Application of an automatic rice mapping system to extract phenological information from time series of MODIS imagery in African environment: first results of Senegal case study

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Abstract. Among the three main cereals harvested in the world, rice it is the most important staple crop in terms of human consumption, especially in low- and lower-middle-income countries of Africa and Asia. The availability of up-to-date information on the crop season results a very important task for supporting food security initiative. In this contest the contribution of Remote Sensing images and technics could provide a strong contribution for near-real time agro-ecosystem monitoring system to retrieve spatial distribution information on large scale. The present paper aims to (i) evaluate the reliability of an automatic image processing methodology developed for rice detection and rice seasonal monitoring, and (ii) quantify remote sensed phenological metrics contribution to describe rice yields variability. The algorithm “PhenoRice”, was applied and tested on Senegal (West Africa), producing rice cropped areas maps and estimations of four phenological metrics: crop seeding/transplanting (MIN), start of season (SoS), peak/flowering (MAX) and maturity (EoS). These indices, together with the maximum value of NDVI in the season (NDVI-max), were estimated for each year of the period 2001 ÷ 2010 using temporal series of vegetation indices from MOD09A1 data. Remote sensing estimations were aggregated at regional and national level and used as independent variables in a multivariate model to explain yearly variability of rice production. Results demonstrate that: i) despite errors due to the well know low-resolution bias, the mapping method was able to detect the crop in the main rice districts of the study area, ii) the remote sensed seasonal indices were able to explain up to 75% of annual yield variability at regional level. The proposed approach can be of fundamental support for early warning monitoring system and for crop modelling simulation in areas where information on crop calendar are absent or not reliable.

Keywords. time series analysis, MODIS, rice, PhenoRice, developing countries, Senegal.

1. Introduction

Timely and accurate information on crop typology and status are required to support crop management and reduce food insecurity. This information is particularly important in Africa where rice is the most rapidly growing food source. It is estimated that about 30 million tons of rice will be needed by 2035, representing an increase of 130% in rice consumption from 2010. In this context, remote sensing represent a very important tool to derive spatially distributed information of crop status. Moreover, remote sensing derived crop mapping and phenological information are important inputs to crop growth models for yield forecasting. The following work is focus on Senegal, West Africa. This developing country is characterize by a strong rate of poverty (35th on the Global Hungry Index) [1] and a strong rice imports dependency: it is the 20th rice importer of the world with 706.700 tons (400% of the internal production) corresponding to value of 294,5 mUS$ (faostat.fao.org). Moreover the population's increase of the last 20 years produces a rice consumption not satisfied by national production, causing an increase of rice price and consequently food insecurity social troubles.

A rule based method, originally developed for rice monitoring and mapping in the Mediterranean environment was applied and tested on sub-tropical environment of Senegal (Africa). The method is based on an approach available in literature [2] that first identifies flood condition that can be related to rice agronomic practices and then checks for vegetation growth. The aim of this approach, named PhenoRice, is to detect paddy rice in a consistent and flexible way minimizing the dependency by local threshold adaptation. Our method presents innovative aspects related to the flood detection, and phenological stages estimation. The roots of PhenoRice are in the works performed by CNR-IREA [2] [3] . The main contribution of the approach proposed is the possibility of extracting phenological information along the actual and past seasons providing relevant information on crop cycle and agro-practices. The present work aims to: (i) evaluate the reliability of an automatic image processing methodology tested in Europe to map rice cultivation in Africa, and (ii) quantify how remote sensed phenological information are able to describe rice yields seasonal variability.

2. Materials

2.1 Study area

We focused our research on the agricultural land of Senegal The general climate condition are tropical, with a succession of the rainy season (from May to November) and a dry season (from December to April). The mean temperatures of the country vary between the 22° (winter) to 30°(summer). The Nord of the region (close to the Sahelian belt) has a strong daily excursion from 14° to 40° and the tropical part of the south has a high moisture. The annual amount of rains follows a latitudinal North-South gradient varying from 400 to 1200 mm/year.

In Senegal, rice agricultural cropping systems can be classified in two different groups: the first one, in the North part of the country around Senegal and Rounoum rivers, is characterized by extensive irrigated rice fields, with higher mechanization level and high seasonal productivity. The second one, mainly around Casamance river in the South, is characterized by small fields, mainly cultivated for livelihood and self-consumption aims. In the country, few information on rice cropping are availed.

2.2 Satellite and ancillary data

We based our work to the 8-days composite MODIS Surface Reflectance product MOD09A1 at 500m spatial resolution. This data product is made from a multi-step process that consider atmospheric, clouds and aerosol corrections and accounts for each pixel of the resultant image the best reflectance data registered during a 8 days' time window. The product is free to download from the United State Geological Survey (USGS) Global Visualization Viewer (GLOVIS) server (glovis.usgs.gov).

For the accuracy assessment of the moderate-resolution rice map, estimated by the algorithm, a higher spatial resolution land cover product were consider as ancillary data. This product's name is Senegal Land Cover Mapping, it was produced during the Global Land Cover Network (GLCN) project founded by the Food and Agriculture Organization (FAO). The land cover were developed with a 1:100.000 resolution scale and refers to the year 2005. Regional and national official yield statistic was also collected from FAO database (faostat.fao.org). These data were used perform regressive analysis with a prototype of yield forecasting system using indicators derived from the interpretation of remote sensing data (see §3.3).

3. Methods

3.1 PhenoRice algorithm

PhenoRice approach [2] [4] was develop to perform rice detection and rice seasonal monitoring by analyzing the continuous temporal signal of spectral indices. We developed a rule based method able to identify rice crop when a clear and unambiguous flood condition is detected and a consistent rapid crop growth is recognized. Once rice is detected the phenological monitoring is performed analyzing the temporal behaviour [3].

The algorithm involves four processing steps: 1) the automatic data acquisition of MODIS MOD09A1 8-days images from NASA archives, 2) the pre-processing that involves the calculation of the noise (B3 and cloud quality flags) and spectral indices, able to highlight the vegetation (NDVI) and flood conditions (LSWI); 3) the smoothing of temporal signal. NDVI series are smoothed using a local polynomial function that weight observation in relation to cloud contamination on the based on Savitzky-Golay filter [6] [7] and finally 4) the signal analysis and rice phenological detection. In this step first derivative of the smoothed signal is calculated and all points of local (relative) minima and local (relative) maxima identified. Rice crop minima (MIN) and maxima (MAX) points are then automatically identified using a series of criteria and then a temporal analysis is performed to derive the occurrence of the starting of rice growing season (Start of Season - SoS) end maturity (End of Season - EoS). These four metrics are able to provide important interpretations on the phenology of rice for the analysed agricultural seasons (Figure 1). The output of the algorithm is constituted by 5 different maps: a binary map on the presence/absence of crops in the study area and four maps reporting the occurrence of phenological stages (MIN, MAX, SoS, EoS). For a more detailed description of this method please refer to our past work [4].

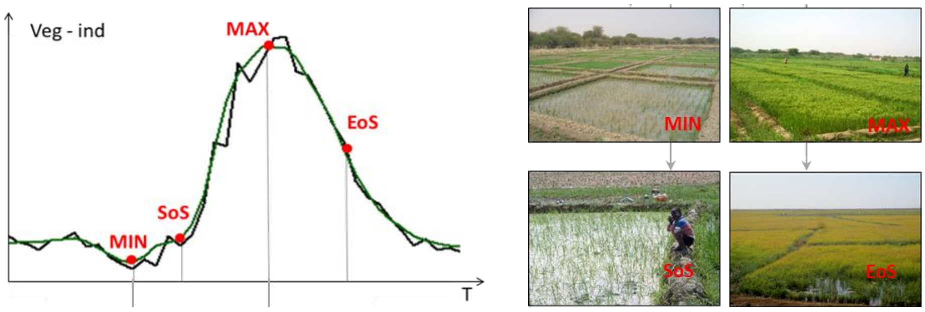

Figure 1. Timely occurrence and representation of phenological stages (MIN, MAX, SoS, EoS).

3.2 Retrieval of representative phenological metrics

In order to compare seasonal parameters extracted from RS with official yield statistics at regional and national scale, representative phenological metrics where extracted for a 25x25 km regular grid (**Errore. L'origine riferimento non è stata trovata.Errore. L'origine riferimento non è stata trovata.Errore. L'origine riferimento non è stata trovata.**Figure 2). This grid is a usually crop modeling standard, it covers all the Senegalese study area, for which meteorological data are available. For each cell a representative NDVI time series were calculated as the median of all the MODIS pixel included in the FAO rice layer polygons (blue layer in Figure 2-C). The time series extracted have been processed with PhenoRice algorithm previously described, for each year from 2001 to 2011. This procedure allowed us to retrieved for each cells, rice seasonal metrics (MIN, SoS, MAX, EoS) and also NDVI value at MAX (Figure 2-D). Once extracted the phenological occurrence, referred to MODIS composite, were reported to a regular ten days step and convert in Day of Year (DOY) time unit.

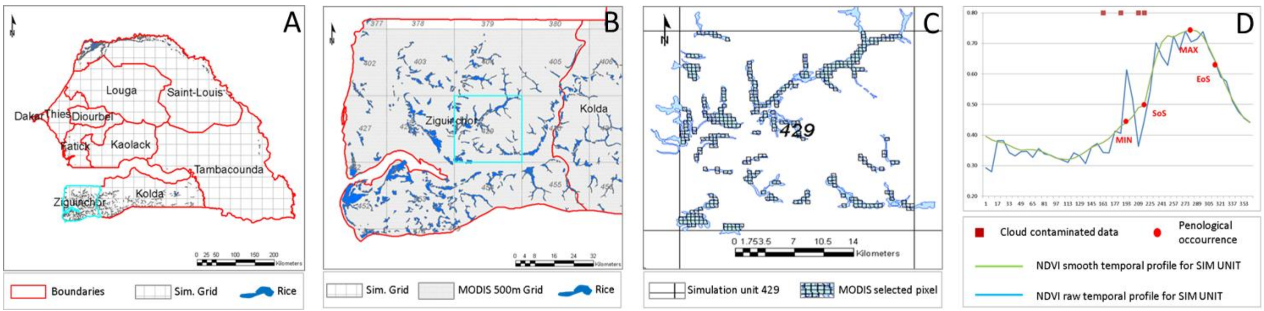

Figure 2. Steps for the retrieval of representative phenological statistics: A) study area, B) selection of a simulation unit grid, C) identification of Modis pixel on FAO rice boundaries and D) extraction of representative VI time series and phenological estimation.

3.3 Statistical analysis and correlation with official rice yields

One of the most widespread methods for crop yield forecasts is based on relationships (usually multiple regressions) between official yields and indicators, i.e. simulated state variables or indices derived from remote sensing (RS) at the moment when the forecast is needed. This relationship – in the form of $Y = f(\text{indicators})$ – is derived using historical series of indicators and official yields, used to predict the yield for the forecasting season, with current season indicators used as regressors. A leave-one-out cross-validation procedure is thus applied to identify, as a percentage, the regression model capability to explain the yearly variability in yields. Once the best regression model is identified, it is applied to the current year to estimate yield from indicators. A prototype of a yield forecasting system was developed for rice in Senegal. The five indicators used in the regression models (MIN, SoS, MAX, EoS, NDVI-max) were obtained and referred to a 25 km grid for each analyzed year, as described in the previous paragraphs. The regressions were performed for all the crop growing seasons, with the aim to provide a forecast triggered at maturity. These indicators were then aggregated at regional and national level, using a weighted mean based on rice area of each grid cell.

4. Results and discussion

4.1 PhenoRice output

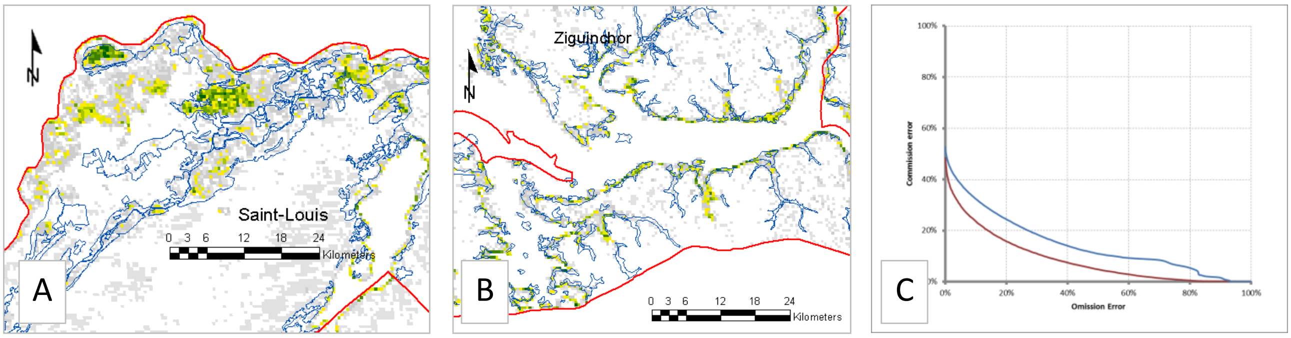

Figure 3. Occurrence of rice detection for the period 2002-2010. Blue and red lines represent respectively GLCN land cover (rice layer) and administrative boundaries. In greenish colors detection identified from 4 to 10 times, in grey detection occurred less than 3 times. A) Zoom on Saint-Louis region, B) Zoom on Ziguinchor region, C) results on Pareto boundary analysis of the Senegalese study area (blu) compared to Italian condition.

Figure 3 reports for two zooms, on Saint-Louis region (Figure 3-A) and Ziguinchor region (Figure 3-B), the results of rice mapping for the period 2002-2010. Rice was easily and consistently identified, more than four time and up to ten, over the large agronomic district of Saint-Louis (Nord of Senegal, Figure 3-A). On the contrary results for the Ziguinchor region (Sud of Senegal, Figure 3-B), indicates that rice detection is more complicate where there is an higher landscape fragmentation characterized by small field. In general it is possible to highlight that the method is able to identify the main rice districts of the study area but it isn't a robust approach to produce rice extent maps in Senegal because of low resolution data used. Pareto boundaries analysis is reported in Figure 3-C, this method can provide an interpretation of the mapping results [8]. The inaccuracy in the mapping is introduced by the difference in spatial resolution between high (FAO-GLCN) and low data (MODIS based) and not related to the performances of classification algorithm [8]. This low resolution bias is a function of shape, size and fragmentation of the ground target under analysis. Blue and red lines of Figure 3-C represents respectively the Pareto boundaries for the Senegal case study and the Italian condition analyzed in a previous research [4]. The figure reveals that Senegal case study has an higher potential bias in the omission/commission error space, up to 60% of comission error, when compared to Italy where the method provided only 13 % of commission error [4].

4.2 RS parameters relation to yield seasonal variability

Figure 4 shows an example of the result obtained after the extraction of phenological metrics (indices) on 25x25 km simulation units. Northern units of Saint-Louis and Louga regions show an emergenge period around July (MIN), a green-up period near August (SoS), a peak in September

(MAX) and a maturity in October/November (EoS). In Zinguichor and Kolda Southern regions, the rice season occur is anticipated, with MIN in April/May, SoS in May, MAX in July/august and EoS in November/December. The analysis reported in figure 4 was performed for each year of the period 2001-2011 and the database produced was statistically analyzed with a multiple regression and compared with official statistics.

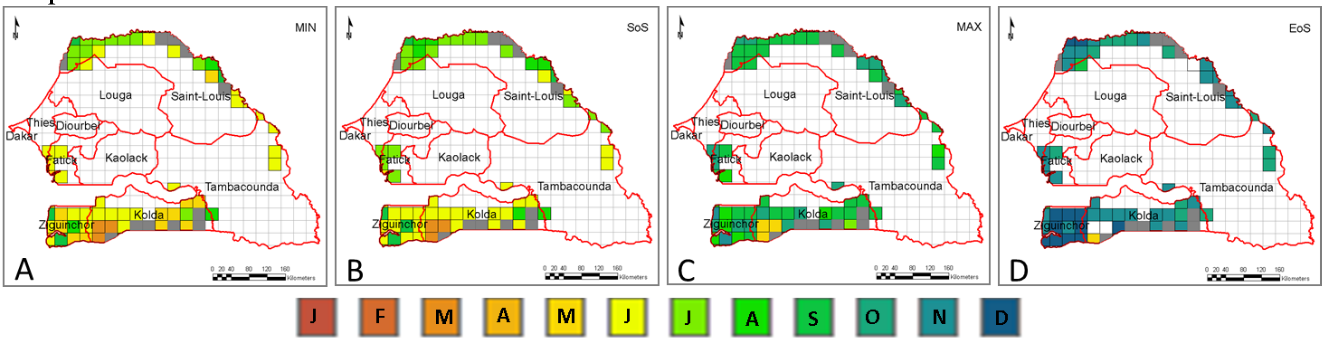

Figure 4. Representation of MIN (A), SoS (B), MAX (C), EoS (D) Remote Sensed indices on the 25km simulation grid for the year 2008. These data were produced for each year of the years 2001-2010.

Table 1 shows the results obtained from the statistical analysis for the period 2001-2010 both at national and regional level. It is reported only the best regression model for each region, based on a stepwise regression with a maximum of four indicators. The RS contribution to the multiple regression it is always significant, and reaches higher value (i.e. > 50%) where there is no trend. Only in one site with no trend (Tambacounda) RS explain less than 30% of the variability, but it is a region with low presence of rice cultivation. In Table 1 the phenological indicators are ordered from the most relevant to the least one. Among the 5 regions the phenological stage of MIN, meanly, is the most significant.

Table 1. Results of multiple regression analysis.

Level	Trend	R^2			Selected indicators
		tot	trend	remote sensing	
Senegal	linear	0.777	0.485	0.292	EoS, Min, Max, NDVImax
Saint-Louis	linear	0.880	0.314	0.566	Min, Max, NDVImax, SoS
Kolda	none	0.776	0	0.776	EoS, Min, Max, SoS
Fatick	quadratic	0.836	0.714	0.122	Min, Max, NDVImax, SoS
Tambacounda	none	0.296	0	0.296	EoS, Min, NDVImax, SoS
Zinguichor	none	0.598	0	0.598	Min, Max, NDVImax, SoS

At national level, the official yields time series (especially for the last three years) is characterized by a marked production increase due to the introduction of technological innovations (i.e., high-performing varieties, more inputs), so a great part of the yearly yields variability (i.e. 48%) is explained by a linear temporal trend (Table1). Results show that globally the best regression model – derived from de-trended official yields – is characterized by a coefficient of determination of 0.78 (Table1), where the contribution of remote sensed indicators explain up to 29% of the variability. The same statistical analysis was performed at regional level for the administrative units where rice is cultivated. Results for two regions are shown as examples: (i) Saint-Louis, at the north of Senegal, where rice is irrigated and yields time series is characterized by a linear trend (less marked then the national one) (Figure 5-1a); (ii) Kolda, at the south of Senegal, where rice is produced for subsistence, where there is no trend in the yields series (Figure 5-2a). In the first case the regressive model explains 88% of yields variability (Figure 5-1b) and only 31% of this is represented by the supposed technological trend (Figure 5-1a). In the second region, where there is no technological trend (Figure 5-2a), RS indicators are able to explain 78% of yields variability (Figure 5-2b).

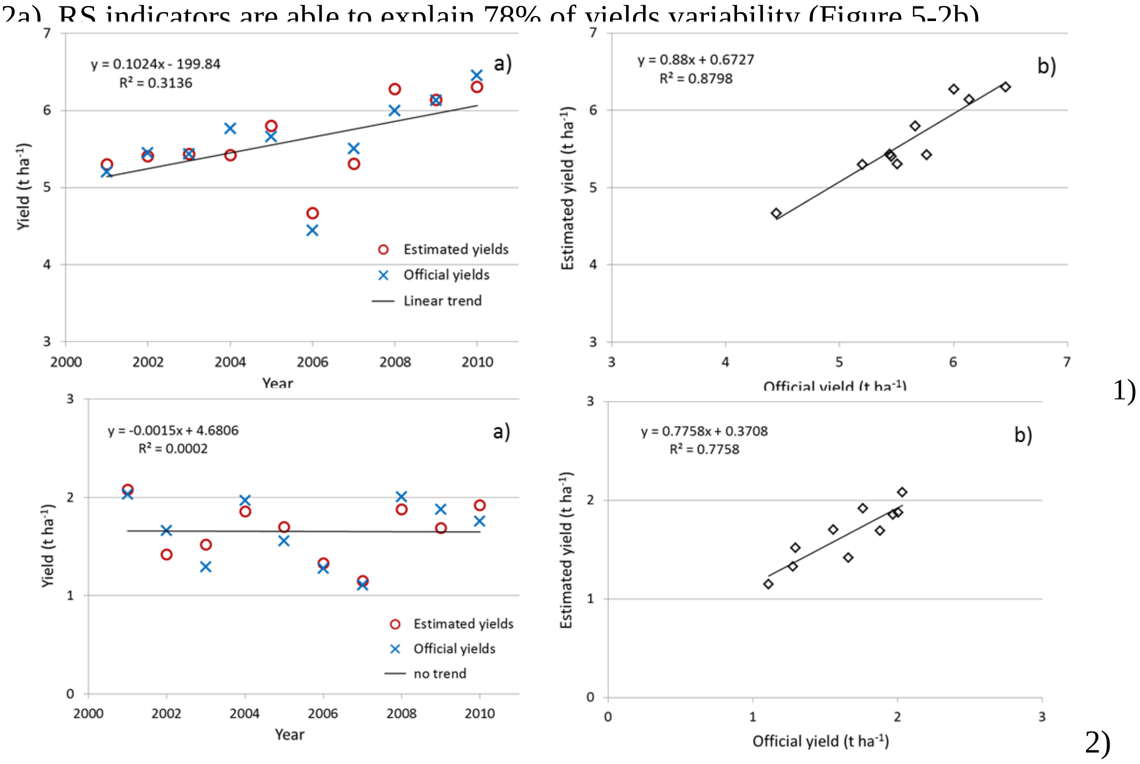

Figure 5. Trend of official and estimated yields in the period 2001-2010 and linear technological trend in the regions of Saint-Louis (1a) and Kolda (2a) and comparison between official and estimated yields in Saint-Louis (1b) and Kolda (2b).

5. Conclusions

We analyzed 10 years (2001-2011) of MODIS data with the PhenoRice algorithm to evaluate the reliability of automatic rice mapping and the contribution of phenological indices to describe rice yield variability. The test was conducted in Senegal were rice production was booming during the last years. Results show that the method, calibrated on temperate area in Europe, was able to detect rice for the majority of the analyzed years, in the larger agronomic districts of the Northern Senegal. However rice detection was critical in the southern fragmented rice systems, with frequents commission errors in the forest areas along the rivers. A specific calibration of the method for this environment should be considered in the future.

The phenological metrics, estimated by time series analysis within rice boundaries of GLCN FAO land cover, resulted of extreme importance for crop monitoring. In particular phenological information were able to explain significantly the seasonal variability even for regions without any temporal trend in rice production (Kolda 77.6%). These preliminary results are very encouraging and suggest that monitoring system based on remote sensing data can provide a useful tool to support food security action. For this reason, further development of this study are related to the integration of these phenological metric information as inputs for spatialized crop growth models for yield forecasting systems.

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