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# **Combining crop models and remote sensing for yield prediction: Concepts, applications and challenges for heterogeneous, smallholder environments**

Report of CCFAS-JRC Workshop  
at Joint Research Centre, Ispra,  
Italy, June 13-14, 2012

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# **Combining Crop Models and Remote Sensing for Yield Prediction: Concepts, Applications and Challenges for Heterogeneous Smallholder Environments**

Report of Joint CCFAS-JRC Workshop

Venue: Joint Research Centre (JRC), Ispra, Italy

Date: June 13-14, 2012

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## Contents

1	Executive summary .....	5
1.1	Context.....	5
1.2	Workshop rationale and objectives .....	5
1.3	Workshop salient findings.....	6
2	Summary of presentations and discussions.....	9
2.1	Data assimilation techniques .....	9
2.2	Crops researched .....	10
2.3	Use of Crop Models.....	11
2.4	Use of Remote Sensing parameters as proxies for biomass production .....	13
2.5	Use of satellite sensors .....	15
2.6	Research locations .....	16
2.7	Spatial scales .....	17
2.8	Heterogeneity .....	17
2.9	Crop masks.....	18
2.10	Crop management factors .....	18
2.11	Uncertainty of predictions .....	19
2.12	Linkage with other sources of information.....	19
3	Presentation Abstracts.....	21
3.1	The challenges of an operational crop yield forecasting system in Sub-Saharan Africa .....	21
3.2	Crop Forecasting within the CCAFS Program.....	23
3.3	Integration of agro-hydrological modelling, remote sensing and geographical information ....	24
3.4	Assimilating remote sensing data into crop models improves predictive performance for spatial application.....	25
3.5	Regional Crop Simulation Modelling for Yield Prediction Using Remote Sensing and GIS: Indian Experiences .....	26
3.6	Integration of MODIS products and a crop simulation model for crop yield estimation .....	27
3.7	Exploring the Response of the Central US Agro-Ecosystem to Climate Change.....	28
3.8	Crop Yield Forecasting Over Various Scales Combining Models and Remote Sensing.....	29
3.9	On the Assimilation of Remote Sensing Data with Crop Models for Crop Yield Forecasting .....	30

3.10	Simultaneous Estimation of Model State Variables and Observation and Forecast Biases using a Two-Stage Hybrid Kalman Filter .....	31
3.11	Satellite image simulations for data assimilation at multiple scales .....	32
3.12	MARS operational crop monitoring and yield forecasting activities in Europe.....	33
3.13	Experiences with data assimilation for regional crop yield forecasting .....	34
3.14	Crop Monitoring and Early Warning Service in Africa .....	35
3.15	Data Assimilation based on the Integration of Satellite Data and Field Sensor Data for Drought Monitoring .....	36
3.16	Data assimilation for the carbon cycle in Sudan savannah smallholder communities.....	37
3.17	Soil-water-crop modelling for decision support in Sub-Saharan west Africa: experiences from Niger and Benin.....	38
3.18	Wheat yield modelling in a stochastic framework within and post season yield estimation in Tunisia	39
4	References .....	41
5	Acronyms and Abbreviations .....	43
6	Workshop Program .....	45
7	Participants .....	47
8	Sponsors.....	48

# 1 Executive summary

## 1.1 Context

There are many factors contributing to the strain on the world's food supply, ranging from insufficient investment in the agricultural sector, a lack of access to markets, climate change and climate variability, water shortages and drought, to simple increased demand for food and changes in diet.

It is a major challenge for the world to feed its growing population. It can easily be seen that agriculture is a key to this challenge. Given the world's environmental problems, simply growing more food is not enough. Agriculture will have to be developed with sustainability built-in from the start.

One of the important subjects in agriculture is crop yield forecasting. Its advent began in the 1970s. Crop yield forecasting is key for government structures at all levels, including NGO's and international organization such as the United Nations as well as companies that are dependent on agricultural produce as an input. Research in crop yield forecasting has seen advancements in response to widespread famine in the Sahel, Ethiopia and other countries in the seventies and eighties. The operational knowledge gained helped predict and partly avoid food shortages in the years after.

The target environments for crop yield forecasting have always been two-fold. In countries with highly mechanised large-scale agriculture, such as the USA, Europe and Russia, crop yield forecasting provides data to governmental structures, companies and farmers. Good yield and price predictions provide a clear strategic advantage. Governments and supra-national bodies (such as the EU) use these data for rationalisation of policy adjustments.

The other crop forecasting arena is formed by developing countries, where low staple food production can have disastrous effects. Predicting food shortages in developing countries early has been the mandate of the crop forecasting units of UN organisations such as FAO and WFP, as well as FEWSNET, JRC and a number of others.

The technical methodology supporting the two operational sectors is largely comparable, although an important difference lies in the type of agriculture studied, distinguishing homogenous large-scale production environments from heterogeneous, smallholder environments.

## 1.2 Workshop rationale and objectives

Predictions of crop yields within the growing season are critical inputs for a range of agricultural and food security decisions. For example, management of agricultural input and credit supplies, agricultural trade, food security safety net and relief programs, agricultural insurance, and recommendations about crop varieties and production technologies depend on or benefit from the best possible estimates of

crop production. They differ primarily in the timing of key actions and hence the required lead-time. Agricultural and food security management can generally benefit from improvements in accuracy (at a given lead-time) and lead-time (at a given threshold of accuracy).

Both simple water balance and process-based crop models are often used to estimate yields within the growing season. In some cases, they are coupled with seasonal climate forecasts to reduce the uncertainty associated with climate. The uncertainties associated with crop models, input data and modelling assumptions – collectively referred to as model error – also contribute to the uncertainty of crop yield forecasts. One way to correct crop model errors is by data assimilation. Data assimilation involves using observed data to update simulated model state variables or to estimate model parameters. Evidence in the literature suggests that data assimilation can improve model performance. Remote sensing (RS) by satellites offers several options for reducing crop forecasting errors, particularly in data-sparse regions. Biophysical variables retrieved from remote sensing data, such as Leaf Area Index (LAI), soil moisture and ET, obtained at adequate spatial and temporal resolutions, can potentially be coupled with crop models to provide valuable information for crop yield forecasting at various scales. However, heterogeneous, smallholder farming environments present significant challenges for the use of remote sensing data assimilation for crop yield forecasting, as field size within these highly fragmented landscapes is often smaller than the pixel size of remote sensing products that are freely available.

JRC and CCAFS jointly sponsored the workshop on June 13-14, 2012, at the JRC in Ispra, Italy, to identify avenues for exploiting remote sensing information to improving crop forecasting in smallholder farming environments. The workshop's objectives were:

- To advance the state-of-knowledge of data assimilation for crop yield forecasting;
- To address challenges and needs for successful applications of data assimilation in forecasting crop yields in heterogeneous, smallholder environments; and
- To enhance collaboration and exchange of knowledge among data assimilation and crop forecasting groups.

The workshop succeeded in bringing together scientists from around the world. This has enabled discussions on research and results and has greatly enhanced collaboration and exchange of knowledge, especially about data assimilation and crop forecasting.

### **1.3 Workshop salient findings**

This workshop was organized to exchange knowledge on crop models and remote sensing for yield prediction, especially for heterogeneous, smallholder environments. Organisations such as JRC and various UN organisations are interested in progress in crop modelling, as it helps to improve their operational yield forecasting. From an operational viewpoint Francois Kayitakire of the EU Joint Research Centre sets the most pressing challenges as follows:



- Advanced remote sensing and modelling techniques have not yet reached operational real-time crop forecasting.
- So far, the spatial resolution of models and feasible remote sensing is hardly adequate for most of cropping systems in Africa.
- About the timing of crop yield forecasting: for operational circumstances it would be best to have good crop forecasts about two months before harvest, although it might be more realistic to have it one month before.
- In smallholder environments, it is still unknown which crops are grown and when.

The workshop shows that there have been clear advances in crop yield forecasting. Important innovations were made in the use of remote sensing-crop model integration through data assimilation. In essence data assimilation is the technique whereby remote sensing data are used as inputs in crop models, to adjust or reset state variables in crop models. Several techniques exist to do this of which the Ensemble Kalman Filter is applied most.

The most noticeable advances have been made in homogenous environments. Good examples of these cropping environments were presented for the mid-western states of the USA and Russia. For these environments, scientists showed that the solution lies in the use of high-resolution remote sensing data integrated with advanced crop models. Some of this research has reached practical applicability. As an example, grain yields can be forecasted using high resolution remote sensing fed into a crop model and subsequently checked against combine harvester data.

This is not (yet) feasible in an African setting. For these environments, low-cost moderate resolution imagery is more feasible, combined with increased knowledge on extracting signatures for targeted crops and cropping systems. In the workshop in-depth research has been presented on smallholder environments in Africa and Asia based on the study of carbon, water and energy cycles. It was showed that the heterogeneous, smallholder cropping environment is slowly being understood in satisfactory detail. Incorporation of other data (e.g. socio-economic data) proved to be needed to understand the crop production to its full extent.

For smallholder environments, some participants advocated the use of high-resolution techniques, coupled with an in-depth knowledge of the area of study. Promising field experiments are being set up in Mali, Niger, India and other countries to study the heterogeneous, smallholder environments. Others felt that (for country of continental scale predictions) low-resolution techniques (remote sensing, models and data) are the way to go forward.

CCAFS theme 2 main goals are to build resilient rural livelihoods, ensure food delivery, trade, and crisis response and enhanced climate information and services. Assisting scientists in the field of crop forecasting is one of the ways to achieve these goals. During the workshop Jim Hansen (Theme 2 leader) of CCAFS led the discussion on how to address the challenges for applying RS data assimilation for crop forecasting in heterogeneous, smallholder environments. With respect to data, high resolution remote sensing was offered (to the m scale) but seems to be unfeasible for operational use in Africa because of scale and cost. Moderate resolution remote sensing combined with downscaling techniques e.g., un-

mixing vegetation signature seems to be interesting, like what is being pursued by IRI/JPL. Fusion of moderate (shorter return period) and high resolution (longer return period) remote sensing was also discussed with some reluctance from the group. In terms of data integration, the state-parameter simultaneous update within the Ensemble Kalman Filter was discouraged especially when using LAI for data assimilation. A framework was proposed in which crop model parameters first are estimated by inverse modelling, and then the calibrated model can be linked with the Ensemble Kalman Filter for the assimilation of LAI for forecasting yield. Proof of concept study was discussed using data from India and Mali.

## 2 Summary of presentations and discussions

During the workshop, crop production has been highlighted from many sides, using a variety of models, satellite parameters and field data. Subjects range from field to continent level, from small scale to large-scale crop production, from tropical to temperate regions, from maize to millet. With the large variety of presented subjects, it is difficult to honour each and every subject in this summary report.

However, trends in crop yield forecasting for heterogeneous, smallholder environments can certainly be observed. Some of the trends and observations discussed in the following pages:

- Data assimilation techniques
- Crops researched
- Use of Crop Models
- Use of Remote Sensing parameters as proxies for biomass production
- Use of satellite sensors
- Research locations
- Spatial scales (from field to continent)
- Heterogeneity
- Crop masks
- Crop management factors
- Uncertainty of predictions
- Linkage with other sources of information

Although the presenters covered a wide range of subjects, the analysis of the presentations has led to some conclusions that are summarized in the following sections.

### 2.1 Data assimilation techniques

During the workshop it has been shown that data assimilation can be applied successfully in crop modelling studies. In general two types of assimilation techniques were demonstrated in the presentations:

1. A recalibration strategy where some uncertain model parameters (for example the emergence date) are optimized by minimizing the difference between the model and the observations available.
2. A sequential updating strategy where model states or parameters are updated during the model run. A prerequisite for this technique is that the model allows adjusting the states or parameters during the model run. Essentially in data assimilation, model parameters in a time-step are re-set or corrected by observations from the real world.

For crop modelling a logical source of these observations is remote sensing. Remotely sensed data are typically sensor data gained from platforms such as satellites, aircraft and surface-bound sensors.

In data assimilation, one could simply replace the model results by observations. In practice this is not a good idea, because:

- Both the external data and the model results contain errors;
- Often a proxy of the state variables is assimilated;
- Almost always one needs to update many (unobserved) state variables using only one or a couple of observations; and
- Continuity of the observations is not guaranteed (cloud cover, satellite failure).

Therefore methods like the Ensembles Kalman filter have to be applied (Pauwels) or re-calibration of model parameters are better options for data assimilation.

Presenters argued that data assimilation in crop growth related models has its challenges:

- The studied processes and models have biases that are not taken care of in some of the algorithms that support data assimilation. Working with biases is often possible by applying corrections for bias to the original algorithms (Pauwels).
- A parallel process to biomass production, or crop growth, is crop development (phenology of the plant). When trying to assimilate a remote-sensing estimation of biomass in a crop growth model, one may be faced by what some authors call a “*phenological shift*” (see Curnel et al. 2011). Basically, a given amount of green biomass may be attained at different stages of the crop season, e.g. in the increasing or the decreasing part of the curve, and forcing this biomass value in a model without knowing the phenology can result in dramatically wrong results.
- It is still unclear which combination of satellite data and crop modelling (input data; calibration; assimilation) is most effective. It needs to be studied which crop data are most suitable for data assimilation at available temporal and spatial scales of satellite images (van Dam)
- Interaction/dependency between parameters may lead to errors in their estimation (Guerif)

## 2.2 Crops researched

The table below shows that most of the research in this workshop is done on Maize and Wheat. Both crops are among the most cultivated in the world (grown in tropical as well as areas with temperate climates), which could explain part of the popularity. Furthermore, these crops are often grown in large fields on large farms with advanced crop management practices like precision farming (Bach), leading to a nicely homogenous crop.

Of the pure tropical crops, rice, sorghum and millet are mentioned most (Table 1). Especially millet and sorghum are grown in the heterogeneous, smallholder environments that are subject of this workshop.

Millet and sorghum are often grown as landraces. Even within a cropped field a large variety of heights, phenology and production exists. For farmers this might have an advantage, as they seem to aim for minimizing risks rather than maximizing production (Akponikpe). It does, however, make research for these crops challenging.

**Table 1. Names of crops mentioned in the presentations**

<b>Crop</b>	<b>No. of Presentations</b>	<b>Total Occurrences</b>
Maize	11	56
Wheat	10	46
Rice	5	61
Soybean	5	34
Sorghum	5	17
Sugar beet	3	22
Millet	3	13
Cereals	2	3
Pulses	1	1
Tubers	1	1

A distinction has been made between C4 crops like maize and C3 crops like wheat and rice. As the C4 crops have a slightly different photosynthetic cycle, their reaction on radiation, CO<sub>2</sub> content and other environmental parameters proved to be different (Drewry).

## 2.3 Use of Crop Models

It is interesting to see which crop models are used most often in research presented. Both statistical and dynamic/mechanistic crop modelling has been used in the workshop.

The models SWAP/WOFOST and DSSAT were most popular among scientists presenting in this workshop (Table 2).

The SWAP/WOFOST model (Soil, Water, Atmosphere and Plant) simulates vertical transport of water, solutes and heat in unsaturated/saturated soils. The program is designed to simulate the transport processes at field scale level and during entire growing seasons. SWAP is open-source and can be downloaded here: <http://www.swap.alterra.nl/>. SWAP incorporates WOFOST, which is also used stand-alone. A standalone version of WOFOST and derived models can be downloaded from <http://www.wageningenur.nl/wofost> other Wageningen models can be downloaded from <http://models.pps.wur.nl>.

The Decision Support System for Agrotechnology Transfer (DSSAT) is a software application program that comprises crop simulation models for over 28 crops. The crop simulation models in DSSAT simulate

growth, development and yield as a function of the soil-plant-atmosphere dynamics. Although DSSAT is not open source, its source code and executables can be requested for free from <http://www.dssat.net/>

Some models are developed by the presenting scientists themselves and not distributed to other groups. These models are often used in precision agriculture for direct advice to farmers (APSIM, <http://www.apsim.info>).

**Table2. Use of models in workshop presentations**

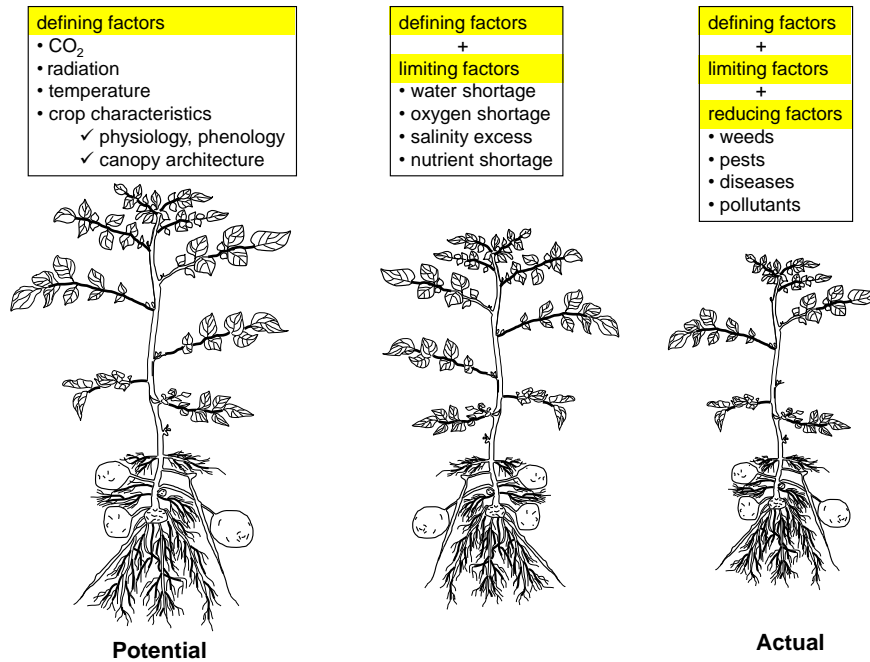
<b>Models</b>	<b>No. of Presentations</b>	<b>Total Occurrences</b>
SWAP	3	18
DSSAT	3	14
CSM	3	14
WOFOST	3	8
PROMET	1	27
MM5	1	11
WTGROWS	1	9
STICS	1	6
MODFLOW	1	3
SUCROS	1	3
ORYZA1	1	2
LINGRA	1	1
WARM	1	1
PROSAIL	1	1
AGROMETSHELL	1	1
APSIM	1	1
MLCan	1	1

The models described in the workshop describe crop biomass production roughly through the study of 3 processes: water cycle (water balance models), energy cycle (radiative transfer models) and carbon cycle. Many models take two or more of these processes into account.

Plant growth models are relatively good in simulating the potential growth, as affected by climate and crop characteristics (Figure 1).

Also the growth inhibiting effects of water shortage, oxygen shortage, salinity excess and nutrient shortage can be simulated quite well with current crop growth models. However, the growth reduction due to weeds, pests, diseases and pollutants is still difficult to simulate. Satellites measure the actual growth conditions, which includes the total effect of all growth reducing factors. This may cause a mismatch between crop growth simulations and measured crop growth by satellites.

Scientists increasingly use “model inversion” whereby the model is fed with output parameters to get a better understanding of the driving input variables/properties (Honda, Guerif and Sehgal).



**Figure 1. Plant growth simulation is affected by defining climate and crop characteristics (potential growth), limiting factors and reducing factors. All factors together result in actual growth.**

## 2.4 Use of Remote Sensing parameters as proxies for biomass production

Proxies for yield and biomass production have been developed over the years from remote sensing derived spectral measurements. The products involve different spectral bands, various retrieval algorithms and corrections. The most popular products (in terms of occurrence in the presentations of this workshop) are mentioned in Table 3.

**Table 3. Occurrence of parameters and proxies in the presentations**

Parameters/Proxy	No. of presentations	Total Occurrences
LAI & GAI (Leaf Area Index & Green Area Index)	11	177
NDVI (Normalized Difference Vegetation Index)	9	83
Evapotranspiration	8	26
Precipitation derived from RS	5	8
fAPAR (fraction of Absorbed Photosynthetically Active Radiation)	4	31
IR (infrared)	2	3
EVI (Enhanced vegetation Index)	1	8
Global Radiation	1	3

The parameters above can be extracted from a variety of satellite platforms. In practice, MODIS, SPOT, NOAA-AVHRR and MSG are often used. The parameters have been used at low, medium and high resolutions at various scales.

The most frequently used parameter is LAI (Leaf Area Index). This parameter has been developed 50 years ago for field experiments. It's defined as half the total developed area of green leaves per unit of ground horizontal area (Chen & Black, 1992). The satellite-based LAI products are generally not the same variables as the LAI in crop growth models or the LAI measured in a field. A main reason for this discrepancy is that available satellite LAI are produced from reflectance obtained from coarse spatial resolution pixels, in which various different types of vegetation covers are present. For the same reason, several scientists have proven that the satellite based LAI can differ considerably from field measured LAI (Honda). Sometimes LAI is referred to as GAI (for Green Area Index). For several crops in which various part of the plant photosynthesis (e.g. cereals), it is actually more appropriate to use this term to refer to the biophysical variable retrieved from remote sensing since the radiance measured by the instrument is made of electromagnetic radiation reflected from all plant organs (Duveiller et al., 2011a).

A biophysical variable that is generally as widely available as LAI is the fraction of Absorbed Photosynthetically Active Radiation (fAPAR). This variable is actually more closely related to yield than LAI. For diverse reasons (one being that fAPAR is generally not a state variable in the current generation of simulation models) it seems to be much less popular for data assimilation in crop models, even though it probably avoids some of the problems/uncertainties encountered with LAI. This point was raised in the workshop and proposed as a justified research direction.

The NDVI (Normalized Difference Vegetation Index) has been used widely. This parameter has been around for quite some time and long historical records exist. Many derivatives/refinements of NDVI are now in use such as DVI (Difference Vegetation Index) and EVI (Enhanced Vegetation Index; used by Hoogenboom).

An estimate of actual evapotranspiration can be based on satellite signals only. Crop models often calculate actual evapotranspiration as output. While the first method is based on evapotranspiration of the entire vegetation by pixel, the second approach makes it possible to be crop-specific. Examples of both approaches were shown.

An issue that returned various times in the discussions was which model variables should be updated at satellite overpass. For instance, if LAI is measured, not only the LAI but also many other model variables that are related to leaf area index (such as plant biomass, green area index, development stage) should be updated. The plant model update should be consistent. Various groups use different methods.

Satellite derived precipitation estimates are used in crop forecasting, but it has been proven that this parameter is related poorly to yields when applied as cumulative over the crop period (Irénikatché). As input to crop models at a daily or dekadal time-step it has however proven its usefulness.



## 2.5 Use of satellite sensors

For data assimilation, satellite based parameters are widely used in combination with crop models. See below a table of the satellites mentioned by the presenters in the workshop where satellite names and sensor names are mixed. Of the satellites/sensors listed below, data from Landsat, NOAA AVHRR, EO, Terra (Aster and MODIS), Aqua (MODIS) and Envisat (MERIS and ASAR) are available free of charge (van Dam).

**Table 4. The use of satellites and sensors**

Platform	Sensor	No. of Presentations	Total Occurrences
Terra and Aqua	MODIS	9	30
SPOT	VEGETATION	5	10
SPOT	HRG/HRV/HRVIR	2	4
NOAA	AVHRR	5	6
LANDSAT	TM/ETM	4	7
MSG (METEOSAT)		2	6
Sentinel (still to be launched)	OLCI	2	2
RapidEye		1	2
Envisat/MERIS	MERIS	1	2
Quickbird		1	2
TRMM		1	2

The MODIS sensors are mentioned most frequently. MODIS (Moderate Resolution Imaging Spectroradiometer) is an instrument aboard the Terra (EOS AM) and Aqua (EOS PM) satellites. Terra MODIS and Aqua MODIS are viewing the entire Earth's surface every 1 to 2 days, acquiring data in 36 spectral bands. MODIS is widely used because its products are free, easily available for download, and some more elaborated products such as LAI and FAPAR are distributed along the usual spectral reflectances and indices.

Although with the higher level products such as LAI a wide range of corrections have been applied, some researchers report that these products have to be used with care and do not always align with the situation on the ground (Honda; van Dam). This is in part due to lack of adequacy between the observation support (i.e. where satellite data was collected) and the field size which is visited on the ground.

A tentative movement away from optical sensors to radar sensors has been noted. Radar penetrates clouds and is therefore less susceptible to atmospheric disturbances (Bakary). However, the passive radar sensors generally have a low resolution, and in general radar signals are still a challenge to use.

Many low-resolution satellite data are available at high frequency, while high resolution data are available at low frequency. Various algorithms exist to combine low and high-resolution data to derive the optimal amount of information (Ines; Honda).

Besides satellite sensors, some scientists use earth-bound sensors on poles as well as small, unmanned airplanes (Drewry, Honda).

## 2.6 Research locations

Most of the research presented has been conducted in Africa, with the country of Niger at the top of the list (Table 5). Niger occurs 33 times in 4 presentations (Akponikpe, Traoré, Bakary, Hansen). Other African countries the presenters mentioned were Senegal, Mali, Sudan and Burkina. Little research from English speaking African countries has been presented with the exception of Kenya and Ghana.

**Table 5. Names of countries, regions and states in all presentations**

Country	No. of Presentations	Total Occurrences
Niger	4	33
Senegal	3	15
Mali	3	10
Europe	3	8
Sudan	3	7
USA	3	7
Belgium	3	6
Netherlands	3	6
Burkina	3	5
Ethiopia	3	4
Nepal	2	4
Ghana	2	4
Kenya	2	2
France	1	9
Thailand	1	4
Egypt	1	3
Japan	1	3
Tunisia	1	3
Armenia	1	2
Iberian	1	1
Tanzania	1	1
Uganda	1	1

Quite some research findings were presented on European countries, mainly The Netherlands, Belgium, Germany, the Iberian Peninsula and Russia. The mid-western states of the United States were frequently used as research locations. These states have an advantage over other study areas due to their relatively homogenous crop covers during the cropping season. This enables the scientists to find “almost pure pixels” in remote sensing imagery.

## 2.7 Spatial scales

The spatial scale of the research matters for the methods and data that can be applied successfully. Studies were presented at a wide range of spatial scales, ranging from field to continent. A somewhat arbitrary list of scales mentioned:

- Field level (van Dam and Bach, Drewry, Akponikpe)
- Village level (Traoré, Akponikpe)
- District level (Seghal, Bakary, Guerif)
- Country level (Marinho, Meroni)
- Sub-continent and continent level (Duveiller and Terink)

Some debate was noticeable among the scientist on the question whether methods at the finer level (e.g. field) can successfully be scaled up to any level above. While some argued that it is just a matter of computing power, others insisted that different models and datasets have to be applied at different spatial scales.

In general, it became apparent that research at the field level helps to understand complex cropping systems and leads to better inputs and management techniques on farm level while research on district and higher scales helps policy makers in governments, NGO’s and international organisations. Ideally a methodology should be developed which addresses both field and regional scale, as for instance shown by Bach.

## 2.8 Heterogeneity

One of the most challenging aspects of the use of remote sensing proved to be the heterogeneity of the crop/vegetation in one pixel. This is most apparent in low-resolution imagery (e.g. > 1 km pixel size). “Pure pixels” for low-resolution imagery can be found in the USA and Russia, but are almost non-existent in Africa and Europe minus Russia. Some recent research has shown, however, that pure enough pixels can be obtained in highly fragmented landscapes in Europe in order to have a crop specific signal (de Wit) if medium spatial resolution imagery such as MODIS (250m) is employed and the spatial response of the instrument is carefully taken into account (Duveiller et al. 2011b). This approach

allows an alternative solution to un-mixing coarse pixels, but on the other hand still requires some a priori information of where the crops are located beforehand.

High-resolution imagery proved to be helpful to detect in-field variability on large-scale farms (Bach). This kind of high spatial resolution imagery is typically available only for a limited geographic extend, and with a temporal revisit capacity which is lower than desired for agricultural monitoring. Although, future satellite constellations (such as the European Spatial Agency's Sentinel-2) aim at making high spatial resolution imagery operationally available worldwide, there remains the challenge of managing this exorbitant amount of data and extract from it a clear and reliable information than can be used for assessing crop status.

In heterogeneous, smallholder environments, even high resolution imagery had to be complemented by extensive field research to successfully describe the heterogeneity of fields and crops (Traoré).

## 2.9 Crop masks

Several researchers noted the lack of good crop masks (Marinho, Kayitakire). Unfortunately, land cover maps just specify agricultural practices (arable land, rangeland etc.), and rarely go down to the crop level. For many areas, such crop masks should ideally be done on a yearly basis to reflect the changes that occur due to crop rotation or expansion/regression of crop extends. Crop rotation is the main limitation in Europe that forces the operational MARS crop yield forecasting system of the European Commission from using crop specific time series (Duveiller).

Another challenge is that crop masks cannot be considered constant as different crops are grown in different years. Even percentage-wise pixel estimates (for example 20% wheat, 30% maize etc.) are only available for some well-researched areas.

Researchers generally put quite some work into crop masks, before the actual research topic was investigated (Traoré, Hoogenboom).

## 2.10 Crop management factors

Crop yields are to a high degree determined by the management practices applied to it (Sehgal). For crop yield forecasting the most important ones are sowing dates, irrigation and nutrient application. Crop model outcome is to a high degree dependent on sowing date (Traoré).

Participants showed several methods to estimate sowing dates:

- Simulated sowing date, based on external parameters (Akponikpe);

- Estimated sowing dates extracted from remote sensing time series (Guerif);
- Establishing sowing dates through field work (Sehgal) or local sensors in fields (Honda).

Obviously the scale of the study (from field to continent) determines the possibilities. At higher scales (country, continent), fieldwork is not a workable solution to determine management factors applied.

## 2.11 Uncertainty of predictions

Uncertainty in crop yield predictions remains a problem. This is particularly the case early in the season. Generally the uncertainty declines towards the end of the season. Uncertainty during the season can be lowered through seasonal climate forecasts (Hansen).

Model uncertainty can partly be addressed by data assimilation techniques, while climate uncertainty can be addressed by seasonal forecasts (Ines).

## 2.12 Linkage with other sources of information

It has been advocated during the workshop that scientists look at linkages with information sources outside the traditional soil-water-plant system. Social economic databases and other sources that explain small-scale farmers livelihoods from a different angle are to be integrated with crop models for a better understanding of crop production systems. Potentially this could go further than establishing simple correlations. Models integrating for example socio economic information with crop production systems are yet to be developed (Guerif).

The recent AgMIP project combines climate, crops and economics (Traoré). Within AgMIP a large number of crop and agronomy modelling groups cooperate to compare modelling results for existing crop datasets and for future conditions, including climate change.



### 3 Presentation Abstracts

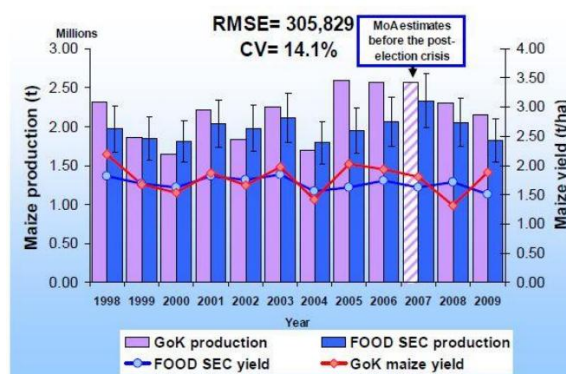
#### 3.1 The challenges of an operational crop yield forecasting system in Sub-Saharan Africa

*Francois Kayitakire, JRC, MARS Unit, FOODSEC Action, Ispra, Italy*

The Food Security Assessment (FOODSEC) Action of the EC-JRC supports the implementation of EU Food Security and Food Assistance policies by providing scientific advice and objective assessment of food security situation. It has been developing pieces of an early warning system to monitor crop and pasture production, with a focus on most food insecure areas, mainly in Sub-Saharan Africa. The system was by large conceived as an extension of the “Monitoring Agriculture with Remote Sensing” (MARS) project to regions outside the European Union. Thus, it relies mainly on remote sensing solutions and to some extent on crop modelling. Low-spatial satellite imagery is extensively used to derive the crop conditions in agricultural areas and pasture availability in pastoral areas. This approach proved effective for qualitative assessment of proxies of food production. In a few cases, tentative to link remote sensing derived indicators to crop yield or production has been done. Those indicators are usually analysed together with those derived from meteorological data, and they make the basis of the MARS crop and food security monitoring reports (<http://mars.jrc.ec.europa.eu/mars/Bulletins-Publications>).

Crop modelling has up-to now played a minor role in the system for several reasons. The main constraint has been the model calibration and the availability of historical yield (and production) statistics. The area of interest of the FOODSEC Action is actually very large, with many different ecological conditions and agricultural systems that are poorly understood and mapped. Moreover, yield statistics that are a key component in any crop forecasting solution are rarely available at the appropriate spatial resolution and temporal coverage. Therefore, JRC opted for a simple crop model (AgrometShell) that was developed by FAO. For instance, it has been used to forecast maize production in Kenya by regressing yield to two variables derived from the AgrometShell model: actual evapotranspiration (ETA) and water requirement satisfaction index (WRSI) (see graph, Rojas 2007).

Building from this experience, JRC, in collaboration with Alterra (Netherlands) implemented the core of the AgrometShell while customizing some modules and introducing a number of improvements in the input data (soil data, crop masks, etc.) to build an application that will help to easily provide analysts with the WRSI at the global level. That is the Global Water Satisfaction Index (GWSI) application (available online through the MARS Viewer: <http://www.marsop.info/marsop3/>).



Results of the FOOD SEC forecasting model for Long rain's maize production (1998-2009). Observed productions are the official statistics from the Government of Kenya (GoK). Note: 2007 figure was done before the post-election crisis; 2008 and 2009 figures still provisional. Note that the yield is the main factor for the maize production estimate in Kenya. This is due to the fact that maize area has a much smaller inter-annual variability (CV = 7.4%) compared to 27% of yield.

However, there's a need of an effective quantitative crop yield forecasting solution. Crop forecasting only makes sense when the conclusions can be published in time. In an ideal case, the forecast of crop production is released 2 months before harvest. It is more realistic to expect estimates 1 month before harvest, but also an analysis that comes in at harvest time is still practical. The forecasting method should also be able to correctly capture the inter-annual variability of yield because such variability is the most critical for food security of vulnerable households.

A crop forecasting system based on crop modelling and remote sensing faces a number of challenges:

- the availability of yield data at sub-national levels;
- the calibration and validation of models;
- the availability of long time series in input data;
- the coarse spatial resolution of input data, such as remote sensing. This spatial resolution is hardly adequate for most of cropping systems in Africa (mixture of crop fields and other land cover types);
- the necessity to know where crops are grown (crop masks).

To address these challenges will require long-term research and developments. But there's perhaps a room for searching for simpler solutions with a reasonable accuracy. This workshop provided some directions to such solutions.



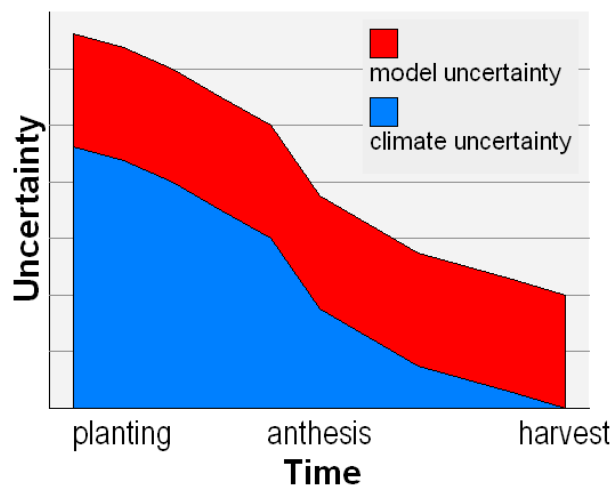
## 3.2 Crop Forecasting within the CCAFS Program

*James Hansen, Theme 2 Leader of the Climate Change, Agriculture and Food Security research program of the CGIAR.*

The CGIAR research program on Climate Change, Agriculture and Food Security (CCAFS) is a major research initiative that aims to: identify and develop pro-poor adaptation and mitigation practices, technologies and policies for agriculture and food systems; and support the inclusion of agricultural issues in climate change policies, and of climate issues in agricultural policies, at all levels. CCAFS work is organized in 4 research themes:

- Theme 1: Adaptation to Progressive Climate Change
- Theme 2: Adaptation through Managing Climate Risk (led by James Hansen)
- Theme 3: Pro-poor Climate Change Mitigation
- Theme 4: Integration for Decision Making

Theme 2 seeks to enhance the resilience of rural livelihoods and food systems to climate-related risk. Improving climate-related information for risk management, across multiple scales, is an important part of the Theme's contribution toward climate-resilience. CCAFS research currently focuses on East and West Africa and South Asia.



A number of agricultural and food security decisions depend on the best possible estimates of the impacts of climate fluctuations on crops. While the decision calendar influences the timing of information needed, most climate-sensitive decisions can benefit from increasing accuracy (at a given lead time) or lead time (at a given accuracy threshold). The uncertainty of a crop forecast consists of climate uncertainty and model uncertainty (encompassing all non-climatic uncertainties). Total uncertainty diminishes, and the contribution of model uncertainty increases, as the season progresses (see graph). Climate uncertainty

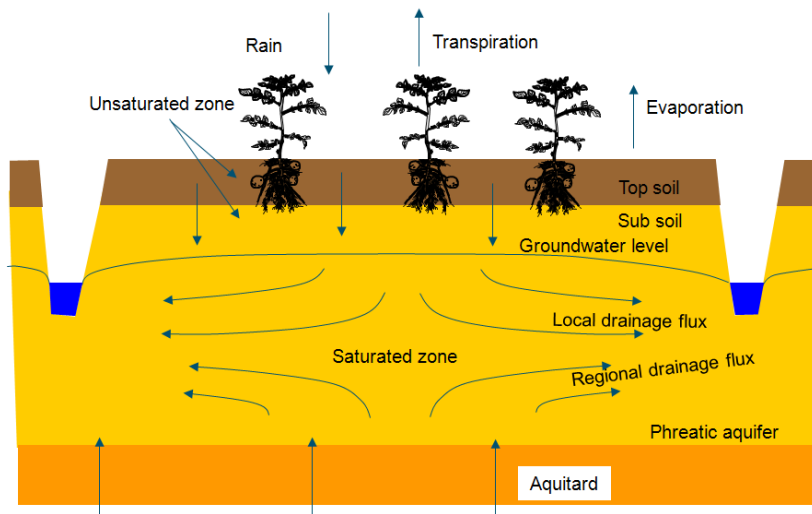
in weather can be reduced by seasonal forecasts. Typically the greatest positive impact on uncertainty occurs early in the season (Hansen et al., 2006). Options for reducing model uncertainty include improving models, improving input data and parameters, and data assimilation techniques. These techniques show the greatest benefit later in the season.

CCAFS contributions to crop forecasting methodology and capacity include: reconstructing historic meteorological inputs, integrating seasonal climate forecasts into crop forecasts, remote sensing data assimilation, and software platform development. However, understanding and fostering the use of that information for decision-making is a particular emphasis.

### 3.3 Integration of agro-hydrological modelling, remote sensing and geographical information

*Jos van Dam, Department of Environmental Science, Wageningen University, The Netherlands*

For many years Wageningen University has been in the forefront of crop modelling leading to well-known crop models as WOFOST, SUCROS and LINTUL. Many of these models can be downloaded from <http://models.pps.wur.nl>. These models have been developed from a thorough understanding of crop production, down to the role of leaf stomata. The agrohydrological model SWAP (Soil Water Atmosphere Plant) combines the crop growth model WOFOST with a detailed soil transport model. The graph below visualizes the processes modelled by SWAP.



Wageningen University has conducted several research projects in India (Sirsa) and Iran (Esfahan) with local partners with the aim to gain knowledge of local cropping systems, study the water cycle and look for ways to aggregate results from field to region. The projects started with data collection (both field data and remote sensing data). The data have been input to the crop model SWAP and WOFOST. A

comparison is made between the crop models run with and without input of remote sensing data through data assimilation.

In the uncorrected SWAP model, the simulated LAI was larger than satellite measured LAI. The main reasons are the difference in scale between model and satellite as well as the fixed harvesting data in the model. The model also showed larger fluctuations than the satellite data, which was also contributed to a spatial and temporal scale effect.

As a second track, remote sensing parameters have been used to reset state variables in the model. The assimilation of satellite-based LAI measurements was most effective. This significantly reduced the bias percentages for predictions one month in advance of harvest. However, bias percentages for predictions two months ahead of harvest were not influenced positively by assimilation with LAI (Vazifedoust et al., 2009). In the near future, Wageningen University intends to apply these methodologies at common sites in Mali and India.

### 3.4 Assimilating remote sensing data into crop models improves predictive performance for spatial application

*Martine Guerif, UMR EMMAH INRA UAPV, Avignon, France*

Crop models are powerful tools for dealing with agro-environmental issues such as the impact of agriculture on soil and water, the impact of agriculture on climate change, the evaluation of cropping systems. Models can help with strategic and tactic decisions for sustainable cropping systems. Models can be applied at different scales: field/farm, region, country and continent.

BIOPHYSICAL VARIABLES		Solar	TIR	μ-wave
Canopy structure	Leaf area index	+++	+	++
	fAPAR	+++		
	Cover fraction	+++	+	+
Leaf characteristics	chlorophyll content	+++		
	water content			++
	temperature		+++	
Soil characteristics	moisture	+		++
	roughness	+		++
	organic matter	++		
	residues	++		

For the use in data assimilation the following parameters can be obtained from three sensor types (solar, TIR and μ-wave). The number of plusses on the figure indicates the applicability level.

INRA uses the crop model STICS, which has a daily time-step. Its main aim is to simulate the effects of the physical medium and crop management schedule variations on crop production and environment at the field scale.

With STICS, three types of data assimilation techniques have been applied:

- **Forcing** of observed variables into the model when the model doesn't simulate this variable (or when the model accepts to replace the simulated value by a prescribed one);
- **Sequential correction** of model predictions. Observations and predictions at the preceding times are considered in the model to produce the prediction for the next time step;
- **Model inversion.** Observations are used in order to estimate parameters and/or initial conditions considered as difficult to estimate and sensitive.

These algorithms have been applied in a number of experiments in France and India on sugar beet and wheat. The conclusions are that remote sensing data assimilation into crop models can improve significantly the predictions of crop models (Varella et al., 2010).

Further research work is needed to determine the most favourable observation configurations to estimate parameters as well as finding the right combinations of different types of RS observations. INRA has great expectations for data availability in the future with a better temporal and spatial resolution (e.g. Sentinel constellation).

### 3.5 Regional Crop Simulation Modelling for Yield Prediction Using Remote Sensing and GIS: Indian Experiences

*Vinay Sehgal, Indian Agricultural Research Institute, New Delhi, India*

IARI is a 106 years old national institute in agricultural research & teaching in India, instrumental in the “Green revolution” as well as the first national institute to introduce Remote Sensing in courses. Remote Sensing (RS) can be of use for crop simulation models at regional scale. It may provide inputs parameters and/or initial conditions as well as improve the accuracy of the model results. This positive effect of data assimilation techniques is due to correction of errors in the structure of the model and the correction of the growth affecting factors like pests, diseases, salinity etc. This can be done by making models self-correcting as well as inserting RS measurements directly into the model as state variables.

Data assimilation algorithms used at IARI:

- Direct use of the driving RS variable in model;
- Forcing: updating of a state variable derived from RS (e.g. LAI);
- Re-initialization: adjustment of an initial condition to obtain a simulation in agreement with RS derived observations;
- Re-calibration: adjustment of the model parameters to obtain a simulation in line with RS;
- Corrective method: error between simulated and RS derived variable to correct yield values.

In the study area of Thanjavur MODIS LAI images are used in the ORYZA1 model (a model for irrigated rice production) to get an estimate of the phenological stage of different rice classes.

In another study the WTGROWS model is applied with the forcing and re-initialization techniques to estimate wheat grain yields at farmer field level. Grain yield estimations improved considerably using this approach.

In India, conventionally, crop forecasting is done by Crop Cutting Experiments (CCE) following a sampling plan that varies from state to state, and the results are then aggregated at higher administrative units. Recent research initiatives have improved crop forecasting in India, namely:

- FASAL (Forecasting Agricultural Output Using Space, Agrometeorology and Land-based Observations). FASAL forecasts different crops using different remote sensing data combined with field data.
- NADAMS (National Agricultural Drought Assessment & Monitoring System). NADAMS uses seasonal NDVI profiles integrated with ground information to estimate crop conditions.

Main findings (Sehgal et al., 2011):

- Crop models need to describe at least three interdependent systems: canopy, root and soil system.
- Crop management practices are the main determinant of variability in crop yields at small scale.
- Remote sensing derived crop phenology (sowing), LAI and soil moisture assimilations at multiple time in crop season are a possible way forward.

### 3.6 Integration of MODIS products and a crop simulation model for crop yield estimation

**Gerrit Hoogenboom**, Washington State University, Prosser, WA, USA, in collaboration with Hongliang Fang, Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences, Beijing, China, and Shunlin Liang, University of Maryland, College Park Maryland, USA.

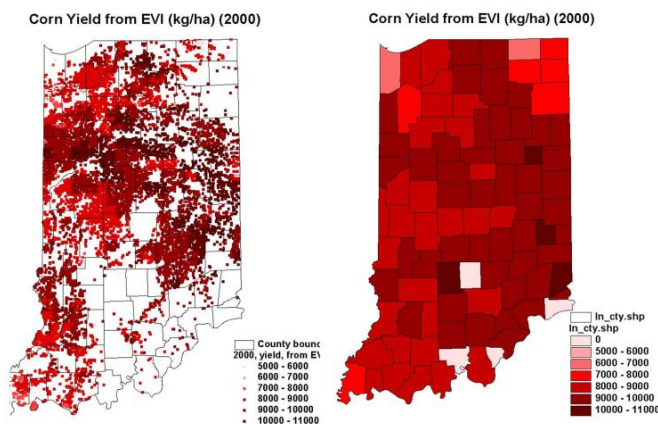
Washington State University, in cooperation with various international partners has developed various methodologies for crop yield estimation with remotely sensed data. The data assimilation techniques used were:

- Direct input: the model uses remotely sensed data as inputs
- Sequential assimilation: replace state variables in the model with remotely sensed data
- Variational assimilation: minimize the difference between variables estimated by remote sensing and crop model simulations

Crop models used were:

- DSSAT (Decision Support System for Agro-technology Transfer)
- CSM-CERES-Maize and CSM-CERES-Wheat for maize/corn and wheat
- CSM-CROPGRO-Soybean for soybean

In the scenarios 5 different remotely sensed datasets were tested for data assimilation into the models above: LAI , EVI (enhanced vegetation index), NDVI, EVI & LAI and NDVI & LAI, all derived from MODIS imagery. In the various models these data were used to adjust planting date, planting population, row spacing and fertilization date and amount. These methods were applied on a regional scale for the state of Indiana in the United States (Fang et al., 2011). These studies showed that regional crop yields can successfully be estimated with the data assimilation approach, whereby the combination of LAI and NDVI performed best against measured USD NASS corn yield data. Furthermore, a method was developed to aggregate the individual maize yields to county level. See maps below.



The conclusions are that MODIS products are useful for crop yield estimation at the regional scale. Field hydrological conditions can also be simulated successfully with this approach. The methodology could be improved if new remote sensing products (e.g., crop percentage at 250 meter grid size) would become available.

### 3.7 Exploring the Response of the Central US Agro-Ecosystem to Climate Change

*Darren Drewry, NASA Jet Propulsion Laboratory / Caltech Climate Physics Group, Pasadena, CA, USA*

Rapid changes in the earth atmosphere have been detected in the last hundred years. This applies to carbon dioxide, methane, nitrous oxide and sulphur. At the same time scale, global warming has been detected with an average increase of about 1 degree Celsius. A relation between the two phenomena is plausible.

An assumption is often made that higher CO<sub>2</sub> levels lead to higher plant production, as one of the growth factors is available at a higher rates. However, some scientists doubt this, as plants appear to close the stomata under influence of elevated CO<sub>2</sub> levels. A Free Air Carbon Enrichment (FACE) experiment has been conducted to find evidence of this effect (see photo).



Field experiments have been done with maize (C4) and soybean (C3) whereby CO<sub>2</sub> levels in the crop were elevated with a ring tube providing extra CO<sub>2</sub> directly in the field. For these experiments, a multi-layer canopy-root-soil system model (MLCan) capable of accurately predicting canopy-atmosphere exchange of CO<sub>2</sub> has been set up. PAR, NIR, LW, U, Ta and Ea were measured from a tower construction in the field.

The CO<sub>2</sub> application causes higher temperatures inside the maize canopy. Furthermore, in soybean, a 10% higher LAI was observed related to an increase in photosynthetic substrate. In soybean, the stomata were recorded to have a more closed state. In maize these effects were not found, although some ecophysiological acclimation was recorded. Regarding the canopy responses to elevated CO<sub>2</sub> the following conclusions were drawn (Drewry et al., 2010):

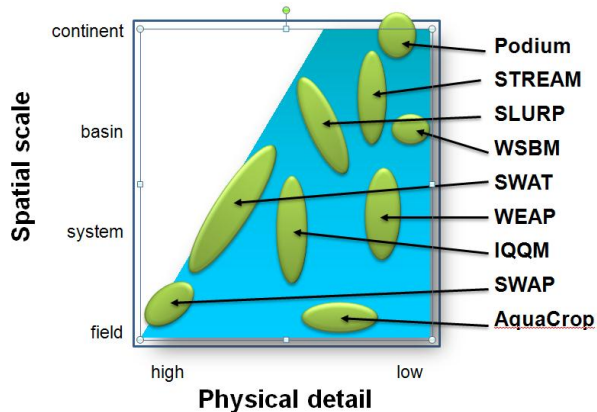
- Modelled gas exchange and leaf state responses to elevated CO<sub>2</sub> are in good agreement with SoyFACE observations for both C3 and C4 crops (soybean and maize);
- Net canopy CO<sub>2</sub>, latent energy and sensible heat were increased by 24%, decreased by 5% and increased by 37% at mid-day for soybean. Structural acclimation & increase in substrate availability offset much of the effect that would have otherwise occurred;
- Net canopy CO<sub>2</sub>, latent energy and sensible heat were increased by 1.5%, decreased by 16% and increased by 47% at mid-day for corn;
- Structural acclimation results in greater shortwave energy absorption in light-saturated upper-canopy;
- In both crops there is a negligible impact of carbon enrichment on carbon uptake.



### 3.8 Crop Yield Forecasting Over Various Scales Combining Models and Remote Sensing

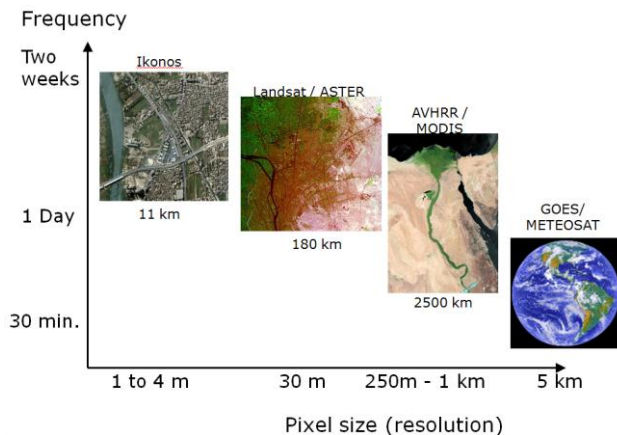
*Wilco Terink, FutureWater, Wageningen, Netherlands*

Crop growth models can be applied at various scales ranging from field to basin and country to even continent.



Some models are more suitable to be applied at field scale, while other models are more suitable to be applied at the basin or continental scale. FutureWater uses (agro)hydrological simulation models that are in the opensource domain. For each project, FutureWater determines which model is most suitable, given the spatial and temporal scales at hand (see graphic).

An important aspect is formed by the trade-off between the physical model detail (model complexity) and the availability of the required data.



As expected, field scale models have generally more physical detail than continental models, where input data are usually scarce and more assumptions have to be made. Similarly, in remote sensing, stratification is possible, based on temporal frequency and spatial resolution (see graphic).

FutureWater conducts projects at various scales as mentioned above. In Egypt it evaluated the (agro)hydrological performance of an farm-level (field scale) irrigation improvement project.. In India the company calibrated at the basin scale a hydrological model with remotely sensed evapotranspiration (Immerzeel and Droogers, 2008). For the 22 countries in the Middle East and North Africa (MENA region), FutureWater performed a water supply and demand analysis for the period 2010-2050.

In every project choices have to be made again. The selection of models and data is determined by:

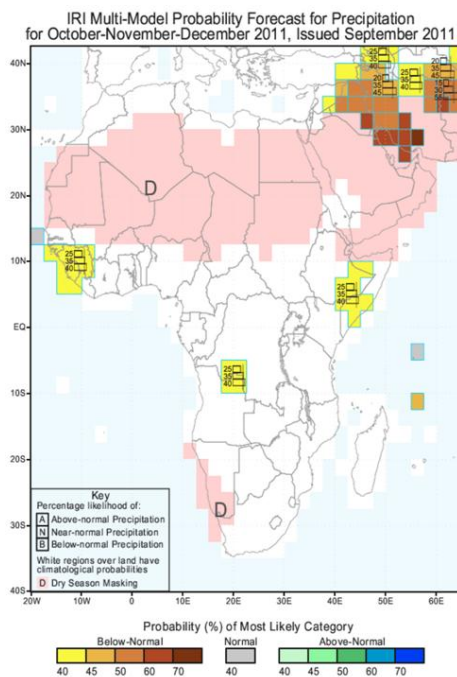
- The trade-off between required resolution, available resolution, and costs
- High resolution inputs are almost always needed for calibration and correcting

Regarding remote sensing data there is a movement from optical to radar based imagery in order to be able to look through clouds.

### 3.9 On the Assimilation of Remote Sensing Data with Crop Models for Crop Yield Forecasting

*Amor Ines, International Research Institute for Climate and Society (IRI), Palisades, NY, USA*

Uncertainty is one of the largest challenges when predicting crop yields. This uncertainty can be attributed to both models and climate data. Uncertainty is highest early in the crop cycle and generally diminishes towards the harvest. Model uncertainty can be lowered partly by data assimilation techniques, while climate uncertainty can be decreased by using seasonal climate forecasts, (e.g. as produced by IRI). Although seasonal forecasts have a low temporal and spatial scale, they have proven to be useful in projects like the WFP Africa Risk Capacity project to reduce the uncertainty a few months before harvest. See example of the scale of the seasonal forecasts in map.



Generally crop models work best in large-scale, homogeneous agro-ecosystems. However, for complex, heterogeneous agricultural systems in the context of smallholder agriculture in developing countries, the fractions of target crops grown are usually small.

Innovations are especially needed in:

- Un-mixing RS vegetation signature, which should result in signals for different crops rather than a mixture of crops and natural vegetation;
- Promising RS soil moisture data are available (based on radar), but the scale is still too coarse (both spatial and temporal) for most modelling applications.

Crop monitoring and yield forecasting have been investigated for the continental United States (especially Georgia and Iowa) using DSSAT-CSM crop models in combination with soil moisture and LAI products from remote sensing. Using AMSR-E soil moisture data with the Kalman filter, did not lead to significantly better results, while the use of MODIS LAI did have a positive effect on accuracy of yield data against USDA yield figures.

Conclusions of research are (Ines et al., 2012):

- Regarding the Ensembles Kalman filter performance applied to DSSAT-CSM crop models, the value of data assimilation with climate forecasts is more evident later in the growing season.
- The skills of climate forecasts is most important in the early part of the growing season.
- The availability of downscaled remotely sensed soil moisture and LAI data would make modelling considerably more accurate.
- Using both soil moisture + LAI gave better results compared to using them independently in the data assimilation - possibly due to the interaction of the two in the simulations.



### 3.10 Simultaneous Estimation of Model State Variables and Observation and Forecast Biases using a Two-Stage Hybrid Kalman Filter

*Valentijn R.N. Pauwels, Laboratory of Hydrology and Water Management, Ghent University, Ghent, Belgium*

In Earth sciences data assimilation is defined as the updating of modelled state variables using external datasets. Therefore, in theory, one could simply replace model results by observations. In practice this is not a good approach because:

- Both the external data and the model results contain errors.
- Many times a proxy of the state variables is assimilated, and not the state variable itself
- Almost always one needs to update many (unobserved) state variables using only one or a couple of observations.

Therefore more complicated methods for data assimilation are developed of which the most popular is the Kalman filter. In the original Kalman Filter (1960), the state variables and observations are assumed to be unbiased. It uses a model state-space representation of the system whereby the state variables are mapped onto observation space.

In an example with soil moisture, the modelled soil moisture is expressed as a volumetric fraction (between 0 and 1). The fact that the observations are in percentages shows that state variables can be updated using any observation they are related to. In this approach, the “Kalman Gain” becomes a weighting factor between the observation error and the model error.

The Kalman filter has been designed for linear, un-biased systems. Unfortunately many data sets (especially remote sensing data) assimilated into hydrologic models contain a significant bias. Many studies remove the bias before the assimilation by removing the long-term difference between the model and the external data. Since models contain bias as well, this may not be the optimal strategy.

Therefore a refinement of the Kalman filter has been developed by Evensen (1994), which is called the Ensemble Kalman Filter. It enables the assimilation of external data into nonlinear biased systems. It essentially estimates forecast and observation biases together with the model state. An essential assumption is that the observation and forecast bias errors are independent of each other and are also independent of the system state errors.

Crop models tend to very complicated (many processes combined in one model), and need a wide variety of data sets, model parameters, and meteorological forcing. This can lead to both random and systematic errors in the model results.

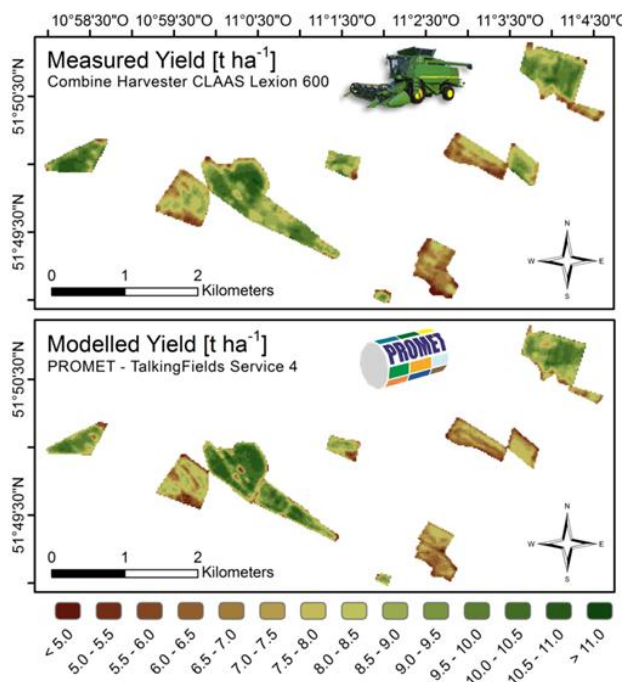
Unfortunately, straightforward application of data assimilation techniques leads to both random and systematic errors. Therefore, if bias is apparent in observations and/or model, this has to be taken into account to get meaningful model outputs (Pauwels and De Lannoy, 2009).

### 3.11 Satellite image simulations for data assimilation at multiple scales

*Heike Bach, VISTA Remote Sensing in Geosciences, Munich, Germany*

VISTA Remote Sensing is a private company (SME) situated in Munich, Germany ([www.vista-geo.de](http://www.vista-geo.de)). Its main expertise is in remote sensing applications in hydrology and agriculture. Vista works in close connection with the University of Munich with the aim to bring (crop) science to practice. For farmers, Vista develops satellite techniques for precision farming in Europe and Russia ([www.talkingfields.de](http://www.talkingfields.de)).

PROMET (Mauser & Bach 2009) and SLC (Verhoef & Bach 2012) are land surface models that couple a crop growth model with a radiative transfer model offering simulated satellite images that can be compared to real ones for data assimilation purposes. SLC uses structural, spectral and observational input data. PROMET is raster-based, and produces a completely closed water and energy balance. Management practices such as sowing date and harvest date can be fed onto the system.



On a field scale, PROMET/SLC has been used to predict wheat yields in a large-scale farm in Germany, producing high resolution (20 m) output, which fit very well with measurements from combine harvester recordings (see graphic from Hank et al., 2012).

In a meso-scale study encompassing the Upper Danube Watershed (76000 km<sup>2</sup>) surface temperatures were calculated with PROMET that correlated very well to similar NOAA-AVHRR extracted temperature data at a resolution of 1 by 1 km.

In a macro-scale study for Central Europe (1.36 million km<sup>2</sup>) the MM5 model (model to simulate or predict atmospheric circulation) was combined with PROMET, where the 45km pixels of the MM5

model were successfully combined with the 1 km PROMET model to deliver an estimate for the average annual evapotranspiration (Zabel et al. 2012).

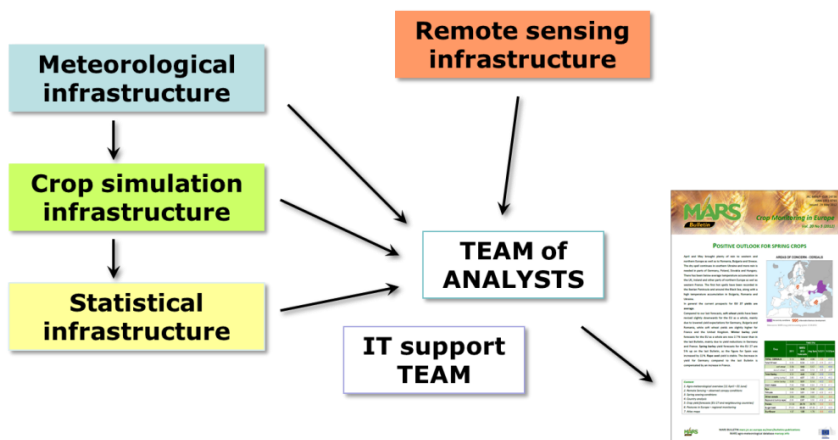
The above-presented examples show that high resolution satellite images now allow observing the current crop status at various scales. The heterogeneities of the land surface can thus be captured. By assimilation of satellite data, improved modelling of the water and carbon cycle can be achieved. PROMET is capable of predicting crop yields at field scale, meso-scale and even macro-scale using the same physical principles and procedures.

### 3.12 MARS operational crop monitoring and yield forecasting activities in Europe

*Gregory Duveiller, AGRI4CAST Action, MARS Unit, JRC, Ispra, Italy*

The European Commission requires in-season crop yield forecasts at a European level as part of the decision making process on market intervention and for policy support. For the past twenty years, the Monitoring Agricultural Resources (MARS) Unit of the European Commission Joint Research Centre (JRC) has operationally produced such forecasts for European member states and for countries in the EU periphery in a tight monthly schedule. This is done using the MARS Crop Yield Forecasting System (MCYFS), a modelling infrastructure driven by agro-meteorological data and assisted by remotely sensed observations. The MCYFS is a decision support system driven by expert knowledge and relying on four main data infrastructures: a meteorological data infrastructure, a remote sensing data infrastructure, a crop simulation infrastructure and a statistical infrastructure. The system uses meteorological data to run crop growth models that provide information on crop status, such as biomass production, soil moisture or biomass of the storage organs. Remote sensing provides an independent assessment of crop status through the use of global and pan-European low-resolution imagery in near real-time (NRT). Finally, the statistical infrastructure includes methods used to analyse, along the season, historical yield records against the information about crop status generated by crop models to produce a forecast that is presented in a monthly bulletin to decision-makers in Brussels. Of course, the team of analysts that

#### MARS Crop Yield Forecasting System



needs to decide what is the most adequate information to base the forecast upon is the keystone of this approach, and is supported by a skilled IT team. The system is articulated by a spatial framework defining the spatial reference upon which all the data is generated (reference grids, administrative units, static spatial layers used by crop models and remote sensing, etc.).

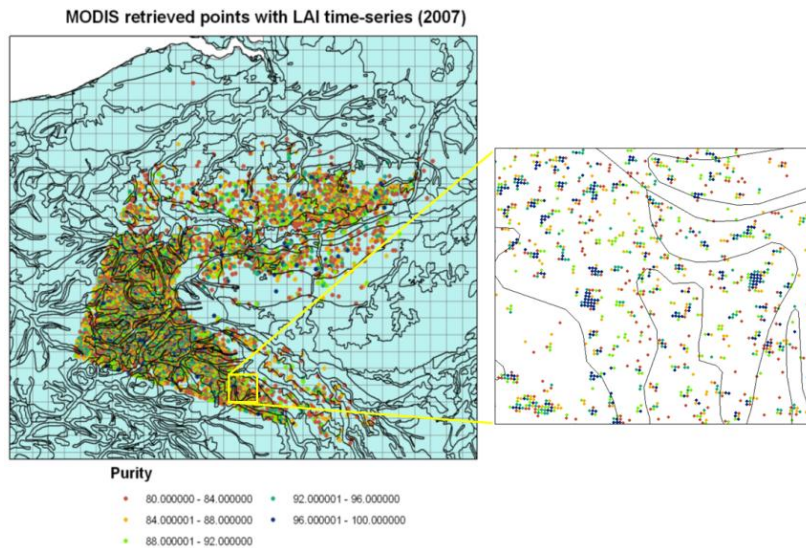
Some research questions that are currently being investigated or that are foreseen in the coming future include the following: (1) using remote sensing to provide improved crop calendars which could help recalibrate models better in the crop modelling infrastructure; (2) develop a method to identify pure enough crop specific time series from MODIS that can be used from crop growth monitoring; (3) exploiting global solar radiation LANSAT products (derived from MSG) as input to the crop models to produce simulations of better quality.

### 3.13 Experiences with data assimilation for regional crop yield forecasting

*Allard de Wit, Alterra, Wageningen, The Netherlands*

The result of a study investigating whether data assimilation techniques could improve regional crop yield forecasting for Europe was presented. A study area was selected in the Walloon area of Belgium and in Northern France. In this area wheat is a dominant crop. The WOFOST crop yield model was applied on these areas on a 10x10 km grid scale. The methodology involved the identification of “pure” wheat pixels (see graphics) using LAI temporal profiles. MODIS GAI ingestion was used for selected wheat pixels for the years 2000 to 2009.

The research involved heavy quality control on MODIS GAI after which the GAI data were applied in WOFOST using parameter optimization. Finally results were validated with the EUROSTAT regional statistics.



Limitations to the use of the Kalman Ensembles data assimilation technique were found. As EnKF originates from meteorology and oceanography (Evensen 1994) it works best with integration of rates of change according to atmospheric physics/hydrodynamics. However, crop models have two processes running: growth and phenology. Phenology can be seen as a parallel controlling process that complicated the application of the EnKF filter.

The main conclusions of the research are (de Wit et al., 2012):

- The Ensemble Kalman filter must be applied with care. It proved to be suitable for soil moisture assimilation, where there is no phenology effect.
- The data assimilation recalibration strategy seems more suitable in general for assimilating canopy variables although crop-specific estimates are needed (no mixed pixels).
- MODIS GAI estimates have shown to be very noisy in W-Europe, as a result of the high level of landscape fragmentation. Post-processing and quality control are very important.
- MODIS GAI estimates have demonstrated to be useful in updating crop model parameters. One of the findings was that the inter-annual variability in the distributions of the optimized model parameters was larger than expected.

### 3.14 Crop Monitoring and Early Warning Service in Africa

*Bakary Djaby, University of Liege, Arlon, Belgium*

University of Liege (ULg) plays an important role in the GMFS (Global Monitoring for Food Security) project, funded by the European Space Agency (see [www.gmfs.info](http://www.gmfs.info)). The main partners in Africa are located in Sudan, Malawi and Niger (AGHRYMET).

The ULg aims at improving early warning services with quantitative estimates of crop yield and pasture biomass in two regions:

- West Africa: Development of crop yields forecast models using remote sensing data in Niger and Senegal;
- East Africa and West Africa: improvement of Livestock Early Warning systems products in West Africa (Niger and Senegal) and East Africa (Ethiopia)

In GMFS Phase 2, the focus of the project has been on intensive training of users in Africa, and the integration of model results into the countries food security bulletins. The model used is the FAO Crop specific soil water balance model (CSSWB), which has been implemented in the software AgrometShell.

Input data differ from application to application, but in general these datasets are used:

- Rainfall estimates from stations and ECMWF era interim reanalysis data
- Remote sensing NOAA-AVHRR GAC, SPOT and MERIS imagery (NDVI, Fapar and DMP)
- Land use data: LULC/ Globcover and FAO crop calendars.
- National Statistics for production data

Remote Sensing data are used to assess the seasonality (sowing, harvest). For this, time series are analyzed with the adaptive Savitzky-Golay filtering method. From this fitted model the beginning and end of the growing season can be extracted. In a next step, these data are input into the water balance calculations.

For validation extensive field surveys have been conducted in Niger and Senegal for 5 years. In Niger 18343 fields with millet, 8548 fields with sorghum and 1791 fields with maize In Senegal 3122 fields with millet and 2743 fields with peanuts. The models are validated by leaving part of the input data out of the calculations and check calculated values against input data later. If little data are available leave-one-out cross validation techniques are used as well as resampling (bootstrap).

Some difficulties were experienced with the accuracy of climate information, e.g. ECMWF versus country station data and uncertainties in land use and country statistical figures.

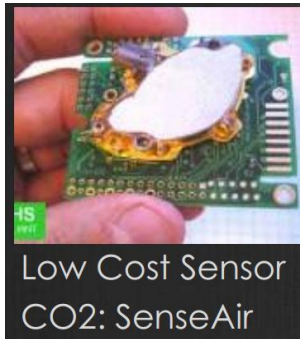
Developments planned in the near future:

- Integration of SAR soil moisture data;
- Two forecast periods in Niger and Senegal for this season (August and September);
- Comparative study of USGS WRSI input versus AgrometShell Water balance and impact.

### 3.15 Data Assimilation based on the Integration of Satellite Data and Field Sensor Data for Drought Monitoring

*Kiyoshi Honda, Int'l Digital Earth Applied Science Research, Center (IDEAS), Chubu Institute for Advanced Studies, Chubu University, Japan*

Chubu University develops methods for crop model calibration based on the Integration of satellite data and field sensor data. In an effort to standardize and have systems communicate easily, cloud-based web services have been developed to disseminate field sensor data.



The Field sensor network cloudSense is based on small and low-cost sensors that provide data through mobile Internet communication. Potentially these sensors can gather information in real-time from anywhere in the world. Possible applications are: disaster preparedness, agriculture, logistics, security, etc.

As the sensor network is essentially open source, anyone can add a sensor to the network. A simple protocol based on an input form needs to be filled in order to add the sensor to the network.

For analysis and visualisation, applications are developed for mobile phones and various computer operating systems. One of the applications aims at fostering confidence in food safety among consumers. It essentially displays crop information to end users of the crop, while the crop is still on the field. In another application greenhouse gasses (CH<sub>4</sub> and N<sub>2</sub>O) are measured and visualised in Thailand. Sensors are fitted onto fixed poles as well as low-cost helicopters and other AUV's.

Remote sensing data can be used in crop models through data assimilation. However, remote sensing generally provides just a few parameters such as LAI, Eta etc. Important parameters such as soil hydraulic parameters, sowing date etc. are difficult to base on satellites. Field sensor data fill this gap. As an example, in Thailand, rice is frequently damaged by dry spells. The damage is assessed in real-time by running the SWAP model assimilated with remote sensing and field sensor data. This research has shown that low October rainfall has the highest adverse impact on rice production.

Field Sensor data have been successfully used to correct MODIS LAI data, as MODIS LAI generally underestimates the LAI on the ground. The satellite LAI was calibrated with ground measurements before it was used in the assimilation process.

Measured soil moisture information is very valuable as assimilated input into crop models. As this cannot be done with satellite measurements, a ground sensor network is proven to be very helpful.

Generally low-resolution satellite data are available at a high frequency, while high-resolution data are available at low frequency. With an algorithm developed at Chubu University, both sources can be combined into a more valuable source of data. As an example, high resolutions LANDSAT / ASTER data have successfully been combined with low resolution AVHRR / MODIS data (Ines and Honda, 2005).

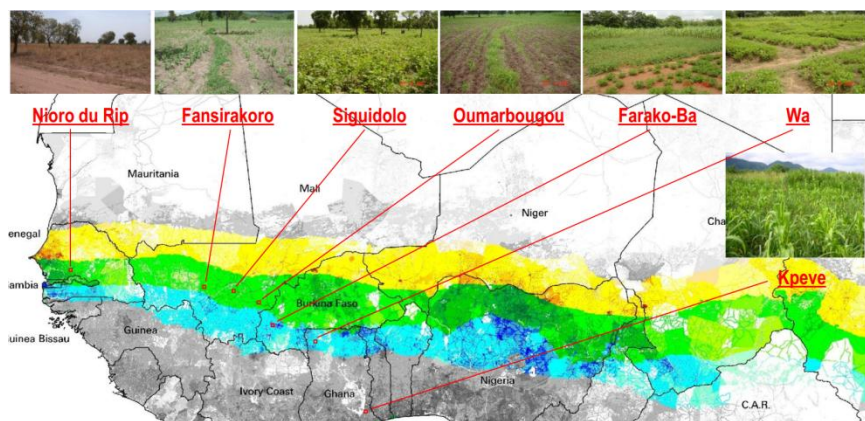


### 3.16 Data assimilation for the carbon cycle in Sudan savannah smallholder communities

*Pierre Traoré, ICRISAT, Bamako, Mali*

Stable soil organic carbon (SOC) plays an important role in soils while it retains water and improves the structure of the soil. Increasing SOC contents in the soil could also potentially help reduce the CO<sub>2</sub> content of the air. These are long-term processes prove difficult to quantify. ICRISAT took up the challenge and used the DSSAT model (DSSAT-CENTURY) together with field measurements and remote sensing to quantify the carbon cycle.

This was applied in Sudanian agricultural systems in Southern Mali, Burkina Faso and Ghana (see map). These areas have heterogeneous management techniques and quite extensive mixed cropping practices, often with low-yielding traditional varieties. The most important crops were maize, yam, millet, sorghum and peanut. Even within a crop like sorghum, 8 to 10 different varieties have been identified that react differently to management practices.



Information on the very detailed cropping patterns was obtained through high-resolution imagery in combination with field work (based on QuickBird NDVI anomalies).

In time, SOC measurements and model outcomes have been studied at both point level and aggregated to areas, where the aim was to minimize uncertainty. At point level simplified DSSAT simulations of SOC have been assimilated with field measurements using the Ensemble Kalman Filter.

At point-level (Jones & al., 2004, 2007; Koo, 2007), using the EnKF reduced measurement uncertainty by around 60%. Furthermore, over space the EnKF reduced uncertainty by 50%, although results proved to be very sensitive to initial estimates of parameters. In other words, there is uncertainty on departure from steady state as well as uncertainty on planting dates.

Besides this research, ICRISAT is instrumental in the worldwide AgMIP project. This is a distributed climate-scenario simulation exercise for historical model intercomparison and future climate change conditions that goes further than just crop modelling. Many crop and agricultural economics modelling groups around the world are contributing. The goals of AgMIP are to improve substantially the characterization of risk of hunger and world food security due to climate change and to enhance adaptation capacity in both developing and developed countries.

### 3.17 Soil-water-crop modelling for decision support in Sub-Saharan west Africa: experiences from Niger and Benin

*Pierre B. Irénikatché AKPONIKPÈ, Faculty of Agronomy, University of Parakou, Benin*

The Sahel region in West Africa suffers from low grain yields (millet yield often lower than 500kg/ha), caused by limited and uncertain rainfall (300-600mm per year) compounded by low soil fertility. Although numerous improvements have been proposed over the years, the impact of agricultural research is still low. Small scale farmers rarely adopt new management methods and inputs. The main reason seems to be that farmers seek to reduce risk while scientists try to increase yields.

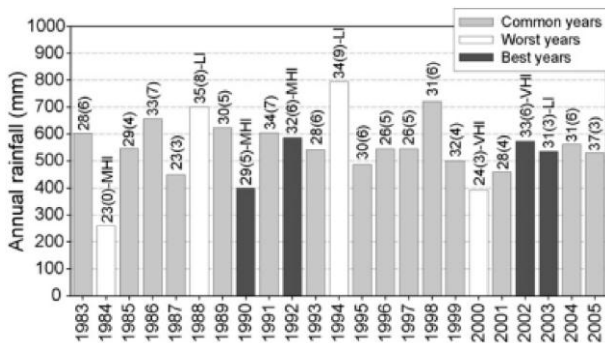
The University of Parakou in Benin has investigated this phenomenon. It has studied climate risk management in S-W Niger where a high temporal rainfall variability is normal (annual coefficient of variance of 17 to 36 %, even 78% at a daily basis). There is also a high spatial rainfall variability. Farmers seem to adapt to the spatial variability by dispersing their fields within the village territory.

The University set out to investigate the hypothesis whether farmers disperse their fields to reduce agro-climatic risk.

A “household field dispersion index” has been developed to test the hypothesis. This index is sensitive to the distance between fields, but independent of the number of farms in the village as well as the total farm area of the farmer. Furthermore a “yield instability index” (to measure inter-annual variation of the household) and a “yield disparity index” (to measure the inter-annual variation of yields relative to the village area) were constructed. Soil fertility gradients were taken into account. Closer to the village soil fertility is usually higher.

The main conclusions were as follows (Akponikpe et al., 2011):

- There is no relation between cumulated annual rainfall and yield (see graph);
- Large spatial rainfall variability generates an even larger spatial variability in yields;
- Field dispersion, as practiced by farmers in western Niger, allows to mitigate inter-annual yield variability at the household level, albeit to a limited extent.



A second study was carried out in Northern Benin investigating the optimal amount of nitrogen that can be applied to farmers fields., the current recommendation being 30 kg per ha.

The University found that grain yields were considerably lower than those assumed with the recommendation above. In part this is explained by farmers using un-improved varieties of millet. The study concludes that that around 15 kg of nitrogen per ha is the best optimum.



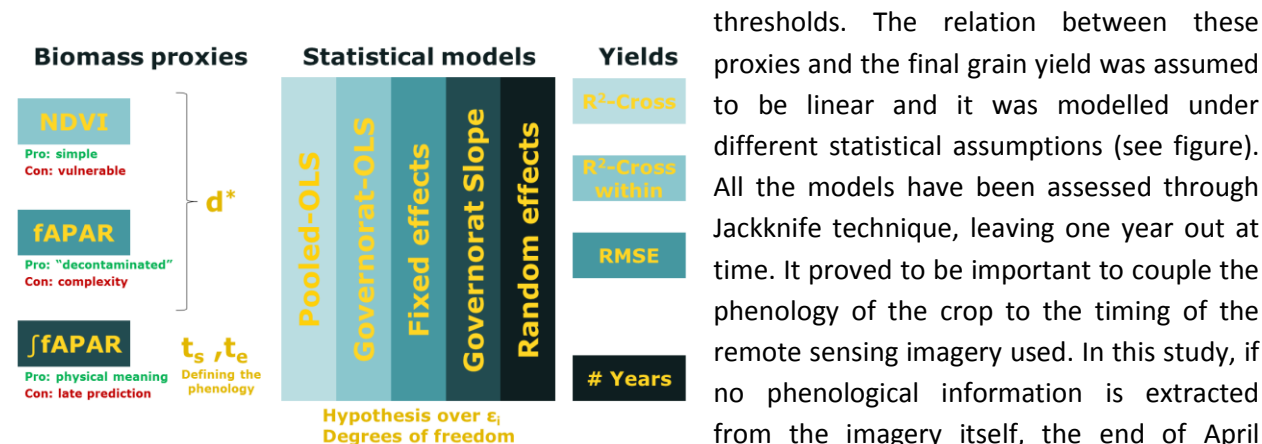
### 3.18 Wheat yield modelling in a stochastic framework within and post season yield estimation in Tunisia

*Eduardo Marinho and Michele Meroni, FOODSEC Action, MARS Unit, JRC, Ispra, Italy*

As it is not possible to directly measure and model grain yields production, it is assumed that grain yields are highly correlated to biomass yields. Three proxies for wheat biomass production and different statistical modelling solutions have been investigated for Tunisia. The aim was to select the proxy and statistical model providing the best predictive capacity in yield estimation avoid over/under-parameterization.

The study area encompassed 10 governorates representing 88% of national production of wheat in Tunisia. The remote sensing data used were 13 years of SPOT-VGT fAPAR & NDVI as well as area fraction masks for cereals from aerial photographs. National yield statistics were available on the level of governorates.

The biomass proxies tested were (1) NDVI and (2) fAPAR at a given dekad, and (3) the Integral of fAPAR during the period of plant activity,  $\int fAPAR$ . The start and end of the season have been extracted pixel by pixel from the fAPAR time series, analyzing the shape of the curve and setting a priori percentage thresholds.



The relation between these proxies and the final grain yield was assumed to be linear and it was modelled under different statistical assumptions (see figure). All the models have been assessed through Jackknife technique, leaving one year out at time. It proved to be important to couple the phenology of the crop to the timing of the remote sensing imagery used. In this study, if no phenological information is extracted from the imagery itself, the end of April

imagery proved to deliver the best results. The most important findings are:

- High yield variability in Tunisia can be estimated by remote sensing techniques, without the involvement of a crop model;
- Improved statistical models (i.e., fixed and random effect) have a significantly positive impact on yield accuracy estimation;
- In Tunisia,  $\int fAPAR$  outperforms other biomass proxies for yield estimation;
- In the absence of ground data, the  $\int fAPAR$  is the best option for measuring crop yields because it is linearly related to pooled yield data (no distinction among governorates);
- Finally, the role played by data scarcity in determining the most suitable approach for yield estimation was addressed. The trade-off between the ability of modeling regional specificities and over-parameterization has been emphasized in the case of a reduced sample size. Results indicate that the selection of the model specification should take into account the number of available observations, and not only the expected spatial heterogeneity on the yield-biophysical parameter relationship.



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## 5 Acronyms and Abbreviations

AGRHYMET	Centre for Agriculture, Hydrology and Meteorology
AgMIP	Agricultural Model Intercomparison and Improvement Project
AGROMETS	FAO Water Balance Model implementation
HELL	
AMSR	Advanced Microwave Scanning Radiometer
AUV	Unmanned Aerial Vehicle
AVHRR	Advanced Very High Resolution Radiometer
C3	Carbon fixation method in photosynthesis for most crops in temperate regions (e.g., wheat)
C4	Carbon fixation method in photosynthesis for some crops in tropical regions (e.g., maize)
CCAFS	Climate Change, Agriculture and Food Security research program of the CGIAR
CCE	Crop Cutting Experiments
CGIAR	Research Program on Climate Change, Agriculture and Food Security
CSM	Cropping System Model
DSSAT	Decision Support System for Agro-technology Transfer
ECMWF	European Centre for Medium-Range Weather Forecasts
EnKF	Ensemble Kalman Filter
EOS	Earth Observing System, a coordinated series of polar-orbiting and low inclination satellites
ESSP	Earth System Science Partnership
ETA	Actual Crop Evapotranspiration
EVI	Enhanced vegetation Index
FACE	Free Air Carbon Enrichment
FAO	Food and Agriculture Organisation of the United Nations
FAPAR	Fraction of Absorbed Photosynthetically Active Radiation
FASAL	Forecasting Agricultural Output Using Space, Agromet and Land Observations (India)
GAI	Green Area Index
GWSI	Global Water Satisfaction Index
IARI	Indian Agricultural Research Institute
ICRISAT	International Crops Research Institute for Semi-Arid Tropics
INRA	French National Institute for Agricultural Research
IRI	International Research Institute for Climate and Society
JRC	Joint Research Centre of the European Commission
LAI	Leaf Area Index
LINGRA	A grass growth model developed by ALTErrA, Wageningen. Based on LINTUL
LINTUL	Light INTERception and Utilization simulator. A simple general crop growth model
MARS	The “Monitoring Agriculture with Remote Sensing” project of the JRC - AGR14CAST
MERIS	MEDium Resolution Imaging Spectrometer
MLCan	Vertically resolved canopy-atmosphere exchange model
MM5	Mesoscale crop growth model of Pennsylvania State University
MODFLOW	Groundwater model

MODIS	MODerate-resolution Imaging Spectroradiometer
MSG	METEOSAT Second Generation
N	Nitrogen
NADAMS	National Agricultural Drought Assessment & Monitoring System (India)
NASA	National Aeronautics and Space Administration (USA)
NDVI	Normalized Difference Vegetation Index
NGO	Non-governmental organization
NIR	Near Infrared
NOAA	National Oceanic and Atmospheric Administration
OLS	Ordinary Least Squares
ORYZA1	Eco-physiological model for irrigated rice production.
PROMET	Crop Growth Model of VISTA (German company)
PROSAIL	Radiative transfer model
RS	Remote Sensing
SAR	Synthetic Aperture Radar
SOC	Stable soil organic carbon
SPOT	Système Pour l'Observation de la Terre (French satellites)
STICS	Generic model for the simulation of crops and their water and nitrogen balances.
SUCROS	Simple and Universal CROp growth Simulator
SWAP	Soil Water Atmosphere Plant model
TM	Thematic Mapper
TRMM	Tropical Rainfall Measuring Mission
USGS	United States Geological Survey
VGT	VEGETATION sensor on board the SPOT satellite
WARM	Rice crop model used at JRC
WFP	World Food Programme
WOFOST	WORld FOod Studies. Simulation model for the quantitative analysis of the growth and production of annual field crops
WRSI	Water Requirement Satisfaction Index
WTGROWS	Crop simulation model for regional wheat yield mapping

## 6 Workshop Program

Wednesday, 13 June 2012

### Opening session

- 09:00-09:10**      *Welcome address, JRC*
- 09:10-09:25**      *Crop Forecasting within the CCAFS Program, James Hansen, CCAFS, IRI-Columbia University*
- 09:25-09:40**      *The challenges of an operational crop yield forecasting system in Sub-Saharan Africa. Is there a realistic and effective solution? Francois Kayitakire, JRC*
- 09:40-10:10**      *Integration of agro-hydrological modelling, remote sensing and geographical information, Jos van Dam, Wageningen University*

### Session 1

- 10:45-11:15**      *Assimilation of remote sensing observations into a crop model improves predictive performance for spatial application, Martine Guerif, INRA*
- 11:15-11:45**      *Regional Crop Simulation Modelling for Yield Prediction using Remote Sensing and GIS: Indian Experiences, Vinay Sehgal, IARI-India*
- 11:45-12:15**      *Using MODIS LAI to estimate maize yield, Gerrit Hoogenboom, Washington State University*
- 12:15-12:30**      **Discussion**

### Session 2

- 14:00-14:30**      *Exploring the climatic response of the central US agro-ecosystem, Darren Drewry, NASA-JPL*
- 15:30-16:00**      *On the assimilation of remotely sensed soil moisture and vegetation with crop simulation models, Amor Ines, IRI, Columbia University*

### Session 3

- 16:30-17:00**      *Simultaneous Estimation of Model State Variables and Observation and Forecast Biases using a Two-Stage Hybrid Kalman Filter, Valentijn Pauwels, Ghent University*
- 17:00-17:30**      *Satellite image simulations for data assimilation at multiple scales, Heike Bach (VISTA) and Wolfram Mauser (University of Munich)*
- 17:30-18:00**      *Estimating crop biophysical properties from remote sensing data by inverting linked radiative transfer and ecophysiological models, Kelly R. Thorp, USDA*

18:00-18:15 Discussion

Thursday, 14 June 2012

#### Session 4

9:00-09:30 *MARS operational crop monitoring and yield forecasting activities in Europe and possible improvements based on remote sensing data*, Gregory Duveiller, JRC

09:30-10:00 *Experiences with satellite data assimilation for regional crop yield forecasting*, Allard de Wit, Alterra

10:00-10:30 *Operational crop yield forecast using remote sensing and agrometeorological in West Africa*, Bernard Tychon and Bakary Djaby, University of Liege

#### Session 5

10:45-11:15 *Data Assimilation based on the Integration of Satellite Data and Field Sensor Data for Drought Monitoring*, Kiyoshi Honda, Chubu University

11:15-11:45 *Data assimilation for the carbon cycle in Sudanian smallholder communities*, Sibiry Traore, ICRISAT

11:45-12:15 *Soil-water-crop modeling for decision support in sub-saharan West Africa: experiences from Niger and Benin*, Pierre Irénikatché AKPONIKPE, Université de Parakou

12:15-12:45 *Wheat yield modelling in a stochastic framework – within and post season yield estimation in Tunisia*, Eduardo Marinho and Michele Meroni, JRC

#### Session 6: Discussion and way forward

14:30-16:30 James Hansen, CCAFS, Chair of the session

16:30-17:00 Meeting conclusions



## 7 Participants

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James Hansen	CCAFS; IRI, Columbia University	USA
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Allard de Wit	Alterra	The Netherlands
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## 8 Sponsors

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#### Abstract

JRC and CCAFS jointly organized a workshop on June 13-14, 2012 in Ispra, Italy with the aim to advance the state-of-knowledge of data assimilation for crop yield forecasting in general, to address challenges and needs for successful applications of data assimilation in forecasting crop yields in heterogeneous, smallholder environments, and to enhance collaboration and exchange of knowledge among data assimilation and crop forecasting groups.

The workshop showed that advances made in crop science are widely applicable to crop forecasting. The presentations of the participants approached the challenge from many sides, leading to ideas for improvement that can be implemented in real-time, operational crop yield forecasting. When applied, this knowledge has the potential to benefit the livelihoods of smallholder farmers in the developing world.

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