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**The impact of climate variability on diets and
child undernutrition in rural Burkina Faso**

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Table of content

Abbreviations	v
List of tables	ix
List of figures	xi
List of appendices.....	xiii
1. Introduction	1
1.1. Child undernutrition and climate change in sub-Saharan Africa.....	1
1.1.1. Promoting child growth and development.....	2
1.1.2. Climate change and variability in West Africa.....	6
1.1.3. Food security, agriculture and dietary diversity during climate change	12
1.2. Problem statement	17
1.2.1. Study rationale.....	17
1.2.2. Conceptual framework.....	20
1.2.3. Study aims and objectives	20
2. Study population, materials and methods	23
2.1. Study region	23
2.1.1. Burkina Faso, West Africa	23
2.1.2. The Nouna Health and Demographic Surveillance System (HDSS).....	25
2.2. Study design	26
2.3. Sample size calculation	28
2.4. Ethical considerations and consent to participate.....	29
2.5. Study procedures and data collection	30
2.5.1. Household socio-economic questionnaire	30
2.5.2. Assessment of children’s diets.....	31
2.5.3. Child anthropometric measurements	32
2.5.4. Rainfall measurements.....	34
2.5.5. Agricultural questionnaire and remote sensing data.....	36
3. Data management and statistical analyses	39
3.1. Data entry	39

3.2. Data cleaning and quality control.....	39
3.3. Handling missing data	40
3.4. Statistical analyses.....	40
3.4.1. Analytical approach according to conceptual framework	40
3.4.2. Demographic and socio-economic characteristics of the study population.....	41
3.4.3. Characterization of child undernutrition.....	42
3.4.4. Diets of children aged <5 years in the Nouna HDSS area.....	43
3.4.5. Indicators of rainfall variability in the Nouna HDSS area.....	46
3.4.6. Estimating yield from remotely sensed satellite data	50
3.5. Synopsis of study components	52
4. Results	53
4.1. Demographic and socio-economic characteristics of the study population.....	53
4.1.1. Sampling and description of the study population.....	53
4.1.2. Characteristics of the study population and their agricultural livelihood	54
4.1.3. Prevalence of child undernutrition.....	57
4.1.4. Child undernutrition and associations with socio-economic risk factors	58
4.2. Diets of children aged <5 years in the Nouna HDSS area.....	62
4.2.1. Characteristics of diets.....	62
4.2.2. Common dietary patterns in the study region.....	63
4.2.3. Associations of dietary indicators with child nutritional status	64
4.3. Rainfall variability in the Nouna HDSS area	67
4.3.1. Amount and distribution of rainfall, trends from 1981 to 2019.....	67
4.3.2. Associations of rainfall variability with child undernutrition at four different time periods.....	69
4.3.3. Rainfall variability and its association with dietary patterns	71
4.3.4. Associations of the Precipitation Variability Score (PVS) with child undernutrition .	72
4.4. Validation of remotely sensed estimates of crop yield at the household level.....	73
5. Discussion	77
5.1. Child undernutrition in West Africa.....	77
5.1.1. Child undernutrition remains a serious problem in rural Burkina Faso.....	77
5.1.2. An increase in extreme rainfall events over fewer days	78

5.1.3. Rainfall variability as a new risk factor for child undernutrition.....	80
5.2. Diets of children aged <5 years in rural Burkina Faso	83
5.2.1. Low dietary diversity and vegetable consumption among children under five	83
5.2.2. A higher dietary diversity was associated with improved child undernutrition	85
5.3. Rainfall variability as a proxy for climate change and children’s diets	87
5.3.1. The time period depicts the impact of rainfall on diets and child undernutrition.....	87
5.3.2. Selection of rainfall database and rainfall variability indicators	90
5.4. Ground validation of high-resolution remote sensing as a method to identify food crop yield at the household level	92
5.5. Study limitations.....	94
5.6. Recommendations for further research.....	95
5.7. Recommendations for policy.....	97
6. Summary	101
Zusammenfassung	103
Exposé	105
References	107
Own publications.....	125
Appendices	127
Appendix A: Household socio-economic and agricultural questionnaires.....	127
Appendix B: Demographic and socio-economic graphs and tables	157
Appendix C: Agricultural graphs and tables	161
Appendix D: Dietary graphs and tables.....	163
Appendix E: Rainfall graphs and tables	173
Curriculum vitae.....	181
Acknowledgements	185
Eidesstattliche Versicherung	189

Abbreviations

ANAM	Agence National de la Météorologie
°C	Degree Celsius
CHIRPS	Climate Hazards Group Infrared Precipitation with Stations
CI	Confidence Interval
CILSS	Comité inter Etats de Lutte contre la Sécheresse au Sahel
cm	Centimeter
CMA	Centre Medical avec Antenna Chirurgical
CO ₂	Carbon dioxide
CRSN	Centre de Recherche en Santé de Nouna
CSPS	Centre de Santé et de Promotion Sociale
DAAD	German Academic Exchange Service
DDS	Dietary Diversity Score
DFG	German Research Foundation
DHS	Demographic and Health Survey
DP	Dietary Pattern
DPS	Dietary Pattern Score
DPSAA	Direction de la Prospective et des Statistiques Agricoles et Alimentaires
EO	Earth Observation
ESA	European Space Agency
ESRI	Environmental Systems Research Institute
ETCCDI	Expert Team from Climate Change Detection and Indices
FAO	Food and Agricultural Organization
FEWS-NET	Famine Early Warning System Network
FFQ	Food Frequency Questionnaire
FG	Food groups
FI	Food items
FOODSEC	Food Security
FVS	Food Variety Score
g	Grams
GDP	Gross Domestic Product

GHI	Global Hunger Index
GMST	Global Mean Surface Temperature
GPS	Global Positioning System
HAD	Height-for-Age difference
HAZ	Height-for-Age z-score
HDI	Human Development Index
HDSS	Health and Demographic Surveillance System
HIGH	Heidelberg Institute of Global Health
IFAD	International Fund for Agricultural Development
IFPRI	International Food Policy Research Institute
INDC	Intended Nationally Determined Contribution
INDEPTH	International Network for the Demographic Evaluation of Populations and their Health
INSD	Institut National de la Statistique et de la Démographie
IPCC	Intergovernmental Panel on Climate Change
ISIMIP	Inter-Sectoral Impact Model Intercomparison Project
IWI	International Wealth Index
Kg	Kilograms
LGF	Landesgraduiertenförderung Baden-Württemberg
LMICs	Low and Middle Income Countries
LSHTM	London School of Hygiene and Tropical Medicine
LSMS	Living Standards Measurement Study
MARS	Monitoring Agricultural ResourceS
MDG	Millennium Development Goals
MGRS	Multicenter Growth Reference Study
MICS	Multiple Indicator Cluster Survey
NAP	National Adaptation Plan
NASA	National Oceanic and Atmospheric Administration
NCDC	National Climate Data Center
NCEI	National Centers for Environmental Information
NCHS	National Center for Health Statistics
NDRE	Normalized Difference Red Edge Index

NDVI	Normalized Difference Vegetation Index
NDWI	Normalized Difference Water Index
NOAA	National Oceanic and Atmospheric Administration
OHCHR	Office of the United Nations High Commissioner for Human Rights
OLS	Ordinary Least Squares
PM	Particulate Matter
PANA	Programme d'Action National d'Adaptation
PCA	Principle Component Analysis
PR	Prevalence Ratio
PVS	Precipitation Variability Score
RE	Retinol Equivalent
RMSE	Root Mean Square Error
RRR	Reduced Rank Regression
RSS	Remote Sensing Solutions GmbH
SD	Standard deviation
SDG	Sustainable Development Goals
SE	Standard Error
SLR	Systematic Literature Review
SPI	Standardized Precipitation Index
SSA	Sub-Saharan Africa
t	Time
UNDP	United Nations Development Program
UNFCCC	United Nations Framework Convention on Climate Change
UNICEF	United Nations International Children's Emergency Fund
USA	United States of America
WASCAL	West African Science Service Center on Climate Change and Adapted Land Use
WFP	World Food Program
WHO	World Health Organization
WHZ	Weight-for-Height z-score
WMO	World Meteorological Organization
24h DR	24 hour Dietary Recall

List of tables

Table 1: Definitions of relevant climate-related terms	8
Table 2: Definitions of relevant nutrition-related terms	13
Table 3: List of food groups and food items included in the 7-day FFQ	32
Table 4: Potential risk factors associated with child undernutrition as used in this study	43
Table 5: 15 rainfall indicators to measure rainfall variability and extremes	48
Table 6: Description of the derived four time periods for the children sampled in 2017 to 2019.....	49
Table 7: Synopsis table of study components	52
Table 8: Distribution of villages, households and children in the open cohort from 2017 to 2019	54
Table 9: Demographic and socio- economic characteristics of 1,439 children aged 7 to 60 months by sex in the Nouna HDSS area	56
Table 10: Univariate associations of statistically significant risk factors of stunting and HAZ and of wasting and WHZ of children aged 7 to 60 months in the Nouna HDSS area.....	60
Table 11: Associations of DDS, FVS and three DPSs with stunting and wasting of children aged 7 to 60 months and adjusted for socio-demographic variables.....	66
Table 12: Rainfall indicators that best describe the RRR-derived PVS	72
Table 13: Multi-level Poisson regression analyses (child-household-village) examining the associations of the PVS with the binary and continuous outcomes of undernutrition of children aged <5 years in the Nouna HDSS area	73
Table 14: Multivariate linear regression model output and model validation parameters for ground data and remotely sensed estimated crop yield quantities by crop type.....	74

List of figures

Figure 1: Picture of a severely undernourished child with its mother at the hospital in Nouna, Burkina Faso	3
Figure 2: Schematic showing the effect of a new climate with an increase in temperatures towards (a) a generally warmer climate, (b) an increased climate variability (more extremes), and (c) an altered shape of the temperature distribution with more extreme climate events	7
Figure 3: Logical framework illustrating the causes and consequences of child undernutrition and its link to climate change.....	11
Figure 4: Pictures of local food items from Burkina Faso: fish (carp), African locust beans (soubala), tô (porridge from sorghum or millet) with leaves, porridge from millet or sorghum, and baobab leaves (from left to right).....	17
Figure 5: Map of Burkina Faso and the Nouna HDSS area	23
Figure 6: Conceptual structure of the dynamic cohort model used by INDEPTH HDSS sites.....	25
Figure 7: Pictures of typical housing and roads during the rainy season in the Nouna HDSS area.....	26
Figure 8: Map of the Nouna HDSS villages, the study villages and the five clusters around the weather stations.....	27
Figure 9: Timeline of the open study cohort over three years of data collection	29
Figure 10: Pictures of an interview with the primary caregiver and with the field agents taking anthropometric measurements of children aged <5 years in the Nouna HDSS area.....	33
Figure 11: Map of rainfall stations located in the in the Nouna HDSS area and its surroundings.....	34
Figure 12: Description of the data collection on the ground towards weighed yield information	37
Figure 13: Scree plot of eigenvalues after PCA to derive dietary patterns	45
Figure 14: Prevalence of stunting and wasting of children aged 7 to 60 months and total annual rainfall by study year	57
Figure 15: Prevalence of stunting and wasting by study region and study year.....	57
Figure 16: Prevalence of stunting and wasting by sex and study year	58
Figure 17: Prevalence of stunting and wasting by age group and study year.....	58
Figure 18: Proportion of food groups consumed over the previous 7-days during the lean season by 1,439 children aged <5 years by study cluster	63
Figure 19: Spider net of the PCA rotated factor loadings of food items for the three identified dietary pattern scores (DPS) among 1,439 children aged <5 years in the Nouna HDSS area.....	64
Figure 20: Annual number of days with extremely wet days (RR >99th percentile) anomaly (z-scores)	67
Figure 21: Total annual rainfall anomaly for the five clusters in the Nouna HDSS area from 1981 to 2019.....	68

Figure 22: Consecutive dry days during the rainy season (CDDws) anomaly (z-scores) (mini-droughts)	68
Figure 23: Multi-level univariate Poisson regression analysis to associate 15 rainfall indicators by four time periods with child stunting (HAZ <-2).....	70
Figure 24: Multi-level univariate Poisson regression analysis to associate 15 rainfall indicators by four time periods with child wasting (WHZ <-2)	70
Figure 25: Spider net of the RRR rotated factor loadings of the rainfall indicators for the year before (t-1) and in the year of the nutrition survey (t-0).....	72
Figure 26: Example of a yield map based on remote sensing with modelled yield amounts per crop-type and the total amount of yield per field in the Nouna HDSS area	75
Figure 27: Summary of regression results representing associations with DDS tertiles and HAZ of children aged <5 years.....	86
Figure 28: Extended logical framework for child undernutrition including climate-sensitive health interventions to prevent child undernutrition and counteract climate change impacts	97

List of appendices

Appendix 1: Household socio-economic questionnaire	127
Appendix 2: Agricultural survey	145
Appendix 3: List of the 33 Nouna HDSS villages situated within a 10 km radius around five local weather stations and their number of population, households and children <5 years selected for sampling	157
Appendix 4: List of indicators and the proportion of missing data-points in the study dataset	158
Appendix 5: Demographic and socio- economic characteristics of 1,439 children aged 7 to 60 months by sex in the Nouna HDSS area (continued).....	159
Appendix 6: Univariate associations of not statistically significant risk factors of stunting and HAZ and of wasting and WHZ of children aged 7 to 60 months.....	160
Appendix 7: Crop growth calendar based on household’s recall combined with rainfall data for Nouna from 2017 to 2019	161
Appendix 8: Yield estimations based on farmers’ recall conducted in 2018	161
Appendix 9: Percentage of farmers (N=473), who reported to have bought or sold selected crops in 2018.....	162
Appendix 10: Overview of food groups and food items for factor analysis	163
Appendix 11: Proportion of food groups consumed over the previous 7-days by 1,439 children aged <5 years considering for differences between study cluster	167
Appendix 12: Proportion of food groups consumed over the previous 7-days by 1,439 children aged <5 years for differences between study years.....	167
Appendix 13: Characteristics of food intake of children aged <5 years across tertiles of DPS	168
Appendix 14: Food groups based on the 7-day FFQ consumed among 1,439 children by age group (in months) and study year.....	169
Appendix 15: Proportion of food items consumed by children aged 7 to 60 months based on the 7-day FFQ.....	169
Appendix 16: Rotated factor loadings of food items for the three identified dietary pattern scores (DPS) among 1,439 children aged <5 years in the Nouna HDSS area	171
Appendix 17: Associations of DDS, FVS and three DPSs with HAZ and WHZ of children aged 7 to 60 months and adjusted for socio-demographic variables.....	172
Appendix 18: Means and z-scores of the 15 rainfall indicators by two different time periods.....	173
Appendix 19: 15 precipitation indicators by weather station cluster from 1981 to 2019.....	174
Appendix 20: Multi-level uni- and multivariate Poisson regression analysis on the association 15 rainfall indicators by four time periods with stunting (HAZ <-2) of 1,364 children.....	175

Appendix 21: Multi-level uni- and multivariate Poisson regression analysis on the association 15
rainfall indicators by four time periods with wasting (WHZ <-2) of 1,364 children 176

Appendix 22: Pearson correlation coefficients (N=1,364) for precipitation indicators (predictor
variables), the RRR-derived precipitation pattern score (PVS), and dietary pattern scores
(response variables)..... 177

Appendix 23: RRR-derived explained variation and rotated factor loadings of rainfall indicators with
the three DPSs 179

1. Introduction

1.1. Child undernutrition and climate change in sub-Saharan Africa

Undernutrition continues to threaten millions of children's health, especially in developing countries. Health is interlinked with the society, economy and environment and equally with the climate. Climate change and variability is projected to exacerbate inequalities and impact child undernutrition and related morbidity and mortality worldwide and so in developing countries (Tong et al., 2016; Watts et al., 2018). Specifically, an increase in climate extremes, frequencies and variability belong to the key drivers behind the recent rise in global hunger and contribution to severe food crises (FAO et al., 2020). The cumulative effect of changes in climate is undermining all dimensions of food security (availability, access, utilization and stability) (FAO et al., 2018). Already an increasing global temperature of 0.5 Celsius degrees (°C) is projected to negatively impact human health and poses a higher risk for undernutrition (Hoegh-Guldberg et al., 2018).

Children aged <5 years are estimated to carry 88 % of the global burden of diseases linked to climate change. The major diseases most sensitive to a changing climate and environment include diarrhea, vector-borne diseases and infections that are associated with undernutrition and impact especially those living in poverty and having the least resources to adapt (UNICEF, 2015). Specifically small-scale subsistence farmers living in rural areas are expected to face increasing vulnerability to health risks and food insecurity as well as poverty as a result of climate variability (Belesova et al., 2019b; Skoufias & Vinha, 2012). Crop and livestock loss is a serious concern in countries located in sub-Saharan Africa (SSA), where small-scale subsistence farmers rely on rainfed agriculture and animal husbandry to feed families and to produce income (Morton, 2007). Climate change is a risk factor impacting the available quantity and quality of crop yields, which has severe negative implications on dietary habits of individuals (Hoegh-Guldberg et al., 2018; Nelson et al., 2010). Worldwide, climatic events have contributed to economic losses (Watts et al., 2018) and have destabilizing effects on society, contributing to conflict and migration of vulnerable population groups (FAO et al., 2020; Nayna Schwerdtle et al., 2020).

The here presented study aims to provide evidence on the association between undernutrition of children aged <5 years and climate variables as exemplified for rural Burkina Faso. Chapter 1 covers the four central components of this study: (i) child undernutrition, (ii) climate change and variability, (iii) agricultural yield, and (iv) diets. Each component is defined and brought into a global context. Chapter 1 ends with the study rationale and study objectives in order to lead to the second part which covers the conducted primary research. Chapter 2 introduces the study population, the sampling approach and the data collection process. In Chapter 3 the management and statistical analyses of the data is covered. It explains the handling of missing data and the choice of analyses to answer the study objectives. The study findings are presented in Chapter 4 starting with general characteristics and child undernutrition to introduce the study population and respective risk factors for child undernutrition

(Objective 1), moving on to the association of child undernutrition with diets (Objective 2) and rainfall variability (Objective 3), and ending by exploring the use of remotely sensed satellite data to quantify crop yields at the household level (Objective 4). Chapter 5 discusses the findings in a scientific context, includes prospects for further global research, and ends with recommendations for policy actions. Lastly, Chapter 6 provides the summary of the study. Parts of the findings or variations thereof have already been published (Karst, Mank et al., 2020; Mank et al., 2020) or are currently under review (Mank et al., 2021).

1.1.1. Promoting child growth and development

1.1.1.1. Definition of child undernutrition

Since the 1970s, an expert group by the World Health Organization (WHO) recommended the use of the National Center for Health Statistics (NCHS) reference data for height and weight to assess the nutritional status of children worldwide. Thirty years later, the limitations of this data, for example, the use of longitudinal data from children in the United States of America (USA) only, led to the review of the reference data and the initiation of the WHO Multicenter Growth Reference Study (MGRS), which took place from 1997 to 2003. The WHO MGRS was unique in its form as it did not only provide a comparison to a reference population, but also added an interpretation to the growth development of a child from birth to 71 months of age, and it included children in countries from all continents (specifically from Brazil, Ghana, India, Norway, Oman and the USA). Following a strict protocol, the researchers found out that all children grow similarly until the age of 5 years (independent of genetic and cultural backgrounds), if (i) they grow up under optimal environmental conditions (including the mothers' not smoking during or after pregnancy, applying breastfeeding practices, living in good dietary and hygienic environments) and (ii) regardless of their ethnicity or socio-economic status. The findings allowed setting up an internationally accepted child growth standard to identify child under- and overnutrition (WHO Multicentre Growth Reference Study Group, 2007).

Undernutrition is “an abnormal physiological condition” caused by inadequate, unbalanced or even excessive consumption of macro- and/ or micronutrients (FAO et al., 2018). Macronutrients consists of carbohydrates, proteins, and fats, while micronutrients include vitamins and minerals (Brown et al., 2014; Victora et al., 2010). Undernutrition is expressed by stunting (chronic undernutrition), underweight (acute undernutrition), and wasting (severe acute undernutrition) and is the opposite of overnutrition (overweight and obesity) (de Onis & Branca, 2016; Victora et al., 2010).

Stunting is indicated by the child's inability to attain the potential height at a particular age such that physical and cognitive delays may be observed in its development. So-called linear growth failure is the most common measure for chronic undernutrition (known as stunting) and measured by a low height-for-age z-score (HAZ). It is considered the best overall indicator of children's well-being and

provides an accurate marker of (social) inequalities in human development. Although stunted children tend to be smaller than their peers, it is often unrecognized as it is not directly visually observable and likely to be neglected or unrecognized in routine health assessments. In some communities, where it is common, it might even be considered as “normal” (de Onis & Branca, 2016; Prendergast & Humphrey, 2014). Additionally, stunting is less likely than other nutrition indicators such as wasting to be impacted by diseases or other temporary stressors such as diarrhea or malaria (de Onis & Branca, 2016; Grace et al., 2012).

Wasting is an indicator of severe acute undernutrition and measured by weight-for-height z-scores (WHZ). It is seen in temporary or cyclical settings such as emergencies, seasonal depressions, or highly infectious disease environments (Reinhardt & Fanzo, 2014). Thus, it is a short-term measure of the nutritional status that is sensitive to more recent and severe events such as diseases or an acute lack of food. Children suffering from acute undernutrition tend to be meager than their peers and have a diseased appearance (Figure 1) (Brown et al., 2014).

While there are specific, evidence-based protocols for the treatment of (severe) acute malnutrition (WHO, 2013a), there are none for the treatment of chronic malnutrition or stunting (Reinhardt & Fanzo, 2014) and, which, thus, calls for preventive measures (de Onis & Branca, 2016; Prendergast & Humphrey, 2014). Specifically, stunting is known for its complex impacts ranging from household, environmental, socio-economic and cultural influences as described in the WHO Conceptual Framework on Childhood Stunting and its various short-term and long-term consequences (Stewart et al., 2013). Among the short-term consequences are increased mortality and morbidity, reduced cognitive and physical development, and increased health expenditures and costs for a sick child. Long-term consequences include a reduced adult stature, increased risk for obesity and associated comorbidities in adulthood (e.g. elevated blood pressure), deprived reproductive health of girls and women, lower school performance and learning capacity, and limited work capacity and productivity (Reinhardt & Fanzo, 2014). In short, children suffering from stunting, but equally from wasting are at higher risk of not reaching their optimal development potential (Stewart et al., 2013; WHO Multicentre Growth Reference Study Group, 2007).



Figure 1: Picture of a severely undernourished child with its mother at the hospital in Nouna, Burkina Faso

Note: Picture taken in 2017. Copyright by Isabel Mank

1.1.1.2. Improving child undernutrition worldwide and in West Africa

Child nutrition is recognized as an important driver for a country's development prospects, wherefore improving child nutrition is considered a “quintessential sustainable development goal”. Improving maternal and child nutrition has positive implications on short- and long-term development of a population as well as a country overall (de Onis & Branca, 2016; Horton & Lo, 2013). In 2015, 193 countries of the United Nations (UN) General Assembly adopted the Agenda 2030 titled “Transforming our world: the 2030 Agenda for Sustainable Development”. Out of 17 Sustainable Development Goals (SDGs), specifically SDG 1 on “No Poverty”, SDG 2 on “Zero Hunger”, SDG 3 on “Good Health and Well-being”, SDG 6 on “Clean Water and Sanitation”, and SDG 13 on “Climate Action” tackle the direct and indirect impacts of climate change on child undernutrition. SDG 2 specifically focuses on the need to tackle global undernutrition. It calls for “ending hunger, achieving food security and improving nutrition as well as promoting sustainable agriculture until 2030”, while focusing on children aged <5 years (<https://sdgs.un.org/goals/goal2>).

The eradication of hunger had already been framed in the Millennium Development Goals (MDGs), which were established by the UN in 2000. Here, MDG 1 aimed to “eradicate extreme poverty and hunger” by halving “the proportion of people who suffer from hunger” by 2015. The MDG 1 targets have greatly been met. In developing countries not only extreme poverty has declined significantly from 47 % in 1990 to 14 % in 2015, but also the proportion of undernourished people dropped from 23 % in 1990 to 1992 to 13 % in 2014 to 2016 (UN, 2015).

A success was also noted for the global rate of child stunting, which decreased by one-third between 2000 and 2019 (FAO et al., 2020). However, this success was unequally distributed across continents. Only SSA struggles to meet the goals and even recorded an increase in the absolute numbers of stunted children from 47 million in 1990 to 58 million in 2014 keeping in mind continuing population growth (UNICEF, 2015). Possible explanations for this negative trend are multifactorial and include, for example, the low adaptive capacity arising from poverty, political and institutional constraints, lack of financial, infrastructural and technological resources, environmental degradation, and repeating social conflicts (Tirado et al., 2015; von Grebmer et al., 2020). Children from a poor family are more than twice as likely to be stunted compared to the wealthier ones (Black et al., 2013; UN, 2015).

Yet, also these developments are not uniform within the African continent. Despite its high poverty rate, promising progress has been made in Burkina Faso over the last years. According to the most recent data available from the Global Hunger Index (GHI) (2020), the FAO (2018) and the Ministry of Health of Burkina Faso (2016), 25 % of the children aged <5 years were stunted, 8 % wasted and 19 % underweight, which are reductions of 16 %, 7 % and 7 % since 2000. Also under-5 mortality decreased by 10% from 2000 to 2018 and was 8% in 2020. In the total population of Burkina Faso, the prevalence of undernourishment declined from 25 % in early 2000 to 19 % by 2019 (von Grebmer et

al., 2020). So far, obesity was only a minor issue with 4.5 % of the adult population and 1 % of the children <5 years being obese in 2016 (FAO et al., 2018).

Despite this progress, the numbers are still alarmingly high. Every third child <5 years in West Africa is stunted (30 % in 2017) (de Onis & Branca, 2016; FAO et al., 2018) and every third child of all stunted children worldwide lives in SSA (UNICEF et al., 2017). In 2020, the global prevalence of stunting for children aged <5 years was estimated at 144 million (21 % of all children) and wasting at 47 million (7 % of all children). In 2018, 5.3 million children died before the age of five, of which many can be linked to undernutrition (FAO et al., 2020). Subsequently, action has to be taken up (also taking into consideration the current COVID-19 pandemic) to get on track to achieve “zero hunger by 2030” (FAO et al., 2020).

1.1.1.3. The first 1,000 days of a child’s life as a window of opportunity

Both, child stunting and wasting, are caused by various direct and indirect factors. The first 1,000 days of life, which comprises the time from conception until 24 months of age, are considered the most important time span of a child, when failure to development may likely lead to stunted growth. It is the time when “the foundations of optimum health, growth, and neuro-development” are established (de Onis & Branca, 2016; UNICEF, 2015). Negative environmental impacts such as poor sanitation and hygiene, exposure to toxins or poor nutrition (lack of protein, energy, fatty acids and micronutrients) may hamper the development of the genetic potential of a child (Reinhardt & Fanzo, 2014). This also applies to the parents, whose exposure to negative factors before conception and during pregnancy may impact the development of the child already before and then in utero (UNICEF, 2015). Yet, in utero development and its impact on the overall child development is still not fully understood and will likely vary across populations (de Onis & Branca, 2016).

Understanding the causes and consequences of child undernutrition supports policies and actions as a sufficient investment will contribute to long-term positive outcomes for the individual and the country as a whole. Specifically, since child undernutrition can even be “passed on” to the next generation, it may create a vicious cycle that is difficult to reverse (Sheffield & Landrigan, 2011; UNICEF, 2013). For example, women, who have been stunted as children, have been found to be more likely to experience complications during delivery or also give birth to a stunted child (Alderman, 2006; de Onis & Branca, 2016). So far, typical indicators that are assumed to impact child growth are linked to the health of the child (e.g. diarrheal and infectious diseases), maternal health and behavior (e.g. age at child birth, BMI and stature, maternal diet, and breastfeeding and feeding practices, pregnancy), health care access and quality, socio-economic characteristics of the mother and household, place of livelihood, and overall the economic and political situation, the environment, social and cultural norms of the respective country (Akombi et al., 2017; Black et al., 2008; Danaei et al., 2016; Reynaldo Martorell & Young, 2012).

Hence, while a child is exposed to several risk factors during its first 1,000 days of life and thus, might not be able to restore its health later on, it is important to add, that these 1,000 days have more and more also been considered a “window of opportunity for growth promotion” (de Onis & Branca, 2016; Victora et al., 2010). Studies investigated the time of so-called “catch up growth”, which may allow to counter growth deficits (Leroy et al., 2014; Prentice et al., 2013). Though, the time span for such “catch up growth” has not yet been found. Some assume that there is a “window of opportunity” among school-aged children (Fink & Rockers, 2014; Lundeen et al., 2014), others consider adolescence as a time for increased health promotion to reverse negative impacts from stunted growth (Prentice et al., 2013). “Catch-up” is defined by an improvement in height-for-age z-score (HAZ) of the child between the second and fifth year of age (HAZ >-2 or >-1) and a decrease in the absolute height-for-age deficit (HAD) between the individual and the reference mean for a healthy population (Desmond & Casale, 2017; Georgiadis et al., 2017; Leroy et al., 2015; Lundeen et al., 2014). There is a big debate on the extent that children can “catch-up” growth and cognitive development delays after two years of age (Cameron et al., 2005; Fink & Rockers, 2014; Leroy et al., 2015; Lundeen et al., 2014; R. Martorell et al., 1994; Outes & Porter, 2013; Prentice et al., 2013).

Most factors that put children at risk, but also promote their health cannot and should not be seen in isolation. It is often a combination, and their interaction and timing as well as the resilience and adaptation capacity children have to counter risk factors (Reinhardt & Fanzo, 2014; Remans et al., 2011). All these and more factors play an integral part in child undernutrition (Black et al., 2008).

1.1.2. Climate change and variability in West Africa

1.1.2.1. Definition of climate change and weather variability

Developing countries are strongly impacted by climate change (Hondula et al., 2012), which has become a constant hazard that threaten to amplify existing risks to health and nutrition (IPCC, 2014b; Watts et al., 2019). These countries have often contributed the least and yet facing the highest vulnerability to climate change due to their low capacity to adapt (IPCC et al., 2014). Climate change is likely to increase health inequities between population groups, disproportionately affecting the most disadvantaged ones living already under environmental pressure (Anderko et al., 2020; Bennett & Friel, 2014; IPCC, 2014b).

The Intergovernmental Panel on Climate Change (IPCC) provides scientific reports on the impact and development of climate change and related events worldwide. The IPCC was established in 1988 and acts as an intergovernmental body to the UN. As part of its scientific work, it contributed to the main international treaty on climate change, the UN Framework Convention on Climate Change (UNFCCC). The UNFCCC was adopted in 1992 in order to tackle climate change and thus, reduce global warming and counts 197 signatory parties. The UNFCCC is regularly extended and revised, lastly by the 2015 Paris Agreement on Climate Change. The 195 signatories of the 2015 Paris

Agreement agreed to take action to stay below a 2°C global warming compared to pre-industrial levels in order to reduce the risks and impacts of a changing climate (UNFCCC, 2015).

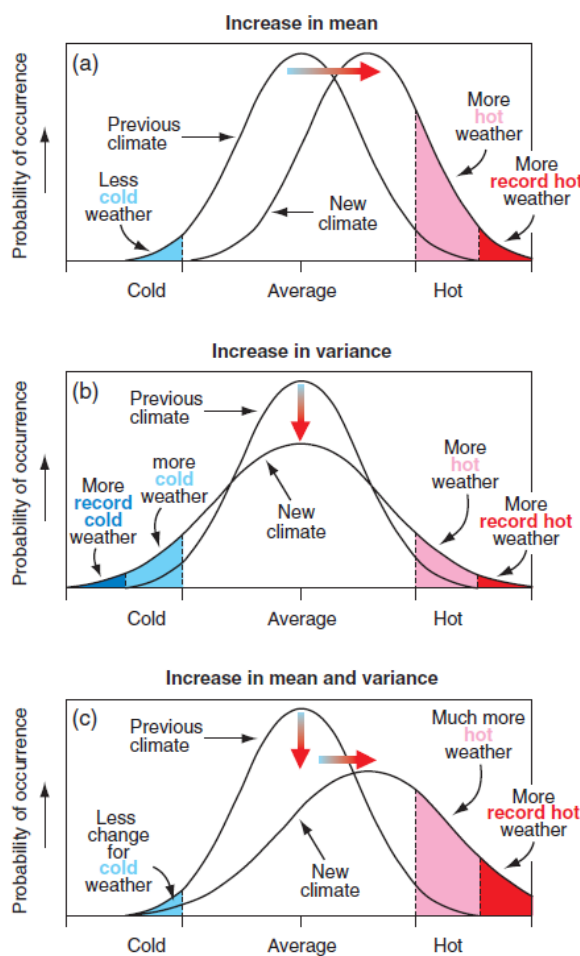


Figure 2: Schematic showing the effect of a new climate with an increase in temperatures towards (a) a generally warmer climate, (b) an increased climate variability (more extremes), and (c) an altered shape of the temperature distribution with more extreme climate events

Source: IPCC (2001)

climate, here using the example of temperature. Accordingly, the new climate is linked with (a) an increase in the mean with more hot weather events, (b) an increase in variance with more extreme weather events occurring interchangeably, and (c) a combined impact of an increase in mean and variance (IPCC, 2001). Such developments can be due to natural circumstances or due to human activity (IPCC, 2007). A summary of relevant climate-related terms can be found in Table 1, which are relevant for the understanding for the subsequent sections.

In order to address global warming and climate change, the signatory parties of the 2015 Paris Agreement regularly report on their plans and achievements in mitigating global warming. Their climate change mitigation policies aim to reduce the negative impacts of global warming, including

According to the Lancet Countdown reports, which are provided by technical and scientific experts and UN agencies and which specifically track advancements made on health linked to climate change, stated that progress to tackle negative climate change impacts has either been limited or moved in the wrong direction: Carbon emissions and global temperatures are still rising, pollution from electricity generation is still high, and fine Particulate Matter (PM 2.5) exposure has constantly increased since 1990 (Watts et al., 2018, 2019). Such developments have and will have detrimental effects on the climate further increasing the intensity and frequency of weather events. Those may include climate extremes such as very high temperatures, heavy rains, flooding, droughts, strong winds and storms, as well as increased rain and temperature variability and uncertainty. Climate change is associated with an increase in intensity and frequency of weather events over an extended period of time, but also an aggravation of climate variability. Figure 2 provides a schematic capturing the likelihood of occurrence of a new compared to the current

the stabilization of greenhouse gas (GHG) concentrations in the atmosphere by reducing carbon dioxide (CO₂) emissions, with, for example, improved agricultural technologies, planting trees as GHG absorbers, or the development of renewable and alternative energy supply sources (Tirado et al., 2015).

Table 1: Definitions of relevant climate-related terms

Global warming	Defines an increase in global mean surface temperature (GMST) averaged over 30 years for a chosen time period (in the past or the future) and compared to pre-industrial levels or otherwise specified.
Climate	Is defined as the average weather in terms of the mean and variability of relevant weather quantities over a long period of time (years to thousands or millions of years). The classical period for averaging climate variables is 30 years, as defined by the World Meteorological Organization (WMO).
Weather	Is the current state of the atmosphere and is represented, in contrast to climate, in a finer time-scale (usually hours to days). The relevant weather variables are temperature, precipitation, wind speed and direction, surface pressure, surface radiation, cloud cover, visibility (fog, mist, smog), and water vapor.
Climate change	Refers to a change in the state of the climate that can be identified by changes in the mean and/ or the variability of its properties, and that persists for an extended period of time.
Climate or weather variability	Refers to variations in the mean state and other statistics (such as standard deviations, the occurrence of extremes, etc.) of the climate/ weather on all spatial and temporal scales beyond that of individual weather events.
Extreme climate events	The occurrence of a value of a weather or climate variable above or below a threshold value near the upper or lower ends of the range of observed values of the variable. An extreme weather event is an event that is rare at a particular place and time of the year. When a pattern of extreme weather persists for some time, such as a season, it may be classed as an extreme climate event, especially if it yields an average or total that is itself extreme (e.g., drought or heavy rainfall).
Mitigation	A human intervention to reduce emissions (and its sources) or enhance absorption of greenhouse gases (GHG) such as of carbon dioxide, methane, nitrous oxide and fluorinated gases.
Adaptation	The process of adjustment to actual or expected climate and its effects in order to moderate harm or exploit beneficial opportunities. Interventions may facilitate those adjustments.
Vulnerability	The predisposition of a population to be adversely (negatively) affected by exposure to worse climate/ weather. Vulnerability encompasses a variety of concepts and elements including sensitivity or susceptibility to harm and lack of capacity to adapt to those threats.

Sources: Summarized from IPCC & Mathews (2018)

Climate change adaptation plans, also defined as National Adaptation Plans (NAPs), are also guided by the UNFCCC. In their NAPs, the signatory parties define national short- and long-term climate change adaptation strategies and programs, in order to reduce vulnerability and increase resilience at the population level. Adaptation is the adjustment to actual or expected climate events in order to

moderate or prevent harm to potentially irreversible effects of climate change. Such strategies may include scaling-up financing for climate-resilient health systems, switching to climate-resilient crops or investing in agricultural irrigation systems. Mitigation and adaptation strategies may equally lead to a number of so-called health co-benefits. For example, a reduction in air pollution may reduce respiratory diseases, while a change to climate-resilient plus nutrient-rich crops may reduce malnutrition and cardiovascular diseases (Watts et al., 2018). Thus, mitigation and adaptation actions might equally constitute a global health opportunity, which efforts may improve overall livelihoods and wellbeing (Watts et al., 2015).

1.1.2.2. Climate variability in West Africa and Burkina Faso

Despite the increasing awareness on the effects of the climate on global health (IPCC, 2014b; Watts et al., 2018), climate change simulations still bear large uncertainties for many regions of the world such as for West Africa (Ben Mohamed, 2011; Hondula et al., 2012; Hulme et al., 2001; Ibrahim et al., 2012; IPCC, 2014b). Even more so since rainfall predictions have a higher spatial and seasonal dependence than other climate indicators (Mouhamed et al., 2013). West Africa is characterized by a large decadal precipitation variability (Masih et al., 2014; Nicholson et al., 2018; Sanogo et al., 2015) and intensity of rainfall and drought events (Ben Mohamed, 2011; De Longueville et al., 2016; IPCC, 2014b; Lodoun et al., 2013). While findings on rainfall are not as uniform as, for example, for temperature, there is a general tendency for an increased total annual rainfall and less maximum number of consecutive wet days, while extreme rainfall events have become more frequent during the last decade (Mouhamed et al., 2013), which was also observed in studies for Burkina Faso (Didi et al., 2020). However, the IPCC reported only low to medium confidence in those observed and expected developments. A low confidence derives from the sparse weather data availability in Africa due to the limited distribution of weather stations and thus, the lack of sufficient observational data (IPCC et al., 2014; Sanogo et al., 2015). Additionally, the data often lacks quality and long-term observations, which makes time trend analyses and data comparison over time difficult (De Longueville et al., 2016).

Despite these uncertainties, an overall positive rainfall time trend was reported for the Sahel region between 1980 and 2010. This recovery in rainfall can be observed due to the long-lasting drought periods that took place in the 1970s and 1980s, while extreme flooding were recorded in 2007, 2010 and 2012 (Salack et al., 2016; Taylor et al., 2017). Yet, the Sahel region did not yet return to the wet conditions from the 1950s and 1960s. Nevertheless, a slight increase of annual rainfall and rainfall variability was observed including precipitation extremes (Salack et al., 2016; Taylor et al., 2017) in combination with an increase towards more extreme temperatures (Ben Mohamed, 2011; Hondula et al., 2012; Hulme et al., 2001; Sylla et al., 2018). The IPCC report (2014) confirms for West Africa that the rainfall intensity increased in general, but showed only slight or no changes at all for selected

heavy precipitation indicators. Additionally, it was observed that there is a decrease in the length of the rainy season, a reduction in rainfall in July, August and September, and less frequent and intense rainfalls. Yet, such observations strongly depend on the database, the region and the methodology applied (Sanogo et al., 2015).

Spatial and temporal rainfall variability was also identified at the country-level for Burkina Faso (Belesova et al., 2019b). Burkina Faso can be divided into three climatic zones: the North, the Center and the South, which are, respectively, characterized by a Sahelian (total annual rainfall <600 mm), a Sudano-Sahelian (total annual rainfall between 600 and 900 mm), and a Sudanian climate (total annual rainfall >900 mm) (De Longueville et al., 2016; PANA Burkina, 2007). Equally as for the West African Sahel, in Burkina Faso a tendency towards higher rainfall and temperatures are projected with an increase in extreme rainfall events, a longer rainy season with 30% of the total annual rain falling in August, and a warming by 0.5 °C to 3 °C by 2100 (Hondula et al., 2012). The population relies heavily on rain-fed agriculture, wherefore their livelihood strongly depends on steady and consistent rainfall, while weather extremes and weather variability pose a threat to harvest output (Belesova et al., 2019b; Hondula et al., 2012; Ibrahim et al., 2012; Sanogo et al., 2015). Common climatic problems in Burkina Faso are (i) excessive rains leading to flooding and soil degradation, loss of yield and social tension; (ii) a lack of rain leading to droughts, declining yield and food insecurity; and (iii) high temperatures such as heatwaves contributing to the multiplication of crop destroying insects. These effects are intensified due to low agricultural mechanization and land insecurity (Dipama, 2016).

1.1.2.3. Climate change as a global threat to child undernutrition

In 1990, UNICEF provided a logical framework on child undernutrition that has been extensively used as a guidance to understand interactions and define interventions to address child undernutrition (Reinhardt & Fanzo, 2014; UNICEF, 2013). Despite this increased knowledge, success is threatened to be reversed given the raising negative impact of climate change on food security. This new knowledge led to the adaptation of the UNICEF logical framework emphasizing this “new” threat climate change (Anderko et al., 2020; Tirado et al., 2015; Watts et al., 2015).

Figure 3 displays this adapted logical framework illustrating the direct and indirect link between climate change, agriculture, nutrition and health. The colored boxes emphasize the focus of the work presented here according to which the direct effects of climate change or variability are directly linked to farming, living conditions, diets, diseases and child undernutrition. Accordingly, child undernutrition is directly as well as indirectly impacted by various factors that are defined here at different levels: (i) basic causes at the community level, (ii) underlying causes at the household level and (iii) immediate causes at the individual level.

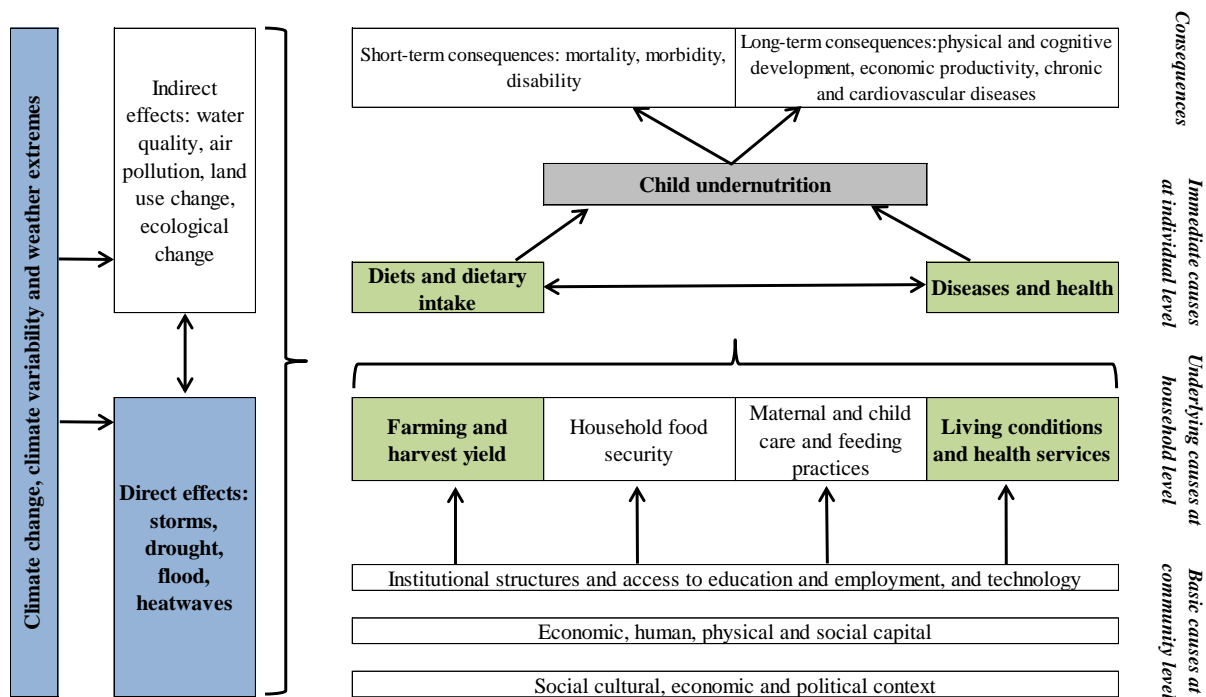


Figure 3: Logical framework illustrating the causes and consequences of child undernutrition and its link to climate change

Source: Adapted according to Anderko et al. (2020), Tirado et al. (2013), UNICEF (1998) and Watts et al. (2015)

Basic causes for child undernutrition at (i) the community level include economic, political, cultural and normative factors, as well as the status of the household in this environment such as defined by access to resources (Reinhardt & Fanzo, 2014). The effectiveness of institutional strategies related to climate change will determine the severity the population will be affected. This entails strategies for health services, social protection, governance, peace and conflict, markets, and human mobility (Tirado et al., 2013).

Underlying causes at (ii) the household level are linked to knowledge and capabilities of the household to access proper nutrition and health care to assure food security, adequate feeding practices, health and disease treatment, and a safe environment. The aspect of agriculture in the form of farming and harvest yield was extracted from the other factors and added to the original UNICEF logical framework to emphasize its link to child undernutrition (Belesova et al., 2019b; Karst, Mank et al., 2020).

Immediate causes at (iii) the individual level include diets and an inadequate food intake in the form of quantity, quality, diversity and the ability to retain nutrients. It also reflects the vulnerability to diseases and infections. Nutrition drives the biological processes that contribute to the growth and development of muscles and the nervous system (Branca & Ferrari, 2002; Reinhardt & Fanzo, 2014).

All of these three categories are directly or indirectly impacted by environmental factors such as climate change and variability, which threaten to impact child health and nutrition (McMichael et al.,

2006; UNICEF et al., 2017) and even reverse the progress made over the last decades. On the left of Figure 3 climate change, climate variability and weather extremes were added, which can be further defined by indirect and direct effects. Children are especially vulnerable to climate effects due to their physiological and cognitive immaturity and their reliance on others (e.g. the parents) to adapt to the current situation and protect them from external factors (Stanberry et al., 2018; UNICEF, 2015). By 2050, alone 76 to 84 million more malnourished children (+ 10 %) are projected under an optimistic climate scenario compared to a no climate change scenario as agricultural productivity reduces, dietary diversity and micronutrient uptake decreases and poverty increases (Nelson et al., 2010). “Climate change is potentially the biggest global health threat in the 21st century” (Costello et al., 2009) and assumed to have the largest single negative impacts on health with a very large number of people being affected (IPCC, 2014a).

1.1.3. Food security, agriculture and dietary diversity during climate change

1.1.3.1. Definition of food and nutrition security

Food and nutrition security are closely linked to child undernutrition. Specifically households with higher rates of food insecurity were found to be more likely to have stunted children (Berra, 2020; Moradi et al., 2019). Enhancing food security and reducing undernutrition have been pledged since 1948 through the Universal Declaration of Human Rights (Article 25): “The right to adequate food is realized, when every man, woman and child, alone or in community with others, has physical and economic access at all times to adequate food or means for its procurement” (OHCHR & FAO, 2010).

In 1996, the FAO stated that food security “exists, when all people, at all times, have physical, social and economic access to sufficient, safe and nutritious food, which meets their dietary needs and food preferences for an active and healthy life” (FAO, 1996). It comprises four essential pillars: (i) availability, (ii) access, (iii) utilization and (iv) stability. Food availability refers to a reliable supply of food of sufficient quantity and quality (e.g. dependent on domestic production, markets and transport). Food access is ensured, when individuals and households have adequate resources to obtain appropriate food (e.g. dependent on equitable distribution and affordability). Food utilization comprises nutritious food that can be adequately metabolized and used by the body (e.g. dependent on feeding practices, food safety, food quality and health). Food stability occurs, when there is permanent and durable access to food (e.g. dependent on all other three pillars and climate, social, economic and political factors) (FAO et al., 2020). Table 2 provides a summary of the definitions of relevant nutrition-related term relevant for the understanding for the subsequent sections.

Table 2: Definitions of relevant nutrition-related terms

Diets	Evolve over time and are “influenced by many social and economic factors that interact in a complex manner to shape individual dietary patterns”. These factors include income, food prices, individual preferences and beliefs, cultural traditions, and geographical and environmental aspects (including climate change).
Dietary patterns	Reflect the complexity of a diet and provide an impression of the overall diet structure. These patterns are derived by combining different food items that are commonly consumed together and the frequency with which they are consumed over a specific recall period.
Dietary diversity	Is a proxy to measure diet quality and nutrient adequacy. Low dietary diversity is an indicator for inadequate diets with low diversity in food groups and food items. It can be measured through Dietary Diversity Scores (DDS) or Food Variety Scores (FVS). A minimum dietary diversity is defined to be met, when at least 5 different food groups were consumed during the previous 24 hours.
Food variety	Defines the consumption of a mixture of food items from the entire range of food groups. A high food variety is an indicator for a higher dietary diversity.
Malnutrition	Refers to all forms of poor nutrition and is caused by a complex array of factors including dietary inadequacy (deficiencies, excess, imbalanced consumption of protein, energy and micronutrients), infections, and socio-cultural factors. It includes under- and overnutrition.
Undernutrition	Exists when a combination of insufficient food intake (in quantity and quality), health and care result in underweight, chronic undernutrition (stunting), acute undernutrition (wasting) or micronutrient deficiencies (deficient in vitamins and minerals).
Food security	Exists “when all people, at all times, have physical, social and economic access to sufficient, safe and nutritious food, which meets their dietary needs and food preferences for an active and healthy life”. Food security is defined by four pillars: availability, access, utilization and stability.
Nutrition security	Encompasses food security, yet adds that not only food, but also environmental factors contribute to undernutrition. Hence, nutrition security furthermore emphasizes the need for a sanitary environment, adequate health services and proper care.
Hunger	Describes a feeling of discomfort from not eating and is associated with a lack of sufficient calories. It is also used to describe food deprivation or undernourishment.
Hidden hunger/ micronutrients	Occurs with a deficiency in micronutrients (vitamins and minerals). Micronutrient deficiencies tend to be invisible or may only appear late through health consequences. This may include a deficiency in vitamin A causing blindness in children or a lack of iron contributing to severe anemia especially among pregnant women with subsequent death during or shortly after childbirth.
Macronutrients	Include proteins, fats, and carbohydrates in contrast to micronutrients, which include vitamins and minerals. Macronutrients are required in large quantities to assure that the body has enough energy. However, overconsumption may cause overweight.

Sources: Summarized from Pangaribowo et al. (2013), Tirado et al. (2013), UNICEF (2019), von Grebmer et al. (2020), Ingram (2020), and WHO (2020a)

Food and nutrition security are often used simultaneously. Nutrition security is given, when a person “consumes food of sufficient quantity and quality in terms of variety, diversity, nutrient content and safety”. This entails that the food is adequately biologically utilized and thus, goes along with personal and environmental health (Pangaribowo et al., 2013; Tirado et al., 2013). Hunger on the other hand is

only one form of malnutrition and describes a state of not eating and thus, not receiving enough dietary energy from macronutrients (Pangaribowo et al., 2013). Hence, food security combines all aspects and may be related to the quantity of foods consumed as well as their quality assuming that enough food does not necessarily result in nutritious food intake and so nutritional security (Pinstrup-Andersen, 2009).

1.1.3.2. The impact of climate change on food security and agricultural practices

Climate change presents not only an increasing risk to child undernutrition, but also to household food security and here specifically to livelihoods of small-scale subsistence farmers living in rural areas. Small-scale subsistence farmers are characterized here as rural producers, who rely on family labor, who produce the majority of the foods they consume, and who own not sufficient land to produce for local markets (Karst, Mank et al., 2020; Morton, 2007). They rely on low-input and highly manual agricultural management. Hence, they are among those suffering the most from the negative impacts of climate change. Their food and nutrition security may be deprived by direct climate impacts such as increased flooding, drought, rainfall variability, high temperatures, and soil erosion or by indirect impacts such as increased pests and diseases on crops and livestock, a rise in food prices, destruction of infrastructure used to transport food, or spoilage of fresh food that had been badly stored (IPCC et al., 2014).

Overall, agricultural production is highly dependent on sufficient and reliable rainfall (Morton, 2007). Given that more than 70 % of the agriculture is rain-fed globally and 98 % in Sub-Saharan Africa, changes in climate might likely lead to an increase in food insecurity and undernutrition (IPCC, 2014a; IPCC et al., 2014). Yet, little is known about farming practices, needs, and adaptation mechanisms, which make farmers' families specifically susceptible to climate change (Sorgho et al., 2020). New technological developments such as the advancement of high resolution remotely sensed imagery allow classifying agricultural land, map areas affected by pests, diseases, droughts or floods and provide yield prediction. This information may then be attributed to households and hence to the nutritional status of children < 5 years living there in order to identify highly vulnerable population groups to food insecurity (Bégué et al., 2018; Mutanga et al., 2017). Remote sensing makes use of satellite technologies to observe and classify earth parameters, and it is repetitive and cost-effective as opposed to on-the-ground assessments (Mutanga et al., 2017). Thus, remotely sensed data may support the detection and so forecast of negative impacts through the climate on plants, crop yields and humans.

In addition, subsistence farmers themselves face a wide range of health risks (e.g. heat stress when working on the fields during the day), economic struggles (e.g. price volatility due to harvest loss and migration of household members as they search for alternative income sources), infrastructural constraints (e.g. limited access to local markets), environmental degradation (e.g. water stress,

desertification, soil poverty and plant pests) as well as governmental uncertainties (e.g. political instability and civil disturbances due to lack of resources and poverty) (Tirado et al., 2015; IPCC 2013). Hence, climate variability and extremes affect food security and agricultural practices in multiple direct and indirect ways (Myers et al., 2017) and may have detrimental effects on agricultural livelihoods (Lobell et al., 2011). The intensity, frequency and timing of weather events and excessive as well as insufficient rainfall have especially strong impacts on agricultural practices and harvest yield (IPCC et al., 2014). There are two main mechanisms through which climate acts on harvest yield.

Firstly, increased heat substantially reduces the work productivity and occupational health of agricultural laborers (Orlov et al., 2020; Watts et al., 2018). The human body has physiological limits and may only be able to work up to a certain hot and humid environment (Kjellstrom et al., 2016; Sahu et al., 2013). Thus, climate change-induced heat extremes may affect the internal temperature regulation of the body causing heat cramps, heat exhaustion, heatstroke, hyperthermia or dehydration (Anderko et al., 2020; Watts et al., 2018).

Secondly, weather extremes and variability are likely to have unfavorable direct impacts on plants and crop yields (Graef et al. 2014). The most detrimental impacts worldwide are projected on wheat, rice and maize given current temperature and precipitation trends (IPCC, 2014a). For example, Rowhani et al. (2011) showed that the modelled seasonal temperature increase of 2 °C would reduce average maize, sorghum, and rice yields by 13 %, 9 %, and 8 %, respectively, in Tanzania by 2050. Additionally, higher temperatures cause greater evapotranspiration (= evaporating water from the soil and plants), which reduces crops' water availability. This may lead to an increase in arid and semi-arid land, which is projected to increase between 5 % to 8 % over whole Africa by the 2080s (Tirado et al., 2015).

1.1.3.3. Nutrient adequacy in plants and diets under climate change

While there is growing evidence on the associations between climate change and variability and crop yields, the link to the quality of foods (nutrient content) and change in diets (dietary diversity) is less explored and lacks observations over several years in order to consider for climatic changes (Scarpa et al., 2020). While elevated CO₂ levels in the atmosphere may promote plant growth and so yield production, it may equally reduce the nutrient content in plants, wherefore causing micronutrient deficiencies of its consumers (Myers et al., 2014; Scheelbeek et al., 2018; Zhu et al., 2018).

Specifically, elevated CO₂ levels were found to reduce the nutrient concentrations of zinc, iron and protein in staple foods such as in potatoes, barley, rice, maize, peas and wheat (Fanzo et al., 2018; IPCC, 2014a; Myers et al., 2014). Therefore, for example, protein deficiency is assumed to affect an additional 148 million people globally by 2050, assuming today's diets and levels of income inequality (Medek et al., 2017). In rural areas of developing countries, diets are mainly based on

starchy staples (provide 60 to 70 % of energy intake) with little or no addition of animal products, fruits and vegetables. Such diets tend to have low quantities of micronutrients lacking iron, zinc and calcium for child growth (Branca & Ferrari, 2002; Mank et al., 2020). However, equally a reduction in legume and vegetable yields due to climatic impacts are predicted (Scheelbeek et al., 2018). Already today, vitamin A, iodine and iron deficiencies are of global concern to public health (WHO, 2014). Overall, 340 million children suffer from micronutrient deficiencies worldwide (FAO et al., 2020).

In addition to the direct impact of CO₂ on plants, which define the nutrient availability in diets, child nutrition is also defined by the environment the child lives in. The latter is another focus of this study. In this regard, nutrient uptake is not only impacted by crop quantity and quality, but also by maternal knowledge and behavior and the living conditions. Hence, if agricultural yields decline or fail, food stocks get empty before the next harvest and food prices will rise causing the families to adapt their food sources and so dietary behavior (Brown et al., 2014; Saronga et al., 2016; Shively et al., 2015). As shown in the adapted logical framework (Figure 3), maternal and child care and feeding practices as underlying causes and diets and dietary intake as immediate causes are centrally linked to child undernutrition (UNICEF, 1998). Nutrition insecurity exists, when food is missing in quantities, but also in nutrient adequacy and dietary diversity (Sibhatu et al., 2015). In low-resource populations, especially from developing countries, child diets are often based on starchy staples with adding little or no animal products (e.g. eggs, dairy, fish or meat) and few fruits and vegetables. However, animal sources provide essential nutrients and vitamin A, iron, zinc and calcium that are crucial for healthy growth and cognitive development (Krasevec et al., 2016; UNICEF, 2019).

Dietary diversity is recognized as a key indicator for the qualitative measurement of diets and thus, nutrient adequacy (FAO, 2010; Ruel, 2003; UNICEF, 2019). If assessed on the household level, it displays food access by the variety of foods available and, thus, reflects the economic ability of a household to access foods; if assessed on the individual level, it can be used as a proxy for nutrient adequacy of the diet (Miller et al., 2020; Sibhatu et al., 2015). Worldwide only every 5th child between 6 and 23 months of age was found to reach the minimum dietary diversity, which should count at least 5 different food groups consumed during the previous 24 hours as is recommended for optimal growth (UNICEF, 2019).

Assessing diet quality and quantity to measure nutrient uptake (= macro- and micronutrients) over several time periods is challenging (FAO et al., 2020). Three indicators were identified that are commonly used to be associated with child undernutrition and health status: the Dietary Diversity Score (DDS), the Food Variety Score (FVS) and Dietary Pattern Scores (DPS). Specifically, dietary diversity for children aged <5 years is often measured through DDS and FVS (Miller et al., 2020). Assessing DDS and FVS are rapid, user-friendly and low-cost assessments as they simply count the number of food groups or food items consumed. Dietary diversity and food variety are proxies for diet quality and nutrient adequacy and allow to easily assess the change of diets over time (Steyn et al., 2006; Zhao et al., 2017). However, there are no commonly applied recommendations on dietary

diversity with regard to number of food groups (DDS) or food items (FVS) that should be consumed by households or children, specifically. Nevertheless, most international dietary guidelines define an increased dietary diversity with an enhanced intake of essential nutrients, and a promotion for good health (Arimond & Ruel, 2002; UNICEF, 2019). A few studies validated dietary diversity against nutrient adequacy in developing countries (Mumu et al., 2020). A summary on those findings can be found in Ruel (2003), who concluded and confirmed a positive association between dietary diversity and nutrient adequacy in developing countries.

Dietary patterns are another approach to receive insights on consumption habits. Dietary patterns are assessed through a combination of food items (Figure 4). They reflect the complexity of a diet and provide a more realistic impression of the overall diet structure compared to dietary diversity indicators (Hu, 2002a; Mank et al., 2020; Melaku et al., 2018). So far, only a few studies conducted exploratory analysis on dietary patterns in West African populations and those were mainly conducted in urban settings (Galbete et al., 2017). Common challenges are, for example, the scarcity of data on nutritional status such as in the case of Burkina Faso (Martin-Prevel et al., 2016) and the different methods and approaches employed in studies affecting the comparability and generalizability of dietary results (Ruel, 2003).

To conclude, there is a need to better understand the effect of climate change and variability on nutrients in plants and foods and the subsequent impact on food quality and dietary behavior. Even if dietary diversity is assured, considering climatic changes over time an increase in nutrient deficiencies and so child undernutrition can be expected (Fanzo et al., 2018).



Figure 4: Pictures of local food items from Burkina Faso: fish (carp), African locust beans (soumbala), tô (porridge from sorghum or millet) with leaves, porridge from millet or sorghum, and baobab leaves (from left to right)

Note: Pictures taken in 2017 and 2018. Copyright by Isabel Mank

1.2. Problem statement

1.2.1. Study rationale

While epidemiological studies on children's nutritional status, its multiple determinants, and assessment of crop yields under different climate scenarios are vast individually, there is a scarcity of studies linking those aspects to each other (Brown et al., 2014; Noromiarilanto et al., 2016). Yet, doing so would allow to better understand their complex relationships and to define where prioritised action

should be placed; specifically in resource-poor countries (Helldén et al., 2021). It is challenging and complex to disentangle factors that contribute to child undernutrition due to vast direct and indirect impacts of social, cultural, environmental and climate systems (Tong et al., 2016). Especially for low- and middle-income countries in SSA, evidence-based insights and interdisciplinary research on climate variability on agricultural yield, diets and nutritional status are often limited (Helldén et al., 2021; Hondula et al., 2012; Morton, 2007).

Several reasons have been identified, why this is the case. Firstly, there is a lack of valid, reliable and long-term data of weather, agricultural practices, nutrition and health in developing countries. Secondly, studies often lack a control group to generate evidence for possible correlations of the impact of climate change on various health outcomes, for example, undernutrition. Thirdly, the link between climate change and health is not always direct and simple. A change in the climate does not necessarily lead to a new disease, but rather intensifies the burden of existing ones (e.g. asthma) or moves a known disease to new regions (e.g. malaria to mountain areas). Fourthly, health is impacted by various confounders and effect modifiers at individual, social and environmental levels, wherefore there are no simple causal pathways, but always a combination of climatic, economic and environmental factors. Fifthly, due to the complexity, collaboration across disciplines is required to study health, climate change and agriculture. Experts from various fields such as public health, medicine, meteorology and agriculture are needed to work together (Sauerborn, 2017).

A significant obstacle for relating health, nutrition, agricultural and climate data is the need for “locally specific, dated, and geolocated datasets that can be linked quantitatively” (Brown et al., 2014). It is not yet common to collect georeferenced health and nutrition data to identify the location of the respondents and to then link them with additional geographic information, for example, climate data to conduct analyses on various temporal- and spatial-scales. A rare example is a study provided by Alfani et al. (2019), who looked at the spatial distribution of stunting over time in the West African Sahel. Overall, the link between climate variables and agricultural output, diets, and child undernutrition has hardly been studied. The Demographic and Health Survey (DHS) started to collect geographic information in the mid-1990s, creating a basis for publicly available health and nutrition data linked to geolocations. In the meantime, more national and international surveys, such as the World Bank’s Living Standards Measurement Study (LSMS) Surveys, provide guidance on assessing geographic information (e.g. on Global Positioning System (GPS)-measurements to assess agricultural land cover) (Carletto et al., 2016). Therefore, connecting such interdisciplinary data becomes a possibility, but is still limited (Bauer & Mburu, 2017; Grace et al., 2014; Johnson & Brown, 2014).

Two systematic literature reviews (SLRs) summarized the existing evidence on the associations between climate change indicators and child undernutrition. Phalkey et al. (2015) conducted a SLR investigating the evidence on the associations between climate variables, agricultural yield and undernutrition (particularly stunting) in children aged <5 years. They found out that climate variables (droughts and floods) were significantly associated with nutritional outcomes of the child (particularly

stunting) in 80% of the studies. The vulnerability increased the younger a child was, the longer the child was exposed to the climate event and the more frequently this event occurred. They also observed that not only most studies were found for the African continent, but that the majority of studies also used secondary data (only five studies used primary data). Belesova et al. (2019a) conducted a SLR focusing specifically on the empirical evidence of drought impact on undernutrition of children <5 years of age in low- and middle income countries (LMICs). Both author teams concluded that the strength of evidence of drought as a risk factor for child undernutrition was limited with only two studies finding a positive association with children being underweight and having anemia. So far, the evidence for an associations between climate change and undernutrition among children aged <5 years are neither sufficient nor comparable due to a lack of robust data and substantial heterogeneity of research methods (Belesova et al., 2019b; Phalkey et al., 2015). A positive development is though, that the number of scientific papers on health and climate change are increasing and their number has even more than tripled over the past decade (Helldén et al., 2021; Watts et al., 2018).

The pathway from climate via agriculture to diets and child undernutrition has been described in the previous chapters (see also Figure 3). To summarize, in a small-scale subsistence farming environment, dietary behavior and nutritional intake are affected to a large extent by the quantity and quality of harvest yields. Thus, in turn they are largely influenced by weather and climate developments. Phalkey et al. (2015) looked at precipitation, temperature, seasonality, humidity and GHG emissions to food crop yields, food prices, food affordability, utilization and access with child undernutrition. Accordingly, they assumed that, when climate change indicators negatively impact crop yield, child undernutrition increases. In addition, maternal and child health and socio-economic status may increase or mediate child undernutrition outcomes. Isolating and clearly identifying causal pathways is an empirical challenge as many potential determinants of child health and nutrition are hidden (Shively, 2017).

Yet, children aged <5 years are often chosen as the target group in research, because they specifically need sufficient food and nutrients for their development and growth, wherefore a lack manifests in a higher risk for stunting, wasting, impeded cognitive development and subsequent death (Arimond & Ruel, 2004; Belesova et al., 2018; Belesova et al., 2019b). They are specifically vulnerable to environmental impacts, which start already in utero and continue into early childhood putting them at greater risk for diseases that manifest in adulthood (Bennett & Friel, 2014; Black et al., 2008; Sheffield & Landrigan, 2011; Watts et al., 2015, 2019; Xu et al., 2012). Both nutrition and health of children are assumed to worsen with the impacts of climate change on the environment and may even hamper efforts taken to reduce undernutrition in the coming decades (Nelson et al., 2010; Schmidhuber & Tubiello, 2007). Thus, in order to provide evidence on the impact of climate change on agriculture, diets and child undernutrition requires several assumptions about climatic and non-climatic factors that will be presented in the subsequent chapters.

1.2.2. Conceptual framework

The primary objective of the study was the investigation of the relationship between climate and undernutrition of children aged <5 years in rural Burkina Faso. In 2017, the study was extended to include a stronger focus on diets of children as a central link between climate change, crop yield and child undernutrition indicators (Figure 3). Overall, the study is build up on the aim to investigate the relative contribution of (i) rainfall variability to (ii) children's diets and hence, (iii) their nutritional status (child undernutrition).

Herein climate variability was approximated by rainfall variability due to its high relevance for food production in the study area (Hondula et al., 2012). Additionally, rainfall variability was defined across different time periods and by location (iv). This was based on the assumption that weather impacts a child's diet on different temporal and spatial scales (Shively 2017). Thus, in order to capture temporal rainfall variability as a potential factor influencing child nutrition, a three-year open cohort design was set up using primary data from five different clusters and for three different years (see Chapter 2.2 for details).

Moreover, the assessment of crop yield through remote sensing satellites was implemented as an integral part of the study in order to identify potential improvements in yield modelling at the household level for further research on the nexus climate change-agriculture-diets-child undernutrition as outlined in Figure 3. A validation study was conducted in 2018 and implemented jointly with the company Remote Sensing Solutions (RSS) GmbH located in Germany. The aim of the validation study was to compare freely available satellite imagery for yield estimations and predictions of small-scale household fields at 10 m spatial resolution and conduct an explorative statistical analysis validating remotely sensed and on the ground crop yield. Through the use of in-situ harvest measurements and monthly images from the satellite, vegetation indices were calculated and five crop-dependent yield models were generated. While this yield modelling approach is no novelty as such (Groten, 1993), it yet demonstrated the potential of remote sensing data for modelling yields of a multitude of crops growing on small household fields in rural West Africa.

1.2.3. Study aims and objectives

The study aimed to provide evidence on the association between undernutrition of children aged <5 years and climate in rural Burkina Faso. In order to reach this goal, the study addressed four objectives that build up on each other in the following order:

- (1) Identify socio-economic risk factors for child undernutrition;
- (2) Investigate associations between diets and child undernutrition;
- (3) Link climate variability to child undernutrition; and
- (4) Validate remotely sensed satellite data to quantify crop yields at the household level.

Objective 1 built the basis of the study in order to characterize the study population and to identify common risk factors for child undernutrition in the study region. By doing so, indicators that require enhanced attention to prevent future child undernutrition were identified. Objective 2 addressed the diets of the sampled children. While there is vast evidence on socio-economic risk factors for child undernutrition, dietary indicators are less likely to be considered; although the diet represents a direct link between socio-economic and nutritional status. Furthermore, the aim was to understand dietary patterns of a child of small-scale subsistence farming families in rural Burkina Faso. Objective 3 investigated the link of climate variability to child undernutrition. As described in the previous chapters, child undernutrition is assumed to worsen due to climate change. By identifying climate patterns and their association with child undernutrition, a contribution to evidence-based interventions was targeted. Objective 4 takes up the agricultural link and aims to validate remote sensing satellite data to quantify and predict yields of crops at household plot level, thus to link crop yield quantities to on the one hand weather variability and on the other hand to agricultural households and the nutritional status of their children aged <5 years.

2. Study population, materials and methods

2.1. Study region

2.1.1. Burkina Faso, West Africa

Burkina Faso is a landlocked country in West Africa sharing its borders with Mali to the North and West, Niger to the East, and Benin, Togo, Ghana and the Ivory Coast to the South (Figure 5). The semi-arid North lies within the Sahel and is characterized by bushes and scrubs. Rainfall can be as low as 300 mm per year, while the South holds the largest bodies of water in the country with a tropical savannah climate, where rain might be as high as 1.100 mm per year. This is also reflected in the agricultural production and reliance on access to local markets to sell and purchase food. Not even two third of the population in the North can live from their own harvest and thus, rely on the South to produce surplus and on food loans and gifts (Dixon & Holt, 2010).

Overall, Burkina Faso is a steady growing country with almost 20 million inhabitants distributed over 45 provinces. The capital city Ouagadougou is with over 2 million inhabitants the biggest city in the country and located in the center. The official language is French, while the country counts more than 70 different local languages. The Mossi present the largest ethnic group (more than 50 %) followed by the Fulani and Gourmantché (< 10 % and > 5 %). Around 61 % of the population is Muslims, 23 % are Christians and 15 % are Protestants or follow indigenous beliefs (INSD & ICF International, 2012).



Figure 5: Map of Burkina Faso and the Nouna HDSS area

Source:
<http://www.humaniburkina.org/pays-burkina-faso/>

Note: The black circle indicates the location of the Nouna HDSS area.

Burkina Faso ranks 182 out of 189 countries on the Human Development Index (HDI) for 2019 (UNDP, 2019). Although improvements can be observed since 2000, it still ranks below the average development of sub-Saharan African countries, which makes it one of the least developed countries in

the world (UNDP, 2018)¹. Reflected in this ranking are 0.6 physicians per 10.000 people (desired doctor-population ratio is 1:1.000) and 371 maternal deaths per 100.000 live births, although 80 % of births were attended by skilled health personnel (in comparison, Germany ranks 4 in the HDI, has 41 physicians per 10.000 people, counts 6 maternal deaths per 100.000 live births, and had 99 % of births attended by skilled health personnel) (UNDP, 2019). Malaria is endemic in the country with a prevalence of approx. 400 cases per 1.000 people at risk (WHO, 2020b).

Furthermore, Burkina Faso faces seasonal food insecurity due to structural poverty, systematic inequalities, deficit in agricultural production, high food prices, climatic shocks, an absence of social protection systems, isolation of production zones from markets, and poor infrastructure and supply chain systems. Agriculture plays a central role in its economy and accounts for 34 % of the gross domestic product (GDP) (WFP, 2018). It employs approximately 86% of the workforce in the country and provides 62 % of the monetary income of agricultural households (cotton is the main source of income and mine extraction (especially of gold) accounts for more than 45 % of export). About 18 % of the foods consumed are imported, 3.5 million people are periodically food-insecure with great seasonal variability, and 18% of the households have been considered moderately food insecure in 2012 (WFP et al., 2014). In the 2020 Global Hunger Index (GHI) report, Burkina Faso ranked 90th out of 107 countries (von Grebmer et al., 2020). Due to weather extremes and related climate change impacts, the country faces new challenges and the risk of increasing poverty again among its population (African Development Bank, 2017; INSD & ICF International, 2012).

In this regard, 80 % of the smallholder farmers rely on rain-fed agriculture during its single annual rainy season to carry on from one year to the next. Its production is constraint by poor land quality, small agricultural plots, and recurrent climatic shocks, poor use of technology, water shortages and limited access to good-quality inputs, credit, weather insurance and markets. Between 2002 and 2013, 19 % of the national territory (5.16 million hectares (ha)) became degraded due to climate-related shocks, pest outbreaks and environmental degradation. Post-harvest losses are high at an estimated 30 % (WFP, 2018).

Around 40 % of the farmers in the country cultivated less than 3 ha of fields and around 50 % had even only 1 to 2 ha (Karst, Mank et al., 2020; WFP et al., 2014). The main agricultural products are cereals (millet, sorghum, maize, rice, fonio), oil seeds (cotton, peanuts, sesame, niébé (beans), soy, voandzou; roots and tubers (igname, patate, manioc, potato); fruits and vegetables (mango, agrumes, tomato, onion, green beans); and sugar canes. The majority of the population consumes cereals such as sorghum, millet, maize, rice and to a smaller part fonio. Those crops occupy 99 % of the sown area and provide 98 % of the production (WHO, 2013b).

¹ 44 % of the population lives on less than USD 1.90 per day (INSD & ICF International, 2012; UNDP, 2019; WFP, 2018).

2.1.2. The Nouna Health and Demographic Surveillance System (HDSS)

The study was conducted in the North-West of Burkina Faso. Nouna, as shown in Figure 5, is located in the Kossi province, which belongs to the Boucle du Mouhoun region. It is located approx. 50 km from the Malian border, 300 km to the West of the capital city Ouagadougou and 200 km to the North of the second biggest city Bobo-Dioulasso. Nouna is the capital city of the Kossi province and has a semi-urban structure.

Nouna is the base of the Nouna Health Research Center (Centre de Recherche en Santé de Nouna (CRSN)) that hosts a Health and Demographic Surveillance System (HDSS) of the International Network for the Demographic Evaluation of Populations and their Health (INDEPTH). INDEPTH is a network of 49 HDSSs based in Africa, Asia and the Pacific regions collecting

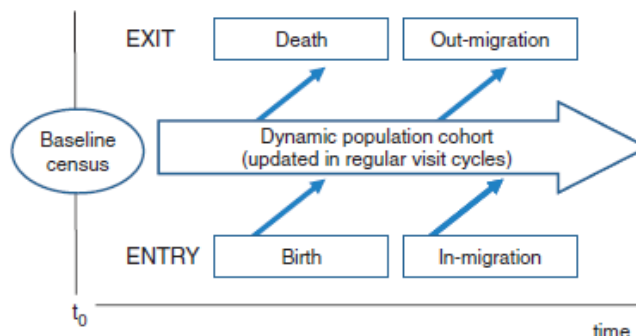


Figure 6: Conceptual structure of the dynamic cohort model used by INDEPTH HDSS sites

Source: Sankoh & Byass (2012)

continuous data of dynamic population cohorts through regular visits in geographically defined areas (Figure 6). The HDSSs investigate population health and monitor births, deaths, in- and out-migration and morbidity in order to understand the origin of diseases and to contribute to their prevention (Arthur et al., 2015; O. Sankoh & Byass, 2012). The Nouna HDSS has been functioning without interruption since 1992 (Sié et al., 2010). From 2017 to 2019, the vital event registration of the Nouna HDSS was briefly suspended and only started data collection again in early 2020, which fell into the time of this research study. By 2015, the Nouna HDSS counted approx. 107.000 inhabitants, 14.000 households and 18.000 children aged <5 years distributed over 59 villages including Nouna town (30.000 inhabitants). The village populations vary between 200 to up to 4.000 inhabitants. The district hospital (known as Centre Medical avec Antenna chirurgical (CMA)) is located in Nouna, while several basic health facilities (locally known as Centre de Santé et de Promotion Sociale (CSPS)) are distributed across the study region.

The Nouna HDSS is located in the Sudano-Sahelian climatic zone with an average annual rainfall of 800 mm, a rainy season from May to October and heavy rainfalls in July and August (Diboulo et al., 2012). Changes in annually climate patterns were observed with regard to the duration of the rainy season, the intensity of rains, and the length of droughts between rainy days (Ministry of Environment and Fishery Resources, 2015). The region is especially affected by seasonal food insecurity with a lean season lasting from June to September, when undernutrition is highest (Dixon & Holt, 2010). The local infrastructure is very simple with mainly gravel and sand roads, which cannot or only partly be accessed during the rainy season, electricity and telecommunication is rare and water is mainly collected from the rain or fetched from wells, ponds or communal pipes (Figure 7).



Figure 7: Pictures of typical housing and roads during the rainy season in the Nouna HDSS area

Note: Pictures taken in 2017. Copyright by Isabel Mank.

2.2. Study design

The study was designed as an open cohort comprising 1,439 children aged 7 to 60 months nested in the Nouna HDSS population. The data collection covered three years (from 2017 to 2019).

For sampling of the study population, firstly, five local weather stations were identified that were located within the Nouna HDSS area (red triangles in Figure 8), which were managed by the local research partner, the Nouna Health Research Center (CRSN). One study objective was to investigate geographical differences by small-spatial variability based on the assumption that weather and specifically rainfall are heterogeneous in space and time. In order to investigate the spatial variability, the five weather stations were divided into five clusters with each covering a 10 km radius of the Nouna HDSS area. A higher radius would have caused the clusters to overlap, while a small radius would have covered too few villages to draw scientific conclusions.

Secondly, out of the 59 Nouna HDSS villages, 33 villages were considered for inclusion in the study as they were situated within the 10 km radius around those five weather stations (clusters). Nouna was not included in the sample due to its semi-urban structure and the focus on rural villages. Figure 8 shows the location of the weather stations labelled by the names of the closest villages and with the following coordinates: Cissé (-3.736°E / 12.896°N), Sono (-3.494°E / 12.828°N), Kodougou (-3.605°E / 12.516°N), Toni (-3.991°E / 12.650°N), and Nouna (-3.861°E / 12.731°N).

Thirdly, a list from the 33 villages with all households that had at least one child aged <60 months during the last HDSS data collection in early 2017 were considered for inclusion in the study (Appendix 3). This age group was selected as it marks the time of gradual weaning and addition of soft and solid foods. Households were defined as independent socio-economic units living in the same compound and sharing resources to meet basic dietary and other vital needs (Sié et al., 2010). However, before the children of those households were randomly selected, the number of villages was reduced for financial and logistical reasons. Subsequently, the number of villages per cluster was

selected randomly, but also proportional to number of villages within a cluster. This led to a total selection of 18 villages.

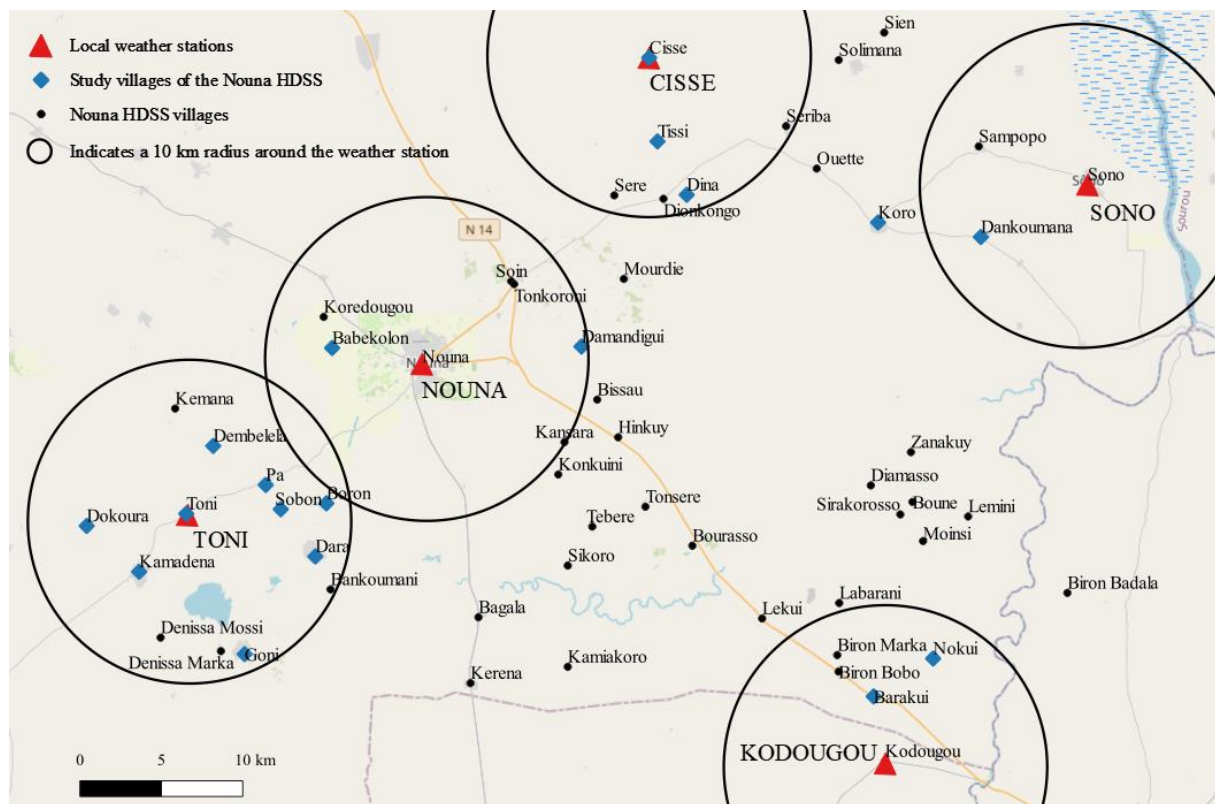


Figure 8: Map of the Nouna HDSS villages, the study villages and the five clusters around the weather stations

Note: One village (Koro) was added in order to assure the representativeness of the less densely populated stratum although it lies a few kilometers outside of the sampling frame.

Fourthly, from those 18 villages and the respective households that had a child aged < 60 months were then the children randomly selected from the Nouna HDSS household list. The number of children was sampled proportional to population size of that cluster. There was no restriction to the number of children per household.

Importantly, due to the open cohort structure, children were only followed-up until they reached their fifth birthday (60 months of age) at the time of the survey (by early August each year). Once a group of children were older than 60 months at the next data collection round, they were randomly replaced by a new cohort (censoring). For their replacement, children were taken of the same village and they were replaced by a new child from the youngest age group (namely a child aged between 7 to 23 months) to ensure young children followed into the cohort. In case a household did not wish to give consent to participate or a young child had moved or passed away, a replacement child was identified from the same age group in the same village. This allowed to keep a fairly constant proportion of children in each age group: 7-23, 24-35, 36-47, and 48-60 months. Nevertheless, this process required

a lot of flexibility by the field agents as there was no updated Nouna HDSS dataset available as the data collection was suspended from early 2017 until early 2020. Subsequently, the field agents were trained to identify children in the youngest age group (i) within the households already in the sample, or (ii) by visiting neighboring households, until a respective child was found and the household agreed to participate.

2.3. Sample size calculation

Keeping in mind the overall study aim and study design, the study sampling approach (i) was selected for population-based surveys, (ii) considered a representative study population selection (cluster sampling), not a simple random sampling, and (iii) was estimated based on the prevalence of child stunting, not child wasting, although both indicators were included for analyses.

In estimating the required sample size, it was assumed that 18.7% of the households in the Nouna HDSS have at least one child aged <5 years. Child stunting prevalence was the focus outcome, which was estimated roughly at 30 % based on previous reports and publications (Beiersmann et al., 2012; Ministère de la Santé Burkina Faso et al., 2016). Given a 5 % alpha-level, a statistical power of 80 %, and a design effect of 1.5 (intra-class correlation), this prevalence was assumed in a sample of 509 children aged <5 years. The required sample size was calculated according to the following formula:

$$N = \frac{[t^2 * p * (1 - p)]}{m^2} * D + C \quad (1)$$

$$N = \frac{[1.96^2 * 0.3 * (1 - 0.3)]}{0.05^2} * 1.5 * 1.05 = 508.24 \sim 509 \text{ children} \quad (2)$$

where,

N represents the required sample size assuming a prevalence of stunting at 30 % in the study area as represented by p . t is the confidence level at 95 % considering a standard value of 1.96, m is the margin of error using a standard value of 5 % and C is the contingency or non-response value as a standard value of 5 %. D represents the design effect of 1.5. The design effect is a correction factor accounting for intra-cluster correlations (= the strength of correlations within clusters), which has to be considered for in cluster sampling. The calculated sample size of 509 children was not equally divided between clusters or villages, but distributed based on proportionality to population size between the five clusters (see also Appendix 3 for details on the 33 villages selected for inclusion). This led to 86 children around Cissé (18 %), 60 children around Kodougou (10 %), 76 children around Nouna (12 %), 49 children around Sono (12 %), and 237 children around Toni (48 %).

Figure 9 displays the structure of the open cohort over three years of data collection (2017 to 2019). Accordingly, the cohort started with an initial sample of 470 children in 2017. The right side of the Figure 9 displays all children that were not followed up as well as those that have left the cohort as they were older than 60 months of age (censoring) or lost to follow-up (due to unavailability, death, or

migration). On the left are all children that were newly added to the cohort (aged 7 to 23 months) and those that have been followed up from one year to the next. Due to loss to follow-up and age, the cohort counted 511 children in 2018 and 458 children in 2019. The final dataset counts 1,439 person-years of which 168 children (504 person-years) were sampled all three years (followed up two times), 173 children (346 person-years) were samples two times (followed up one time) and 590 children were sampled only one time (no follow-up). 931 children contributed 1 person-year over the study duration.

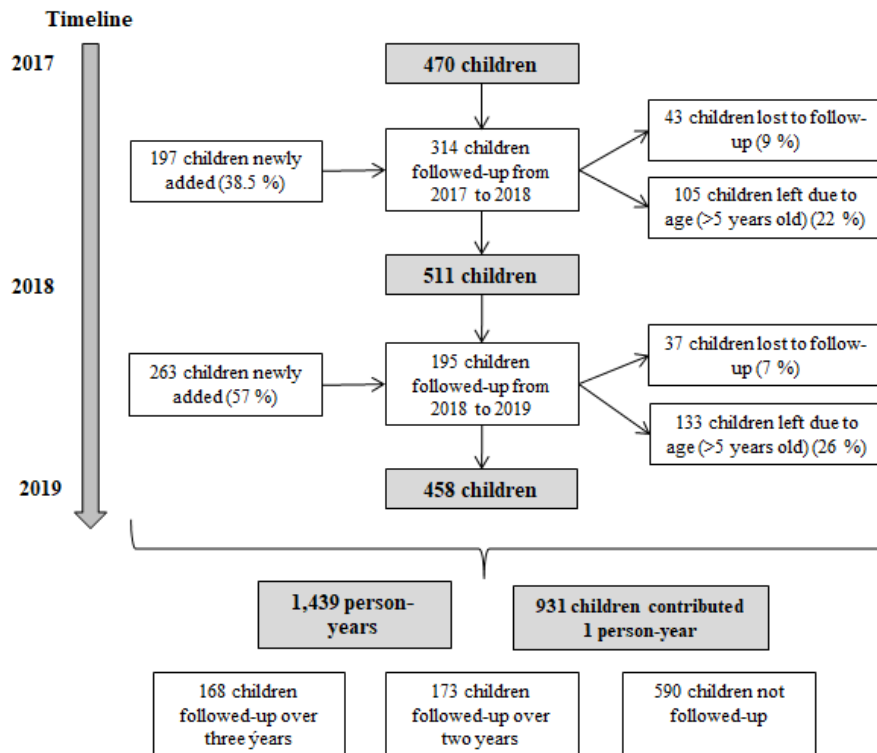


Figure 9: Timeline of the open study cohort over three years of data collection

2.4. Ethical considerations and consent to participate

The study was conducted in accordance with the most recent version of the ethical principles of the Declaration of Helsinki, which is applicable for national and international regulatory requirements. Ethical approval was obtained from the Heidelberg University Ethical Committee (S-180/2017) and the Nouna Health Research Center Ethical Committee. Children found severely undernourished (HAZ and/ or WHZ < -3 with +/- 10 % variance) during the data collection were revisited to receive a referral document. The mothers or caregivers were highly encouraged to go with the respective child to the closest health care center (CSPS) for a check-up and consultation. This applied to 60 children in 2017, 59 children in 2018, and 49 children in 2019. A small financial incentive was given to the mother of each identified child to afford transportation to and from the next health care center.

2.5. Study procedures and data collection

Before each data collection, the village heads were informed about the planned study and were asked for permission to visit the households. Equally, the household heads were informed about the study proceedings and permission was requested. No data was collected without written informed consent. Once informed consent was given, the selected households were visited once per year between August through September in 2017 to 2019. These two months were within the lean season and thus cover the period of the greatest food shortage in the region (FAO, 2010; Swindale & Bilinsky, 2006).

Each year the same household questionnaire was applied (see Chapter 2.5.1 and Appendix 1) to collect quantitative data on (i) the children aged 7 to 60 months (through their mother), (ii) their mother, and (iii) the household head (for the household socio-economic situation), and (iv) the households' living situation. The content and structure of the survey was carefully adapted to the location situation based on the Nouna HDSS census survey from 2010, the UNICEF Multiple Indicator Cluster Survey (MICS) 6 version from March 2017 for households and children <5 years of age, and local nutrition surveys (Becquey et al., 2010; Martin-Prevel et al., 2016). Additionally, the survey was adapted during the trainings of the local field agents.

2.5.1. Household socio-economic questionnaire

The household questionnaire (Appendix 1) included questions on a variety of topics that aimed to assess covariates of child undernutrition from those children in the sample. Those include questions on (i) the child, (ii) their mother and the household head, and (iii) their socio-economic status.

- (i) Child characteristics include their sex and age in months. Information was also collected on any new episodes of diarrhea and fever within two weeks prior to the questionnaire. This was reported by the mother. Additionally, feeding practices were assessed to understand current breastfeeding status and age of the child when soups and solid foods were introduced. From this information, a variable on exclusive breastfeeding until 6 months of age was generated according to when the child started receiving soup and the age when the child stopped being breastfed. Yet, information on the consumption of water during the first 6 months of life was not assessed.
- (ii) Characteristics of their mother and household head were collected with regard to educational level, ethnic group, marital status and primary occupation. Education was classified into four categories (illiterate, literate, primary, and secondary education) and ethnic group into five categories (Dafing, Bwaba, Mossi, Fulani, and other). The marital status of mothers and household heads was divided into being in a polygamy marriage (having more than one wife or being one of several wives). The principal occupation for the mother was simplified into being a housewife or not, and for the household head into being a farmer or not.

Household characteristics included were the number of household members and the number of children aged <5 years living in the same household. The latter should not be confused with the number of children aged <5 years the mother of the focus child had.

- (iii) Additionally, information on housing structure, household assets and agricultural assets were collected. Household wealth was assessed through asset ownership and is described below. Household-specific information on agricultural assets was collected on field ownership, crop types sown, field size, and tool and animal ownership.

2.5.2. Assessment of children's diets

Diets of the children in the sample were assessed through two different methods: (i) a single 24-hour dietary recall (24h DR) and (ii) a 7-day Food Frequency Questionnaire (FFQ). The 7-day FFQ was asked after the 24h DR in order to control and precise food items consumed considering daily variations. The same field agents, who administered the household questionnaire and took anthropometric measurements, also assessed the diets.

- (i) The 24h DR captured the number of meals per day, the time of consumption, and the food item combinations. It is widely used to describe diet practices and food combinations.
- (ii) A culturally adapted semi-quantitative FFQ assessed the child's food intake frequency over the preceding 7 days. This FFQ listed locally available food items in pre-defined food categories. The recall period of the FFQ was limited to the past 7 days in order to reduce memory bias and increase accuracy of the recall (Swindale & Bilinsky, 2006).

The recalls were answered by the mothers or primary caregiver on a random day of the week, weekend, or atypical day (e.g. local festivities). Thus, the assessment was done retrospectively and aimed to provide a description of the diets as nutrient intake in the form of macro- and micronutrients or food quantities were not assessed. The 7-day FFQ and the 24h DR included information on the form the respective food item was prepared for consumption (raw, porridge, grilled or roasted, cooked or steamed, and dried), where applicable. Furthermore, it was asked on how many of the seven previous days this food item was consumed, if this food item was consumed all year round, and from which source this food item originates (own field production or own animal, bought, gift, chased or fished, food aid, or other sources).

The 7-day FFQ counted 117 food items in total of which 103 food items have been consumed in at least one of the three years during data collection. Table 3 lists all food items classified by food group that were mentioned. For this study, the food items were split between ten food groups as proposed by the FAO (2010) and Hatloy et al. (2000), who conducted a study with children 6 to 9 months of age living in rural and urban Mali. Despite its importance, there is not yet an international consensus on methods to measure dietary diversity and on approaches to develop and validate respective indicators (Swindale & Bilinsky, 2006).

Table 3: List of food groups and food items included in the 7-day FFQ

No	Food groups	Food items
1	Cereals, starchy roots, tubers and their products	Rice, fonio, dry maize, fresh maize, couscous, sorghum, millet, bread, wheat, pasta (macaroni), maize porridge, broken millet porridge, bread of Ghana, cassava, potato, yam tuber, banana plantain, sweet potato
2	Pulses, nuts, seeds and their products	African locust bean seeds (soubala), cotton seed, palm seeds, cashew nut, néré flesh, groundnuts (voandzou), soja, lentils, peanuts, sesame, cowpea beans (niébé), coconut, peanut flour, peanut butter
3	Vegetables	Carrot, zucchini, tomatoes, eggplant, avocado, cucumber, okra, onion, garlic, kapokier leaves, lettuce, cabbage
4	Fruits	Papaye, roselle fruit (datou), shea fruit/ flesh, sweet banana, watermelon, dattes, dattock (kagha), lemon, tamarind fruit, monkey bread (fruit), pineapple, finsan l'anacarde, orange, liane (zaban), jujube, apple, goyave, mango, pumpkin
5	Vitamin A rich fruits and vegetables*	Onion leaves, pepper, drumstick leaves (Moringa), parsley, spinach, bay leaves, jute leaves, roselle leaves, African locus bean fruit, baobab leaves, melon, cowpea bean leaves
6	Meat**	Chicken, beef, pork, guinea fowl, goat, rabbit, sheep, caterpillar
7	Fish and seafood	Perch fish (Nil), catfish, African carp, shiny-nose (capitaine), sardine, carp, tuna
8	Oils and fats	Shea butter, peanut oil, cottonseed oil, olive/ vegetable oil, palm oil
9	Milk and milk products	Mother's milk, animal milk, milk formula for infants, milk powder, yogurt, cheese
10	Eggs	Chicken eggs, guinea fowl eggs

* Plants providing 120 retinol equivalents (RE) per 100g or roughly 60 retinol activity equivalents (RAE) and liquids providing 60 RE or 30 RAE per 100 g (Kennedy et al., 2011); ** excl. organ meat

2.5.3. Child anthropometric measurements

Anthropometric measurements were chosen as a reliable measure for food insecurity estimation (Pinstrup-Andersen, 2009). From every child in the sample, the birth date and sex were noted down. The birth date was compared with the date written in the Nouna HDSS dataset and the one written on the health card, which a majority of mothers had at hand during the data collection. In the same instance when the health card was available, information on birth height and weight were written down. Children from the same household and/ or twins were not excluded from the dataset.

Anthropometric measurements on length/ height and weight were taken twice by the same field agent at the same point in time from all sampled children (Figure 10). Recumbent length measurement devices (Seca 417; measuring range 10 to 100 cm) were used for all children, who were not yet be able to stand up and/ or who were smaller than 85 cm; stadiometers (Seca 213; measuring range 20 to 205 cm) to measure height were used for children, who were able to stand straight and/ or were taller than 85 cm; and tared weighing scales (Seca 878; measuring range up to 200 kg, uncalibrated) were chosen for measuring the weight of the child, according to WHO standards (WHO, 2006, 2008). Given the tared function of the scale, weight was also noted down from the mother, if she carried the child. The

height was measured to the nearest 0.1 cm in a standing position, with the head in the Frankfurt plane (= referred to as the parallel position of the head to the ground), the feet together and knees straight. Weight was measured to the nearest 0.05 kg. All measurements were taken in light clothing and without shoes, head scarfs or caps (van Stuijvenberg et al., 2015). The mean of the two measurements was used as the final count.



Figure 10: Pictures of an interview with the primary caregiver and with the field agents taking anthropometric measurements of children aged <5 years in the Nouna HDSS area

Note: The primary caregiver was here the father of the respective child as the mother was at the hospital for a couple of days. Therefore he was responsible for providing the meals to his children. Pictures taken in 2017 and 2018. Copyright by Isabel Mank.

Up to 15 local field agents were trained each year in conducting the household socio-economic questionnaire and taking anthropometric measurements including recording (tared) weight, recumbent length, and standing height of the children. They had at least an advanced school degree, a good command of French and the local languages and showed a good understanding of the study during the training. Of the field agents, two were chosen to act as field supervisors to support the field agents on the ground and to assure the good conduct of the study. The field supervisors had at least five years of working experience with the CRSN and a good working record.

The training was conducted on the ground by the research supervisor in 2017 and 2018 and by CRSN staff in 2019, who participated in the training the previous two years. The training covered theoretical and practical sessions. During the theoretical sessions, each question in the questionnaire was discussed and revised whenever needed. During these sessions, also all food items for the dietary assessment were discussed to assure the availability, consumption and correct naming of local food items. This was followed by a practical session, in which the field agents worked in pairs and conducted the survey in French and in the local languages, Dioula (regional lingua franca similar to Bambara of Mali) and/ or Moré. Ethical aspects of data collection in the field were presented and discussed in detail, as approved by the Ethical Committees.

During the practical session, the devices used for the anthropometric measurements were presented, the conduct of taking measurements of children explained and their use practiced in the class room as well as in the field. A nurse from the pediatric ward of the Nouna hospital (CMA) was present to guide and provide support for the correct measurements. Each field agent had to take the measurements twice - one with a child below and one with a child above 2 years of age. Their experience in conducting the measurements was discussed afterwards in a feedback round to eliminate difficulties and inconsistencies. The practical training was repeated every year.

2.5.4. Rainfall measurements

Originally the study was designed based on five clusters each covering an area of 10 km radius around a local weather station (Figure 8). Since data from these weather stations (Figure 11) turned out to show large periods of missing data over long time periods due to broken weather stations, alternatives were investigated to keep the objective to investigate geographical differences by small-spatial variability based on the assumption that weather and specifically rainfalls are heterogeneous in space and time (De Longueville et al., 2016; Ebi, Boyer, et al., 2018; Skoufias & Vinha, 2012). A 10 km radius around each weather station was chosen as the maximum assumed variability, as an even smaller radius would have reduced the number of possibly included villages drastically and would have led to substantial overlap of parameters (Figure 11) (Hulme et al., 2001). Furthermore, a 10 km radius was considered sufficient to provide a rough aggregation of environmental conditions in each area (Davenport et al., 2017a; Grace et al., 2015).

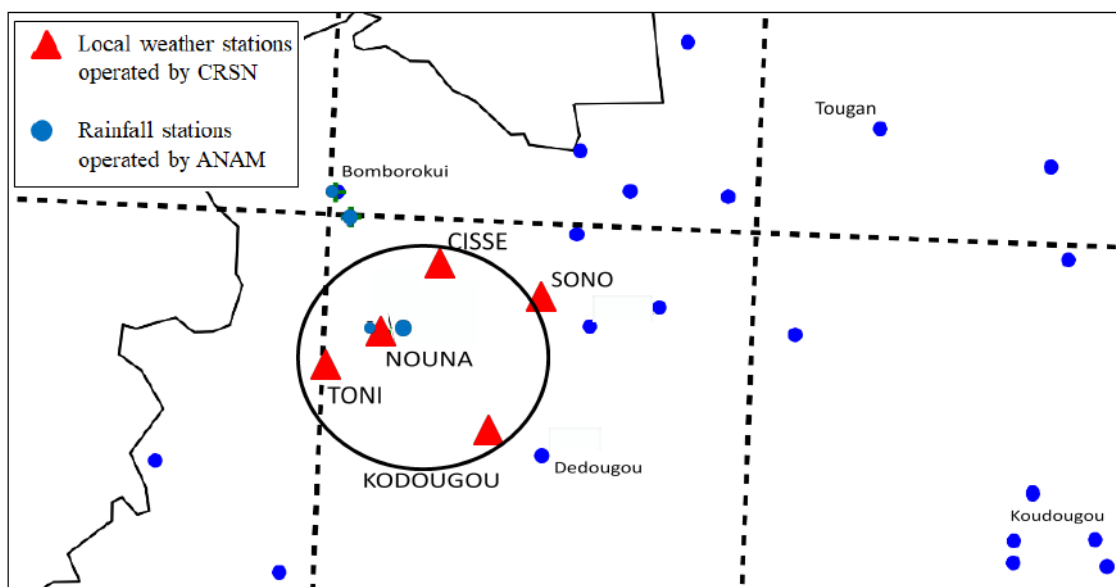


Figure 11: Map of rainfall stations located in the in the Nouna HDSS area and its surroundings

Source: Map provided by Dr. Bliefernicht

Note: The black circulate locates the Nouna HDSS area. The weather station operated by ANAM (=the Burkinabé weather service) in Nouna is the only synoptical/ automatic weather station.

A reliable alternative data source that fitted the study aim was found to be the Climate Hazards Group Infrared Precipitation with Stations (CHIRPS) dataset. A detailed description of the process and validation of the CHIRPS dataset can be found in Funk et al. (2015). In very short, CHIRPS is a gridded rainfall dataset. This means that it applies spatial interpolation methods with data from multiple sources such as on the ground rain gauges and earth-observation satellites (e.g. from satellites operated by NOAA) to derive an improved rainfall dataset (Funk et al., 2015).

It has a high spatial resolution of 0.05° (5x5 km), a long-temporal coverage (starting in 1981), and it has been explicitly designed to support drought analysis in food insecure regions, which makes it advantage for the present study. CHIRPS benefits from additional data from rainfall stations not available in global archives (Funk et al., 2015). Although satellite precipitation observations bear uncertainties and should only be considered as an alternative to available, reliable station-data, the gridded satellite rainfall product CHIRPS is advantageous to other satellite data. Dembélé and Zwart (2016) showed that CHIRPS outperform other satellite products for Burkina Faso.

The CHIRPS rainfall dataset was not derived from the local weather stations of the CRSN (red triangles on the map in Figure 11), but was kindly provided by Dr. Bliefernicht. He works at the Institute of Geography at the Augsburg University in Germany and works with the West African Science Service Centre on Climate Change and Adapted Land Use (WASCAL) observation network. This network manages a novel quality-controlled precipitation dataset (Bliefernicht et al., 2019; Salack et al., 2019) and does so in cooperation with the Agence Nationale de la Météorologie (ANAM) in Ouagadougou, Burkina Faso. This dataset was based on a combination of direct and indirect rainfall data derived from satellite observations and local weather stations located in the Nouna HDSS area and its surroundings (the blue dots on the map in Figure 11). The CHIRPS rainfall dataset included daily data from 1981 to 2016. Rainfall data from a local weather station in Nouna were obtained from the ANAM.

Following this, a stochastic resampling method was carried out by Dr. Bliefernicht to generate daily time series for the required time period for the centers of the five study clusters using the measurements of the surrounding rainfall network. In comparison to common spatial interpolation methods (Li & Heap, 2014), the stochastic approach has the advantage that the variability of the precipitation process is maintained so that rainfall characteristics like rainfall extremes and dry spells are better captured. Since the rainfall climatology of satellite observations can differ a lot in comparison to observations from rainfall stations (Yang et al., 2016), a statistical correction of the CHIRPS dataset was performed for the five cluster using quantile-mapping (Rauch et al., 2019; Yang et al., 2016). This ensures that the precipitation climatology of the CHIRPS dataset is consistent to the climatology of the on the ground observations.

2.5.5. Agricultural questionnaire and remote sensing data

An agricultural questionnaire (Appendix 2) was developed to collect data on food crop types and yield for the validation of remotely sensed yield of household fields. The questionnaire was based on an agricultural report published by the Ministry of Agriculture and Hydraulic Installations in Burkina Faso (Direction de la Prospective et des Statistiques Agricoles et Alimentaires (DPSAA), 2011). This approach was perceived as the most feasible and reliable for the study area compared to other methods (Fermont & Benson, 2011).

Two enumerators from the local Agricultural Service in Nouna were trained in conducting the agricultural survey. The field assessment was carried out from September to November 2018 in four steps: (i) global positioning system (GPS)-based mapping of field boundaries using Garmin eTrex 10 GPS handheld devices; (ii) farmer survey on agricultural practices; (iii) weighing of a sample of crop yields for each crop type with the Salter Model 235 6S; and (iv) recall of the farmers after the harvest as an assessment of general crop conditions and anomalies.

Figure 12 provides a brief visual description of the data collection on the ground towards weighed yield information, while a detailed description can be found in Karst, Mank et al. (2020). Accordingly, ground data was collected for 5x5 m squares within a random location of the field, which was marked through pickets. Once the farmer started harvesting, s/he informed the field agent. The field agent then harvested the yield of the square, dried it and weighed it. The weighed yield then allowed estimating the yield of the entire field as well as validate this amount with the remotely sensed yield estimates. The agricultural questionnaire included only food crop fields with sorghum, millet, maize, beans, and peanuts plants. From each crop field, at least 40 samples were considered necessary in order to draw statistically significant conclusions and accounting for errors in the measurements. This led to a total sample size of 200 fields.

The remote sensing data was derived from the cost-free Sentinel-2 satellite by Dr. Franke und Ms. Karst from the Remote Sensing Solutions (RSS) GmbH in Munich, Germany. The satellite provides multi-spectral images over an orbital swath width of 290 km, which it revisits every five days. Due to these regular overflights, it increased the chances to acquire cloud-free images, which can be challenging during the rainy season. The Sentinel-2 satellite provides data for vegetation monitoring through ten spectral bands, of which four have a spatial resolution of 10 meters and six of 20 meters. For this project, all available Sentinel-2 images for the growing season 2018 were used (March 9th through December 29th) leading to a total of 188 images.

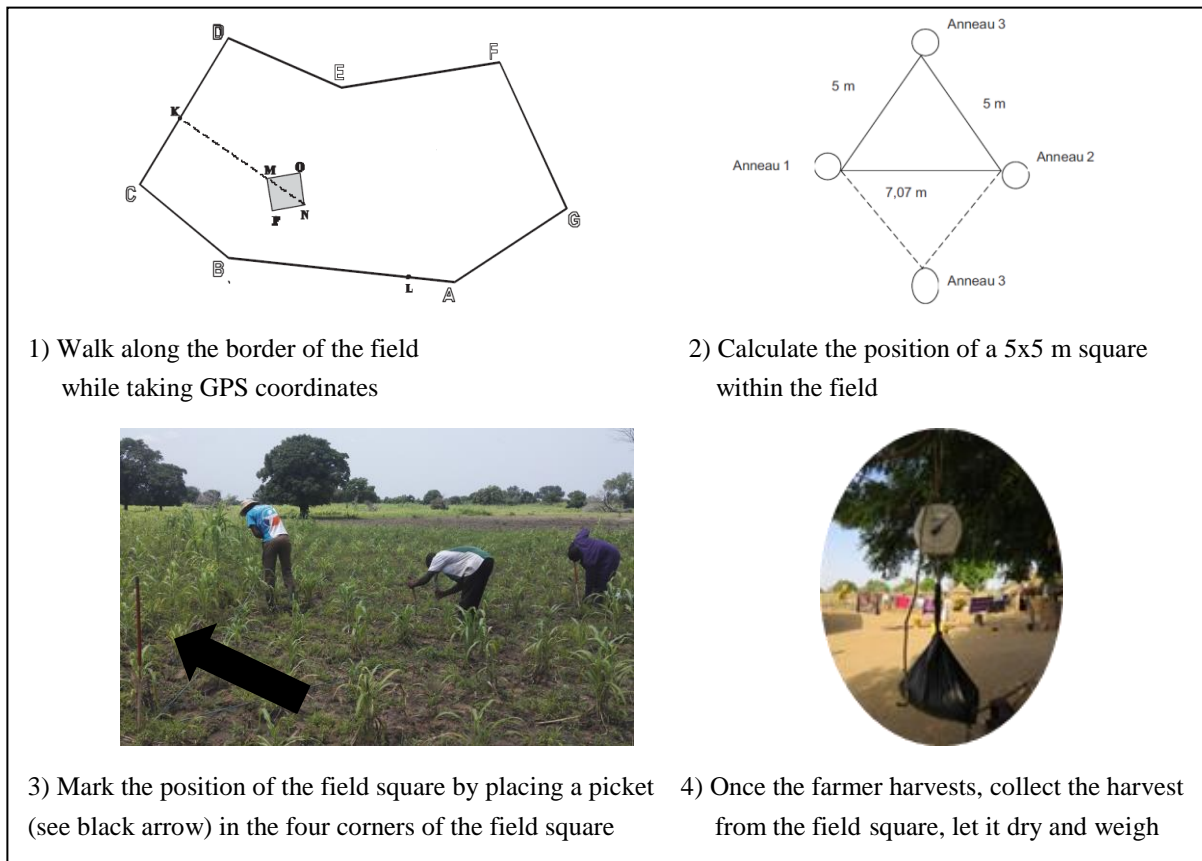


Figure 12: Description of the data collection on the ground towards weighed yield information

Source: Direction de la Prospective et des Statistiques Agricoles et Alimentaires (DPSAA) (2011) and Karst, Mank et al. (2020).

Note: The picture to the bottom-left shows the two field agents and the farmer of the field himself putting in the pickets for the field square. Pictures taken in 2018. Copyright by Isabel Mank.

3. Data management and statistical analyses

3.1. Data entry

The survey data was collected annually between August and September in 2017, 2018 and 2019. For each child a survey form (Appendix 1) was filled out with a pen and checked at the end of the day by the field supervisors for completeness, plausibility and readability. Upon completed data collection, double data entry was carried out by two CRSN data clerks and the data entered into EpiInfo 3.5.3 software. A CRSN staff member reviewed the entered data for potential divergence and completeness and followed up on any incongruence. The data were then exported to Microsoft Excel 2010, while the cleaning and analyses were done with StataIC 15, R version 3.4.3., and SAS software (SAS Institute, Inc., Cary, North Carolina).

3.2. Data cleaning and quality control

During data collection in the field and after data entry, the research supervisor checked the data for missing and implausible information. Information on each child was thoroughly checked with regard to sex and birth date based on the birth date provided on the Nouna HDSS dataset from 2017, the reported age of the child by the mother and/ or the written age in the health card, if available. Since sex and age of the child were essential for the calculation of the prevalence of stunting and wasting, high priority was set on the completeness and correctness of this information, in particular. If the deviation of the reported and written birth dates was not significantly impacting the anthropometric result, the child was not excluded from the dataset. Overall, reporting on the age of the child was difficult in this setting as the perception of the significance of an exact birth date was not high and a high illiteracy prevented mothers to correctly remember the birth day or even month. Additionally, it was observed that children tend to receive a first name only up to seven days after birth, which is assumed to have caused some deviation in reported and written birth dates. In case of doubt, the child was excluded from the analyses.

Equally, anthropometric measurements were checked during and after data collection for plausibility by the research supervisor. Unreadable numbers on the survey form or implausible measurements based on age of the child were checked by the field agents and their supervisor immediately and corrected, where possible. Since two measurements of the same child were taken at the same time, differences between the two measurements were calculated. Accordingly, if the two measurements differed by more than 0.8 kg for weight and more than 2 cm for height, the measurements were considered to be falsely reported and hence, excluded. Moreover, the z-score output was carefully examined based on the anthropometric measurements. According to the guidelines by the WHO (WHO, 2006, 2008), biologically impossible values are defined for HAZ, if they exceed <-6 or >6 and for WHZ, if they exceed <-5 or >5 . Measurements falling outside those z-scores were taken out and

subsequently data-points dropped. Finally, information on birth length and weight were captured from the child's health cards. However, if the recorded measurements were <1,580 g or >5,600 g and/ or <31 cm, the information was discarded as implausible.

3.3. Handling missing data

All data-points were checked for missing's (i) within a variable (= number of children with no information on e.g. "birth weight") and (ii) within the data from each child (= number of missing variables per child). Appendix 4 provides a list of all collected variables and the number of data-points per variable overall and for each year. If a variable had more than 10 % missing, it was excluded from the regression analyses. This applied to two variables that would have otherwise been included: birth weight and mother's age at birth.

Additionally, the missing data were checked per child. Accordingly, 1,235 out of 1,439 children showed no missing (85.82 %), 155 children showed one missing (10.77 %), 38 children had two missing (2.64 %) and 11 children had three or more missing variables (0.42 %). Given that the latter are mainly to be found for agricultural information, the data-points were not dropped from the dataset, but rather the variables. Multiple imputation was applied to impute a few missing's among the socio-economic and clinical indicators. Subsequently, 35 indicators and five WHZ measurements were imputed as they had at least one missing value. The final dataset included 1,439 person-years or data-points combined for three years.

For the multi-level analysis, 78 children were excluded due to missing values among the socio-economic explanatory variables. While multiple imputation to treat missing data in multi-level research is possible, its application is not yet satisfactorily evaluated to be applied in practice (Grund et al., 2018). Additionally, since the combined dataset provided a sufficiently large sample size, multiple imputation was not applied in the multi-level analysis. This led to a total of 1,364 children for the HAZ dataset and 1,359 children for the WHZ dataset.

3.4. Statistical analyses

3.4.1. Analytical approach according to conceptual framework

In order to provide evidence on the associations between undernutrition of children aged <5 years, diets and climate variables in rural Burkina Faso, a variety of analysis methods were applied.

Accordingly, (i) z-scores were calculated for child height and weight as well as for rainfall indicators to describe their standard deviation from the means of the respective reference data on one common scale; (ii) dietary assessments were based on recalls from the mothers; (iii) principle component analysis (PCA) as a dimension reduction technique was applied to identify exploratory dietary patterns

for the study population; (iv) reduced rank regression (RRR) was applied as another dimension reduction technique to derive a precipitation variability score (PVS) related to the dietary patterns; and (v) and food crop yield was weighed from sampled fields to validate remotely sensed yield estimates. The associations between various exposure and mediators were identified through univariate and multivariate linear regression analyses (ordinary least squares (OLS) regression) for continuous outcomes and univariate and multivariate Poisson regression analyses for binary outcomes. Multi-level regression analyses were applied, were appropriate to account for the various levels of the data: the child, the household and the village level. All methods are described in detail in the following sections.

3.4.2. Demographic and socio-economic characteristics of the study population

3.4.2.1. The study population

General characteristics were collected on the child, the mother, the household head, the household and its livelihood. The demographic, socio-economic, agricultural, clinical, and anthropometric characteristics are presented for the total study population and according to sex. Categorical data are displayed as proportions and absolute numbers (n), and continuous variables are displayed as means and standard deviations (SD). The continuous variables were checked for normal distribution before further analyses. Descriptive data is presented on agricultural practices and estimated yield.

3.4.2.2. Construction of household wealth indices

Household wealth was calculated according to the asset-based International Wealth Index (IWI) proposed by Smits and Steendijk (2015). It was preferred over other wealth index calculations such as simple item count, which, in contrast, includes animal ownership (Hatløy et al., 2000). Income and expenditure information or price values of assets (e.g. Schoeps et al., 2014) were not assessed due to the additional time it would have taken from interviewed mothers and children and the little additional value with regard to the presented research objectives. Thus, the IWI was chosen as it is easily reproducible and comparable across nations and regions and reflects rather on material need satisfaction than on price values.

The IWI is based on twelve household assets including housing characteristics, access to basic sanitary facilities and household possessions. The IWI for the households in the Nouna HDSS was derived on eleven assets as the variable on “number of household members per sleeping room” was not asked. The eleven assets were (1) ownership of durables (television, refrigerator, mobile phone, car, bicycle), (2) expensive assets (motorbike and dvd player), (3) cheap assets (radio and plow), (4) housing characteristics (floor material with high quality (tiles), medium quality (cement) or low quality (soil); and toilet access (high quality (none in the study area), medium quality (located in the house, or yard

and/ or public) and low quality (nature)), and (5) public assets (access to electricity defined as utilization of a supply cord or a solar panel, and water source (high quality (faucet or bottle), medium quality (borehole/ pomp) or low quality (draw well, river or rain)). The toilet facility was defined by location due to the similarity of toilets across the region. The scale of each asset may have two-categories (yes-no) or three-categories (low, middle high).

The assets were subjected to PCA for reducing the number of variables and to compute asset weights for a raw wealth score. However, the raw wealth score has a distribution with a minimum score of -2.318 and a maximum score of 6.953. To make it more intuitive the score was scaled to the range 0 to 100. Accordingly, an IWI of 0 displays the lowest and 100 the highest number of assets and quality of housing and services. In order to create this new scale, the following formula was applied:

$$IWI = 100 * \frac{(\sum \beta_n * x_n + 2.318)}{9.271} = 25.004 + \sum \beta'_n * x_n \quad (3)$$

Here β_n is the estimated indicator weight of the n th asset and x_n is the indicator variable of the n th asset. In order to obtain the new scale range, the scale values were multiplied by 100 and 2.318 were added to each household score to reach 0, wherefore the maximum value increased to 9.271 (= 6.953 + 2.318). β'_n represents now the rescaled asset weights after multiplying the original weight by 10.785. Together with the constant 25.004, the rescaled asset weights make up the IWI formula (Smits & Steendijk, 2015).

The asset weights reflect the possibility that a household that owns one specific asset also owns other assets. Subsequently, in case a household's situation changes and it increases its assets or improves its living situation, the asset weight would be rescaled. Although households might reach the same IWI, this is not an indication of having the same assets, but rather having reached the same level of material need satisfaction. Thus, owning a phone increases the household's value on the IWI scale in the same extent as improving the toilet facility (Smits & Steendijk, 2015). The here calculated wealth index was divided into quintiles with 1 being the poorest and 5 being the wealthiest household.

3.4.3. Characterization of child undernutrition

3.4.3.1. Constructing anthropometric indices

The anthropometric data were entered and analyzed using the WHO Child Growth Standards R igrowup package (R version 3.4.3.) (WHO, 2008). This program compares sex- and age-specific weight-for-height (WHZ) and height-for-age (HAZ) of the child with the WHO reference population of children showing ideal physiological growth under optimal environmental and feeding conditions and independent of ethnicity and socio-economic status (WHO, 2006). Accordingly, moderate stunting and wasting were defined as HAZ and WHZ of <-2, respectively. Similarly, severe stunting and

wasting were defined as HAZ and WHZ of <-3 , respectively (de Onis et al., 2013; WHO, 2006). Low birth weight was defined according to the WHO cutoff value for birth weight $<2,500$ g (Brown et al., 2014; Grace et al., 2015).

3.4.3.2. Association of socio-demographic factors with child undernutrition

Univariate Poisson (for binary outcomes) and linear (for continuous outcomes) regression analysis was conducted with socio-demographic factors relating to the child, mother, household head and household as independent variables and child stunting/ HAZ and wasting/ WHZ as dependent variables. The results were presented as prevalence ratios (PR) and their 95 % confidence intervals (CIs) for stunting and wasting and as beta-coefficients and their 95 % CIs for HAZ and WHZ.

The regression analyses allowed to identify possible factors that contributed to child undernutrition in the study area. The association was considered statistically significant at a p-value <0.05 . Table 4 displays 21 potential risk factors for child undernutrition used in this study according to the UNICEF Framework for Child Undernutrition (UNICEF, 1998). The variables were selected based on previous work in the study area and best available scientific evidence. Yet, the list is not complete as discussed in Chapter 5.5, but allows to account for socio-economic confounding. The risk factors were selected based Arimond & Ruel (2002), Poda et al. (2017), Sié et al. (2018) and Smith & Shively (2019), and data completeness (see Chapter 3.3).

Table 4: Potential risk factors associated with child undernutrition as used in this study

Immediate causes	Underlying causes	Basic determinants
Age in months	Mother's age at birth	Ethnicity of the mother
Sex of child	Education of the mother	Ethnicity of the household head
Birth weight	Sex of the household head	Field size
Twin	Education of the household head	Garden ownership
Diarrhea past 2 weeks	Marital status of the household head	
Fever past 2 weeks	Water source	
Currently breastfeeding	Toilet access	
	Household wealth	
	Household members	
	Siblings < 5 yrs	

3.4.4. Diets of children aged <5 years in the Nouna HDSS area

3.4.4.1. Characterization of food intake and meal timings

Dietary habits were analyzed using the 24h DR and the 7-day FFQ data. The 24h DR fulfilled the purpose to identify food combinations and meal timings. Furthermore, it was used to adapt the 7-day FFQ in case any food items were missing, which led to minor additions and/ or removals of a few food

items in the 2018 and 2019 survey. The distributions of food intake frequencies and meal timings are presented according to age groups, study years and geographic cluster.

3.4.4.2. Construction of the Dietary Diversity Score (DDS) and the Food Variety Score (FVS)

Two diet diversity scores were constructed using the FFQ data of the preceding 7 days: the Dietary Diversity Score (DDS) and the Food Variety Score (FVS). The DDS was calculated as the sum of consumed food groups (FGs), while the FVS was defined as the sum of consumed food items (FIs) during the respective recall period (Ruel, 2003; Sibhatu et al., 2015).

Since there is no international consensus on the assignment of food groups to the DDS (Hatløy et al., 2000; Sié et al., 2018; Swindale & Bilinsky, 2006), the number of food groups and the respective allocation of food items were guided by the FAO (2010) and Hatloy et al. (2000) (Table 3): (1) cereals, starchy roots, tubers and their products; (2) pulses, nuts, seeds and their products; (3) vegetables; (4) fruits, (5) vitamin A-rich fruits and vegetables; (6) meat; (7) fish and seafood; (8) oils and fats; (9) milk and milk products; and (10) eggs. The number and nature of the food groups were identical for each age group in order to assure comparability of results. The remaining items (11) spices and condiments, (12) oils and fats, (13) sweets, and (14) beverages were not considered for the DDS and FVS due to their low nutrient content, although oil is an important contributor to energy density and improves the absorption of plant sources, carotenoids and fat-soluble vitamins (FAO, 2010). It has to be kept in mind that the DDS and FVS do not allow assumptions about quantity of foods consumed as quantities might highly differ between food groups. Hence, even a high DDS should not exclude a low food quantity and nutrient intake (FAO, 2013).

3.4.4.3. Creation of dietary patterns

Dietary patterns were identified through PCA using the intake frequencies of food items as assessed by the 7-day FFQ (Hu, 2002b; Vankaiah et al., 2011). PCA is a dimension-reduction technique that uses the correlation structure of intake frequencies to identify underlying food combinations and to reduce the dataset to interpretable underlying factors (Balder et al., 2003; Vankaiah et al., 2011). In nutrition epidemiology, PCA is a commonly-used method to derive eating patterns as it reduces data into patterns based on intercorrelations between food items. This means PCA identifies foods that are often eaten together. Exploratory PCA is an “a posteriori” approach as opposed to an “a priori” approach. It is therefore purely data-driven, which means that no outcome is specified in advance compared to a hypothesis-based approach and so the output is based on the actual reported food intake frequencies (Vankaiah et al., 2011).

For the present dietary pattern identification, food items were excluded from the PCA, when they were never consumed by more than 95 % of the children. Also, a food item was excluded when it did not contribute to variation in the diet, e.g., when it was consumed by more than 80 % of the children. Certain food items were collapsed into the food groups that were subjected to the PCA. Food grouping was based on similar structure and/ or nutrient content. This led to a total of 30 (out of 88) food groups for the factor analysis (Appendix 10). The food groups for the factor analysis differed from the food groups created to calculate the DDS owing to the different purposes of the two analyses.

In order to derive dietary patterns, an orthogonal rotation (varimax) was applied to ensure that the factors remained uncorrelated. The criteria to extract the optimal number of dietary patterns comprised the scree plot, an eigenvalue of >1.5 , and the interpretability of the dietary patterns. Figure 13 shows the scree plot, which is defined as a lineplot that determines the number of factors to retain in an exploratory PCA. In practice, only dietary patterns that had an eigenvalue >1.5 were considered to be sufficiently distinct from the other dietary patterns (= big jump in the scree plot), and that were characterized by at least 3 different food groups were extracted. Foods with absolute factor loadings of $\geq |0.40|$ were considered as major contributors to the dietary patterns. The larger the factor loading of the food group, the greater is its correlation to the dietary patterns. A negative factor loading indicates that the food group was inversely associated with the dietary patterns (Balder et al., 2003). In other words: positive factor loadings indicate that the dietary patterns was characterized by frequent intakes of such food group, while negative factor loadings indicate that the dietary patterns was characterized by rare consumption of the respective food item.

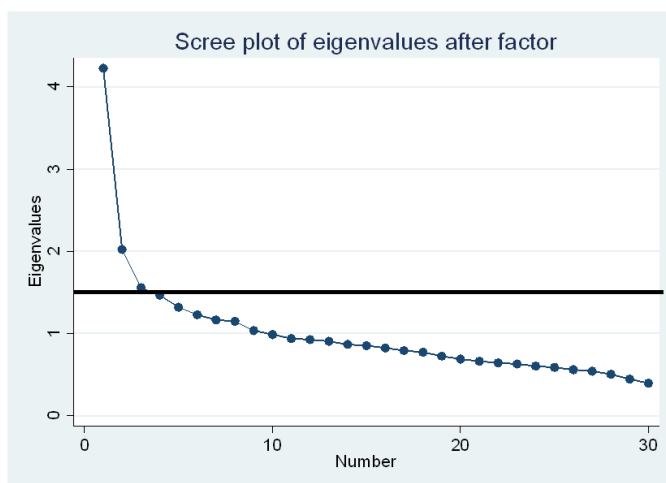


Figure 13: Scree plot of eigenvalues after PCA to derive dietary patterns

Each child received an individual score point for each dietary pattern, called a Dietary Pattern Score (DPS), based on the factor loadings for the specific food item consumed and based on the frequency the child consumed this food item over the preceding 7 days. This showed the variation of each child to the respective dietary patterns. Each DPS was then split into tertiles based on sample distribution (Melaku et al., 2018) to assess the distributions of socio-economic characteristics and food intake frequencies across the sample.

3.4.4.4. *Associations of dietary indicators with child undernutrition*

Regression models were fitted in order to identify the associations of the dietary indicators, namely the DDS, FVS and the DPS as the predictor variables, with stunting (HAZ <-2) and wasting (WHZ <-2) as the outcome variables. The possibility of an association was investigated using fixed-effect Poisson regression by calculating prevalence ratios (PR) and their 95 % confidence intervals (CIs) for stunting and wasting (as binary outcomes) and using linear regression by calculating beta-coefficients and their 95 % CIs for HAZ and WHZ (as continuous outcomes).

For the regression analyses, the children were divided into equally large tertiles based on their individual DDS and FVS in order to define low (<7 food groups/ <10 food items), average (7 food groups/ 10-14 food items) and high diet diversity scores (>7 food groups/ >14 food items). The same method was applied to divide the children into DPSs tertiles based on low, medium and high variation to the respective dietary pattern. Thus, each tertile included a similar number of children to assure a good representation of each group. For all three diet indicators, tertile 1 represented the lowest and tertile 3 the highest variation of the child to the respective indicator. Tertile 1 was chosen as the reference category (Hatløy et al., 2000). Additionally to the logistic regression, a linear association was presented by the prevalence ratio of stunting and wasting for a 1-point score increase of the DDS, the FVS and the DPS, respectively.

Associations were presented as a crude model and an adjusted model in order to control for potential socio-economic confounding factors. Adjustments were made for the following confounders: age and sex of the child, study cluster, year of data collection, education (illiterate, literate, primary and secondary education) and ethnicity (Dafing, Bwaba, Mossi, Fulani, and other) of the mother and the household head, household wealth (IWI), number of siblings aged <5 years living in the same household, history of diarrhea in the past two weeks (yes/ no), history of fever (yes/ no) in the past two weeks, and breastfeeding status (yes/ no). The associations were defined as statistically significant at a p-value <0.05.

3.4.5. Indicators of rainfall variability in the Nouna HDSS area

3.4.5.1. *Distribution of rainfall measures*

Data on rainfall was derived for five clusters in the Nouna HDSS area from 1981 to 2019 as described in Chapter 2.5.4. Each rainfall indicator is presented as means, standard deviations (SD), minimum, and maximum over 1981 to 2019 and by study cluster. A non-parametric test for trend across ordered groups (years) was used to identify a trend in the respective rainfall indicators (“nptrend”). Additionally, an oneway analysis of variance (ANOVA) was conducted to identify whether there are statistically significant differences between clusters. P-values for variance over time within a cluster and p-values for differences in means across clusters were calculated and found statistically significant at a p-value <0.05.

3.4.5.2. *Identification of rainfall indicators*

Daily rainfall data for the five study clusters were processed to generate 15 selected rainfall indicators (Table 5). These indicators were chosen as they provide (i) general indicators such as total annual rainfall, (ii) indicators for rainfall extreme events such as the number of heavy and very heavy rainfall days or the number of consecutive dry days during the rainy season (= mini-droughts), and (iii) seasonal indicators relevant for plant growth such as the length of the rainy season. The inter-seasonal change of rainfall (items (ii) and (iii)) are key to plant growth. The presented indicators can be used as proxies to assess climate change based on rainfall variability and extremes, and allow to measure different rainfall events as impacting factors on agricultural yield.

Out of the 15 rainfall indicators, nine were derived from the Expert Team from Climate Change Detection and Indices (ETCCDI) (<http://etccdi.pacificclimate.org/>). Those indices were calculated using the R software package “RClimDex (1.0)” as developed by Bryon Gleason from the National Climate Data Centre (NCDC) and developed further by Zhang & Yang (2004) from the Meteorological Service of Canada.

Two indicators were added providing indication of the length of the wet season and the maximum number of consecutive dry days (RR <1 mm) during the wet season, also called mini-droughts, as proposed by De Longueville et al. (2016). These two indicators required to define the beginning and end of the wet season, which are part of the agronomic method based on agricultural needs (Sivakumar, 1988). According to De Longueville et al. (2016), the rainy season started any day after the first of April, when altogether >20 mm of rain falls over three days and there are no dry spells of >7 days thereafter. A dry spell was defined by <1 mm of rain. The end of the rainy season was defined to occur, when less than <5 mm of rain fell over a period of twenty days any day after the first of September. This definition of the beginning and end of the wet season was slightly adapted to the local conditions of the Nouna HDSS area due to regular dry spells/ mini-droughts during the rainy season. The start of the wet season was defined as any date after 1st May when two times >10 mm rain fell within 14 days, and the end of the wet season was defined as any date after 1st September when there was 0 mm rain over 15 days. Lastly, four more indicators were added based on West et al. (2008), which reflect important indicators for crop growth in the study area: the number of days of so-called very heavy rains (R >20 mm) and the amount of rain falling in each month of July and August (also Hondula et al. (2012)).

The 15 rainfall indicators were standardized to z-scores to present a common unit. The z-scores represent the deviation of the annual precipitation data of the respective year from the reference rainfall data (1981 to 2019), calculated by cluster. The higher the z-score, the further away the precipitation indicator was from the reference value, translating into stronger annual variability (Appendix 18).

Table 5: 15 rainfall indicators to measure rainfall variability and extremes

No	Indicator	Indicator name	Definition	Unit
1	PRCPTOT	Annual total wet-day precipitation	Annual total PRCP in wet days (RR \geq 1mm)	mm
2	SDII	Simple daily intensity index	Annual total precipitation by number of wet days (PRCP \geq 1mm)	mm/day
3	CWD	Consecutive wet days	Maximum number of consecutive days with RR \geq 1mm	days
4	CDD	Consecutive dry days	Maximum number of consecutive days with RR $<$ 1mm	days
5	R95p	Very wet days	Annual number of days with RR $>$ 95th percentile	days
6	R99p	Extremely wet days	Annual number of days with RR $>$ 99th percentile	days
7	R10	Number of heavy precipitation days	Annual count of days when PRCP \geq 10mm	days
8	R20	Number of very heavy precipitation days	Annual count of days when PRCP \geq 20mm	days
9	R25	Number of very heavy precipitation days	Annual count of days when PRCP \geq 25mm	days
10	CDDws	Mini-drought	Max. number of consecutive dry days (RR $<$ 1 mm) during wet season	days
11	Lws	Duration wet season	Length of the wet season	days
12	PRCPJUL	Total wet-day precipitation in July	Monthly total PRCP in wet days (RR \geq 1mm)	mm
13	R20Jul	Number of very heavy rains in July	Count of days when PRCP \geq 20mm	days
14	PRCPAUG	Total wet-day precipitation in August	Monthly total PRCP in wet days (RR \geq 1mm)	mm
15	R20Aug	Number of very heavy rains in August	Count of days when PRCP \geq 20mm	days

3.4.5.3. Associations of rainfall variability indicators with child undernutrition

For the associations of child undernutrition with rainfall variability, the each rainfall indicators was calculated for four different time periods. Table 6 explains how the four time periods were constructed for each age group. The four time periods considered were: the year before (t-3) and of birth (t-2), and the year before (t-1) and of the nutrition survey (t-0). Children, who were aged 48 to 59 months in August/ September 2017, were in utero and born in 2012, while children, who were aged 7 to 11 months in the same time, were in utero in 2016 and born in 2016 or 2017. According to each child's birth month, the respective rainfall data was used to calculate the specific variability z-score.

Associations between the 15 rainfall indicators by four time periods and child stunting and wasting (as binary outcomes) were assessed through multi-level mixed-effect Poisson regression analyses: the village, the household and the child level. The rainfall variability anomalies were adapted to binary variables in the analysis defining a reduction (<0 SD) or stable/ increase (≥ 0) in rainfall. Univariate regression analyses and multivariate regression analyses with adjustments for child's age and sex, education and ethnicity of the mother and the household head, household wealth, siblings aged <5 years, child's fever and diarrhea the previous two weeks, and breastfeeding status were conducted. The associations were considered significant with a p-value <0.05 .

Table 6: Description of the derived four time periods for the children sampled in 2017 to 2019

	2012	2013	2014	2015	2016	2017	2018	2019
						Years of the survey (t-0)		
					Years before the survey (t-1)			
Years before birth (t-3)	in utero	in utero	in utero	in utero	in utero	in utero		
Years of birth (t-2)	birth*	birth	birth	birth	birth	birth	birth	
		7 to 11 mo	7 to 11 mo	7 to 11 mo	7 to 11 mo	7 to 11 mo	7 to 11 mo	7 to 11 mo
			12 to 23 mo	12 to 23 mo	12 to 23 mo	12 to 23 mo	12 to 23 mo	12 to 23 mo
				24 to 35 mo	24 to 35 mo	24 to 35 mo	24 to 35 mo	24 to 35 mo
					36 to 47 mo	36 to 47 mo	36 to 47 mo	36 to 47 mo
						48 to 59 mo	48 to 59 mo	48 to 59 mo

Note: * Only children born from October 2012 onwards were included in the sample as they were just <5 years of age at the start of the data collection in August 2017; mo = month

3.4.5.4. Identification of a Precipitation Variability Score (PVS)

Additionally, an explorative and hypothesis-based approach from nutrition epidemiology was applied in order to associate the rainfall indicators not only with child stunting and wasting, but also with diets. In order to do so, a Reduced Rank Regression (RRR) analysis was identified as the most suitable approach for reasons explained below. RRR is a dimension reduction technique, but compared to PCA, which applies a data-driven approach, allows identifying latent risk factors that explain as much variation as possible in a respective response variable. Hence, in this case RRR two hypotheses were followed:

- (i) rainfall indicators do commonly occur together and explain most of the variation in the normally distributed dietary patterns of children aged <5 years in the study area; and
- (ii) rainfall impacts stunting and wasting in two different time periods, namely (a) the year before the nutrition survey (t-1), and (b) the year of the nutrition survey (t-0). Subsequently, the rainfall data were only considered for the years 2016 to 2019, which covered the time period when nutrition data were available (2017 to 2019).

Thus, through RRR, latent risk factors can be identified that explain as much variation as possible in the response variables. Latent defines that the predictor factors are not yet known and their impact needs to be explored. Subsequently, the proposed approach is based on the assumption that there is a linear relation between rainfall and diets. The rainfall indicators were here the predictor variables, while the three DPSs were the response variables. Moreover, through the application of RRR it is assumed that the three DPSs were related with child undernutrition indicators (stunting and wasting) as assessed in advance in the present study.

The RRR analysis was applied using the SAS 9.4 software (Hoffmann, 2004; Weikert & Schulze, 2016). Once the data (namely the rainfall indicators for two time periods) were entered into the

software, only the first RRR-pattern score was extracted; which explained the highest variance in the response variables (here the DPSs). The rainfall indicators with factor loadings of $\geq |0.20|$ were considered to be major contributors to the derived patterns. This pattern was then labelled precipitation variability score (PVS). Then, each child received his or her PVS.

Additionally, a parametric Pearson correlation test was applied to identify the strength of the linear relationship as hypothesized above. The output shows the relationship of the PVS with the 15 precipitation indicators by two time periods (t-1 and t-0) and the DPSs. The correlations are presented as unadjusted coefficients and adjusted for age and sex of the child, and cluster.

3.4.5.5. Associations between the Precipitation Variability Score and child undernutrition

Associations between the RRR-derived PVS with child stunting (HAZ <-2) and wasting (WHZ <-2) were assessed through multi-level mixed-effect Poisson regression models and with HAZ and WHZ through multi-level linear regression models. Three levels were considered relevant in order to account for repeated measurements at the same level: the village, the household and the child level. The models were presented as a crude and an adjusted model.

The data is presented in tertiles of the PVS to identify whether a higher tertile compared to the lowest one is associated with child undernutrition and for a 10-point score increase in the PVS. Tertile 1 represented the lowest variation, while tertile 3 defined the highest variation of the PVS. The possibility of an association was investigated using Poisson regression by calculating prevalence ratios (PR) and their 95 % confidence intervals (CIs) for stunting and wasting (as binary outcomes) and using linear regression by calculating beta-coefficients and their 95 % CIs for HAZ and WHZ (as continuous outcomes).

Two models were constructed to control for confounding factors of socio-economic and health variables. Adjustments were made for age and sex of the child, education and ethnicity of the mother and the household head, household wealth, number of siblings aged <5 years, diarrhea episodes in the past two weeks, fever episodes in the past two weeks, and breastfeeding status. The associations were defined as statistically significant at a p-value <0.05 .

3.4.6. Estimating yield from remotely sensed satellite data

The remotely sensed satellite data allowed deriving different vegetation indices that represent plant biomass and crop growth conditions. Out of several vegetation indices, three were chosen that proved to be best suitable for the study aim to estimate crop yield: the Normalized Difference Vegetation Index (NDVI), the Normalized Difference Red Edge Index (NDRE) and the Normalized Difference Water Index (NDWI). These are specifically sensitive to vegetation, density of crops, crop growth and

water content of vegetation (moisture), respectively. The decision on vegetation indices and the calculations summarized below were conducted by Dr. Franke and Ms. Karst from the Remote Sensing Solutions (RSS) GmbH in Munich, Germany.

Firstly, the GPS data on field boundaries and yield squares as assessed through the agricultural survey were post-edited in a Geographic Information System (QGIS). Here, all trees and bushes and all harvest squares set too close to a fields' boundary or near large, shadow-casting trees were excluded. This was necessary in order to prepare the data for a multivariate linear regression analysis.

Secondly, for each of the above-mentioned vegetation indices, the maximal monthly values per pixel were extracted from all available satellite images by analyzing the time series pixelwise and creating a synthetic image of the maximal monthly index values. This led to the production of ten images per vegetation index from March to December, in order to display the time period when crop planting and harvesting occurred. These maximal monthly index values were then used as input values for the yield modeling. Accordingly, an explorative analysis of the data was done to optimize the model parameters and verify all relevant assumptions for implementing a multivariate linear regression. This entailed the assumption that there is a direct linear relationship between biomass/ vegetation conditions over the crop growth period that can be described by the three vegetation indices (predictor variables) and yield measurements (outcome variable). Simple scatterplots with linear regression models were used to confirm this linear relationship. Since more than one predictor variable was considered, a multivariate linear regression model was calculated:

$$Y_i = \beta_0 + \beta_1 * x_{i1} * + \beta_2 * x_{i2} + \dots + \beta_p * x_{ip} + \varepsilon \quad (4)$$

Here, for every individual i , Y is the model response (yield measurements), β_0 is the intercept, β_p is the regression coefficient of the respective x , which are the distinct predictor variables (the vegetation indices), and ε is the residual error. The final model predictors for the multivariate linear regression were chosen by mixed selection, which applies forward selection adding variables with a significance level at p-value <0.05, but also excluding those again when the p-values changed negatively with the addition of a new predictor. This was continued until all model predictors provided p-values <0.05.

The overall best model fit was based on the adjusted R^2 and the ANOVA test. The adjusted R^2 accounts for noise added by irrelevant additional variables. A high R^2 indicates a small test error in the model and was thus favored ($0 \leq R^2 \leq 1$). The ANOVA test additionally offered insights on the significance of the established model, which was set to a p-value <0.05. The model outputs then allowed to quantitatively predict yield for all surveyed fields per household.

3.5. Synopsis of study components

As this study was build up on a variety of components from various research fields, outside support was requested. Table 7 provides a synopsis of the study components applied and clarifies the contributions made by outside experts. Dr. Jan Bliefernicht, an expert in hydrometeorology from the Augsburg University, improved a CHIRPS dataset with local rainfall data to derive small-scale rainfall data for 5 clusters in the Nouna HDSS area (Chapter 2.5.4). Dr. Jonas Frank, a geographer and remote sensor, together with Ms. Isabel Karst and Ms. Kim-Jana Stückemann from Remote Sensing Solutions (RSS) GmbH, conducted the statistical analysis to validate agricultural yield from the ground data with the remotely sensed satellite data (Chapter 3.4.6).

Table 7: Synopsis table of study components

Study components	Study rationale	Study objective	Prepared by	Reason for asking for outside help	Publication	
Household socio-economic questionnaire	Aimed to characterize the study population and identify possible confounders for child undernutrition	(1)	Ms. Isabel Mank		Mank, I., Vandormael, A., Traoré, I., Ouédraogo, W. A., Sauerborn, R. †, & Danquah, I. † (2020)	
Child anthropometry	Provided measurements on height and weight of the children to calculate the prevalence of stunting and wasting		Ms. Isabel Mank			
Food Frequency Questionnaire (FFQ)	Assessed the pre-defined food items consumed by the children over the previous 7 days	(2)	Ms. Isabel Mank			
24h dietary recall (24hDR)	Assessed the food items consumed by the children over the previous 24 hours		Ms. Isabel Mank			
Rainfall data (CHIRPS)	Locally improved CHIRSP dataset to derive small-scale rainfall data for 5 clusters in the Nouna HDSS area	(3)	Dr. Jan Bliefernicht	Weather station data provided by the local partner turned out to be incomplete and inconsistent, wherefore an alternative source of rainfall data was sought and found to follow the study objectives.		Mank, I., Belesova, K., Bliefernicht, J., Traoré, I., Wilkinson, P., Danquah, I. †, & Sauerborn, R. † (2021/ under review)
Remote sensing of crop harvest quantity	Characterized crop types and modelled harvest yield of small-scale agricultural fields	(4)	Dr. Jonas Frank, Ms. Isabel Karst, Ms. Kim-Jana Stückemann	In order to be independent of costly ground measurements of household food harvest, remote sensing using free-of-charge Sentinel-2 data was derived and validated with on the ground measurements for future studies.		Karst, I. † G., Mank, I. †, Traoré, I., Sorgho, R., Stückemann, K.-J., Simboro, S., Sié, A., Franke, J. †, & Sauerborn, R. † (2020).
Ground validation of the remotely sensed data	Assessed crop type and harvest quantity on the ground through observation and direct measurement		Ms. Isabel Mank			

† equal contribution/ shared first authorship; ‡ Equal contribution/ shared last authorship

4. Results

This chapter presents the results of the study. Here, the link between rainfall variability, diets and child undernutrition was explored for rural Burkina Faso using the framework shown in Figure 3. The hypotheses followed were that rainfall variability has (i) a direct effect on child undernutrition as well as (ii) an indirect effect on child undernutrition through its diet. The remainder of the chapter is structured along the four objectives that build up on each other (see Chapter 1.2.3):

- (1) Identify socio-economic risk factors for child undernutrition (4.1);
- (2) Investigate associations between diets and child undernutrition (4.2);
- (3) Link climate variability to child undernutrition (4.3); and
- (4) Validate remotely sensed satellite data to quantify crop yields at the household level (4.4).

Chapter 4.1 provides an overview of the dataset, the characteristics of the study population as well as the socio-economic risk factors identified for undernutrition of children aged <5 years in the Nouna HDSS area. Chapter 4.2 focuses on the diets of the sampled children. Following a description of the meal structures, specific dietary patterns that define the combination of foods typically consumed by the children were described. The dietary diversity and food variety scores and the dietary patterns were then associated with child undernutrition as well as controlled for socio-economic factors to explore the impact of the diet on stunting and wasting. Chapter 4.3 takes this approach even further and displays the climate or precisely the rainfall variability as an additional risk factor to child undernutrition. After a brief description of the development of the local weather in the area, rainfall variability and child undernutrition were linked. The results chapter concludes with Chapter 4.4, which covers a validation study on estimating yield at the household level through remotely sensed satellite data. The presented findings provide evidence on how to assess household-level crop yield in order to investigate the link climate change, agriculture, diets and child undernutrition further.

4.1. Demographic and socio-economic characteristics of the study population

4.1.1. Sampling and description of the study population

The study was carried out in three annual rounds of data collection during the rainy season between August and September, from 2017 to 2019. Table 8 provides an overview of the number of villages, the distribution of sampled households and the number of included children. This is shown for each of the five clusters by study year. The villages and children were sampled proportional to village number and population size, wherefore the numbers of children per region differed significantly. Out of the 18 randomly selected villages, three were located around Cissé, two villages each around Kodougou, Nouna, and Sono, and nine villages around Toni. The cluster of Toni has the highest population

density, hence it represents between 43 % and 48 % of the whole sample each year. The Sono cluster is the least populated one, wherefore an additional village, Koro, which is located just two kilometers outside of the 10 km radius, was added. Sono represents only 9 % to 11 % of the sample.

The children from the selected villages located within a cluster had the same probability to be sampled; no restrictions were made to the number of children per household. As a result of the application of an open cohort as described in Chapter 2.2, the proportion of children within each cluster did only vary slightly from year to year due to natural circumstances or for statistical reasons. The cohort started with an initial sample of 470 children in 2017. Because of censoring (= children leaving the cohort of a certain age limit) and loss to follow-up, the cohort counted 511 children in 2018 and 458 children in 2019. The final dataset included 1,439 person-years (= refers to a data-point of a child).

Table 8: Distribution of villages, households and children in the open cohort from 2017 to 2019

Cluster	Villages	2017			2018			2019		
		Households	Children		Households	Children		Households	Children	
		n	n	%	n	n	%	n	n	%
CISSE	3	49	83	18	58	87	17	52	81	17
KODOUGOU	2	28	55	12	35	61	12	32	59	13
NOUNA	2	36	63	13	47	73	14	36	72	16
SONO	2	28	43	9	33	51	10	36	49	11
TONI	9	144	226	48	167	239	47	141	197	43
N	18	285	470	100	340	511	100	297	458	100

4.1.2. Characteristics of the study population and their agricultural livelihood

Table 9 and Appendix 5 display the characteristics of the study population overall and by gender of the child for the combined dataset from 2017 to 2019. The table is divided into child, socio-economic and agricultural indicators. Over the three years, data on 1,439 children living in the Nouna HDSS area were collected with an equal distribution between boys (48 %) and girls (52 %) and an overall mean age of 36 ± 14.5 months (7 to 60 months).

According to the mothers, 32 % of the sampled children had fever and 16 % diarrhea during the past two weeks prior to the survey. 26 % of the mothers mentioned to currently breastfeed their child. At 23 ± 4.5 months of age of the child, mothers tended to stop breastfeeding. Birth weight was noted down from the child's health card, if available. Accordingly, 10 % of the children had a low birth weight (<2,500 g). There were no differences between boys and girls, despite slightly more girls, who had a low birth weight (11 %) compared to boys (9 %).

A single household consisted of a mean of 12 ± 7 household members and 3 ± 2 children aged <5 years. The mothers of the children had a mean age of 29 ± 7 years, which went as low as 13 years for some mothers, when they gave birth to the respective child in the sample. The majority of mothers

were illiterate (78 %) and housewives (92 %). Among the household heads, 74 % were illiterate, 88 % worked primarily as farmers and 38 % lived in a polygamous marriage. The Darfing were the most represented ethnic group (31 %), followed by Bwaba, Mossi and Peul. With regard to the living situation, 72 % of the households received their drinking water from an open well and 35 % practice open defecation.

Agriculture is the main livelihood for the population in the region, who rely on subsistence farming for family nutrition and income. Based on the household socio-economic questionnaire, 75 % of the households owned 2 to 5 different crop fields with a mean total size of 6 hectares (ha) and a single field of a mean of 2 ha. Sorghum was the most common crop sown (89 %), followed by maize (80 %), sesame (78 %), millet (75 %), beans (65 %), peanuts (48 %), cotton (28 %), rice (23 %) and fonio (12 %) (Appendix 5). Within the questionnaire, the farmers estimated the month, when they started sowing the seeds and harvesting their fields. Based on this information, a crop calendar was created for each study year (Appendix 7). Overall, the sowing season took place on average from June to July, with the harvest of the crops taking place from October to December, with moderate timing variations by crops. Peanuts, sesame and beans were only sown as late as August, which is also considered the wettest month of the year. Maize and fonio may already be harvested by mid- or end-September. The sowing and harvesting is in line with the rainy season, which starts around May and ends around mid-October. The farmers' recall revealed that more than half of them applied either a chemical or an organic fertilizer (56 %). Only 43 % of the farmers used pesticides, although 13% mentioned struggling with *Striga*, a root-parasitic plant.

With regard to agricultural output, sorghum was not only the most typical crop sown, but provided also the highest yield. According to a farmers' recall from 2018 (Appendix 8), the farmers harvest a median of $1,100 \pm 1,665$ kg sorghum. Millet and maize provided the second and third highest outputs ($864 \pm 1,164$ kg and 360 ± 857 kg), while peanuts and beans provided a much lower yield (60 ± 86 kg and 48 ± 45 kg). Sesame and cotton are typical cash crops and were commonly sold by the farmers in the region. On the contrary, the food crops sorghum, millet, maize and rice were also bought for consumption during the rainy season (Appendix 9).

Animal ownership was common in the study area. 92 % of the mothers reported to have at least one chicken, 89 % had at least one horse, donkey or cattle as well as one sheep or goat, and 24 % had at least one pig (Appendix 5). Gardening was not commonly practiced with only 18 % reported to own a home garden with vegetables.

Table 9: Demographic and socio- economic characteristics of 1,439 children aged 7 to 60 months by sex in the Nouna HDSS area

Characteristics		Nouna HDSS		Boys		Girls	
Variables	Units	%	n	%	n	%	n
N	2017-2019	100.00	1,439	48.02	691	51.98	748
Child indicators							
Child's age	Months (mean)	35.93	1,439	36.17	691	35.71	748
Birth weight	Gramm (mean)	3,022	1,106	3,046	536	3,000	570
Low birth weight	<2500g	10.13	112	9.33	50	10.88	62
Currently breastfeeding	Yes	25.63	368	25.07	173	26.14	195
Age stopped breastfeeding	Months (mean)	23.12	1,022	23.23	497	23.01	525
Diarrhea the last 2 weeks	Yes	16.18	231	15.82	109	16.15	122
Fever the last 2 weeks	Yes	31.53	449	31.73	217	31.35	232
Height	cm (mean)	89.73	1,439	90.37	691	89.14	748
Weight	kg (mean)	12.46	1,434	12.76	690	12.18	744
Socio-economic indicators							
Mothers' age	Years (mean)	28.96	1,171	29.19	560	28.75	611
Mothers' education	Illiterate	78.67	1,125	79.12	542	78.26	583
	Literate	4.90	70	4.82	33	4.97	37
	Primary	13.01	186	13.43	92	12.62	94
	Secondary	3.43	49	2.63	18	4.16	31
Household heads' education	Illiterate	73.73	1058	73.26	504	74.16	554
	Literate	11.08	159	12.06	83	10.17	76
	Primary	12.61	181	11.92	82	13.25	99
	Secondary	2.58	37	2.76	19	2.41	18
Mothers' ethnicity	Dafing	31.48	452	31.64	218	31.33	234
	Bwaba	22.08	317	22.35	154	21.82	163
	Mossi	21.03	302	20.32	140	21.69	162
	Peul	18.31	263	18.72	129	17.94	134
	Other	7.10	102	6.97	48	7.23	54
Household heads' ethnicity	Dafing	30.92	445	31.26	216	30.61	229
	Bwaba	22.38	322	22.72	157	22.06	165
	Mossi	19.46	280	18.96	131	19.92	149
	Peul	19.94	287	20.12	139	19.79	148
	Other	7.30	105	6.95	48	7.62	57
Wealth index (IWI) quintiles	Poorest	20.06	282	23.22	157	17.12	125
	Poor	20.13	283	22.04	149	18.36	134
	Middle	19.84	279	18.64	126	20.96	153
	Rich	21.91	308	20.71	140	23.01	168
	Richest	18.07	254	15.38	104	20.55	150
Household size	(mean)	12.26	1,411	11.84	681	12.66	730
Siblings <5 years	(mean)	2.81	1,435	2.71	689	2.91	746
Open well for drinking-water	Yes	71.28	1,025	73.37	507	69.34	518
Open defecation (nature)	Yes	35.32	504	36.64	251	34.10	253
Agricultural indicators							
Number of crop fields	1 field	11.33	163	11.87	82	10.83	81
	2-5 fields	74.50	1,072	72.36	500	76.47	572
	6-10 fields	12.44	179	13.89	96	11.10	83
	>10 fields	1.46	21	1.74	12	1.20	9
	0 fields	0.28	4	0.14	1	0.40	3
Total field size	Hectar (mean)	6.38	1,406	6.10	677	6.64	729
Average field size	Hectar (mean)	2.26	1,392	2.11	671	2.40	721

4.1.3. Prevalence of child undernutrition

Child undernutrition continued to be high in the study area. Figure 14 presents the prevalence of stunting (HAZ <-2) and wasting (WHZ <-2) of children aged 7 to 60 months by study year in the Nouna HDSS area. From 2017 to 2019, the prevalence of child stunting decreased significantly from 27 % to 19 %, but was lower for wasting, which decreased from 6 % to 5 %. In Addition, Figure 14 displays the total annual rainfall from 2016 to 2019 to display the change of rainfall for Nouna for the year before and the years during the nutrition survey. The highest amount of rain fell with 858 mm in 2016, which dropped to 690 mm in 2017 and increased to 777 mm and 776 mm in 2018 and 2019, respectively.

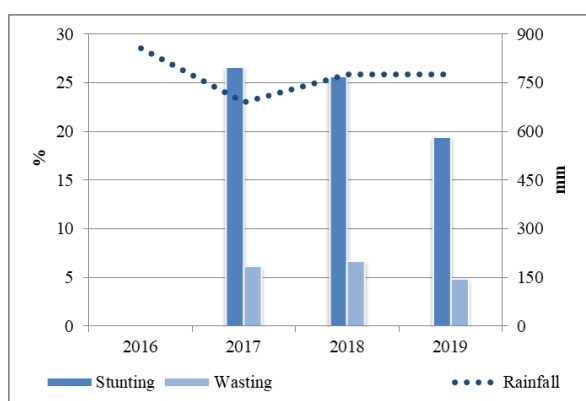


Figure 14: Prevalence of stunting and wasting of children aged 7 to 60 months and total annual rainfall by study year

Note: no sign. differences for stunting and wasting between years

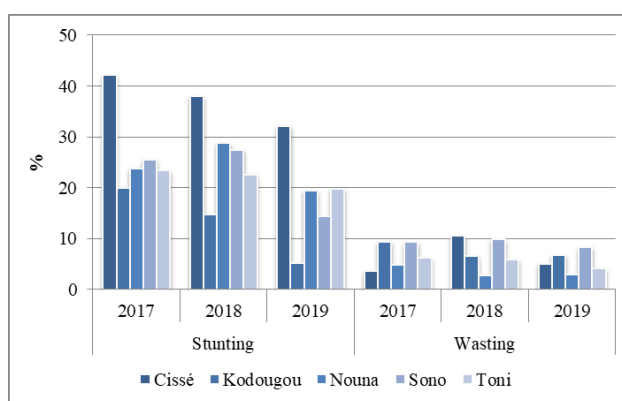


Figure 15: Prevalence of stunting and wasting by study region and study year

Note: sign. differences for stunting between clusters at p-value <0.001; no. sign. differences for wasting between clusters

Figure 15 displays the spatial differences for child stunting and wasting for the five clusters and by study year. Children living in the cluster around Cissé had the highest stunting prevalence across all three study years (42 %, 38 %, and 32 %), while the children living around Kodougou showed the lowest stunting prevalence (20 %, 15 %, and 5 %). The prevalence of wasting was continuously high in Sono (9 %, 10 %, and 8 %) and Kodougou (9 %, 7 %, and 7 %) and slightly lower in the area around Nouna (5 %, 3 % and 3 %). Cluster differences were statistically significant for stunting in 2017 (p-value <0.05), but not for wasting.

With regard to gender of the children, boys had a slightly higher prevalence of stunting and wasting than girls (Figure 16). This was specifically prominent in 2019, when 23 % of the boys versus 16 % of the girls were stunted (p-value <0.05), and in 2017, when 9 % of the boys versus 3% of the girls suffered from wasting (p-value <0.01). Additionally, a disparity was observed among age groups. Accordingly, stunting was more prominent among children aged between 24 to 47 months and wasting

among children aged 7 to 35 months (Figure 17). Statistically significant differences were found for wasting in all three study years.

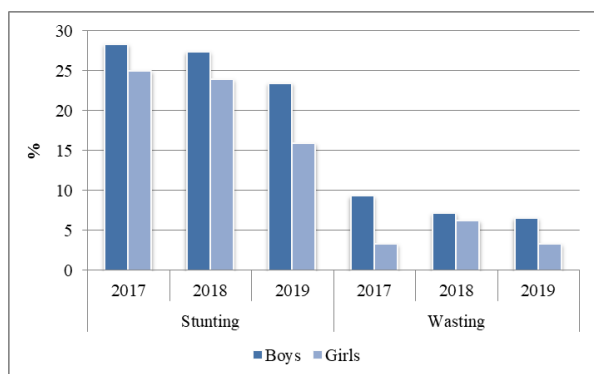


Figure 16: Prevalence of stunting and wasting by sex and study year

Note: no. sign. differences for stunting between sexes; sign. differences for wasting between sexes at p-value <0.05

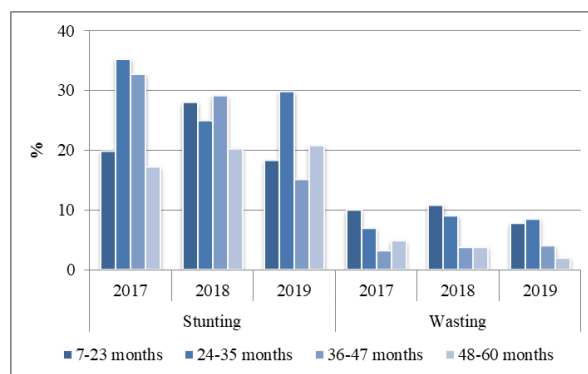


Figure 17: Prevalence of stunting and wasting by age group and study year

Note: sign. differences for stunting between age groups at p-value <0.05; sign. differences for wasting between age groups at p-value <0.001

4.1.4. Child undernutrition and associations with socio-economic risk factors

A univariate regression analysis was conducted to associate risk factors to child undernutrition in order to identify possible explanatory impacts for child stunting and wasting in the study area. As described in Chapter 3.4.3, all variables that could be associated with child stunting and wasting have been considered here. For better readability, the variables were grouped based on the UNICEF conceptual framework for child undernutrition into (i) immediate causes, (ii) underlying causes and (iii) basic determinants. 21 variables were included in the univariate regression analysis for associations with the continuous outcomes HAZ and WHZ and the binary outcomes stunting (HAZ <-2) and wasting (WHZ <-2). Table 10 displays only the statistically significant associations based on a p-value of <0.05. All indicators that were not statistically significant with neither stunting and wasting nor HAZ and WHZ can be found in Appendix 6.

Statistically significant associations (p-value <0.05) with both the binary and continuous outcomes for child undernutrition were only the age of the child and the ethnicity of the mother. Children aged 24 to 25 months were by 36 % more likely to be stunted, but 15 % less likely to be wasted than the youngest age group (7 to 23 months). While the probability for wasting was much lower among the oldest age group (48 to 60 months) by 65 % compared to the youngest one. With regard to ethnicity, children from a mother, who belonged to the Peul, had a two times higher probability to be stunted and a 85 % higher probability to be wasted than a child from a Darfing mother. Similar numbers can be found for children, who belong to a Peul household had. Children from a Bwaba household were less likely to be stunted, and children from a Mossi household less likely to be wasted.

For stunting or HAZ alone, 8 additional risk factors were found to be statistically significant. Specifically, children born with an extreme birth weight (<2.5 kg or >3.9 kg) were by 85 % more likely to be stunted. Additionally, children, who had a twin, had diarrhea over the previous two weeks received their drinking-water from a pump (improved water source) or who lived in a polygame household or in a very large household (>15 household members) had a higher probability for stunting. While those children, who were breastfed at the time of the survey or belonged to a mother, who was at least literate, were less likely to be wasted. For wasting or WHZ alone, only 4 additional risk factors were found to be statistically significant. Here, children, who had fever over the previous 2 weeks or were breastfed at the time of the survey, were more likely to be wasted. Being a girl or, controversially, having access to a pit latrine (improved toilet) showed to be positively associated with child wasting.

No statistically significant associations were found for mother's age at birth, sex of the household head, household heads' education, cooking source, wealth, having siblings aged <5 years, crop field size ownership or garden ownership.

Table 10: Univariate associations of statistically significant risk factors of stunting and HAZ and of wasting and WHZ of children aged 7 to 60 months in the Nouna HDSS area

Risk factors	Stunting (HAZ <-2)				HAZ			Wasting (WHZ <-2)				WHZ			
	N	PR	95 % CI	p-value	β-coef.	95 % CI	p-value	N	PR	95 % CI	p-value	β-coef.	95 % CI	p-value	
Immediate causes															
Child's age group	7-23 months	384	1.00		0.037*	0.00		0.000***	381	1.00		0.001**	0.00		0.000***
	24-35 months	275	1.36	1.01, 1.85		-0.47	-0.69, -0.24		275	0.85	0.50, 1.44		0.24	0.07, 0.42	
	36-47 months	388	1.16	0.87, 1.55		-0.36	-0.56, -0.17		387	0.38	0.21, 0.71		0.44	0.29, 0.58	
	48-60 months	392	0.89	0.65, 1.21		-0.22	-0.41, -0.03		391	0.35	0.19, 0.66		0.36	0.22, 0.51	
Child's sex	Boys	691	1.00		0.062	0.00		0.112	690	1.00		0.010*	0.00		0.461
	Girls	748	0.82	0.66, 1.01		0.11	-0.03, 0.25		744	0.56	0.36, 0.87		-0.04	-0.15, 0.07	
Birth weight	2.5 - 3.9 kg	955	1.00		0.000***	0.00		0.000***	952	1.00		0.266	0.00		0.101
	<2.5 or >3.9 kg	151	1.85	1.38, 2.50		-0.50	-0.72, -0.27		151	1.43	0.76, 2.67		-0.15	-0.34, 0.03	
Twin	No	1352	1.00		0.044*	0.00		0.000***	1347	1.00		0.620	0.00		0.626
	Yes	84	1.48	1.01, 2.16		-0.48	-0.74, -0.22		84	1.23	0.54, 2.83		-0.06	-0.29, 0.17	
Diarrhea the past 2 weeks	No	1197	1.00		0.034*	0.00		0.082	1193	1.00		0.506	0.00		0.522
	Yes	231	1.33	1.02, 1.73		-0.17	-0.37, 0.02		230	1.20	0.70, 2.07		-0.05	-0.20, 0.10	
Fever the past 2 weeks	No	975	1.00		0.801	0.00		0.275	971	1.00		0.048*	0.00		0.005**
	Yes	449	1.03	0.82, 1.29		-0.08	-0.23, 0.06		448	1.55	1.00, 2.39		-0.17	-0.29, -0.05	
Currently breastfeeding	No	1069	1.00		0.720	0.00		0.008**	1065	1.00		0.000***	0.00		0.000***
	Yes	368	0.96	0.75, 1.22		0.24	0.06, 0.41		366	2.47	1.61, 3.89		-0.40	-0.53, -0.27	
Underlying causes															
Mothers' education	Illiterate	1125	1.00		0.018*	0.00		0.026*	1123	1.00		0.381	0.00		0.983
	Literate	70	0.88	0.53, 1.46		0.26	-0.10, 0.63		70	0.47	0.12, 1.93		-0.01	-0.25, 0.24	
	Primary	186	0.62	0.43, 0.90		0.19	0.01, 0.37		183	1.26	0.71, 2.25		-0.01	-0.17, 0.16	
	Secondary	49	0.39	0.16, 0.95		0.32	0.03, 0.61		49	0.34	0.05, 2.43		0.05	-0.20, 0.30	
Polygame marriage	No	898	1.00		0.545	0.00		0.029*	895	1.00		0.308	0.00		0.078
	Yes	540	1.07	0.86, 1.33		-0.15	-0.29, -0.02		538	0.79	0.50, 1.25		0.09	-0.01, 0.20	
Pump for drinking water	No	1025	1.00		0.000***	0.00		0.000***	1021	1.00		0.916	0.00		0.855
	Yes	413	1.61	1.30, 2.00		-0.42	-0.57, -0.27		412	0.98	0.61, 1.56		-0.01	-0.13, 0.11	
Pit latrine access	No	504	1.00		0.513	0.00		0.053	500	1.00		0.023*	0.00		0.003**
	Yes	923	1.08	0.86, 1.35		-0.14	-0.29, 0.00		922	0.61	0.40, 0.93		0.17	0.05, 0.28	

Continued on the next page

Risk factors		Stunting (HAZ <-2)				HAZ			Wasting (WHZ <-2)				WHZ		
		N	PR	95 % CI	p-value	β-coef.	95 % CI	p-value	N	PR	95 % CI	p-value	β-coef.	95 % CI	p-value
Household size	<6 members		1.00		0.148	0.00		0.002**		1.00		0.537	0.00		0.692
	6-10 members		1.02	0.72, 1.44		0.05	-0.17, 0.27			0.71	0.39, 1.30		0.09	-0.09, 0.27	
	11-15 members		0.92	0.63, 1.34		0.02	-0.21, 0.25			0.62	0.31, 1.23		0.11	-0.08, 0.30	
	>15 members		1.28	0.90, 1.82		-0.28	-0.51, -0.05			0.68	0.35, 1.31		0.10	-0.09, 0.29	
Basic determinants															
Mothers' ethnicity	Dafing	452	1.00		0.000***	0.00		0.000***	450	1.00		0.012*	0.00		0.000***
	Bwaba	317	0.74	0.53, 1.04		0.26	β-β7, 0.45		316	1.08	0.60, 1.97		-0.07	-0.21, 0.09	
	Mossi	302	0.95	0.69, 1.30		-0.02	-0.20, 0.17		301	0.54	0.25, 1.15		0.02	-0.13, 0.16	
	Peul	263	2.02	1.54, 2.64		-0.72	-0.92, -0.52		262	1.85	1.08, 3.20		-0.32	-0.47, -0.15	
	Other	102	0.81	0.49, 1.35		0.07	-0.20, 0.33		102	0.88	0.34, 2.30		0.05	-0.15, 0.26	
Household heads' ethnicity	Dafing	445	1.00		0.000***	0.00		0.000***	443	1.00		0.089	0.00		0.001**
	Bwaba	322	0.74	0.53, 1.05		0.23	0.04, 0.42		321	1.19	0.65, 2.20		-0.08	-0.23, 0.07	
	Mossi	280	1.06	0.77, 1.46		-0.05	-0.24, 0.14		278	0.80	0.39, 1.64		-0.05	-0.20, 0.10	
	Peul	287	2.01	1.53, 2.62		-0.68	-0.87, -0.49		287	1.89	1.08, 3.33		-0.31	-0.46, -0.16	
	Other	105	0.91	0.56, 1.48		-0.07	-0.35, 0.20		105	1.15	0.47, 2.84		0.00	-0.20, 0.21	

* p-value <0.05, ** p-value <0.01, *** p-value <0.001

4.2. Diets of children aged <5 years in the Nouna HDSS area

4.2.1. Characteristics of diets

The diets of the children in the Nouna HDSS area were assessed through a 24 hour dietary recall (24 h DR) and a food frequency questionnaire (FFQ) with a recall of 7 days. In the 7-day FFQ, mothers were asked to choose from 117 food items to report, whether her child consumed the respective food item during the previous 7 days. Each day was counted the same independent of a religious day, a festivity or a market day. Out of the 117 selectable food items, 32 were selected in 2017, 36 in 2018 and 27 in 2019.

The most common foods consumed by the children during the lean season (August and September) were energy-dense foods such as cereal products including maize, sorghum and millet, oils and fats, and legumes. Maize is likely to be prepared as a thin porridge (either as an enriched broth in the more liquid form or based on cereals in the more firm form) with a sauce made out of leaves. Fish or meat may be added to the sauce, if available. Based on pre-defined food groups as explained in Chapter 3.4.4, 97 % of the children consumed cereals, starchy roots, tubers and their products at least once per week. This was followed by vitamin A-rich leaves (93 %), oils and fats (88 %), pulses, nuts, seeds and their products (80 %), sweets (70 %), fruits (68 %), vegetables (62 %), fish and seafood (60 %), beverages including tea and coffee (54 %), milk and milk products (53 %), meat (48 %) and eggs (13 %) (Appendix 11).

Dietary diversity was found to be generally low in the study population. The minimum dietary diversity of 5 or more food groups (UNICEF, 2019) during the previous 7-day was not reached by 11 % of the children. According to the 24h DR data, even 92 % of the children did not reach this international recommendation. The median Dietary Diversity Score (DDS) was 7 ± 2 food groups across study years, sex and age groups of the children. The median Food Variety Score (FVS) was 12 ± 7 food items across study years and sex of the children. The FVS was not statistically significant different between sexes, but between age groups (p -value <0.001). The younger children (7 to 23 months) consumed a median of 11 ± 6 food items compared to the oldest age group with 13 ± 5 food items (Appendix 13).

With regard to dietary diversity based on the DDS, Figure 18 displays the variation in food groups by study clusters (also Appendix 11). Statistically significant differences for all foods groups were found between the clusters (p -value <0.01). The children living around Sono consumed specifically low proportions for pulses, nuts, seeds and their products (59 %), fruits (42 %) and vegetables (32 %) compared to the children living in the other clusters. The children in Toni were found to consume a higher proportion of fish and seafood (74 %) compared to the others. Meat and egg consumption was found to be low in all clusters.

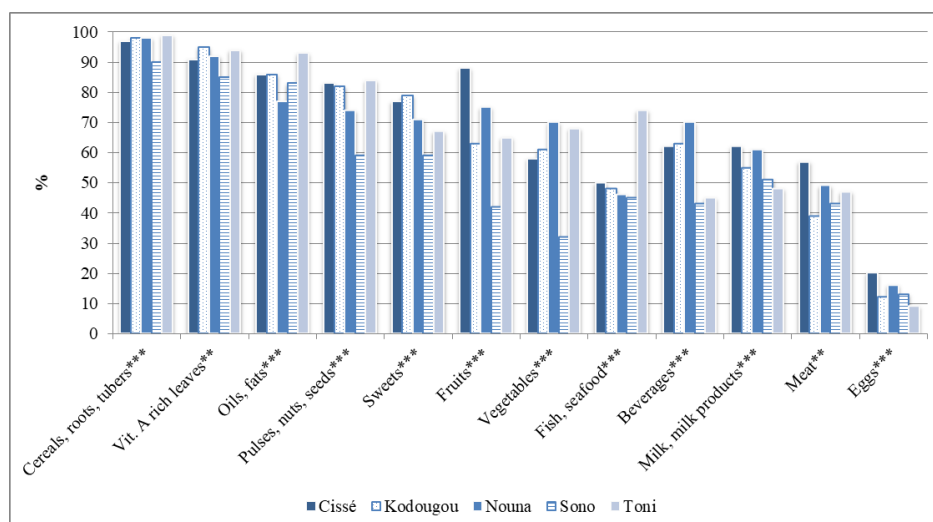


Figure 18: Proportion of food groups consumed over the previous 7-days during the lean season by 1,439 children aged <5 years by study cluster

* p-value <0.05, ** p-value <0.01, *** p-value <0.001

Temporal differences between study years for the 12 food groups are shown in Appendix 12. Accordingly, all food groups differed statistically significantly from 2017 to 2019 (p-values <0.05). A drop in food group diversity was specifically dominant for 2019, where the vegetable consumption dropped to 30 % from previous 76 % in 2017. Only the consumption of pulses, nuts and seeds increased from 72 % in 2017 to 81 % in 2019. Cereals, starchy roots, tubers and their products and vitamin A-rich leaves stayed central aspects in the children's diets in all three study years.

With regard to age, differences in diets were visible. The data showed that older children (36-60 months) had a higher consumption of meat and fish products (23 % to 40 %) than their younger peers (10 % to 27 %). On the contrary, younger children (7-23 months) consumed more milk products including maternal milk (37 % to 50 %) (Appendix 14 and Appendix 15). Differences by age groups were highly statistically significant (p-value <0.001) for all food groups except eggs. Specifically the youngest age group (11 to 23 months) had a lower dietary diversity and thus, consumed less of the various food groups compared to the older children. There were no significant differences between sexes for food groups. Yet, the data revealed that a higher wealth status was associated with a slightly higher DDS (p-value <0.001) (Appendix 13).

4.2.2. Common dietary patterns in the study region

As an addition to DDS and FVS, three data driven, distinct dietary patterns were identified through PCA. Those three dietary patterns explained 26 % of the total variation in food intake by children 7 to 60 months of age in the Nouna HDSS area during the lean season (Appendix 16). Figure 19 displays a spider net of the PCA rotated factor loadings with the food items and their contribution to the respective dietary pattern. The three distinct dietary patterns were labeled as "market-based diet" (DP1), "legume-based diet" (DP2) and "vegetable-based diet" (DP3). The market-based diet explained 10 % of the variation in food intake in the study population and correlated positively with the intakes of pasta, eggs, poultry, sweets, bread, beverages, rice and cassava, of which most were found at the

market. The legume-based diet includes food items from the family of legumes. The legume-based diet explained 8 % of food intake and was characterized by high intakes of African locus bean/soumbala, oils and fats, leaves, peanuts, millet and tea. The vegetable-based diet explained 8 % of food intake and was characterized by frequent intakes of okra, tomatoes, eggplants, maize, coffee, fish, and oils and fats.

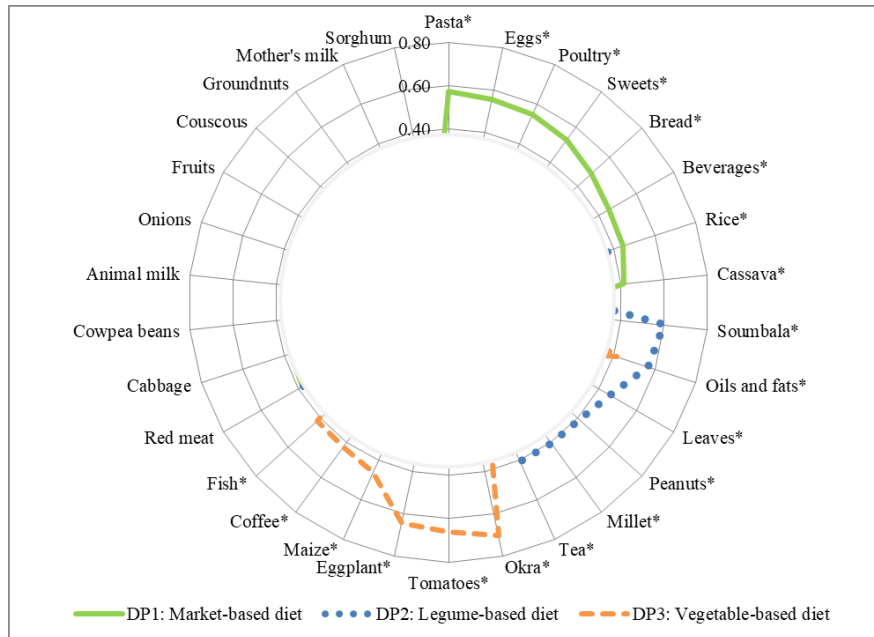


Figure 19: Spider net of the PCA rotated factor loadings of food items for the three identified dietary pattern scores (DPS) among 1,439 children aged <5 years in the Nouna HDSS area

Note: * Factor loading scores of $\geq |0.40|$ indicate relevant contributions to the DPS.

In order to receive a more comprehensive picture of the variation by age group and sex to the respective dietary patterns, the three DPSs were divided into equally large tertiles. Across all three dietary patterns, children in the lowest tertiles tend to be younger than children in the higher ones. Children from all age groups were equally distributed across the three dietary patterns, wherefore it cannot be assumed that one diet was more likely to be consumed by a specific age group than another. There were no significant dietary differences between boys and girls in the sample. Across diets and within dietary pattern tertiles, boys and girls were equally represented.

4.2.3. Associations of dietary indicators with child nutritional status

Table 11 presents the Poisson regression associations of the DDS, FVS and the three DPS with the binary outcomes stunting (HAZ <-2) and wasting (WHZ <-2). The table with the continuous outcomes HAZ and WHZ can be found in the Appendix (Appendix 17). The findings are displayed as tertiles for each dietary quality score with the lowest tertile being the reference in order to compare a higher adherence with the lower adherence to the respective dietary pattern. Additionally, the table displays the linear associations with child undernutrition per 1-score point increase of the DPS. The analyses were done for two models: a crude model and an adjusted model with selected socio-economic confounders.

The results output for child stunting indicate that children, who had a higher DDS and FVS had a lower probability to be stunted than children, who had a lower DDS. These findings were, however, only statistically significant for stunting with the DDS in the adjusted model, where stunting decreased by 3 % per 1-point score increase in DDS (p-value <0.05). With regard to the three dietary patterns, stunting prevalence increased with a higher adherence to the legume-based diet (DP2) in the crude model. The effect was reversed after adjusting for the socio-economic factors. Across all three dietary patterns, the adjusted models were statistically significant and positively associated with stunting (p-value <0.01). Stunting prevalence reduced by 2 to 3 % in the fully adjusted models per 1 score-point increase. In the sensitivity analysis with the continuous outcome HAZ (Appendix 17), the associations were less significant. Only the fully adjusted models for the market-based (DP1) and vegetable-based diets (DP2) were significant (p-value <0.05) and improved HAZ by a β -coef. of 0.02 (DP1) and of 0.01 (DP2). Overall, a higher DDS and FVS and a stronger adherence specifically to the market-based and vegetable-based diets reduced the probability for stunting.

With regard to wasting, a child was found less likely to be wasted with a higher DDS and FVS. Here, the crude models showed statistically significant associations. Wasting prevalence reduced by 9 % with an increase in DDS (p-value <0.01) and by 4 % with an increase in FVS (p-value <0.01) in the crude models. These associations attenuated after adjusting for socio-economic factors. All associations of the three dietary patterns with child wasting were statistically significant (p-value <0.01). In the crude models, children, who followed either of the three dietary patterns were less likely to be wasted. The prevalence reduced by 4 to 5 % per 1-point score increase in the DPSs. For WHZ (Appendix 17), the associations were only significant for the vegetable-based diet (DP3) with an improved WHZ by a β -coef. of 0.01 (p-value <0.05). In the fully adjusted model the associations were for the binary and continuous outcomes slightly weaker, but still positive. Only for the market-based diet (DP1), the adjusted model showed an increased prevalence for wasting with a higher adherence to that dietary pattern. Overall, also here, a higher DDS and FVS reduced the wasting prevalence, while specifically a stronger adherence to the vegetable-based diet reduced the probability for wasting.

Table 11: Associations of DDS, FVS and three DPSs with stunting and wasting of children aged 7 to 60 months and adjusted for socio-demographic variables

		Tertile 1		Tertile 2		Tertile 3		Per 1 score-point increase			
			PR	95 % CI		PR	95 % CI		PR	95 % CI	P-value
Stunting (HAZ <-2) (N=1,439)											
DDS: Dietary Diversity Score											
Crude model	Ref.	1.11	1.00, 1.24		0.90	0.81, 1.00		1.01	0.98, 1.03		0.601
Adj. model ^a	Ref.	0.99	0.89, 1.11		0.80	0.72, 0.90		0.97	0.95, 1.00		0.040*
FVS: Food Variety Score											
Crude model	Ref.	1.09	0.98, 1.21		0.99	0.89, 1.11		1.01	1.00, 1.01		0.153
Adj. model ^a	Ref.	1.05	0.94, 1.17		0.88	0.77, 0.99		1.00	0.99, 1.00		0.289
DP1: Market-based diet											
Crude model	Ref.	0.94	0.85, 1.05		0.83	0.75, 0.92		0.98	0.97, 0.99		0.000**
Adj. model ^a	Ref.	0.87	0.78, 0.97		0.68	0.60, 0.76		0.97	0.96, 0.98		0.000**
DP2: Legume-based diet											
Crude model	Ref.	1.01	0.91, 1.12		1.10	0.99, 1.22		1.00	1.00, 1.01		0.242
Adj. model ^a	Ref.	0.83	0.74, 0.93		0.79	0.70, 0.90		0.98	0.98, 0.99		0.000**
DP3: Vegetable-based diet											
Crude model	Ref.	0.91	0.82, 1.01		0.80	0.72, 0.90		0.99	0.99, 1.00		0.086
Adj. model ^a	Ref.	0.88	0.79, 0.99		0.68	0.60, 0.77		0.98	0.97, 0.99		0.000**
Wasting (WHZ <-2) (N=1,434)											
DDS: Dietary Diversity Score											
Crude model	Ref.	0.74	0.59, 0.92		0.64	0.52, 0.78		0.91	0.87, 0.95		0.000**
Adj. model ^a	Ref.	0.79	0.63, 1.00		0.68	0.54, 0.85		0.97	0.92, 1.01		0.173
FVS: Food Variety Score											
Crude model	Ref.	0.63	0.51, 0.77		0.66	0.53, 0.81		0.96	0.94, 0.98		0.000**
Adj. model ^a	Ref.	0.67	0.54, 0.84		0.78	0.61, 0.99		0.98	0.96, 1.00		0.073
DP1: Market-based diet											
Crude model	Ref.	0.90	0.73, 1.11		0.83	0.67, 1.03		0.95	0.93, 0.93		0.000**
Adj. model ^a	Ref.	1.00	0.80, 1.25		1.09	0.86, 1.38		0.97	0.95, 0.99		0.006**
DP2: Legume-based diet											
Crude model	Ref.	0.78	0.64, 0.95		0.58	0.47, 0.72		0.96	0.95, 0.97		0.000**
Adj. model ^a	Ref.	0.92	0.74, 1.15		0.66	0.51, 0.85		0.98	0.96, 0.99		0.001**
DP3: Vegetable-based diet											
Crude model	Ref.	0.69	0.56, 0.85		0.66	0.54, 0.82		0.95	0.93, 0.97		0.000**
Adj. model ^a	Ref.	0.85	0.68, 1.06		0.70	0.55, 0.89		0.96	0.94, 0.98		0.000**

^a Adj. for child's age and sex, cluster and year of data collection, education and ethnicity of the mother and the household head, household wealth, siblings aged <5 years, child's fever and diarrhea the previous two weeks, and breastfeeding status; * p-value <0.05

4.3. Rainfall variability in the Nouna HDSS area

4.3.1. Amount and distribution of rainfall, trends from 1981 to 2019

Spatial and temporal rainfall variability was assessed for each of the 15 precipitation indicators from the rainfall dataset. For each cluster individual rainfall information was from 1981 to 2019. Appendix 19 displays the mean, standard deviation (SD), minimum, maximum and slope of these 15 indicators by the five clusters.

Significant spatial rainfall variability was identified for extremely wet days (R99p) and consecutive wet days (CWD). Accordingly, Nouna registered less extreme wet days (0.5 days) and less consecutive wet days (3 days) than the other clusters. Figure 20 displays the z-scores of the extremely wet day-indicator by cluster and over time. Single bars indicate that there is at least one cluster each year that experienced an increased number of extremely wet days, while the others had less extremely wet days.

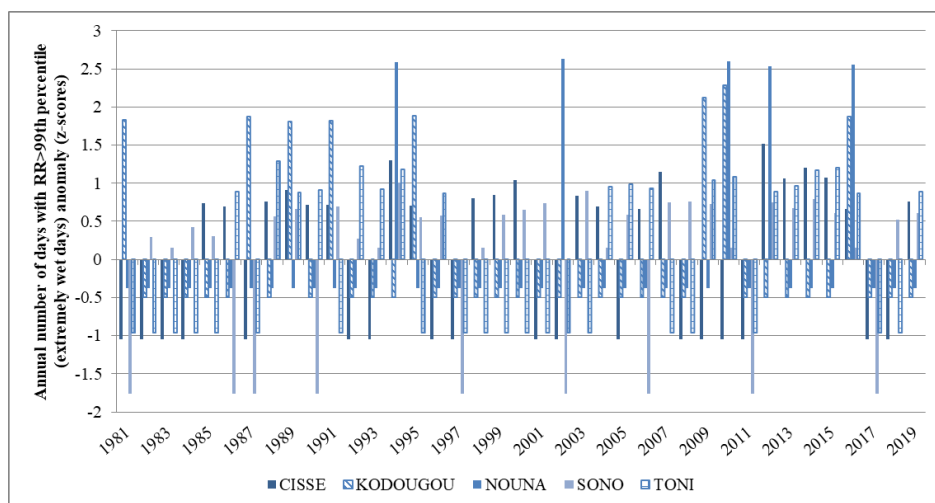


Figure 20: Annual number of days with extremely wet days (RR >99th percentile) anomaly (z-scores)

Note: No sign. differences between years for all cluster; sign. diff. between clusters at p-value <0.01

Significant temporal rainfall variability was measured for most of the rainfall indicators. Specifically an increase in rainfall and rainfall variability can be observed as shown by the time trend slope in Appendix 19. All clusters experience a significant increase in total annual rainfall since 1981. Figure 21 displays the total annual rainfall anomaly (z-score) for the five clusters. The anomaly is defined by z-scores and represents the standard deviation of the mean total annual rainfall by cluster. As shown in the Figure, an increase in rainfall anomaly can be observed specifically since the last 10 years, while the 1980s were specifically characterized by a reduced total annual rainfall. Despite this time trend, no differences in total annual rainfall can be found between clusters. The mean annual rainfall from 1981 to 2019 was 724 mm in Cissé, 778 mm in Kodougou, 730 mm in Nouna and Sono and 744 mm in Toni. Although no spatial differences were found over time, they can be observed within individual years. For example, in 2016, Cissé measured a total annual rainfall of 664 mm and Nouna of 858 mm. This indicates a strong rainfall variability between clusters within a year rather than across the time line. As indicated in Figure 21, in 2016, Cissé experienced a reduction in total annual rainfall and

Nouna an increase in total annual rainfall for that year compared to the average total rainfall over the whole time.

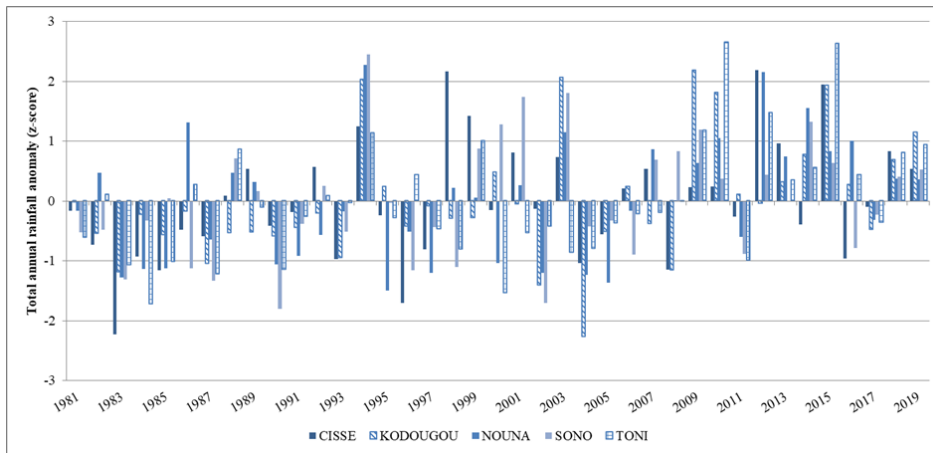


Figure 21: Total annual rainfall anomaly for the five clusters in the Nouna HDSS area from 1981 to 2019

Note: Sign. differences between years for all clusters at p-value <0.01; no sign. difference in total annual rainfall anomaly (z-scores) between clusters

Overall, four out of the 15 rainfall indicators showed to statistically significant increase over time, namely annual total precipitation (PRCPTOT), very wet days (R95p), the number of consecutive dry days per year (CDD) and extremely wet days (R99p). Another eight indicators increased significantly for some clusters, but not for others. For example, the seasonal rainfall indicators described by rainfall in July and August, increased significantly in Cissé and Toni, but showed no change for July in Kodougou, Nouna and Sono. Overall, one-third of the total annual rain fell in July (on average 187 mm) and another third fell in August (on average 231 mm). All other rainfall variability indicators showed relatively stable changes over time with also no significantly differences between clusters across the time line. Nevertheless, even no change can have negative implications on small-scale subsistence farmers such as with regard to mini-droughts. Indeed, the rainfall data measured that the clusters experience on average 10 days with consecutive dry days during the wet season (CDDws). Figure 22 displays the time trend of the mini-droughts across clusters and over time. While there was a reduction in mini-droughts over the last three to four years, yearly differences should be closely monitored.

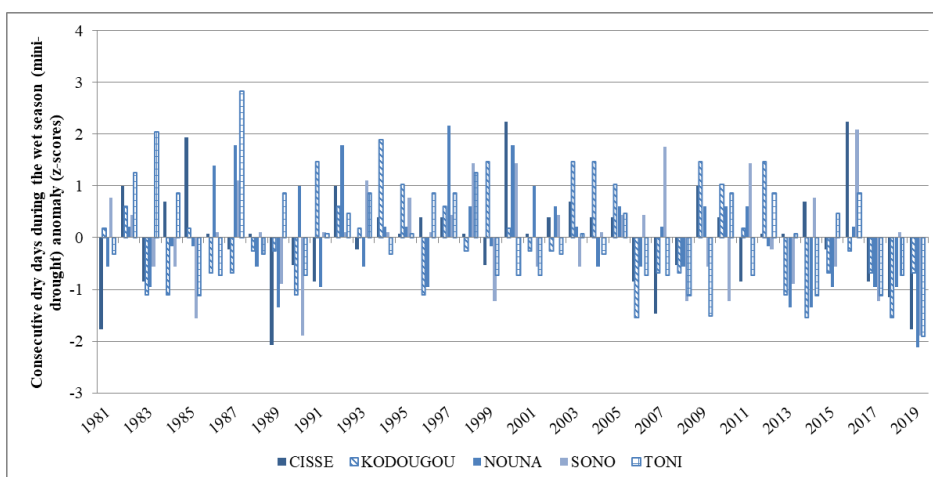


Figure 22: Consecutive dry days during the rainy season (CDDws) anomaly (z-scores) (mini-droughts)

Note: No sign. differences between years for all cluster; no sign. difference between clusters

4.3.2. Associations of rainfall variability with child undernutrition at four different time periods

Multi-level uni- and multivariate Poisson regression analyses display the association of the 15 rainfall indicators by four time periods, namely the year before (t-3) and of birth (t-2), and the year before (t-1) and of the nutrition survey (t-0), with stunting and wasting as binary outcomes. The findings are displayed separately in Figure 23 for stunting (HAZ <-2) and in Figure 24 for wasting (WHZ <-2) for the univariate analyses. The results of the uni- and multivariate analyses can be found in Appendix 20 and Appendix 21.

For stunting, the year before the nutrition survey (t-1), hence the year before the anthropometric measurements were taken, was significantly associated with stunting. Here, an increase in rainfall variability towards positive extremes was associated with a reduction in stunting. In the year before the nutrition survey, an increase in total precipitation (PRCPTOT), more rainy days in August (PRCPAUG) and an increase in consecutive wet days (CWD) were associated with a reduction in stunting by 23 %, 24 % and 28 % (all p-values <0.01). Equally, in the same time period (t-1), an increase in days with heavy rainfall (R10) and an increase in mini-droughts during the rainy season (CDDws) were associated with a reduction in stunting by 22 % and 15 % (both p-values <0.05). Only the year of the nutrition survey (t-0) showed to increase the prevalence risk by 38 % for an increase in mini-droughts during the wet season (CDDws) (p-value <0.001).

For wasting, the associations were weaker. Overall only three rainfall variability indicators were significantly associated with wasting. All of them were found in the year of birth (t-2). Precisely, an increase in heavy (R10) and in very heavy rainfall (R25) and in very wet days (R95p) reduced the prevalence for wasting by 38 %, 54 % and 54 % (all p-values <0.05). For both stunting and wasting, other time periods and rainfall variability indicators showed too large confidence intervals (95% CI) to draw statistically significant conclusions (see Appendix 20 and Appendix 21). Equally, in the multivariate analyses the findings were not significant anymore. Only very heavy rainfall (R25) in the year of birth was significantly associated with child wasting and reduced the probability by 49 %. These findings need further investigation.

To summarize, the findings indicate that rainfall variability towards an increase in rainfall had a positive effect on child undernutrition. At the same time, an increase in rainfall in the year of birth (t-2) and the year of the nutrition survey (t-0) had more indicators to also increase the probability for wasting such as an increase of rainfall in August (PRCPAUG) and in mini-droughts during the rainy season (CDDws) and a longer rainy season (Lws) (not sign.).

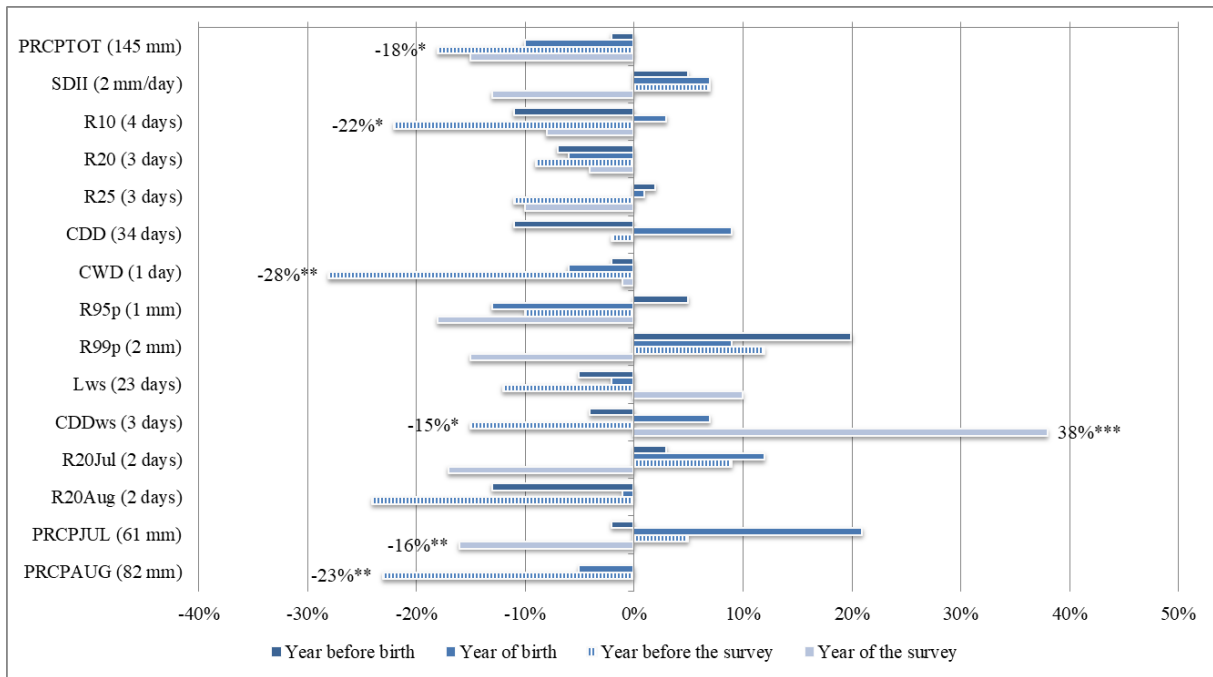


Figure 23: Multi-level univariate Poisson regression analysis to associate 15 rainfall indicators by four time periods with child stunting (HAZ <-2)

*p-value <0.05, ** p-value <0.01, *** p-value <0.001

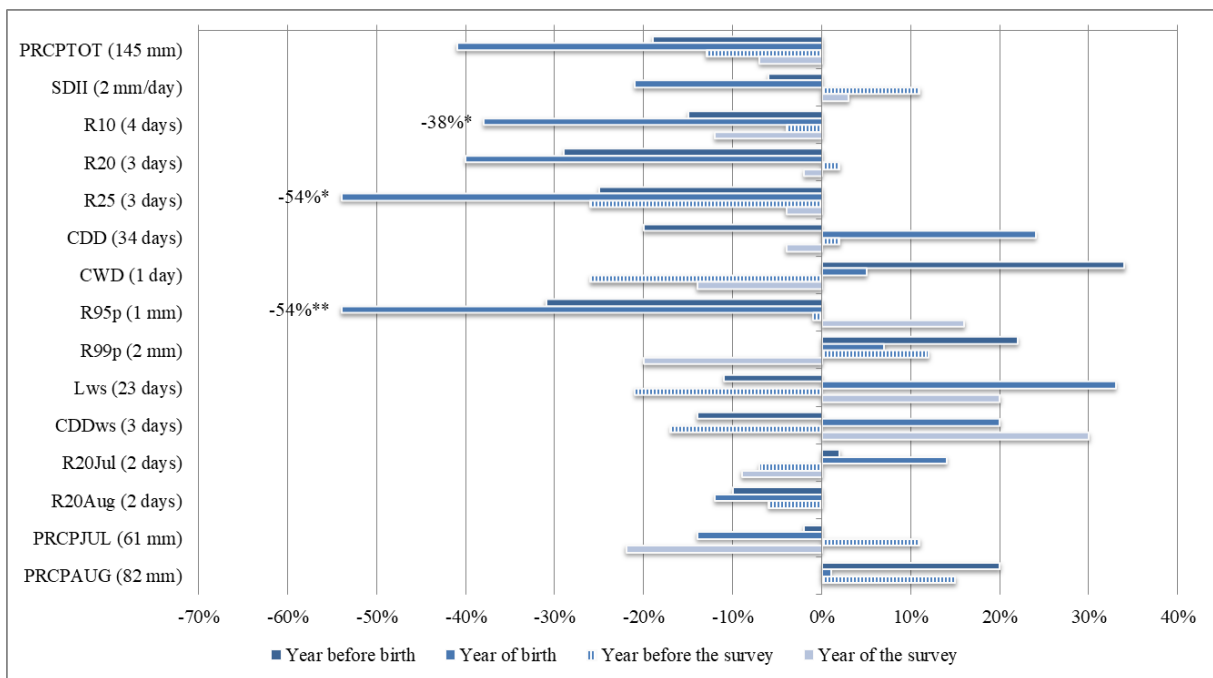


Figure 24: Multi-level univariate Poisson regression analysis to associate 15 rainfall indicators by four time periods with child wasting (WHZ <-2)

*p-value <0.05, ** p-value <0.01

4.3.3. Rainfall variability and its association with dietary patterns

While the previous results presented the associations of child undernutrition with dietary patterns (Chapter 4.2.3) and with rainfall variability (Chapter 4.3.2), the association between rainfall variability and dietary patterns is now presented below. In an exploratory, hypothesis-driven approach, a RRR analysis was applied defining a here called precipitation variability score (PVS). The PVS is defined by a combination of rainfall indicators that were found to commonly occur together and explain most of the variation in the normally distributed dietary patterns of the children. Accordingly, the PVS extracted by RRR explained 17 % of the variance in all rainfall indicators (the predictor variables) and 14 % of the total variance in DPS (the response variables).

Specifically, the PVS explained 10 % of the variance in the market-based diet (DP1), 8 % of the variance in the legume-based diet (DP2), and 25 % of the variance in the vegetable-based diet (DP3). This indicates that the PVS was positively correlated with all DPSs, but the strongest positive relationship was seen with the vegetable-based diet. The strength of the linear relationship between the three DPSs and the PVS was confirmed by the parametric Pearson correlation test. As shown in Appendix 22, the partial correlation coefficients for the precipitation indicators and the three DPSs ranged from -0.61 to +0.71 (adj. for age and sex of the child and cluster). The strongest correlations of the rainfall indicators by time period were seen with the vegetable-based diet. It confirms that an increasing PVS supports a higher variation to the consumption of the vegetable-based, market-based and legume-based diets by the children in this sample.

The characteristics of the RRR-derived PVS are presented in Figure 25 and Appendix 23. The PVS was characterized based on the factor loadings that showed $\geq |0.20|$ given that the maximum factor reached 0.31 and -0.27, respectively. Since the PVS is based on anomalies, thus standardized deviations from the reference rainfall data (1981 to 2019), a positive factor loading indicated an upward deviation (increase) of the respective rainfall indicator and a negative factor loading indicated a downward deviation (reduction). As summarized in Table 12, the PVS was characterized by a positive deviation (increase) of consecutive dry days during the wet season/ mini-droughts (CDDws), cumulative rainfall in July (PRCPJUL) and extremely wet days (R99p) in the year before the nutrition survey. Additionally, the PVS was characterized by a negative deviation (reduction) of cumulative rainfall in August (PRCPAUG), heavy precipitation days (R10), days with very heavy rains in August (R20Aug) and consecutive dry days (CDD) in the year before the nutrition survey, and of extremely wet days (R99p), annual cumulative precipitation (PRCPTOT), cumulative rainfall in August (PRCPAUG), days with very heavy rains in July (R20Jul) and cumulative rainfall in July (PRCPJUL) in the year of the nutrition survey.

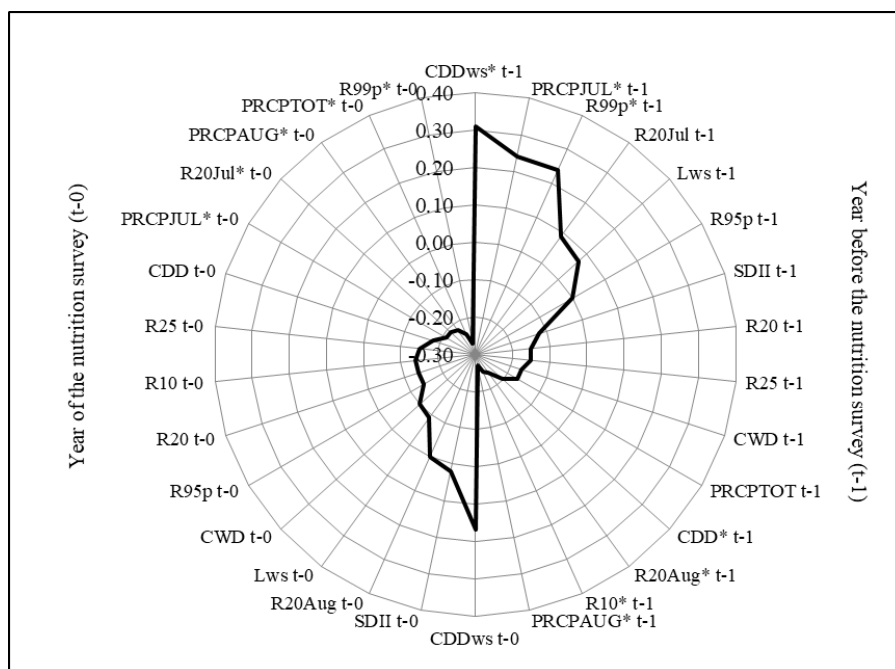


Figure 25: Spider net of the RRR rotated factor loadings of the rainfall indicators for the year before (t-1) and in the year of the nutrition survey (t-0)

Note: * Rainfall indicators with factor loadings of $\geq |0.20|$ indicate relevant contributions to the PVS.

Table 12: Rainfall indicators that best describe the RRR-derived PVS

Year before the nutrition survey (t-1)		Year of the nutrition survey (t-0)
Positive deviation*	Negative deviation	Negative deviation
Consecutive dry days in wet season/mini-droughts (CDDws)	Cumulative rainfall in August (PRCPAUG),	Extremely wet days (R99p)
Cumulative rainfall in July (PRCPJUL)	Heavy precipitation days (R10)	Annual total precipitation (PRCPTOT)
Extremely wet days (R99p)	Days with very heavy rains in August (R20Aug)	Cumulative rainfall in August (PRCPAUG)
	Consecutive dry days (CDD)	Days with very heavy rains in July (R20Jul)
		Cumulative rainfall in July (PRCPJUL)

Note: A positive deviation indicates a higher manifestation (increase) of the respective rainfall indicators, while a negative deviation indicates a lower manifestation (reduction).

4.3.4. Associations of the Precipitation Variability Score (PVS) with child undernutrition

Table 13 displays the multi-level Poisson regression associations of the in Chapter 4.3.3 described PVS with the binary (stunting and wasting) and continuous (HAZ and WHZ) outcomes of child undernutrition. The findings are displayed as PVS tertiles with the lowest PVS tertile being the reference in order to compare a higher variation in the PVS with the lower variation. Additionally, the table displays the linear associations with child undernutrition per 10-points increase of the PVS. The analyses were done for two models: a crude model and an adjusted model with selected socio-economic confounders.

For stunting or HAZ, an increase in the PVS was associated with an increased stunting prevalence in the crude and adjusted models. The findings were only statistically significant for the continuous outcome HAZ (p-value <0.05). Here, an increase in the PVS increased (thus worsened) HAZ by a β -

coef. of 0.27 SD in the crude and of 0.26 SD in the adjusted model. The socio-economic model did not change the associations, therefore indicating a reduced effect on child stunting and a stronger impact by rainfall.

For wasting or WHZ, only the adjusted model with the continuous outcome was statistically significant. Here an increase in the PVS was associated with an increase in WHZ by a β -coef. of 0.27 SD. The crude associations with the binary outcome were controversial to the findings of WHZ with the PVS, but they were also not significant. Overall, in the case of WHZ, the adjusted model with the socio-economic confounders indicated a mediating effect on child wasting. In comparison, the associations of rainfall were found stronger with child stunting and HAZ than with child wasting and WHZ.

Table 13: Multi-level Poisson regression analyses (child-household-village) examining the associations of the PVS with the binary and continuous outcomes of undernutrition of children aged <5 years in the Nouna HDSS area

Variation to the PVS	Ref.	Second tertile		Third tertile		Per 10-points increase of the PVS	
	Low	Medium		High			
Stunting (N=1,364)	Ref	PR	95 % CI	PR	95 % CI	PR	95 % CI
Unadj. model	1.00	1.25	1.01, 1.54	1.30	0.90, 1.88	1.05	0.99, 1.12
Adj. model ^a	1.00	1.10	0.86, 1.40	1.14	0.75, 1.72	1.03	0.96, 1.10
HAZ (N=1,364)	Ref	β-coef.	95 % CI	β-coef.	95 % CI	β-coef.	95 % CI
Unadj. model	0.00	-0.12	-0.25, 0.01	-0.15	-0.28, -0.02	-0.27*	-0.49, -0.04
Adj. model ^a	0.00	-0.06	-0.20, 0.07	-0.12	-0.27, 0.02	-0.26*	-0.51, 0.00
Wasting (N=1,359)	Ref	PR	95 % CI	PR	95 % CI	PR	95 % CI
Unadj. model	1.00	1.23	0.73, 2.09	1.22	0.78, 1.91	1.04	0.95, 1.13
Adj. model ^a	1.00	1.06	0.60, 1.88	0.96	0.58, 1.58	0.99	0.91, 1.09
WHZ (N=1,359)	Ref	β-coef.	95 % CI	β-coef.	95 % CI	β-coef.	95 % CI
Unadj. model	0.00	-0.08	-0.20, 0.03	0.03	-0.08, 0.14	0.10	-0.10, 0.30
Adj. model ^a	0.00	-0.03	-0.15, 0.09	0.12	0.00, 0.24	0.27*	0.05, 0.48

^a Adj. for child's age and sex, education and ethnicity of the mother and the household head, household wealth, siblings aged <5 years, child's fever and diarrhea the previous two weeks, and breastfeeding status; * p-value <0.05

4.4. Validation of remotely sensed estimates of crop yield at the household level

From the main food crops harvested in the study region, namely beans, maize, sorghum, millet and peanuts, at least 40 fields were randomly selected. This led to a total of 213 sampled fields. Of those, 17 harvest measurements had to be excluded as large tree or bushes covered the field area or as harvest squares were identified too close to the field's boundary and thus, not representative enough for the field harvest yield. This led to a total of 196 included field measurements. Specifically, the data

comprised 31 harvest measurements for beans, 31 for maize, 32 for peanuts, 45 for millet, and 57 for sorghum fields.

In order to assess the validation of the remotely sensed data, the relation of harvested yield measured by weighing on the ground and the calculated vegetation indices were correlated. This analysis was conducted by our research partners from the RSS GmbH and published in the joint paper by Karst, Mank et al. (2020). Table 14 shows the output of the multivariate linear regression model and the model validation parameters. This analysis followed the assumption that there is a direct linear relationship between biomass over the crop growth period that can be described by the vegetation indices, the Normalized Difference Vegetation Index (NDVI), the Normalized Difference Red Edge Index (NDRE) and the Normalized Difference Water Index (NDWI), and yield measurements (outcome variable).

Table 14: Multivariate linear regression model output and model validation parameters for ground data and remotely sensed estimated crop yield quantities by crop type

	Beans	Maize	Sorghum	Millet	Peanuts
Number of predictors months	3	3	4	5	1
Predictor months	July, August, October	June, August	March, July, September, November	May, July, September, November	September
Correlation coefficient (R)	0.74	0.68	0.66	0.63	0.35
Coefficient of determination (R^2)	0.54	0.46	0.44	0.40	0.12
Adjusted R^2	0.50	0.40	0.40	0.32	0.10
Root Mean Square Error (RMSE) ($\text{kg}\cdot\text{m}^2$)	0.94	2.38	1.24	1.52	1.13
Harvest value range ($\text{kg}\cdot\text{m}^2$)	6.3	13.3	8.7	9	4.6
Model significance	0.000***	0.000***	0.000***	0.001**	0.048*

* p-value <0.05, ** p-value <0.01, *** p-value <0.001

Source: Karst, Mank et al. (2020) (shared first authorship)

The predictor months describe the months, when the plants grew the most based on the three vegetation indices. The selected plants started growing in July with a significant increase in NDVI in August and September, when they reached their full height. Between October and November the NDVI decreased substantially indicating the harvest time. Plant growth occurred exactly during the rainy season: starting in June and ending in late October (see also Appendix 7 for the crop growth calendar).

The overall best model fit for validating the remotely sensed crop yield with the weighed ground yield was based on the adjusted R^2 and the Root Mean Square Error (RMSE) as displayed in Table 14. The RMSE indicates how close the observed data (weighed yield) is to the predicted values (remotely sensed yield). The lower RMSE indicate here that the model can relatively well predict the yield. In

addition, the adjusted R^2 is used, which accounts for noise added by irrelevant additional variables. A high R^2 indicates a small test error in the model and was thus favored ($0 \leq R^2 \leq 1$). The ANOVA test offered insights on the significance of the established model, which was set to a p-value <0.05 . Accordingly, the multivariate linear regression model showed that beans performed the best with an adj. R^2 of 0.50, followed by maize and sorghum (both with an adj. $R^2 = 0.40$) and millet (adj. $R^2 = 0.32$). All four models were statistically significant at <0.001 . However, the model for peanuts had only an adj. R^2 of 0.10. Given this low adj. R^2 , the correlation was considered weak.

All model outputs showed a good model fit for estimating yields. Hence, the multivariate linear regression model generated yield estimates for all surveyed fields in the study area, which resulted in a yield map. Figure 26 presents an example of such a yield map including information on the estimated amount of yield at 10 m spatial resolution. Accordingly, each pixel contains the estimated amount of yield in kg per square meter (kg/m^2) and the total amount of harvest yield in kg for each individual field. The estimated crop yield was then linked to the respective household with the support of the agricultural field survey. The model outputs then allowed to quantitatively predict yield for all surveyed fields per household.

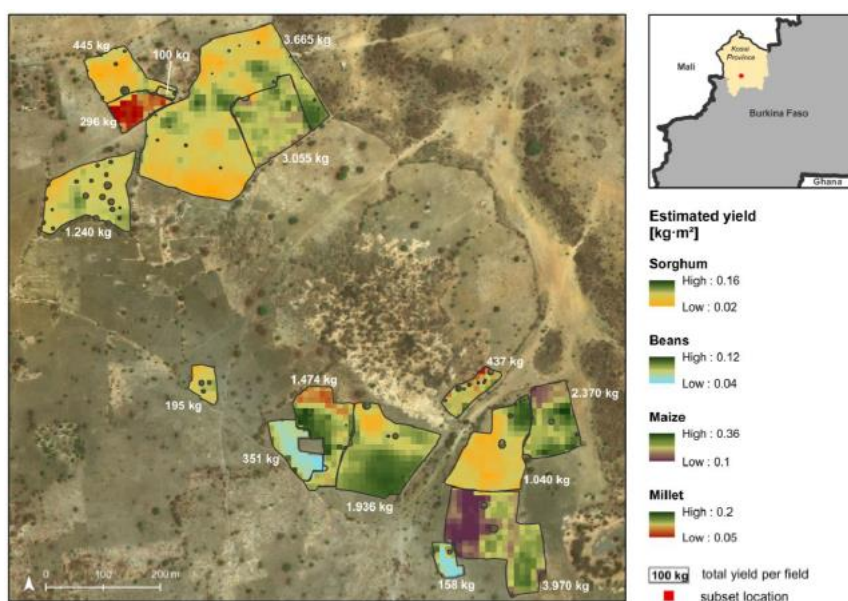


Figure 26: Example of a yield map based on remote sensing with modelled yield amounts per crop-type and the total amount of yield per field in the Nouna HDSS area

Source: Karst, Mank et al. (2020) (shared first authorship)

5. Discussion

The presented study assessed the association between climate variability indicators and undernutrition of children aged <5 years in rural Burkina Faso. It extended its focus to diets of children as a nexus indicator to climate-agriculture-undernutrition as described in the conceptual framework (Figure 3). Both nutrition and health of children change and often worsen with climate change and increased variability of weather events. Indeed, climate change may even reverse efforts made to reduce undernutrition (Nelson et al., 2010; Schmidhuber & Tubiello, 2007). This research addressed four objectives to better understand the risk factors of child undernutrition in the Nouna HDSS area moving from (i) socio-economic risk factors for child undernutrition, and (ii) associations between diets and child undernutrition, to (iii) the link between rainfall variability and child undernutrition. Additionally, (iv) a validation study was conducted to estimate and predict yield of small-scale household fields at 10 m spatial resolution using freely available satellite imagery. The objectives were addressed through the use of a variety of study instruments and statistical approaches, namely univariate, multivariate and multi-level regression analyses as well as two dimension-reduction techniques (PCA and RRR). The interdisciplinary nature of this research combining health, nutrition and climate indicators and methods made the analyses and findings unique in its current form.

Overall, the results showed that climate variability impacts diets and child undernutrition in rural Burkina Faso. The findings are critically discussed below and brought within the context of the global literature on the subject. Following this, prospects for further research recommendations for evidence-based policy actions and adaptations were discussed.

5.1. Child undernutrition in West Africa

5.1.1. Child undernutrition remains a serious problem in rural Burkina Faso

The present study found that child stunting and wasting continue to be high in the Nouna HDSS area. At the start of the study in 2017, 27 % of the sampled children were stunted and 6 % were wasted as measured during the lean season (= the season, just before the next harvest, when crop stocks tend to be lowest). Nevertheless, Burkina Faso has seen great progress in fighting food insecurity and child undernutrition over the past decades (von Grebmer et al., 2020), which is also applicable to the Nouna HDSS area.

A study conducted by Beiersmann et al. (2012) compared child stunting and wasting prevalence from 2009 with measurements from 1999 as well as between months within a year (between June and December) in the same study area. They found that the stunting prevalence improved from 45 % in 1999 to 30 % in June 2009. In ten years, this is a reduction by 15 %. Adding another ten years with the data of the present study, the prevalence decreased by an additional 11 % to 19 % in 2019. A similar drop can be observed for the prevalence of wasting. While it stayed high at 26 % from June 1999 to

2009, wasting dropped to 5 % in 2019 as assessed through this study. The prevalence was within the same range as found by Sié et al. (2018) for two study villages in the Nouna HDSS area in July 2017. While they reported a 21 % stunting prevalence, wasting was slightly higher at 10 % among children in the same age group. An explanation for the significant drops in child undernutrition might be the positive effect of the free-of-charge healthcare policy implemented by the Government of Burkina Faso in 2016. The policy aimed to improve health of children aged <5 years, and of pregnant and lactating women. The impact was found to be positive on the screening of malaria cases of children aged <5 years due to an increased use of health services, testing, treatment and general surveillance of health and diseases (Ouédraogo et al., 2020; Ridde & Yaméogo, 2018). Although no study was identified on the effects of the free-of-charge healthcare policy on child undernutrition specifically, a surge in healthcare uptake might have also positively impacted child care practice counselling and so undernutrition treatment.

Additionally to decadal prevalence trends, Beiersmann et al. (2012) looked at stunting and wasting differences within a year moving from June to December in 2009. While 30 % of the children aged <3 years were stunted in June 2009, 45 % were stunted in the same year in December. On the contrary, 26 % were wasted in June and 16 % were wasted in December in 2009. The results mirror the findings of the present study as the lean season represents low food stocks leading to acute undernutrition, while those affects can only be observed on chronic undernutrition (stunting) once several months have passed. Hence, an increase in child stunting may only be observed with a delay of several months to 12 months after an external exposure occurred (Brown et al., 2014). Such exposures may include extreme climate events. While child wasting is an acute form of undernutrition and may be associated with current weather events (short-term impact), stunting may be caused by the weather of the previous months or year (long-term impact). This could explain the high wasting prevalence in June (= the time of the rainy season and thus, an increased risk for infectious diseases) and the high stunting prevalence in December (= half a year following the rainy season). Whether the climate or precisely the climate variability might be a risk factor for child undernutrition in the Nouna HDSS area is further discussed in Chapters 5.1.3 and 5.3.1.

5.1.2. An increase in extreme rainfall events over fewer days

In Burkina Faso, an overall decline of total annual rainfall since the 1950s with a slight recovery of rainfall since the late 1990s, can be observed. However, the recovery is recorded due to the severe droughts of the 1970s and 1980s in the region, which emphasizes the importance for long-term data to specify climate trends (Salack et al., 2016; Taylor et al., 2017). The drought of the 1980s can also be observed for the Nouna HDSS area with a high negative rainfall anomaly (= very low total annual rainfall compared to the average from 1981 to 2019) for the year 1983. Yet, it is not mainly the cumulative annual rainfall that causes crop yield and child undernutrition, but increased rainfall

variability and its extremes, such as mini-droughts within the rainy season and torrential rainfall events. In order to investigate their association with child undernutrition, 15 rainfall indicators were selected that can be divided into three sections: (i) general rainfall indicators, (ii) extreme rainfall indicators, and (iii) seasonal rainfall indicators.

The general rainfall indicators include total annual rainfall as it is relevant for annual comparisons and time trend observations. The data from the five clusters of the Nouna HDSS area showed an increase in total annual rainfall from on average 740 mm per year from 1981 to 2019, which was also observed at a national scale for Burkina Faso (Didi et al., 2020). Despite this increase in annual rainfall, the data also showed an increase in very heavy rains and an increase in extremely wet days. Lodoun et al. (2013) confirmed this observation for Burkina Faso in a study using weather data from 1941 to 2000. They observed an increase in extreme weather events during the rainy season including longer dry spells (mini-droughts) with no rainfall. These weather extremes go along with a decrease in the overall number of rainy days (Ministry of Environment and Fishery Resources, 2015) during the agricultural season (August and September) (Lodoun et al., 2013), a reduction in the number of consecutive dry days during the wet season (mini-droughts), and a decrease in the length of the wet season in Burkina Faso (De Longueville et al., 2016; Lodoun et al., 2013). Keeping in mind an increasing total annual rainfall over fewer rainy days, such rainfall extremes emphasize a change in climate towards heavier rains per day. Those can be devastating for plant growth due to excessive flooding.

In addition to these observations on temporal variability, the data also accounted for spatial variability of climate variables (Ben Mohamed, 2011; Lodoun et al., 2013; Ministry of Environment and Fishery Resources, 2015). Indeed, the five cluster of 10 km radius, which were on average only 15 km apart (Figure 8), indicated significant variation in rainfall among each other. Yet, this might be depending on the chosen indicator. While one cluster might be affected by very heavy rains, another cluster might suffer under prolonged droughts or a delay of the start of the rainy season. Specifically, cluster differences within a year were observed rather than aggregated over several years. Hence, rainfall has a very fine-grain spatial and temporal variability. In contrast, most of studies focus on the very coarse measure of cumulative annual rainfall and inter-annual differences.

With regard to seasonal rainfall variability, an upward time trend in heavy rainfall was found specifically in July and August with more than 50 % of the total annual rainfall (over 400 mm of the average annual amount of 740 mm). This aligns with the observations made by Hondula et al. (2012) in the same study region. These two months define the success or failure of the harvest of subsistence farmers and thus, whether they will be able to have enough food until the next harvest to feed their families and provide financial income (Saronga et al., 2016; West et al., 2008). Ingram et al. (2002) provided five indicators named by farmers to be of high importance for agricultural output and for decisions linked to the next agricultural season: (i) the starting date of the crop growth period or rainy season, (ii) the end date of the crop growth period; (iii) the rainfall amount per day; (iv) the number of rainy days; and (v) the total amount of rainfall in the previous year(s). This traditional knowledge was

another reason, why the present study considered the overall length and start of the rainy season in addition to rainfall variability as essential indicators for successful crop growth (Hondula et al., 2012; Sivakumar, 1988).

5.1.3. Rainfall variability as a new risk factor for child undernutrition

The interdisciplinary nature of this research combining health, diet and climate made the analyses and findings unique in its current form. While the conventional risk factors for child undernutrition are well known and studied, climate change, using rainfall variability as a proxy, is a new risk factor that is not yet well understood. This is already reflected in a simple Pubmed search (conducted in May 2021), where over 8,000 articles were suggested for associations of child undernutrition with the conventional risk factors and only slightly over 300 articles for associations of child undernutrition with “climate” and even fewer with “climate change”. In two systematic literature reviews (SLR) on the associations of undernutrition and climate change, Phalkey et al. (2015) identified 15 studies of which only 13 studies were peer-reviewed. Six years later, Helldén et al. (2021) conducted a scoping review looking at risk factors for child health (aged <18 years) to climate change and variability. Although they identified 371 documents, only 202 were original articles, and of those only 38 articles (22 %) covered low- and middle income countries.

The present study provided an explorative assessment of the associations of undernutrition of children aged <5 years and rainfall variability. In addition, the study integrated an assessment of the conventional risk factors in order to consider for socio-economic covariates that may directly or indirectly effect child growth and development.

(i) Climate change and rainfall variability

Climate change is predicted to increase child undernutrition by 25.2 million compared with the counterfactual scenario without climate change (Nelson et al., 2010). Despite this knowledge, there were only few studies looking into the association of child undernutrition with climate change and variability (Helldén et al., 2021). The present study contributed to fill this knowledge gap. Specifically, the study followed the hypotheses that (i) rainfall impacts child undernutrition differently in geographical regions defined here by study clusters and (ii) it does so differently for four different time periods: (a) the year before the birth of the child (t-3), (b) the year of birth (t-2), (c) the year before the nutrition survey (t-1), and (d) the year of the nutrition survey (t-0). So far, it was not yet clear, which time period predicts and explains child nutritional outcomes the best (Davenport et al., 2017; Grace et al., 2015). In the same study region, Belesova et al. (2019b) investigated the negative impact of low crop yield in the year of birth on child survival up to the age of five years. An increase in child mortality was identified with an increase in crop yield variations accounting for unfavorable weather conditions in the study area. These findings were adjusted for various potential confounders as done for the present study. However, the study did not account for spatial differences as done here.

The presented data revealed that spatial differences exist with regard to stunting and wasting prevalence. For example, children living in the area around Cissé had a much higher risk for stunting and wasting than those living in the other clusters. Children, who lived around Sono were identified to be more prone to wasting. Similar findings were made by Sankoh et al. (2001) in the same study area, who confirmed cluster differences for child mortality. Using Nouna HDSS data from 1993 to 1998, they found a specifically high rate of child mortality in the cluster around, but also in the village of Cissé. The authors cannot explain this constantly high mortality rate as socio-economic risk factors such as ethnicity, religion or distance to a health care center did not seem to explain these cluster differences. The study did not (yet) include any climate variability indicators, wherefore the investigation of this aspect as a new risk factor for child undernutrition was encouraged. As discussed in the previous chapter (Chapter 5.1.2), rainfall distribution indeed differed between clusters for some of the selected rainfall indicators.

Nevertheless, other studies found that conventional risk factors for child undernutrition might modify the effect of weather on child growth or have a stronger impact than weather alone (Davenport et al., 2017; I. Mueller et al., 2001; Wright et al., 2001). For example, Shively (2017) conducted a study looking at patterns of stunting and wasting among children below the age of 5 years in Nepal and Uganda. They found that greater road density and improved access to health facilities mitigated a child's sensitivity to variations in precipitation, suggesting a protective effect of health services against climate variability. The study confirms that socio-economic factors play a significant role in mediating the associations of rainfall variability and child undernutrition. This topic is further discussed in Chapter 5.3.1, while the conventional risk factors of child undernutrition are outlined below.

(ii) Conventional risk factors of child undernutrition

The conventional risk factors identified through the present study are in line with the screened publications and literature reviews on child undernutrition (Akombi et al., 2017; Black et al., 2008; Danaei et al., 2016). Three important SLR on risk factors associated with child stunting and/ or wasting shall be briefly highlighted here. Akombi et al. (2017) looked at risk factors of child stunting, wasting and underweight specifically for sub-Saharan Africa, Vilcins et al. (2018) focused specifically on environmental risk factors associated with child stunting, and Danaei et al. (2016) analyzed the risk factors for child stunting in 137 developing countries. Despite their important contribution to understand causes of child undernutrition, all authors did not include or refer to any climate-related indicators as potential risk factors. Environmental risk factors were limited to arsenic contamination in drinking water, or mycotoxins or pesticides on foods (Vilcins et al., 2018) or access to sanitary facilities and safe drinking-water and cooking sources (Danaei et al., 2016).

With regard to socio-economic risk factors, gender and age groups of a child were significantly associated with an increased risk of both stunting and wasting. Although young children in the study area were in general less likely to receive treatment for illnesses, no such differences were observed

for different sexes in the study area, e.g. as by Sauerborn et al. (1996a). However, in the present study boys were more likely to be stunted or wasted than girls. This finding was also confirmed by a SLR looking specifically at sex differences for undernutrition of children aged 0 to 59 months worldwide (Thurstans et al., 2020). Here, the authors confirmed the higher likelihood for boys to be wasted and stunted compared to girls. Specific justifications were not identified and found to be “often speculative rather than informed by direct evidence” (Thurstans et al., 2020). Overall these findings are controversial to the common assumption that boys are socially preferred over girls, which the authors identified for studies from South and South East Asian, but not for African countries. Further evidence is needed to understand the gender-based vulnerability, including research accounting for differences between boys and girls.

With regard to age groups, the present results confirm the global observations on age-related vulnerability to undernutrition. Acute undernutrition among low-birth infants was found to decline once the children reach their 3rd to about 15th month of age after which the weight might either stabilize or increase (Victora et al., 2010). A decreasing prevalence of stunting occurs specifically up to 3 years of age as the children experience maximal growth velocity during the first few months of life (Allen & Gillespie, 2001; Reinhardt & Fanzo, 2014; Victora et al., 2010). The present study found a higher prevalence of child stunting among those aged 24 to 47 months, while wasting was found especially among the youngest age groups (7 to 23 months and 24 to 35 months). This is in line with the published literature. These differences might be explained as follows: children below 24 months are within the critical time span of the “1,000 days of life” (de Onis & Branca, 2016), i.e. between conception and 24 months of age, as described in Chapter 1.1.1. This age span represents a critical window for health, nutrition, growth and, most importantly, cognitive development (de Onis & Branca, 2016; Ministère de la Santé Burkina Faso et al., 2016; Poda et al., 2017).

Second, vulnerability to undernutrition may also be due to the increased risk for infectious diseases in this age group (7 to 60 months of age) (Sankoh et al., 2001; Stich et al., 2006). The mothers were asked about fever or diarrheal episodes during the previous two weeks prior to data collection. Children with fever had a significantly higher risk for wasting (55 %), while those with diarrhea had a significantly higher risk for stunting (33 %). Many pathogenic agents and their vectors prefer a wetter environment for breeding and transmission. Further risk factors for infectious diseases, particularly diarrhea, are, of course, the lack of environmental and personal hygiene, to name just a few. For example, malaria is endemic in Burkina Faso specifically during the rainy season and thus, making children more vulnerable to diseases and undernutrition (Ouédraogo et al., 2020; Wehner et al., 2017). This could be an indicator for and confirmation of a high malaria prevalence at the time of the assessment.

Third, child undernutrition proved to be associated with birth weight as expected from the literature (Black et al., 2008; Victora et al., 2008). Children, who were born too small (<2.5 kg) or too big (>3.9 kg) had a higher probability of being stunted or wasted. Overall, 10 % of the children in the sample

were born with a low birth weight, which was similar to the national number of 13 % in 2015 for whole Burkina Faso (UNICEF, 2019). The associations between birth weight and child undernutrition is currently examined in a larger cohort (2,000 children <5 years) that was assembled in 2020 in the framework of a Research Unit “Climate Change and Health in sub-Saharan Africa” funded by the German Research Foundation (DFG) (<https://www.cch-africa.de/>). Further investigation is needed to associate child undernutrition with breastfeeding practices of the mother, which was not the main focus of this study. Overall, the proportion of mothers breastfeeding was higher in the Nouna HDSS area (78 % of the mother with children aged 7 to 23 months reported to breastfed at the time of the survey) than the nationally reported one (48 % for whole Burkina Faso based on data from 2015 (UNICEF, 2019)). This proportion is in line with the international recommendations to continue breastfeeding until 23 months of age (FAO et al., 2019).

Last, the study confirmed the relationship between parental education and ethnicity. Specifically, education of the mother (expressed as literacy) had a significant protective effect against child stunting, which increased linearly with educational level. The effect of parental education was less pronounced for child wasting. This corroborates a large body of evidence on the effect of education on child health and nutrition as found, e.g. summarized in a systematic review (Ngandu et al., 2019). Moreover, children from mothers and household heads of the Fulani (in French “Peul”) showed an exceptionally high prevalence of stunting and wasting compared to the other ethnic groups in the Nouna HDSS area. The same observation was made in the same study area by Beiersmann et al. (2013) in 2009. The causes for this link have not yet been investigated and invite for further research.

5.2. Diets of children aged <5 years in rural Burkina Faso

5.2.1. Low dietary diversity and vegetable consumption among children under five

While only few studies conducted in the Nouna HDSS area have so far included anthropometric measurements of children aged <5 years (Beiersmann et al., 2012, 2013), even fewer assessed their diets (Sié et al., 2018) and none looked at the relationship with climate variables. The present study is unique in that (i) it assessed a variety of diet indicators to receive a better picture of children’s diets, namely dietary groups and individual food items. This allowed the construction of dietary pattern scores (DPSs) for analyzing the combination of foods commonly consumed together by the children. Further, this assessment allowed (ii) to relate the nutritional status (stunting and wasting) with dietary patterns and (iii) to link those to rainfall variability indicators as further discussed in Chapter 5.3.1.

First, the study showed that the sampled children had a low dietary diversity during the rainy season, which indicates a low nutrient adequacy. 92 % of the children did not reach the minimum dietary diversity of at least 5 food groups (which was raised from the older threshold of at least 4 food groups (UNICEF, 2019) and which 70 % of the children would not have met). The median Dietary Diversity Score (DDS) derived from the 7-day dietary recall was 7 out of 10 food groups, which is in line with a

similar study by Sié et al. (2018). They reported an average of 6 out of 11 food groups for children in the Nouna HDSS over a 7-day recall period. Nikiéma et al. (2017) counted only 2 out of 9 food groups for children in the same age group in rural Houndé, a village located about 200 km south-west of Nouna. They reported that only 25 % of the children met their minimum dietary diversity of at least 4 food groups (UNICEF, 2019). However, it has to be noted that the latter recall was done only during the previous 24 hours.

Second, the data revealed that the children's diets were characterized by a low intake of fruits and vegetables. According to data provided by UNICEF (2019), 75 % of the children aged 6 to 23 months in Burkina Faso did not consume fruits or vegetables. In the present study, 21 % of the children consumed no vegetables and 39 % consumed no fruits during the previous 7 days. Yet, an alternative healthy source was vitamin A-rich leaves. Those were consumed by 94 % of the children and comprised a central part of their diet during the rainy season. Fresh as well as dried vitamin A-rich leaves, such as Baobab leaves, are rich sources of minerals and vitamins and contain all of the essential amino acids (Hyacinthe et al., 2015; Tirado et al., 2015). The leaves were often provided as a sauce, enriched by peanut paste, and combined with locally produced maize and rice, which tend to be prepared to a form of porridge (called "bouillie enrichie" (enriched broth) in the more liquid form and "tô" in the firm form of the cereal base). Moreover, 64 % of the children in the Nouna HDSS area received the African locust bean, which provides a healthy alternative to animal-sourced protein and is rich in carbohydrates, proteins, lipids and fibers (Nyadanu et al., 2017). National and international food-based dietary guidelines provide recommendations on diets for children that promote optimal growth and cognitive development. These guidelines encourage dietary diversity through the provision of whole grains and starchy foods, at least five portions of fruits and vegetables a day, the consumption of lean protein and dairy foods and a limited intake of sugar, fat and salt (UNICEF, 2019). Unfortunately, for Burkina Faso, national food-based dietary guidelines could not be identified.

Third, the study identified three dietary patterns that describe typical food combinations. Those were labelled as: market-based, legume-based and vegetables-based diets. Given the individuality of dietary patterns, no studies with similar patterns looking at child undernutrition were identified, wherefore no comparisons can be made. In short, all dietary patterns were positively associated with child undernutrition. Specifically, children, who followed the market- or legume-based diet, were found less likely to be stunted, and children, who followed the vegetable-based diet, had a lower risk for wasting. Here, specifically the market-based diet came to a surprise as such a combination seemed unusual for a subsistence farming environment in Burkina Faso. It consisted mainly of pasta, eggs, poultry, sweets, bread, beverages, rice and cassava, which are products that tend to be bought on the market. An explanation could be that the study was conducted during the rainy or lean season, when stocks tend to be low from the previous year's harvest. Therefore, the subsistence farmers' families adapted their diet to the food availability. Sauerborn et al. (1996b) found that household expenditure in the Nouna area was higher during the rainy season, namely from July to September, while household revenues

decreased during the same time period. Such higher expenditures could be explained by the purchasing of foods to compensate for the higher physical activity and the decreasing stock of available foods. However, this came with a price for health seeking treatment, choice of treatment and disease perception. All three factors decreased substantially from the dry season (64 % sought treatment) to the rainy season (34 %) despite the higher risk for Malaria, infectious diseases and child undernutrition (Mank et al., 2020; Sauerborn et al., 1996b; Wehner et al., 2017). Hence, subsistence farmers and mothers are forced to change the diets for their children during the lean season: either by reducing the number of meals per day and/ or by switching to alternative food sources that may include food items bought on the market, if the financial situation allows, or taken from vegetable gardens, of which the latter is mainly maintained during the dry season (Olney et al., 2015; Saronga et al., 2016; Sorgho et al., 2020).

5.2.2. A higher dietary diversity was associated with improved child undernutrition

In the present study a higher dietary diversity (>7 food groups), defined by the Dietary Diversity Score (DDS), was associated with a reduction in stunting (-10 %) and wasting prevalence (-36 %) of the sample of children aged 7 to 60 months in the Nouna HDSS area. Specifically, the present study assessed the effect of three diet quality indicators on child stunting and wasting, while considering for socio-economic confounders. The three dietary quality indicators of concern were the Dietary Diversity Scores (DDS), Food Variety Scores (FVS) and three Dietary Pattern Scores (DPS). The first part of this section discusses the associations of dietary diversity and child undernutrition, while the second part looks at the effect of adjusted models, when considering for socio-economic confounders.

In the same season and year as the present study, Sié et al. (2018) conducted a study on the associations of DDS with child nutritional status in the Nouna HDSS area. Despite the similar research questions, some similarities and important differences shall briefly be highlighted: (i) both studies investigated dietary diversity of children aged 6 to 59 months of age; (ii) the present study included 18 villages located in the Nouna HDSS, increasing the representativeness of the findings, while Sié et al. included only two villages; (iii) equally, the sample size differ significantly (N=251 (Sié et al., 2018) versus N=1,439 in the study reported here); (iv) the present study associated dietary diversity with child undernutrition while adjusting for conventional confounders of child undernutrition; and (v) both conducted dietary recall over the previous 7-days, while the present study constructed the dietary scores based on a food item recall. This means that not only the consumption of food groups was asked, but each food item recalled individually. Subsequently, additionally to the DDS, also a FVS and DPSs were created, which was not yet done for the study area.

Bearing those differences and similarities in mind, both studies found a significant association of DDS with stunting, which indicates a reduction in stunting prevalence risk with an increase in dietary diversity. The results of the present study were conform with a meta-synthesis conducted by Arimond

& Ruel (2004) on the associations between dietary diversity and stunting of children 6 to 23 months. They used data from 11 standardized Demographic and Health Surveys (DHS) in low- and middle-income countries. The authors found that most studies showed positive associations between stunting (HAZ) and high dietary diversity, as measured by DDS. In other words, the more varied the diet, the smaller the risk of stunting for the children. These associations are illustrated in Figure 27 together with the here reported results for Burkina Faso (in the blue rectangle). All studies confirm that a higher dietary diversity is associated with improved child stunting. However, (i) the strength of the effect varied between countries as shown by the beta-coefficient, which was <0.2 for seven countries including Burkina Faso; and (ii) the associations of the middle versus the lower DDS went in opposite directions for four countries also including Burkina Faso. This indicates the controversial result that child stunting is more likely to occur with a medium high dietary diversity compared to a low dietary diversity. It has to be kept in mind though that the data is not aggregated by age, which was found to impact dietary diversity and child nutritional status and might therefore explain the contradictory findings.

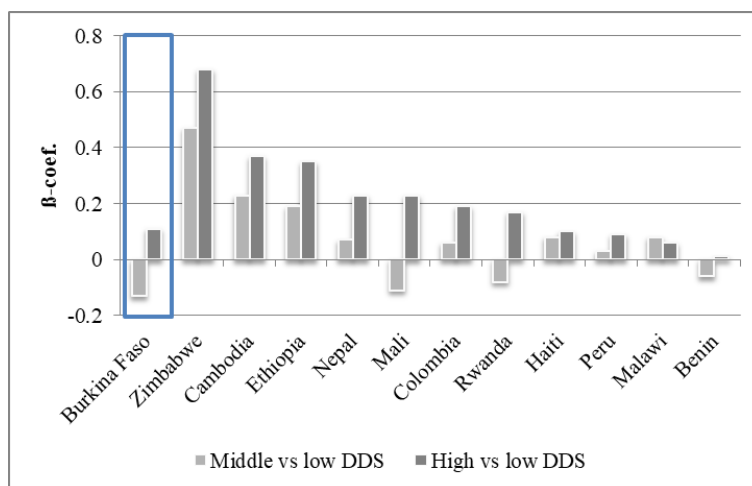


Figure 27: Summary of regression results representing associations with DDS tertiles and HAZ of children aged <5 years

Source: Arimond & Ruel (2004) and own data for Burkina Faso

Moreover, the present study confirmed a positive and significant association with wasting for the sampled children (Mank et al., 2020), which was not in line with other studies. For example, no association were found for DDS with wasting (WHZ) of children aged 6 to 59 months for a study in rural Mali (Hatloy et al., 2000) or in Sri Lanka (Perkins et al., 2018). Siè et al. (2018) justified this stronger association with stunting than with wasting as the DDS is “reflective of longer-term nutritional habits”. Hence, a change in food groups over the year might be less likely than a change in specific food items, due to their smaller number. In the present study, 10 food groups were used to assess the DDS, while over 117 food items were listed to construct the FVS.

Despite direct associations between dietary diversity and child undernutrition, socio-economic confounders were found to positively and significantly influence those associations. An association between dietary diversity (DDS and FVS) and socio-economic status as defined by household assets was identified by Hatoloy et al. (2000) in their study from rural and urban Mali with children aged 6 to

59 months. In urban as well as in rural areas, they found that the socio-economic status increased dietary diversity. The same was found for the present population. Households in the higher wealth quintile had higher dietary diversity scores compared to the households in the lowest quintile. Equally, a dietary pattern defined by market- and legume-based diets were significantly more likely to be consumed by the richest population group compared to the poorest, while the opposite was the case for the legume-based diet. Children, who mainly followed a legume-based dietary pattern, were also more likely to be in the poorest wealth quintile (Appendix 15).

The present findings, therefore, confirm that it is not solely the diet that contributes to child undernutrition, but also the socio-economic situation, disease episodes and environment. Although the selected measures of socio-economic factors might not be complete, the present study covered a broad range of indicators that can be associated with child undernutrition and dietary diversity. Hence, it is encouraged to promote dietary diversity in parallel to the livelihood in interventions and policy actions.

5.3. Rainfall variability as a proxy for climate change and children's diets

5.3.1. The time period depicts the impact of rainfall on diets and child undernutrition

The impact of rainfall variability on child nutritional status was based on two hypotheses: (i) rainfall directly impacts stunting and wasting across different time periods, and (ii) rainfall variability indicators can be associated with dietary patterns through a hypothesis-driven rainfall variability pattern.

(i) Hypothesis I: Rainfall directly impacts stunting and wasting across different time periods

A slowly increasing number of studies explore the current and future influence of climate change and variability on child undernutrition and health (Helldén et al., 2021; Lloyd et al., 2011). However, most studies do not account for temporal differences and thus, the lifetime exposure a child experiences from conception to current health. This lack of methodological approach might contribute to the contradictory evidence for direct associations over a single time period (often the current weather); moving from significant associations of seasonality of rainfall with (i) child wasting at the Horn of Africa (Chotard et al., 2010) and (ii) stunting in Papua New Guinea (Ivo Mueller & Smith, 1999) to (iii) no association with child underweight in Zimbabwe (Wright et al., 2001).

The first hypothesis takes into account the “first 1,000 days of a child's life”, which are essential for its growth and development. A child starts to already be exposed to environmental impacts through the mother before conception (reflecting the diet and environmental exposure of the mother), as well as during pregnancy (in utero). These impacts then continue in child- and adulthood (Sheffield & Landrigan, 2011). Subsequently, the diet and living conditions of a mother prior to a child's birth may have (additional) implications on child growth and development (Davenport et al., 2017). Davenport et

al. (2017) chose “sum of temperature and rainfall by trimester prior to the date of birth” for associations with birth weight outcomes and mean rainfall and temperature during the rainy season for stunting outcomes. They found that a reduction in rainfall reduced stunting prevalence (HAZ), when accounting for socio-economic development (e.g. through maternal education and electricity access), while the associations with birth weight were slightly weaker. A stronger association between increasing temperature and lower precipitation with birth weight was identified by Grace et al. (2015). Both author groups assumed that child undernutrition manifests itself already in utero or even before conception, for example, due to heat stress and dehydration of the mother; and emphasize that positive socio-economic development may be able to mitigate the negative climate impacts such as increased temperatures and less rainfall.

These observations inspired the interpretation of the reported findings hypothesizing that rainfall impact child stunting and wasting at different time periods. Therefore, four time periods were chosen and associations with child stunting and wasting investigated: the year before (t-3) and of birth (t-2), and the year before (t-1) and of the nutrition survey (t-0). The data indicated that there were differences in associations between stunting and wasting by various time periods. Accordingly, the prevalence for child stunting was found to be significantly lower with an increase in rainfall in the year before the nutrition survey, while the prevalence for child wasting was significantly lower with an increase in rainfall in the year of birth. These associations were not significant after adjustments were made for socio-economic confounders. No other study was yet identified that could support the interpretation of these observations, wherefore the study underlines its contribution to generate evidence and knowledge on possible pathways of associations between climate variability and child undernutrition.

Overall, only a few studies could be identified that associated child undernutrition with climate indicators for different time periods; yet, they differed from those presented here. For example, Skoufias & Vinha (2012) linked weather shocks with chronic undernutrition of children aged 12 to 47 months in rural Mexico using two different time periods. They calculated rainfall shocks defined by rainfall days for one and for two years prior to anthropometric measurements. They showed that positive rainfall shocks (= more severe rainfall than normal) in the preceding agricultural year showed to have a negative impact on stunting for some regions in Mexico. The findings of the present study contradict those as an increase in those rainfall indicators showed that heavy rainfall is associated with a reduction in stunting in the year before the nutrition survey. A possible explanation for this contradiction might be that Burkina Faso is a semi-arid country, wherefore wetter conditions might result in positive agricultural food production and so an improved livelihood. Cooper et al. (2019) examined the association of extreme rainfall as well as drought for child cohorts in two agro-ecological different regions, namely Ghana, a drier countries, and Bangladesh, a wetter country. They applied a standardized precipitation index (SPI) on child anthropometry accounting for five different time periods accumulated from 12 to 60 months. The findings were differed between the countries.

Short excessive rainfall events taking place for 12 months were significant predictors of lower wasting prevalence (WHZ), while excessive rainfall over longer time periods of 36 months was significantly associated with a lower risk for stunting (HAZ) in Ghana. In Bangladesh, however, the SPI was neither a significant predictor for stunting (HAZ) nor for wasting (WHZ). The authors explained this due to the small sample size for Bangladesh causing less statistical power for inference. This assumption should also be further explored for the Nouna HDSS dataset as the number of children with wasting was much smaller ($n \sim 80$) than with stunting ($n \sim 270$).

(ii) Hypothesis II: Rainfall variability indicators can be associated with dietary patterns through a hypothesis-driven rainfall variability pattern

The second hypothesis was that rainfall variability may be associated with dietary patterns as a link to child undernutrition. So far, only studies linking climate change and weather and child undernutrition either directly or via agricultural yield were identified as described above (Belesova et al., 2019b).

Here, a method originating from nutrition epidemiology was applied, which combines an exploratory and hypothesis-oriented approach: Reduced Rank Regression (RRR). In RRR, it is assumed that not a single indicator (e.g. a single food item or a single rainfall indicator) determines health or disease status, but rather a combination of indicators (Hoffmann, 2004). This method allowed to identify a set of precipitation indicators, which (i) commonly occur together and (ii) explain most of the variation in the normally distributed dietary patterns of children aged <5 years in the study area. Due to the variety of indicators that may explain rainfall variability, RRR seemed to be a good fit. Through its dimension-reduction technique, it allowed to display a rainfall variability pattern rather than using solely a single rainfall indicator. A single indicator oversimplifies the complexity and interlinkage of climate events (Belesova et al., 2019a).

Given that studies have not yet applied diets as mediators between climate change, agriculture and nutritional status (Cooper et al., 2019; Kinyoki et al., 2016) and/ or lacked to account for weather impacts when associating child undernutrition and seasonality of diets (Kigutha et al., 1995; Somé & Jones, 2018), the RRR approach allowed to explore this respective link. No other studies were identified that linked diets and child undernutrition to climate change and could have been used as guidance for the design of the present study. The same applies for the statistical treatment of the optimal combinations of rainfall variability indicators. Only recently a study was published that associated dietary diversity of children aged <5 years with climate impacts (Niles et al., 2021). The authors utilized hierarchical linear models with DHS data from 19 countries and CHIRPS rainfall and temperature data. They found that an increase in rainfall can be associated with an increase in dietary diversity, here defined by the DDS. However, contrary to other findings discussed above, conventional risk factors did not mediate the negative effects of climate variability. Overall, more research on the impact of climate change on child undernutrition is encouraged to improve the generalizability of the findings.

5.3.2. Selection of rainfall database and rainfall variability indicators

Climate plays a central role in the livelihood of subsistence farmers in Burkina Faso and has severe implications for food crop harvest and hence, child undernutrition. This study provided a description of the local climate using retrospective rainfall data from 38 years (1981 to 2019) and from five clusters of 10 km radius. Only a few studies described the change of rainfall for Burkina Faso given the sparse number of weather stations and a lack of available high-quality, long-term weather data (Dai et al., 2004; Diboulo et al., 2012; Hondula et al., 2012; IPCC, 2014b). In the following sections, the selection of the methodological approach with regard to (i) identifying a valid rainfall database for the study population and according to the study aim and (ii) the rationale for choosing appropriate indicators for rainfall variability as proxies for climate change are discussed.

(i) Identification of a rainfall database

While several databases exist to obtain rainfall data, those identified did not meet the requirements for the present study aim. For example, Hondula et al. (2012) used monthly weather data provided by the National Oceanic and Atmospheric Administration (NASA) through the National Oceanic and Atmospheric Administration's (NOAA) National Centers for Environmental Information (NCEI) (www.ncdc.noaa.gov). NOAA is a satellite developed by NASA, which provides data by a spatial scale of 0.5° x 0.5° grid cells (25 km). Depending on the study aim, alternative satellites may be accessed to retrieve, for example, NDVI composites (Johnson & Brown, 2014). Alternative to NASA, regional data can be obtained such as from the West African Sahelian "Comité inter Etats de Lutte contre la Sécheresse au Sahel" (CILSS), which provided data from 1950 to 1998, to observe rainfall and temperature trends for the Sahel region (Ben Mohamed, 2011) or local data from national weather agencies such as the Direction Générale de la Météorologie du Burkina Faso (De Longueville et al., 2016).

Local weather data from the Agence National de la Météorologie du Burkina Faso was obtained for the present study. However, due to the limited number of weather stations distributed over the country and specifically the Nouna HDSS area, a Climate Hazards Group Infrared Precipitation with Stations dataset (CHIRPS) (<https://www.chc.ucsb.edu/data>) was selected and improved by a hydro-meteorologist from the Augsburg University, Dr. Bliefernicht (see Chapter 3.5). CHIRPS is a gridded rainfall dataset that applies spatial interpolation using data from multiple sources such as rain gauges and satellites to represent sparsely gauged locations. It was identified as a reliable database for this study as it uses a high spatial resolution of 0.05° (5x5 km), has a long-temporal coverage (starting in 1981), provides daily data, and was used in several other comparable studies on the nexus of climate change, diet and child undernutrition (Davenport et al., 2017; Grace et al., 2015; Niles et al., 2021; Shively, 2017). Additionally, the use of CHIRPS data was validated in a study conducted by Dembélé & Zwart (2016) in comparison to other satellite-based rainfall products and in correlation to rain-gauge data. Overall, they found weak correlations of daily, but good correlations of decadal rain-gauge

data for all rainfall products including CHIRPS and recommended CHIRPS specifically for flood monitoring in Burkina Faso. An addressed limitation of this evaluation was the low spatial distribution of weather stations in the country and gaps in the rain-gauge dataset. This might have weakened the assessment reliability. Overall, satellite-based products are likely to underestimate intensity and overestimate frequency of rainfall and should therefore be interpreted with a certain care. Nevertheless, the product was found to be reliable for extreme weather analysis (Atiah et al., 2020; Didi et al., 2020).

(ii) Selection of rainfall variability indicators as proxies for climate change

Following the identification of a reliable rainfall database, appropriate indicators for rainfall variability as proxies for climate change had to be selected. Since the study aim was to account for and so investigate yearly and spatial variability of rainfall and so its extremes, a thorough investigation on appropriate rainfall indicators was done. The following climate change and/ or rainfall variability indicators were identified:

- (1) Single climate indicators such as cumulative annual rainfall or temperature shocks (as standard deviations of the norm) without taking into account a combination of weather indicators occurring simultaneously (Rabassa et al., 2014; Shively et al., 2015; Skoufias & Vinha, 2012),
- (2) A combination of environmental or land cover indicators (e.g. the Normalized Difference Vegetation Index (NDVI), altitude, relief of terrain or living location) as proxies for climate change (Brown et al., 2014; Jankowska et al., 2012; Ivo Mueller & Smith, 1999),
- (3) Seasonal differences (e.g. years of drought, monsoon season, born during the rainy season, birth month) to approximate climate variability (Chotard et al., 2010; Grace et al., 2015; Panter-Brick, 1997), and
- (4) Climate variability and extreme indicators (De Longueville et al., 2016; Nouaceur & Murarescu, 2020; West et al., 2008).

For the present study, the choice fell on the selection of climate variability and extreme indicators as introduced among others by De Longueville et al. (2016) and as described in Chapter 3.4.5. These indicators were chosen as they provide a mixture of general indicators (e.g. total annual rainfall), indicators for rainfall extreme events (e.g. the number of heavy and very heavy rainfall days) and seasonal indicators relevant for plant growth (e.g. the length of the rainy season). Therefore, they can be used as proxies to assess climate change over time and space. De Longueville et al. (2016) provided the most recent analysis using all of the 15 rainfall indicators for Burkina Faso covering the years 1950 to 2013. In addition, other studies were identified, which used these indicators or a selection thereof for the Sahel region or several West African countries were identified (Didi et al., 2020). Therefore, they deemed appropriate for the present study, particularly in view of a comparison and potential confirmation of findings.

Nevertheless, while rainfall variability was discussed in the present study, an additional indicator of relevance in climate change assessments is, of course, temperature. In addition to rainfall variability indicators, the ETCCDI also provides 11 extreme temperature indices such as min. and max. daily temperature. De Longueville et al. (2016) used those indicators and reported a long-term warming with a reduction in the occurrence of cool days and nights and a significant increase in hot days and nights based on data from 1950 to 2013 for Burkina Faso. However, temperature was not included in the present study as (i) it is usually measured on a larger spatial and temporal scale, which does not allow for small-spatial analysis as done here (of 10 km radius around the weather stations) and (ii) since it tends to be colder during the rainy season due to increased cloud cover. This suppresses incoming solar radiation and increases the cooling effect due to evaporation of ground and atmosphere moisture (Hondula et al., 2012). Thus, rainfall was considered a key determinant of child undernutrition, while temperature should be added when looking at plant growth in the study area (Belesova et al., 2019b; Dos Santos & Henry, 2008).

5.4. Ground validation of high-resolution remote sensing as a method to identify food crop yield at the household level

Satellite remote sensing analyses showed to be effective for assessing agricultural parameters such as crop types, yield and management practices (Bégué et al., 2018; Carletto et al., 2016; Sorgho et al., 2018) through yield-relevant crop indicators (e.g. the leaf area index, nitrogen status or plant biomass). The present study validated the use of remote sensing data against weighed harvest of food crops of small-scale agricultural household fields together with research partners from Remote Sensing Solutions (RSS) GmbH (see Chapter 3.5). The advantage of satellite remotely sensed crop yield data is briefly discussed in the following.

First, monitoring small-spatial units such as of fields of subsistence farmers is challenging. In this study, crop yields (= harvest per unit of harvested area (kg/m^2)) of fields with a median size of 1.4 ha were estimated. So far, only very few studies were identified, which provided yield estimations in such small spatial units such as for household fields (Jin et al., 2017). Most studies on remote sensing-based yield estimates and predictions were so far developed in and for large, more industrialized farming systems (between 20 to 150 ha) (Bégué et al., 2018). Yet, the validation of such small units became possible due to the availability of the cost-free data from the most recent European Sentinel-2 satellites. These offer new monitoring possibilities through (i) increased availability of Earth Observation (EO) data, with (ii) improved spatial resolutions, (iii) more extensive coverage, and (iv) shorter revisiting cycles of the same area by the satellite. These new developments permit moving the assessments on food security from a national level with a spatial resolution of 250 m for West Africa (Gessner et al., 2015) or 30 m for Burkina Faso (Knauer et al., 2017) to even the household level with a high spatial resolution of 10 m as explored here.

Second, ground data is essential to validate and “train” the algorithm applied to the satellite signals. This includes (i) the categorization of the characteristics of the respective geographic areas for remote sensing validation and (ii) the identification of the factors that influenced the quality of the model output that may predict crop yield. This is only possible with detailed information on cultivated crop types, intercropping practices (= non-uniform crop plots) and finally the weighing of a sample of the harvest crops. Although intercropping reduces the likelihood of soil erosion, improve soil quality, increase soil water retention, and prevent crop diseases, it challenges remote sensing imagery to distinguish between crop types. Additional information required from the ground is on factors that might have destroyed the plants or crops such as pests, animals or post-harvest losses. Such external factors may cause differences in the correlation of the remotely sensed and field data.

Third, all of the food crops included in the present study showed a positive correlation between remotely sensed vegetation indices and weighed yield for maize, beans, sorghum, and millet. The correlation was only slightly weaker for peanuts, which might be explained by the plant structure as the peanuts grow below ground. In the end, the validation study showed great potential to predict yields for maize, beans, sorghum and millet each a month prior to or during harvest. Forecasting yield could be applied to all cultivated fields through agricultural mapping, which becomes easier due to the higher resolution imagery such as provided by Sentinel-2 satellites (Groten, 1993; Rembold et al., 2013). A few platforms are already registering crop growth and vegetation stress to estimate (non-crop specific) yield anomalies on a regional level (e.g., the Famine Early Warning System Network by USAID (FEWS-NET) or the Food Security (FOODSEC) and Monitoring Agricultural Resources (MARS) by the European Commission). On this basis, a near-real-time warning system could be implemented that feed into weather index-based crop insurance (Fonta et al., 2018) or warn farmers and the local agricultural district offices to take action preventing serious food crop losses before households, and especially children even suffer from undernutrition.

Last, this validation study is now further adapted in follow-up research with the aim to link food crop yield to households and child nutritional status. Only a limited number of studies applied such an approach. For example, Noromiarilanto et al. (2016) assessed food self-sufficiency in smallholder farming systems of South-Western Madagascar using remote sensing, household socio-demographic, and food consumption data or Nelson et al. (2012) related remote sensing to household-level expenditure to explain poverty patterns in Uganda. Only Shively et al. (2015) and Johnson and Brown (2014) merged remotely sensed data and health aspects and here specifically stunting, wasting and survival of children aged <5 years in Nepal and West Africa (Benin, Burkina Faso, Guinea, and Mali). In combining the yield amount per field and the corresponding household, it may be possible to further link it to food insecurity information. Specifically in rural subsistence farming systems, where people live from what they grow, harvest deficits quickly translate to household food insecurity, low dietary diversity and thus, child undernutrition (Belesova et al., 2019b).

5.5. Study limitations

This study was designed as an open cohort with a calculated sample size of 509 children aged between 7 and 60 months, who were registered to be followed-up over three study years. By design, children, who reached their fifth birthday were censored, i.e. they left the cohort. The study registered a loss to follow-up for other reasons than age. Accordingly, in 2018, 9 % and in 2019, 7 % of the children left the cohort mainly due to death, absence or migration. The overall motivation to participate in this research study was perceived as positive based on feedback provided by the field agents and supervisors. Hence, the overall participation of households was good with little disinterest or rejection to participate. Yet, the sample size turned out slightly lower with 1,439 person-years in contrast to planned 1,527 person-years over three years. Overall, 168 children were followed up over all three years (504 person-years), 173 children were followed-up over two years (346 person-years) and 590 children were only visited once.

Second, the reliability of anthropometric measurements by studying intra- and inter-observer errors during the training sessions of the field agents was not assessed. As suggested among others by the WHO Multicentre Growth Reference Study Group, regular standardization training sessions throughout data collection should be conducted to assure the reliability and comparability of the measured data. In order to assess intra- and inter-observer errors, a lead anthropometrist is needed, who acts as the standard throughout the data collection period (de Onis et al., 2004). Such standardization was not realized for the following practical obstacles: (i) a lead anthropometrist was not available throughout the whole duration of the training, although a trained nurse joined the practical sessions to guide and correct the field agents, where needed; (ii) a child was at maximum available for four to five measurement rounds before the child and/ or mother got tired, which complicated comparison of data, and (iii) the field workers did not conduct the training measurements blinded, but observed and advised their fellow field workers.

Third, the children's diets were assessed through mothers' reporting. Such a recall may cause (i) a memory bias, as mothers cannot always remember what the child consumed over the chosen recall period, or (ii) a social desirability bias in case the mother reports falsely on the consumption of food items (Miller et al., 2020; Mumu et al., 2020; Savy et al., 2007). The latter might occur in case the mothers are aware of the importance of a diverse diet or have heard that certain food items should be given to their children without having access to these food items. In order to avoid blame or embarrassment such incorrect reporting might occur. In order to reduce this risk, the field workers were trained to emphasize that no judgement or shaming should be done and that no collected information would be shared with a third person.

Lastly, despite the fact that the household socio-economic questionnaire included various covariates of child undernutrition, data collected on child health was rather limited in order not to overburden the questionnaire. In keeping with the research objectives, the health-related information was focused on

recent episodes of diarrhea and fever. The same applies to the birth weight of the child. The only source to collect birth weight information was from the health card, which the field workers were trained to request, but not all mothers or caregivers were able or willing to search these health cards. Therefore 23 % of the data-points had no data on birth weight. Additionally, questions on immunization status and health care visits were not asked. This information would have improved the understanding of child undernutrition in the region and would be encouraged to be emphasized in follow-up studies.

5.6. Recommendations for further research

(i) Integrate the “first 1,000 days of a child’s life” into climate research

The present study started at the child’s age of 7 months in order to focus on solid food consumption of the child due to the expected link of the diet with rainfall and agricultural yield. A study integrating the first 1,000 days of a child’s life would require the additional obtainment of health and nutritional information on the mother before and/ or during pregnancy, further, her exposure to weather variables. Brown et al. (2014) provided a timeline diagram showing that the month prior to the measurement might be the month impacting child wasting, while child stunting might extend well beyond the last 12 months or even the time before birth. Subsequently, expanding the scope of inquiry by including data on the pregnancy and the mothers’ health would be suggested for further investigation.

(ii) Conduct lifecycle analyses to monitor child development and health in later life

Prospective monitoring and surveillance of children currently aged <5 years is highly recommended for further researcher. A life cycle assessment through the collection of long-term data would allow to better understand child growth, its respective risk factors and short- and long-term outcomes linked to diets, environmental and societal changes. Such long-term follow-up would allow (i) to observe the impact of climate change on child undernutrition, (ii) to relate it with associate climate-sensitive health outcomes such as respiratory, infectious and nutrition-related diseases (e.g. diabetes), and (iii) to study early life undernutrition with later life outcomes such as cognitive development, school performance or labor market productivity. While climate change is an event measured over several to up to 30 years, longitudinal data on child health and nutrition would support the analyses on delayed health outcomes that might only be visible after several years of exposure (Ebi, Boyer, et al., 2018).

(iii) Associate seasonal dietary diversity with child undernutrition

Further research would be encouraged in investigating seasonal and yearly variations in diets and their association with child undernutrition, which is likely to differ from the dry or post-harvest season (Nikièma et al., 2017). The present study took place exclusively during the rainy season, which overlaps with the lean season. The choice for this time window fell based on the research objective to assess the nutritional status of the children <5 years during the most difficult time of the year, when

harvest stocks are empty, an assessment of child undernutrition and diets over different seasons is encouraged. For example, Somé and Jones (2018) looked at household dietary diversity by four seasons in Burkina Faso in 2014. They found that dietary diversity was significantly higher during the beginning of the lean season (around June), during the lean season (around July to September) and the highest during the harvest seasons (around October to December) compared to the post-harvest season (December to February). Yet, the authors did not use anthropometric data in their analyses, wherefore further research looking at child undernutrition and its time-lagged association with dietary diversity would be recommended. Such a study is already on its way extending the present research. From 2021 onwards data collection is planned two-times a year to also cover the dry season in the Nouna HDSS area.

(iv) Measure food quantities to derive macro- and micronutrient contents of child diets

While the present study assessed dietary quality as proxied by Dietary Diversity Scores (DDS), Food Variety Scores (FVS) and Dietary Pattern Scores (DPSs), additional knowledge on food quantities and thus, micro- and macronutrient intake and adequacy is recommended. So far there is no gold standard of dietary assessments on how to best assess both diet quantity and quality including nutrient intake (Miller et al., 2020). Dietary recalls such as used in the present study may include dietary measurement methods such as weighed or estimated food quantities. However, such recalls are difficult to implement especially among population groups with a high illiteracy rates, wherefore more personnel and financial resources need to be administered. Equally, the identification of an appropriate assessment method of food quantity and quality that takes into account local eating habits would need to be set up and assessed. This was clearly beyond the scope of this present study. Overall, a closer observation of dietary quality and quantity would be recommended for the study region keeping in mind the impact of climate change on plant nutrient quality as a possible link to child undernutrition (Hoegh-Guldberg et al., 2018; Nelson et al., 2010).

(v) Project the future impact of climate on nutrition using climate models

Building on the present results and of those from other authors such as of Belesova et al. (2019b), who projected the impact of weather on crop yield and child mortality, further research on the projection of climate impacts is needed. Here, climate-nutrition response functions could be fed into climate-impact models (e.g. of the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP): <https://www.isimip.org/>) to project the future impact of climate change on child nutrition and health over various time horizons and under different scenarios. Research on its applicability is currently conducted within a Research Unit “Climate Change and Health in sub-Saharan Africa” funded by the German Research Foundation (DFG) (<https://www.cch-africa.de/>) and will strengthen the evidence of climate change as a risk factor for child undernutrition.

5.7. Recommendations for policy

Climate change is not only a global health threat, but also an opportunity to implement mitigation and adaptation actions that improve resilience, address poverty and encourage innovative approaches (Watts et al., 2015). This study encourages policy actions to integrate current and possible future climate impacts in their decision making to act and prevent direct and indirect effects on child health and nutrition. This requires the use of high-quality and long-term population-based health data as was the case in the present study (Sauerborn, 2017). Figure 28 provides an extended logistical framework for child undernutrition including climate-sensitive interventions to prevent child undernutrition and counteract climate change impacts. Specifically, these interventions may act as barriers to prevent or at least reduce the negative effects of climate change on all levels of population health in general and child undernutrition specifically. The actions cover (i) climate-sensitive health interventions, (ii) nutrition-specific and nutrition-sensitive interventions, and (iii) adaptation and mitigation actions to climate change focusing on agricultural management. All three aspects are further discussed below.

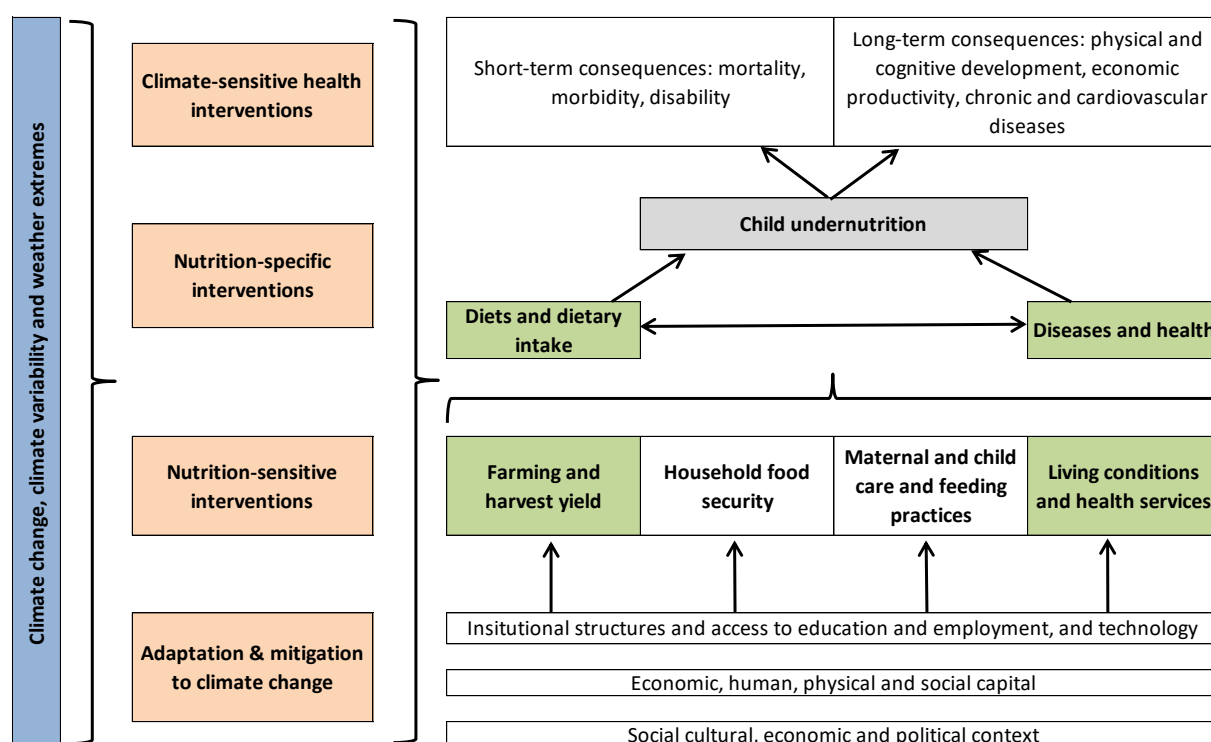


Figure 28: Extended logical framework for child undernutrition including climate-sensitive health interventions to prevent child undernutrition and counteract climate change impacts

Source: Adapted according to Figure 3 and Black et al. (2013)

(i) Integrate climate-sensitive health interventions in first-line health facilities

Climate-sensitive health interventions describe actions that target the reduction of health outcomes aggravated to or associated with climate change and variability. Specifically, they aim to reduce the

health vulnerability to climate-induced events, such as extreme temperatures and rainfall, low air quality, lack of food and (safe) water and increased vector-borne diseases (Ebi, Berry, et al., 2018).

Another option is building climate-resilient health care systems including capacity strengthening of health care professionals to communicate increased climate-diseases outcomes, or vulnerability assessments to identify those population groups and regions that require the most urgent support and/or will be risk-prone in the future (Ebi, Boyer, et al., 2018; Tong et al., 2016; von Grebmer et al., 2020; WHO, 2015).

In order to address climate-sensitive health outcomes, an entry point for action are the basic health care facilities. They are located in close proximity to the villages and provide the first contact point to get treatment and to receive health information. The present study has shown that child undernutrition is directly associated with diarrhea and fever episodes (likely linked to malaria), safe water sources for drinking and cooking and maternal practices on breastfeeding. Health personal should be trained on their relationship with climate to increase action during the rainy season, when the disease incidence increases as well as provide counselling and guidance over the year to prevent those (Sauerborn et al., 1996b).

Additionally, the health care system should provide special attention to mothers during pregnancy, as they are likely to be increasingly exposed to heat stress and unhygienic conditions due to flooding. Mothers, who were exposed to extreme weather events, were more likely to give birth to a child with low birth weight than those than those, who were not exposed (Davenport et al., 2017; Grace et al., 2015).

(ii) Promote dietary diversity and climate resilience through nutrition programs and vegetable gardens

Optimal child nutrition and development in the context of increased climate change should be addressed through a combination of actions to increase resilience of specifically vulnerable population groups (Watts et al., 2019). Hence, a combination of so-called nutrition-specific and nutrition-sensitive interventions should be implemented. They address the underlying causes of child undernutrition and incorporate socio-economic development and climate change adaptation and mitigation programs (de Onis & Branca, 2016; Herforth et al., 2012; Ruel & Alderman, 2013).

Nutrition-specific interventions act at the individual level and include optimal infant and young child feeding practices (micronutrient supplementation, breastfeeding promotion, complementary feeding, food diversification and fortification, or disease treatment) (Reinhardt & Fanzo, 2014). Those actions go along with the climate-sensitive health actions and may be addressed at the individual and household level. This includes counseling on healthy and diverse diets for children, adolescents and mothers, food supplementation and fortification, as well as nutrition interventions during emergencies. The latter includes actions during food shortages such as during the rainy season, which overlaps with the lean season. Specifically, during these months with an increased risk for household food shortages,

actions are required by providing food aid (e.g. Plumpy'Nut a peanut-based paste to treat severe acute malnutrition) or financial support.

Nutrition-sensitive interventions can support the self-sufficiency of households in parallel to nutrition-specific actions, as they act on the social and economic level and include agricultural interventions, social safety nets, education, sanitation, or voluntary family planning (Herforth et al., 2012). Specifically, home gardens and animal husbandry could act to increase self-sufficiency, dietary diversity and climate resilience. Home gardens are one of the oldest, wide-spread and most enduring practices of cultivation. They are defined as small-scale production systems, located close to the house for security, convenience and special care, requiring low capital input and simple technology and providing for home and animal consumption (Galhena et al., 2013; Masset et al., 2012). Such gardens are specifically useful and effective in low-resource communities as is the Nouna HDSS area. Their advantage is the addition of vegetable, fruits, spices and herbs, which may contribute to the consumption of vegetables and fruits and thus, contribute to dietary diversity.

An intervention trial on the effectiveness and acceptability of both home garden and nutrition counselling is currently implemented in the Nouna HDSS area. In the form of a randomized controlled trial (RCT), 300 children will receive nutrition counselling and home gardening support and 300 children will act as the control group to measure the effect difference. Similar projects were already implemented in Burkina Faso specifically targeting rural subsistence farming environments in the Southern rural areas of the country (Gross & Jaubert, 2019; Olney et al., 2015) and in urban schools (Schreinemachers et al., 2019). In both settings positive outcomes on child and adolescent health and an increased dietary diversity were measured (Downs & Demmler, 2020; Olney et al., 2015) and encourage further implementation or scale-up of such interventions.

(iii) Use small-scale weather and household food crop yield data to reduce food insecurity

Although crop yield forecasting is not a new field, e.g. Sentinel-2 satellites made forecasting yield shortages on the household level possible. The present study validated its effectiveness in predicting food crop harvests. Crop growth monitoring through remote sensing may portray subsistence farming food crop production and the vulnerability of smallholder farmers to a lack or loss of yield as one of the central determinants of child undernutrition. Through the use of satellite remote sensing, crop growth and yield of small-scale subsistence farmers allows to (i) forecast vulnerable villages that are affected by weather variability and extremes, (ii) monitor abnormal events that reduce agricultural yield (e.g. droughts or environmental disasters), and (iii) observe farming management strategies and differences of yield between groups and regions and their benefit to food crop production.

One major application would be in the growing field of weather-based crop insurance (Fonta et al., 2018; Leblois & Quirion, 2013). The advantages of the CHIRPS dataset consists in providing highly specially-resolved weather data, which makes it possible to derive climate variability indicators and their exposure at the village or even the household field resolution. This would be in contrast to the

current use of a national weather data, which is limited to a few areas and, therefore, only available at larger-scale. Improved and more spatially resolved weather information could be combined to exploring the gap in harvest by subsistence farmers combining high-resolution weather data with satellite-based harvest quantification or even prediction and measuring the climate-induced gap of food crop harvest. A weather-based crop insurance could then react and provide customized benefit payments to villages or even individual farmers. Subsequently, remote sensing applications may contribute to the prevention of household food insecurity and child undernutrition through the provision of timely spatial observations, predictions and forecasts. Therefore, crop yield forecasting would allow developing an early-warning system for decision-makers to counter food crop shortage and prevent household food insecurity and child undernutrition.

Overall, this study encourages public health authorities, policy makers and researchers to promote and evaluate measures to adapt to the adverse impacts of climate variability to prevent child undernutrition.

6. Summary

Undernutrition continues to threaten millions of children's lives, especially in developing countries. Climate change is projected to exacerbate inequalities and negatively impact child undernutrition directly and indirectly. The present study assessed the association between undernutrition of children aged <5 years living in subsistence farming households and climate change, as proxied by rainfall variability in rural Burkina Faso. Both children's nutrition and health are likely to worsen with climate change. Indeed, climate change may halt or reverse efforts made to date to reduce undernutrition.

This research was structured around four objectives (i) socio-economic risk factors for and (ii) associations of diets with child undernutrition, and (iii) the link between rainfall variability and child undernutrition. Additionally, (iv) a validation study was conducted to compare weighed agricultural yield of small-scale household fields against freely available satellite imagery as an additional link to child undernutrition. These objectives were addressed through the use of a variety of study instruments and statistical approaches requiring the involvement of outside domain experts. The interdisciplinary nature of this research combining health, diet and climate made the analyses and findings unique in its current form. Data was analyzed from an open dynamic cohort of initially 470 children between 7 and 60 months contributing to 1,439 person-years during three years of follow-up. The study design accounted for five local weather stations located in the Nouna Health and Demographic Surveillance System (HDSS) area to investigate the associations on different geographical- and time-scales.

The following findings were made:

First, undernutrition of children aged <5 years was found to remain a serious problem in the study area. In 2019, 19 % of the children in this study were stunted (chronic undernutrition) and 5 % were wasted (acute undernutrition). These children were found highly vulnerable to demographic and socio-economic factors including disease episodes and ethnical background, but also location, i.e. the geographical cluster they lived in.

Second, dietary diversity was low in the study population. 92 % of the children did not reach the internationally recommend minimum dietary diversity of 5 or more food groups over the previous 24 hours. They commonly consumed sorghum, rice, Vitamin-A rich leaves, and oils and fats during the data collection period (the rainy season). The consumed foods were found to differ significantly between study clusters, but were undistinguishable between boys and girls. Based on a 7-day dietary recall, dietary patterns were identified through principal component analysis (PCA), which yielded three patterns of foods commonly consumed together: (i) market-based (pasta, eggs, poultry, sweets), legume-based (African locust bean, oils and fats, leaves, peanuts) and vegetable-based (okra, tomatoes, eggplant). Children, who followed the market- or legume-based diet were found less likely to be stunted, while children, who followed the vegetable-based diet had a lower risk for wasting.

Third, the link between child undernutrition with rainfall variability was investigated through (i) direct associations of single rainfall variability indicators, and (ii) a hypothesis-driven approach by which the three dietary patterns (market-, legume- and vegetable-based diets) interacted with rainfall and child undernutrition.

In total, 15 individual rainfall variability indicators were constructed for four time periods to identify their association with child stunting and wasting: the years prior to and of birth, and the years prior to and of the nutrition survey. The direct associations revealed that child stunting was significantly associated with rainfall of the year before the survey and child wasting with the year of birth. In the hypothesis-driven approach, a “precipitation variability score (PVS)” was constructed through Reduced Rank Regression (RRR), a method used in nutrition epidemiology. The PVS was based on a combination of the 15 rainfall indicators and their association with the three dietary patterns. In sum, when the PVS pattern and so rainfall variability increased, the children had a higher risk for stunting.

Lastly, an agricultural validation study was conducted in 2018 comparing weighed samples of food crop field harvests with remotely sensed estimates (using Sentinel-2 satellites) as jointly developed with a cooperation partner. The model was validated with on the ground weighed harvest and trained for future harvest quantification based on remote sensing alone. It showed good fit to estimate agricultural yields at small-scale spatial resolution of individual household fields. Furthermore, it was able to predict yield of individual food crops before the actual harvest occurred.

To conclude, the findings of the study contributed a range of different insights into the associations of climate variability and child undernutrition. This study encourages policy actions to integrate climate change in their national and local decisions to act on its direct and indirect impacts on child health. Possible adaptation actions include the awareness of climate-sensitive diseases in health care systems, the scale-up of vegetable gardens to enhance dietary diversity, and the monitoring and forecasting of crop yield through satellite remote sensing. Equally, adaptation measures should consider for different geographic and time impacts of climate change on child undernutrition.

Zusammenfassung

Unterernährung bedroht weiterhin das Leben von Millionen von Kindern, insbesondere in Entwicklungsländern. Der Klimawandel verschärft die Ungleichheiten, die sich direkt und indirekt negativ auf die Ernährung von Kindern auswirken. In der vorliegenden Studie wurde der Zusammenhang zwischen Unterernährung von Kindern unter 5 Jahren und dem Klimawandel untersucht, der durch die Variabilität der Niederschläge im ländlichen Burkina Faso betrachtet wird. Es ist wahrscheinlich, dass sich die Ernährung als auch die Gesundheit von Kindern mit dem Klimawandel verschlechtern werden. In der Tat gefährdet der Klimawandel die bisher unternommenen Anstrengungen zur Verringerung der Unterernährung.

Diese Forschung untersuchte den Zusammenhang von Unterernährung mit (i) sozioökonomischen Risikofaktoren, (ii) Diäten und (iii) Niederschlagsvariabilität. Zusätzlich wurde (iv) eine Validierungsstudie durchgeführt, um gewogene Ernteerträgen mit frei verfügbaren Satellitenbildern als zusätzlichen Zusammenhang zur Unterernährung von Kindern zu vergleichen. Diese Ziele wurden durch den Einsatz verschiedener Studieninstrumente und statistischer Ansätze untersucht, die die Einbeziehung externer Fachleute erforderte. Der interdisziplinäre Charakter dieser Forschung, der Gesundheit, Ernährung und Klima kombinierte, macht die Analysen und Ergebnisse in ihrer gegenwärtigen Form einzigartig. Die Daten wurden aus einer offenen dynamischen Kohorte von anfänglich 470 Kindern zwischen 7 und 60 Monaten analysiert, die während drei Jahren Follow-up zu 1.439 Personenjahren beitrugen. Das Studiendesign umfasste fünf lokale Wetterstationen im Gebiet des Nouna Health and Demographic Surveillance System (HDSS), um die Assoziationen auf verschiedenen räumlichen und zeitlichen Skalen zu untersuchen.

Folgende Feststellungen wurden gemacht:

Erstens wurde festgestellt, dass die Unterernährung von Kindern unter 5 Jahren im Untersuchungsgebiet weiterhin ein ernstes Problem darstellt. 2019 waren 19 % der Kinder in dieser Studie chronisch und 5% akut unterernährt. Diese Kinder waren sehr anfällig für demografische und sozioökonomische Einflüsse, einschließlich Krankheitsepisoden und ethnischem Hintergrund, aber auch für den Wohnort, in dem sie lebten.

Zweitens war die Ernährungsvielfalt in der Studienpopulation gering. 92% der Kinder haben in den letzten 24 Stunden die international empfohlene Mindestdiätvielfalt von 5 oder mehr Lebensmittelgruppen nicht erreicht. Während der Datenerfassungsperiode (der Regenzeit) konsumierten sie üblicherweise Sorghum, Reis, Blätter sowie Öle und Fette. Die konsumierten Lebensmittel unterschieden sich signifikant zwischen den Wohnregionen, waren jedoch zwischen Jungen und Mädchen nicht zu unterscheiden. Basierend auf einem 7-tägigen Ernährungsfragebogen wurden Ernährungsmuster durch eine Hauptkomponentenanalyse (PCA) identifiziert. Diese Muster kombinieren Lebensmittel, die üblicherweise zusammen konsumiert werden, welche sind: (i) eine

marktbasiert (Nudeln, Eier, Geflügel, Süßigkeiten), eine hülsenfruchtbasierte (Afrikanische Johannisbrotbohne, Öle und Fette, Blätter, Erdnüsse) und eine pflanzenbasiert (Okra, Tomaten, Auberginen) Diät. Kinder, die die markt- oder hülsenfruchtbasierte Diät befolgten, waren weniger chronisch unterernährt, während Kinder, die die pflanzenbasierte Diät befolgten, ein geringeres Risiko für akute Unterernährung hatten.

Drittens wurde der Zusammenhang zwischen Unterernährung und Niederschlagsvariabilität durch zwei verschiedene Ansätze untersucht: (i) direkte Assoziationen einzelner Indikatoren der Niederschlagsvariabilität und (ii) ein hypothesengetriebener Ansatz, mit dem die drei Ernährungsmuster (markt-, hülsenfrucht- und pflanzenbasierte Diäten) mit Regenfällen und Unterernährung von Kindern interagiert wurden.

Insgesamt wurden 15 individuelle Indikatoren zur Niederschlagsvariabilität für vier Zeiträume erstellt, um ihren Zusammenhang mit chronischer und akuter Unterernährung von Kindern zu identifizieren: die Jahre vor und nach der Geburt sowie die Jahre vor und nach der Ernährungsumfrage. Die direkten Assoziationen ergaben, dass chronische Unterernährung signifikant mit dem Niederschlag des Jahres vor der Umfrage und akute Unterernährung mit dem des Geburtsjahres verbunden war. Bei dem hypothesengetriebenen Ansatz wurde ein „Niederschlagsvariabilitäts-Muster (PVS)“ durch Reduced Rank Regression (RRR) erstellt, eine Methode aus der Ernährungsepidemiologie. Das PVS-Muster basierte auf einer Kombination der 15 Niederschlagsindikatoren und ihrer Assoziation mit den drei Ernährungsmustern. In der Summe hatten die Kinder ein höheres Risiko für die chronische Unterernährung, wenn das PVS-Muster und damit die Niederschlagsvariabilität zunahmen.

Zusätzlich wurde 2018 eine landwirtschaftliche Validierungsstudie durchgeführt. Hierfür wurden gewogene Feldfruchtproben mit fernerkundeten Schätzungen (Sentinel-2-Satellitenbildern) verglichen. Das Modell wurde mit vor Ort gewogener Ernte validiert, um in der Zukunft Erntequantifizierung allein anhand der Fernerkundung durchzuführen. Es zeigte eine gute Übereinstimmung der landwirtschaftlichen Erträge bei kleinräumiger Auflösung einzelner Haushaltsfelder. Darüber hinaus konnte der Ertrag einzelner Feldfrüchte vor der eigentlichen Ernte vorhergesagt werden.

Zusammenfassend lieferten die Ergebnisse der Studie verschiedene Einblicke in die Zusammenhänge von Klimavariabilität und Unterernährung von Kindern. Diese Studie ermutigt zu politischen Maßnahmen, in denen der Klimawandel und seine direkten und indirekten Auswirkungen auf die Gesundheit von Kindern in Entscheidungen mit einfließen. Mögliche Anpassungsmaßnahmen umfassen das Bewusstsein für klimasensitive Krankheiten in Gesundheitssystemen, der Anbau von Gemüsegärten zur Verbesserung der Ernährungsvielfalt sowie die Erfassung und Vorhersage von Ernteerträgen durch Satellitenfernerkundung. Ebenso sollten Anpassungsmaßnahmen unterschiedliche räumliche und zeitliche Auswirkungen des Klimawandels auf die Unterernährung von Kindern berücksichtigen.

Exposé

La malnutrition continue de menacer la vie de millions d'enfants, en particulier dans les pays en développement. Le changement climatique devrait exacerber les inégalités et avoir un impact négatif direct et indirect sur la malnutrition des enfants. La présente étude a évalué l'association entre la malnutrition des enfants âgés de moins de 5 ans vivant dans des ménages d'agriculture de subsistance et le changement climatique, montrée par la variabilité des précipitations dans les zones rurales du Burkina Faso. La nutrition et la santé des enfants vont probablement empirer avec le changement climatique. En effet, le changement climatique peut arrêter ou inverser les efforts déployés à ce jour pour réduire la malnutrition.

Cette recherche s'est structurée autour de quatre objectifs : (i) les facteurs de risque socio-économiques à la et (ii) les associations de régimes alimentaires avec la malnutrition, et (iii) le lien entre la variabilité pluviométrique et la malnutrition des enfants. En outre, (iv) une étude de validation a été menée pour comparer le rendement agricole pondéré des champs des ménages à l'imagerie satellite disponible gratuitement comme lien supplémentaire avec la malnutrition des enfants. Ces objectifs ont été atteints grâce à l'utilisation d'une variété d'instruments d'étude et d'approches statistiques nécessitant la participation des experts du domaine extérieur. Le caractère interdisciplinaire de cette recherche, combinant santé, alimentation et climat, a rendu les analyses et les résultats uniques dans sa forme actuelle. Les données ont été analysées à partir d'une cohorte dynamique ouverte de 470 enfants initialement âgés de 7 à 60 mois contribuant à 1 439 personnes-années pendant trois ans de suivi. La conception de l'étude a pris en compte cinq stations météorologiques locales situées dans la zone du Health and Demographic Surveillance System (HDSS) de Nouna pour enquêter sur les associations à différentes échelles géographiques et temporelles.

Les constatations suivantes ont été faites:

Premièrement, la malnutrition des enfants âgés de moins de 5 ans reste un problème sérieux dans la zone d'étude. En 2019, 19% des enfants de cette étude présentaient un retard de croissance (malnutrition chronique) et 5% étaient sévèrement aigüé (malnutrition aigüé). Ces enfants ont été jugés très vulnérables aux facteurs démographiques et socio-économiques, y compris les épisodes de maladie et l'origine ethnique, mais aussi l'emplacement, c'est-à-dire la place dans laquelle ils vivaient.

Deuxièmement, la diversité alimentaire était faible dans la population étudiée. 92% des enfants n'ont pas atteint la diversité alimentaire minimale recommandée au niveau international de 5 groupes d'aliments ou plus au cours des dernières 24 heures. Ils consommaient couramment du sorgho, du riz, des feuilles riches en vitamine A et des huiles et des graisses pendant la période de collecte des données (la saison des pluies). On a constaté que les aliments consommés différaient considérablement entre les groupes d'étude, mais n'étaient pas distinguables entre les garçons et les filles. Sur la base d'un rappel alimentaire de 7 jours, les schémas alimentaires ont été identifiés grâce à l'analyse en composantes principales (PCA), qui a donné trois schémas d'aliments couramment consommés

ensemble: (i) basés du marché (pâtes, œufs, volaille, bonbons), basés des légumineuses (nééré, huiles et graisses, feuilles, arachides) et basés des végétales (gombo, tomates, aubergines). Les enfants qui suivaient le régime basés du marché ou basés des légumineuses étaient moins susceptibles d'avoir un retard de croissance, tandis que les enfants, qui suivaient le régime basés des légumes, avaient un risque moindre de malnutrition aiguë.

Troisièmement, le lien entre la malnutrition des enfants et la variabilité des précipitations a été étudié à travers (i) des associations directes des indicateurs uniques de variabilité des précipitations, et (ii) une approche basée sur des hypothèses par laquelle les trois schémas d'aliments (basés du marché, des légumineuse et des légumes) interagissaient avec les précipitations et la malnutrition des enfants.

Au total, 15 indicateurs individuels de variabilité des précipitations ont été construits pour quatre périodes afin d'identifier leur association avec le retard de croissance et la malnutrition aiguë chez les enfants: les années avant et après la naissance, et les années avant et de l'enquête nutritionnelle. Les associations directes ont révélé que le retard de croissance des enfants était significativement associé aux précipitations de l'année précédant l'enquête et la malnutrition aiguë des enfants avec les d'année de naissance. Dans l'approche basée sur des hypothèses, un «modèle de variabilité des précipitations (PVS)» a été construit par Reduced Rank Regression (RRR), une méthode utilisée en épidémiologie de la nutrition. Le PVS était basé sur une combinaison des 15 indicateurs de précipitations et de leur association avec les trois schémas d'aliments. En somme, lorsque le modèle PVS et donc la variabilité des précipitations augmentaient, les enfants avaient un risque plus élevé de retard de croissance.

Enfin, une étude de validation agricole a été menée en 2018 en comparant des échantillons pesés de récoltes vivrières au champ avec des estimations par télédétection (utilisant l'imagerie satellite Sentinel-2) développées conjointement avec un partenaire de coopération. Le modèle a été validé avec des récoltes pesées au sol et formé pour la quantification future de la récolte basée uniquement sur la télédétection. Il a montré un bon ajustement pour estimer les rendements agricoles à une résolution spatiale à petite échelle des champs des ménages individuels. De plus, il a pu prédire le rendement des cultures vivrières individuelles avant la récolte effective.

Pour conclure, les résultats de l'étude ont fourni une gamme de points de vue différents sur les associations de la variabilité climatique et de la malnutrition des enfants. Cette étude encourage les actions politiques visant à intégrer le changement climatique dans leurs décisions nationales et locales afin d'agir sur ses impacts directs et indirects sur la santé des enfants. Les mesures d'adaptation possibles comprennent la sensibilisation aux maladies sensibles au climat dans les systèmes de soins de santé, l'extension des jardins potagers pour améliorer la diversité alimentaire, et la surveillance et la prévision du rendement des cultures grâce à la télédétection par satellite. De même, les mesures d'adaptation devraient tenir compte des différents impacts géographiques et temporelles du changement climatique sur la malnutrition des enfants.

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Own publications

This study was part of a research project that started in 2014 and continues up to today. The project idea was developed by Prof. Dr. Dr. Rainer Sauerborn and was first published as a feasibility study investigating the link between child undernutrition and crop yield through satellite remote sensing in the Nouna HDSS area in Burkina Faso from 2014 to 2015 (Sorgho et al., 2016). The here presented study extended this work substantially to deepen its statistical power and methodological approach. This includes the extension of the socio-economic household questionnaire, a detailed questionnaire on diets of children aged <5 years and a novel assessment protocol on the validation of remote sensing data through ground harvest weight. The study procedures, the data collection and the data analyses were carried out entirely by me. The output of the remote sensing analysis and the creation of the improved rainfall data set (CHIRPS) were provided in collaboration with research partners, namely Dr. Jonas Franke from Remote Sensing Solutions (RSS) GmbH and Dr. Jan Bliedernicht from the Augsburg University (see Chapter 3.5 for a synopsis of study components). The joint work and the respective contributions made were published in peer-reviewed papers as listed below.

Aspects of the here presented study contributed to and are still carried out within individual research projects of a Research Unit funded by the German Research Foundation (Deutsche Forschungsgemeinschaft, DFG) entitled „Climate Change and Health in sub-Saharan Africa“ (2020 – 2023). The Research Unit runs under the leadership of Prof. Dr. Dr. Rainer Sauerborn and Jun.-Prof. Dr. Ina Danquah (<https://www.cch-africa.de/>).

Partial results of the presented work were published in advance in the following publications:

1. **Mank, I.**, Belesova, K., Bliedernicht, J., Traoré, I., Wilkinson, P., Danquah, I., & Sauerborn, R. (2021). The impact of rainfall variability on diets and undernutrition of children <5 years in rural Burkina Faso. *Frontiers in Public Health* (submitted). (shared last authorship) (IF 2.4)
2. **Mank, I.**, Vandormael, A., Traoré, I., Ouédraogo, W. A., Sauerborn, R., & Danquah, I. (2020). Dietary habits associated with growth development of children aged < 5 years in the Nouna Health and Demographic Surveillance System, Burkina Faso. *Nutrition Journal*, 19(1), 81. <https://doi.org/10.1186/s12937-020-00591-3> (shared last authorship) (IF 2.6)
3. Karst IG, **Mank I**, Traoré I, Sorgho R, Stückemann K-J, Simboro S, Sié A, Franke J, Sauerborn R (2020). Estimating Yields of Household Fields in Rural Subsistence Farming Systems to Study Food Security in Burkina Faso. *Remote Sens.* 12(11), 1717. <https://doi.org/10.3390/rs12111717> (shared first and shared last authorship) (IF 4.5)

Publication 1 was not yet published, but under review at the time of the submission of this dissertation. The publication was based on the results presented in Chapter 4.3.3 and Chapter 4.3.4. Parts of the discussion in Chapter 5.3 on rainfall variability and child undernutrition were taken up and included in the publication. Publication 2 focused on children's diets in the Nouna HDSS area using solely data from 2018. The statistical approach was mirrored for the here presented results as outlined in Chapter

3.4.4. Parts of the work can also be found in Chapter 4.2 and Chapter 5.2. Publication 3 was jointly written with Ms. Karst, wherefore shared first authorship was agreed on. Ms. Karst was in charge of the methodological approach and statistical analysis. My own contribution was the agricultural questionnaire development, the data collection approach and supervision on the ground and the discussion with regard to the scientific contribution of this work. Parts of this publication can be found in Chapter 3.4.6, Chapter 4.4 and Chapter 5.4.

Additional own publications:

4. Sorgho, R., **Mank, I.**, Kagoné, M., Souares, A., Danquah, I., & Sauerborn, R. (2020). “We Will Always Ask Ourselves the Question of How to Feed the Family”: Subsistence Farmers’ Perceptions on Adaptation to Climate Change in Burkina Faso. *International Journal of Environmental Research and Public Health*, 17(19), 7200. <https://doi.org/10.3390/ijerph17197200> (shared last authorship) (IF 2.8)
5. Yeboah E, Bunker A, Dambach P, **Mank I**, Sorgho R, De Allegri M, Vounatsou P, Sié A, Munga S, Bärnighausen T, Sauerborn R, Danquah I (2020). Transformative adaptations for health impacts of climate change in Burkina Faso and Kenya: Agricultural bio-diversification, cool roofs, index-based weather insurance, and larviciding against malaria vectors. In: Filho L et al. (eds). *African Handbook of Climate Change. Adaptation*. Springer Verlag, Heidelberg.
6. Nayna Schwerdtle, P., McMichael, C., **Mank, I.**, Sauerborn, R., Danquah, I., & Bowen, K. (2020). Health and migration in the context of a changing climate: A systematic literature assessment. *Environmental Research Letters*. <https://doi.org/10.1088/1748-9326/ab9ece> (IF 6.1)

Appendices

Appendix A: Household socio-economic and agricultural questionnaires

Appendix 1: Household socio-economic questionnaire

QUESTIONNAIRE MENAGE

Nom et prénom de l'enquêteur _____	Code enquêteur _ _ _
Date de visite _ _ _ _ _ _ _ _ _	Heure de visite _ _ _ _
Nom de village _____	ID de ménage _ _ - _ _ _ - _ - _
Nom d'enfant _____	ID d'enfant _ _ _ _ _ _ _ _ _ _
Nom et prénom de superviseur _____	Code superviseur _ _ _

Présentation d'enquêteur

- Mon nom est ... et je fais partie de l'équipe du Centre de Recherche en Santé de Nouna.
- Nous faisons une étude sur la nutrition des enfants à cause de rapide changement de temps et ses effets sur la nourriture dans le district. Nous sommes intéressés par la situation des enfants, des familles, et des ménages. [Nous étions déjà chez vous l'année dernière et nous voulons poser des questions similaires cette fois-ci.]
- Maintenant, j'aimerais poser quelques questions sur votre ménage et parler avec vous (le chef de ménage), le responsable d'agriculture si ce n'est pas vous, et votre femme qui a l'enfant moins de 5 ans.
- Ces questions nous aiderons à savoir si votre enfant est mal nourri et les causes possibles. Vos réponses nous aiderons aussi à comprendre les raisons derrière la malnutrition de votre enfant. La malnutrition est un stade où les enfants ont faim, et manque de vitamines et minérales. Ce n'est pas tous le temps visible, mais ça a des effets sur le développement de votre enfant. Pour la collecte de donné, je voudrais prendre des informations sur la taille, le poids et le tour de bras de l'enfant.
- Les informations que vous allez nous donner seront traitées d'une façon confidentielle. Tout ce que vous me direz sera utilisé uniquement pour notre recherche.
- Les informations que vous allez nous donner vont aider à la planification des interventions pour le contrôle de la nutrition et d'autres maladies dans votre région.
- Si vous acceptez de participer, je vous poserais des questions qui vont prendre à peu près 30 minutes pour vous (et le responsable d'agriculture) et 1 ou 1.30 heure pour votre femme (par enfant). Vous pouvez refuser de participer ou arrêter à un moment donné et il n'y aura **pas** de conséquences négatives.
- Je voudrais vous donner le consentement éclairé. S'il vous plaît vous pouvez le lire et me posez des questions si vous avez quelques-unes. Si vous préférez je peux vous le lire. [Donnez-lui/-elle le consentement éclairé.] C'est d'accord de commencer maintenant ?

	Premièrement		
QM01	Le consentement éclairé est-il signé ?	Oui=1, Non=2	_
<i>Si NON, remerciez la/ les personne/s et terminez l'enquête.</i>			
<i>Si OUI, continuez avec les questions suivantes.</i>			
QM02	Langue utilisée	Dioula=1, Mooré=2, Français=3, autre langue=4 (précisez)	_
QM03	Qui est le/la répondant/e principal/e?	Nom, prénom (âge en ans)	_____ _ _

QUESTIONNAIRE SOCIO-ECONOMIQUE

J'aimerais tout d'abord vous poser des questions sur le chef de ménage (vous) et à propos de votre ménage, des conditions de votre habitation et de votre accès à des réseaux d'eau.

Le chef de ménage ou son représentant si ce n'est pas possible pour le chef d'être la			
QM04	Nom, prénom de chef de ménage	_____	
QM05	Date de naissance (ou âge) de CM	jour/mois/ année (ou âge)	_ _ _ _ _ _ _ (_ _)
QM06	Sexe de CM	Masculin=1, Féminin=2	_
QM07	Niveau d'éducation de CM	Aucun=1, alphabétisé=2, primaire=3, secondaire=4	_
QM08	Ethnie de CM	Bwaba=1, Mossi =2, Peul=3, Samo=4, Marka (Dafing)=5, Dogon=6, Autre=7 (précisez)	_
QM09	Religion de CM	Aucun=1, Animiste=2, Musulman=3, Catholique=4, Autre=5 (précisez)	_
QM10	Statut matrimonial de CM	Célibataire=1, Monogame=2, Polygame=3, Veuf/-ve =4, Divorcé(e)=5, Autre=6 (précisez)	_
QM11	Occupation principale de CM	Agriculteur=1, Eleveur=2, Agriculteur et éleveur=3, Commerçant=4, Autre=5 (précisez)	_
Les membres de ménage			
QM12	Combien de personnes y a-t-il dans ce ménage?	Nombre	_ _
QM13	Combien de personnes y a-t-il dans ce ménage qui sont de votre famille ?	Nombre	_ _
QM14	Combien de personnes vivent dans une chambre en général ?	Nombre	_ _
QM15	Combien des enfants y a-t-il dans votre ménage de moins de 5 ans ?	Nombre	_ _
Les biens de ménage			
<i>Avec quels matériaux avez-vous construit la maison de votre habitation ? [demandez et observez en même temps]</i>			
QS01	Toit	Tôles ou équivalent=1, paille/ chaume=2, terre battue=3, bois=4, autre=5 (précisez)	_
QS02	Mur	Dur (béton)=1, pierre taillée=2, banco amélioré=3, terre-battue=4, bois, végétaux, nattes=5, tente=6, autre=7 (précisez)	_
QS03	Sols	Ciment pure=1, terre-battue=2, carreau=3, autre=4 (précisez)	_
QS04	Source de l'eau consommable	Robinet/ borne-fontaine=1, pompe/ forage=2, puits=3, cours d'eau/marigot=4, pluie=5, bouteille/ sachet=6, autre=7 (précisez)	_
QS05	Source de l'eau pour se laver les mains	Robinet/ borne-fontaine=1, pompe/forage=2, puits=3, cours d'eau/marigot=4, pluie=5, autre=6 (précisez)	_
QS06	Lieu de l'eau	Dans le bâtiment=1, dans la cour=2, chez le voisin=3, forage/ puits public=4, autre=5 (précisez)	_

QS07	Latrines	Latrine dans un bâtiment=1, latrine dans la cour (ciel ouvert)=2, latrine public=3, nature=4, autre=5 (précisez)	_ _
QS08	Éclairage	Electricité=1, batteries=2, piles/ torches=3, gaz=4, pétrole=5, bougie=6, plaques/ lampe solaires=7, autre=8 (précisez)	_ _
QS09	Source d'énergie pour cuisinière	Bois de chauffe=1, charbon de bois=2, gaz=3, résidus agricoles=4, bouse d'animaux=5, ordure=6, autre=7 (précisez)	_ _
QS10	Jardin potager (avec des légumes)	Oui=1, Non=2	_ _
QS11	Arbre fruitier	Nombre	_ _

Maintenant je voudrais vous poser des questions sur les biens matériels en BON ETAT et les animaux de votre ménage. Pour chaque bien/animal que je vais citer, ce n'est pas important d'indiquer le propriétaire direct, mais plutôt le nombre total d'éléments qu'on trouve dans votre ménage. Ceci n'a rien à voir avec les impôts ! Est-ce qu'il y a dans ce ménage : ?

Biens							
QS12	Bicyclette	Nombre	_ _	QS19	Lecteur DVD	Nombre	_ _
QS13	Mobylette/ moto	Nombre	_ _	QS20	Frigo	Nombre	_ _
QS14	Voiture	Nombre	_ _	QS21	Cuisinière	Nombre	_ _
QS15	Machine à coudre	Nombre	_ _	QS22	Radio	Nombre	_ _
QS16	Appareil K7/ CDs	Nombre	_ _	QS23	TV	Nombre	_ _
QS17	Téléphone portable	Nombre	_ _	QS24	Groupe électrogène	Nombre	_ _
QS18	Internet (Wifi) dans le ménage	Oui=1, Non=2	_	QS25	Ordinateur	Nombre	_ _
Animaux							
QS26	Volaille	Nombre	_ _	QS31	Ane	Nombre	_ _
QS27	Mouton	Nombre	_ _	QS32	Lapin	Nombre	_ _
QS28	Chèvre	Nombre	_ _	QS33	Porc	Nombre	_ _
QS29	Bœuf	Nombre	_ _	QS34	Chien	Nombre	_ _
QS30	Cheval	Nombre	_ _	QS35	Autre (précisez)	Nombre	_ _

Pratique agricole

Et plus, j'aimerais vous (ou le responsable des champs) poser des questions sur le statut agriculture et vos champs.

Les travailleurs sur les champs			
QA01	Combien de personnes travaillent sur vos champs en général?	Nombre	_ _
QA02	Combien de ces personnes sont des personnes de votre ménage ?	Nombre	_ _
QA03	Avez-vous d'autres personnes que de votre ménage que vous payez pour travailler sur vos champs ?	Oui=1, Non=2	_

Je voudrais vous poser des questions sur les dispositifs agricoles de votre ménage. Pour chaque dispositif que je vais citer, ce n'est pas important d'indiquer le propriétaire direct, mais le nombre en total qu'on trouve dans votre ménage. Est-ce qu'il y a...?

Dispositifs agricoles							
QA03	Faucille	Nombre	_ _	QA09	Tracteur	Nombre	_ _
QA04	Chariot grand	Nombre	_ _	QA10	Charrues	Nombre	_ _
QA05	Chariot petite	Nombre	_ _	QA11	Charrettes	Nombre	_ _
QA06	Pioche	Nombre	_ _	QA12	Houe	Nombre	_ _
QA07	Daba	Nombre	_ _	QA13	Machette	Nombre	_ _
QA08	Hache	Nombre	_ _				
Les cultures et champs							
QA14	Combien de champs de céréales avez-vous cette année (2018) ?		Nombre				_ _
QA15	Combien d'hectares en total (estimation)?		Hectares				_ _ _ , _ _ hectares
QA16	Y a-t-il eu pénurie alimentaire depuis la dernière récolte (2017)?		Oui=1, Non=2				_
QA17	La pénurie a concerné quelle culture ? (non applicable=99)		_____ _ _				
Quelles cultures avez-vous cette année et combien de champs avec ces cultures?							
	Nom de culture	Nombre de champs avec ces cultures	Association de cultures, si applicable (non applicable=99)		Nom de culture	Nombre de champs avec ces cultures	Association de cultures, si applicable (non applicable=99)
QA18	Sorgho	_ _		QA23	Arachide	_ _	
QA19	Petit mil	_ _		QA24	Sésame	_ _	
QA20	Fonio	_ _		QA25	Coton	_ _	
QA21	Mais	_ _		QA26	Haricot (niébé)	_ _	
QA22	Riz	_ _					
Revenu monétaire							
QR01	Principale source de revenu du ménage		Vente des produits agricoles=1, Vente de produits maraîchers=2, Vente d'animaux = 3, Commerce=4, Orpaillage=5, Travail agricole=6, Autre=7 (précisez)				_
QR02	Le ménage a-t-il reçu de l'argent cette année (2018), p.ex., d'une personne appartenant à la famille, un ami, émigrés en dehors du pays, etc?			Oui=1, Non=2			_
QR03	Si oui, de quelle(s) personne(s)? (non applicable=99)			_____ _ _			

Quels produits agricoles avez-vous vendu et lesquels avez-vous acheté cette année (2018) (notez dessous)?									
		Produits agricoles vendus				Produits agricoles achetés			
	Nom de produit	Vendu au marché ? Oui=1, Non=2	Montant du mois précédent	Montant des 5 mois passé	Prix au mois précédent (stable=1, supérieur=2, inférieur=3)	Acheté au marché ? Oui=1, Non=2	Montant du mois précédent	Montant des 5 mois passé	Prix au mois précédent (stable=1, supérieur=2, inférieur=3)
QR04	Sorgho	_			_	_			_
QR05	Petit mil	_			_	_			_
QR06	Fonio	_			_	_			_
QR07	Mais	_			_	_			_
QR08	Riz	_			_	_			_
QR09	Arachide	_			_	_			_
QR10	Sésame	_			_	_			_
QR11	Coton	_			_	_			_
QR12	Haricot/ niébé	_			_	_			_
QR13	Le ménage a-t-il vendu autres produits agricoles que ceux cités en haut ces 5 derniers mois? Si oui, précisez.				Oui=1, Non=2	_ _____			
QR14	Le ménage a-t-il vendu des légumes ou fruits ces 5 derniers mois? Si oui, précisez.				Oui=1, Non=2	_ _____			

Remerciez bien le chef de ménage (et/ ou le responsable de champs) et donnez-lui l'opportunité de vous poser des questions s'il y en a. Demandez maintenant de parler avec sa femme et leur enfant de moins de 5 ans.

QUESTIONNAIRE ANTHROPOMETRIQUE

Maintenant je voudrais poser quelques questions à votre femme sur la santé de votre enfant de moins de 5 ans et je voudrais prendre aussi des mesures de taille, poids et le tour de bras gauche. Après je voudrais continuer avec les questions sur la santé de votre femme et l'alimentation de votre enfant de moins de 5 ans. Je peux commencer ?

QN01	Nom, prénom de la mère	_____	
QN02	Nom, prénom et ID de l'enfant moins de 5 ans	_____	
QN03	Est-ce que l'enfant est-il présent?	Oui=1, Non=2	
QN04	Carnet de santé de l'enfant disponible	Oui=1, Non=2	
QN05	Date de naissance de l'enfant	jour/mois/ année	
QN06	Sexe de l'enfant	Masculin=1, Féminin=2	
QN07	L'enfant a-t-il eu de la fièvre au cours des 2 dernières semaines ?	Oui=1, Non=2	
QN08	L'enfant a-t-il eu la diarrhée au cours des 2 dernières semaines ?	Oui=1, Non=2	
QN09	Observez. L'enfant a-t-il une forme d godet (œdème) ?	Oui=1, Non=2	
QN10	L'enfant a-t-il eu d'autres maladies les 2 dernières semaines?	Oui=1, Non=2	
QN11	Avez-vous visitez un centre de santé/ un hôpital au cours des 2 dernières semaines parce que l'enfant était malade?	Oui=1, Non=2	

MESURES ANTHROPOMETRIQUES

De l'enfant				
Demandez à la mère de l'enfant s'il a un carnet de santé avec la taille à la naissance. Notez l'information dessous. Après demandez à la mère d'enlever la chaussure, les vêtements lourdes et/ ou de couche lourde de l'enfant. La mère doit enlever son chaussure. Informez la mère que vous allez prendre de mesures deux fois une après l'autre.				
Taille et poids à la naissance (le carnet de santé)	Mesures (Oui=1, Non=2)	Taille aujourd'hui	Poids aujourd'hui	Périmètre brachial (MUAC)
Taille , centimètre	Couché (moins de 2 ans ou moins de 85 cm)	1. , centimètre	1. , kilogramme	1. , centimètre
Poids gramme	Debout (plus de 2 ans ou plus de 85 cm)	2. , centimètre	2. , kilogramme	2. , centimètre
De la mère (si pesé avec l'enfant)				
Poids aujourd'hui		1. , kilogramme	2. , kilogramme	

QUESTIONNAIRE NUTRITION

Maintenant je voudrais poser quelques questions à votre femme sur la santé et l'alimentation de votre enfant de moins de 5 ans.

Premièrement : L'enfant de moins de 5 ans		
QN01	Nom, prénom et ID de l'enfant	_____
QN02	Date de naissance de l'enfant	jour/mois/ année
QN03	Sexe de l'enfant	Masculin=1, Féminin=2
Deuxièmement: La mère ou la personne qui s'occupe de l'enfant		
QN04	C'est la mère qui s'occupe de l'enfant ?	Oui=1, Non=2
QN05	Est-ce que la mère est présente lors de l'enquête?	Oui=1, Non=2
QN06	La mère et le père de l'enfant sont-ils vivants?	Oui, les deux sont vivent=1, mère seule vit=2, père seul vit=3, aucun ne vit=4
QN07	Date de naissance ou l'âge de la mère	jour/mois/ année (ou âge) ()
QN08	Niveau d'éducation de la mère	Aucun=1, alphabétisé=2, primaire=3, secondaire=4
QN09	Ethnie de la mère	Bwaba=1, Mossi =2, Peul=3, Samo=4, Marka (Dafing)=5, Dogon=6, Autre=7 (précisez)
QN10	Religion de la mère	Aucun=1, Animiste=2, Musulman=3, Catholique=4, Autre=5 (précisez)
QN11	Co-épouse	Oui=1, Non=2
QN12	Est-ce qu'elle sait lire et écrire en français?	Oui=1, Non=2
QN13	Occupation principale de la mère	Ménagère=1, Agriculteur=2, Ménagère et agriculteur=3, Eleveur=4, Agriculteur et éleveur=5, Commerçante=6, Autre=7 (précisez)
L'enfant		
QN14	La mère avait-elle eu des complications pendant la gestation ou l'accouchement?	Oui=1, Non=2
QN15	La grossesse a duré combien de mois?	Moins de 7 mois =1, 7 à 8 mois=2, 9 mois=3, plus de 9 mois=4
QN16	L'enfant, est-il né seul ou jumeaux ?	Seul=1, jumeaux=2
QN17	Avez-vous donné le premier lait à l'enfant ?	Oui=1, Non=2
QN18	L'enfant continue-t-il de téter aujourd'hui?	Oui=1, Non=2
QN19	Si non, à quel âge l'avez-vous sevré?	Âge en mois (non applicable=99) mois

QN20	A quel âge aviez-vous commencé à lui donner de la bouillie ?	Âge en mois (non applicable=99)	_ _ _ mois
QN21	À quel âge avez-vous introduit des aliments solides?	Mois d'enfant (non applicable=99)	_ _ _ mois
QN23	Au cours des dernières 24 heures, l'enfant a-t-il mangé moins, autant ou plus que d'habitude?	Moins que d'habitude=1, autant que d'habitude=2, plus que d'habitude=3	_
La santé d'enfant			
QN22	L'enfant avait-il été diagnostiqué avec le palu les 2 dernières semaines ?	Oui=1, Non=2	_
QN24	Votre enfant, a-t-il déjà participé à une intervention alimentaire ?	Oui=1, Non=2	_
QN25	Si oui, quand ?	Âge en mois (non applicable=99)	_ _ _ mois
QN26	L'enfant a-t-il déjà été diagnostiqué malnutri?	Oui=1, Non=2	_
QN27	Si oui, quand ?	Âge en mois (non applicable=99)	_ _ _ mois

Maintenant je voudrais vous poser des questions générales sur le régime alimentaire de votre ménage.

	Questions sur l'accès à la sécurité alimentaire des ménages	Oui=1 (si oui, continuez sur la droite), Non=2	Rarement=1, Parfois=2, Souvent=3
QG01	Au cours des 30 derniers jours, avez-vous été inquiets par le fait que votre ménage puisse <u>manquer</u> de nourriture?	_	_
QG02	Au cours des 30 derniers jours, est-ce que un membre de votre ménage <u>n'a pas pu manger les aliments préférés</u> en raison d'un manque de ressources?	_	_
QG03	Au cours des 30 derniers jours, est-ce que un membre de votre ménage a mangé <u>le même aliment</u> (e.g. chaque jour la même chose) en raison d'un manque de ressources?	_	_
QG04	Au cours des 30 derniers jours, est-ce que un membre de votre ménage a mangé des aliments que vous <u>ne souhaitiez vraiment pas</u> manger en raison d'un manque de ressources pour obtenir d'autres types d'aliments?	_	_
QG05	Au cours des 30 derniers jours, est-ce que un membre de votre ménage a mangé <u>une quantité de repas plus réduite</u> que ce dont il pensait avoir besoin parce qu'il n'y avait pas assez de nourriture?	_	_
QG06	Au cours des 30 derniers jours, est-ce que un membre de votre ménage a mangé <u>moins de repas</u> (nombre de repas) en un jour parce qu'il n'y avait pas assez de nourriture?	_	_
QG07	Au cours des 30 derniers jours, est-il arrivé qu'il n'y ait <u>pas du tout de nourriture</u> dans votre ménage à cause du manque de ressources pour obtenir de la nourriture?	_	_
QG08	Au cours des 30 derniers jours, est-ce que un membre de votre ménage <u>allé au lit la nuit</u> sans manger parce qu'il n'y avait pas assez de nourriture?	_	_
QG09	Au cours des 30 derniers jours, est-ce que un membre de votre ménage a passé <u>toute la journée et toute la nuit</u> sans manger parce qu'il n'y avait pas assez de nourriture?	_	_

QUESTIONNAIRE RAPPEL REGIME ALIMENTAIRE DES 24-HEURES DE L'ENFANT

Maintenant je voudrais vous poser des questions sur tout ce que votre ENFANT a mangé hier durant le jour et la nuit (de matin à la nuit). S'il-vous-plaît essayez d'être précis.

QR01	Hier était-t-il un jour spécial? Y avait-il une fête?		Un jour comme toujours=1, une fête de la famille=2, un jour religieux=3, autre (précisez)=4				_	
	Temps de consommation	Nom de l'aliment (précisez les ingrédients, si c'est une recette comme le <i>tô</i>)	Heure de consommation	Forme de cuisson	Quantité consommé hier	C'était plus ou moins que d'habitude?	Consommé tout l'année ?	Source de l'aliment (Plusieurs réponses possibles)
		Nom	p.ex. 09h00 ou 14h45	Cru=1, bouillie=2, grillé=3, cuit/ frit=4, non applicable=9	Montrez les différentes jauges et demandez la quantité ou le nombre E.g. 1 petit bol, 2 grands bols, 2 tomates, 1 morceaux de carpe (sauce), 1 demi gobelet	Plus=1, Moins=2, Même quantité=3	Tout l'année=1, depuis la saison de pluie=2, depuis la saison de récolte=3, depuis la saison séché=4, seulement le jour de fête=5	Propre production agricole/ animale=1, achat=2, cadeau/ dons=3, cueillette/ chasse/ pêche=4, aide alimentaire officiel=5, autre (lait maternel)=6 (précisez)
QR02	Le matin: avant 9h		_ _ _ h _ _ _	_		_	_	_ _ _
QR03			_ _ _ h _ _ _	_		_	_	_ _ _
QR04			_ _ _ h _ _ _	_		_	_	_ _ _
QR05			_ _ _ h _ _ _	_		_	_	_ _ _
QR06	Milieu de matinée: 9h-12h		_ _ _ h _ _ _	_		_	_	_ _ _
QR07			_ _ _ h _ _ _	_		_	_	_ _ _
QR08			_ _ _ h _ _ _	_		_	_	_ _ _
QR09			_ _ _ h _ _ _	_		_	_	_ _ _
QR10	À midi: 12h-14h		_ _ _ h _ _ _	_		_	_	_ _ _
QR11			_ _ _ h _ _ _	_		_	_	_ _ _
QR12			_ _ _ h _ _ _	_		_	_	_ _ _
QR13			_ _ _ h _ _ _	_		_	_	_ _ _

	Heure de consommation	Nom de l'aliment (précisez les ingrédients, si c'est une recette comme le tô)	Heure de consommation	Forme de cuisson	Quantité consommé hier	C'était plus ou moins que d'habitude?	Consommé tout l'année ?	Source de l'aliment (Plusieurs réponses possibles)
		Nom	p.ex. 9:00 ou 14 :45	Cru=1, bouillie=2, grillé=3, cuit/ frit=4, non applicable=9	Montrez les différentes jauges et demandez la quantité ou le nombre E.g. 1 petit bol, 2 grands bols, 2 tomates, 1 morceaux de carpe (sauce), 1 demi gobelet	Plus=1, Moins=2, Même quantité=3	Tout l'année=1, depuis la saison de pluie=2, depuis la saison de récolte=3, depuis la saison séché=4, seulement le jour de fête=5	Propre production agricole/ animale=1, achat=2, cadeau/ dons=3, cueillette/ chasse/ pêche=4, aide alimentaire officiel=5, autre (lait maternel)=6 (précisez)
QR14	Après-midi: 14h-17h		_ _ _ h _ _ _	_		_	_	_ _ _
QR15			_ _ _ h _ _ _	_		_	_	_ _ _
QR16			_ _ _ h _ _ _	_		_	_	_ _ _
QR17			_ _ _ h _ _ _	_		_	_	_ _ _
QR18	Le soir: 17h-20h		_ _ _ h _ _ _	_		_	_	_ _ _
QR19			_ _ _ h _ _ _	_		_	_	_ _ _
QR20			_ _ _ h _ _ _	_		_	_	_ _ _
QR21			_ _ _ h _ _ _	_		_	_	_ _ _
QR22	Nuit: après 20h		_ _ _ h _ _ _	_		_	_	_ _ _
QR23			_ _ _ h _ _ _	_		_	_	_ _ _
QR24			_ _ _ h _ _ _	_		_	_	_ _ _
QR25			_ _ _ h _ _ _	_		_	_	_ _ _

QUESTIONNAIRE DE FREQUENCE ALIMENTAIRE DES 7-JOURS (FFQ) DE L'ENFANT

Et plus je voudrais vous poser des questions sur tout ce que votre ENFANT a mangé durant les 7 derniers jours. Je vais lister les aliments et s'il-vous-plaît dites « oui » ou « non » si votre enfant les mangent les 7 derniers jours.

0	Les sept derniers jours avez-vous célébré une fête?	Une semaine comme toujours=1, une semaine avec un jour de fête de la famille=2, une semaine avec un jour religieux=3, autre (précisez)=4				_		
N°	Nom des aliments	Consommé le dernier 7 jours	Forme de cuisson	Combien de jours consommé pendant le derniers 7 jours	Quantité consommé PAR JOUR	C'était plus ou moins que d'habitude?	Consommé tout l'année ?	Source de l'aliment (Plusieurs réponses possibles)
		Oui=1, Non=2	Cru=1, bouillie=2, grillé=3, cuit/ frit=4, non applicable=9	Nombre de jour	Montrez les différentes jauges et demandez la quantité ou le nombre E.g. 1 petit bol, 2 grands bols, 2 tomates, 1 morceaux de carpe (sauce), 1 demi gobelet	Plus=1, Moins=2, Même quantité=3	Tout l'année=1, depuis la saison de pluie=2, depuis la saison de récolte=3, depuis la saison séché=4, seulement le jour de fête=5	Propre production agricole/ animale=1, achat=2, cadeau/ dons=3, cueillette/ chasse/ pêche=4, aide alimentaire officiel=5, autre (lait maternel)=6 (précisez)
I	Céréales							
1	Riz	_	_	_		_	_	_ _ _
2	Fonio	_	_	_		_	_	_ _ _
3	Mais sec	_	_	_		_	_	_ _ _
4	Mais frais	_	_	_		_	_	_ _ _
5	Le couscous	_	_	_		_	_	_ _ _
6	Sorgho	_	_	_		_	_	_ _ _
7	Petit mil	_	_	_		_	_	_ _ _
8	Pain (miche)	_	_	_		_	_	_ _ _
9	Blé	_	_	_		_	_	_ _ _
10	Pâtes alimentaires (macaroni)	_	_	_		_	_	_ _ _
11	Bouillie de maïs	_	_	_		_	_	_ _ _
12	Brisure de mil bouillie	_	_	_		_	_	_ _ _

N°	Nom des aliments	Consommé le dernier 7 jours	Forme de cuisson	Combien de jours consommé pendant le derniers 7 jours	Quantité consommé PAR JOUR	C'était plus ou moins que d'habitude?	Consommé tout l'année ?	Source de l'aliment (Plusieurs réponses possibles)
		Oui=1, Non=2	Cru=1, bouillie=2, grillé=3, cuit/ frit=4, non applicable=9	Nombre de jour	Montrez les différentes jauges et demandez la quantité ou le nombre E.g. 1 petit bol, 2 grands bols, 2 tomates, 1 morceaux de carpe (sauce), 1 demi gobelet	Plus=1, Moins=2, Même quantité=3	Tout l'année=1, depuis la saison de pluie=2, depuis la saison de récolte=3, depuis la saison séché=4, seulement le jour de fête=5	Propre production agricole/ animale=1, achat=2, cadeau/ dons=3, cueillette/ chasse/ pêche=4, aide alimentaire officiel=5, autre (lait maternel)=6 (précisez)
13	Pain du ghana	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
II	Racines & tubercules							
14	Manioc	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
15	Pommes de terre	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
16	Patate douce	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
17	Igname (racine)	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
18	Banane plantain	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
III	Légumineuse, noix & graines							
19	Soumbala	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
20	Graines de coton	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
21	Graine de palme	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
22	Noix de cajou	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
23	Néré	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
24	Pois de terre (voandzou)	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
25	Soja	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
26	Lentille	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
27	Arachide	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>

N°	Nom des aliments	Consommé le dernier 7 jours	Forme de cuisson	Combien de jours consommé pendant le derniers 7 jours	Quantité consommé PAR JOUR	C'était plus ou moins que d'habitude?	Consommé tout l'année ?	Source de l'aliment (Plusieurs réponses possibles)
		Oui=1, Non=2	Cru=1, bouillie=2, grillé=3, cuit/ frit=4, non applicable=9	Nombre de jour	Montrez les différentes jauges et demandez la quantité ou le nombre E.g. 1 petit bol, 2 grands bols, 2 tomates, 1 morceaux de carpe (sauce), 1 demi gobelet	Plus=1, Moins=2, Même quantité=3	Tout l'année=1, depuis la saison de pluie=2, depuis la saison de récolte=3, depuis la saison séché=4, seulement le jour de fête=5	Propre production agricole/ animale=1, achat=2, cadeau/dons=3, cueillette/ chasse/ pêche=4, aide alimentaire officiel=5, autre (lait maternel)=6 (précisez)
28	Sésame	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
29	Haricot (niébé)	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
30	Noix de coco	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
31	Farine d'arachide	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
32	Pâte d'arachide	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
V	Légumes feuilles verts							
33	Feuilles d'oignon	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
34	Epinard	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
35	Salade	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
36	Feuille d'haricot	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
37	Feuille de baobab	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
38	Feuille laurier	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
39	Feuille de sobon	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
40	Feuille d'oseille	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
41	Oseille (dasogo)	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
42	Chou	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
43	Feuille de Moringa	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>

N°	Nom des aliments	Consommé le dernier 7 jours	Forme de cuisson	Combien de jours consommé pendant le derniers 7 jours	Quantité consommé PAR JOUR	C'était plus ou moins que d'habitude?	Consommé tout l'année ?	Source de l'aliment (Plusieurs réponses possibles)
		Oui=1, Non=2	Cru=1, bouillie=2, grillé=3, cuit/ frit=4, non applicable=9	Nombre de jour	Montrez les différentes jauges et demandez la quantité ou le nombre E.g. 1 petit bol, 2 grands bols, 2 tomates, 1 morceaux de carpe (sauce), 1 demi gobelet	Plus=1, Moins=2, Même quantité=3	Tout l'année=1, depuis la saison de pluie=2, depuis la saison de récolte=3, depuis la saison séché=4, seulement le jour de fête=5	Propre production agricole/ animale=1, achat=2, cadeau/ dons=3, cueillette/ chasse/ pêche=4, aide alimentaire officiel=5, autre (lait maternel)=6 (précisez)
IV	Légumes							
44	Carotte	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
45	Courgette	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
46	Citrouille/ courge	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
47	Persil	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
48	Poivron	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
49	Tomate	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
50	Aubergine	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
51	Avocat	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
52	Concombre	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
53	Gombo	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
54	Oignon	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
55	Ail	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
56	Fleur de kapokier	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
VI	Fruits							
57	Mangue	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
58	Pain de singe	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>

N°	Nom des aliments	Consommé le dernier 7 jours	Forme de cuisson	Combien de jours consommé pendant le derniers 7 jours	Quantité consommé PAR JOUR	C'était plus ou moins que d'habitude?	Consommé tout l'année ?	Source de l'aliment (Plusieurs réponses possibles)
		Oui=1, Non=2	Cru=1, bouillie=2, grillé=3, cuit/ frit=4, non applicable=9	Nombre de jour	Montrez les différentes jauges et demandez la quantité ou le nombre E.g. 1 petit bol, 2 grands bols, 2 tomates, 1 morceaux de carpe (sauce), 1 demi gobelet	Plus=1, Moins=2, Même quantité=3	Tout l'année=1, depuis la saison de pluie=2, depuis la saison de récolte=3, depuis la saison séché=4, seulement le jour de fête=5	Propre production agricole/ animale=1, achat=2, cadeau/dons=3, cueillette/ chasse/ pêche=4, aide alimentaire officiel=5, autre (lait maternel)=6 (précisez)
59	Ananas	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
60	Banane douce	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
61	Citron	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
62	Finsan (l'anacarde)	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
63	Orange	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
64	Liane (zaban)	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
65	Fruit d'oseille (dahtou)	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
66	Fruit de tamarin	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
67	Melon	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
68	Pastèque	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
69	Dattes	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
70	Jujube	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
71	Pulpe de karité	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
72	Pomme	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
73	Goyave	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
74	Papaye	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
75	Détar (Kagha)	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>

N°	Nom des aliments	Consommé le dernier 7 jours	Forme de cuisson	Combien de jours consommé pendant le derniers 7 jours	Quantité consommé PAR JOUR	C'était plus ou moins que d'habitude?	Consommé tout l'année ?	Source de l'aliment (Plusieurs réponses possibles)
		Oui=1, Non=2	Cru=1, bouillie=2, grillé=3, cuit/ frit=4, non applicable=9	Nombre de jour	Montrez les différentes jauges et demandez la quantité ou le nombre E.g. 1 petit bol, 2 grands bols, 2 tomates, 1 morceaux de carpe (sauce), 1 demi gobelet	Plus=1, Moins=2, Même quantité=3	Tout l'année=1, depuis la saison de pluie=2, depuis la saison de récolte=3, depuis la saison séché=4, seulement le jour de fête=5	Propre production agricole/ animale=1, achat=2, cadeau/ dons=3, cueillette/ chasse/ pêche=4, aide alimentaire officiel=5, autre (lait maternel)=6 (précisez)
VII	Viande							
76	Poulet	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
77	Bœuf	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
78	Porcs	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
79	Pintade	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
80	Mouton	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
81	Lapin	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
82	Chèvre	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
83	Chenille	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
IX	Poisson							
84	Capitaine (Nil)	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
85	Silure	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
86	Carpe d'Afrique	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
87	Capitaine de mer	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
88	Sardines	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
89	Carpe	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
90	Thon	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>

N°	Nom des aliments	Consommé le dernier 7 jours	Forme de cuisson	Combien de jours consommé pendant le derniers 7 jours	Quantité consommé PAR JOUR	C'était plus ou moins que d'habitude?	Consommé tout l'année ?	Source de l'aliment (Plusieurs réponses possibles)
		Oui=1, Non=2	Cru=1, bouillie=2, grillé=3, cuit/ frit=4, non applicable=9	Nombre de jour	Montrez les différentes jauges et demandez la quantité ou le nombre E.g. 1 petit bol, 2 grands bols, 2 tomates, 1 morceaux de carpe (sauce), 1 demi gobelet	Plus=1, Moins=2, Même quantité=3	Tout l'année=1, depuis la saison de pluie=2, depuis la saison de récolte=3, depuis la saison séché=4, seulement le jour de fête=5	Propre production agricole/ animale=1, achat=2, cadeau/ dons=3, cueillette/ chasse/ pêche=4, aide alimentaire officiel=5, autre (lait maternel)=6 (précisez)
X	Graisses & huiles							
91	Beurre de karité	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
92	Huile d'arachide	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
93	Huile de coton	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
94	Huile d'olive	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
95	Huile de palme	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
XI	Lait							
96	Lait maternel	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
97	Lait d'animal	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
98	Formule infantile commercialisée (substitute du lait maternel)	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
99	Lait en poudre	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
100	Yaourt	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
101	Fromage	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
XII	Œufs							
102	Œuf de poule	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
103	Œuf de pintade	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>

N°	Nom des aliments	Consommé le dernier 7 jours	Forme de cuisson	Combien de jours consommé pendant le derniers 7 jours	Quantité consommé PAR JOUR	C'était plus ou moins que d'habitude?	Consommé tout l'année ?	Source de l'aliment (Plusieurs réponses possibles)
		Oui=1, Non=2	Cru=1, bouillie=2, grillé=3, cuit/ frit=4, non applicable=9	Nombre de jour	Montrez les différentes jauges et demandez la quantité ou le nombre E.g. 1 petit bol, 2 grands bols, 2 tomates, 1 morceaux de carpe (sauce), 1 demi gobelet	Plus=1, Moins=2, Même quantité=3	Tout l'année=1, depuis la saison de pluie=2, depuis la saison de récolte=3, depuis la saison séché=4, seulement le jour de fête=5	Propre production agricole/ animale=1, achat=2, cadeau/dons=3, cueillette/ chasse/ pêche=4, aide alimentaire officiel=5, autre (lait maternel)=6 (précisez)
XIII	Miel & sucre							
104	Biscuit	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
105	Miel	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
106	Confiture	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
107	Sucre/ bonbon	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
XIV	Boisson							
108	Eau	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
109	Coca cola, fanta, sprite (sucré)	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
110	Thé lipton	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
111	Nescafé	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
112	Jus d'orange	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
113	Jus de citron	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>
114	Jus de tamarin	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/> <input type="checkbox"/> <input type="checkbox"/>

Terminez ici votre enquête. Remerciez bien la mère de l'enfant et l'enfant et aussi encore une fois le chef de ménage si il est encore présent et donnez-le l'opportunité de vous poser des questions s'il y en a. Remerciez aussi toutes les personnes qui ont participé. Vérifiez sur place que le questionnaire est complet. Retirez-vous et prenez le temps de **REMPLIR l'ID ménage en haut de chaque page**.

Appendix 2: Agricultural survey

QUESTIONNAIRE D'AGRICULTEUR




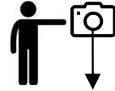


Nom et prénom de l'enquêteur _____	Code enquêteur _ _ _ _
Date de première visite _ _ _ _ _ _ _ _	Heure de première visite _ _ _ _
Nom de village _____	ID de ménage _ _ - _ _ _ - _ - _

Présentation d'enquêteur

- Mon nom est ... et je fais partie de l'équipe du Centre de Recherche en Santé de Nouna.
- Nous faisons une étude sur la nutrition des enfants à cause du changement rapide de temps et ses effets sur la nourriture dans le district. Nous sommes intéressés par la situation des enfants, des familles, et des ménages. Je voudrais discuter avec vous sur ces sujets.
- Nous voulons collecter des informations sur vos champs et poser quelques questions sur vos cultures récoltées, et sur vos pratiques agricoles. Cette collecte de données nous aiderons à déterminer l'état nutritionnel de vos enfants, particulièrement ce qui sont malnutries, et aussi à comprendre les raisons derrière cet états nutritionnelles. La malnutrition est un stade où les enfants ont faim et manque de vitamines et sels minérales.
- Pendant nos visites passées nous avons posé des questions sur la nutrition de votre enfant et sur votre ménage.
- Les informations que vous allez nous donner seront traitées d'une façon confidentielle. Tout ce que vous nous direz sera utilisé uniquement pour notre recherche.
- Les informations que vous allez nous donner vont aider pour la planification des interventions de santé, comme les contrôles nutritionnelles dans votre région.
- Si vous acceptez de participer, nous voudrions visiter vos champs. Ces visites prendront entre 30 minutes et 1 heure. Vous pouvez refuser de participer ou arrêter à n'importe qu'elle moment. Il n'y aura **pas** de conséquences négatives.
- S'il vous plaît vous pouvez nous poser des questions si vous avez quelques-unes.

	Le répondant		
QM01	Langue utilisée	Dioula=1, Moré=2, Français=3, autre langue=4 (précisiez)	_
QM02	Qui est le/la répondant/e principal/e?	Prénom, Nom (âge en ans)	_____ _____ _____ _ _ ans
QM03	Coordonnées GPS de ménage (entre de ménage)	Code GPS du ménage (ID de ménage-menage)	Longitude Latitude
		_ _ _ _ _ _ _ -menage	_ _ . _ _ _ _ _ _ _ . _ _ _ _ _

L'ÉCHANTILLON DE CHAMPS À FAIRE DANS CHAQUE SITE

Au ménage					
Demandez si c'est possible d'aller aux champs et faire des observations . Nous voulons les faire cette semaine jusqu'à la récolte prochaine. Prenez l'autre document et expliquez que vous voulez prendre des photos des champs et prendre des mesures pour suivre le développement des cultures. Si ce n'est pas possible tout de suite demandez un rendez-vous.					
Si le chef de ménage est d'accord, demandez-lui de visiter tous les champs avec une seule récolte:					
(1) Sorgho (2) Petit mil (3) Mais (4) Arachide (5) Haricot (niébé)			(6) Riz (7) Sésame (8) Fonio (9) Coton		
Aux champs					
1.		Notez les informations de l'agriculteur comme indiqué ci-dessous.			
2.		Avec le GPS faire le contour (périmètre) du champ qui est cultivé par culture unique et notez le numéro de champ s'il y a plusieurs champs avec la même culture.			
3.		Prendre une (1) photo du champ de l'extérieur (image de vue complète).			
4.		Prendre trois (3) photos du champ de l'extérieur. Les photos doivent être à hauteur de poitrine du canopée des récoltes et l'appareil légèrement tournée vers le bas (environ 80 degrés) du ouvert forestier. Faire cela à 3 endroits aléatoires dans le champ et écrivez les numéros d'image sur cette feuille.			
5.		Mesurez les hauteurs des plantes dans le carré (mini, maxi et moyenne) par champ avec une tige de mesure.			
6.		Noubliez pas de noter toutes les informations sur cette feuille.			
En plus, demandez de visiter 4 ou 5 champs qui sont intercalées et notez les récoltes et un point de GPS au centre du champ:					
Association de culture				Champs en jachère (sans culture)	
	Culture 1	Culture 2	Point GPS (Nom de region_culture 1_culture 2)		Point GPS (Nom de region_SP1)
CH1			_____ - _____ - _____	SP1	_____ - SP1
CH2			_____ - _____ - _____	SP2	_____ - SP2
CH3			_____ - _____ - _____	SP3	_____ - SP3

**OBSERVATION ET GPS DES CHAMPS AVEC
FONIO, RIZ, SESAME, ET COTON**

Quand vous arrivés au champs avec le chef de ménage ou le responsable de champs, vous commencez avec l'observation des champs. Les coordonnées de GPS du champ doivent être notées sur cette feuille, et sauvegardées dans votre appareil. Ensuite, quatre photos du champ doivent être faites comme précédemment expliqué.

Culture sur le champ	Numéro de champs	2ième culture sur le terrain?	Type de semence	Date d'ensemencement	Date prévu de récolte	Hauteur des cultures	Code GPS de champ	GPS de la limite extérieure du champ	Superficie de la parcelle	1 photo avec vue complète (3 m de champ)	Photos de 3 points différents de champ (vue du haut du terrain) ID de ménage-culture-numéro-numéro d'image		
											Numéro 1	Numéro 2	Numéro 3
Oui=1, Non=2	Numéro	Oui=1 (nom de culture), Non=2	Local=1, Améliorer=2, OGM=3	Jour/mois/ année	Jour/mois/ année	Minimum et maximum en cm	ID de ménage- culture-numéro de champ	GPS du point de départ (longitude et latitude)	En ha	ID ménage- culture-numéro- numéro d'image	Numéro 1	Numéro 2	Numéro 3
Fonio	_1_	_	_	_ _ _ _	_ _ _ _	_ _ _ _ mini _ _ _ _ maxi	_ _ _ _ FON1	_ _ _ _ _ _ _ _ _ _	_ _ _ _ _ _ _ _ _ ha	_ _ _ _ _ _ _ _ _ FON1-0	_ _ _ _ _ _ _ _ _ FON1-1	_ _ _ _ _ _ _ _ _ FON1-2	_ _ _ _ _ _ _ _ _ FON1-3
Fonio	_2_	_	_	_ _ _ _	_ _ _ _	_ _ _ _ mini _ _ _ _ maxi	_ _ _ _ FON2	_ _ _ _ _ _ _ _ _	_ _ _ _ _ _ _ _ _ ha	_ _ _ _ _ _ _ _ _ FON2-0	_ _ _ _ _ _ _ _ _ FON2-1	_ _ _ _ _ _ _ _ _ FON2-2	_ _ _ _ _ _ _ _ _ FON2-3
Riz	_1_	_	_	_ _ _ _	_ _ _ _	_ _ _ _ mini _ _ _ _ maxi	_ _ _ _ RIZ1	_ _ _ _ _ _ _ _ _	_ _ _ _ _ _ _ _ _ ha	_ _ _ _ _ _ _ _ _ RIZ1-0	_ _ _ _ _ _ _ _ _ RIZ1-1	_ _ _ _ _ _ _ _ _ RIZ1-2	_ _ _ _ _ _ _ _ _ RIZ1-3
Riz	_2_	_	_	_ _ _ _	_ _ _ _	_ _ _ _ mini _ _ _ _ maxi	_ _ _ _ RIZ2	_ _ _ _ _ _ _ _ _	_ _ _ _ _ _ _ _ _ ha	_ _ _ _ _ _ _ _ _ RIZ2-0	_ _ _ _ _ _ _ _ _ RIZ2-1	_ _ _ _ _ _ _ _ _ RIZ2-2	_ _ _ _ _ _ _ _ _ RIZ2-3
Sésame	_1_	_	_	_ _ _ _	_ _ _ _	_ _ _ _ mini _ _ _ _ maxi	_ _ _ _ SES1	_ _ _ _ _ _ _ _ _	_ _ _ _ _ _ _ _ _ ha	_ _ _ _ _ _ _ _ _ SES1-0	_ _ _ _ _ _ _ _ _ SES1-1	_ _ _ _ _ _ _ _ _ SES1-2	_ _ _ _ _ _ _ _ _ SES1-3

Culture sur le champ	Numéro de champs	2ième culture sur le terrain?	Type de semence	Date d'ensemencement	Date prévu de récolte	Hauteur des cultures	Code GPS de champ	GPS de la limite extérieure du champ	Superficie de la parcelle	1 photo avec vue complète (3 m de champ)	Photos de 3 points différents de champ (vue du haut du terrain) ID de ménage-culture-numéro-numéro d'image		
											Numéro 1	Numéro 2	Numéro 3
Oui=1, Non=2	Numéro	Oui=1 (nom de culture), Non=2	Local=1, Améliorer=2, OGM=3	Jour/mois/année	Jour/mois/année	Minimum et maximum en cm	ID de ménage-culture-numéro de champ	GPS du point de départ	En ha	ID ménage-culture-numéro-numéro d'image			
Sésame _	_2_	_	_	_ _ _ _	_ _ _ _	_ mini _ maxi	_ _ _ SES2	_ . _ _ _ _ . _	_ , _ ha	_ _ _ SES2-0	_ _ _ SES2-1	_ _ _ SES2-2	_ _ _ _ _ SES2-3
Coton _	_1_	_	_	_ _ _ _	_ _ _ _	_ mini _ maxi	_ _ _ COT1	_ . _ _ _ _ . _	_ , _ ha	_ _ _ COT1-0	_ _ _ COT1-1	_ _ _ COT1-2	_ _ _ _ _ COT1-3
Coton _	_2_	_	_	_ _ _ _	_ _ _ _	_ mini _ maxi	_ _ _ COT2	_ . _ _ _ _ . _	_ , _ ha	_ _ _ COT2-0	_ _ _ COT2-1	_ _ _ COT2-2	_ _ _ _ _ COT2-3
_____ - _	_3_	_	_	_ _ _ _	_ _ _ _	_ mini _ maxi	_ _ _ ____3	_ . _ _ _ _ . _	_ , _ ha	_ _ _ ____3-0	_ _ _ ____3-1	_ _ _ ____3- 2	_ _ _ _ _ ____3-3

OBSERVATION ET GPS DES CHAMPS AVEC SORGHO, MIL, MAIS, ARACHIDE, ET HARICOT (NIEBE)

A cette étape, le carré devrait déjà être mis en place pour le pesage des récoltes plus tard. De cela, nous avons également besoin des coordonnées de GPS. Une fois que le chef de ménage vous a contactés pour la récolte, rendez-lui visite et assurez-vous que vous récoltez le carré de rendement. Une fois que la récolte est sèche, battez la récolte et ne pesez que les grains.

Culture sur le champ	Numéro de champ	2ième culture sur le terrain?	Type de semence	Date d'ensemencement	Date prévu de récolte	Hauteur des cultures		Code GPS de champ	GPS de la limite extérieure du champ	1 photo avec vue complète (3 m de champ)	Photos de 3 points différents de champ (vue du haut du terrain) ID de ménage-culture-numéro-numéro d'image			
Oui=1, Non=2	Numéro comme sur le piquet	Oui=1 (nom de culture), Non=2	Local=1, Améliorer=2, OGM=3	Jour/mois/année	Jour/mois/année	Minimum et maximum en cm		ID de ménage-culture-numéro de champ	GPS du point de départ	ID ménage-culture-numéro-numéro d'image	Numéro 1	Numéro 2	Numéro 3	
Sorgho	_1_	_	_	_ _ _ _ _ _	_ _ _ _ _ _	_ _ _ mini _ _ _ maxi	_ _ _ _ _ _ SOR1	_ _ . _ _ _ _ _ _ . _ _ _ _	_ _ _ _ _ _ SOR1-0	_ _ _ _ _ _ SOR1-1	_ _ _ _ _ _ SOR1-2	_ _ _ _ _ _ SOR1-3		
	Code GPS de carré de rendement		Point GPS du carré	Superficie de la parcelle	Position du carré de rendement				PESAGE DE RECOLTE	Date de récolte	Mesure de carré de rendement			
	ID de ménage-culture-numéro de champ-carré		GPS du centre de carré	En ha	Périmètre (en m)	½ Périmètre (en m)	1er nombre aléatoire	2è nombre aléatoire		Jour/mois/année	Poids net (en kg)	Facteur de perte (Oui=1, Non=2)	Date pesée (jour/mois/année)	
	_ _ _ _ _ _ _ SOR1-CAR		_ _ . _ _ _ _ _ _ . _ _ _ _	_ , _ _ _ ha	_ _ _ , _ _	_ _ _ , _ _	_ _ _ _ _ _	_ _ _ _ _ _		_ _ _ _ _ _	_ _ , _ _	_ _ _ _	_ _ _ _ _ _ _ _	
Sorgho	_2_	_	_	_ _ _ _ _ _	_ _ _ _ _ _	_ _ _ mini _ _ _ maxi	_ _ _ _ _ _ SOR2	_ _ . _ _ _ _ _ _ . _ _ _ _		_ _ _ _ _ _ SOR2-0	_ _ _ _ _ _ SOR2-1	_ _ _ _ _ _ SOR2-2	_ _ _ _ _ _ SOR2-3	
	Code GPS de carré de rendement		Point GPS du carré	Superficie de la parcelle	Position du carré de rendement				PESAGE DE RECOLTE	Date de récolte	Mesure de carré de rendement			
	ID de ménage-culture-numéro de champ-carré		GPS du centre de carré	En ha	Périmètre (en m)	½ Périmètre (en m)	1er nombre aléatoire	2è nombre aléatoire		Jour/mois/année	Poids net (en kg)	Facteur de perte (Oui=1, Non=2)	Date pesée (jour/mois/année)	
	_ _ _ _ _ _ _ SOR2-CAR		_ _ . _ _ _ _ _ _ . _ _ _ _	_ , _ _ _ ha	_ _ _ , _ _	_ _ _ , _ _	_ _ _ _ _ _	_ _ _ _ _ _		_ _ _ _ _ _	_ _ , _ _	_ _ _ _	_ _ _ _ _ _ _ _	

Culture sur le champ	Numéro de champ	2ième culture sur le terrain?	Type de semence	Date d'ensemencement	Date prévu de récolte	Hauteur des cultures		Code GPS de champ	GPS de la limite extérieure du champ	1 photo avec vue complète (3 m de champ)	Photos de 3 points différents de champ (vue du haut du terrain) ID de ménage-culture-numéro-numéro d'image			
Oui=1, Non=2	Numéro comme sur le piquet	Oui=1 (nom de culture), Non=2	Local=1, Améliorer=2, OGM=3	Jour/mois/année	Jour/mois/année	Minimum et maximum en cm		ID de ménage-culture-numéro de champ	GPS du point de départ	ID ménage-culture-numéro-numéro d'image	Numéro 1	Numéro 2	Numéro 3	
Mais	_1_	_	_	_ _ _ _ _ _	_ _ _ _ _ _	_ _ _ mini _ _ _ maxi	_ _ _ _ _ MAI1	_ _ . _ _ _ _ _ _ . _ _ _ _	_ _ _ _ _ _ MAI1-0	_ _ _ _ _ _ MAI1-1	_ _ _ _ _ _ MAI1-2	_ _ _ _ _ _ MAI1-3		
	_	Code GPS de carré de rendement		Point GPS du carré	Superficie de la parcelle	Position du carré de rendement				PESAGE DE RECOLTE	Date de récolte	Mesure de carré de rendement		
		ID de ménage-culture-numéro de champ-carre	GPS du centre de carré	En ha	Périmètre (en m)	½ Périmètre (en m)	1er nombre aléatoire	2è nombre aléatoire	Jour/mois/année		Poids net (en kg)	Facteur de perte (Oui=1, Non=2)	Date pesée (jour/mois/année)	
		_ _ _ _ _ _ _ MAI1-CAR	_ _ . _ _ _ _ _ _ _ . _ _ _ _ _	_ , _ _ _ _ ha	_ _ _ _ , _ _	_ _ _ _ , _ _	_ _ _ _ _ _	_ _ _ _ _ _	_ _ _ _ _ _ _ _		_ _ , _ _	_ _ _ _	_ _ _ _ _ _ _ _	_ _ _ _ _ _ _ _
Culture sur le champ	Numéro de champ	2ième culture sur le terrain?	Type de semence	Date d'ensemencement	Date prévu de récolte	Hauteur des cultures		Code GPS de champ	GPS de la limite extérieure du champ	1 photo avec vue complète (3 m de champ)	Photos de 3 points différents de champ (vue du haut du terrain) ID de ménage-culture-numéro-numéro d'image			
Oui=1, Non=2	Numéro comme sur le piquet	Oui=1 (nom de culture), Non=2	Local=1, Améliorer=2, OGM=3	Jour/mois/année	Jour/mois/année	Minimum et maximum en cm		ID de ménage-culture-numéro de champ	GPS du point de départ	ID ménage-culture-numéro-numéro d'image	Numéro 1	Numéro 2	Numéro 3	
Mais	_2_	_	_	_ _ _ _ _ _	_ _ _ _ _ _	_ _ _ mini _ _ _ maxi	_ _ _ _ _ MAI2	_ _ . _ _ _ _ _ _ . _ _ _ _	_ _ _ _ _ _ MAI2-0	_ _ _ _ _ _ MAI2-1	_ _ _ _ _ _ MAI2-2	_ _ _ _ _ _ MAI2-3		
	_	Code GPS de carré de rendement		Point GPS du carré	Superficie de la parcelle	Position du carré de rendement				PESAGE DE RECOLTE	Date de récolte	Mesure de carré de rendement		
		ID de ménage-culture-numéro de champ-carre	GPS du centre de carré	En ha	Périmètre (en m)	½ Périmètre (en m)	1er nombre aléatoire	2è nombre aléatoire	Jour/mois/année		Poids net (en kg)	Facteur de perte (Oui=1, Non=2)	Date pesée (jour/mois/année)	
		_ _ _ _ _ _ _ MAI2-CAR	_ _ . _ _ _ _ _ _ _ . _ _ _ _ _	_ , _ _ _ _ ha	_ _ _ _ , _ _	_ _ _ _ , _ _	_ _ _ _ _ _	_ _ _ _ _ _	_ _ _ _ _ _ _ _		_ _ , _ _	_ _ _ _	_ _ _ _ _ _ _ _	_ _ _ _ _ _ _ _

Culture sur le champ	Numéro de champ	2ième culture sur le terrain?	Type de semence	Date d'ensemencement	Date prévu de récolte	Hauteur des cultures		Code GPS de champ	GPS de la limite extérieure du champ	1 photo avec vue complète (3 m de champ)	Photos de 3 points différents de champ (vue du haut du terrain) ID de ménage-culture-numéro-numéro d'image			
Oui=1, Non=2	Numéro comme sur le piquet	Oui=1 (nom de culture), Non=2	Local=1, Améliorer=2, OGM=3	Jour/mois/année	Jour/mois/année	Minimum et maximum en cm		ID de ménage-culture-numéro de champ	GPS du point de départ	ID ménage-culture-numéro-numéro d'image	Numéro 1	Numéro 2	Numéro 3	
Haricot (niébé)	_1_	_	_	_ _ _ _ _ _	_ _ _ _ _ _	_ _ _ mini _ _ _ maxi	_ _ _ _ _ HAR1	_ _ . _ _ _ _ _ _ . _ _ _ _	_ _ _ _ _ _ HAR1-0	_ _ _ _ _ _ HAR1-1	_ _ _ _ _ _ HAR1-2	_ _ _ _ _ _ HAR1-3		
	_	Code GPS de carré de rendement		Point GPS du carré	Superficie de la parcelle	Position du carré de rendement				PESAGE DE RECOLTE	Date de récolte	Mesure de carré de rendement		
		ID de ménage-culture-numéro de champ-carre	GPS du centre de carré	En ha	Périmètre (en m)	½ Périmètre (en m)	1er nombre aléatoire	2è nombre aléatoire	Jour/mois/année		Poids net (en kg)	Facteur de perte (Oui=1, Non=2)	Date pesée (jour/mois/année)	
		_ _ _ _ _ _ _ HAR1-CAR	_ _ . _ _ _ _ _ _ _ . _ _ _ _ _	_ , _ _ _ _ ha	_ _ _ _ , _ _	_ _ _ _ , _ _	_ _ _ _ _ _	_ _ _ _ _ _	_ _ _ _ _ _ _ _		_ _ , _ _	_ _ _ _	_ _ _ _ _ _ _ _	
Culture sur le champ	Numéro de champ	2ième culture sur le terrain?	Type de semence	Date d'ensemencement	Date prévu de récolte	Hauteur des cultures		Code GPS de champ	GPS de la limite extérieure du champ	1 photo avec vue complète (3 m de champ)	Photos de 3 points différents de champ (vue du haut du terrain) ID de ménage-culture-numéro-numéro d'image			
Oui=1, Non=2	Numéro comme sur le piquet	Oui=1 (nom de culture), Non=2	Local=1, Améliorer=2, OGM=3	Jour/mois/année	Jour/mois/année	Minimum et maximum en cm		ID de ménage-culture-numéro de champ	GPS du point de départ	ID ménage-culture-numéro-numéro d'image	Numéro 1	Numéro 2	Numéro 3	
Haricot (niébé)	_2_	_	_	_ _ _ _ _ _	_ _ _ _ _ _	_ _ _ mini _ _ _ maxi	_ _ _ _ _ HAR2	_ _ . _ _ _ _ _ _ . _ _ _ _	_ _ _ _ _ _ HAR2-0	_ _ _ _ _ _ HAR2-1	_ _ _ _ _ _ HAR2-2	_ _ _ _ _ _ HAR2-3		
	_	Code GPS de carré de rendement		Point GPS du carré	Superficie de la parcelle	Position du carré de rendement				PESAGE DE RECOLTE	Date de récolte	Mesure de carré de rendement		
		ID de ménage-culture-numéro de champ-carre	GPS du centre de carré	En ha	Périmètre (en m)	½ Périmètre (en m)	1er nombre aléatoire	2è nombre aléatoire	Jour/mois/année		Poids net (en kg)	Facteur de perte (Oui=1, Non=2)	Date pesée (jour/mois/année)	
		_ _ _ _ _ _ _ HAR2-CAR	_ _ . _ _ _ _ _ _ _ . _ _ _ _ _	_ , _ _ _ _ ha	_ _ _ _ , _ _	_ _ _ _ , _ _	_ _ _ _ _ _	_ _ _ _ _ _	_ _ _ _ _ _ _ _		_ _ , _ _	_ _ _ _	_ _ _ _ _ _ _ _	

RAPPEL D'AGRICULTEUR: SORGHO, MIL, MAIS, ARACHIDE, ET HARICOT (NIEBE)

Après la récolte ou la pesage, demandez au chef de ménage quelques questions supplémentaires sur la récolte.

Culture	Numéro de champ	Estimation de quantité par culture 2018				Utilisation de fertilisant			Utilisation de pesticide		Aléas climatique
Nom	Numéro comme sur le piquet	Estimation en kg (si pas possible=999)	Quantité en Sac de 100 kg=1, Tine=2, Charrette=3	Combien de sac à 100 kg/ tine/ charrette ?	Moins que l'année passée=1, Même quantité=2, Plus que l'année passée=3, non applicable=9	Oui, chimique=1, Oui, organique=2, Oui, le deux types=3, Aucune=4	Nom d'engrais	Chaque semaine=1, chaque mois=2, une fois=3, autre=4	Oui=1, Aucun=2	Application chaque semaine=1, chaque mois=2, une fois=3, autre=4	Rien=1, Sol sec=2, Trop de l'eau=3, Pest /, Parasite=4, Striga=5, Autre=6 (Précisiez)
Sorgho	_1_	_____ kg	□	□□□□	□	□		□	□	□	□
Sorgho	_2_	_____ kg	□	□□□□	□	□		□	□	□	□
Mil	_1_	_____ kg	□	□□□□	□	□		□	□	□	□
Mil	_2_	_____ kg	□	□□□□	□	□		□	□	□	□
Mais	_1_	_____ kg	□	□□□□	□	□		□	□	□	□
Mais	_2_	_____ kg	□	□□□□	□	□		□	□	□	□
Arachide	_1_	_____ kg	□	□□□□	□	□		□	□	□	□
Arachide	_2_	_____ kg	□	□□□□	□	□		□	□	□	□
Haricot (niébé)	_1_	_____ kg	□	□□□□	□	□		□	□	□	□
Haricot (niébé)	_2_	_____ kg	□	□□□□	□	□		□	□	□	□

Culture	Numéro de champ	Estimation de quantité par culture 2018				Utilisation de fertilisant			Utilisation de pesticide		Aléas climatique		
		Nom	Numéro comme sur le piquet	Estimation en kg (si pas possible=999)	Quantité en Sac de 100 kg=1, Tine=2, Charrette=3	Combien de sac à 100 kg/ tine/ charrette ?	Moins que l'année passée=1, Même quantité=2, Plus que l'année passée=3, non applicable=9	Oui, chimique=1, Oui, organique=2, Oui, le deux types=3, Aucune=4	Nom d'engrais	Chaque semaine=1, chaque mois=2, une fois=3, autre=4		Oui=1, Aucun=2	Application chaque semaine=1, chaque mois=2, une fois=3, autre=4
	3		_____ kg	<input type="checkbox"/>	_____	<input type="checkbox"/>			<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	
	3		_____ kg	<input type="checkbox"/>	_____	<input type="checkbox"/>			<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	

Terminez ici votre enquête. Remerciez bien le chef de ménage (ou le responsable de champs) et donnez-lui l'opportunité de vous poser des questions s'il en a. Remerciez aussi toutes les personnes qui ont participé. Vérifier sur place que le questionnaire est complet. **Retirez-vous et prenez le temps de REMPLIR l'ID ménage en haut de chaque page.**

Appendix B: Demographic and socio-economic graphs and tables

Appendix 3: List of the 33 Nouna HDSS villages situated within a 10 km radius around five local weather stations and their number of population, households and children <5 years selected for sampling

	Village	Selected village	Cluster	Population	Households	Children <5 yrs
1	Cissé	Yes	Cissé	1,753	219	359
2	Dina	Yes	Cissé	254	33	53
3	Dionkongo		Cissé	1,387	162	266
4	Sère		Cissé	1,146	136	183
5	Sériba		Cissé	2,060	247	412
6	Tissi	Yes	Cissé	1,243	150	223
7	Barakui	Yes	Kodougou	895	133	178
8	Biron		Kodougou	1,469	265	280
9	Kodougou		Kodougou	1,761	185	325
10	Labarani		Kodougou	1,251	146	223
11	Nokui	Yes	Kodougou	1,739	157	315
12	Sobon	Yes	Kodougou	1,553	211	299
13	Babikolon	Yes	Nouna	776	52	155
14	Damandigui	Yes	Nouna	691	69	137
15	Hinkuy		Nouna	300	54	62
16	Kansara		Nouna	930	182	203
17	Korédougou		Nouna	252	24	47
18	Soïn		Nouna	1,737	178	332
19	Tonkoroni		Nouna	450	71	95
20	Dankoumana	Yes	Sono	1,102	132	211
21	Koro	Yes	Sono	3,732	403	653
22	Sanpopo		Sono	1,083	138	205
23	Bankoumani		Toni	2,378	332	392
24	Boron	Yes	Toni	874	128	146
25	Dara	Yes	Toni	3,206	446	546
26	Dembéléla	Yes	Toni	607	55	110
27	Denissa		Toni	1,306	139	239
28	Dokoura	Yes	Toni	559	53	109
29	Goni	Yes	Toni	4,156	521	645
30	Kamadena	Yes	Toni	2,862	377	489
31	Kèmana		Toni	3,412	462	655
32	Pâ	Yes	Toni	1,662	180	302
33	Toni	Yes	Toni	2,798	388	529
	Total			51,384	6,428	9,378

Appendix 4: List of indicators and the proportion of missing data-points in the study dataset

Theme	No	Indicators	Indicator type	2017	2018	2019	N	Missing	Missing %
Children	1	Years	cat	470	511	458	1439	0	0.00
	2	Villages	cat	470	511	458	1439	0	0.00
Child	3	Child's sex	binary	470	511	458	1439	0	0.00
	4	Child's age (in months)	cont	470	511	458	1439	0	0.00
	5	Height	cont	470	511	458	1439	0	0.00
	6	Weight	cont	469	509	456	1434	5	0.35
Health	7	Birth weight	cont	332	406	368	1106	333	23.14
	8	Fever	binary	458	510	456	1424	15	1.04
	9	Diarrhea	binary	461	510	457	1428	11	0.76
Nutrition	10	Currently breastfeeding	binary	467	511	458	1436	3	0.21
	11	Age stopped breastfeeding	cont	326	370	326	1022	417	28.98
Mother	12	Mother's age	cont	357	359	455	1171	268	18.62
	13	Education	cat	469	506	455	1430	9	0.63
	14	Ethnicity	binary	469	510	457	1436	3	0.21
	15	Marital status	binary	463	510	455	1428	11	0.76
	16	Housewife	binary	469	507	453	1429	10	0.69
Household head	17	Sex of hh head	binary	468	511	457	1436	3	0.21
	18	Education	cat	470	508	457	1435	4	0.28
	19	Ethnicity	cat	470	511	458	1439	0	0.00
	20	Marital status	cat	469	511	458	1438	1	0.07
	21	Farmer	cat	470	499	457	1426	13	0.90
Household	22	Hh members	cont	465	489	457	1411	28	1.95
	23	Children <5	cont	470	510	455	1435	4	0.28
	24	Wealth quint	cat	461	493	453	1407	32	2.22
	25	Water source	binary	470	510	458	1438	1	0.07
	26	Toilet location	binary	469	500	458	1427	12	0.83
Agriculture	27	Crop fields	cont	469	505	458	1432	7	0.49
	28	Total field size	cont	442	507	457	1406	33	2.29
	29	Average field size per field	cont	442	501	449	1392	47	3.27
	30	Garden ownership	binary	468	507	458	1433	6	0.42
	31	Carts or wagons	binary	470	508	458	1436	3	0.21
	32	Plow	binary	469	508	457	1434	5	0.35
	33	Chicken	binary	468	506	458	1432	7	0.49
	34	Pigs	binary	470	507	458	1435	4	0.28
	35	Sheep or goats	binary	470	507	458	1435	4	0.28
	36	Horses, donkeys or cattle	binary	470	507	458	1435	4	0.28

Appendix 5: Demographic and socio- economic characteristics of 1,439 children aged 7 to 60 months by sex in the Nouna HDSS area (continued)

Characteristics		Nouna HDSS		Boys		Girls	
Variable	Units	%	n	%	n	%	n
N	2017-2019	100.00	1439	48.02	691	51.98	748
Demographics							
Region	Cissé	17.44	251	16.35	113	18.45	138
	Kodougou	12.16	175	11.72	81	12.57	94
	Nouna	14.45	208	15.92	110	13.10	98
	Sono	9.94	143	9.70	67	10.16	76
	Toni	46.00	662	46.31	320	45.72	342
Socio-economic indicators							
Sex of household head	Male	97.91	1406	97.82	647	97.99	732
Mothers' marital status	Polygame	35.92	513	35.91	246	35.94	267
Household heads' marital status	Polygame	37.55	540	36.32	251	38.69	289
Mothers' occupation	Housewives	92.23	1318	93.74	644	90.84	674
Household heads' occupation	Farmers	88.15	1257	88.89	608	87.47	649
Agricultural indicators							
Sorghum field	Yes	88.51	1271	88.97	613	88.09	658
Millet field	Yes	75.07	1078	76.05	524	74.16	554
Fonio field	Yes	11.79	169	14.70	101	9.10	68
Maize field	Yes	79.60	1143	79.54	548	79.65	595
Rice field	Yes	22.70	326	22.35	154	23.03	172
Peanut field	Yes	47.52	681	47.45	326	47.59	355
Sesame field	Yes	77.74	1114	77.44	532	78.02	582
Cotton field	Yes	27.63	396	28.53	196	26.81	200
Beans field ~	Yes	65.18	627	68.98	318	61.68	309
Garden ownership	Yes	17.52	251	15.70	108	19.19	143
Carts or wagons	Yes	70.96	1019	68.94	475	72.82	544
Plow	Yes	74.55	1069	74.85	515	74.26	554
Chicken	Yes	91.97	1317	92.29	634	91.68	683
Pigs	Yes	23.55	338	22.21	153	24.80	185
Sheep or goats	Yes	87.67	1258	86.50	596	88.74	662
Horses, donkeys or cattle	Yes	88.85	1275	88.82	612	88.87	663

* Mean \pm SD; ~ Data only from 2018 and 2019

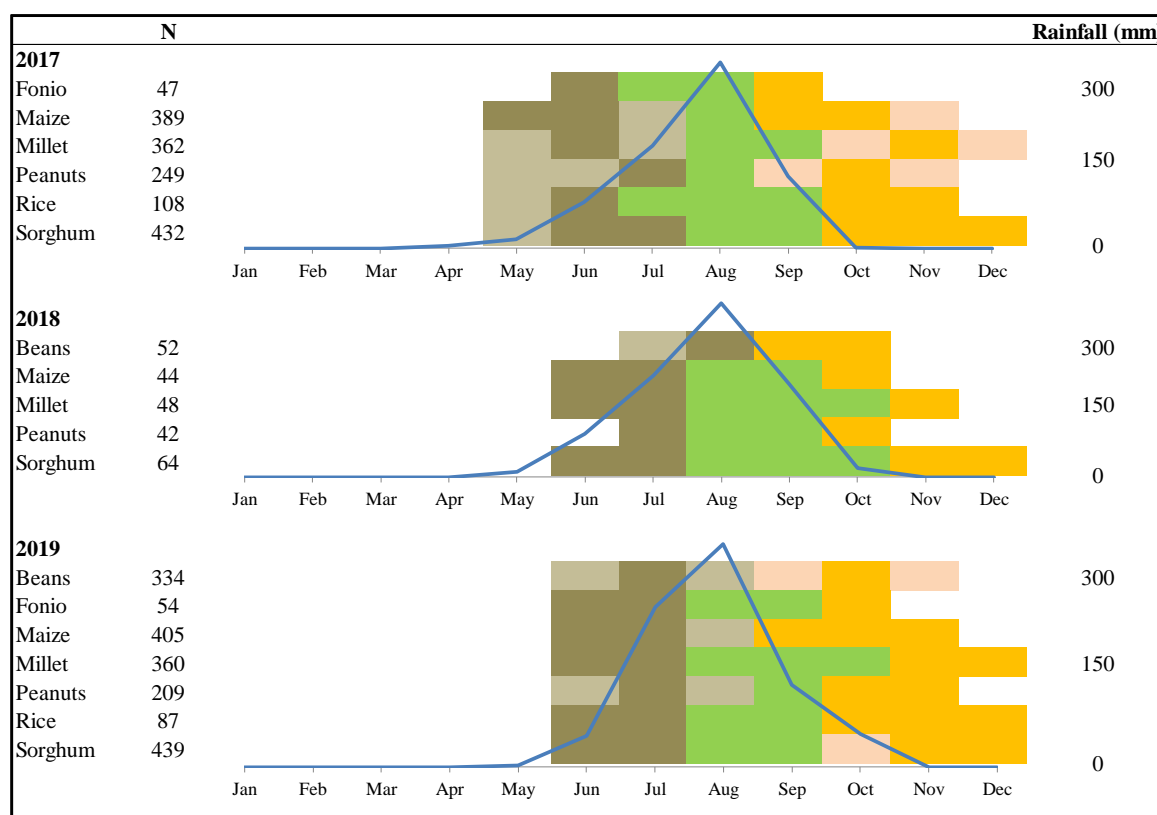
Appendix 6: Univariate associations of not statistically significant risk factors of stunting and HAZ and of wasting and WHZ of children aged 7 to 60 months

Risk factors	Stunting (HAZ < -2)						Wasting (WHZ < -2)						
	N	P	95 %	p-	β-	95 %	N	P	95 %	p-	β-	95 %	p-
	R	CI	valu	coef	CI	valu	R	CI	e	.	CI	e	valu
Underlying causes													
Mothers' age group at birth	< 20 years	24	1.00	0.79	0.00	0.66	24	1.00	0.95	0.00			0.57
	20-35 years	82	1.03	0.76, 1.39	0.00	-0.20, 0.20	82	0.92	0.51, 1.64	0.07		-0.08, 0.22	
	> 35 years	10	0.88	0.53, 1.47	0.13	0.45	10	0.95	0.37, 2.44	0.11		-0.13, 0.34	
Sex of household head	Female	30	1.00	0.41	0.00	0.29	30	1.00	0.85	0.00			0.70
	Male	14	1.44	0.60, 3.49	0.22	-0.20, 0.64	14	0.88	0.22, 3.57	0.07		-0.28, 0.42	
Household heads' education	Illiterate	10	1.00	0.84	0.00	0.39	10	1.00	0.81	0.00			0.46
	Literate Primary	18	0.85	0.61, 1.20	0.19	-0.04, 0.42	18	1.13	0.61, 2.09	0.07		-0.10, 0.24	
	Secondary	37	0.99	0.69, 1.92	0.14	-0.19, 0.56	37	0.46	0.41, 3.31	0.11		-0.06, 0.29	
Wealth index (IWI)	Poorest	28	1.00	0.88	0.00	0.77	28	1.00	0.06	0.00			0.22
	Poor	28	0.84	0.60, 1.19	0.02	-0.19, 0.23	28	0.87	0.49, 1.55	0.09		-0.09, 0.27	
	Middle	27	0.95	0.68, 1.33	0.06	-0.17, 0.29	27	0.48	0.24, 0.96	0.18		0.01, 0.36	
	Rich	30	0.97	0.70, 1.34	0.07	-0.29, 0.14	30	0.43	0.22, 0.87	0.18		0.01, 0.34	
	Richest	25	0.99	0.70, 1.38	0.04	-0.26, 0.18	25	0.62	0.32, 1.19	0.11		-0.06, 0.28	
Siblings <5 years	No	31	1.00	0.71	0.00	0.14	31	1.00	0.25	0.00			0.26
	Yes	11	1.05	0.81, 1.36	0.13	-0.31, 0.05	11	0.76	0.47, 1.23	0.08		-0.06, 0.21	
Basic determinants													
Field size ownership	< 4 hectar	48	1.00	0.62	0.00	0.33	48	1.00	0.91	0.00			0.50
	4-6 hectar	50	1.00	0.77, 1.30	0.10	-0.25, 0.06	50	1.02	0.62, 1.67	0.01		-0.12, 0.13	
	> 7 hectar	40	1.12	0.86, 1.46	0.12	-0.30, 0.06	40	0.91	0.53, 1.57	0.08		-0.06, 0.21	
Garden ownership	No	11	1.00	0.15	0.00	0.13	11	1.00	0.78	0.00			0.81
	Yes	82	0.80	0.60, 1.08	0.13	-0.04, 0.32	82	0.92	0.52, 1.64	0.02		-0.11, 0.15	

* p-value <0.05, ** p-value <0.01, *** p-value <0.001

Appendix C: Agricultural graphs and tables

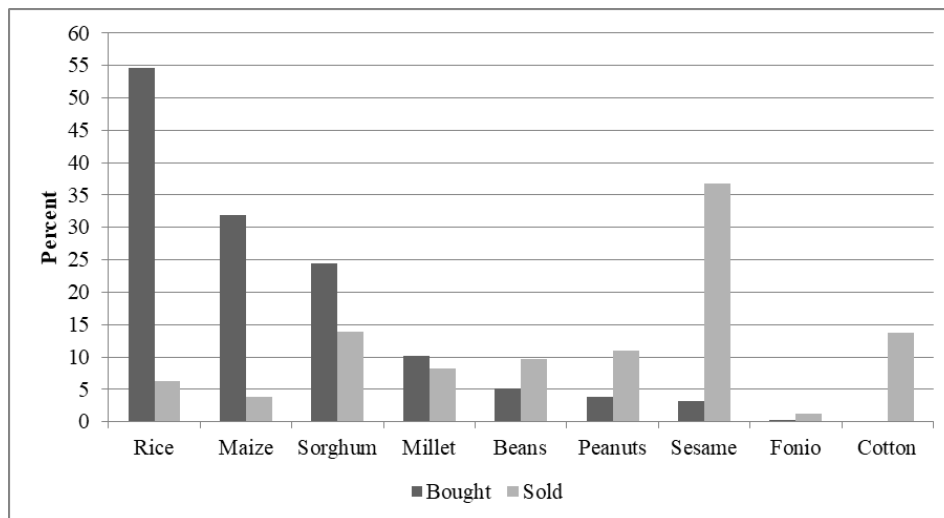
Appendix 7: Crop growth calendar based on household's recall combined with rainfall data for Nouna from 2017 to 2019



Note: Brown represents the seed sowing, green the plant growing and orange the crop harvest period. The light colors represent the outliers, when some farmers' started to sow or harvest earlier or later than the majority. The blue line represents the mean monthly rainfall (in mm) using the rainfall data for Nouna.

Appendix 8: Yield estimations based on farmers' recall conducted in 2018

	N	Median	IQR	Min	Max
<i>Estimations in kg</i>					
Peanuts	37	60	86	5	1,920
Beans	37	48	45	6	160
Maize	44	360	857	18	6,336
Millet	46	864	1,164	114	8,550
Sorghum	64	1,110	1,665	108	13,875
<i>Estimations converted from local products</i>					
Peanuts	36	75	150	17	1,600
Beans	33	50	33	17	166
Maize	44	300	850	17	6,000
Millet	46	800	1,100	199	6,000
Sorghum	66	800	1,200	66	10,000

Appendix 9: Percentage of farmers (N=473), who reported to have bought or sold selected crops in 2018

Appendix D: Dietary graphs and tables

Appendix 10: Overview of food groups and food items for factor analysis

FG	DDS food group	FVS food item	2017			2018			2019			Input variable for factor analysis	Scientific rationale
			n	% consumed	% not consumed	n	% consumed	% not consumed	n	% consumed	% not consumed		
1	Cereales, starchy roots, tubers and their products	Banana plantain	1	0.20	99.80	2	0.38	99.62					Excluded, because >99% never consumed this item
		Bread	86	17.34	82.66	58	11.07	88.93	54	10.93	89.07	Bread	
		Broken millet porridge	54	10.89	89.11	100	19.08	80.92	32	6.48	93.52	Millet	Food items combined
		Millet (small)	168	33.87	66.13	189	36.07	63.93	182	36.84	63.16		
		Cassava	19	3.83	96.17	53	10.11	89.89	54	10.93	89.07	Cassava	
		Couscous	93	18.75	81.25	45	8.59	91.41	43	8.70	91.30	Couscous	
		Dry maize				285	54.39	45.61	192	38.87	61.13	Maize	Food items combined
		Fresh maize				106	20.23	79.77	16	3.24	96.76		
		Maize	355	71.57	28.43								
		Maize porridge	172	34.68	65.32	156	29.77	70.23	91	18.42	81.58		
		Fonio	15	3.02	96.98	8	1.53	98.47	11	2.23	97.77		Excluded, because >96% never consumed this item
		Pasta (macaroni)	121	24.40	75.60	116	22.14	77.86	75	15.18	84.82	Pasta (macaroni)	
		Potato	2	0.40	99.60	1	0.19	99.81					Excluded, because >99% never consumed this item
		Rice	309	62.30	37.70	360	68.70	31.30	275	55.67	44.33	Rice	
Sorghum	260	52.42	47.58	262	50.00	50.00	269	54.45	45.55	Sorghum			
Yam tuber	1	0.20	99.80	1	0.19	99.81					Excluded, because >99% never consumed this item		
2	Pulses, nuts, seeds and their products	African locust bean/soumbala	296	59.68	40.32	349	66.60	33.40	330	66.80	33.20	African locust bean/soumbala	
		Bambara groundnuts (voandzou)	28	5.65	94.35	19	3.63	96.37	55	11.13	88.87	Bambara groundnuts	
		Cowpea beans (niébé)	154	31.05	68.95	138	26.34	73.66	138	27.94	72.06	Cowpea beans (niébé)	

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FG	DDS food group	FVS food item	2017			2018			2019			Input variable for factor analysis	Scientific rationale
			n	% consumed	% not consumed	n	% consumed	% not consumed	n	% consumed	% not consumed		
2	Pulses, nuts, seeds and their products	Palm seeds/ nuts	1	0.20	99.80	1	0.19	99.81					Excluded, because >99% never consumed this item
		Peanut butter				182	34.73	65.27	98	19.84	80.16	Peanuts	Food items combined
		Peanut flour	119	23.99	76.01	32	6.11	93.89					
		Peanuts				169	32.25	67.75	169	34.21	65.79		
		Sesame				11	2.10	97.90	4	0.81	99.19		Excluded, because >97% never consumed this item
		Soya bean	6	1.21	98.79	3	0.57	99.43	2	0.40	99.60		Excluded, because >98% never consumed this item
3	Vegetables and fruits	Papaya	2	0.40	99.60	1	0.19	99.81	1	0.20	99.80	Fruits	Food items combined
		Roselle fruit	330	66.53	33.47	284	54.20	45.80	302	61.13	38.87		
		Shea fruit/ flesh	97	19.56	80.44	15	2.86	97.14	70	14.17	85.83		
		Sweet banana	1	0.20	99.80	10	1.91	98.09	6	1.21	98.79		
		Watermelon	2	0.40	99.60	2	0.38	99.62					
		Dates	5	1.01	98.99	5	0.95	99.05	2	0.40	99.60		
		Lemon	2	0.40	99.60	1	0.19	99.81					
		Tamarind fruit	86	17.34	82.66	118	22.52	77.48	60	12.15	87.85		
		Avocado				1	0.19	99.81	1	0.20	99.80		Excluded, because >99% never consumed this item
		Cabbage	24	4.84	95.16	70	13.36	86.64	2	0.40	99.60	Cabbage	
		Cucumber	4	0.81	99.19	4	0.76	99.24	5	1.01	98.99		Excluded, because >98% never consumed this item
		Garlic	16	3.23	96.77	25	4.77	95.23	6	1.21	98.79		Excluded, because >95% never consumed this item
		Lettuce	3	0.60	99.40	1	0.19	99.81	1	0.20	99.80		Excluded, because >99% never consumed this item
		Eggplant	158	31.85	68.15	118	22.52	77.48	16	3.24	96.76	Eggplant	
		Okra	317	63.91	36.09	319	60.88	39.12	69	13.97	86.03	Okra	
Onions	61	12.30	87.70	160	30.53	69.47	117	23.68	76.32	Onions			
Tomatoes	114	22.98	77.02	95	18.13	81.87	10	2.02	97.98	Tomatoes			

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FG	DDS food group	FVS food item	2017			2018			2019			Input variable for factor analysis	Scientific rationale
			n	% consumed	% not consumed	n	% consumed	% not consumed	n	% consumed	% not consumed		
4	Vitamin A rich fruits, vegetables and tubers	African locust bean fruit	8	1.61	98.39	6	1.15	98.85					Excluded, because >98% never consumed this item
		Baobab leaves	418	84.27	15.73	412	78.63	21.37	421	85.22	14.78	Vitamin A rich leaves	Food items combined
		Bay leaves	4	0.81	99.19	10	1.91	98.09	1	0.20	99.80		
		Cowpea bean leaves	285	57.46	42.54	200	38.17	61.83	116	23.48	76.52		
		Drumstick leaves	15	3.02	96.98	11	2.10	97.90	5	1.01	98.99		
		Jute leaves	199	40.12	59.88	204	38.93	61.07	232	46.96	53.04		
		Onion leaves	60	12.10	87.90	45	8.59	91.41	15	3.04	96.96		
		Roselle leaves	312	62.90	37.10	305	58.21	41.79	207	41.90	58.10		
		Spinach	76	15.32	84.68	72	13.74	86.26	30	6.07	93.93		
		Melon	12	2.42	97.58	3	0.57	99.43					Excluded, because >97% never consumed this item
		Parsley				3	0.57	99.43	3	0.61	99.39		Excluded, because >99% never consumed this item
Sweet potato	4	0.81	99.19	1	0.19	99.81					Excluded, because >99% never consumed this item		
5	Meat	Caterpillar	4	0.81	99.19	2	0.38	99.62	2	0.40	99.60		Excluded, because >99% never consumed this item
		Chicken meat	70	14.11	85.89	65	12.40	87.60	51	10.32	89.68	Poultry	
		Goat meat	62	12.50	87.50	111	21.18	78.82	73	14.78	85.22	Red meat	Food items combined
		Beef meat	31	6.25	93.75	41	7.82	92.18	34	6.88	93.12		
		Sheep meat	115	23.19	76.81	155	29.58	70.42	44	8.91	91.09		
		Pork meat	35	7.06	92.94	25	4.77	95.23	22	4.45	95.55		
		Guinea fowl meat				15	2.86	97.14	3	0.61	99.39		Excluded, because >97% never consumed this item
		Rabbit meat	2	0.40	99.60	5	0.95	99.05	4	0.81	99.19		Excluded, because >99% never consumed this item
		Guinea fowl meat				15	2.86	97.14	3	0.61	99.39		Excluded, because >97% never consumed this item
Rabbit meat	2	0.40	99.60	5	0.95	99.05	4	0.81	99.19		Excluded, because >99% never consumed this item		

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FG	DDS food group	FVS food item	2017			2018			2019			Input variable for factor analysis	Scientific rationale
			n	% consumed	% not consumed	n	% consumed	% not consumed	n	% consumed	% not consumed		
6	Fish and seafood	African carp	110	22.18	77.82	62	11.83	88.17	121	24.49	75.51	Fish	Food items combined
		Carp	111	22.38	77.62	48	9.16	90.84	78	15.79	84.21		
		Catfish	136	27.42	72.58	144	27.48	72.52	122	24.70	75.30		
		Perch fish (Nil)				5	0.95	99.05	2	0.40	99.60		
		Sardine	2	0.40	99.60	3	0.57	99.43	1	0.20	99.80		
		Shiny-nose (capitaine)	1	0.20	99.80	7	1.34	98.66	5	1.01	98.99		
		Tuna	8	1.61	98.39	2	0.38	99.62	1	0.20	99.80		
7	Oils and fats	Cottonseed oil	5	1.01	98.99	73	13.93	86.07	16	3.24	96.76	Oils and fats	Food items combined
		Olive/ vegetable oil	15	3.02	96.98	8	1.53	98.47	2	0.40	99.60		
		Palm oil	4	0.81	99.19	3	0.57	99.43	3	0.61	99.39		
		Peanut oil	236	47.58	52.42	218	41.60	58.40	326	65.99	34.01		
		Shea butter	386	77.82	22.18	401	76.53	23.47	145	29.35	70.65		
8	Milk and milk products	Animal milk	249	50.20	49.80	193	36.83	63.17	140	28.34	71.66	Animal milk	
		Milk powder	13	2.62	97.38	22	4.20	95.80	18	3.64	96.36		Excluded, because >95% never consumed this item
		Mother's milk	121	24.40	75.60	114	21.76	78.24	105	21.26	78.74	Mother's milk	
		Yoghurt	5	1.01	98.99	1	0.19	99.81	1	0.20	99.80		Excluded, because >98% never consumed this item
9	Eggs	Chicken eggs	95	19.15	80.85	18	3.44	96.56	22	4.45	95.55	Eggs	Food items combined
		Guinea fowl eggs				39	7.44	92.56	31	6.28	93.72		
10	Sweets	Biscuit	208	41.94	58.06	196	37.40	62.60	175	35.43	64.57	Sweets/ sugar	Food items combined
		Honey	5	1.01	98.99	3	0.57	99.43	3	0.61	99.39		
		Sugar/ bonbons	378	76.21	23.79	306	58.40	41.60	229	46.36	53.64		
11	Beverages	Lipton tea	83	16.73	83.27	165	31.49	68.51	134	27.13	72.87	Lipton tea	
		Nescafé	312	62.90	37.10	60	11.45	88.55	111	22.47	77.53	Nescafé	
		Cola, fanta, sprite	10	2.02	97.98	18	3.44	96.56	7	1.42	98.58	Beverages	Food items combined
		Orange juice	4	0.81	99.19	5	0.95	99.05	4	0.81	99.19		
		Tamarind juice	1	0.20	99.80	2	0.38	99.62					

Appendix 11: Proportion of food groups consumed over the previous 7-days by 1,439 children aged <5 years considering for differences between study cluster

Food groups	Nouna HDSS	Cissé	Kodougou	Nouna	Sono	Toni
1 Cereals, roots, tubers***	97	97	98	98	90	99
2 Vit. A rich leaves**	93	91	95	92	85	94
3 Oils, fats***	88	86	86	77	83	93
4 Pulses, nuts, seeds***	80	83	82	74	59	84
5 Sweets***	70	77	79	71	59	67
6 Fruits***	68	88	63	75	42	65
7 Vegetables***	62	58	61	70	32	68
8 Fish, seafood***	60	50	48	46	45	74
9 Beverages***	54	62	63	70	43	45
10 Milk, milk products***	53	62	55	61	51	48
11 Meat**	48	57	39	49	43	47
12 Eggs***	13	20	12	16	13	9

* p-value <0.05, ** p-value <0.01, *** p-value <0.001

Appendix 12: Proportion of food groups consumed over the previous 7-days by 1,439 children aged <5 years for differences between study years

Food groups	2017	2018	2019
1 Cereals, roots, tubers*	97	99	96
2 Vit. A rich leaves***	95	94	89
3 Oils, fats***	90	92	81
4 Pulses, nuts, seeds***	72	85	81
5 Sweets***	82	71	57
6 Fruits***	79	61	64
7 Vegetables***	76	78	30
8 Fish, seafood***	68	49	63
9 Beverages***	67	45	49
10 Milk, milk products***	63	52	45
11 Meat***	49	58	35
12 Eggs**	16	10	11

* p-value <0.05, ** p-value <0.01, *** p-value <0.001

Appendix 13: Characteristics of food intake of children aged <5 years across tertiles of DPS

Variables	Tertile 1		Tertile 2		Tertile 3		P-value
	Mean / %	(SD / SE)	Mean / %	(SD / SE)	Mean / %	(SD / SE)	
Dietary Diversity Score (DDS)	608	42.25	618	42.95	213	14.80	
Tertile scores	4.87	1.43	7.46	0.50	9.26	0.44	
Demographics							
Child's sex: Boys	40.67	1.87	45.88	1.90	13.46	1.30	0.0794
Child's sex: Girls	43.72	1.81	40.24	1.79	16.04	1.34	
Child's age in months	35.08	15.29	36.82	13.56	35.77	14.42	0.106
Wealth: poorest quintile	45.04	2.97	47.52	2.98	7.45	1.57	0.000***
Wealth: richest quintile	44.49	3.12	39.76	3.08	15.75	2.29	
Food Variety Score (FVS)	547	38.01	503	34.95	389	27.03	
Tertile scores	7.27	2.56	12.94	1.38	19.36	3.58	
Demographics							
Child's sex: Boys	39.80	1.86	33.86	1.80	26.34	1.68	0.406
Child's sex: Girls	36.36	1.76	35.96	1.76	27.67	1.64	
Child's age in months	34.55	15.71	36.69	13.47	36.89	13.70	0.017*
Wealth: poorest quintile	35.46	2.85	43.26	2.96	21.28	2.44	0.339
Wealth: richest quintile	39.37	3.07	37.01	3.04	23.62	2.67	
Market-based diet (DP1)	482	33.50	478	33.22	479	33.29	
Tertile scores	3.45	1.59	7.75	1.27	14.13	4.19	
Demographics							
Child's sex: Boys	32.42	1.78	35.02	1.82	32.56	1.78	0.373
Child's sex: Girls	34.49	1.74	31.55	1.7	33.96	1.73	
Child's age in months	33.77	15.92	36.13	13.47	37.13	13.62	0.000***
Wealth: poorest quintile	43.26	2.96	32.98	2.80	23.76	2.54	0.014*
Wealth: richest quintile	32.68	2.95	32.68	2.95	34.65	2.99	
Legume-based diet (DP2)	480	33.36	480	33.36	479	33.29	
Tertile scores	6.05	3.79	13.40	1.57	21.46	4.42	
Demographics							
Child's sex: Boys	32.56	1.78	34.73	1.81	32.71	1.79	0.566
Child's sex: Girls	34.09	1.73	32.09	1.71	33.82	1.73	
Child's age in months	31.28	15.79	37.92	13.52	38.60	12.75	0.000***
Wealth: poorest quintile	38.30	2.90	36.17	2.87	25.53	2.60	0.000***
Wealth: richest quintile	31.50	2.92	30.71	2.90	37.80	3.05	
Vegetable-based diet (DP3)	480	33.36	480	33.36	479	33.29	
Tertile scores	4.13	2.02	8.89	1.23	15.94	4.50	
Demographics							
Child's sex: Boys	32.56	1.78	33.29	1.79	34.15	1.81	0.759
Child's sex: Girls	34.09	1.73	33.42	1.73	32.49	1.71	
Child's age in months	33.70	16.15	37.93	13.40	36.16	13.35	0.000***
Wealth: poorest quintile	33.33	2.81	27.66	2.67	39.01	2.91	0.000***
Wealth: richest quintile	37.40	3.04	40.94	3.09	21.65	2.59	

* p-value <0.05, ** p-value <0.01, *** p-value <0.001

Appendix 14: Food groups based on the 7-day FFQ consumed among 1,439 children by age group (in months) and study year

Food group	2017				2018				2019			
	11-23	24-35	36-47	48-59	8-23	24-35	36-47	48-59	7-23	24-35	36-47	48-60
1 Cereals, starchy roots, tubers and their products***	93	98	100	98	95	100	100	100	86	100	100	100
2 Pulses, nuts, seeds and their products***	70	70	70	78	78	93	84	88	56	89	94	90
3 Vegetables***	74	78	77	75	67	82	81	85	21	26	37	34
4 Fruits***	70	83	84	79	52	61	66	67	50	81	66	69
5 Vitamin A rich leaves, fruits and vegetables***	88	98	96	99	84	97	99	95	66	98	98	99
6 Meat***	43	51	51	51	42	57	69	62	25	45	38	39
7 Fish and seafood***	62	74	69	69	42	52	49	54	42	60	71	75
8 Oils and fats***	84	91	91	93	83	98	93	96	55	89	91	92
9 Milk and milk products***	94	59	48	50	86	39	39	41	82	26	35	29
10 Eggs	17	20	11	19	8	9	12	12	11	17	7	12
11 Sweets***	81	85	79	84	63	78	78	65	53	72	63	52
12 Beverages***	67	74	69	59	34	50	49	47	34	57	60	49

* p-value <0.05, ** p-value <0.01, *** p-value <0.001

Appendix 15: Proportion of food items consumed by children aged 7 to 60 months based on the 7-day FFQ

Children aged 7-60 months (N=1,467)			Children aged 7-23 months (N=389)		
Food items	n	%	Food items	n	%
Baobab leaves	1216	82.89	Mother's milk	302	77.63
African locust bean	946	64.49	Baobab leaves	273	70.18
Rice	923	62.92	Sugar/ bonbons	219	56.30
Shea butter	914	62.30	African locust bean	216	55.53
Sugar/ bonbons	889	60.60	Rice	208	53.47
Roselle fruit	887	60.46	Shea butter	201	51.67
Roselle leaves	801	54.60	Roselle fruit	196	50.39
Sorghum	768	52.35	Roselle leaves	179	46.02
Peanut oil	762	51.94	Sorghum	175	44.99
Okra	688	46.90	Okra	169	43.44
Jute leaves	615	41.92	Peanut oil	166	42.67
Cowpea bean leaves	581	39.60	Biscuit	143	36.76
Animal milk	569	38.79	Animal milk	141	36.25
Biscuit	559	38.10	Jute leaves	135	34.70
Millet	523	35.65	Cowpea bean leaves	129	33.16
Coffee	470	32.04	Maize porridge	127	32.65
Dry maize	465	31.70	Millet	114	28.31
Cowpea beans (niébé)	417	28.43	Coffee	106	27.25
Maize porridge	409	27.88	Dry maize	103	26.48
Catfish	384	26.18	Cowpea beans (niébé)	94	24.16

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Children aged 7-60 months (N=1,467)			Children aged 7-23 months (N=389)		
Food items	n	%	Food items	n	%
Tea	378	25.77	Catfish	90	23.14
Maize	350	23.86	Maize	80	20.57
Mother's milk	337	22.97	Pasta (macaroni)	80	20.57
Peanuts	322	21.95	Tea	79	20.31
Onions	321	21.88	Tamarind fruit	71	18.25
Sheep meat	311	21.20	Eggplant	69	17.74
Pasta (macaroni)	306	20.86	Onions	63	16.20
African carp	288	19.63	African carp	59	15.17
Eggplant	284	19.36	Goat meat	58	14.91
Peanut butter	270	18.40	Broken millet porridge	53	13.62
Tamarind fruit	258	17.59	Tomatoes	53	13.62
Goat meat	240	16.36	Peanut butter	50	12.85
Carp	230	15.68	Peanuts	50	12.85
Tomatoes	215	14.66	Carp	43	11.05
Bread	194	13.22	Sheep meat	43	11.05
Pepper	188	12.82	Chicken meat	42	10.80
Broken millet porridge	182	12.41	Peanut flour	42	10.80
Chicken meat	180	12.27	Pepper	38	9.77
Couscous	171	11.66	Bread	33	8.48
Spinach	171	11.66	Onion leaves	33	8.48
Peanut flour	149	10.16	Spinach	33	8.48
Cassava	121	8.25	Couscous	32	8.23
Fresh maize	121	8.25	Cottonseed oil	27	6.94
Onion leaves	117	7.98	Eggs	26	6.68
Bambara groundnuts	100	6.82	Shea flesh	22	5.66
Shea flesh	97	6.61			
Cabbage	95	6.48			
Eggs	95	6.48			
Cottonseed oil	93	6.34			
Shea fruit	83	5.66			

Note: Excluding food items that were consumed by <5 % of the children

Appendix 16: Rotated factor loadings of food items for the three identified dietary pattern scores (DPS) among 1,439 children aged <5 years in the Nouna HDSS area

Food groups	DP1	DP2	DP3
	Market-based diet	Legume-based diet	Vegetable-based diet
Pasta	0.57*	0.24	0.10
Eggs	0.56*	-0.07	0.05
Poultry	0.55*	-0.03	0.09
Sweets	0.52*	0.19	0.25
Bread	0.49*	0.07	0.06
Beverages	0.46*	-0.11	0.01
Rice	0.45*	0.40	0.03
Cassava	0.41*	0.06	-0.09
Soumbala	0.05	0.60*	0.09
Oils and fats	-0.01	0.57*	0.42*
Leaves	0.26	0.46*	0.03
Peanuts	0.35	0.41*	-0.06
Millet	-0.09	0.41*	-0.03
Tea	0.10	0.41*	0.02
Okra	-0.05	0.05	0.70*
Tomatoes	0.08	-0.02	0.66*
Eggplant	0.07	0.14	0.64*
Maize	0.09	-0.17	0.46*
Coffee	0.21	0.04	0.43*
Fish	0.16	0.29	0.42*
Red meat	0.38	0.37	-0.03
Cabbage	0.37	0.13	-0.08
Cowpea beans	0.27	0.02	0.28
Animal milk	0.26	0.30	0.12
Onions	0.25	0.39	-0.09
Fruits	0.25	0.11	0.19
Couscous	0.20	0.24	0.02
Groundnuts	0.18	0.13	-0.13
Mother's milk	0.02	-0.36	-0.03
Sorghum	-0.08	0.27	0.01
Explained variance	9.88 %	8.28 %	7.87 %

* Factor loading scores of $\geq |0.40|$ indicate relevant contributions to the DPS.

Appendix 17: Associations of DDS, FVS and three DPSs with HAZ and WHZ of children aged 7 to 60 months and adjusted for socio-demographic variables

		Tertile 1		Tertile 2		Tertile 3		Per 1 score-point increase			
			β -coef.	95 % CI		β -coef.	95 % CI		β -coef.	95 % CI	p-value
Height-for-Age zscore (HAZ) (N=1,439)											
DDS: Dietary Diversity Score											
	Crude model	Ref.	-0.20	-0.37, -0.03		0.03	-0.13, 0.18		-0.01	-0.04, 0.03	0.652
	Adj. model ^a	Ref.	-0.13	-0.30, 0.04		0.11	-0.05, 0.27		0.02	-0.02, 0.06	0.298
FVS: Food Variety Score											
	Crude model	Ref.	-0.14	-0.32, 0.03		-0.02	-0.19, 0.14		-0.01	-0.02, 0.01	0.394
	Adj. model ^a	Ref.	-0.12	-0.29, 0.05		0.04	-0.14, 0.21		0.02	-0.01, 0.02	0.798
DPS1: Market-based diet											
	Crude model	Ref.	-0.02	-0.20, 0.15		0.07	-0.10, 0.24		0.01	0.00, 0.02	0.222
	Adj. model ^a	Ref.	0.04	-0.13, 0.20		0.22	0.05, 0.38		0.02	0.01, 0.03	0.003*
DPS2: Legume-based diet											
	Crude model	Ref.	-0.02	-0.19, 0.16		-0.13	-0.29, 0.03		-0.01	-0.02, 0.00	0.115
	Adj. model ^a	Ref.	0.19	0.02, 0.37		0.17	0.00, 0.33		0.01	0.00, 0.02	0.037*
DPS3: Vegetable-based diet											
	Crude model	Ref.	-0.03	-0.20, 0.14		0.04	-0.14, 0.21		0.00	-0.01, 0.01	0.991
	Adj. model ^a	Ref.	-0.03	-0.20, 0.14		0.09	-0.10, 0.28		0.00	-0.01, 0.02	0.495
Weight-for-Height zscore (WHZ) (N=1,434)											
DDS: Dietary Diversity Score											
	Crude model	Ref.	0.03	-0.11, 0.17		0.06	-0.06, 0.18		0.02	-0.01, 0.05	0.177
	Adj. model ^a	Ref.	-0.01	-0.15, 0.13		0.02	-0.11, 0.14		0.00	-0.03, 0.03	0.828
FVS: Food Variety Score											
	Crude model	Ref.	0.05	-0.09, 0.18		0.02	-0.12, 0.15		0.00	0.00, 0.01	0.313
	Adj. model ^a	Ref.	-0.01	-0.14, 0.13		-0.06	-0.20, 0.09		0.00	-0.01, 0.01	0.621
DPS1: Market-based diet											
	Crude model	Ref.	0.03	-0.10, 0.16		0.00	-0.13, 0.13		0.00	-0.01, 0.01	0.456
	Adj. model ^a	Ref.	-0.06	-0.19, 0.07		-0.13	-0.27, 0.01		-0.01	-0.02, 0.01	0.293
DPS2: Legume-based diet											
	Crude model	Ref.	0.05	-0.08, 0.19		0.04	-0.09, 0.17		0.01	0.00, 0.01	0.087
	Adj. model ^a	Ref.	-0.04	-0.18, 0.10		-0.05	-0.19, 0.09		0.00	-0.01, 0.01	0.810
DPS3: Vegetable-based diet											
	Crude model	Ref.	0.06	-0.07, 0.19		0.09	-0.05, 0.22		0.01	0.00, 0.02	0.047*
	Adj. model ^a	Ref.	-0.05	-0.18, 0.08		-0.01	-0.16, 0.14		0.00	-0.01, 0.01	0.947

^a Adj. for child's age and sex, cluster and year of data collection, education and ethnicity of the mother and the household head, household wealth, siblings aged <5 years, child's fever and diarrhea the previous two weeks, and breastfeeding status

* p-value <0.05, ** p-value <0.01

Appendix E: Rainfall graphs and tables

Appendix 18: Means and z-scores of the 15 rainfall indicators by two different time periods

Rainfall indicators		Mean (SD) of rainfall	Means (SD) of rainfall indicators		Mean z-scores of rainfall indicators	
ID (unit)	Indicator name	1981-2019	Year before the nutrition survey t-1	Year of the nutrition survey t-0	Year before the nutrition survey t-1	Year of the nutrition survey t-0
PRCPTOT (mm)	Annual total precipitation	741 (145)	762 (87)	798 (80)	0.15	0.39
SDII (mm/day)	Simple daily intensity index	15 (2)	15 (1)	15 (1)	-0.06	-0.01
R10 (days)	Days with heavy precipitation	25 (4)	27 (4)	29 (3)	0.36	0.81
R20 (days)	Days with very heavy precipitation	13 (3)	14 (3)	15 (3)	0.23	0.63
R25 (days)	Days with very heavy precipitation	10 (3)	10 (2)	11 (2)	0.17	0.41
CDD (days)	Consecutive dry days	164 (34)	183 (25)	196 (23)	0.58	0.98
CWD (days)	Consecutive wet days	4 (1)	5 (1)	5 (1)	0.55	0.76
R95p (days)	Very wet days	5 (1)	5 (1)	5 (1)	0.05	0.03
R99p (days)	Extremely wet days	2 (2)	2 (2)	1 (2)	-0.18	-0.40
Lws (days)	Duration wet season	137 (23)	131 (13)	124 (13)	-0.22	-0.49
CDDws (days)	Consecutive dry days in wet season (mini-drought)	10 (3)	9 (3)	7 (2)	-0.30	-1.19
R20Jul (days)	Days with very heavy rains in July	4 (2)	4 (1)	4 (2)	0.10	0.44
R20Aug (days)	Days with very heavy rains in August	5 (2)	7 (2)	8 (1)	1.11	1.64
PRCPJUL (mm)	Total precipitation in July	187 (61)	201 (34)	203 (32)	0.19	0.23
PRCPAUG (mm)	Total precipitation in August	231 (82)	305 (61)	341 (26)	0.97	1.40

Appendix 19: 15 precipitation indicators by weather station cluster from 1981 to 2019

Indicator			Cissé			Kodougou			Nouna			Sono			Toni			Diff. in means
ID (unit)	Indicator name	Definitions	Mean ± SD	Min-Max	Trend ^a	Mean ± SD	Min-Max	Trend ^a	Mean ± SD	Min-Max	Trend ^a	Mean ± SD	Min-Max	Trend ^a	Mean ± SD	Min-Max	Trend ^a	p-value
PRCPTOT (mm)	Annual total precipitation	Annual total PRCP in wet days (RR>=1mm)	724 ± 166	355 - 1087	↑*	778 ± 153	430 - 1113	↑**	730 ± 127	540 - 1019	↑*	730 ± 135	486 - 1062	↑*	744 ± 139	504 - 1115	↑**	0.477
R95p (days)	Very wet days	Annual number of days with RR>95th percentile	5 ± 1	0 - 6	↑*	4 ± 2	0 - 6	↗	5 ± 1	0 - 6	↑	4 ± 2	0 - 6	↑	4 ± 2	0 - 6	↑	0.1091
CDD (days)	Consecutive dry days	Max. no. of consecutive days with RR<1mm	171 ± 34	64 - 222	↑*	164 ± 37	81 - 238	↗	161 ± 33	97 - 238	↑*	164 ± 31	80 - 236	↗	161 ± 34	63 - 211	↗	0.715
R99p (days)	Extremely wet days	Annual number of days with RR>99th percentile	2 ± 2	0 - 6	↑	1 ± 2	0 - 5	→	1 ± 2	0 - 5	↗	4 ± 2	0 - 6	↑	2 ± 2	0 - 5	↗	0.000**
R20Aug (days)	Days with very heavy rains in Aug	Count of days when PRCP>=20mm	5 ± 2	0 - 9	↗*	5 ± 2	0 - 9	↗*	4 ± 2	1 - 8	↗**	5 ± 2	0 - 9	↗	5 ± 2	2 - 8	↗*	0.787
PRCPAUG (mm)	Total precipitation in Aug	Cumulative rainfall in August (RR>=1mm)	243 ± 106	57 - 561	↗*	227 ± 68	150 - 480	↗**	224 ± 76	87 - 379	↗**	231 ± 82	78 - 378	↗	230 ± 75	124 - 397	↗**	0.869
PRCPJUL (mm)	Total precipitation in July	Cumulative rainfall in July (RR>=1mm)	181 ± 66	63 - 300	↗*	196 ± 63	85 - 359	→	183 ± 51	64 - 298	→	182 ± 59	70 - 367	→	193 ± 67	32 - 316	↗**	0.737
R20Jul (days)	Days with very heavy rains in July	Count of days when PRCP>=20mm	4 ± 2	1 - 8	↗	4 ± 2	1 - 8	→	4 ± 2	1 - 7	→	3 ± 2	1 - 9	→	4 ± 2	0 - 8	↗*	0.793
R10 (days)	Days with heavy precipitation	Annual count of days when PRCP>=10mm	25 ± 5	15 - 37	↗*	27 ± 5	18 - 39	↗**	25 ± 4	17 - 33	↗	25 ± 4	19 - 32	→**	25 ± 4	18 - 38	→*	0.360
SDII (mm/day)	Simple daily intensity index	Annual total precipitation by no. of wet days (PRCP>=1mm)	15 ± 3	9 - 22	↗**	15 ± 2	12 - 20	→	15 ± 2	11 - 20	→	15 ± 2	9 - 20	→	15 ± 2	12 - 19	→*	0.717
R20 (days)	Days with very heavy precipitation	Annual count of days when PRCP>=20mm	13 ± 4	3 - 21	↗	14 ± 3	6 - 21	→*	13 ± 3	7 - 20	→	13 ± 4	4 - 23	→	13 ± 3	8 - 19	→*	0.437
R25 (days)	Days with very heavy precipitation	Annual count of days when PRCP>=25mm	9 ± 4	1 - 17	↗*	10 ± 3	3 - 17	→	9 ± 3	3 - 15	→	9 ± 3	1 - 16	→	10 ± 3	5 - 18	→**	0.325
CWD (days)	Consecutive wet days	Max. no. of consecutive days with RR>=1mm	4 ± 1	2 - 9	→	4 ± 2	3 - 8	→	3 ± 1	2 - 6	→	4 ± 1	3 - 6	→	4 ± 1	2 - 8	→	0.015*
Lws (days)	Duration wet season	Length of the wet season	132 ± 23	88 - 177	→	142 ± 21	94 - 179	→	136 ± 23	77 - 179	→	138 ± 24	85 - 182	→	135 ± 23	77 - 177	→	0.359
CDDws (days)	Consecutive dry days in wet season (mini-drought)	Max. no. of consecutive dry days (RR<1 mm) during wet season	10 ± 3	3 - 17	→	11 ± 2	7 - 15	→	9 ± 3	4 - 15	↘	11 ± 3	5 - 17	→	10 ± 3	5 - 17	↘*	0.182

^aSlope = steep increase (↑), when > 1.0; light increase (↗), when < 1.00 and > 0.10; no change (→), when > -0.10 and < 0.10; light decrease (↘), when < -0.10; * p-value < 0.05, ** p-value < 0.01

Appendix 20: Multi-level uni- and multivariate Poisson regression analysis on the association 15 rainfall indicators by four time periods with stunting (HAZ <-2) of 1,364 children

			Year before birth (t-3)			Year of birth (t-2)			Year before the nutrition survey (t-1)			Year of the nutrition survey (t-0)		
			PR	95% CI		PR	95% CI		PR	95% CI		PR	95% CI	
Univariate regression analysis														
1	PRCPTOT	Annual total precipitation	0.98	0.76	1.25	0.90	0.67	1.21	0.82 *	0.71	0.96	0.85	0.65	1.10
2	SDII	Simple daily intensity index	1.05	0.82	1.35	1.07	0.78	1.48	1.07	0.81	1.41	0.87	0.71	1.06
3	R10	Days with heavy precipitation	0.89	0.69	1.14	1.03	0.84	1.28	0.78 *	0.61	0.98	0.92	0.66	1.29
4	R20	Days with very heavy precipitation	0.93	0.69	1.26	0.94	0.70	1.25	0.91	0.78	1.07	0.96	0.69	1.32
5	R25	Days with very heavy precipitation	1.02	0.78	1.34	1.01	0.71	1.45	0.89	0.74	1.07	0.90	0.70	1.17
6	CDD	Consecutive dry days	0.89	0.70	1.14	1.09	0.88	1.35	0.98	0.79	1.23	1.00	0.78	1.27
7	CWD	Consecutive wet days	0.98	0.79	1.22	0.94	0.69	1.28	0.72 **	0.56	0.91	0.99	0.78	1.26
8	R95p	Very wet days	1.05	0.75	1.46	0.87	0.62	1.22	0.90	0.64	1.27	0.82	0.67	1.01
9	R99p	Extremely wet days	1.20	0.91	1.59	1.09	0.81	1.46	1.12	0.86	1.47	0.85	0.65	1.09
10	Lws	Duration wet season	0.95	0.74	1.23	0.98	0.73	1.31	0.88	0.76	1.02	1.10	0.98	1.25
11	CDDws	Consecutive dry days in wet season (mini-drought)	0.96	0.73	1.26	1.07	0.87	1.31	0.85 *	0.73	0.98	1.38 ***	1.19	1.60
12	R20Jul	Days with "big rains" in July	1.03	0.73	1.45	1.12	0.86	1.47	1.09	0.89	1.34	0.83	0.62	1.10
13	R20Aug	Days with "big rains" in August	0.87	0.66	1.14	0.99	0.79	1.25	0.76 **	0.63	0.90	omitted		
14	PRCPJUL	Total precipitation in July	0.98	0.69	1.38	1.21	0.94	1.57	1.05	0.74	1.47	0.84	0.63	1.13
15	PRCPAUG	Total precipitation in August	1.00	0.80	1.25	0.95	0.65	1.38	0.77 **	0.64	0.93	omitted		
Multivariate regression analysis														
1	PRCPTOT	Annual total precipitation	0.89	0.67	1.18	0.87	0.70	1.07	0.89	0.76	1.03	0.93	0.68	1.27
2	SDII	Simple daily intensity index	0.98	0.74	1.27	1.07	0.78	1.46	1.07	0.76	1.50	0.98	0.76	1.27
3	R10	Days with heavy precipitation	0.87	0.68	1.12	1.07	0.89	1.29	0.88	0.64	1.21	1.02	0.70	1.49
4	R20	Days with very heavy precipitation	0.89	0.67	1.18	0.90	0.71	1.14	0.94	0.78	1.14	1.01	0.69	1.46
5	R25	Days with very heavy precipitation	0.95	0.73	1.22	0.96	0.73	1.26	0.94	0.77	1.15	0.93	0.68	1.28
6	CDD	Consecutive dry days	0.93	0.72	1.21	1.13	0.91	1.41	1.01	0.81	1.26	1.04	0.81	1.34
7	CWD	Consecutive wet days	0.98	0.83	1.15	0.89	0.63	1.26	0.79	0.61	1.03	1.05	0.81	1.36
8	R95p	Very wet days	0.88	0.54	1.43	0.97	0.60	1.26	0.95	0.66	1.38	0.83	0.64	1.07
9	R99p	Extremely wet days	1.15	0.81	1.61	1.08	0.84	1.38	1.04	0.76	1.42	1.01	0.73	1.39
10	Lws	Duration wet season	0.99	0.76	1.29	1.03	0.76	1.40	0.95	0.80	1.12	1.05	0.92	1.21
11	CDDws	Consecutive dry days in wet season (mini-drought)	0.96	0.72	1.29	1.06	0.88	1.28	0.90	0.78	1.05	1.31	0.99	1.75
12	R20Jul	Days with "big rains" in July	1.02	0.73	1.43	1.08	0.84	1.39	1.09	0.88	1.36	0.88	0.61	1.27
13	R20Aug	Days with "big rains" in August	0.87	0.69	1.11	0.98	0.79	1.23	0.81	0.62	1.05	omitted		
14	PRCPJUL	Total precipitation in July	0.96	0.69	1.34	1.16	0.92	1.45	1.04	0.71	1.50	0.96	0.69	1.34
15	PRCPAUG	Total precipitation in August	0.97	0.81	1.16	0.90	0.61	1.34	0.83	0.62	1.11	omitted		

* p-value <0.05, ** p-value <0.01, *** p-value <0.001; Note: Omitted variables had no data for a reduction in rainfall.

Appendix 21: Multi-level uni- and multivariate Poisson regression analysis on the association 15 rainfall indicators by four time periods with wasting (WHZ <-2) of 1,364 children

			Year before birth (t-3)			Year of birth (t-2)			Year before the nutrition survey (t-1)			Year of the nutrition survey (t-0)		
			PR	95% CI		PR	95% CI		PR	95% CI		PR	95% CI	
Univariate regression analysis														
1	PRCPTOT	Annual total precipitation	0.81	0.44	1.49	0.59	0.33	1.05	0.87	0.62	1.22	0.93	0.60	1.45
2	SDII	Simple daily intensity index	0.94	0.55	1.62	0.79	0.46	1.33	1.11	0.77	1.62	1.03	0.64	1.64
3	R10	Days with heavy precipitation	0.85	0.50	1.42	0.62 *	0.39	0.99	0.96	0.61	1.50	0.88	0.63	1.21
4	R20	Days with very heavy precipitation	0.71	0.33	1.53	0.60	0.29	1.26	1.02	0.62	1.69	0.98	0.70	1.39
5	R25	Days with very heavy precipitation	0.75	0.41	1.36	0.46 *	0.26	0.84	0.74	0.52	1.03	0.96	0.60	1.54
6	CDD	Consecutive dry days	0.80	0.52	1.24	1.24	0.75	2.05	1.02	0.72	1.44	0.96	0.48	1.94
7	CWD	Consecutive wet days	1.34	0.86	2.09	1.05	0.65	1.71	0.74	0.49	1.11	0.86	0.45	1.66
8	R95p	Very wet days	0.69	0.42	1.15	0.46 **	0.27	0.77	0.99	0.67	1.44	1.16	0.66	2.04
9	R99p	Extremely wet days	1.22	0.71	2.07	1.07	0.54	2.14	1.12	0.73	1.73	0.80	0.53	1.23
10	Lws	Duration wet season	0.89	0.54	1.48	1.33	0.82	2.17	0.79	0.50	1.24	1.20	0.78	1.86
11	CDDws	Consecutive dry days in wet season (mini-drought)	0.86	0.55	1.36	1.20	0.77	1.86	0.83	0.57	1.23	1.30	0.75	2.24
12	R20Jul	Days with "big rains" in July	1.02	0.66	1.57	1.14	0.61	2.15	0.93	0.63	1.37	0.91	0.68	1.23
13	R20Aug	Days with "big rains" in August	0.90	0.46	1.77	0.88	0.45	1.72	0.94	0.45	1.97	omitted		
14	PRCPJUL	Total precipitation in July	0.98	0.55	1.74	0.86	0.46	1.62	1.11	0.77	1.59	0.78	0.61	1.01
15	PRCPAUG	Total precipitation in August	1.20	0.57	2.50	1.01	0.63	1.62	1.15	0.41	3.22	omitted		
Multivariate regression analysis														
1	PRCPTOT	Annual total precipitation	0.96	0.53	1.74	0.68	0.38	1.22	0.91	0.63	1.30	1.08	0.69	1.70
2	SDII	Simple daily intensity index	1.02	0.70	1.48	1.09	0.61	1.96	1.10	0.77	1.57	1.17	0.70	1.94
3	R10	Days with heavy precipitation	1.04	0.57	1.91	0.77	0.49	1.21	1.20	0.71	2.03	0.95	0.67	1.34
4	R20	Days with very heavy precipitation	0.73	0.34	1.55	0.70	0.36	1.36	1.28	0.79	2.07	1.06	0.75	1.51
5	R25	Days with very heavy precipitation	0.78	0.43	1.42	0.51 *	0.27	0.97	0.84	0.62	1.15	1.11	0.68	1.82
6	CDD	Consecutive dry days	0.85	0.57	1.27	1.20	0.76	1.90	1.01	0.73	1.41	1.21	0.65	2.27
7	CWD	Consecutive wet days	1.03	0.66	1.58	0.68	0.42	1.10	0.67	0.47	0.97	0.88	0.49	1.61
8	R95p	Very wet days	0.95	0.49	1.85	0.65	0.33	1.29	0.90	0.60	1.36	1.10	0.70	1.73
9	R99p	Extremely wet days	1.24	0.76	2.02	1.28	0.67	2.44	0.99	0.64	1.51	1.06	0.66	1.70
10	Lws	Duration wet season	1.12	0.68	1.83	1.15	0.67	1.97	0.84	0.53	1.33	1.17	0.75	1.83
11	CDDws	Consecutive dry days in wet season (mini-drought)	0.85	0.52	1.40	1.30	0.82	2.08	0.87	0.59	1.33	1.64	0.95	2.86
12	R20Jul	Days with "big rains" in July	0.91	0.53	1.59	1.20	0.62	2.32	1.02	0.71	1.46	1.01	0.74	1.37
13	R20Aug	Days with "big rains" in August	0.81	0.42	1.56	0.76	0.41	1.39	1.08	0.58	2.01	omitted		
14	PRCPJUL	Total precipitation in July	1.05	0.56	1.95	1.04	0.57	1.90	0.98	0.64	1.51	0.96	0.69	1.33
15	PRCPAUG	Total precipitation in August	0.97	0.48	1.97	0.68	0.40	1.16	1.19	0.48	2.97	omitted		

* p-value <0.05, ** p-value <0.01, *** p-value <0.001; Note: Omitted variables had no data for a reduction in rainfall.

Appendix 22: Pearson correlation coefficients (N=1,364) for precipitation indicators (predictor variables), the RRR-derived precipitation pattern score (PVS), and dietary pattern scores (response variables)

Predictor variables			PVS		Market-based DPS (DPS1)		Legume-based DPS (DPS2)		Vegetable-based DPS (DPS3)	
			Model 1	Model 2a	Model 1	Model 2a	Model 1	Model 2a	Model 1	Model 2a
CDDws (days)	bs	Consecutive dry days in wet season	0.70***	0.71***	0.20***	0.21***	0.12***	0.14***	0.40***	0.41***
R99p (mm)	ys	Extremely wet days	-0.61***	-0.61***	-0.15***	-0.16***	-0.09***	-0.11***	-0.37***	-0.38***
R10 (days)	bs	Days with heavy precipitation	-0.57***	-0.59***	-0.10***	-0.12***	-0.07*	-0.10***	-0.39***	-0.40***
CDD (days)	bs	Consecutive dry days	-0.44***	-0.58***	-0.11***	-0.19***	-0.12**	-0.16***	-0.26***	-0.26***
PRCPAUG (mm)	bs	Cumulative rainfall in August	-0.60***	-0.58***	-0.21***	-0.17***	-0.12***	-0.12***	-0.31***	-0.34***
R20Jul (days)	ys	Days with very heavy rains in July	-0.48***	-0.58***	-0.08**	-0.17***	-0.01	-0.06*	-0.35***	-0.37***
PRCPJUL (mm)	ys	Cumulative rainfall in July	-0.47***	-0.56***	-0.06*	-0.13***	0.00	-0.05	-0.36***	-0.38***
PRCPTOT (mm)	ys	Annual total wet-day precipitation	-0.54***	-0.55***	-0.17***	-0.18***	0.02	0.00	-0.36***	-0.37***
R99p (mm)	bs	Extremely wet days	0.55***	0.55***	0.19***	0.19***	0.00	0.01	0.35***	0.35***
R20Aug (days)	bs	Days with very heavy rains in August	-0.54***	-0.53***	-0.18***	-0.17***	-0.04	-0.05*	-0.33***	-0.34***
CDD (days)	ys	Consecutive dry days	-0.40***	-0.52***	0.01	-0.07**	-0.07*	-0.13***	-0.31***	-0.34***
PRCPJUL (mm)	bs	Total wet-day precipitation in July	0.55***	0.52***	0.18***	0.13***	0.06*	0.05	0.32***	0.35***
PRCPAUG (mm)	ys	Cumulative rainfall in August	-0.51***	-0.47***	-0.21***	-0.14***	-0.11***	-0.10***	-0.23***	-0.28***
CWD (days)	bs	Consecutive wet days	-0.39***	-0.40***	-0.06*	-0.07**	-0.05	-0.06*	-0.27***	-0.27***
PRCPTOT (mm)	bs	Annual total wet-day precipitation	-0.40***	-0.37***	-0.09***	-0.07*	-0.11***	-0.12***	-0.22***	-0.23***
R20 (days)	bs	Days with very heavy precipitation	-0.34***	-0.36***	-0.02	-0.05	-0.05	-0.09**	-0.25***	-0.26***
R25 (days)	ys	Days with very heavy precipitation	-0.34***	-0.36***	-0.05	-0.07**	0.06*	0.01	-0.29***	-0.31***
CDDws (days)	ys	Consecutive dry days in wet season	0.35***	0.36***	0.04	0.05	0.04	0.07*	0.25***	0.26***

Continued on the next page

Predictor variables			PVS		Market-based DPS (DPS1)		Legume-based DPS (DPS2)		Vegetable-based DPS (DPS3)	
			Model 1	Model 2a	Model 1	Model 2a	Model 1	Model 2a	Model 1	Model 2a
R20 (days)	ys	Days with very heavy precipitation	-0.32***	-0.35***	-0.07**	-0.11***	0.04	0.00	-0.24***	-0.25***
R10 (days)	ys	Days with heavy precipitation	-0.33***	-0.34***	-0.08**	-0.10***	0.01	0.00	-0.23***	-0.24***
R25 (days)	bs	Days with very heavy precipitation	-0.34***	-0.33***	-0.06*	-0.05*	-0.11***	-0.13***	-0.18***	-0.19***
SDII (mm/day)	bs	Simple daily intensity index	-0.28***	-0.32***	-0.07**	-0.10***	-0.19***	-0.22***	-0.09**	-0.09**
R95p (mm)	ys	Very wet days	-0.32***	-0.27***	-0.17***	-0.11***	0.00	0.03	-0.16***	-0.19***
CWD (days)	ys	Consecutive wet days	-0.23***	-0.22***	-0.06*	-0.05	-0.02	-0.02	-0.15***	-0.15***
Lws (days)	ys	Length of wet season	-0.21***	-0.21***	-0.10***	-0.10***	-0.04	-0.03	-0.10***	-0.10***
R20Jul (days)	bs	Days with very heavy rains in July	0.21***	0.18***	0.11***	0.08**	0.06*	0.04	0.08**	0.08**
Lws (days)	bs	Duration wet season	0.16***	0.16***	0.08**	0.08**	0.01	0.01	0.08**	0.08**
R95p (mm)	bs	Very wet days	0.00	0.09***	-0.07**	0.02	-0.05	0.01	0.07**	0.07**
R20Aug (days)	ys	Days with very heavy rains in August	-0.01	0.05	-0.04	0.01	-0.03	0.02	0.03	0.03
SDII (mm/day)	ys	Simple daily intensity index	0.04	-0.04	0.12***	0.05	0.10***	0.05*	-0.10***	-0.11***
Total					0.32***	0.29***	0.28***	0.28***	0.50***	0.51***

^a Adjusted for child's age and sex, and cluster; t-1 = year before the nutrition survey; t-0 = year of the nutrition survey;

Note: Correlations are considered weak: 0-0.30, moderate: 0.31-0.50, and strong: 0.51-1.00; * p-value <0.05; ** p-value <0.01; *** p-value <0.001

Appendix 23: RRR-derived explained variation and rotated factor loadings of rainfall indicators with the three DPSs

Extracted factors			Explained variation (%)	Factor loadings	Factor weights
<i>Predictor variables</i>					
CDDws	t-1	Consecutive dry days in wet season (mini-drought) (RR<1 mm)	49.06	0.31*	0.80
PRCPJUL	t-1	Cumulative rainfall in July (RR>=1mm)	29.96	0.24*	0.81
R99p	t-1	Extremely wet days (Annual PRCP when RR>99th percentile)	30.42	0.24*	-0.27
CDDws	t-0	Consecutive dry days in wet season (mini-drought) (RR<1 mm)	12.58	0.17	0.00
R20Jul	t-1	Days with very heavy rains in July (PRCP>=20mm)	4.57	0.09	-0.49
Lws	t-1	Length wet season	2.59	0.07	-0.34
SDII	t-0	Simple daily intensity index (annual precipitation by number of wet days (PRCP>=1mm))	0.16	0.02	0.00
R95p	t-1	Very wet days (Annual PRCP when RR>95th percentile)	0.00	0.00	-0.27
R20Aug	t-0	Days with very heavy rains in August (PRCP>=20mm)	0.01	0.00	0.00
Lws	t-0	Length of wet season	4.53	-0.09	0.00
CWD	t-0	Consecutive wet days (RR>=1mm)	5.16	-0.10	0.00
SDII	t-1	Simple daily intensity index (annual precipitation by number of wet days (PRCP>=1mm))	7.89	-0.12	-0.41
R10	t-0	Days with heavy precipitation (PRCP>=10mm)	10.83	-0.14	0.00
R20	t-0	Days with very heavy precipitation (PRCP>=20mm)	10.01	-0.14	0.00
R95p	t-0	Very wet days (Annual PRCP when RR>95th percentile)	10.39	-0.14	0.00
R20	t-1	Days with very heavy precipitation (PRCP>=20mm)	11.64	-0.15	0.18
R25	t-1	Days with very heavy precipitation (PRCP>=25mm)	11.23	-0.15	0.84
R25	t-0	Days with very heavy precipitation (PRCP>=25mm)	11.80	-0.15	0.00
CWD	t-1	Consecutive wet days (RR>=1mm)	15.24	-0.17	0.07
PRCPTOT	t-1	Annual total precipitation (RR>=1mm)	15.66	-0.17	-0.52
CDD	t-0	Consecutive dry days (RR<1mm)	16.11	-0.18	0.00
CDD	t-1	Consecutive dry days (RR<1mm)	19.77	-0.20*	-0.31
PRCPJUL	t-0	Cumulative rainfall in July (RR>=1mm)	21.86	-0.21*	0.00
R20Jul	t-0	Days with very heavy rains in July (PRCP>=20mm)	23.07	-0.21*	0.00
PRCPAUG	t-0	Cumulative rainfall in August (RR>=1mm)	25.56	-0.22*	0.00
R20Aug	t-1	Days with very heavy rains in August (PRCP>=20mm)	29.48	-0.24*	0.14
PRCPTOT	t-0	Annual total precipitation (RR>=1mm)	29.43	-0.24*	0.00
R10	t-1	Days with heavy precipitation (PRCP>=10mm)	32.63	-0.25*	0.11
PRCPAUG	t-1	Cumulative rainfall in August (RR>=1mm)	36.48	-0.27*	0.00
R99p	t-0	Extremely wet days (Annual PRCP when RR>99th percentile)	37.15	-0.27*	0.00
Explained variance (%)			17.18		
<i>Response variables</i>					
DP1		Market-based diet	10.11		0.49
DP2		Legume-based diet	7.71		0.41
DP3		Vegetable-based diet	24.51		0.77
Explained variance (%)			14.11		

Note: t-0 = year of the nutrition survey, t-1 = year before the nutrition survey; * Precipitation indicators with factor loadings of $\geq |0.20|$ indicate relevant contributions to the precipitation pattern score

Curriculum vitae

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Education

2017 - today	<p>University Hospital Heidelberg/ Heidelberg University, Heidelberg Institute of Global Health (HIGH), Germany – candidate Dr.sc.hum.</p> <p>Dr.sc.hum. dissertation: <i>The impact of climate variability on diets and child undernutrition in rural Burkina Faso</i></p> <p>→ Doctoral Fellowship, Landesgraduiertenförderung (LGF), Germany (08/2017 – 01/2020)</p> <p>→ DAAD Stipend, upgrade to the LGF (Aufstockungsstipendium) for research in Burkina Faso, Germany (10/2017 – 11/2017)</p> <p>→ Stipend, Heidelberg Institute of Global Health (HIGH), Heidelberg University, Germany (01/2017 – 06/2017)</p>
2013 – 2015	<p>Diplomatic Academy Vienna and Vienna University of Technology, Austria - MSc in Environmental Technology & International Affairs (ETIA)</p> <p>Master thesis: <i>Energy blackouts and water outages: A risk management approach towards raising awareness and assuming responsibility.</i></p> <p>→ Honored with a scientific award 2016 given by the Austrian Gas and Water Association</p> <p>→ Honored with a scientific award 2015 given by the Vienna Municipal Department for Environmental Matters together with the Municipal Department Vienna Water</p>
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2011	<p>Maastricht University, The Netherlands – Bachelor Erasmus Semester in European Public Health</p> <p>→ Erasmus Stipend, European Public Health, Maastricht University, The Netherlands</p>
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Work Experience

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2017 – 2019	University Hospital Heidelberg/ Heidelberg University , Heidelberg Institute of Global Health (HIGH), Heidelberg, Germany – Research Assistant
2016	German Development Institute / Deutsches Institut für Entwicklungspolitik (DIE) , Bi- and Multilateral Development Cooperation, Bonn, Germany – Researcher

Internships

2015 – 2016	Deutsche Gesellschaft für Internationale Zusammenarbeit (GIZ) GmbH , Global Program “Adaptation to Climate Change in the Health Sector”, Bonn, Germany - Technical and administrative assistant
2014	International Atomic Energy Agency (IAEA) , Department of Nuclear Sciences and Applications, Isotope Hydrology Section, Vienna, Austria - Assistant to the Section Head
2014	Embassy and Permanent Mission of The Islamic Republic of Afghanistan in Vienna , Austria - Administrative assistant
2012	Solidarité & Développement , Lomé, Togo - Project assistant
2011	Deutsche Stiftung Weltbevölkerung , Hanover, Germany - Project assistant
2010 – 2011	Bielefeld University , Faculty of Health Sciences, Department of Epidemiology & International Public Health, Bielefeld, Germany – Intern and student research assistant

Poster and project presentations

- Karst IG, **Mank I**, Traoré I, Sorgho R, Stückemann K, Simboro S, Sié A, Franke J, Sauerborn R. Remotely Sensed Yield Modelling of Household Fields to Monitor Child Undernutrition and Climate Change Impacts, virtual Tropentag 2020, September 9-11, 2020.
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Eidesstattliche Versicherung

1. Bei der eingereichten Dissertation zu dem Thema „**The impact of climate variability on diets and child undernutrition in rural Burkina Faso**“ handelt es sich um meine eigenständig erbrachte Leistung.
2. Ich habe nur die angegebenen Quellen und Hilfsmittel benutzt und mich keiner unzulässigen Hilfe Dritter bedient. Insbesondere habe ich wörtlich oder sinngemäß aus anderen Werken übernommene Inhalte als solche kenntlich gemacht.
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