PREDICTING SUGARCANE YIELDS IN KHUZESTAN USING A LARGE TIME-SERIES OF REMOTE SENSING IMAGERY REGION

M. Khosravirad[1], M. Omid[2*], F. Sarmadian[3], S. Hosseinpour[4]

[1] Agricultural Mechanization, Faculty of Agricultural Engineering and Technology, College of Agriculture and Natural Resources, University of Tehran, Karaj: Iran - mkhosravirad@ut.ac.ir

[2] Department of Agricultural Machinery Engineering, Faculty of Agricultural Engineering and Technology, College of Agriculture and Natural Resources, University of Tehran, Karaj: Iran – omid@ut.ac.ir

[3] Department of Science and Soil Engineering, Faculty of Agricultural Engineering and Technology, College of Agriculture and Natural Resources, University of Tehran, Karaj: Iran – fsarmad@ut.ac.ir

[4] Department of Agricultural Machinery Engineering, Faculty of Agricultural Engineering and Technology, College of Agriculture and Natural Resources, University of Tehran, Karaj: Iran – shosseinpour @ut.ac.ir

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ABSTRACT:

This study aimed to evaluate the power of various vegetation indices for sugarcane yield modelling in Shoeibeyeh area in Khuzestan province of Iran. Seven indices were extracted from satellite images and were then converted to seven days' time-series via interpolation. To eliminate noise from the time-series data, all of them were reconstructed using the Savitzky-Golay algorithm. Thus seven different time-series of vegetation indices were obtained. The growth profile was drawn via averaging of NDVI time-series data and was divided into three growth intervals. Then the accumulative values of vegetation indices related to first and second periods of growth (from 2004 to 2016 extracted from time-series data) were evaluated by simple linear regression models against the average observed yields efficiency. The result showed the accumulative IAVI (γ=1.4) vegetation index relative to first period of growth with R^2=0.66 and RMSE=3.78 ton/ha and the accumulative NDI vegetation index relative to second period of growth with R^2=0.66 and RMSE=3.79 ton/ha and the accumulative NDI vegetation index relative to sum of the first and the second growth periods with R^2=0.78 and RMSE=3.09 ton/ha had good agreement with sugarcane stem yield efficiency at the middle of growth and before harvesting season.

1. INTRODUCTION

Sugarcane (Saccharum spp. L.) is a widely grown semi-perennial crop that plays a major role in global agriculture for the production of sugar and other by-products/co-products such as bioethanol, rum, bagasse, fertilizer, filter muds etc.(Duveiller, López-Lozano, & Baruth, 2013). It is a tropical crop which grows between latitude 35°N and latitude 30°S. The ideal climate for sugarcane is a long, warm growing season and a fairly dry, sunny, cool, but frost-free ripening and harvest season (Humbert, 1968). The growth of sugarcane is characterized by three development stages: (i) sprouting and tillering, (ii) stalk growth, and (iii) maturation. The maturation is triggered by a decrease in soil water content, temperature, and nitrogen availability and it is characterized by the end of stalk growth and modifications in the stalks and leaves; sucrose accumulates and chlorophyll, leaf water content and turgor decline (Hsiao, 1973). More than 27 million hectares of agricultural land is devoted to growing sugarcane globally. Brasil, India and China with respectively 10419113,5012000,1768 hectares ranked first to third. Iran with 93677 ha of sugarcane is tanked 27th place in the world (FAOSTAT, 2017). Though Iran sugarcane production fluctuated substantially in recent years, it tended to increase through 1965 - 2014 period ending at 6.59 million tones in 2014. The cane planting area in Iran is dispersed only on Khouzestan province and covers about 120000 ha.

Remotely sensed data are the most widely used means of studying global vegetation changes, especially in light of climate change concerns (Julien & Sobrino, 2010). Time series of vegetation indices are used in numerous applications ranging from ecology to climatology and agriculture. Often, these time-series have to be filtered for a specific application (Atzberger & Eilers, 2011). In Mianab region of Iran sugarcane yield was estimated via time series evaluation of NDVI, GNDVI and EVI vegetation indices and the results showed that NDVI and GNDVI vegetation indices with R^2=0.63, RMSE=4.71 ton/ha and R^2=0.60, RMSE 4.93 ton/ha, respectively, have good relations with sugarcane stem yield efficiency in regional scale (Khosravirad, Omid, Sarmadian, & Hosseinpour, 2019).

Many time-series smoothing methods can be used for reducing noise and extracting plant phonological parameters from remotely-sensed data, but there is still no conclusive evidence in favour of one method over the others (Cai, Jönsson, Jin, & Eklundh, 2017). There is a clear interest for managers and decision-makers to have tools capable of monitoring continuously the vegetative vigour of sugarcane and providing timely information regarding potential short-term impacts of weather conditions on yield expectations. Crop growth information provided weekly in the crop season is essential to appropriately plan irrigation and fertilizing operation. Early and accurate crop forecasts offer substantial benefits to the sugarcane industry through better logistical management, increased profitability and improved customer satisfaction(Everingham et al., 2002).

Currently, the in-season estimation of yield is undertaken using visual or destructive sampling techniques by either growers or

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mill funded productivity experts. However, this method is labour intensive with accuracies influenced by varied seasonal climatic conditions, crop age due to an extended harvest period and human error (Robson, Abbott, Lamb, & Bramley, 2012); Rahman and Robson, 2016). The spectral equations were used in this study are tabulated in Table 1.

VI	EQUATION	Reference
NDVI	$(R_{NIR}-R_{red})/(R_{NIR}+R_{red})$	(Rouse et al, 1974)
NDI	$(R_{NIR}-R_{MIR})/(R_{NIR}+R_{MIR})$	(Mcnairn & Protz, 1993)
GNDVI	$(R_{NIR}-R_{green})/(R_{NIR}+R_{green})$	(Gitelson et al, 1996)
SAVI	$2(R_{NIR}-R_{red})/(R_{NIR}+R_{red}+1)$	(A. R. Huete, 1988)
EVI	$2.5(R_{NIR}-R_{red})/(R_{NIR}+6R_{red}-7.5R_{blue}+1)$	(A. Huete et al, 1994)
IAVI	$\{R_{NIR}-[R_{red}-\gamma(R_{blue}-R_{red})]\}/\{R_{NIR}+[R_{red}-\gamma(R_{blue}-R_{red})]\}$	(Zhang, Rao, & Liao, 1996)
GARI	$\{R_{NIR}-[R_{green}-\lambda(R_{blue}-R_{red})]\}/\{R_{NIR}+[R_{green}-\lambda(R_{blue}-R_{red})]\}$	(Gitelson et al., 1996)

Table 1. Spectral Equation of Vegetation Indices

This research aimed to determine the sugarcane growth profile based on the time-series of NDVI vegetation index and then evaluate seven vegetation indices for sugarcane modelling and, finally, indicate the appropriate vegetation index for predicting sugarcane yield at the middle and end of the growth period.

2. MAIN BODY

2.1 Study Area

The study was carried out at Imam Khomeini sugarcane Agro-industry in Shoeibeyeh region located in the north of Khuzestan in Iran. The area is located between longitudes 48˚38'34"E and 48˚50'14"E, and latitudes 31˚39'2"N and 31˚55'23"N covering an area of 12000 ha.

2.2 Remote Sensing Data

In total, 474 Landsat 7 satellite images from March 2003 to February 2017 were examined and evaluated. All of the images were calibrated and were converted to surface reflectance via FLAASH algorithm. For each vegetation index, the individual time-series was formed from 2003 to 2017. Each of the seven time-series was converted to 7-day time-series via interpolation and then it was corrected using the Sawitzky-Golay smoothing method. By averaging the NDVI time-series, the sugarcane growth profile was modelled in the studied area. Because of climatic conditions, from the four growth profile standard stages of including germination, vegetative growth, flowering and maturing, no two late stages in the studied region in Iran was observed. The end of the development of sugarcane stems was considered as the beginning of the stage of the maturity. So the sugarcane growth profile was split into three stages. Finally, the cumulative value of seven vegetation indices for the first and second growth stages for 2003 to 2016 were extracted from related time-series.

2.3 Observed Sugarcane Yield

The observed sugarcane stem yields in the studied area were extracted from the database archives of Imam Khomeini Sugarcane Industrial Company, Table 2.

Year	2004	2006	2007	2010	2011	2012	2013	2014	2015	2016
Yield	88.32	86.83	75.02	86.05	81.11	67.63	74.77	79.88	78.6	84.52

Table 2. observed sugarcane yield(ton/ha)

2.4 Sugarcane Yield Models

Simple regression method was used for determination of the appropriate vegetation index for sugarcane yield modelling. The cumulative vegetation index related to first, second, and total growth stages were extracted from time-series data and they were related to final sugarcane stem yields via three different models. Data from the third stage of the growth profile due to harvesting were not used in modelling. By evaluating R^2 and RMSE indices, suitable models for growth stages were selected. The data of 2017 was used for validating and testing of the selected models.

3. RESULTS

In Figure 1 the time-series of three vegetation indices which provided good results against NDVI are shown.

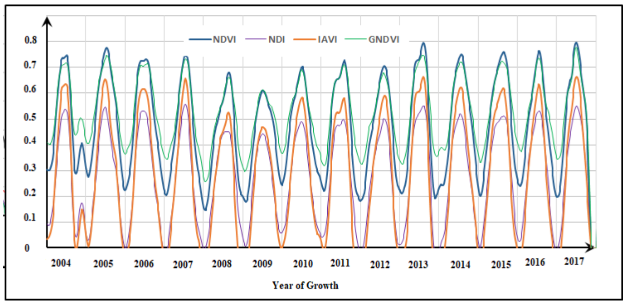

Figure 1. Time series of NDVI, NDI, IAVI, GNDVI

By averaging the NDVI time-series, the sugarcane growth profile was modelled in the studied area (Figure 2). The curve fitting tool in MATLAB was used to parameterize the growth profile. The fourth-degree polynomial equation was selected because it had the best correlation to real data (R^2=0.99).

$$Y = aX^4 + bX^3 + cX^2 + dX + e \quad (1)$$

where
X= Days distance from first of year {6,7,8,…,186}
Y=model value for NDVI
a=0.000000000518
b=-0.000000382
c=0.0000737
d=-0.00122
e=0.248

The minimum, maximum and turning points of curve were calculated directly by the differential operation. Based on these important points growth profile was split into three stages. In the start of the first stage, plant growth begins and growth velocity is reached to the maximum at the end of stage. In the second stage, the growth vegetation continues but growth velocity is decreased so that at the end of this stage it will be equal to zero. At stage three, maturity starts due to irrigation stopping and temperature decreasing. Due to the beginning of the harvesting season in the third stage of growth, Equation 1 is not valid for this stage and it doesn't apply in modelling.

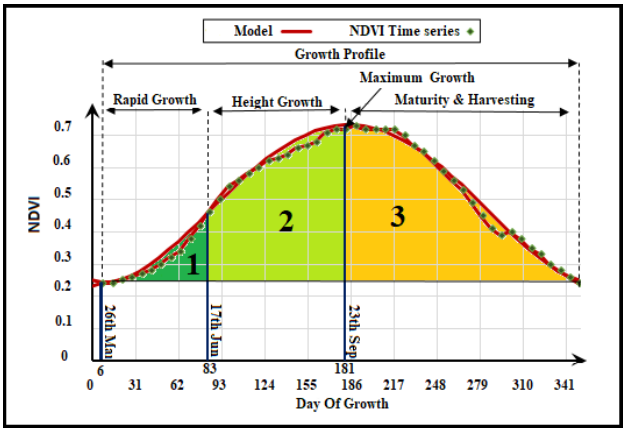

Figure 2. sugarcane growth profile based on NDVI

To model the sugarcane yield, the values of cumulative vegetation index were related to observed sugarcane stem yields. Three methods with seven vegetation indices resulted in 21 different models that each model was examined separately. In Table 3, the coefficients of determination (R^2) and RMSE of these models are presented for comparison. Methods 1 to 3 are corresponded to first, second and sum of first and second stages of growth profile, respectively.

GARI	IAVI	EVI	SAVI	GNDVI	NDI	NDVI		Method
0.65	**0.66**	0.47	0.53	0.56	0.55	0.60	R^2	1
3.86	**3.78**	4.73	4.46	4.33	4.35	4.1	RMSE	
0.61	0.59	0.53	0.51	0.53	**0.66**	0.53	R^2	2
4.04	4.18	4.46	4.54	4.45	**3.79**	4.45	RMSE	
0.73	0.73	0.65	0.66	0.77	**0.78**	0.74	R^2	3
3.36	3.37	4.04	3.82	3.14	**3.09**	3.32	RMSE	

Table 3. comparison of model evaluation coefficients

The results show that the IAVI vegetation index with R^2=0.66 and RMSE=3.78 ton/ha is the best indicator for sugarcane modelling at the end of the first stage of growth. Also, the results showed that the NDI vegetation index with R^2=0.66 and RMSE=3.79 ton/ha for stage two, and R^2=0.78 and RMSE=3.09 ton/ha for the sum of stages one and two is the best indicator for sugarcane stem yield modelling. The results show popular vegetation indices like NDVI are not appropriate for monitoring the second stage of sugarcane growth and is confirming other researcher results. Some researchers reported that the NDVI can saturate in large biomass crops such as sugarcane with an LAI greater than three (Benvenuti and Weill, 2010; Bégué et al., 2010). The parameters of the selected models are given in Table 4.

Yield equation	Coefficients		Growth Stage		VI	model
	a	b	۲	۱		
$Y=ax_1+b$	10.04	68.61		✓	IAVI(γ=1.4)	۱
$Y=ax_2+b$	11.49	10.36	✓		NDI	۲
$Y=a(x_1+x_2)+b$	7.69	22.68	✓	✓	NDI	۳

Table 4. Selected models parameters

Using the third model, the sugarcane yield in 2017 was estimated as 85.57 ton/ha, which was 0.25 ton/ha more than the actual value.

4. CONCLUSION

Based on the results, the suitability of IAVI index (with γ=1.4) for in-season sugarcane monitoring was confirmed. Also, results have shown NDI vegetation index has a very good ability to predict sugarcane yield one month before harvesting season.
The NDI vegetation index uses short-infrared to normalize the near-infrared. So in the NDI equation, it does not use visual spectrum. Maybe this is the reason for better response to the second stage of growth. On the other hand, according to the results, the NDI can be used for sugarcane growth monitoring instead of other vegetation indices. The results of this research are satisfied with the study region but it should be examined for other regions.

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