COMBINING CROP MODEL AND REMOTE SENSING DATA AT HIGH RESOLUTION FOR THE ASSESSMENT OF RICE AGRICULTURAL PRACTICES IN THE SOUTH-EASTERN FRANCE
(TAKE 5 EXPERIMENT SPOT4-SPOT5)

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ABSTRACT

Crop systems are constantly changing due to modifications in the agricultural practices to respond to market changes, the constraints of the environment, the climate hazards... Rice cultivation practiced in the Camargue region (SE France) have decreased these last years, however rice plays a crucial role for the hydrological balance of the region and for crop systems desalinizing soils. The aim of this study is to analyze the potentialities of remote sensing data acquired at high spatial and temporal resolution (HRST) to identify the main agricultural practices and estimate their impact on rice production. A large dataset acquired over the Camargue from the Take5 experiment (SPOT4 in 2013 and SPOT5 in 2015), completed by Landsat data has been used. Two assimilation methods of HRST data were evaluated within a crop model. Results showed the impact of the spatial variability of practices on the yields. The sowing dates were retrieved from inverse procedures and gave satisfactory results compared to ground surveys.

1 INTRODUCTION

In Europe and in many parts of the world, agriculture remains a key component of the social and economic dynamics. However, these last years, many external factors such as the climate change, the environment protection, the market evolution led to significant changes in the crops systems [1]. Rice cropping practiced in the Rhône Delta area (SE France, 43°36'4.31N – 4°33'23.22E) called Camargue region have shown, these last years, great variations in the cultivated surfaces and in the yields. Various factors can explain this variability such as agricultural policy and technological development, climate hazards, soil and agricultural practice variability. In the Camargue region, rice plays a crucial role for the hydrological balance. The aquifer functioning is strongly influenced by water inflows related to agricultural activities (irrigation, flooded crop). Flooding of rice fields with water from the Rhone river contributes to control the soil salinity of groundwaters and ponds. Most of farmers cultivate rice crop because: (a) the flooded conditions reduce the salinity level and form irrigated lands useful for dry cereal crops in rotation and (b) the availability of fresh water is high. A wide variability is observed in agricultural practices from organic farming to high level of herbicides and fertilizer uses, inducing negative impacts on the environment. The agronomists are continuously struggling to enhance crop production with the use of minimum resources. This requires strategies to efficiently manage available resources with variable climatic conditions to increase productivity of agriculture. Crop models are useful tools to test different scenarios by varying climate, practices and soils conditions to analyze the impact on the yield and on the environment. A first step is to know the range of variability of the most important parameters of the model to apply it on a given region. If the implementation of crop models at plot scale is relatively simple because the information relating to soil and farming practices is easily accessible, the extrapolation to larger scales (farm scale or production area) is more difficult because soils and practices vary a lot in space, and can induce great differences in yields. Remote sensing, particularly acquired at fine spatial resolution can provide useful information for the spatialization of surface characteristics [8, 9]. Various types of crop models have been developed. They are characterized by their complexity and therefore their ability to be informed and thus spatialized [3]. Among them, STICS is a generic crop model developed since 1996 at INRA by [2], which can simulate rice among other crops, taking into account the main technical practices and the most common plant varieties encountered in Europe. It has been already used combined with FORMOSAT-2 data to map grassland productions in the Southeastern France [4] and with SPOT-VEGETATION images at France scale to improve pasture production diagnostic in the ISOP French system [5]. The Take 5 experiment[1] initiated by CNES and ESA[2] with the depointing of SPOT 4 in 2013 and SPOT 5 in 2015 has resulted in large time series of multi spectral images acquired at high resolution (described below) over the Camargue area. The aim of this study was then to evaluate the potentialities of such data close to Sentinel 2 configuration for rice monitoring and agricultural practice detection.

2 DATA SET AND METHODS USED

2.1 Data set description

The Take 5 experiment (described in http://www.cesbio.ups-tlse.fr/multitemp/?cat=72) was initiated by the CNES team (Toulouse) to simulate the image time series of Sentinel 2 before the launch of this last sensor, with a time revisit of 5 days for two periods: in 2013, from February to mid June with SPOT4 (20 m for the spatial resolution), and in 2015, from April to September in 2015 with SPOT5 (resolution 10m). Numerous scenes were acquired over 150 sites selected according to submitted projects. This dataset has been completed over our study area by Landsat data (LC8) downloaded from http://earthexplorer.usgs.gov/. All images were georeferenced and corrected from atmospheric effects according to the method described by [6] based on the use of multi-temporal images. 12 cloud free SPOT4 and 8 LC8 images were acquired over the Camargue area in 2013; 16 SPOT5 and 8 LC8 images in 2015. Landsat images were also used in 2011 (7 images) and in 2014 (11) in order to analyze the evolution of the rice surfaces for the last years. Additionally to this dataset, an accurate landuse map established by the natural reserve of Camargue has been used, including 40 classes, and a vector layer of the plot boundaries (figure 1)

Figure 1. Location of the study area with the footprints of the remote sensing images used (SPOT4 in red, LC8 in green and SPOT 5 blue) and the vector layer of the plot boundaries.

For the calibration of the crop model, we have used parameters provided by the dataset of F Ruget (INRA Avignon) and UMR innovation (INRA Montpellier) collected over more than one hundred rice fields the last years. Surveys were conducted with a few farmers in 2015, in order to know the key dates of agricultural practices: flooding, sowing and harvest dates, variety, nitrogen quantity brought and productions obtained.

2.2 Methods

- 1) The first stage of image processing consisted in computing vegetation index (NDVI) and analyzing the temporal profile of each rice field in order to identify some practices (flooding, sowing dates). Supervised classifications were elaborated each year considering several dates and all the spectral bands to better distinguish the different crops. Ground surveys performed were used to define reference classes. -2) Leaf Area Index (LAI), which is a key biophysical variable involved in the main processes that drive soil–plant–atmosphere exchanges and biomass accumulation, was then computed according to two methods described in [7]. The first method was based on the use of an empirical relationship with NDVI ‘described in [7], and the second one, relied on the combination of a radiative transfer model with a neural network [10]. Temporal interpolation was made using a non - linear fitting with 5 parameters to get daily LAI. -3) The third step was the use of the STICS crop model according to two strategies to get different information on rice crops. STICS runs at a daily time step with inputs describing climate, soil, plant and crop system. This model can either simulate LAI evolution varying according to water and nitrogen stress, or use daily values of LAI provided from remote sensing (RS) data. The quantities/doses of water and fertilizers can be also imposed as an input variable or calculated by the model. In a first stage, daily LAI interpolated from RS data were used as STICS inputs to quantify the impact of LAI variability on rice production at farm scale (all the other parameters were the same for the various study cases analyzed). For the second stage, punctual LAI values were assimilated in STICS according to the simplex optimization method to retrieve the sowing dates. In order to take into account the variability of farming systems encountered in Camargue area, we chose seven different types of crop systems defined by Delmotte [1,12]. Some farmers practiced rotation each year and sowed cereals after rice, while others made only rice. Few of them were organic farms beside others which used large quantity of herbicides and fertilizers. Performances of the crop model were evaluated comparing the outputs to the surveys made at farm scale.

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[1] http://www.cesbio.ups-tlse.fr/multitemp/?p=5784

[2] *CNES : Centre d’étude Spatiale, ESA : European Spatial Agency*

3 RESULTS

3.1 Evolution of Rice surface since 2011

Landuse classifications derived from RS data allowed a first analysis of the evolution of the rice surfaces since 2011. A decrease trend was observed on all the farms studied as shown in figure 2. For this example, in 2011 all the fields (32 plots) were in rice (in blue on the first color composite on 22/5/2011), in 2013, 14 fields became cereals fields (in red on 14/5/2013), in 2014:6 fields were cereals fields and in 2015, 10 from 32. A decrease of rice surface was also observed of around 30% on the other farms studied from 2011 to 2015.

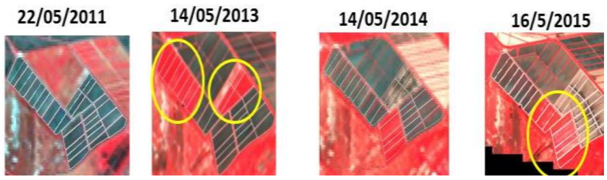


Figure 2. Rice fields at farm scale at different dates in May. (In red cereals, in blue rice, color composite obtained with green red and near-infrared spectral bands of SPOT4, SPOT5 and LC8)

There are various factors explaining this evolution, among them, the climatic conditions and the market variations are those mostly cited [1]. One of the task of the ScenaRice project (coordinated by UMR Innovation from Montpellier, France *see* http://umr-innovation.cirad.fr/projets/evaluation-integree-de-systemes-de-production-rizicoles-durables.-exploration-de-scenarios-probables-plausibles-et-possibles) is currently working on this topic among others.

3.2. Identification of some agricultural practices

The high spatial and temporal resolution of Take5 data allowed detecting the different practices before flooding such as the first labor to prepare the soil and the second sowing made by some farmers to prevent weeds as displayed in figure 3.

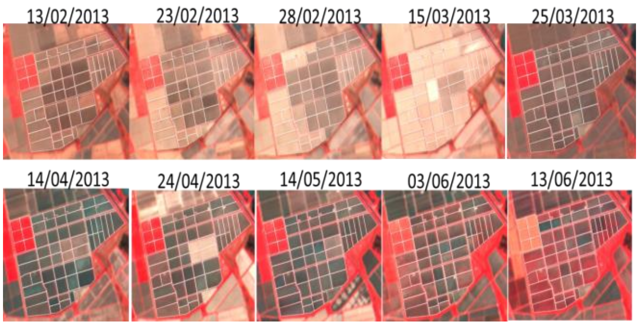


Figure 3. Color composites using Green, Red, and Near-infrared bands of SPOT4 over a farm of the Camargue region from February to June 2013. (In red cereals, in brown rice fields)

The plots at the center of the farm appeared darker than the others at 13/2/2013. They were plowed later than the other surrounding plots. The surface roughness and soil moisture of these plots conducted to low reflectances, compared to the fields around which appeared with higher reflectance values (light brown later the 23/2 and 15/3). The last fields were plowed and sown earlier. This time variability at farm scale induced a significant variability for the rice development (in the last image 13/6/2013, the young rice plants appear in red on the boundary of the agricultural domain).

The Figure 4 shows a comparison of the mean temporal NDVI profiles obtained for different farm types. The flooding can be well identified by the lowest values as already noticed by [8]. In 2013, different minimum peaks were observed. They corresponded to a second sowing. The climatic conditions were very bad in spring for soil preparation with a lot of rain in April and May. All farmers have not the same practices. Some farmers have chosen to plant again some plots because of bad seedlings and thus a second sowing can be identified from NDVI profiles.

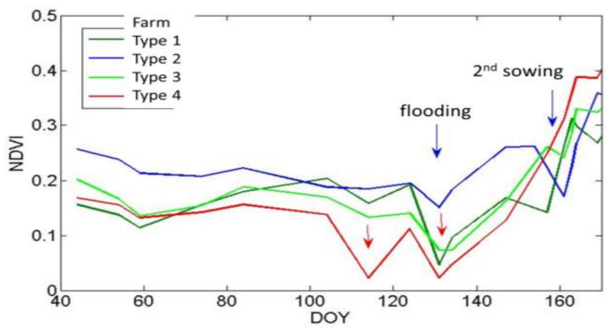


Figure 4. Comparison of temporal NDVI profiles for 3 farm types (Types 1 and 4 corresponded to 2 farms (36 and 32 plots respectively) partially organic with 70% rice, type 2: farm with breading and 35% rice (28 plots), Type 4: breading & 86 plots mixed cereal and rice).

A comparison of the NDVI profiles obtained for the different studied years (Figure 5) showed clearly that the high temporal revisit (in 2013 Take 5 experiment with an image every 5 days from Februry to June) allowed to detect more accurately the different agricultural practices performed at the beginning of the rice cycle. In 2011 and 2014 only Landsat data were available (with 8 and 9 images per year according to the cloud frequency). The time revisit appears not sufficient to capture these agricultural practices.

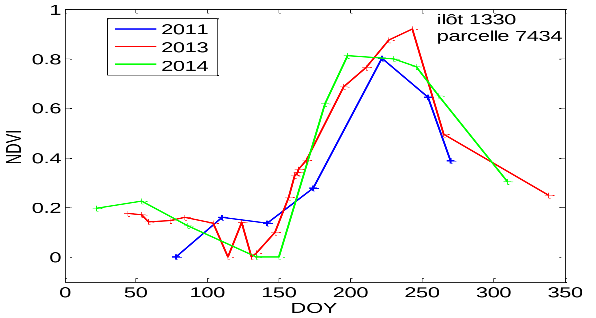


Figure 5. Comparison of NDVI profiles obtained for a rice field of the farm type 2 (îlot 1330) for the 3 years studied.

3.3 LAI analysis

A large variability of LAI has been observed at farm scale (Figure 6a). This variability can be due to different factors: differences in soils, fertilization, variety… but also due to variation in the sowing and flooding dates as shown in figure 6b. On this example, it was more the sowing date than the other factors which explained the two LAI groups observed in figure 6a. On the figure 6b obtained from ground surveys, we saw clearly two groups for the sowing: the first group at left was sown later on 10/5 when the other plots were already sown a week earlier around 2-3/5. A map of the maximum growth can be derived from the LAI profile corresponding to the inflexion point in the first period (figure 6c). Other heterogeneities appear which can be due to the soil or irrigation variations.

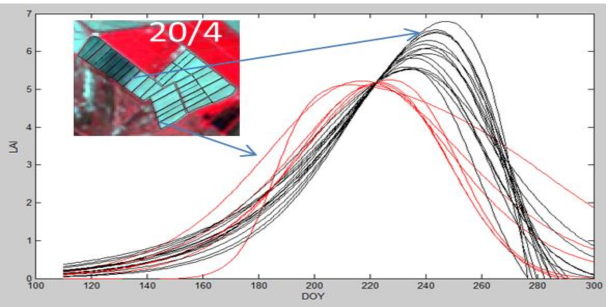
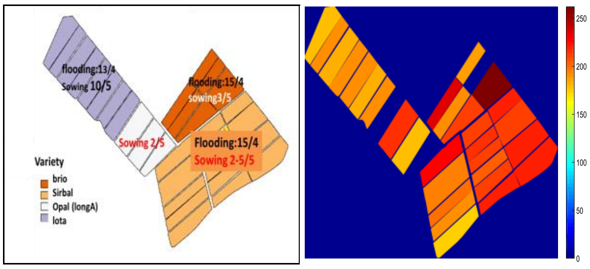


Figure 6.a) LAI profiles interpolated using a non – linear fitting with 5 parameters, for each plot of the farm displayed in figure 1.



b) Map of rice varieties encountered on the farm with the indications of the sowing and flooding dates in 2011 (obtained from surveys). c) Map of the date corresponding to the maximum growth obtained from the extraction of the inflexion point on the LAI profile at the beginning of the season.

3.4 Impact of LAI variability on rice production

Figure 7 show the production variability obtained for the same studied farm in figure 6 considering LAI derived from remote sensing data as forcing inputs in the STICS crop model. The rice variety and the soil parameters were identical for all the plots. A variability from 2 to 4 ton/ha was observed due to the LAI differences. The variability is much wider in 2013 than in 2011 and 2014, due to the bad climatic conditions encountered in 2013 at the beginning of the season as explained before.

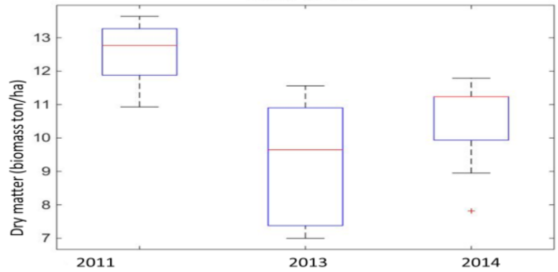


Figure 7. Variability of productions obtained at farm scale for the three years studied (expressed in dry matter simulated by the crop model using LAI derived from RS as input data).

Comparisons of some key parameters on phenology stages or production between years and farms represent useful information which can be derived from images and help to refine the crop system classification (Figure 7).

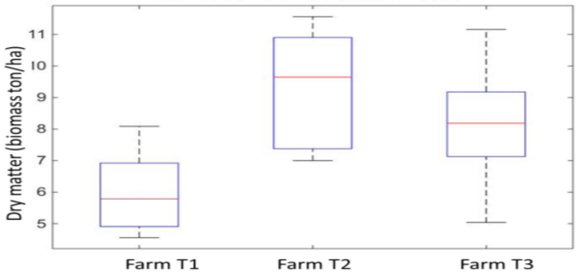


Figure 8. Boxplot obtained for the production of dry matter simulated by STICS for three different farm types in 2013 (see figure 4 caption for the main characteristics of the types).

3.5 Retrieval of the sowing date by inversion

The optimization has been done to obtain the sowing date assimilating the LAI observations for few study cases in 2013. Simulations gave a large variability from day of year DOY 113 (23/4/2013) to DOY 148 (28/5), with more than 75% of the plots between 122-137. Ground surveys gave a range between 112 and 130. Other simulations are necessary for different farms and years to test the method robustness. This work is currently underway.

4. CONCLUSION

The methods proposed here can be applied at different crops in various contexts and confirm the potential of remote sensing acquired at fine resolution such as the Sentinel2 system for agriculture applications and environment monitoring.

Acknowledgment

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