dbplyr_2.1.1
compiler_3.6.3
[21] httr_1.4.2                 backports_1.2.1
assertthat_0.2.1           fastmap_1.1.0
[25] cli_2.5.0                  htmltools_0.5.1.1
prettyunits_1.1.1          tools_3.6.3
[29] gtable_0.3.0               glue_1.4.2                 Rcpp_1.0.5
carData_3.0-3
```

```
[33] cellranger_1.1.0          vctrs_0.3.8               nlme_3.1-152
assertive.files_0.0-2
[37] xfun_0.23                 ps_1.6.0                  openxlsx_4.2.:
testthat_3.0.2
[41] rvest_1.0.0               lifecycle_1.0.0           rstatix_0.7.0
MASS_7.3-54
[45] scales_1.1.1              hms_1.1.0                 curl_4.3.1
memoise_2.0.0
[49] stringi_1.6.2             desc_1.3.0                boot_1.3-28
pkgbuild_1.2.0
[53] zip_2.2.0                 rlang_0.4.11
pkgconfig_2.0.3          evaluate_0.14
[57] lattice_0.20-44           htmlwidgets_1.5.3
assertive.properties_0.0-4 tidyselect_1.1.1
[61] processx_3.5.2            R6_2.5.0                  magick_2.7.2
generics_0.1.0
[65] DBI_1.1.1                 pillar_1.6.1              haven_2.4.1
foreign_0.8-76
[69] withr_2.4.2               assertive.numbers_0.0-2   abind_1.4-5
modelr_0.1.8
[73] crayon_1.4.1              car_3.0-10
assertive.types_0.0-3     utf8_1.2.1
[77] rmarkdown_2.8             grid_3.6.3                readxl_1.3.1
data.table_1.14.0
[81] callr_3.7.0               reprex_2.0.0              digest_0.6.27
gridGraphics_0.5-1
[85] munsell_0.5.0             sessioninfo_1.1.1
```

Figure A.10: **Version number of all R packages used.** To see which package was used in which calculation, check the scripts available on `https://github.com/AnnikaErtel/CropDiversity_NutritionalSupply`

Bachelors's thesis statement of originality

I hereby confirm that I have written the accompanying thesis by myself, without contributions from any sources other than those cited in the text and acknowledgements. This applies also to all graphics, drawings, maps and images included in the thesis.

Place and date

Signature