Linking Weather Data, Satellite Imagery and Field Observations to Household Food Production and Child Undernutrition: An Exploratory Study in Burkina Faso

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Abstract Worldwide, 50 million children under five are acutely malnourished, while 16 million amongst them suffer from severe wasting. Chronic malnutrition is more common and accounts for an estimated 159 million children, meaning that approximately 23.8% of all children under five worldwide are stunted. The proportion of stunted children has decreased worldwide between 1990 (39.6%) and 2014 (23.8%), but the progress has been unequal. While Asia as a whole reduced stunting by half (-47.0%) between 1990 and 2014, there are still 78 million stunted children in South Asia alone. Unlike Asia, the African continent has reduced stunting by just one quarter (24.0%). In contrast, the absolute number of stunted children in Africa has still increased, from 47 million in 1990, to 58 million in 2014. Under-nutrition is caused by a complex web of interdependent environmental/climatic, agricultural and socio-economic factors. Climate change has recently been identified as a major risk factor for childhood undernutrition. However, the scientific evidence base for this is weak. No study has so far simultaneously combined of the well-known drivers of undernutrition with climate change while being grounded in one population in one-time and in one location. Such studies are prerequisite for the relative attribution of the various risk factors, including climate chance, as causes of childhood undernutrition. In this exploratory study, methods from multiple sectors were applied to 20 randomly selected households in Bourasso in rural Burkina Faso, where more than 80% of the population are subsistence farmers, i.e. live off their fields. Well-tested methods, such as household-level agricultural and nutritional surveys, anthropometric measurement of undernutrition with innovative methods, measuring household level-crop yields, were combined. This was done by participatory mapping of each household's plots. Remote sensing algorithms were applied to RapidEye satellite scenes covering the study area in order to map the actual cultivated area and to derive qualitative harvest

estimates for the surveyed micro-fields. Weather data were obtained from a research meteorological field station, about 20 km away from Bourasso. In addition to bringing field methods from different sectors together through the lens of a household, one further advanced method was integrated: The linkage between each household plot limits and their integration into the satellite scene making it possible to estimate crop yields at the plot level for each household and linking this to the nutritional status of that specific household. Thus the exploratory study produced the following results: High-resolution remote sensing data can assist studies on malnutrition in Burkina Faso; RapidEye is a promising data source in regard to the spatial resolution for micro-field assessments; The strong inter-annual variation of malnutrition is suggestive that climate is a casual factor in the absence of other explanatory factors (political unrest, price shocks of inputs, epidemics). Population-based studies replicating the described multi-sectoral toolbox should be upscaled to larger sample sizes and longer observational time series. This could contribute to generating crucial climatehealth impact functions, in this case for malnutrition.

Keywords Malnutrition (MeSH D044342), Agriculture (MeSH D000383), Climate (MeSH D002980), Remote Sensing Technology (MeSH D058998), Western Africa (MeSH D000354), Child Nutrition Science (MeSH D053198), Infant Nutritional Science (MeSH D053198)

1. Introduction

The commonly used term malnutrition comprises both over- and under-nutrition. This paper focuses on the latter. Under-nutrition, is customarily divided into macro- and micronutrient deficiencies. This paper addresses macronutrient deficiency, which can be broken down further into acute and chronic malnutrition: Acute malnutrition or 'wasting' is measured as a deficit in weight for height (2 standard deviations (SD) below the median), while chronic malnutrition or 'stunting' is measured as a deficit in height for age (2 SD below the median). In a 2016 factsheet on reducing child mortality, the World Health Organization reported that approximately 45% of all the 5.9 million deaths in children under five in 2015 were linked to malnutrition [1]. The recent global estimates of the WHO, The World Bank, and United Nation's Children's Fund, show that the global burden on under nourished children is rising [2].Worldwide 7.4% (50 million) children under five are wasted, while 2.4% (16 million) amongst them suffer from severe wasting. Stunting is much more common: An estimated 159 million or 23.8% of all children under five children worldwide are stunted. The proportion of stunted children has decreased worldwide between 1990 (39.6%) and 2014 (23.8%), but the progress has been unequal [3]. While Asia as a whole reduced stunting by half (47.0%) between 1990 and 2014, there are still 78 million stunted children in South Asia alone. Unlike Asia, the African continent has reduced stunting by just one quarter (24.0%). Unfortunately, the absolute number of stunted children in Africa has increased, from 47 million in 1990, to 58 million in 2014 [3].

Under-nutrition is caused by a complex web of interdependent environmental, agricultural and socioeconomic factors. Climate change has recently been identified as a major risk factor for childhood under-nutrition [4]. Fig 1 shows the major pathways leading to malnutrition, which are depicted in three main groups; Climate change, agriculture and socio-economic factors, the outcome being nutritional status. While this graph cannot claim to be a complete portrait of all known risk factors for under-nutrition, it does show the complexity of the interacting factors [5]. It calls for a holistic methodological approach in order to attribute the relative weights of the major risk factors, importantly the recently identified risk factor of climate change. This multi-sectoral bundle of methods captured the entirety of the pathway steps.

A wide range of studies have focused on elements of this web of causation. Such studies link infectious diseases, particularly malaria, pneumonia and diarrhea to undernutrition [6]. Other studies link decreasing crop yields, particularly in sub-Saharan Africa and South Asia, to climate change [7]. Some authors focus the relationship of malnutrition to socio-economic factors such as maternal health or lack of caloric intake other authors focus on food prices and the effect of policies [5, 8].

This study advances the empirical approach to attribute risk of malnutrition to climate change in two main ways: First, a large number of the well-known drivers of under-nutrition with meteorological assessment in one population at one time and one space were simultaneously combined. Third, ground the analysis at the household or micro-level was conducted. Such studies are believed to be a pre-requisite for the relative attribution of the various risk factors, including climate change, as causes of childhood undernutrition.



Figure 1. The connection between climate, agriculture and child malnutrition. Each arrow indicates a relationship between factors. This figure is adapted from 2015 publication by co-author Phalkey (2015)

The purpose of this study is not to provide definitive answers to the respective attribution of the various risk

factors including weather variability. For this, it lacks the sample size and the large longitudinal follow up of populations. Rather, the value of this study lies in the demonstration that such comprehensive studies can and should be undertaken. This approach to focus all methods through the prism of the household level is essential to this form interdisciplinary research. This is particularly true for the mapping of agricultural plots, and the estimation of the harvest from these fields through a remote sensing method.

The study poses the following research questions: Is it feasible to explore the relationship between malnutrition, climate change, and agriculture simultaneously at the household level? What tools and methods are required to conduct such a comprehensive study? Can remote sensing be utilized on a subsistence farming level to extract information about household crops (land use, biomass, vitality, yields)?

The focus of this approach is clearly in subsistence farming settings. There is no claim that the approach is valid in urban areas or other settings where food is largely sold and purchased. In such urban settings prices and markets as well as policy interventions such as subsidies play a dominant role.

With this caveat in mind, it is suggested that existing sector-bound assessments fail to provide the necessary evidence base for decisions on how subsistence farming households can best prepare to combat the nutritional impacts of weather/climate variability. Therefore, there is an urgent need to develop integrated comprehensive assessment methods and tools that can investigate the impacts of weather/climate variability on childhood undernutrition mediated through crop yields simultaneously. This proof-ofconcept study aims to demonstrate how existing tools can be combined to achieve this.

2. Population and Methods

2.1. Source Population and Study Sample

The exploratory study was conducted in Bourasso, a village within a district covered by a Health and Demographic Surveillance System (HDSS) in Burkina Faso in sub-Saharan Africa [9]. The village has 12,548 inhabitants, in the middle of "the multi-ethnic Kossi province which is dominated by subsistence farmers and cattle keepers [10]. The sample constitutes of a total of 156 individuals, including 29 children under the age of five living in the 20 selected households. Two sets of households were selected, 10 with normally nourished children and 10 with undernourished wasted children. The former was randomly selected in 2014 out of all households with children less than 5 years of age (sample 1). As the study village was part of a demographic surveillance system (HDSS), its database could be used as a sampling frame. The latter sample was drawn in 2015 from the register of malnourished children in the household of the health local dispensary (sample 2). The dispensary is the only health center in the village of Bourasso

where cases of malnutrition are initially reported and firstline nutritional rehabilitation is provided.

2.2. Household Survey on Socioeconomic Status, Reported Health, and Child Nutrition

The Nouna household panel questionnaire was applied as a base to all 20 households [10, 11]. It elicits socio-economic household characteristics, such as assets, revenue and expenditures, reported harvest, converted in weight units, reported illnesses, and health seeking behavior (see Appendix).

In addition, a nutritional module was developed, which contained a 24-hour nutritional recall survey covering all foods consumed by all children under five in the 20 selected households. The origin of the food was distinguished, whether the food items were home-grown or purchased was captured and recorded (see Appendix).

2.3. Anthropometric Measurements,

Children's height and weight were measure according to WHO standards. -2SD z-score was used as a cut-off for acute (weight/height) and chronic (height/age) malnutrition. The age of the children was calculated using the birth date from HDSS. All children who were 2 standard deviations or less, under the median were considered undernourished. Before each field visit in 2014 and 2015, the head nurse of the Bourasso dispensary held a training session for all field agents on the proper utilization of anthropometric equipment. To measure height, the same stadiometer from the CSPS was utilized by the field agents. To measure height, the child was asked to stand up straight on a flat platform barefoot and the indicator was slid along the side of a vertical bar all the way to the top of the child's head. For the weight measurement, a child weight balance and trouser sack was hung from a tree. The child was placed in the bag and suspended until the weight was read off the display

2.4. Household Survey on Agricultural and Field Maps

The agricultural module elicited information on household agricultural assets including agricultural tools, income from agricultural sales, income from other sources, loans, and household expenditures for food and non-food items (see Appendix 1), reported yield from preceding years, number and size of plots (Fig. 5).

The agricultural survey comprised questions regarding two periods in the agricultural calendar: First during planting season (pre-harvest), and second after the harvest (postharvest). The interviews concerned the number and types of crops the household had sown and harvested on each of their plots. The data collected on household crops spanned over two years: 2014, 2015.

Once this data was collected, the mapping of the households' fields was carried out with the farmer, the

household head, and a GPS expert. A GPS tool, Garmin Etrex 10, was used to delineate the contours of each plot polygon. A trained field person walked with each household head around the limits of each of his fields and generated the geographic coordinates of each corner of the polygons. This information was used to add an additional layer to the existing geographic information system of the village. The household plots could therefore be overlaid with the remotely sensed scenes of cultivation area around the village to identify the exact field polygons within the scenes (Fig. 5). It was thus feasible to reconcile the remotely sensed yield estimate with the type of crop grown for each field for each of the 20 households.

2.4 Remote Sensing and Crop Harvest

Crop yields are influenced by biotic and abiotic factors that determine the crop growth during the whole growing period. These factors include parameters such as temperature, rainfall, soil type, crop stress caused by pathogens or insects etc., but also management practices. The combined impact of these factors has a direct influence on plant vitality. Remote sensing techniques are appropriate tools to measure relevant crop parameters (leaf area index, nitrogen status, biomass etc.) and can reflect the crop growth heterogeneity within fields [12, 13]. Most crop types show a relationship between these crop parameters and yield, which allows the use of multitemporal satellite data to establish regression models for yield estimation. Such remote sensing based approaches for yield estimation are already well developed [14, 15]. Lowresolution satellite data with large area coverage are often used to assess and predict yield anomalies on a regional level (e.g. the service of the Famine Early Warning System (FEWS). However, studies on malnutrition at householdlevel require information of yields of the respective microfields. Current satellite sensors offer high-resolution data that for the first time allow monitoring of crop parameters over the growing period in small spatial units.

The RapidEye satellite constellation is a very promising data source for such small-scale agricultural monitoring, since it provides data with a spatial resolution of 6.5m with very short revisiting periods. In addition, RapidEye has a rededge band that is particularly suitable for crop monitoring. RapidEye data has already been used for yield estimation of different crops in previous studies [16, 17]. In this study, the acquisition of RapidEye images was tasked with the minimum requirement to capture at least two dates in the growing season. Due to persistent cloud cover in the planned acquisition period (late dry season), images could only be acquired within a short period, i.e. on 10 September 2014 and 21 September 2014 (Fig. 2). The RapidEye satellite was used covered an area of 3500km² around Nouna, including the agricultural fields of the 20 selected households and their agricultural fields.



Figure 2. Two RapidEye images (R:5, G:4, B:3) from 10.09.2014 and 21.09.2014 showing an overlay of some agricultural fields on the RapidEye image.

Site-specific yield estimations via remote sensing require different consecutive steps of image analysis. First, the actual cultivated area is identified, before crop types are further differentiated via classification of typical phonologies in the second step. The information on crop type is an important parameter, since yield models are calibrated to crop-specific characteristics. As a last step, crop-specific regression models are applied to the remote sensing-based time series of crop parameters. Every step requires multi-temporal remote sensing data that cover the whole growing period. Since only two RapidEye scenes were available that cover a short period, setting up robust regression models for a quantitative yield estimation was not possible. Instead, a qualitative yield estimation for the surveyed micro-fields was realized in this feasibility study by using bi-temporal vegetation indices such as the Normalized Difference Vegetation Index (NDVI) and the Normalized Difference Red Edge Index (NDRE). The NDVI is related to crop parameters such as leaf area index, biomass and fractional vegetation cover, whereas the NDRE characterizes the chlorophyll/nitrogen status of crop canopies. These two indices from each RapidEye observation date (including minimum and maximum values) and their changes between the observations were used to qualitatively predict vield relative to each crop in the surveyed micro-fields. A quantitative yield estimation (e.g. in t/ha) would require more satellite observations as well as more in-situ yield samples per micro-field.

The remote sensing based approach is highly dependent on reference data that is required for the calibration and validation of the models. Therefore, some spatially explicit field information on micro-field delineation, crop type, ground cover and yield (if available) is fundamental. In the best case, these data are collected regularly over the growing period in some pilot sites. The more accurate and precise the reference data, the lower the uncertainty of the yield estimations.

(ii) Validation ("ground-truthing") of crops grown in households' fields. To collect this agricultural data, households were visited twice, first before, and second immediately after the harvest. The pre-harvest visit was in August 2014, during the planting season, when farmers were preparing their fields by clearing (manually or through controlled burning) and begin to plant their crops. At this time, the head of each household provided information about which crops would be planted and how many fields the households own. Following this initial interview, the household head accompanied the field agent to every field mentioned. Upon arrival at each field, the clear delimitation of the field was discussed, and then the parameter of the field was measured with a GPS tool, recording the GPS coordinates and the surface area of the field (Fig. 4). This process was replicated for every single field. During the preharvest questionnaires, the ten households reported 64 different fields. Upon the follow up visit during the postharvest period, four fields were added to the count, raising the total to 68 (Fig. 5). The post-harvest season is between October and December, when households are harvesting crops and when agricultural yields were recorded.

(iii) Reported Harvest. Farmers were asked to estimate the weight of their harvest. They did so in local terms (e-g- "a closed donkey cart full of maize"), which were converted into kilograms with the help of local agricultural extension workers.

(iv) Measurement local rainfall. The HDSS has 10 meteorological measurement stations; the nearest one for Bourasso (22 km) is in the district capital of Nouna. Standard WMO equipment was used. The metrological parameters were automatically recorded daily on a memory chip and read out every month. For the purpose of this study the rainfall data was aggregated to monthly averages (Fig. 3) between 2013 and 2014. The rainfall pattern and amount in these two years were chosen, as they drove the harvest, which in turn influenced child nutrition in the subsequent years of 2014 and 2015. The field methods are summarized in Table 1.

3. Results

3.1. Rainfall Pattern

Figure 3 illustrates the monthly cumulative rainfall collected in nearby Nouna in 2013 and 2014. The total rainfall in 2013 was 614.2 millimeters and 679.8 millimeters in 2014. However, in addition to the cumulative amount of rainfall, the distribution of rain is also important for agriculture. Figure 3 shows that in 2013, the rains stopped prematurely in September, which is very unfavorable for the maturation of the crops. In addition there is a significant peak in August in 2013, while the rainfall pattern in 2014 is more evenly distributed and lasts, as usual, through October.

Type of Data	Sample		Voor	Mathad	Information Collected
	1	2	rear	Methou	information Conected
Agricultural Data	x	x	2014 2015	Agricultural Survey	 Number of fields Crop types Crop yields Crop storage Crop consumption Crop selling strategy
	x		2014	Field Cartography	 Households coordinates Field coordinates
			2014	Remote Sensing Satellite	- Field surface areas - Field delimitations
			2014	Ground Thruthing	- Remote Sensing scenes
Nutrition Data	x	x	2014 2015	Anthropometric Measurements	 Child height Child weigh Child MUAC
			2015	24Hour Nutritional Recall Journal	 Child food consumption Food from the household fields Food from market (purchased) Child recent health events Child health facility visits
				Health Episodes Survey	
Socioeco nomic Data	x	x	2014 2015	Household Socioeconomic Survey	 Household belongings Sources of income Household loans Household spending

Table 1. Overview of field methods in both samples and type of collected data



Figure 3. Recorded rainfall in the district capital of Nouna situated 22km from the village of Bourasso. The figure displays the monthly cumulative rainfall for the years 2013 and 2014 in millimeters.



Figure 4. Weigh-for-Height expressed in z-score. Both sample one's (randomly sampled and normally nourished children) and sample two's (dispensaryregistered sampled and under nourished children) z-scores are expressed in their change from the year 2014 and 2015. *The z-score of child 15 could <u>not</u> <u>be not</u> calculated due to an incomplete data.

3.2. Household Socioeconomic Status

The two household samples ranged in household size, from 3 to 23 members. The average household size for sample 1 was 7 members per household and the average for households in sample 2 was slightly higher, 9 members per household. The total household monetary revenue of sample 1 was 12,103,000 francs CFA (20,867.24 US dollars) and that of sample 2 was 2,208,900 francs CFA (3,799.31 US dollars). All but one household's financial revenue was from the sale of part of their agricultural products. Household number 12 of sample 2 reported having regular income outside of selling their agricultural products. Although average annual income of households in sample 1, 2,086.24 USD, (302.42 USD per capita), is approximately 5.5 times higher than that of households in sample 2, 401.53 USD, (46.15 USD per capita), the average yearly spending of households in sample 1 (965.24 USD) is also 5.6 times higher than that of the households in sample 2 (172.30 USD). On average, the households in sample 1, who had healthier children, had higher spending but also higher revenue than the households in sample 2.

3.3. Anthropometric Measurements

In 2014, 15/17 (88%) children were well nourished, while 2/17 were borderline malnourished (at the -2SD cut-off). In 2015, all but 2/17 children had either improved or maintained their nutritional status, shown in the upward movement of the lines in figure 4. Only 2/17 children had a lower z-score than in 2014, but these children were still above the mean in 2015. Of the 11 children, who were undernourished in 2014 all had improved their nutritional status anywhere from 1 to 4 SD standard deviations by 2015. These changes are plausible given the difference in rainfall amount and distributions

between the years 2013, influencing the sample measured in 2014 before the harvest, and the improvement as a consequence of the "normal" rainfall pattern in 2014, impacting on child nutrition in the subsequent year 2015.

3.4. Reported Feeding Practices

It is important to note that the collection of the nutritional data proved difficult with regards to the household and primary care givers understanding of malnutrition. Malnutrition is not well understood, or recognized in the study village of Bourassa. The word malnutrition does not directly translate in the local language Bwamou, used for the questionnaires and interviews. Therefore, the best approximation of malnutrition employed was ("domouni bana" or "biro vanmou"), which loosely translates to "the sickness related to food". Therefore, before any data on nutrition and anthropometry could be collected, a lengthy explanation of the relationship between nutrition and child health had to be covered in each household by the enquirers prior to data collection.

The 24-hour nutritional recall survey was administered to all 29 children from the 2 samples. The data for child number 15 was excluded because it was incomplete and it was removed from the anthropometric data set. Furthermore, four of the remaining 28 children were exclusively breastfed, so the nutritional data depicted below also excludes these 4 children, leaving 23 children in the final analysis.

Of the total 132 food items, consumed by the 23 children, which derived directly from their household's agricultural field. The pattern is typical for the area. The meals contained for the most part a cereal starch made of either millet or maize accompanied by a sauce. In addition to this core meal children consumed few food items. These food items were purchased outside the home. The food items purchased by households for the consumption of the children included flour-based snacks (sweet cakes, sweet breads, beignets and biscuits), fresh fruits, eggs, meat, fish, rice, beans and spaghetti. All but two households, both in sample 1, did not report purchasing food for their children under five.

3.5. Household Agriculture and Field Maps

Across the 20 households, 6 main crops were cultivated over the three relevant years 2013, 2014 and 2015: Millet/sorghum and maize as staple cereals, peanuts, beans, cowpeas as leguminous and sesame as a cash crop. Millet/sorghum was cultivated by all 20 households in 2013, 19/20 households in 2014 and by 19/20 households in 2015. Maize was cultivated by 16/20 households in 2013, 17/20 households in 2014 and by 18/20 households in 2015. Peanuts were cultivated 3/20 households in 2013, 3/20 households in 2014 and 5/20 households in 2015. Cowpeas were cultivated by 12/20 households in 2013, 6/20 households in 2014 and, by 1/20 household in 2015. Beans were cultivated by 6/20 households in 2013, 10/20 households in 2014 and, by 16/20 households in 2015.Sesame was cultivated by all 20 households during all three years. There were no obvious differences in the crop distribution between the two samples studied.

Furthermore, it is important to note that many of the crops were planted in association with other crops. 'Intercropping' is a well know practice, in which farmers plant two crops in a mixed manner, either through random mixing, or alternating rows of crops [18]. 17 of the 68 harvested fields contained two or more crops on the same field. Crop associations occurred between all 6 primary crops: millet, maize, sesame, cowpeas, beans and peanuts.

Of the 20 households in sample 1 and sample 2, all 20 households cultivated sesame in the years 2013, 2014, and 2015. Of the remaining 5 primary crops, their planting frequencies were in the descending order of, millet, maize, beans, cowpeas and lastly peanuts.Peanuts were the most infrequently planted crop over the three year period.

There were three others crops, which were of minor prevalence in the fields of the 20 households. These crops were: Cotton, cultivated by just 3 different families in 2015 Peas, cultivated by 2 different families, once in 2013 and once in 2014, and lastly Acah, cultivated by one family during all three years.

The 10 households constituting sample 1 were interviewed in 2014 on farming practices. They provided the following information, 6/10 households used improved seed varieties or "fast-growing" seeds for maize, millet, cowpeas, and sesame. The remaining four households did not use any improved seed varieties. 3/10 household heads considered their harvest yields satisfactory, enabling them to feed their family in the subsequent year. The 7/10 farmers who classified their crop yield as unsatisfactory mentioned the following as primary causes for their harvest short falls: Low rainfall, changing rainfall, and consumption of crops by animals or destruction of crops by "harsh sun". In the case of sesame, 6/10 households who grew sesame referred to the recent appearance of a crop pest, which led to "sesame diseases".

The reported results of the 2014 harvest of the sample 1 households showed that even with the devastating effects of the sesame pest, sesame was the crop with the largest production in the 10 households at 15,635 total kilograms. This was followed by a total reported millet/sorghum production of 12,117.5 kilograms, maize at 7463.1 kilograms, cowpeas at 2624.4 kilogram, beans at 107.4 kilograms then lastly peanuts at a total of 47.5 kilograms. The above measured outputs can be further examined at the household level, with household 7 displaying the highest total crop production of 7,588.7 kilograms and household 4 with a significantly smaller total production of 973.1 kilograms.

In the same interview with the households of sample 1 in 2014, 4/10 households reported that they had the capacity to keep grains from the previous two years in storage. 5/10 households reported keeping grains in their granary from the previous year, and the remaining households had no stores left from the previous year. Households sold substantial amounts of their harvest to generate cash for non-food expenditures: 4/10 reported that they sold about half of their harvest; 3/10 sold a third and 2/10 sold about one fifth. One household did not wish to disclose their crop sales.

Although the proportion of grains sold by households varied, the reasons for selling crops were similar. Households sold grain for two reasons; first they sold when in need of immediate cash and secondly, they sold grains when prices on the market were attractive. All households unanimously described the use of a stall tactic for the sale of crops; The longer households could delay the sale of crops, the higher the price they would receive.. This strategy was only abandoned in cases of immediate cash need, such as for health care.

One agricultural feature all households shared, was the existence of a small land plot close to the concession, referred to as a "women's garden" or a "family garden". It is planted and entirely cared for by the women of the household. The vegetables and spices harvested from this land plot were exclusively for household food preparation, providing the sauce accompanying the main cereal staple, "tô" in the local language. Although the shape and extent of these 'women gardens' varied, their existence to provide the household with small quantities of vegetables and spices such as, tomatoes, hot pepper, okra, sorrel, and other consumable plants was similar. 'Tô' and sauce constituted the majority of all meals for children above the age of approximately 1 year. 'Tô' is the traditional carbohydrate base of the average meal in Burkina Faso. It is most often made of ground maize or millet flour. The flour is mixed, stirred, and beaten over low heat during a two-stage process with water, making it simple and affordable. 'Tô' is eaten in combination with a variety of sauces. The sauces are named after their primary ingredient, which is the plant ripe for harvesting in the family garden. The most common sauces between the months of July and

November, listed in no specific order, are okra, baobab, hibiscus, and sorrel.

The inventory of all fields of sample 1 were established. There were 68 total fields between the 10 households, with household 10 having the most fields 12, and households 3 and 4 being tied with the least number of fields 3. That is 3 fields below the average of 6 fields per household. These 68 fields are displayed in figure 5.

The GPS based mapping carried out while walking around each field with the household head was integrated in the Geographic Information System of the HDSS. The ten households surveyed reported a total of 68 fields, which were plotted with GIS Maps. Figure 5 shows a part of this GIS map.

The RapidEye image from September 21st, 2014 was first used to classify the land use by a supervised object-based classification approach using eCognition (Trimble, Germany). The objective was to quantify the actual cultivated area of the total agricultural area as depicted in Figure 6. Agriculture is the dominant land use in the study area (ca. 67% of the study area with a total size of 23,360 ha) 46% of which was cultivated in September 2014. This basic information about current land use could be used to empirically estimate the harvest levels at a regional scale using statistics collected during field surveys such as percentages of crop types and average yield values. However, studies ata household level require a more detailed spatial analysis, which is described below.



Figure 5. Field maps and superposition with a remotely sensed scene. The left panel illustrates polygon overlays of the households' agricultural fields on the existing GIS system of the health and demographic surveillance system. The green polygons represent individual agricultural fields surface areas. The black squares show the 10 selected households of sample 1. The red cross represents the local health post, which serves the village of Bourasso. The right most panel illustrates the selected cluster of polygons from the middle panel integrated in the satellite scene.

3.4. Remote Sensing and Crop Harvest Results



Figure 6. Derived land cover/use map with the actual cultivated area for September 2014. The bottom right cluster of households (red dots) represent the village of Bourasso from the superposed households layer on the GIS of HDSS.



Figure 7. A RapidEye scene subset with the in-field delineated millet (MIL) and sesame (SES) micro-fields (black outline). The figure also displaces broad categories of yields ranging from high to low.

Qualitative yield predictions that reflect broad categories of harvest (high, medium, low) could be conducted with the use of the vegetation indices and their changes between the two observation dates. Figure 7 shows a RapidEye subset with the delineated micro-fields (black outline) from the field survey. The reference data in this area covered fields cultivated with sesame and millet, for which different qualitative harvest predictions were performed based on the RapidEye images (overlaid and color-scaled per crop type). This assessment shows that the RapidEye-based yield predictions reflect small-scale variations within the microfields. The results suggest that the farmers did not cultivate the whole delineated reference fields equally, but rather left some parts uncultivated. For instance, the red parts of the sesame fields as well as the blue parts of the millet fields shown in Figure 7, indicate that there was no cultivation at this time. This is an example, of when a satellite-based approach can reveal uncertainties of in-field assessments on field delineation.

4. Discussion

Numerous studies in Sub-Saharan Africa have been conducted using GIS. The majority of these studies used GIS to track the spread of vectors or diseases such malaria [19]. A number of studies have gone further by using remote sensing to highlight the importance of analyzing and projecting changing environmental patterns which effect the health of humans, such as droughts and famines. Many studies have coupled climate projections with food relevant warning systems, such as drought warnings for food security, especially in the horn of Africa [20, 21, 22].

The studies in low-income countries attempting to incorporate an inter-sectoral breadth of methods applied simultaneously at the household level and while also capturing a large number of the known key influences in depth, in addition to capturing weather variability, are few but varied (23, 24). They range from studies that worked to associate climate variables to nutrition through empirical data to studies based purely on modeling nationally aggregated data [24]. A 2011 study validated global food models by utilizing national food availability and undernutrition data to forecast future estimation on stunting across the globe using modeling [24]. Another Kenyan study was conducted using multi-level regression models and did not provide the depth of detail on household agricultural and child food intake as this study [22].

One of the publications thematically closest to this study is the 2014 article entitled "Environmental risk factors and child nutritional status and survival in a context of climate variability and change",investigated a data set derived from GIS points, demographic health system data and a climate proxy. This study was paired with Advanced Very High Resolution Radiometer (AVHRR) satellite remote sensing data [24].

In this study, apart from bringing field methods from different sectors together through the lens of a households, one key method was further advanced and integrated: The link between each household plot limits and their integration into the satellite scene making it henceforth possible to quantify crop yields at the plot level for each household and linking this to the nutritional status of that specific household.

GIS maps of the households' agricultural fields could be constructed through participatory mapping. It was possible to convert reported yields of the six primary crops from local measurements to standardized kilograms. These reported yields could then be connected to the corresponding house, fields and children.

Lastly, this pilot study on how high-resolution remote sensing data can assist studies on malnutrition in Burkina Faso showed that RapidEye is a promising data source in regard to the spatial resolution for micro-field assessments. Longer time series with regular intervals over the growing season would allow more detailed assessments of crop types and yield estimation.

This feasibility study showed promising results on the use of high-resolution satellite data for field studies on household/micro-field level through the visualization and calculation of biomass diversity, land utilization, crop try differentiation, and yield densities. However, some key questions still require further research. For example, it must be clarified which crop types can be differentiated (e.g. pea, cowpeas, peanuts) suitably for yield estimation using regression models. In addition, the minimum number and optimal interval of required satellite image acquisitions for yield estimations must be assessed in order to suggest an approach with minimal data costs. Therefore, the effect of reducing the number of scenes on the accuracy of the yield models should be analyzed in the future. The two Sentinel-2 satellites with up to 10m spatial resolution are a promising source of additional data. Sentinel-2 has the required spectral characteristics (10 spectral bands with 10-20m spatial resolution) to monitor crop parameters and the data is free of cost. The short repetition cycle of 5 days increases the probability of acquiring cloud-free images. This will be

fundamental for quantifying and monitoring annual crop yields (food and cash) of sampled households via satellite imaging.

The strong inter-annual variation of malnutrition is suggestive of climate as cause in the absence of other explanatory factors (political unrest, price shocks of inputs, epidemics). Belesova et al. (2017) found a similar relationship between the amount and distribution of rainfall, harvest yields and childhood malnutrition[27]. However, this conclusion must await final judgment based on a larger scale and longer-term study. Such a study would also allow the attribution of the causes of undernutrition to climate change and the large number of known non-climatic factors, such as concurrent infectious diseases, market prices, family composition and more.

5. Strengths and limitations

In the scope of this small-scale study, a plethora of methods were applied, which constructed a holistic view of the environmental, nutritional and health factors affecting study participants. Through the powerful combination of household-level agricultural, nutritional and anthropometric surveys, weather data, participatory mapping, and the use of innovative remote sensing RapidEye satellite imaging much, from the environmental construct of the study villages' land, to details of the nutritional construct of children daily meals could be observed and examined. The ability to cover such a breath of aspects capturing a wide range of influential factors while keeping the focus centrally on the nutrition status of children under five was both a challenge for the pilot study but ultimately constituted a major strength. The success of this toolbox is important, as this is the kind of approach, holistic yet specific, which is essential when researching the effect of climate change and climate variability on nutrition and on the health of humans.

In identifying the strength of the pilot, it is equally important to note that by design, the samples explored in the study represented few children: 29 in 20 households. These numbers, although appropriate for an exploratory study, fall short of providing numbers large enough for statistically significant inferences. Furthermore, this proposed methodological toolkit was adapted for a subsistencefarming context. Any extrapolation to other settings, such as urban populations would have to be done with great care.

Harvest estimates from analyzing the satellite scenes were only possible in broad categories and not in kilograms or tonnes per field. This was due to the limited number of sequential satellite images. Another limitation was the fact the RapidEye data used in this feasibility study only covered a short period of the growing season (11 days in September, 2014). A robust quantitative yield modeling was therefore not possible, due to insufficient time series on crop parameters and due to the low number of surveyed fields. Only qualitative yield predictions could be done with the use of the collected reference data. The availability of new satellite systems such as Sentinel-2 with short repetition cycles will increase the probability to use a time series of satellite images of around 5 sequential scenes. A limitation of the remote sensing approach will be in case of intercropping, which complicates the quantitative yield estimation, and requires further research.

Finally, for practical reasons, all study components applied of in 2014 could not be applied in the following year.

Conclusions

This study demonstrates that simultaneous application of all the above methods in the context of one relevant area and population is feasible (proof of concept). Although this was not the primary objective of this study, with a pilot consisting of a small sample size, insights could be gleaned in the strong link between weather variability and malnutrition. Proper up scaling of the proposed "toolkit" would provide statistically robust answers regarding the relative contribution of weather variability/climate change to childhood malnutrition.

6. Recommendations

With the advent of the Sentinel-2 satellite images which are free of charge, the main disadvantage of the RapidEye scenes, which was their considerable costs, will be eliminated. Daily weather data can be retrieved from various websites at no cost for most villages and towns in low and middle-income countries, where the network of meteorological stations may not be dense enough.

This method toolkit is therefore not only innovative in its combination, powerful in its value for characterizing and projecting health impacts from climate change, it is also affordable for most research projects and countries for that matter (e.g. As sentinel sites). One important extension of this toolkit would be the inclusion of micronutrient deficiency.

Population-based studies replicating the described multisectoral toolbox should be upscaled by using larger sample sizes and longer observational time series. There are many populations under long-term health surveillance, some 3, 5 million in over 45 individual sites in more than 20 countries, which have observation lengths of an average of 20 years (INDEPTH). Such long-term time series have the potential to generate crucial climate-health impact functions, in this case for malnutrition, but also for most of the other 50+ climatesensitive diseases. This will be the basis for integrating health into climate models. Empirically based projections of health impacts from climate change in 2030, 2050 and 2100 (the main policy-relevant time horizons) could finally be seen. By the same token, the effect of adaptation behavior and policies, such as fast response early warning systems could be analyzed at the district, province, and national levels.

Burkina Faso's 2015 National Climate Change Adaptation Plan (NAP) cited ensuring sustainable food and nutrition security as one of its medium term goals, but did not explicitly describe and project the degree to which climate change will affect malnutrition and food security, especially of vulnerable groups such as women and children [29]. The launch a properly dimensioned (s.a.) longitudinal climate/nutrition study including the sectors and variables connected in this study would make the next NAP more quantitatively specific in terms of the climate impact on childhood undernutrition in Burkina Faso. Studies of this kind could lead to better attribution and quantification of malnutrition from climate change, and hence evidence-based surveillance and early warning systems, which would trigger adaptation strategies, which in turn could shield children from the added adverse impact of climate change on their nutritional status.

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List of Abbreviations

NUTRICLIM - Nutrition and Climate Change CRSN - Centre de Recherche en Santé de Nouna CSPS - Centre de Santé et de Promotion Social HDSS - Health Demographic Surveillance System INDPTH – Network for Better Health Information for Better Health Policy HFA – Height-for-Age MUAC - The Mid-Upper Arm Circumference RSS - Remote Sensing Solutions SOHPS - Socioeconomic and Health Panel Survey

NAP - National Adaptation Plan

Ethics Approval and Consent to Participate

The study NUTRICLIM was approved by the Heidelberg University ethical committee "Ethik Kommission Medizinische Fakultät Heidelberg". In observation of ethically appropriate scientific research, NUTRICLIM followed the procedures of the ongoing Nouna Socioeconomic and Health Panel Survey (SOHPS). This is the process, which has been utilized by the CRSN research center since 2000. For the anthropometric component of the survey NUTRICLIM followed standard WHO procedures. The study team ensured that all malnutrition cases discovered during the course of the study would be presented to the CSPS and if needed be referred to Centre de Rehabilitation Nutritional (CREN) in the district capital Nouna. The project contributed 50% of all rehabilitation and care cost for such children. Furthermore, the project will have no environment impact.

All participants consented verbally and in written form to partake in study. Participation in the research study was entirely voluntary; It had and will continue to have no effects or repercussions on the work or social life of participants. Participants were free to change their minds at any point, ceasing participation at will. There were no costs associated with participation nor were there financial incentives. The information collected in the framework of this research project was confidential. This information was stored in a file number anonymously. All consequent files were replaced with a unique identification number. No information was shared with anybody outside the research team. The knowledge gained from this research will be published so that other interested persons may learn from the research.

Competing Interests

The authors declare that they have no competing interests.

Funding

This pilot study was entirely funded by the Institute of Public Health.

Author's Contribution

Raïssa Sorgho – Data collection, methods, results, conclusion and discussion

Jonas Franke – Methods and results (remote sensing) Seraphin Simboro – Methods (GPS & GIS)

Sandra Barteit – Methods and Results (nutrition analysis) Revati Phalkey – Introduction

Rainer Sauerborn – Study design, introduction, discussion and conclusion

Acknowledgements

We thank the staff of the CRSN for their support during data collection. We would also like to thank the people of Bourasso, who with good-will, donated their time to participate in this pilot study.

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