## 1.2 Crop Yield

Earth Observation (EO) methods have long been established as a promising approach to support agricultural activities and food security at multiple spatio-temporal scales. Indeed, satellite remote sensing is increasingly being used to support government agencies ability to monitor agricultural water use, yield and irrigation delimitation at large spatial scales, allowing to support policy making, account for natural resources and mitigate the effects of climate change on agricultural production and food security, especially in data-scarce regions such as the African continent. Over the years, different methods have been developed to estimate crop yield based on EO imagery.

These techniques can be largely grouped into 1) regression-based empirical models, 2) light-use efficiency (LUE) models, 3) data assimilation methods that calibrate/force crop growth models using remote sensing data and 4) hybrid models that use crop growth models to train remote sensing-based regression models.

**1.2.1 Empirical models**

There is a large body of literature that have demonstrated a strong relation between crop yield and vegetation indices (VIs) from satellite imagery [[1]](#footnote-2) [[2]](#footnote-3) [[3]](#footnote-4) . Indeed, these methods generally establish an empirical relationship between VIs and observed crop yield. Subsequently, these calibrated empirical models are applied to predict and/or forecast crop yield for upcoming seasons. Most of the developed models used aggregated VIs over a period of time, rather than instantaneous satellite overpasses, as the relation of crop yield and spectral characteristics varies with crop growth, while temporal aggregation also limits the effects of other factors (e.g. clouds, soils) that affect the vegetation spectral response[[4]](#footnote-5). Indeed, there is a general consensus that the relationship between spectral VIs and crop yield is largely dependent on the seasonal timing of observation and aggregation. The extensive literature on the NDVI-yield relationship suggest mid-to-late season NDVI better represents yield estimates than maximum NDVI or other seasonal integration3. For example, Rasmussen (1992)[[5]](#footnote-6) demonstrated that early season NDVI had no significant relationship with millet yield (r2 > 0.1), while NDVI values 30 days after the peak maximum NDVI explained 90% of the variance of observed yields in Burkina Faso. Bognár et al. (2011)1 found that they could could successfully forecast county-level winter wheat yield in Hungary up to 50 days before harvest and county-level corn up to 70 days harvest using near-infrared (NIR)-based spectral indices from the National Oceanic and Atmospheric Administration’s (NOAA) Advanced Very High Resolution Radiometer (AVHRR). The study by Funk and Budde (2009)3 also stressed the importance of temporal smoothing to reduce atmospheric contamination and applying masks to remove non-agricultural vegetation signals, including removing pre-season vegetation signals for increased robustness, in developing scale-invariant empirical models in in East Africa (i.e., Kenya and Zimbabwe).

While most empirical models for crop yield have been based using VIs from the shortwave optical region (i.e. 0.4-2.5 µm), certain studies have also explore the use of thermal infrared (TIR: 8-14 µm) remote sensing to better incorporate the effects of seasonal droughts on crop yield predictions. Johnson (2014)[[6]](#footnote-7) showed strong empirical relations combining both MODIS-based NDVI and land surface temperature (LST) with corn and soybean yield over the midwest USA. Similarly, Anderson et al. (2016)[[7]](#footnote-8) showed that the evaporative stress index (ESI) from MODIS showed higher correlation with observed yield of major crops in Brazil compared to traditionally indices such as leaf area index (LAI), including showing an earlier response (10 – 25 days) to extreme events. Gómez-Candón et al. (2021)[[8]](#footnote-9) also suggested the high utility of surface energy balancing (SEB) modeling of ET, which combines both LAI and LST inputs, as en important indicator for crop yield. Indeed, Franch et al. (2019)2 also incorporated the evaporative fraction, estimated through a SEB model, as a predictive variable in their empirical model to estimate winter wheat yield for USA and Ukraine at the county and *oblast* level, respectively.

**1.2.2 Light-use efficiency (LUE) models**

The Monteith Light-Use Efficiency (LUE) concept [[9]](#footnote-10) has been widely applied to model vegetation carbon uptake, which can be related to crop yield with the so called harvest index (i.e. the ratio of yield to aboveground biomass). This approach suggests that a proportional relationship exists between carbon uptake or Gross Primary Production (GPP) and incoming solar radiation at the canopy level. GPP is function of incoming photosynthetically active radiation (PAR), the fraction of absorbed PAR (fAPAR) and a light use efficiency (LUE) term that quantifies the rate of the conversion of absorbed radiation into biomass[[10]](#footnote-11). As suggested by Gitelson (2006)[[11]](#footnote-12), chlorophyll content can be used a proxy for LUE and fAPAR and be directly utilized, in conjunction with PAR, to estimate GPP. Vegetation indices (VI) may be used as a proxy for chlorophyll and have been directly used to quantify LUE and fAPAR [[12]](#footnote-13). Various chlorophyll related VI have been tested with varying degrees of success to estimate chlorophyll content [[13]](#footnote-14) and GPP [[14]](#footnote-15). Vegetation indices using broad band wavelength intervals such as Normalized Difference Vegetation Index (NDVI) or Green Chlorophyll Index have been applied relatively successfully for GPP simulations (Gitelson et al., 2012, 2006; Rossini et al., 2012). Indeed, Dong et al. (2020)[[15]](#footnote-16) applied a NDVI-based LUE model using Landsat imagery and was able to effectively capture the spatial and inter-annual variability of winter wheat yields. LUE can also be retrieved through hypeerspectral remote sensing using the photochemical reflectance index (PRI) [[16]](#footnote-17), which exploits narrow variations around the 0.531 um point, and more recently, through estimations of sun-induced chlorophyll fluorescence signal (SIF). The SIF-GPP relationship has recently gained traction due to the direct link between photosynthesis and SIF [[17]](#footnote-18).

**1.2.3 Crop growth models with remote sensing data assimilation**

Crop growth models allow to simulate and represent crop development and yield, considering different meteorological, agricultural management and soil conditions, among other variables. Agroecosystem modeling, which simulate the soil-vegetation-atmosphere continuum, incorporate both physiological processes of plant and their interactions with abiotic factors, but also different management scenarios [[18]](#footnote-19).These models are highly useful to assess the multidimensional relationships between different factors affecting crop development and yield, including evaluating the effect of a changing climate and seasonal weather patterns, irrigation management and fertilizer application [[19]](#footnote-20). Some of the most widely used crop growth models, among others, include the Decision Support System for Agrotechnology Transfer (DSSAT[[20]](#footnote-21), the World Food Studies (WOFOST[[21]](#footnote-22)), Agricultural Production System sIMulator (APSIM[[22]](#footnote-23) ), Simulateur mulTIdisciplinaire pour les Cultures Standard (STICS[[23]](#footnote-24)), the Model for Nitrogen and Carbon Dynamics in agro-ecosystems (MONICA[[24]](#footnote-25)), Daisy model[[25]](#footnote-26)and AquaCrop model[[26]](#footnote-27). These crop simulations models can dynamically ingest inputs and produce the outputs by updating the state variables, while model parameters can be calibrated depending on seasonal growth period and crop species [[27]](#footnote-28). As such, several efforts have been made to use remote sensing information to replace or adjust model state variables that affect vegetation development, such as LAI, biomass, chlorophyll content, water content, evapotranspiration, within crop growth models to improve the spatio-temporal dimensions of the outputs. Data assimilation techniques have been used to characterize the agro-ecosystem by combining data and information from various sources in different temporal and spatial scales. In general, remote sensing data is used to either **calibrate** model parameters or state variables, **forced** within the model by replacing a state variable or **updating** the model state variables whenever an observation is made [[28]](#footnote-29). However, since there are often important errors associated with remote sensing observations, data assimilation techniques need to also consider the error variance of these ‘observations’, through, for example, the use of Kalman filters [[29]](#footnote-30). For more details, refer to the comprehensive review on data assimilation techniques to combine remote sensing data with crop growth models by Dorigo et al. (2007).

**1.2.4 Hybrid Crop Growth Regression models**

Due to the complexity and large data requirements needed to run crop growth models, they are not particularly well suited for large spatial scale applications, especially in data scarce regions, being computationally intensive and requiring site-specific information. However, alternative or **hybrid** approaches have been developed to use complex crop models to train simpler statistical models that relate yield with one or several remote sensing indicators used as predictors. In this way, these methods largely bypass the need for computationally intensive methods to calibrate crop growth models. For example, Sibley et al. (2014)[[30]](#footnote-31) developed a simple linear model relating maize LAI and yield through simulations from a crop growth model (i.e. Hybrid-Maize model) and then applied the regression using both MODIS and Landsat imagery. The achieved high accuracy at predicting field scale maize yield using Landsat imagery, while this method also performed better than a more computationally expensive method using a crop growth model calibrated by satellite LAI (section 1.2.3) and a LUE modeling approach (section 1.2.2). Similarly, Lobell et al. (2015)[[31]](#footnote-32) developed the Scalable satellite-based Crop Yield Mapper (SCYM) that associated crop yield with spectral VIs and weather co-variates. This approach consists in four main steps: 1) crop model simulations over a realistic range of soil, climate and management conditions, 2) establishing pseudo-observations by converting daily model outputs to indicators observable by remote sensing (i.e. LAI to VIs relationship), 3) training the statistical model and 4) applying the yield models using image acquisitions from satellites. Jin et al. (2017)[[32]](#footnote-33) further improved the SCYM approach, using an ensemble of three crop models, including calibrating the phenology parameters in one the models, and using simulated biomass instead of yield to train the empirical model. They reported that simpler methods that relate crop biomass with yield, such as the constant harvest index, often outperform mechanistic simulations of grain formation. The integration of different remote sensing domains, such as thermal infrared or radar, to be used as predictive variables in these hybrid models remains largely unexplored, including the use of non-linear or machine learning statistical models.

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