A comparison of two coupling methods for improving a sugarcane model yield estimation with a NDVI-derived variable.

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ABSTRACT

Coupling remote sensing data with crop model has been shown to improve accuracy of the model yield estimation. MOSICAS model simulates sugarcane yield in controlled conditions plot, based on different variables, including the interception efficiency index (ε_i). In this paper, we assessed the use of remote sensing data to sugarcane growth modeling by 1) comparing the sugarcane yield simulated with and without satellite data integration in the model, and 2) comparing two approaches of satellite data forcing. The forcing variable is the interception efficiency index (ε_i). The yield simulations are evaluated on a data set of cane biomass measured on four on-farm fields, over three years, in Reunion Island. Satellite data are derived from a SPOT 10 m resolution time series acquired during the same period. Three types of simulations have been made: a raw simulation (where the only input data are daily precipitations, daily temperatures and daily global radiations), a partial forcing coupling method (where MOSICAS computed values of ε_i have been replaced by NDVI computed ε_i for each available satellite image), and complete forcing method (where all MOSICAS simulated ε_i have been replaced by NDVI computed ε_i). Results showed significant improvements of the yield's estimation with complete forcing approach (with an estimation of the yield 8.3 % superior to the observed yield), but minimal differences between the yields computed with raw simulations and those computed with partial forcing approach (with a mean overestimation of respectively 34.7 and 35.4 %). Several enhancements can be made, especially by optimizing MOSICAS parameters, or by using other remote sensing index, like NDWI.

Keywords: sugarcane, yield, growth model, NDVI, interception efficiency, forcing

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1. INTRODUCTION

In La Réunion, sugarcane is strongly linked to the island’s socioeconomic landscape, as it involves up to 10500 people [7]. Contrasted climate conditions and various cultural practices induce highly contrasted yields. In order to improve the management of sugarcane harvest, an accurate estimation of yield is of the utmost importance. This prospective exercise is performed each year using a sugarcane growth simulation model, MOSICAS [17]. MOSICAS is a semi-empirical model, based on a water balance module and on a growth module. It simulates the growth of a sugarcane plot under controlled conditions. Whereas the water balance module assesses the effect of water deficit on the growth, no such module exists to assess the effect of nutrient lack, disease or pests. Consequently, simulating the yield of an agricultural plot (*i.e*., that is not under controlled conditions) with MOSICAS often leads to an overestimation of the results. The use of coupling methods with MOSICAS and remote sensing data should allow reducing the gap between the field measured yield and the simulated one.

Coupling remote sensing data with crop model improves accuracy of model's yield estimation [15, 8, 5]. Indeed, remote sensing tools can provide representative data of the development of vegetal plots [18], and use of time series gives information about biophysical indicators of the cultural history of the plots [2, 4] that can then be included in the model. Several coupling methods have been described in the literature [9, 6, 10], most of them allowing to compute new datasets of the model state variables or parameters. We can thus distinguish forcing and assimilation methods, which work on the state variables, from the calibration, which aims to compute new values of the model parameters. Forcing and assimilation approaches are simpler than calibration, and are generally implemented through the use of the leaf area index or the interception efficiency index derived from remote sensing time series [1, 3]. Both bio-physical variables are generally assessed from the Normalized Difference Vegetation Index (NDVI), computed from red and infrared spectral bands [18] that exist on most of the earth observing systems.

In this paper, we assess the potential contribution of remote sensing data to sugarcane growth modeling by 1) comparing the sugarcane yield simulated with and without satellite data integration in the model, and 2) comparing two ways of satellite data forcing in the model. Model forcing is made through the interception efficiency index (ε_i). The yield simulations are evaluated on a data set of cane biomass measured on four on-farm fields, over three years, in Reunion Island. Satellite data are derived from a SPOT 10 m resolution time series acquired during the same period.

2. MATERIAL AND METHOD

2.1. Ground measurements

The experiment was conducted in 2011 and 2012, in the southern part of La Réunion Island (21° 20'S, 55°30'E). The region is characterized by a tropical climate with a mean annual rainfall of 1007 mm year^{-1}.

Interception efficiency index (ε_i) was measured all along the growing cycle on two sugarcane on-farm fields (Table 1, fields 12 and 19), between October 2011 and June 2012. Nine sampled plots of four measurements of ε_i were measured in each field, and averaged to decrease the effect of the spatial heterogeneity. The interception efficiency was measured with a LP-80 Accupar ceptometer. Above and below the canopy measurements were made between 10:00 am and 1:00 pm, with low nebulosity conditions, and ε_i was calculated as:

$$\varepsilon_i = (PAR-PAR_t)/PAR \qquad (1)$$

where PAR is the photosynthetically active radiation measured above the canopy (µmol/m²/s) and PAR_t is the photosynthetically active radiation measured below the canopy (µmol/m²/s). As the vegetation became senescent, PAR_t was measured above the senescent leaves layer in order to measure only the radiation intercepted by green material.

Table 1: Summary of the fields.

Field #	Cultivar	Area (ha)	Altitude (m)	Irrigation	ε_i measurements (number of values)	Years with available yields
1	R570	11.6	120	X	0	2010, 2011 & 2012
12	R570	25.6	255	X	7	2010 & 2011
16	R570	15.3	178	X	0	2010 & 2011
19	R570	13.9	184	X	6	2010 & 2011

2.2. Satellite images

Remote sensing data were acquired between February 2010 and June 2012 using SPOT4 and SPOT5 satellites. Those images belong to the ISLE-Reunion database (http://kalideos.cnes.fr/) set up by the Centre National d'Études Spatiales (CNES).

The four spectral bands on SPOT4 and SPOT5 are Green, Red, Near Infrared and Shortwave Infrared. Spatial resolution varies between 2.5 and 10 m. Images were corrected in "Top of Canopy" reflectance, orthorectified, ensuring cross-comparison on time and space.

The NDVI median values of the pixels contained within the studied fields boundaries were computed for each satellite image.

Table 2. Summary of the satellite images.

YEAR 2010			YEAR 2011			YEAR 2012		
Date	Satellite	Resolution (m)	Date	Satellite	Resolution (m)	Date	Satellite	Resolution (m)
06/02/10	SPOT5	10	15/01/11	SPOT5	2.5	08/02/12	SPOT4	10
15/05/10	SPOT4	10	02/04/11	SPOT4	10	24/02/12	SPOT4	10
06/06/10	SPOT5	10	08/05/11	SPOT4	10	07/03/12	SPOT5	10
06/08/10	SPOT4	10	21/05/11	SPOT5	10	15/03/12	SPOT4	10
01/09/10	SPOT4	10	30/05/11	SPOT5	10	31/03/12	SPOT4	10
12/10/10	SPOT4	10	09/06/11	SPOT4	10	01/05/12	SPOT4	10
			24/06/11	SPOT4	10	16/05/12	SPOT4	10
			04/07/11	SPOT4	10	01/06/12	SPOT4	10
			14/07/11	SPOT4	10			
			11/08/11	SPOT5	10			
			06/10/11	SPOT4	10			
			12/12/11	SPOT4	10			
			30/12/11	SPOT5	10			

2.3. Sugarcane growth model

MOSICAS is a semi-mechanistic model dedicated to sugarcane growth simulation. It has been validated according to La Réunion physical and cropping characteristics. The sugarcane cultivar R570, widely spread, is the reference cultivar of MOSICAS. Accordingly we decided to focus our measurements on this cultivar. MOSICAS computes the yield of a simulated field on a daily time-step, based on meteorological data, cultivar coefficients and cultural practices.

The model is made of a water-balance module and of a growth module. The water-balance module takes into account daily rainfall, potential evapotranspiration (PET) and irrigation and computes a crop available water content (AWC) (Figure 1).

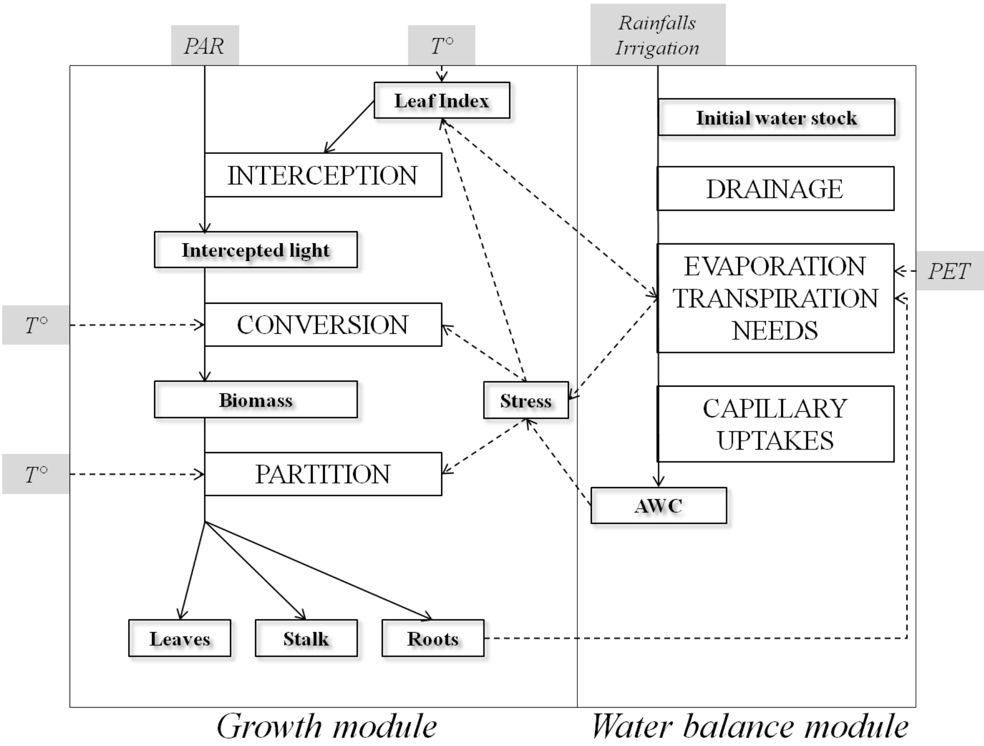

Figure 1. Simplified schema of the main components of MOSICAS (from Martiné [17]).

Based on mean daily temperature, MOSICAS computes degree day values for each simulation date, with a base temperature of 12 °C. Growth module integrates daily intercepted photosynthetically active radiation (PAR), converts intercepted PAR into biomass, and finally, calculates biomass partition into leaves, stalk (which includes sugar and fiber), and roots.

2.4. MOSICAS simulations

Three simulation experiments were conducted and compared:

- MOSICAS simulation (referred hereafter as MOS): the model is run with climatic, agronomic and pedologic constraints.
- MOSICAS + partial forcing of satellite data simulation (referred hereafter as MOS-PF): the simulated state variable ε_i is replaced by the observed one whenever a satellite image is available.
- MOSICAS + complete forcing of satellite data (referred hereafter as MOS-CF): the simulated state variable ε_i is replaced at every time-step of the simulation (daily) by observed ones.

To run MOS-PF and MOS-CF simulations, we converted NDVI values in ε_i values using an exponential function. As NDVI data acquisition days were different from those of ground ε_i measurements, we first fitted a logistic function to model ε_i dynamics in function of degree day. Then we used this logistic model to compute ε_i values for each acquisition date (that was previously converted in degree days).

To run MOS-CF simulation, daily ε_i values were obtained by fitting satellite-derived ε_i values at the field scale using a model initially proposed to simulate NDVI dynamics [4]:

$$\varepsilon_i = \left(\frac{M}{1+e^{-a\times(t-t_i)}}\right) - \left(\frac{M}{1+e^{-b\times(t-t_f)}}\right) \quad (2)$$

Equation 2 describes ε_i in two parts, growth and senescence. The independent variable *t* is defined as the accumulated daily mean air temperature above 12°C starting from sowing. The growth period is defined by a logistic equation with parameter *a* being the relative growth rate at the inflexion point $_{ti}$. The senescence is determined by a second logistic equation with parameter *b* being the relative growth rate at the inflexion point t_f. The parameter *M* describes the amplitude of maximal ε_i.

3. RESULTS AND DISCUSSION

3.1. Experimental relationship between ε_i and NDVI

As mentioned before, to compute the ε_i-NDVI transfer function, we had first to calculate ε_i values at days of image acquisition. Figure 2 illustrates the result of the logistic model used to interpolate ε_i values at any date, obtained for the irrigated R570 cultivar.

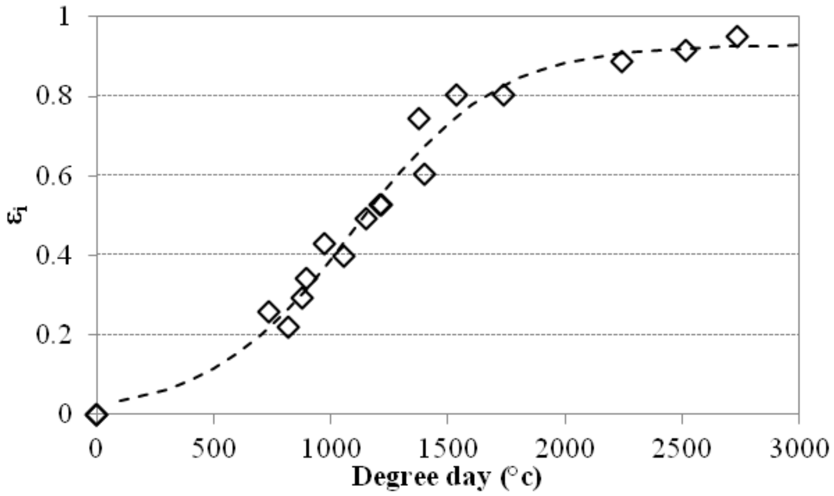

Figure 2. Example of the "R570 cultivar/irrigated" interception efficiency dynamics modeled as a function of degree days.

An exponential regression between median NDVI of each field and ε_i has then been computed, based on computed values of ε_i, calculated with same degree day values of median NDVI (Figure 3).

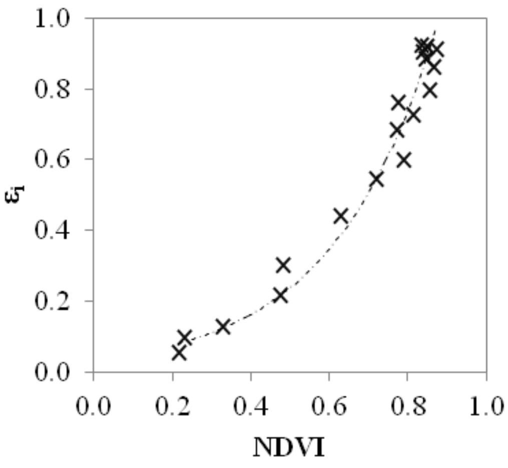

Figure 3. Relation between median NDVI and interception efficiency at the field scale.

The NDVI-ε_i regression is highly significant fit (R^2 = 0.97; Eq. 3), but somewhat noisy. The NDVI-ε_i scatter can be attributed to dead canopy material and canopy architecture. Corrections of ε_i by empirical greenness factors improved the correlations [12] and should be tested later.

$$\varepsilon_i = 0.0361e^{(3.7739\times NDVI)} \tag{3}$$

3.2. Interception efficiency data for complete forcing

In the complete forcing approach (MOS-CF), the simulated state variable ε_i is replaced at each time-step of the simulation (daily). In order to compute daily ε_i values for each field, ε_i dynamics was modeled for each field (Eq. 2; Figure 4)

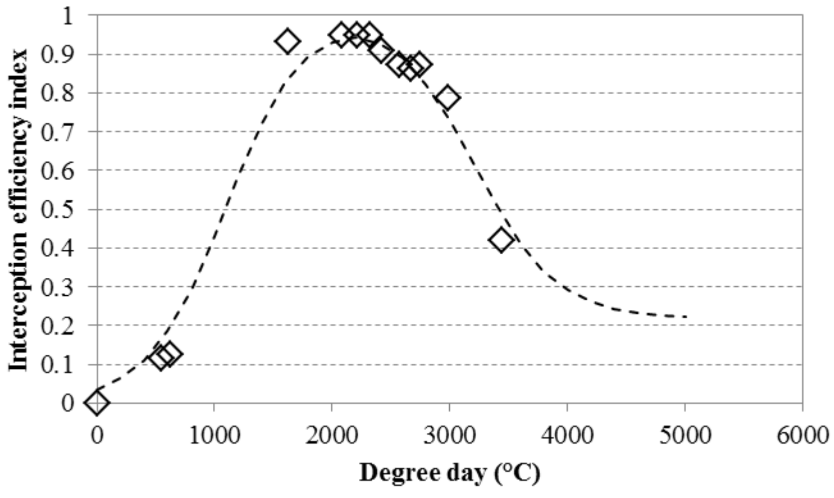

Figure 4. Example of interception efficiency index modeled as a function of degree day, field 12, year 2011.

Double logistic regression showed good results, with R^2 varying from 0.93 to 0.99.

3.3. Simulations results

MOS, MOS-PF and MOS-CF simulations were made for the four irrigated fields presented in table 3, with R570 cultivar, over years 2010, 2011 and 2012, and compared in terms of yield (cane biomass at harvest) measured at the field scale (Figure 5).

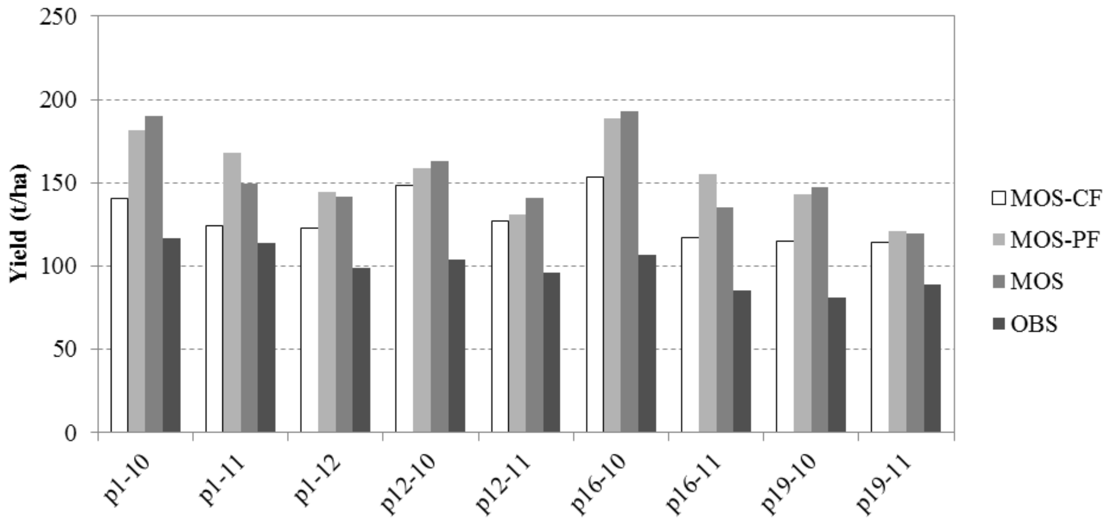

Figure 5. Comparison of simulated yields and observed yields. "px" indicates the field number, while the second number indicates the year. p12-11 therefore stands for field 12 on year 2011.

We observed that all the simulations overestimate the yield. Maximum error between field-measured values of yield and simulated ones is observed for a MOS simulation on field 19, year 2010 (+45.0 %). The most accurate simulation is for field11, year 2011, with MOS-CF simulation (+8.3 %).

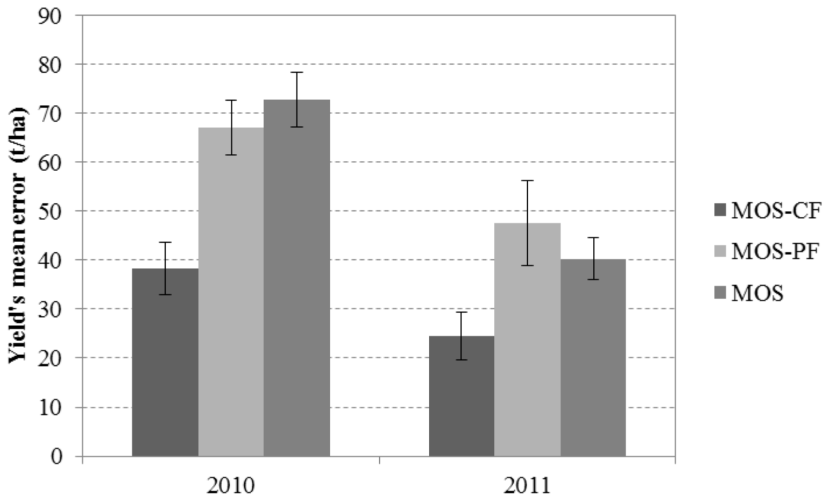

Figure 6. Comparison of the mean error of each simulation's method for years 2010 and 2011.

Simulations for the year 2010 have a mean error superior to those of year 2011; whereas the mean value of the error for year 2010 is 59.5 t/ha, the mean value of the error computed for year 2011 is 37.5 t/ha. This could be explained by the fact that measured rainfalls for year 2010 are significantly higher (900 mm) than the rainfalls of year 2011 (659 mm). Thus, the water stress computed by the model was lower in 2010. Other crop growth limiting factors, not simulated, may have impacted the actual yield.

However, we can notice that there's significant improvements in the estimated yield with the MOS-CF (*i.e*, a simulation with a complete forcing) approach, with a mean error of +21.3 % of the observed yield, versus +34.7 % with the MOS simulation.

There's minimal difference between the MOS and MOS-PF simulations. This can be explained by the fact that the partial forcing approach does not give enough material for counterbalance the overestimation of the model.

As noticed previously, all simulations tend to overestimate the yield. The fact that we have strong uncertainties remaining on parameters (total soil available water content, rooting depth, transpiration threshold,…) that cannot be taken into account with interception efficiency index may explain those differences.

However, this is preliminary study, and results need to be confirmed with more ground measurements and simulations. New remote sensing index should be used, like the normalized difference water index (NDWI), giving us a better monitoring of the water balance on the field. Recalibration approach should allow us to compute more accurate values of some parameters of the model, also helping us to calculate a more precise water balance.

4. CONCLUSION

This paper shows that there's significant difference between the complete forcing approach and the two other types of simulation. However, minimal differences were noticed for the partial forcing and the classical, raw simulation. This can be explained by the fact that the partial forcing approach does not give enough information to counterbalance the model's deviation. Significant gaps with the observed yields are still noticed. This can be explained by the fact that there are strong uncertainties with the model's water balance. The use of some other remote sensing index, like Normalized Difference Water Index (NDWI), might help to improve the water balance accuracy. Furthermore, some parameters of the model are poorly estimated, since there is no accurate measurement methodology available. Working with the calibration approach should help us to optimize the values of some parameters of the model without heavy field measurements survey.

Another perspective is the use of other coupling approaches (*i.e*, assimilation and calibration). Assimilation method will be used as well with ε_i datasets, while calibration approach might be used with the Crop Water Stress Index (CWSI) [13, 14, 16], to compute new, optimized values of the transpiration threshold of the field and of its rooting depth, both parameters of MOSICAS.

5. ACKNOLEDGEMENTS

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6. REFERENCES

[1] Asrar, G., Fuchs, M., Kanemasu, E. T. and Haffield, J. L., "Estimating absorbed photosynthetic radiation and leaf area index from spectral reflectance in wheat", Agronomy Journal, 76, 300-308 (1984).

[2] Bappel, E., "Apport de la télédétection aérospatiale pour l'aide à la gestion de la sole cannière réunionnaise" PhD Thesis, University of La Réunion, St Denis (FR), 193 p, (2005).

[3] Bégué, A., "Leaf Area Index, intercepted photosynthetically active radiation, and spectral vegetations indices: A sensitivity analysis for regular-clumped canopies", Remote Sensing of Environment, 46(1), 45-59 (1993).

[4] Bégué, A., Lebourgeois, V., Bappel, E., Todoroff, P., Pellegrino, A., Baillarin, F. and Siegmund, B., "Spatio-temporal variability of sugarcane fields and recommendations for yield forecast using NDVI", International Journal of Remote Sensing, 31(20), 5391-5407 (2010).

[5] Casa, R., Varella, H., Buis, S., Guérif, M., De Solan, B. and Baret, F., "Forcing a wheat crop model with LAI data to access agronomic variables: Evaluation of the impact of model and LAI uncertainties and comparison with an empirical approach", European Journal of Agronomy, 37(1), 1-10 (2012).

[6] Dadhwal, V. K., "Crop growth and productivity monitoring and simulation using remote sensing and GIS", proc. Satellite Remote Sensing and GIS Applications in Agricultural Meteorology, 263-289 (2003).

[7] Direction de l'Alimentation, de l'Agriculture et de la Forêt (DAAF), "Canne à sucre", http://www.daf974.agriculture.gouv.fr/Canne-a-sucre (17 April 2012).

[8] de Wit, A. J. W. and van Diepen, C. A., "Crop model data assimilation with the Ensemble Kalman filter for improving regional crop yield forecasts", Agricultural and Forest Meteorology, 146(1-2), 38-56 (2007).

[9] Delécolle, R., Maas, S. J., Guérif, M. and Baret, F., "Remote sensing and crop production models: present trends", Journal of Photogrammetry and Remote Sensing, 47 (2-3), 145-161 (1992).

[10] Dorigo, W. A., Zurita-Milla, R., de Wit, A. J. W., Brazile, J., Singh, R. and Schaepman, M. E., "A review on reflective remote sensing and data assimilation techniques for enhanced agroecosystem modeling", International Journal of Applied Earth Observation and Geoinformation, 9(2), 165-193 (2007).

[11] Fensholt, R., Sandholt, I., Rasmussen, M. S. W., "Evaluation of MODIS LAI, fAPAR and the relation between fAPAR and NDVI in a semi-arid environment using in situ measurements", Remote Sensing of Environment 91, 490-507 (2004).

[12] Gamon, J. A., Field, C. B., Goulden, M., Griffin, K., Hartley, A., Joel, G., Peñuelas, J, Valentini, R., "Relationships between NDVI, canopy structure, and photosynthetic activity in three Californian vegetation types", Ecological Application 5(1), 28–41 (1995).

[13] Idso, S. B., Jackson, R. D., Pinter Jr, P. J., Reginato, R. J., and Hatfield, J. L., "Normalizing the stress-degree-day parameter for environmental variability", Agricultural Meteorology, 24, 45-55 (1981).

[14] Jackson, R. D., Idso, S. B., Reginato, R. J., and Pinter Jr, P. J., "Canopy Temperature as a Crop Water Stress Indicator", Water Resources Research, 17(4), 1133-1138 (1981).

[15] Launay, M. and Guérif, M., "Assimilating remote sensing data into a crop model to improve predictive performance for spatial applications", Agriculture, Ecosystems and Environment, 111(1-4), 321-339 (2005).

[16] Lebourgeois, V., Chopart, J-L., Bégué, A., and Le Mézo, L., "Towards using a thermal infrared index combined with water balance modelling to monitor sugarcane irrigation in a tropical environment", Agricultural Water Management, 97, 75-82 (2010).

[17] Martiné, J-F., "Modélisation de la production potentielle de canne à sucre en zone tropicale, sous conditions hydriques et thermiques contrastées. Applications du modèle", PhD Thesis, Institut National Agronomique Paris-Grignon, 132 p (2003).

[18] Tucker, C. J., "Red and photographic infrared linear combinations for monitoring vegetation", Remote Sensing of Environment, 8(2), 127-150 (1979).