

# Remotely Sensed Yield Modelling of Household Fields to Monitor Child Undernutrition and Climate Change Impacts

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## INTRODUCTION

- Climate change is a driver for increased rainfall variability and weather extremes in West Africa (Fig. 1). This has detrimental effects on yields of small-scale subsistence farmers living in the Nouna Health and Demographic Surveillance (HDSS) area in Burkina Faso, West Africa (Belesova et al., 2019).

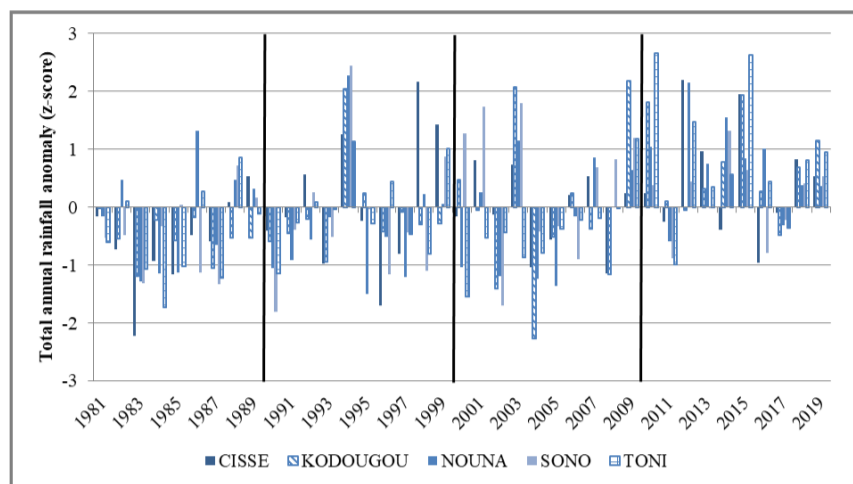


Figure 1: Total annual rainfall anomaly (z score) for five strata in the Nouna HDSS, Kossi province, in Burkina Faso from 1981 to 2019 (not yet published)

- A family's nutritional well-being is defined by their agricultural yield. With high levels of food insecurity, child undernutrition is high (in the study area in 2018, stunting lies at 26% and wasting at 7% for children <5 years) (Mank et al., 2020).

→ Our study aimed to quantify and predict crop yields of household fields (median 1.4 ha) using high resolution Sentinel-2 data in the Nouna HDSS (Fig. 2).

→ This enabled the novel investigation of the link between yield, child undernutrition and food insecurity at the household level (very small spatial scale of 10 m).



Figure 2: Study Area located in the Kossi province (green) in Burkina Faso

## RESULTS

- The MLR model applied to known fields of four different crop types (Sorghum, Millet, Maize, Beans) results in yield predictions at 10 m spatial resolution (Fig. 3).
- Depending on the crop type, the MLR model produced  $R^2$  values between 0.40 and 0.54 (adj.  $R^2$  0.32 to 0.50). Underlining the methodologically assumed correlation between a crop's biomass and its respective yield.
- Results showed considerable variations in normalized yields between crop types, meaning that productivity varies depending on the crop type. Yield variation were also found between household, potentially resulting from field location, water availability and management practices.
- Each field is associated with one farmer, enabling a household specific dietary assessment. This links food security and yield modelling, especially since predictions are possible up to two months prior to harvest (maize).

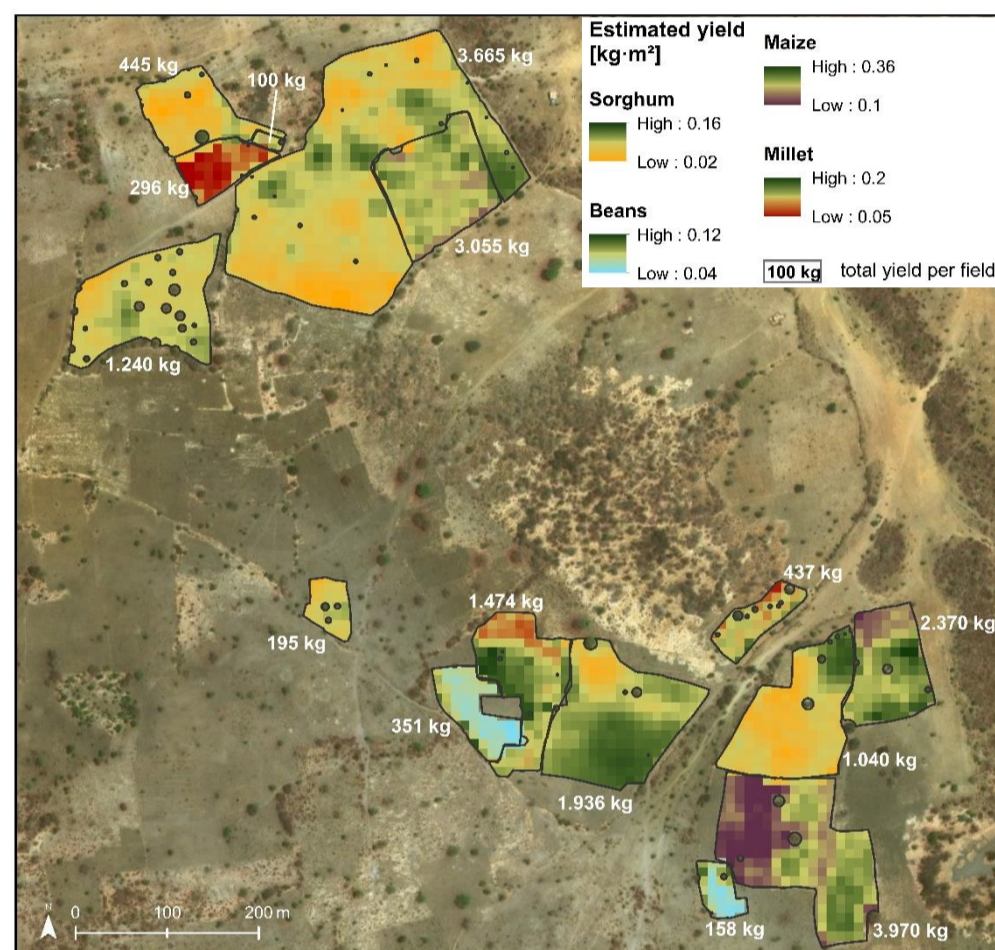
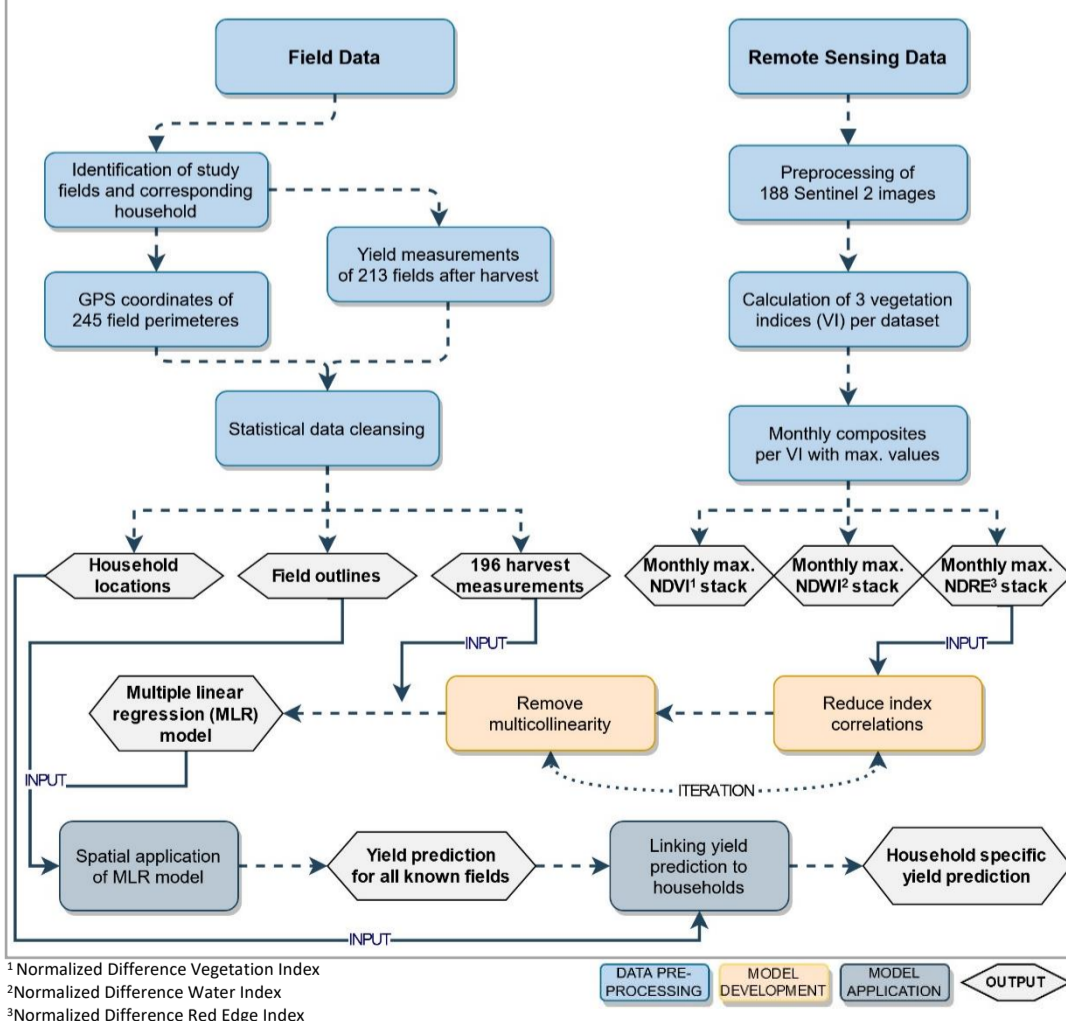


Figure 3: Excerpt of study area showing agricultural fields with modelled yield (color scale differs depending on crop type) and corresponding total amounts of yield per field in kg

## METHODOLOGY



<sup>1</sup>Normalized Difference Vegetation Index  
<sup>2</sup>Normalized Difference Water Index  
<sup>3</sup>Normalized Difference Red Edge Index

## DISCUSSION & CONCLUSION

Pests influence the plant's yield but not the biomass measured by remote sensing. This leads to discrepancies of modelled and measured values	Trees and other non-crop vegetation on fields influences the remotely sensed signals and the consequential calculation of vegetation indices
<b>Influencing factors for the reliability of the MLR model output</b>	
Variations in the in-situ yield measurements, such as drying time, wind losses or animals, potentially influence the outcome of the yield's weight.	While the correlation of in-situ yield measurements to remotely sensed biomass was shown, an additional weighing of the total biomass on the field could counteract potential model unreliabilities

- The application of the model supports the evaluation of the impact of climatic factors, agricultural interventions or farming practices to prevent household food insecurity and child undernutrition.
- Future extensions of the models should include further model parameters, such as climate variables, to obtain better reliability and offset potentially yield- and model-damaging factors.

Belesova et al. (2019). <https://doi.org/10.1016/j.scitotenv.2019.07.027>  
Karst, I. G., Mank, I., et al. (2020). <https://doi.org/10.3390/rs12111717>  
Mank et al. (2020). <https://doi.org/10.1186/s12937-020-00591-3>

## TAKE AWAYS

- We proved that remote sensing can be used as a proxy for harvest yield quantification and prediction at 10 m spatial resolution.
- The results can be used for forecasting local yield shortages and implementing counter measures prior to child undernutrition and food insecurity