Review of Crop Yield Forecasting Methods and Early Warning Systems

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Abstract

The following review paper presents an overview of the current crop yield forecasting methods and early warning systems for the global strategy to improve agricultural and rural statistics across the globe. Different sections describing simulation models, remote sensing, yield gap analysis, and methods to yield forecasting compose the manuscript.

1. Rationale

Sustainable land management for crop production is a hierarchy of systems operating in—and interacting with—economic, ecological, social, and political components of the Earth. This hierarchy ranges from a field managed by a single farmer to regional, national, and global scales where policies and decisions influence crop production, resource use, economics, and ecosystems at other levels. Because sustainability concepts must integrate these diverse issues, agricultural researchers who wish to develop sustainable productive systems and policy makers who attempt to influence agricultural production are confronted with many challenges. A multiplicity of problems can prevent production systems from being sustainable; on the other hand, with sufficient attention to indicators of sustainability, a number of practices and policies could be implemented to accelerate progress. Indicators to quantify changes in crop production systems over time at different hierarchical levels are needed for evaluating the sustainability of different land management strategies. To develop and test sustainability concepts and yield forecast methods globally, it requires the implementation of long-term crop and soil management experiments that include measurements of crop yields, soil properties, biogeochemical fluxes, and relevant socio-economic indicators. Long-term field experiments cannot be conducted with sufficient detail in space and time to find the best land management practices suitable for sustainable crop production. Crop and soil simulation models, when suitably tested in reasonably diverse space and time, provide a critical tool for finding combinations of management strategies to reach multiple goals required for sustainable crop production. The models can help provide land managers and policy makers with a tool to extrapolate experimental results from one location to others where there is a lack of response information.

Agricultural production is significantly affected by environmental factors. Weather influences crop growth and development, causing large intra-seasonal yield variability. In addition, spatial variability of soil properties, interacting with the weather, cause spatial yield variability. Crop agronomic management (e.g. planting, fertilizer application, irrigation, tillage, and so on) can be used to offset the loss in yield due to effects of weather. As a result, yield forecasting represents an important tool for optimizing crop yield and to evaluate the crop-area insurance contracts.

2. Crop Simulation Models

2.1. Background

Crop Simulation Models (CSM) are computerized representations of crop growth, development and yield, simulated through mathematical equations as functions of soil conditions, weather and management practices (Hogenboom et al., 2004). The strength of the CSM is in their ability to extrapolate the temporal patterns of crop growth and yield beyond a single experimental site. Crop Simulation Models (CSM) can be used to gain new scientific knowledge of crop physiological processes or to evaluate the impact of agronomic practices on farmers' incomes and environments. Crop models are only an approximation of the real world and many do not account for important factors such as weeds, diseases, insects, tillage and phosphorus (Jones et al., 2001). Nevertheless, CSM have played important roles in the interpretation of agronomic results, and their application as decision support systems for farmers is increasing. Models range from simple to complex. The purpose a crop model is to be used determines to a large extent the complexity of a model. Simple models are often used for yield estimation across large land areas based on statistical information related to climate and historical yields and include little detail about the soil-plant system. More complex mechanistic models may provide detailed explanations of the soil-plant-atmosphere system and require a large amount of input data, some of which may not be available. Models can be broadly classified into two general groups: deterministic and stochastic. Deterministic models produce a specific outcome for a given set of conditions, assuming all plants and soil within the simulation space is uniform. Stochastic models produce outcomes that incorporate uncertainty associated with the simulations. The uncertainty may arise because of spatial variability of soil properties, weather conditions and other abiotic and biotic factors not accounted for in a deterministic model. To overcome some of the problems with spatial soil variability, soil properties are subdivided into small homogenous units and results using deterministic models are aggregated to provide the entire field yield. Stochastic models are needed when the exactness of input information is uncertain. The crop growth system in general is more stochastic than deterministic because many parts of the agroecosystem are heterogeneous. However, to date, crop models using a stochastic approach have not been developed to a level of usefulness in decision making except in cases where year–to–year variations in weather are accounted for using deterministic models. Deterministic crop models can be classified into three basic types: statistical, mechanistic, and functional. The number of data inputs and the number and degree of sophistication of functions help to contrast model types (Addiscott and Wagenett 1985).

Statistical Models

The first models used for large-scale yield simulations were statistical. Average yields from large areas (counties or crop reporting districts) and for many years were regressed on time to reveal a general trend in crop yields (Thompson, 1969; Gage and Safir 2011). The trend for the past several decades has been usually been upward and accounts for technological advancements in genetic and management s especially the increased use of fertilizers. Deviations from the trend have been correlated with regionally averaged monthly weather data for each year. Thompson (1986) used a statistical type model to determine the impact of climate change and weather variability on corn production in five Midwestern states in the USA. He found pre-season precipitation (September –June), June temperature, and temperature and rainfall in July and August to be closely correlated with corn yield variations from the trend. Recently Gage and Safir (2011) incorporated climate effect with the use of the Crop Stress Index (CSI) into the regional yield trend. This approached significantly improved predictions of historical yields of corn and soybean. Lobell et al. (2011, 2013) used statistical models to determine the effects of increases in temperature on maize yield in USA concluding that temperature increase will play a large role in yield decrease under climate change. In general, the results of statistical models cannot be extrapolated to other space and time because of variation in soils, landscapes, and weather not included in the population of information from whence the statistical information was derived. Hence, the applicability of this type of crop-weather model to any areas and times outside the area and time of the regression is limited. When simulating yield using statistical models, the effects of changes in agricultural technology have to be subjectively extrapolated into time when the mix of the technology is unknown for that period. Hence a principal problem associated with statistical crop models is that the yield simulations may be made outside the range of weather and technology information from which the model was developed. Statistical models can provide many insights about past yields and historical influences and can be used to inform the other kinds of models (Gage and Safir, 2011; Lobell et al., 2011)

Mechanistic Models

Mechanistic models attempt to use fundamental mechanisms of plant and soil processes to simulate specific outcomes. Soon after computers became available for science, mechanistic models were developed to simulate photosynthetic processes such as light interception, uptake of carbon dioxide (CO_2), respiration and production of biomass partitioning biomass into various plant organs, and loss of CO_2 during respiration. In the soil system, the mechanistic approach was used to simulate the dynamics of water in the soil water due to infiltration, evaporation, drainage, and root uptake. de Wit (1965) recommended to distinguish between two levels, the system level and the next lower (explanatory) process level. Crop models typically consider the processes of plant development, light interception, CO2 assimilation and respiration, and the partitioning of biomass to plant organs and their growth. Including more detail at the process level ultimately increases model complexity and calculation time. Developments in computer science have progressively shortened calculation times and supported the consideration of more explanatory detail. This and the increasing complexity of problems to be addressed have resulted in the development of more complex models. Mechanistic models usually describe instantaneous rates of plant processes that change rapidly over short time scales. For example, photosynthetic and transpiration processes change rapidly during the day as the radiation and temperature conditions change. A relatively large amount of input information is required to run such a model. Uncertainty in some assumptions makes mechanistic model outcomes less certain and often makes them less useful to those outside of the model development group. Mechanistic models are seldom used for problem solving purposes; rather, they are often used for academic purposes to gain a better understanding of specific processes and interactions.

Functional Models

Functional models use simplified approaches to simulate complex processes. In some cases, mechanistic models can provide useful information that can be simplified into empirical functions for models. For example, many functional models use daily solar radiation as the amount of energy available for photosynthesis. The energy intercepted by the crop is approximated using feedback information from the plant leaf area index to approximate the biomass production using a simple concept of radiation use efficiency, e.g. the biomass produced per unit of radiation intercepted. Although this type function is much simpler than the more complicated ones, it usually produces reasonable results when compared to field measurements (Ritchie, 1980). Evapotranspiration is also simulated using only daily weather inputs by incorporating similar concepts to those used for biomass production simulation. In fact, the functional Penman equation for simulating potential evapotranspiration was being used two decades before computers were available for modeling and continues to be used, with some modifications, in crop models.

Functional models usually use simplified equations and logic to partition the simulated biomass into various organs in the plant, ultimately resulting in total biomass and economic yield. Evapotranspiration is used in a water soil balance equation to approximate when deficits or excesses in soil water or nutrients will impact potential biomass production and evapotranspiration. Functional models practically always use capacity concepts to describe the amount of water available to plants as compared to using instantaneous rate concepts from soil physics. A lower and upper limit of water capacity is defined as inputs, and water inputs and outflows in the soil provide the feedback to determine water availability to plants.

Functional models are usually run on daily time increments by using the daily inputs of rainfall, temperature, radiation, and irrigation. The models use much less input data compared to mechanistic models, making it more simple and useful for those not familiar with the biophysical processes involved in the simulations**.** These type models, when properly tested can provide an appropriate level of detail needed for assessing several issues affecting crop production.

Functional type models are now routinely used in decision support systems. Most of the discussions in this paper hereafter will focus around the functional models that are used in climate change assessment and to explore management issues related to crop production.

Advance in technology made possible the development of simple and complex CSM. The main point to take into consideration is therefore the availability of information needed to run the model. CSM need information of several aspects regarding crop management, soil, and atmosphere (Table 1). There is a level of complexity in the input data as well, as they range between hourly, daily, and weekly (Nix, 1984). However, CSM used for agrotechnology transfer will preferentially run using daily input data. Hunt and Boote (1998) defined a Minimum Data

Set (MDS) for operating CSM that are used in agrotechnology transfer. MDS is defined as the minimum amount of input data needed to run a CSM at a given site (Table 1).

The first step in acquiring input data for a CSM is to know the site where the model is to be run, by gathering information such as the geographical coordinates (e.g. latitude, longitude, and elevation). The required minimum weather data consists of daily incident solar radiation, minimum and maximum temperature, and rainfall. If more details are available they can be used to parameterize more complex functions within the CSM. For example, the MDS is generally used to calculate potential evapotranspiration using the Priestly-Taylor method. If humidity and wind speed are available then the FAO-56 approach can be used. The soil minimum information requires soil type, texture, organic carbon, and bulk density. If soil hydraulic limits (e.g. saturation, drain upper limit, and lower limit) and drainage coefficients are not available they can be estimated with commonly used pedo-transfer functions. Management and initial conditions can be obtained by farms' surveys, expert knowledge, or published material.

Table 1. Minimum data set needed to operate a crop simulation model.

	Input for CSM
1.	*Site description*:
•	Latitude and longitude, elevation, average annual temperature
•	Slope and aspects of the site
2.	*Weather*
•	*Daily global soil radiation, daily maximum and minimum temperature, daily rainfall*.
3.	*Soil*
•	Soil type, soil depth (divided by n layers), soil texture, soil organic carbon, bulk density, soil nitrogen, pH
4.	*Initial condition of the system*
•	Previous crop, residues left on the soil (if any), initial soil water and soil nitrogen
5.	*Crop and field management*
•	Cultivar name and type, planting date and type, row space, plants per square meter, irrigation/nitrogen amount, method, dates of irrigation/fertilization, fertilizer type

3. Remote Sensing

Remote Sensing (RS) is defined as the science of acquiring information about an object through the analysis of data obtained by a device that is not in contact with the object (Lillesand and Keifer, 1994). Remotely sensed data can be of many forms, including variations in force distribution, acoustic wave distribution or electromagnetic energy distributions. The data can be obtained from a variety of platforms such as satellite, airplanes, unmanned vehicles, and handheld radiometers. They may be gathered by different devices like sensors, film camera, digital cameras, and video recorders. The instruments used for measuring electromagnetic radiation are called *sensors*. Sensors are *passive* when they do not have their own source of radiation and they are sensitive only to radiation from a natural origin; and *active* when they have a built-in source of radiation.

Chlorophyll does not absorb all wavelengths of sunlight; it absorbs the blue (Blue) and red (Red) wavelengths, while green (Green) light is reflected (Cambpell, 1996). The reflection of visible radiation is mainly function of leaf pigments, whereas the Near-Infrared (NIR) is reflected by the internal mesophyll structure of leaves. NIR radiation passes through the first layer of the leaf (the palisade tissue); when it reaches the mesophyll and the internal leaf cavities it is scattered both upwards (which is referred as reflected radiation) and downwards (transmitted radiation) as shown in Figure 1 (Gausman et al., 1969). The behavior of the NIR reflectance is also a function of leaf area index (LAI), cell turgor, leaf thickness, leaf internal air and water content.

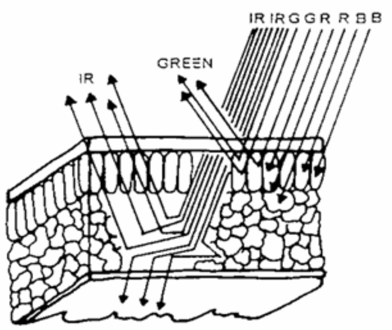

Figure 1. Section of a leaf and interactions between leaf structure and solar radiation (adapted from Campbell, 1996).

The relative decrease in reflectance is higher in the visible spectrum than in the NIR, because of the effects of the transmittance of the NIR through the leaves and the absorption of red and blue from the chlorophyll pigment. The visible light is absorbed or reflected by the first leaf layers, while the NIR is transmitted downwards and reflected upwards partly from the soil and partly during its passage through the canopy. These two reflected NIR wavelengths may be detected by a sensor positioned above the crop. As a result of the above mechanism, healthy crops will show high values of reflectance in the NIR and low values in the visible spectrum. During senescence and in crops subjected to stress (e.g. disease, pests, nitrogen and water shortages), the lower chlorophyll content allows for the expression of other leaf pigments such as carotenes and xanthophyll, causing a broadening of the green reflectance peak at 550 nm and an increase in visible light reflectance (Pinter et al., 2003). At the same time, there is a decrease in the relative reflectance in the NIR, as a consequence of less absorption of visible light in the leaves (Asner, 1998). The soil reflectance increases monotonically from the visible to the NIR regions of the electromagnetic spectrum and its slope varies according to soil type (Huete, 1987). In the visible region, leaf reflectance is lower than soil reflectance, whereas in the NIR leaf reflectance is higher than soil reflectance (Figure 2).This behavior is useful for explaining the utility of these reflectance measurements in agricultural applications and for the separation of crops from soil (Bausch, 1993). The spectral reflectance of soil is a function of soil constituents (such as soil organic matter, iron oxides), and soil roughness (such as particle and aggregate size) (Rondeaux et al., 1996).

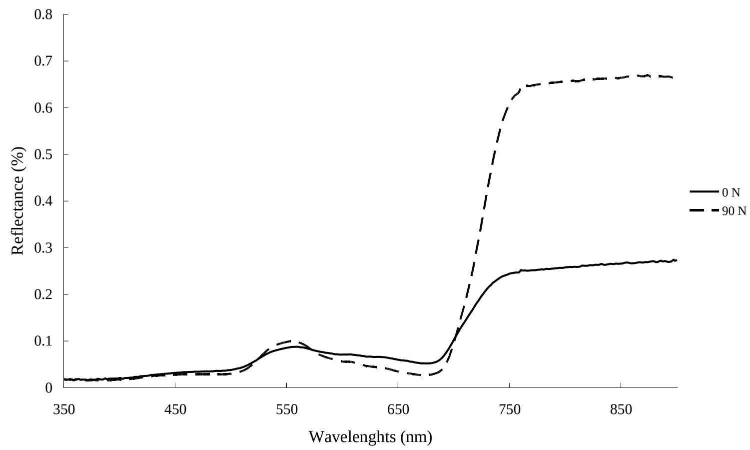

Figure 2.2. Percentage of visible and Near-Infrared (NIR) radiation reflected by wheat crop at Foggia (southern Italy) with no nitrogen fertilisation (0 N) and with 90 kg N/ha as split application (90 N) (Cammarano, 2010). Measurements are taken at the growth stage DC 30 (Pseudo-stem elongation, Zadoks et al., 1974).

3.1. Vegetation indices

Vegetation indices (VIs) are mathematical combinations or ratios of mainly red, green and infrared spectral bands; they are designed to find functional relationships between crop characteristics and remote sensing observations (Wiegand et al., 1990). Vegetation indices are strongly modulated by the interaction of solar radiation with crop photosynthesis and thus are indicative of the dynamics of biophysical properties related to crop status. But at early crop developmental stages, the effects of soil reflectance influence the values of some vegetation indices for the detection of crop stress (Huete et al., 1985). Daughtry et al. (2000) classified VIs into two categories: the *intrinsic indices* that include ratios of two or more bands in the visible and NIR wavelengths, these indices are sensitive to soil background reflectance and are often difficult to interpret at low Leaf Area Index (LAI) (Daughtry et al.,2000; Rondeaux et al., 1996). The second category is the *soil-line* VIs that uses the information of a regression line using the soil reflectance in the NIR-Red space to reduce the effect of the soil on canopy reflectance. On the other hand, Baret and Guyot (1991) have classified VIs into two categories: Indices characterized by "*slope*": RVI; and indices characterized by "*distance*". One of the first index developed is the RVI is the Ratio Vegetation Index (Jordan, 1969) which is the ratio between NIR and Red. The most commonly used index is the NDVI is the Normalized Difference Vegetation Index (Rouse et al., 1973). A list of most common the VIs is presented in Table 2 and an extensive list is discussed in Cammarano (2010).

Table 2. List of the common Vegetation Indices (VIs), their mathematical formula, the scale at which they have been developed and the parameter that they estimate (adapted from Cammarano, 2010).

Index	**Formula**	**Reference**	**Scale**	**Parameter**
NDVI (Normalized Difference Vegetation Index)	$\frac{(NIR - Red)}{(NIR + Red)}$	Rouse *et al.*, 1974	Canopy	Biomass; Vegetation Fraction
GNDVI (Green Normalized Difference Vegetation Index)	$\frac{(NIR - Green)}{(NIR + Green)}$	Gitelson *et al.*, 1996	Canopy	Chlorophyll; Vegetation Fraction
PRI (Photochemical Reflectance Index)	$\frac{(R570 - R531)}{(R570 + R531)}$	Gamon *et al.*, 1992	Canopy	Photosynthesis efficiency/ RUE
NDRE (Normalized Difference Red Edge)	$\frac{(R790 - R720)}{(R790 + R720)}$	Barnes *et al.*, 2000	Canopy	Chlorophyll/ Nitrogen
CCCI (Canopy Chlorophyll Content Index)	$\frac{(NDRE - NDRE_{min})}{(NDRE_{max} - NDRE_{min})}$	Fitzgerald *et al.*, 2006	Canopy	N Status/ Chlorophyll
RVI (Ratio Vegetation Index)	$\frac{NIR}{Red}$	Jordan, 1969	Leaf	Biomass
EVI (Enhanced Vegetation Index)	$2.5 * \frac{(NIR - Red)}{(NIR + C1 * Red - C2 * Blue + L)}$ $[C1 = 6; C2 = 7.5; L = 1]$	Huete et al., 2002	Canopy/ Regional	Biomass/ Vegetation Cover
EVI 2 (Enhanced Vegetation Index 2)	$G * \frac{NIR - Red}{NIR + \left(6 - \frac{7.5}{c}\right) * Red + 1}$ $Red = c * Blue$ $G = f(c)$	Jiang et al., 2008	Canopy/ Regional	Biomass/ Vegetation Cover
VARIgreen (Visible Atmospherically Resistant Index)	$\frac{(Green - Red)}{(Green + Red + Blue)}$	Gitelson et al., 2002	Canopy/ Regional	Vegetation Fraction/ LAI
VARI700 (Visible Atmospherically Resistant Index; 700 nm)	$\frac{(R700 - 1.7 * Red - 0.7 * Blue)}{(R700 + 2.3 * Red - 1.3 * Blue)}$	Gitelson et al., 2002	Canopy/ Regional	Vegetation Fraction/ LAI
TVI (Triangular Vegetation Index)	$0.5 * [120 * (R750 - R550) - 200 * (R670 - R550)]$	Brodge and Leblanc, 2000	Canopy	Chlorophyll
MTVI 1(Modified Triangular Vegetation Index 1)	$1.2 * [1.2 * (R800 - R550) - 2.5 * (R670 - R550)]$	Haboudane et al., 2004	Canopy	Chlorophyll
MTVI 2 (Modified Triangular Vegetation Index 2)	$\frac{1.5 * [1.2 * (R800 - R550) - 2.5 * (R670 - R550)]}{\sqrt{(2 * R800 + 1)^2 - (6 * R800 - 5 * \sqrt{R670}) - 0.5}}$	Haboudane et al., 2004	Canopy	Chlorophyll
MTCI	$\frac{R735.75 - R708.75}{R708.75 - R681.25}$	Dash and Curran, 2007	Canopy	Chlorophyll

CAR (Chlorophyll Absorption Reflectance)	$\frac{\lvert(a*670+R670+b)\rvert}{\sqrt{(a^2+1)}}$ $\begin{bmatrix} a=(R700-R550)/150 \\ b=R550-(a*550) \end{bmatrix}$	Kim *et al.*, 1994	Canopy	Chlorophyll
CARI (Chlorophyll Absorption Reflectance Index)	$\frac{\lvert(a*670+R670+b)\rvert}{\sqrt{(a^2+1)}}*\frac{R700}{R670}$	Kim *et al.*, 1994	Canopy	Chlorophyll
MCARI (Modified Chlorophyll Absorption Reflectance Index)	$[(R700-R670)-0.2*(R700-R550)]*\frac{R700}{R670}$	Daugthry *et al.*, 2000	Leaf/ Canopy	Chlorophyll/ LAI/ Soil Reflectance
MCARI 1	$1.2*[2.5*(R800-R670)-1.3*(R800-R550)]$	Haboudane *et al.*, 2004	Canopy	Chlorophyll/ LAI/ Soil Reflectance
MCARI2	$\frac{1.5*[2.5*(R800-R670)-1.3*(R800-R550)]}{\sqrt{(2*R800+1)^2-(6*R800-5*\sqrt{R680})-0.5}}$	Haboudane *et al.*, 2004	Canopy	Chlorophyll/ LAI/ Soil Reflectance
TCARI (Transformed Chlorophyll Absorption Reflectance Index)	$3*[(R700-R700)-0.2*(R700-R550)*(R700/R670)]$	Haboudane *et al.*, 2002	Canopy	Chlorophyll/ LAI/ Soil Reflectance
WDVI (Weighted Difference Vegetation Index)	$NIR-a*\mathrm{Re}\,d$	Clevers, 1989	Canopy	LAI/ Biophysical Parameters
PVI (Perpendicular Vegetation Index)	$\frac{1}{\sqrt{a^2+1*(NIR-a*\mathrm{Re}\,d-b)}}$	Richardson and Wiegand, 1977	Canopy	Canopy Biophysical Parameters
SAVI (Soil-Adjusted Vegetation Index)	$\frac{(1+L^a)*(R800-R670)}{(R800+R670)+L}$	Huete et al., 1988	Canopy	Canopy Biophysical Parameters
TSAVI (Transformed Soil-Adjusted Vegetation Index)	$\frac{a^b*(R800-a*R670-b^c)}{[a*R800+R670-a*b]}$	Baret et al., 1989	Canopy	Canopy Biophysical Parameters
OSAVI (Optimized Soil-Adjusted Vegetation Index)	$\frac{(1+0.16)*(NIR-\mathrm{Re}\,d)}{(NIR+\mathrm{Re}\,d+0.16)}$	Rondeaux et al., 1996	Canopy	Canopy Biophysical Parameters
MSAVI (Modified Soil-Adjusted Vegetation Index)	$\frac{(1+L^e)*(R800-R670)}{(R800+R670+L)}$	Qi et al., 1994	Canopy	Canopy Biophysical Parameters

[a] L is a soil-adjustment factor and is set to be 0.5

[b and c] a and b are soil-line coefficients derived from the following equation: $NIR_{soil} = a * RED_{soil} + b$

[d] χ is an adjustment factor for minimizing the soil background effects and is set to be 0.08

[e] L is a self-adjustment factor derived from the following equation: L= 1 – 2*a*NDVI*WDVI

4. Crop Yield Forecast

There are several methods of yield forecasting. The traditional method of yield forecasting is the evaluation of crop status by experts. Observations and measurements are made throughout the crop growing season, such as tiller number, spikelet number and their fertility percentage, percentage of damage from pests and fungi, percentage of weeds infestation, and so on. From the data obtained in this way yield can be forecasted using regression methods, or by the knowledge from local expertizes. Other two methods used to forecast crop yield are the use of remote sensing and crop simulation models. The objective of the yield forecast is to give a precise, scientific sound and independent forecasts of crops' yield as early as possible during the crops' growing season by considering the effect of the weather and climate. The differences between forecasts and final estimates are in the timing of the release. Forecasts are made before the entire crop has been harvested whereas estimates are made after the crop has been harvested. Indications are the result of applying a statistical estimator to the survey data and the resulting point estimates are interpreted by commodity statisticians to make forecasts and estimates. Historically, farmers have been always making "forecasts" in order to plan their agronomic practices. For example, the planting window, the choice of a cultivar, the amount of fertilizer to apply depend on the climate. If farmers know that the subsequent week there is a good chance for rain, then they will rush into the field to sown their seeds. Forecasting crop yield means also knowing or forecasting other important parameters. For example, quantifying the area planted at the starting of the growing season and quantifying the area harvested.

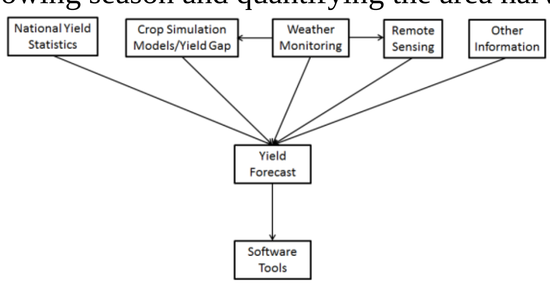

Fig. 3. Diagram of yield forecast methods

4.1. Weather impact on crop yield variability: methods used to assess the direct and indirect effects

4.1.1. Crop Yield Forecast using Statistical Models

Yield forecast using agrometeorological inputs into a statistical regression is rather common and used in many yield forecasts research and programs (NASS, 2006; Lobell et al., 2009). In general, a simple statistical model is build using a matrix with historic yield and several agrometeorological parameters (e.g. temperature and rainfall). Then, a regression equation is derived between yields as function of one or several agronometeorological parameters. The NASS (2006) program uses a statistical model to forecast crop yield and production. They use two methods to forecast yield, the former refer to the use sample-derived models for forecasting yields and their component; the latter, is use models at state and regional levels. For example the

NASS (2006) system for corn forecast is based on the two levels described above. A corn objective yield survey was first conducted in the 10 major corn-producing countries. They conduct some detailed field surveys for determination of yield components which can be used for the field-level yield forecast. While to obtain state/regional estimates an aggregation of the input is done first and then a statistical model is used. The advantages of a statistical model is that the calculation is easy, less time is required to run the model and the data requirements are limited. However, they are limited in the information they can provide outside the range of values for which the model is parameterized. Also the output of such models might not have any agronomic meaning, while statistically are still correct. In addition, they do not take into consideration the soil-plant-atmosphere continuum, which is important when dealing with regions having different soil types. For example, the response of a crop to a given amount of rainfall on a sandy soil is different than a crop on a clay soil. The timing of the water stress occurring during the growing season is also important and often ignored. For example, a heat stress occurring at flowering will reduce yield more than a heat stress happening during the vegetative phase. This is important for correctly forecasting yield and for giving farmers important agronomic advices (e.g. timing and amount of fertilizer, time of sowing, irrigation, and so on). There are efforts of include more meaning into the statistical models in order to avoid some of the problems described. For example, the inclusion of crop evapotranspiration, and/or the initial soil moisture content (obtained through microwave sensing) as parameters of the model improve the predictability power but leave the agronomic questions unanswered.

4.1.2. Crop Yield Forecast using Process-Based Models

Agroecosystems are complex entities where crop yield is the resultant of many interactions such as soil, atmosphere, water, and socio-economic factors. CSMs are built with the aim to consider the continuum soil-plant-atmosphere and its daily changes on the daily accumulation of biomass and nitrogen. There are many CSM around the world, for example, Asseng et al. (2013) used more 27 wheat models in their intercomparison. Not all the models are the same. Some are very simple with no more than 7 parameters needed to describe a particular cultivar (Bondeau et al., 2007), to other which take into account detailed processed like photosynthesis at leaf level and therefore need many user-specified parameters. CSM have been extensively used to evaluate the agronomic consequences from the inter-annual climate variability (Paz et al., 2007; Semenov and Doblas-Reyes, 2007; Challinor and Wheeler, 2008). For example, CSM can capture the effects of and timing of wet/dry cycles on crop growth; which can significantly help famers in planning their agronomic management (Shin et al., 2009). Not all the CSM can be or will be used for agrotechnology transfer; successful applications of a CSM to yield forecast is function of many things but the most important is the amount of parameters needed to describe crop-soil-atmosphere. A successful example of a CSM application is the yield prophet (http://www.yieldprophet.com.au/yp/wfLogin.aspx) which is an on-line CSM designed to inform farmers and consultants with real-time information about their crops, giving risk-assessment information and monitoring decision support relevant to farm management. The system is operated as a web interface for the Agricultural Production Systems Simulator (APSIM).

Another succesfful application of web-based simple interface crop simulation model is the SALUS model as described by Basso et al., (2012, 2010) (www.salusmodel.net). The model is designed to be used by farmers or extension specialists to quantify the impact of management, soil and weather interaction on yield and environmental impact. The SALUS (System Approach to Land Use Sustainability) model is an ongoing team effort started by Joe Ritchie at Michigan State University in late nineties and currently carried on by Bruno Basso (Basso et al.2006; Basso et al. 2010). SALUS is similar in detail to the DSSAT family of models but is designed to simulate crop yield in rotation, soil, water and nutrient dynamic as function of management strategies for multiple years (Fig. 1). SALUS accounts for the effects of rotations, planting dates, plant populations, irrigation and fertilizer applications, and tillage practices. The models simulates daily plant growth and soil dynamics processes on a daily time step during the growing season and fallow periods. SALUS contains: i) crop growth modules; ii) soil organic matter and nutrient cycling module and; iii) soil water balance and temperature module. The model simulated the effects of soil-climate and management interaction on the water balance, soil organic matter, nitrogen and phosphorus (P) dynamics, heat balance, plant growth and plant development. i-Salus is also a web-based agronomic decision support system - named i-Salus - to help farmers optimize their irrigation and nitrogen management practices over space and time. i-Salus allows users to evaluate the best management strategy to improve yield and quality of the crops, to increase economic net return and at the same time to reduce greenhouse gas emissions and groundwater contamination from nitrate leaching. i-Salus is composed by two interfaces: a simple interface and Web-GIS interface. SALUS with the simple interface is a user friendly system s targets at farmers or extension specialists who can simulate the impact of different management strategies on yield, and environmental impact. SALUS-WebGIS is a web-based GIS integrated with Google Earth and Salus model to simulate in a spatial explicit manner the effect of climate-soil-genotype-management interaction on crop yield and environmental impact. Both systems are available at www.salusmodel.net

The difficulties of adopting CSM has usually been associated with the intensive data for models' parameterization. The need for calibration can be quite data extensive and not applicable to some developing countries (Gommes, R, 1998). In fact, it has been argued that several variables are needed to calibrate/evaluate the CSMs, concluding the usefulness of CSMs in some "*real*" situation because of the impossibility of gathering inputs and calibration datasets. However, a more critical look at the literature and the work done by other researcher points out that the CSM can be run using "*Minimum Data Set*" (MDS) inputs (as discussed earlier). Models, like the i-Salus example reported above, have shown to be easy to use by anyone but still maintain its robustness in yield predictions. It has been pointed that another limitation of the CSM is that they are "*point-based*" and inadequate to run at regional/national scale. However, Bondeau et al. (2007) and Challinor et al. (2004) developed a simple CSM that can be run at regional and national scale with less demands on inputs and calibration dataset.

4.1.3. Yield forecast with remote sensing

Hatfield (1983) divided the models used for yield forecast from RS into *spectral models* (Tucker et al., 1980); *albedo models* (Idso et al., 1978), *and thermal models* (Idso et al., 1977 and Walker and Hatfield, 1979). Horie et al. (1992) identified three models used to forecast crop growth and yield from RS, *the empirical regression model*, *the biomass production model as a function of absorbed or intercepted solar radiation*, and *the stress-degree-day model*. The meteorological models used for forecasting yield are mainly based on two variable, temperature and precipitation because they are related to crop yields (Barnett and Thompson, 1982) and can be easily obtained from meteorological stations or from satellite measurements such as the NASA Prediction Of Worldwide Energy Resource Project (POWER; White et al., 2011). These two inputs can be used singularly, or as a combination. They can be used as daily or monthly variables. Such models are generally a simple regression, and three main methods are commonly used: time-series; based on changes in space and time; and based on changes in space (Lobell and Burke, 2010). Fisher (1924) used a statistical approach to successfully predict wheat yield as a function of growing season rainfall. In rainfed agricultural regions, rainfall is the most important factor affecting crop growth and yield. French and Schultz (1984), proposed a rainfall-based models to calculate the upper limit of potential yield. In Australia this approach is still used by farmers and consultants alike. Robertson and Kirkegaard (2005) pointed out that with such model yield can be overestimates because the formula does not account for rainfall distribution, runoff, drainage or access to stored soil water. Fiztpatrick and Nix (1969) used the ratio of actual to potential evapotranspiration to forecast wheat yield. However, Unger (1966) concluded that in order to successfully use agrometorological models for yield estimation it needs to be taken into account the daily effects of temperature, soil moisture, the energy balance of the crop or any of the yield components. Rudorff and Batista (1990) concluded that when such models are applied at regional level they cannot fully simulate the different crop growing conditions within the region. The application of agrometeorological models is more common nowadays because of the integration with RS. Doraiswamy et al. (2003) reported one of the first examples in which production is forecasted through satellite remote sensing and measured meteorological observations on the ground. The Large Area Crop Inventory Experiment (LACIE) project, which was launched in 1974, used satellite remote sensing to forecast wheat production in the major wheat-producing countries. For example, in 1977 LACIE forecasted 30% reduction of spring wheat production in the former Soviet Union, an estimate that came close to the official figures released after the harvesting (Myers, 1983). The models used in LACIE were statistical models, in which yields is modeled as function of air temperature and rainfall (Doraiswamy et al., 2003). Tucker et al (1980) used such approach to related yield and NDVI, while Shibayama & Munakata (1986) used reflectance data collected during the grain-filling period to forecast rice yield. Remotely data obtained from the National Oceanic and Atmospheric Administration's (NOAA) Advanced Very High Resolution Radiometer (AVHRR) have been used to monitor large scale cropping systems and to forecast yield since the 1980's

(Tucker et al., 1985). Benedetti and Rossini (1993) used the AVHRR satellite-derived NDVI data for wheat forecast and monitoring in a region of Italy. They derived a simple linear regression model for wheat yield estimate and forecast based on NDVI images during the wheat grain filling period. They validated their results against official data and found good correlations between the two. Doraiswamy et al. (2003) used the AVHRR NDVI data as proxy inputs to an agro-meteorological model for the estimation of wheat yield at two different spatial resolutions in North Dakota. Kogan et al. (2012) estimated winter wheat, sorghum and corn yields 3/4 months before harvest using the AVHRR data. The errors of yield estimated were 8%, 6%, and 3% for wheat, sorghum and corn, respectively. In Mediterranean African Countries, Maselli and Rembold (2001) used the NDVI derived from the AVHRR platform to estimate cereal production. While Meroni et al. (2013) using the SPOT platform (Satellite Pour l'Observation de la Terre) and a statistical model quantified wheat yield in north Tunisia and concluded that where crop conditions need to be quantified without ground measurements for calibration, the biomass proxies are preferred. In Senegal, Rasmussen (1999) used the AVHRR data to estimate millet yield, by using the NDVI integrated during the reproductive phase of millet development. He also investigated if it was possible to reduce both the inter-annual and environmental variability by taking into account areas of homogeneous production levels. Ray et al. (1999) used the Indian Remote Sensing satellite (ISR) to estimate cotton yields at a district level using relationship between actual evapotranspiration and non-irrigated cotton yield. The use of low resolution satellite images, along with the high temporal frequency, their wide geographical coverage, and their unitary low costs per area, means that these images are a good choice for yield estimation as showed by many reported findings. In Western Australia Smith et al. (1995) used the AVHRR satellite to estimate wheat yield over 70% of the wheat growing area of the state. For each developmental stage the amount of variability explained by the NDVI-based model to predict wheat yield. At stem elongation, the model built explained 45% of the variation in final yield; 56% of variance was explained around anthesis. However, after anthesis the amount of yield explained was only 48%. Smith et al. (1995) concluded that the high correlation of the NDVI taken during the growing season indicates the capability of correctly forecasting wheat yield well ahead the end of the growing season.

Another platform that is commonly used is the National Aeronautics and Space Administration's (NASA) Moderate Resolution Imaging Spectroradiometer (MODIS), which has been demonstrated to give better spectral and spatial resolution relative to the AVHRR (Doraiswamy et al., 2001; Ren et al., 2008; Funk and Budde, 2009; Becker-Reshef et al., 2010). AVHRR and MODIS have high frequency observations; but, both spatial resolutions are rather coarse. For example, MODIS data are at a resolution of 250-m, 500-m, and 1000-m according to the chosen product (Justice et al., 1998); while the AVHRR data have a spatial resolution of 1.1 km for local coverage and 4 km for global coverage (Kidwell, 1998). Bolton and Friedl (2013) used satellite data from

MODIS to develop empirical models for maize and soybean yield forecast in the Central United States. The EVI2 index (Table 2) showed better ability to predict maize yield than the NDVI, and the use of crop phenology information from MODIS improved the model predictability. Although MODIS has a low spatial resolution, the authors showed that MODIS was still able to identify the agricultural areas without affecting model's output compared to the higher-spatial resolution crop-type maps developed by the USDA. Kogan et al. (2013) used NDVI values from the MODIS, at 250 m spatial resolution for forecasting wheat yield in Ukraine. In Kenya the MODIS was used to derive images for six sugarcane management zones, over nine years, to estimate sugarcane yield based on each zone. Because of the zoning, the different management strategies were taken into account using the temporal series of NDVI which was normalized by a weighting method that includes sugarcane growth and the time-series of the NDVI. The challenge is to estimate the yield in small-holder farmers where the fields are often smaller that the spatial resolution of the MODIS used (250 m).

A platform with better spatial resolution (30 m) is the Landstat Thematic Mapper (Hammond, 1975) and has been also used for yield forecast purposes (Rudorff and Batista, 1990; Thenkabail et al., 1994). However, the Landsat temporal resolution is higher than the other two which might be a problem if frequent observations are needed at sensitive crop growth stages. Idso et al. (1980) used the LANDSAT reflectance data and the crop senescence to forecast grain yield. This was achieved by using the concept of crop albedo variations through the growing season (Idso et al., 1977, 1978). Wheat-field albedo always decreased from the time of heading until the beginning of senescence. When crop is subjected to water stress senescence began to appear earlier compared to well watered crops. Thus, Idso et al. (1980) used the senescence rates and their correlation with grain yield to forecast production. Rudoff and Batista (1990) estimated sugarcane in Brasil using remote sensing and an agrometeorological model based on a model developed by Doorenbos and Kassam (1979) where yield is related to multiple regression technique used to integrate the vegetation index from Landsat and the yield from the agrometeorological model. Such estimations explained 69%, 54%, and 50% of the yield variation in the 3 growing seasons analyzed. The authors also tested the accuracy of sugarcane yield estimations using only the RS or the agrometeorological model only. The results were poorer compared to the combinations of both (Rudorf and Batista, 1990).

Recent studies have used both higher spatial resolution data from Landsat with higher temporal frequency data from MODIS or AVHRR (e.g., Genovese et al., 2001; Becker-Reshef et al., 2010; Mkhabela et al., 2011). To generalize such models and make sure that they are reliable, the use of physiological concepts has been introduced. One of the most frequent concepts used is the Photosynthetically Active Radiation (PAR). The PAR is defined as the amount of light available for photosynthesis that ranges between 400 and 700 nanometer (McKree, 1972). Monteith (1977) proposed a simple model relating crop biomass, at any moment of the crop growth, with the PAR accumulated; this model has been further validate by experimental evidences (Shibles & Weber, 1966; Gallagher & Biscoe, 1978; Kumar and Monteith, 1982;

Sinclair & Horie, 1989; Daughtry et al.,1992; Gower et al., 1999). Bastiaanssen and Ali (2003) combined the PAR model with a light use efficiency model developed by Field et al. (1995) and the surface energy model of Bastiaanssen et al. (1998) to estimate crop growth and forecast crop yield using the AVHRR data, for wheat, rice, sugarcane and cotton. The authors concluded that even if AVHRR has a coarse resolution for field scale estimation it still provides useful yield forecasts. The forecast of crop yield in sub-optimal growing conditions is harder to obtain. However, the use of RS and physiological concepts such as the PAR can help to gain real-time information of the crop growing conditions at any stage during the crop growing season (Clevers, 1997). The use of PAR estimated from RS is used to predict sugar beet yield in Europe. The parameters of model were not empirical estimates, but were derived using physiological concepts. Another important crop parameter, the Leaf Area Index (LAI) has been linked with remotely sensed data. LAI is defined as the total leaf area per unit of ground area (Watson, 1937). It is considered an important factor for describing several processes such as crop evapotranspiration, photosynthesis, and yield (Price and Bausch, 1995). LAI is also a good indicator of canopy ground cover; therefore, remote sensing has been used to link LAI (Richardson & Wiegand. 1977: Tucker et al., 1979) or greenness (GR) (Rice et al.. 1980). The Vls and greenness are linearly related to PAR absorption rate of crop canopies (Hatfield et al.,1984; Asrar et al., 1985; Wiegand et al., 1979; Weigand & Richardson, 1990). Hence, crop-absorbed PAR can be estimated from remotely sensed VI or greenness and PAR observed at ground stations. This has been utilized for many crops to remotely estimate yields with satisfactory results (Asrar et al., 1985: Wiegand et ai., 1989: Wiegand & Richardson, 1990). This method, however, gives a potential crop yield rather than an actual yield: the constant radiation conversion efficiency and constant harvest index are assumed. Radiation conversion efficiency is affected by nitrogen deficiency (Sinclair & Horie, 1989) and water stress, while harvest index is influenced by water or temperature stress during reproductive and grain-filling stages (Horie, 1987). Casanova et al. (1998) used VIs, and PAR to estimate LAI and biomass, and concluded that estimation of biomass is more reliable of estimation of LAI. In fact at early growth stages the low LAI and high soil reflectance makes it difficult to isolate the plant signal, affecting relationships developed between spectral and canopy biophysical properties (Huete, 1988). Later in the season, high values of LAI cause some VIs to lose sensitivity for detecting crop stress. Carlson and Ripley (1997) found that when LAI values ranged between 3 and 6 NDVI become ineffective. Daughtry et al. (2000) demonstrated that LAI is the main variable affecting VIs for the estimation of leaf chlorophyll concentration.

The other model used in the integration of RS and yield forecast is based on the canopy temperature measurements. The rationale behind this approach is that water stress causes elevated plant temperatures which negatively affect plant photosynthesis and crop yield (Idso et al., 1977; Idso, 1968). Idso et al. (1978) refer to this model as Stress Degree Day (SDD), where canopy yield is inversely and linearly related to the accumulated SDD over a given period of time during crop development. ldso et al. (1977) showed that the differences in canopy-air temperatures at midday (SDD) were related to yield when cumulated over a period of time. This model was used as a base for the forecast of crop yield and crop water status by RS. However, the differences in temperatures between the leaf and the air is strongly influenced by the vapor pressure deficit of the air and by soil moistures; therefore, the SDD application is somehow limited to environments where the vapor pressure deficit is relatively constant (Horie, 1992). Jackson et al. (1981) improved the SDD by creating the Crop Water Stress Index (CWSI) where the vapor pressure deficit effects are taken into account. Gardner et al. (1981) proposed a Temperature-Stress-Day (TSD) index, in which the temperature of the canopy and the field are compared at an unknown stress level and for a fully-watered field with the same crop. Reginato et al. (1978) found that for yield prediction the cumulative SDD for grain crops is calculated from head appearance and awns to the end of plant growth. Idso et al. (1978) integrated the SDD concept with the growing degree days (GDD) to better predict both grain yield and end of crop growth. Yield forecast through RS and models has been made for several cropping systems. On vineyards, the final yield was evaluated using high spatial resolution RS for the estimation of canopy vigor and yield components (Hall and Wilson, 2013).

RS techniques have been extensively used in research for yield forecast but played a small role in understanding the cause of spatial yield variability. Also, it has been argued that while RS might not be suitable in developing countries because of their stratified agricultural systems and very small farm sizes. However, this problem is hard to overcome in the near-future because of the inability of RS to estimate yield in mixed agriculture. But, the increased availability of high-spatial resolution RS at a reasonable cost make this technique a possible interesting alternative for yield forecast. In fact, RS is often use in Early Warning Systems (next section) in developing countries.

4.1.4. Yield Gap

The yield gap concept has been used for many years to define the difference between yield potential and actual averages yield (van Ittersum et al., 2013). This is done in order to understand the causes of yield gap and if the actual yields can be raised by better management practices (Lobell et al., 2009). Crop yield potential (Yp) is defined as the crop yield obtained when a crop is grown without limitations of water or nutrients, and in the absence of any pests, diseases and weeds (Figure 4). In a given location crop yield potential is solely function of solar radiation, air temperature and crop genetics feature (van Ittersum et al., 2003). In rain-fed environments, the potential yield concept takes into account the constraints due to a water-limited environment (Yw) in which crop growth (Figure 4). This means that along with factors affecting Yp, crop yield is also dependent by soil characteristics (Lobell et al., 2009). The yield potential of a crop can be experimentally determined in a field or obtained from well-managed farmer fields. This is either costly or often hard to achieve (Lobell et al., 2005). Crop models have been used to estimate Yp and Yw for specific fields, farms and regions (Lobell et al., 2009). In addition to quantifying a potential yield, crop models have been used to understand the reasons for a yield gap, the difference between actual and potential yield (Yp, Yw). Lobell (2013) added that in assessing yield gap there is a spatial and temporal variability of agricultural land. Therefore, when the yield gap is evaluated there is a mismatch in terms of reporting actual yield which are reported at the level of administrative units; and the Yp that is generally quantified at field level by using field trials, or point-based simulation models. However, the scale mismatch is often ignored as well as the different management existing between a single farm and many farms aggregated at an administrative level. Another example of using a CSM to find the yield potential and the cause of lower yield has been described by Bachelor et al. (2002). The authors used a crop model to attribute portions of a yield gap to disease, weeds and water stress effects.

Another important application of the RS is to forecast yield gaps. RS is an interesting alternative for understanding the spatial and temporal variability of crop yield. RS has been extensively used to estimate actual yield, but for the potential yield estimation several approaches can be used. One approach consists in using Yp calculated in other ways and couples them with RS estimations. But, Lobell (2013) concluded that such approach is not practical because if Yp is known than actual yields are known as well and RS is not useful. The screening of large areas over time is used to identify the highest yielding pixel and use it as a proxy for Yp as demonstrated by Lobell et al. (2009). Lobell et al. (2002), and Bastiaanssen and Ali (2003) used satellite data to derive the 95 percentile of the yield distribution. The main advantage of the yield gap concept lies in its agronomic concept used to develop it, and the global approach for evaluating simulated vs. observed Yp, Yw, and actual yields as described by Van Ittersum et al. (2013). The main disadvantages are in the availability of global quality data, especially for crops that are not common worldwide (e.g. cassava) or for developing nations where data are rather sparse. However, as data are becoming widely available and several efforts to gather quality data worldwide are underway this approach might become an appealing alternative to other simplistic methods.

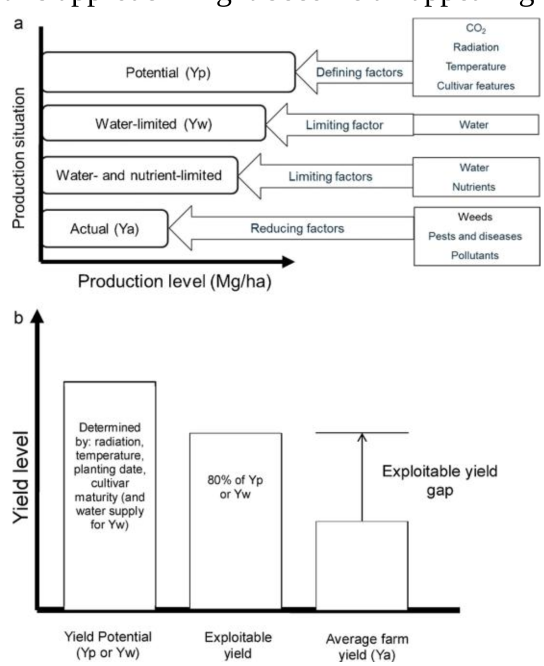

Figure 4. (*a*) Yields affected by defining, limiting and reducing factors for irrigated yield potential (Yp) and rainfed yield (Yw). (*b*) Gap between average yields and 80% of Yp or Yw (from Van Ittersum et al., 2013).

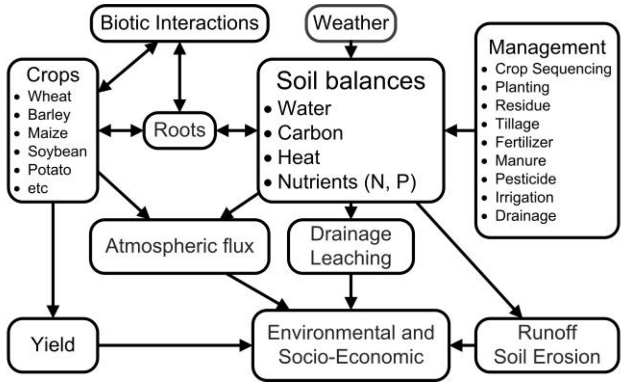

Figure 5. A diagram to illustrate the interaction between soil-plant-atmosphere as accounted in the SALUS model (www.salusmodel.net)

5. Remote Sensing and Precision Agriculture

The past research efforts on remote sensing have provided a rich background of potential application to site-specific management of agricultural crops. In spite of the extensive scientific knowledge, there few examples of direct application of remote sensing techniques to precision agriculture in the literature. The reasons are mainly due to the difficulty and expense of acquisition of satellite images or aerial photography in timely fashion. With the progress in GPS and sensor technology direct application of remote sensed data is increasing. Now an image can be displayed on the computer screen with real-time position superimposed on it. This allows for navigation in the field to predetermined points of interest on the photograph. Blackmer et al., (1995) proposed a system for N application to corn based on photometric sensors mounted on the applicator machine. They showed that corn canopy reflectance changed with N rate within hybrids, and the yield was correlated with the reflected light. Aerial photographs were used to show areas across the field that did not have sufficient N. The machine reads canopy colors directly and applies the appropriate N rate based on the canopy color of the control (well fertilized) plots (Blackmer and Schepers, 1996; Schepers et al., 1996).

Management zones can be extracted using VIs maps and with the use of a GIS be viewed over a remotely sensed image. The computer monitor displayed the image along with the current position as the applicator machine moved on the field. When interfaced with variable rate sprayer equipment, real time canopy sensors could supply site-specific application requirements improving nutrient use efficiency and minimizing contamination of groundwater (Schepers and Francis, 1998).

Indirect Applications

The most common indirect use of remote sensing images is as a base map on which other information is layered in a GIS. Other indirect applications include use of remotely measured soil and plant parameters to improve soil sampling strategies, remote sensed vegetation parameters in crop simulation models, and use in understanding causes and location of crop stress such as weeds, insect, and diseases.

Moran et al. (1997) in their excellent review on opportunities and limitations for image-based remote sensing in precision agriculture, classify the information required for site specific management in information on seasonally stable conditions, information on seasonally variable conditions, and information to find the causes for yield spatial variability and to develop a management strategy. The first class of information includes conditions that do not vary during the season (soil properties) and only need to be determined at the beginning of the season. Seasonally variable conditions, instead, are those that are dynamic within the season (soil moisture, weeds or insect infestation, crop diseases) and thus need to be monitored throughout the entire season for proper management. The third category is comprehensive of the previous two to determine the causes of the variability. Remote sensing can be useful in all three types of information required for a successful precision agriculture implementation. Muller and James (1994) suggested a set of multi-temporal images to overcome the uncertainty in mapping soil texture due to differences in soil moisture and soil roughness. Moran et al. (1997) also suggested that multi-spectral images of bare soil could be used to map soil types across a field.

Crop growth and intercepted radiation

Remote sensing techniques have also been applied to monitor seasonally variable soil and crop conditions. Knowledge of crop phenology is important for management strategies. Information on the stage of the crop could be detected with seasonal shifts in the “red edge” (Railyan and Korobov, 1993), bidirectional reflectance measurements (Zipoli and Grifoni, 1994), and temporal analysis of NDVI (Boissard et al., 1993; Van Niel and McVicar 2004a). Moreover Wiegand *et al.* (1991) consider them as a measure of vegetation density, LAI, biomass, photosynthetically active biomass, green leaf density, photosynthesis rate, amount of photosynthetically active tissue and photosynthetic size of canopies. Aparicio *et al.* (2000) using three VIs (NDVI; Simple Ratio; Photochemical Reflectance Index) to estimate changes in biomass, green area and yield in durum wheat. They results suggest that under adequate growing conditions, NDVI may be useful in the later crop stage, as grain filling, where LAI values are around 2. SR, under rainfed condition, correlated better with crop growth (total biomass or photosynthetic area) and grain yield than NDVI. This fact is supported by the nature of relationship between these two indices and LAI. SR and LAI show a linear relationship, compared to the exponential relationship between LAI and NDVI. However the utility of both indices, as suggested by the authors, for predicting green area and grain yield is limited to environments or crop stages in which the LAI values are < 3. They found that in rainfed conditions, the VIs measured at any stage were positively correlated ($P < 0.05$) with LAI and yield. Under irrigation, correlations were only significant during the second half of the grain filling. The integration of either NDVI, SR, or PRI from heading to maturity explained 52, 59 and 39% of the variability in yield within twenty-five genotypes in rainfed conditions and 39, 28 and 26% under irrigation. Shanahan *et al.* (2001) use three different kinds of VIs (NDVI, TSAVI, GNDVI) to asses canopy variation and its resultant impact on corn (*Zea mays* L.) grain yield. Their results suggest that GNDVI values acquired during grain filling were highly correlated with grain yield, correlations were 0.7 in 1997 and 0.92 in

1998. Moreover they found that normalizing GNDVI and grain yield variability, within treatments of four hybrids and five N rates, improved the correlations in the two year of experiment (1997; 1998). Correlation, however, increases with a net rate in 1997 from 0.7 to 0.82 rather than in 1998 (0.92 to 0.95). Therefore, the authors suggest that the use of GNDVI, especially acquiring measurements during grain filling is useful to produce relative yield maps that show the spatial variability in field, offering an alternative to use of combine yield monitor.

Raun *et al.* (2001) determined the capability of the prediction potential grain yield of winter wheat (*Triticum aestivum* L.) using in-season spectral measurements collected between January and March. NDVI was computed in January and March and the estimated yield was computed using the sum of the two postdormancy NDVI measurements divided by the Cumulative Growing Degree Days from the first to the second reading. Significant relationships were observed between grain yield and estimated yield, with $R^2 = 0.50$ and $P > 0.0001$ across two years experiment and different (nine) locations. In some sites the estimation of potential grain yield, made in March and measured grain yield made in mid-July differed due to some factors that affected yield. The capability of VIs to estimate physiological parameters, as fAPAR, is studied on other crops, faba bean (*Vicia faba* L.) and semileafless pea (*Pisum sativum* L.) that grows under different water condition, as an experiment followed by Ridao *et al.* (1998) where crops see above grew both under irrigated and rainfed conditions. They have computed several indices (RVI, NDVI, SAVI2, TSAVI, RDVI, PVI) and linear, exponential and power relationship between VI and fAPAR were constructed to assess fAPAR from VIs measurements. During the pre-LAI*max* phase, in both species, all VIs correlated highly with fAPAR, however R^2 at this stage did not differ significantly between indices that consider soil line (SAVI2 and TSAVI) and those that did not consider it (NDVI, RVI, RDVI). In post-LAI*max* phase the same behaviour was observed. All VIs are affected by the hour of measurement at solar angles grater than 45°. Authors conclude that simple indices as RVI and NDVI, can be used to accurately assess canopy development in both crops, allowing good and fast estimation of fAPAR and LAI.

Nutrient Management

Appropriate management of nutrients is one of the main challenges of agriculture productions and at the same environmental impact. Remote sensing is able to provide valuable diagnostic methods that allow for the detection of nutrient deficiency and remedy it with the proper application. Several studies have been carried out with the objective of using remote sensing and vegetation indices to determine crop nutrient requirements (Schepers et al., 1992; Blackmer et al., 1993; Blackmer et al., 1994; Blackmer et al., 1996a; Blackmer et al., 1994b; Blackmer and Schepers 1996; Daughtry et al. (2000). Results from these studied concluded that remote sensing imagery can be a better and quicker method compared to traditional method for managing nitrogen efficiently. Bausch and Duke (1996) developed a N reflectance index (NRI) from green and NIR reflectance of an irrigated corn crop. The NRI was highly correlated to with an N sufficiency index calculated from SPAD chlorophyll meter data. Because the index is based on plant canopy as opposed to the individual leaf measurements obtained with SPAD readings, it has great potential for larger scale applications and direct input into a variable rate application of fertilizer. Ma et al. (1996) studied the possibility to evaluate if canopy reflectance and greenness can measure changes in Maize yield response to N fertility. They have derived NDVI at three growing stage: preanthesis, anthesis and postanthesis. NDVI is well correlated with leaf area and greenness. At preanthesis NDVI showed high correlation with field greenness. At anthesis correlation coefficient of NDVI with the interaction between leaf area and chlorophyll content was not significant with yield. Ma et al. (1996) summarized that reflectance measurements took prior to anthesis predict grain yield and may provide in-season indications of N deficiency.

Gitelson *et al.* (1996) pointed out that in some conditions, as variation in leaf chlorophyll concentration; GNDVI is more sensitive than NDVI. In particular is the green band, used in the computing GNDVI that is more sensitive than the red band used in NDVI. This change occurs when some biophysical parameters as LAI or leaf chlorophyll concentration reach moderate to high values. Fertility levels, water stress and temperature can affect the rate of senescence during maturation of crops. In particular Adamsen *et al.* (1999) used three different methods to measure greenness during senescence on spring wheat (*Triticum aestivum* L.): digital camera, SPAD, hand-held radiometer. They derived G/R (green to red) from digital camera, NDVI from an hand-held radiometer and SPAD readings was obtained from randomly selected flag leaves. All three methods showed the similar temporal behaviour. Relationship between G/R and NDVI showed significant coefficient of determination and their relationship were described by a third order polynomial equation ($R^2 = 0.96$; $P < 0.001$). Relation is linear until G/R > 1, when canopy approach to maturity (G/R < 1) NDVI is still sensitive to the continued decline in senescence than did G/R. This fact suggests that the use of the visible band is limited in such conditions. However authors found that G/R is more sensitive than SPAD measurements. Daughtry *et al.* (2000) have studied the wavelengths sensitive to leaf chlorophyll concentration in Maize (*Zea mays* L.). VIs as NIR/Red, NDVI, SAVI and OSAVI, have shown LAI as the main variable, accounting for > 98% of the variation. Chlorophyll, LAI, and their interaction accounted for > 93% of the variation in indices that compute the green band. Background effect accounted for less than 1% of the variation of each index, except for GNDVI, which was 2.5%. Serrano et al., (2000) studied the relationship between VIs and canopy variables (aboveground biomass, LAI canopy chlorophyll A content and the fraction of intercepted photosynthetic active radiation (fIPAR) for a wheat crop growing under different N supplies. The VIs-LAI relationships varied among N treatments. The authors also showed that VI were robust indicators of fIPAR independently of N treatments and phenology.

Li et al. (2001) studied spectral and agronomic responses to irrigation and N fertilization on cotton (*Gossypium hirsutum* L.) to determine simple and cross correlation among cotton reflectance, plant growth, N uptake, lint yield, site elevation, soil water and texture. NIR reflectance was positively correlated with plant growth, N uptake. Red and middle-infrared reflectance increased with site elevation. Li et al. (2001) found that soil in depression areas contains more sand on the surface than on upslope areas. This behaviour modified reflectance patterns. As a result, a dependence on sand content was shown by NDVI with higher values in the depression areas and lower values in areas where the soil had more clay. In addition cotton NIR reflectance, NDVI, soil water, N uptake and lint yield were significantly affected by irrigation ($P < 0.0012$). The N treatment had no effect on spectral parameters, and interaction between irrigation and N fertilizer was significant on NIR reflectance ($P < 0.0027$).

Wright (2003) investigated the spectral signatures of wheat under different N rates, and the response to a midseason application at heading. VIs were computed (RVI, NDVI, DVI, GNDVI) and spectral data were compared with pre-anthesis tissue samples and post-harvest grain quality. The author found that imagery and tissue samples were significantly correlated with pre-anthesis tissue samples and post-harvest grain quality. The second application of N at heading improved protein only marginally. GNDVI was significantly correlated with nitrogen content of plants. VIs used in the study, whether from satellite or aircraft correlated well with preseason N and plant tissue analysis, but had lower correlation with protein. Osborne et al. (2002a; 2002b) demonstrated that hyperspectral data in distinguishing difference in N and P at the leaf and canopy level, but the relationship were not constant over all plant growth stages. Adams et al. (2000) have detected Fe, Mn, Zn and Cu deficiency in soybean using hyperspectral reflectance techniques and proposing a Yellowness Index (Adam et al. 1999) that evaluated leaf chlorosis based on the shape of the reflectance spectrum between 570 nm and 670 nm.

Pest Management

Remote sensing has also shown great potential for detecting and identifying crop diseases (Hatfield and Pinter, 1993) and weeds. Visible and NIR bands can be useful for detecting healthy plants versus infected plants because diseased plant react with changes in LAI, or canopy structure. Malthus and Madeira, 1993, using hyperspectral information in visible and NIR bands, were able to detect changes in remotely sensed reflectance before disease symptoms were visible to the human eye. Weed management represent an important agronomic practice to growers. Weeds compete for water, nutrient, light and often reduce crop yield and quality. Decisions concerning their control must be made early in the crop growth cycle. Inappropriate herbicide application can also have the undesirable effect on the environment and a side effect to the crop. With the advent of precision agriculture, there has been a chance from uniform application to the adoption of herbicide-ready crop and to apply herbicide only when and where needed. This kind of approach is economically efficient and environmentally sound but site-specific herbicide management requires spatial information on the weeds. The discrimination between crops and weeds is usually accomplished based on the differences in the visible/NIR spectral signatures of crops and specific weeds (Gausman et al., 1981; Brown et al., 1994) or by acquiring images when weed coloring is particularly distinctive. Richardson et al., (1985) demonstrated that multispectral aerial video images could be used to distinguish uniform plot of Johnsongrass and pigweed from sorghum, cotton and cantaloupe plots. Several other authors have utilized spectral imagery to separate crops from weeds based on spectral signatures of species and bare soil (Hanks and Beck, 1998) or based on the leaf shape determine by the machine vision technology

(Franz et al., 1995; Tian et al., 1999). Basso et al., 2004 used the handheld radiometer CropScan to determine if a wheat field with various level of pappy (*Papever Rhoeas*) infestation could be detected by the multispectral radiometer. The study showed that the reflectance in the Red and NIR of the highly infested areas with pappy of the durum wheat field was significantly different from the no infestations of lower levels of weed presence. Remote sensing can also be used to determine herbicide injury to the crop for insurance purposes (Hickman et al., 1991; Donald, 1998a, Donald 1999b). To improve application efficiency of herbicides, Sudduth and Hummel (1993) developed a portable NIR spectrophotometer for use in estimating soil organic matter as part of the estimation procedure for the amount of herbicide to be sprayed. Several studies have also been carried out using remote sensing for identifying and managing insects, mite and nematode populations. Such studies have been able to demonstrate that remote sensing is able to detect actual changes in plant pigments caused by pest presence, damages by pest and to identify areas susceptible to infestation. Riedell and Blackmer (1999) infested wheat seedlings with aphids and after 3 weeks they measured the reflectance properties of individual leaves. The leaves of the infected plants had lower chlorophyll concentration and displayed significant changes in reflectance spectra at certain wavelengths (500 to 525, 625 to 635 and 680 to 695 nm). This study in combination with others (Cook et al., 1999; Elliot et al., 1999; Willers et al., 1999) suggests the potential usefulness of canopy spectra for identifying outbreaks in actual field situations and to guide field scouts to specific areas for directed sampling. Site specific pesticide application can reduce the impact of toxic chemicals on the environment by 40 percent (Dupont et al., 2000).

Remote sensing and Crop Yield Estimation

Remote sensing can provide valuable information of yield assessment and show spatial variation across the field. There are two approaches for yield estimation; the first is a direct method in which predictions are derived directly from remote sensing measurements (Figure 6). The second method is an indirect one, where remotely sensed data are incorporated into simulation model for crop growth and development either as within season calibration checks of model output (LAI, biomass) or in a feedback loop used to adjust model starting conditions (Maas, 1988). The direct method for prediction yield using remote sensing can be based on reflectance or thermal-based. Both methods have been applied with case of successes on various crops like corn, soybean, wheat, alfalfa (Tucker et al, 1979; Tucker et al., 1981; Idso et al., 1977; Pinter et al., 1981). Hatfield (1981) in his survey of 82 different varieties of wheat was not able to find a consistent relationship between spectral indices and yield. Hatfield (1983b) coupled frequent spectral reflectance and thermal observation in a more physiological method to predict yields in wheat and sorghum. This method requires TIR daily measurements during grain filling period to estimate crop stress. Shanahan et al., (2001) demonstrated that the time of corn pollination was not a good growth stage to estimate yield because of the various that can cause tassel emergence dates to vary. Yang et al., (2000) found similar results, concluding that images from images taken at grain filling can provide good relationships between VIs and yield.

Reliability of imagery for use in yield estimation decreases as the time before harvest increases because there are more opportunities for factors like various nature of stresses to influence yield. Aase and Siddoway (1981) had cautioned that the relationships of spectral indices to yield were dependent upon normal grain-filling conditions for the crop. Similar results were found by Basso et al., 2004 (personal communication, unpublished data) where the NDVI images on a rainfed durum wheat field showed different correlation to yield depending on the time of the image selected. In this specific case, spatial variability of soil texture and soil water uptake by plants affected by drought varied at anthesis presenting different scenarios from the one predicted by the NDVI estimation.

6. Link between crop models and remote sensing for Yield Forecasting

The integration of RS and CSM for crop yield forecasting has been researched for almost three decades, and is justified by the fact that RS can quantify crop status at any given time during the growing season, while CSM can describe crop growth every day throughout the season (Maas, 1988). RS indirectly can provide measure for canopy state variables used by the CSM as well as both spatial and temporal information about those variables which can then be used to adjust the model simulation. Since the first satellite information became available to scientists, they have developed algorithms to estimate canopy state variables, such as LAI, vegetation fraction and fraction of APAR. One of the main integration procedures between RS and CSM focuses on adjusting the LAI simulated with the crop models against the one estimated through RS. LAI it is an important agronomic parameter because leaves are where water and CO_2 are exchanged between the plant and the atmosphere; in addition, the LAI is used to model crop evapotranspiration, biomass accumulation and final yield (Strachan et al., 2005). Researchers working on such integrations generally adopted three basic steps: (i) estimate canopy variables with RS; (ii) run the CSM; (iii) use a proper integration method to adjust model runs. The first step can affect the subsequent results of the integration because, if the crop variable is not properly estimated, then adjusting the model with a biased variable will lead to a wrong model evaluation. There are two ways of using RS for the estimation of canopy variables: through the use of statistical/empirical relationships; and the Physical Reflectance Models that simulate the interactions between solar beams (which is a definition of the concentrated stream of particle, such as the light flux) and the various canopy components through the use of physical laws in which the LAI can be entered as input obtained from the crop model (Dorigo et al., 2007).

The first methods consist of building relationships between the crop variables and RS or VIs, such as the relationship between the Weighted Difference Vegetation Index (WDVI) and the LAI (Clevers, 1989). Such models are built through the use of simple or multiple regressions, stepwise multiple regressions, partial least square regressions (Hansen and Schjoerring, 2003; Yoder and Pettigrew-Crosby, 1995). They are simple to build, easy to evaluate and do not require a lot of computational effort. Successful application of this technique is reported in many studies, such as the development of indices for the global estimation of crop parameters that are sensitive to high biomass levels and less influenced by soil reflectance and atmospheric effects

(Jiang et al., 2008). The main limitation of the empirical/statistical methods is that, for every year of measurement in the same field or for different sites, the relationships have to be recalibrated because of changes in soil reflectance, canopy type and architecture. Notwithstanding, this approach has been successfully used for the validation of crop models in a precision agriculture context, because the simplicity of using NDVI maps and their empirical relationship with yield help to characterise spatial patterns of crop growth variability, and the crop model will only be validated in the areas defined by the RS map (Basso et al., 2001).

The second method involves the use of Physical Reflectance Models, which can simulate either leaf reflectance or that of the overall canopy (Verhoef, 1984; Jacquemonod and Baret, 1990); for practical purposes, physical models that simulate canopy reflectance are preferred because the measured reflectance is collected in the field on an area base. Canopy reflectance models are built on the radiative transfer theory that considers the canopy to be a turbid medium with leaves that are small and distributed randomly. Canopy reflectance models are usually inverted to find the best set of parameters that minimise the differences between the observed and simulated canopy reflectance, and the methods used to find the best solution to the inversion are the iterative technique, look-up tables and artificial neural networks (Moulin et al., 1998; Dorigo et al., 2007). One problem of the inversion technique is that the solution does not produce a unique value, because the variables affecting the overall canopy spectral signature have synergic effects and compensation for this will affect the outcome (Fourty and Baret, 1997). For example, in their review Baret and Guyot (1991) found that the modeled reflectance of sparse canopies with horizontal leaves was similar to that of dense canopies with vertical leaves.

Farmers tend to use one or a few remote-sensed images for crop management, to retrieve canopy variables with empirical or statistical methods, as this is more practical than the modeling approach because it is simple and does not require extensive time, calculation or interpretation. Moreover, canopy reflectance models require knowledge about the nature of the inputs and the techniques required for the inversion, whereas in the statistical approach only the variable of interest is taken into account. For example, taking remote observations before the application of N fertilization and using a functional relationship between VIs and canopy N stress are more practical for farmers and agronomists, who might not find the use of canopy reflectance models attractive because of their greater complexity. It must be acknowledged, however, that canopy reflectance models are an important tool for research purposes and for understanding the effects of both crop architecture and soil reflectance on the overall canopy spectral signature. Therefore the two methods might be considered complementary because, while scientists use physical modeling approaches to either design new indices or understand the patterns of crop spectral responses, agronomists can use the knowledge gained from models to derive empirical models for better crop management (Cammarano, 2010). The other important step in the integration of crop models and RS is the technique used to combine them. Maas (1988) analyzed four ways of integration between RS and CSM, which are divided as follows:

Method 1. Evaluate driving variables: this technique is rather simple and uses RS information to evaluate driving variables. Remote observations should be performed frequently during the growing season, or at least frequently enough to perform interpolation techniques to obtain the daily values of the RS estimated variable. Therefore, a limitation of this technique is that remote observations are needed for each time-step of the simulation, which is not feasible either practically or economically (Cammarano, 2010).

Method 2. Update model State Variables (SV): the daily values of the SV are simulated with the CSM and, when RS data are available, the new values are simply updated into the CSM. For example, many crop models use LAI to estimate biomass accumulation. The values of LAI and biomass are simulated by the model and, when LAI estimated with RS is available. For this technique, the accuracy of the variable updated is a function of the latest remote observation and, because RS data carry some degree of error, the SV updated might present bias in its value that cannot be minimized by more frequent remote observations; another limiting factor is that in the model all the SV should be updated after RS acquisition (Cammarano, 2010).

Method 3. Re-initialize model State Variables (SV): This technique modifies the initial condition of the SV in the crop model so that a new simulation will be in agreement with RS observations. Indeed, different values of SV initial conditions in the crop model could lead to different simulation scenarios. For example, when remote observations are available, the SV is estimated from RS and there would likely be discrepancies between observed and simulated SV. This effect is taken into account by considering the sum of the absolute errors between simulated and observed values. This will lead to the creation of an error function and, through an iterative numerical analysis technique (e.g. the secant method), it is possible to solve such a function and find a new value of the SV; the new value will replace the old value required to initialize the model. Re-initialization can be performed on one or more SV, leading to a uni– or multi-dimensional solution of the problem. For example, this method has been used to derive new values of LAI and used to calibrate the model (Maas, 1988). The re-initialisation procedure provides good results in the estimation of biomass and final yield compared to previous integration strategies, because RS is used to modify the SV in the model and at the same time reduce the random error present in RS data. However, one limitation of this technique is in the nature of the empirical relationship between RS and LAI; for example, NDVI values tend to reach saturation levels at LAI values greater than 3 (Aparico et al., 2000), making NDVI insensitive to changes in LAI after saturation in dense canopies. Also, such relationships may have only local meaning and must be recalibrated for each new site.

Method 4. Re-parameterise model parameters: this technique is similar to the previous one with the difference that the model parameters are modified after their estimation with RS observation. The main difference is that typically a model has more parameters than SV and the minimising procedure is more complicated, requiring more computational power. Indeed, while for re-initialisation the error function is often two-dimensional, for the re-parameterisation it will depend on the number of parameters involved. Therefore, the solution of the error function is multi-dimensional and all the parameters should receive the same relative amount of change (Cammarano, 2010). Since Maas (1988) published his ideas, many other conceptual models for the integration of RS and CSM have been proposed, such as the reviewed classification for an integration, which also identifies an “assimilation” technique (Moulin et al., 1998) in which RS is directly used to re-parameterize or re-initialize the model. In this case, the daily crop reflectance can be simulated with Physical Reflectance Models, and then the differences in simulated and observed reflectance will be minimized by adjusting the initial conditions or the model parameters of the CSM. An LAI simulated with CSM is first used as input in the canopy reflectance model and then, once the errors between RS observed and simulated are minimized, the new value of LAI can be adjusted in the CSM. But with this method, the number of parameters that can be adjusted is a function of the frequency and the timing of RS observations. Launay and Guerif (2005) used this assimilation procedure to spatially link the RS and CSM. They found that in drought conditions CSM does not properly estimate LAI and its use in the canopy reflectance model will not improve the robustness of such a method.

One of the key points for a successful integration of RS and CSM for in-season and between-season crop management is that the whole system, defined as RS observation, crop simulation and soil–crop–weather, is properly understood. One of the most challenging problems in the use of both CSM and RS is trying to interpret, understand and evaluate the results in order to develop the optimum agronomic management strategy that minimizes the observed variability in crop production. Factors affecting crop growth, development and yield are well understood and evidence of yield variability is normally provided but not explained (Cammarano, 2010). For instance, final yield is a function of the complex temporal interaction of several variables such as genotype, crop population, management, weather and stress (Bachelor et al., 2002). A CSM, to some extent, takes into account the above effects, plus the temporal effects of stresses on crop growth and development. However, the use of both model results and measured data to understand the causes of particular spatial and temporal crop variability, and how it can be managed from agronomic, economic and environmental point of view, is challenging. RS, through the observation of the spatial patterns of VIs, allows the collection of information about crop variability (Blackmer and White, 1998). Therefore, an integration strategy of RS and CSM can be useful for in-season crop management and offers explanation of the causes of field variability and how this can be managed. As a result, CSM should be used with the aim of understanding crop temporal variability and RS images should be used to map the actual distribution of crop spatial variability at a given time during the growing season. An example of a spatial integration approach is described in Basso et al. (2001), in which a CROPGRO soybean model (Boote et al., 1998) was used to validate three management areas across the field, individuated with an NDVI map with a supervised classification technique. Soil properties and average crop population were measured in each zone with targeted sampling and subsequently used as inputs in the CROPGRO model. The model run was made only for those three zones without calibration for the season, and the model simulated yield for these three zones with an RMSE of 101 kg ha-1 with an average measured yield of 3000 kg ha-1. This technique has a twofold advantage: it reduces the costs of using CSM for precision agriculture applications; and model inputs and model parameterization are scale-independent because the scale is controlled by the observed variation in the field, which is the scale where the model is applied (Bachelor et al., 2002). The other approach to link RS and CSM is through the concept that the biomass produced by a crop is function of the the amount of photosynthetically active solar radiation (PAR) absorbed, along with the air temperature and soil conditions. The amount of absorbed solar radiation if function of the incoming radiation and capability of crop's interception of such light. The latter is mainly function of the LAI. Such relationship LAI and PAR-intercepted has been object of several reviews and studies (Asrar et al., 1984; Gallo et al., 1985; Tucker and Sellers, 1986; Sellers, 1987; Baret and Guyot, 1991; Field et al., 1995; Frouin and Pinker, 1995; Serrano et al., 2000; Goetz et al., 2005; Vina and Gitelson, 2005; Garbulsky et al., 2011; Wang et al., 2013). The first steps that helped researchers to link RS and PAR was the equation developed by Monteith in 1977 to quantify the PAR absorbed by the crop (fAPAR) (Monteith, 1977). fAPAR depends mostly on LAI of the canopy and Monteith (1977) proposed an exponential relation between LAI and fAPAR. fAPAR is quantified from RS because has been found a good predictive ability by NDVI (Baret and Guyot, 1991). The close link between NDVI and fAPAR has been confirmed in theoretical studies and later confirmed in experimental studies (Sellers, 1985; Sellers et al., 1997). The relationship between fAPAR and NDVI is justified because the PAR intercepted and NDVI depend on LAI, leaf pigment concentrations, leaf angle orientation, and soil reflectance features (Baret et al., 1989; Huete, 1985).

7. Early Warning Systems

7.1. Early Warning Systems history and definition

Humans have coped with natural disasters for centuries. However, the increase in human population, the heavy anthropic modifications to the ecosystems and the effects of changing climate make humans more susceptible to any disaster. Developing countries will suffer most from any kind of disaster, like drought, floods, fires, bacterial and pests' outbreaks and so on (Deverux, 2009). Nowadays, scientific advance in many fields makes possible to use technologies that can help to monitor several natural phenomena in a real-time both in time and space. Therefore, an Early Warning System (EWS) is defined as an integrated system for monitoring, data collection, analysis, and communicating to people in order to make early decisions to protect peoples and the environment (Davies et al. 1991). The importance of a EWS is because any degradation of the agricultural environment will cause famine, hunger, disease, and death to millions of people. The FAO estimates that 1.02 billion people are hungry and undernourished (FAO, 2013). For example, the UNEP (2002) estimated that in India more than U.S.$10 billion is lost annually from anthropogenic land degradation, which in turns cause a loss in productivity estimated around U.S.$2.4 billion (UNEP, 2002). Even in developed countries agro-ecosystem degradation causes economic losses; for instance, in the USA soil erosion causes losses for about $4 billion per year (Hrubovcak et al., 1995). To tackle this problem, governments, United Nations (UN), Non-profit Organization (NGO), and academic institutions have collaborated to implement systems to help reducing or preventing further environmental degradation. There could be many reasons why the EWS is built, and that depends on the objective of the system monitored. A EWS for agriculture will have a different structure than a EWS that monitor human disease spread. Examples of integrated EWS are:

- US Agency for International Development's (USAID) Famine Early Warning System (FEWS; USGS-EROS, 2010).
- South African Development Cooperation's (SADC) Food Security Programme (UNCCD and Italian Cooperation, 1999).
- Food and Agricultural Organization's (FAO) Global Information & Early Warning System (GIEWS) on Food and Agriculture (ISDR, 2009)
- United Nation Environmental Programme's (UNEP) Division of Early Warning and Assessment (DEWA) (ISDR, 2010)
- World Food Programme's (WFP) Vulnerability Analysis and Mapping (VAM) (UNCCD and Italian Cooperation, 1999)
- Monitoring Agricultural Resources (MARS, 1988) of the European Union.

There are several commonalities among these systems, which are: (a) the way the work across disciplines in collecting data and analyzing them; (b) the way the results are spread to the scientific community, the general public, the stakeholders, and policy-makers; and (c) the way the warning systems are implemented and how fast they can respond to a warning.

One of the first examples of EWS that were developed for use in forecasts was developed with the aim of predicting the impact of El Nino on famine in Sub-Saharan Africa (Glantz, 1994). But, the main cause of developing EWS was the response to food crisis in West Africa and the Horn of Africa during the 70s and the 80s. For example, the GIEWS was developed in response of the food crisis of the 70s. Nowadays it includes UN, donors, 117 national governments, 60 NGOs, and many research institutions (Rashid, 1997). The GIEWS that monitor crop status is supported by the FAO Environment and Natural Resources Service with the help of the FAO's Africa Real Time Environmental Monitoring Information System (ARETMIS), and the support of the experts in agrometorology, crops, and social science. In USA the severe drought in 1984-1985 that caused more than a million deaths between Ethiopia and Sudan, made the Congress to create the FEWS.

7.2. ***Early Warning Systems applications***

Early Warning Introduction and ENSO

Examples of EWS application in agriculture need to take into account the constant crop monitoring in a simple, timely and accurate manner. Provide forecasts and impact assessments at national and regional levels of spatial and temporal variability of crop production and to a large risk of famines. Most of the EWS use remotely sensed data for crop monitoring and early screening for signs of drought, for flood, and for climate change impacts. Each EWS uses a different satellite like the AVHRR, SPOT, and MODIS. Multi-years VIs images during the growing season can help to identify years in which the crop had better or worse conditions from an historical trend. Also, the seasonal patterns of NDVI in East Africa have been associated with El Nino/Southern Oscillation (ENSO) index. Such index is derived from the atmospheric pressure patterns in the Pacific sea, the temperature anomalies of the sea surface, and the anomalies in the outgoing long-wave radiation. If the ENSO information can be translated into practical advices and spread in a timely manner, farmers can adjust their management factors (such as planting, fertilization, irrigation) in order to gain positive impacts on food security and crop production. For example, in Mexico the economic gains of a EWS based on the ENSO has been estimated of about US$ 10 million annually (Adams et al., 2003). The El Nino events are known to cause issues to farmers in South East Asia as well. For example, an El Nino event in Indonesia means delayed rainfall and less planted rice areas reducing the amount of rice produced for that growing season, thus increasing the risk of annual rice deficits (Naylor et al., 2007). Predictions of what could happen in the next 50 years suggested that farmers need to adopt new management strategies to cope with reduced rainfall during the important crop stages. The 1997-98 El Nino events, which was considered one of the strongest of the previous 50 years, was related to vegetation patterns monitored by NDVI in Africa by Kogan (1998). Naylor et al. (2007) concluded that increased investments in water storage, drought-tolerant crops, crop diversification, and EWS can be adaptation strategies Indonesians' farmers could adopt to offset the negative effects of El Nino events in the future. Another part of the world where the Southern Oscillation is known to affect crop yield is Australia. Rimmington and Nicholls (1993) discussed how the wheat yields in Australia are correlated with values of the Southern Oscillation Index, which affects growing season rainfall. Information of the Southern Oscillation Index is generally available around the sowing date, and therefore can provide interesting yield forecasts.

Early Warning Drought and Yield

Drought events in Africa are important to forecast and prevent, because the lack of resources means that a drought event will cause severe reduction of production and famine (Haile, 2005). For example, 17 million people in East Africa are in drought-prone zones, and the recent recurrence of drought makes these people at risk of food insecurity (Funk and Verdin, 2010). Funk et al. (2003), using the FEWS system found that the agricultural areas of Ethiopia had a net decline in growing season rainfall over the years, and that Ethiopia is facing an increase of food shortages. This was caused by the anomaly warming in the Indian Ocean causing dryness in Eastern Africa. Funk et al. (2008) linked this warming, to some extent, to anthropogenic activities. Funk and Verdin (2010) argue that a combination of simple water and food balances, still a useful tool for quantifying the evolution of the risk, coupled with spatial and temporal analysis can be useful in providing information about early warnings. For example, the spatial information of water per capita was used to derive information regarding the spatial patterns of water availability per household (Funk et al., 2005). Then this information was used to derive 3 main zones of water security; the authors found a correlation between areas of low rainfall and water security, but the urbanization of those areas compete for water used in agriculture. Two points are interesting from Funk et al. (2005), firstly, that the vulnerable zones are increasing and secondly, that there are some areas of water surplus. Ceccato et al. (2007) used remote sensing for monitoring variations in rainfall and crop growth to help policy-makers in Sub-Saharan countries to quantify the risk of desert locusts and malaria outbreaks. The monitoring of crop yield, especially in rainfed areas like in many African countries, needs also to take into account the temporal and spatial variability of rainfall. The AVHRR-NDVI product has also been used to build a GIS system for detections of parasites in East Africa that can affect livestock and humans alike (Malone, 1998). In Burkina Faso the cereal production is function of the amount and timing of the growing season rainfall. The use of crop simulation model, Geographical Information Systems (GIS), and RS has been used to build an early warning system for production anomalies (Thornton et al., 1997). One limitation of the use of crop models in such locations is that the weather station networks are very sparse and can present many gaps in data (Washington et al., 2004), and that is why most researchers focus their attention on the use of RS, like the Satellite Rainfall Estimation (RFE) to fill in gaps of missing rainfall. The droughts events are also associated to the seat temperature anomalies and linked to anomalies in RS VIs. Using 8 years of satellite data, Myemi et al. (1996) found correlations between the sea temperature of the Pacific and NDVI anomalies that are considered anomalies in rainfall patterns in the arid and semi-arid Africa, Australia and South America. Such results were also found in another study of Ayamba and Eastman (1996). They used AVHRR NDVI for 4 years to study the trends of vegetation greenness in Africa and the climate trends. They found a signal affecting Southern Africa, where there is a significant relationship with the ENSO. In addition, in East Africa and the Sahel, Ayamba and Eastman (1996) found that there is no correlation with ENSO in these areas and concluded that the NDVI-ENSO is specific to certain regions of Africa. Another system for drought monitoring is the seasonal rainfall forecasts, which is becoming widely available in Africa as highlighted by Goddard et al. (2001). The FAO developed the Water Requirement Satisfaction Index (WRSI; Frere and Popov, 1986) which estimated the effects of rainfall on crop production in rainfed areas. The index uses decadal information of rainfall observations and soil water holding capacity. The water demand is calculated using the potential evapotranspiration approach of the FAO (Allen et al., 1998), while the supply is calculated from rainfall and soil water. Spatial versions of the WRSI have been developed for Monazbique and for other African countries using RS-NDVI and point WRSI to derive spatial maps for EWS (Rojas and Amade, 1998). In Algeria, the use of growing season rainfall has been used to empirically plan for drought planning; but, El Mourid and Watts (1989) pointed out that in such area the approach is not fully working because there is no correlation between autumn and spring rainfall, which is the period for crops being more sensitive to drought. Monnik (2000) discuss of a EWS in South Africa where an increase of droughts extremes has been experienced in the last 2 decades. In South Africa farmers have the responsibility to plan for and survive droughts with minimum intervention from the government, and therefore the EWS is vital to survival. For example in South Africa, a EWS based on decile rainfall, the water satisfaction index, satellite NDVI, and crop/pasture models is currently used.

The relationship of rainfall vs. seasonal NDVI has been also confirmed in other environments, like the dry areas of the Negev Desert in Israel where this approach was used to quantify vegetation cover (Schmidt and Karnieli, 2000). In fact, vegetation cover can be considered another factor that might be implemented in EWS as a proxy for a desertification monitoring system. Symeonakis and Drake (2004) estimated the vegetation cover and RUE using the NDVI in Sub-Saharan Africa. In addition, they used the Meteosat data to derive rainfall, they also calculated soil run-off and soil topography, in order to determine soil erosion. In this way they can monitor in a real time the spatial and temporal trend of land degradation Symeonakis and Drake (2004).

Early Warning and Climate Change

The IPCC reported that the temperature in Africa will increase 0.2 and 0.5°C per decade (IPCC, 2001). While future changes in rainfall amount is highly spatial variable. However, contrasting results on the amount of temperature and rainfall changes are published (IPCC, 2001; Held et al., 2005; Kamga et al., 2005; Huntingford et al., 2005). However, one thing it seems certain is that the extreme events (e.g. drought, flood, heat spells) will be more frequent and this will seriously impact crop production (Coppola and Giorgi 2005). For assessing future crop production and implementing long term EWS is important to understand which tool can be used to assess the impact of climate change on crop yield. Challinor et al. (2007) discussed several approaches used, such as crop simulation models, empirical models, and yield transfer functions. One of the most used empirical approaches like the FAO method (Doorenbos and Kassam 1979) is relatively robust because based on conservative relationship between biomass and water use (Hsiao and Bradford, 1983; and Hsiao,1993). However, such approach is well suited for large scale applications because of its level of complexity. CSM can also be used at such large scale as they have been modified to run at regional/national levels (Challinor et al., 2004; Bondeau et al., 2017). Fischer et al. (2002) found that in 2080s projections of the GDP in Africa is lower under climate change than in the relevant reference scenarios. A EWS therefore will help to understand what are the measures that can adopted in response to such changes. For example, the adoption of new cultivars, new management strategies (e.g. planting dates), new infrastructures (e.g. better irrigation infrastructure) are some strategies to adopt in the next 10 years to offset negative effects of climate (Reilly and Schimmelpfennig 1999). But, while planting dates can be easily taken into account in crop models and therefore in impact assessment, new cultivars, or infrastructure are harder to consider because of difficulties in parameterizing them causing an increase in uncertainties (Southworth et al. 2002; Rosegrant and Cline 2003; Parry et al. 2004;

Challinor et al., 2007). Another interesting measure is expanding agriculture in new areas. In East Europe, the re-use of abandoned farmland can help to offset some of the food decline due to climate change (Alcantara et al., 2012). However, in Africa and South East Asia it is difficult to create new cropland. The suitability of land for crop production is function of climate and soil, as modeled by Ramankutty et al. (2002). In addition, in Africa the increase of food production are not only related to agronomic practices but also to a series of socio-economic problems, such as the growth of national economies, infrastructure improvements, and growth of income. Unfortunately, yields in Africa are still amongst the lowest in the world; for instance, in sub-Saharan regions the average rainfed cereal yields are 0.8 t ha^{-1}, which 50% below the lowest yield for other regions of the world (Cooper 2004; FAOSTAT, 2013). Some of the remedies famers are currently used to cope with changes in weather can become insufficient in the future when extreme events will be more common. However, the EWS has to take into account the social aspects of a particular area. An example on what a EWS should consider in case of climate extremes is during the last Zimbabwe drought (Bird and Shepherd, 2003). The drought significantly affected the availability and access to seed. Although there are systems such as the Direct Seed Distribution (DSD), or Seeds and Tools (S&T), which have been created in to extreme situations, several findings in Eastern and Southern Africa indicates that rarely the local seed stocks are completely depleted, and alternative strategies may be more appropriate (Sperling et al. 2004). In general, the problem is the access to the seed which is constrained by many other factors. This example highlights the importance of a EWS that is cross-discipline, from climate and crop scientists, agronomists, economists, and social scientists. So, building an EWS for seed systems to climate change requires science (research into drought tolerant crops) and policy, such as, government to optimize the seed system, law reforms for cross-border movement of seed (Tripp 2001). In the subsequent years farmers face another important challenge, to manage water supplies (irrigation or rainfall) more efficiently (Cooper 2004). Ellis-Jones and Tenberg (2000) showed how collaborative research between scientists and farmers helped developing efficient rainwater harvesting techniques, such as the improving of fallow water storage through the use of agroforestry species (Kwesiga et al. 2005). But, even with such techniques, some zones in Africa will no longer be suitable of certain crops. For example, Dietz et al. (2004) showed that maize in the drier areas and groundnuts in the dryer zones of the Sahel are at risk. Researchers acknowledge that African farmers have been successfully adapting to changes in climate in the past (Boserup, 1965; Hill 1963). Reij and Waters-Bayer (2001) discussed on how farmers have been adapting to changes in climate and what kind of technology and management they have introduced to offset yield decline. This has been also found true in many African regions (Haggleblade et al. 1989; Tiffen et al. 1994). However, the adaptation capabilities are of little use for coping with extreme without a proper EWS in place.

8. Conclusion

The main conclusion of this review can be summarized as follows:

1. Statistical models are simple in their usage and less parameter-intensive, but they are limited in the information they can provide outside the range of values for which the model is parameterized. They do not take into consideration the soil-plant-atmosphere continuum, the timing of the stresses occurring during the growing season, and do not give farmers any important agronomic advices (e.g. timing and amount of fertilizer, time of sowing, irrigation, and so on).

2. Crop simulation models vary greatly between them. Some of them are rather hard to use and parameterize. The need for calibration can be quite data extensive and not applicable to some developing countries. New models like SALUS have been developed to overcome these limitation

3. RS techniques have been extensively used in research for yield forecast but might not be suitable in developing countries because of their stratified agricultural systems and very small farm sizes. However, this problem is hard to overcome in the near-future because of the inability of RS to estimate yield in mixed agriculture. But, the increased availability of high-spatial resolution RS at a reasonable cost make this technique a possible interesting alternative for yield forecast. In fact, RS is often use in Early Warning Systems in developing countries.

4. The integration of RS, yield gap and CSM represents an interesting alternative in crop yield forecasting. RS can quantify crop status at any given time during the growing season in a spatial context, while CSM can describe crop growth every day throughout the season (Maas, 1988). RS indirectly can provide measure for canopy state variables used by the CSM as well as both spatial and temporal information about those variables which can then be used to adjust the model simulation. While the yield gap can provide strong agronomic foundations of the yield potentials and the causes leading to the gap.

9. References

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