Dynamics modeling for sugarcane sucrose estimation using time series satellite imagery

Yu Zhao*[a], Diego Della Justina[b], Yoriko Kazama[a], Jansle Vieira Rocha[b], Paulo Sergio Graziano[b], Rubens Augusto Camargo Lamparelli[b]
[a]Hitachi, Ltd., Research & Development Group, 1-280, Higashi-koigakubo, Kokubunji-shi, Tokyo, 185-8601 Japan; [b] Univ. Estadual de Campinas, Campinas-SP, Brazil;

Abstract

Sugarcane, as one of the most mainstay crop in Brazil, plays an essential role in ethanol production. To monitor sugarcane crop growth and predict sugarcane sucrose content, remote sensing technology plays an essential role while accurate and timely crop growth information is significant, in particularly for large scale farming. We focused on the issues of sugarcane sucrose content estimation using time-series satellite image. Firstly, we calculated the spectral features and vegetation indices to make them be correspondence to the sucrose accumulation biological mechanism. Secondly, we improved the statistical regression model considering more other factors. The evaluation was performed and we got precision of 90% which is about 20% higher than the conventional method. The validation results showed that prediction accuracy using our sugarcane growth modeling and improved mix model is satisfied.

1. INTRODUCTION

Agriculture is one of the most important markets all over the world. The recent trend of agriculture is moving towards precision farming, which gives rise to great demands for IT supports. For the agriculture production efficiency and cost reduction, the modern agriculture no longer exists in farm fields only, but expands quickly in information fields as well. The future of precision agriculture is considered highly promising, and lots of solution packages will be developed to support farming activities during the entire farming cycle.

As one of the most important agricultural derivatives, Ethanol production has been paid attention and there is increasing demand for quantity and quality incensement. Sugarcane, as one of the most mainstay crop in Brazil, plays an essential role in ethanol production. Sugarcane is a semi-perennial crop of high biomass production and rapid plant development. Currently, sugarcane crop is cultivated in approximately 80 countries in different climatic zones (tropical, semitropical, and subtropical). The main economic attraction is to produce large amounts of sugar and ethanol. Brazil has almost half of the world's sugarcane production and over about 50% of Brazil's sugarcane harvest is used for ethanol production. In Brazil, as in other countries, sugarcane quality is determined based on its sugar content, known as commercial cane sugar (CCS). CCS is derived from Brix (soluble solids content), Pol (sugar content measured using the property of optical activity which causes polarized light to be rotated) and fiber content (Nawi et al., 2013). It is believed that sugarcane dry matter production is related to stalk sucrose accumulation. Therefore, in sugarcane crop quality monitoring (sucrose per hectare), a technique has to be created to evaluate sucrose spatial distribution. Thus and analysis of the spatial distribution of dry matter production (and yield) is first required.

To monitor crop growth and predict crop yield, accurate and timely crop growth information is significant, in particularly for sugarcane large scale farming. As the large-scale farming field in the countries like Brazil, ground observation has the limits. Accordingly, remote sensing observation using satellite imagery gives rise to great potential for observing and mapping the ground objects.

In remote sensing observation, high-resolution image is useful to get accurate stationary information for monitoring the crop. However, there are some issues to be solved. One factor is that a considerable volume of high resolution satellite image data, which is very expensive, is required to cover large areas of farm land, and it eventually makes the data cost too expensive to be operational, and another factor is data availability. Because high resolution satellites revisit the same place on the Earth surface at an interval of several days, additionally disturbance of weather conditions, such as cloud, its valid data is relatively limited. Therefore, low-resolution image with reasonable price and good data availability is considered to be well suitable for monitoring. However, because of the low resolution, there is a problem on analysis

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precision. If we can strengthen the analysis precision, the low-resolution will meet the need for large-scale agriculture. Another consideration is that, if both of high and low resolution satellite images could be combined in modeling, it could be a reduction of total cost as well as a promotion for the final prediction accuracy.

Our goal of this research is utilize the time-series satellite imagery to model the sugarcane growth. Our objectives are as the follows:

- To develop an optimized crop growth model to predict the sugarcane sucrose content using combined satellite imagery, we set the target precision as 85%;
- To verify the feasibility of method and try to attain a feasible performance;
- To demonstrate an alternative with good cost performance for building up an operational agriculture crop monitoring and yield estimation service.

2. RESEARCH METHODOLOGY

2.1 Vegetation analysis using spectral information of satellite imagery

Traditional crop analysis methods based on remote sensing data use the statistic and semi- empirical relationships between Ground Biomass and vegetation index, which are the combinations of different bands. The bands for calculating vegetation index for crop analysis can be extracted from satellite imagery. Crop field polygon which contains location and shape information is used to mask the satellite imagery and extract our interest farming fields, from which, the spectrum information can be obtained. Spectrum is light intensity distribution as a function of wavelength.

What we can know from the crop spectrum is showed in Fig1. Different crop growth situation will have different spectral information. All the information can be described by a popular vegetation index, NDVI (Normalized Difference Vegetation Index) (1). NDVI indicates vegetation growth activity and has strong correlation with crop's dry matter which affects the final yield of crop. Therefore, NDVI is often used in vegetation analysis such as yield prediction.

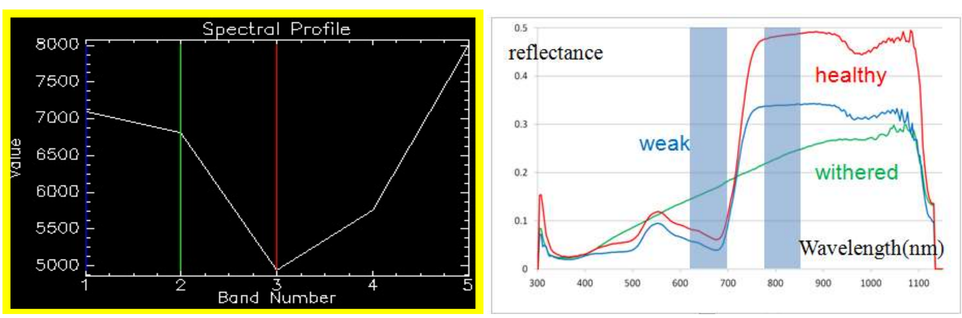


Figure 1: Information in satellite imagery

$$NDVI = \frac{IR - R}{IR + R} \qquad (1)$$

where R and IR stand for the spectral reflectance measurements acquired in the visible (red) and infrared regions, respectively. The advantage of NDVI over a simple infrared/red ratio is therefore generally limited to any possible linearity of its functional relationship with vegetation properties (e.g. biomass). Nevertheless, the normalized calculation can be performed in other two bands except red and infrared red, which can be called NDVI_XY. NDVI_XY also could indicates some vegetation growth situation and widely used in vegetation analysis.

In this research, as we have mentioned before, we tend to develop the sugarcane growth model to predict sugarcane yield using tame-series satellite imagery. Conventional method [3] firstly chooses all the NDVI data as the independent variable for the yield prediction. Then, mean, maximum and minimum value of the whole NDVI data set is calculated and set as the independent variable. Moreover, they analyze the correlation of the yield and the temperature which is also used as one of the independent variable. Using the NDVI data and statistical calculated data as the index, yield is set as the dependent variable for which regression analysis is applied for yield prediction.

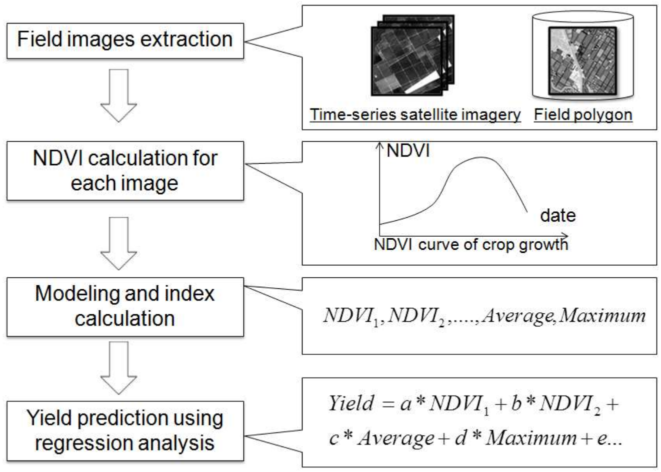


Figure 2: Conventional method of yield prediction

In this research, we will take the framework as the basic reference and propose methods on some issues in the part of conventional modeling and index calculation. Conventionally, biological growth stage cannot be well modeled using pure time-series vegetation index. The model and index which is calculated by some statistical model can hardly illustrate the true growth mechanism of crop and even for the yield component formation. A model integrating biological model and statistical model is considered more feasible to illustrate the crop growth process and predict crop yield.

2.2 Sugarcane growth process

The growth stage of the sugarcane may be divided in four phases: initial, vegetative growth, in which growth is slow, a rapid growth phase, with the emergence and elongation of internodes, which accumulates about 75% of total dry matter, and the final phase, with the slowing down of biomass accumulation rates, sucrose concentration, a natural ripening process in the sugarcane stalks, ending with the harvest.

The duration of the whole cycle is 12 to 18 months for the cane plant, depending on the period of the year in which the cane is planted. After the cane plant harvest, a new 12- month cycle begins, known as the ratoon cane. Basically, the ratoon cane has a 12-month cycle in a five years period (five harvests) decreasing yield after each harvest.
Sugarcane crop, as briefly mentioned above, has four different growing stages showed as Fig.3:

1) Germination (0-60 days): the sprouting phase. In this step the sprout breaks the leaves from the bud and develops straight to the soil surface, whilst increasing the root system and forming the primary shoot;

2) Tillering (60-150 days): Tiller is a shoot that sprouts and tillering is the ability to accomplish that. Tillering is a primordial characteristic of sugarcane: the main sink of the result of photosynthesis are the stalks formed from the growth of the tillers, and therefore the profitability of the crop depends primarily on the tillers produced that will dictate the final number of harvestable stalks [1].

3) Development/elongation (150-240 days): This stage is characterized by intense division, differentiation, and cell elongation. As a consequence, there is an increase in size and total dry plant matter. This is known as the "great period of growth". It starts slowly, grows rapidly to reach a maximum, and then decreases the amount of dry matter produced [1][4].

4) Ripening (240-360 days): This is the maturation period characterized by the active import of sugars from the leaves. Sucrose, the principal end product is accumulated in storage parenchyma of the stem [5].

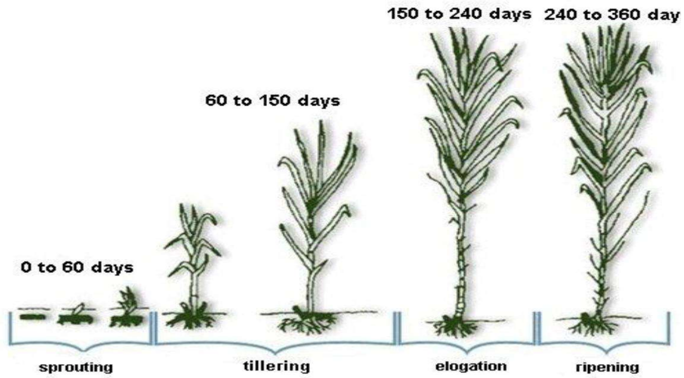


Figure 3: Sugarcane growth stages [6].

2.3 Remote sensing for sucrose prediction

Sugarcane quality is determined based on its sugar content, known as commercial cane sugar (CCS). It is believed that sugarcane dry matter production is related to stalk sucrose accumulation. Therefore, in sugarcane crop quality monitoring (sucrose per hectare), a technique has to be created to evaluate sucrose spatial distribution.

Because of the need for constant monitoring of sugarcane quality parameters and to detect peak of sucrose, simple and easy methods are needed (Terauchi et al., 2012). The application of remote sensing technology for vegetation monitoring has been studied extensively for several decades, promoting periodic assess of changes in crop growth and development.

Hyper spectral remote sensing technologies are alternatives for biophysical parameter estimation that requires high sensitivity measurements. Apan et al. (2004) reported that development of canopy reflectance data acquired by the Earth Observing-1 (EO-1) Hyperion hyper spectral imagery could detect sugarcane orange rust disease caused by Puccinia kuehnii in Australia. In Brazil, Galvão et al. (2005, 2006) used EO-1 Hyperion data and in United States, Johnson et al. (2008) used a fiber optic sensor (Ocean Optics SD-2000) to discriminate sugarcane genotypes.

Numerous studies have reported methods that utilize near infrared spectroscopy to predict sucrose in the extracted sugarcane juice (Tewari & Irudayaraj, 2003; Valderrama et al., 2007; Sorol et al. 2010, Nawi et al., 2014, 2013, 2012). Yet these methodologies are applied in the juice extracted from sugarcane, which requires many preparation procedures, such as cutting, milling, pressing, clarification, and further analysis on a saccharimeter or optical analysis equipment using radiation wavelength near infrared (NIR). This process requires time and chemicals (potentially toxic), rendering the method impractical (Melquiades et al, 2012).

Nawi et al, (2013) showed that field spectrometry of the cane stalk can be applied to estimate sugar yield. Reflectance data of the stalk were correlated with the BRIXS of sugarcane through regression analysis by partial least squares (PLS – Partial Least Squares) and artificial neural networks (ANN – Artificial Neural Network). The model obtained by PLS resulted in coefficient of determination (R^2) of 0.91, and the accuracy obtained by ANN ranged between 50% and 100%. Nevertheless, for space borne sensors, this methodology is not feasible, since the spectral response of the stem cannot be obtained. Most authors are unaware of attempts to predict sugarcane sucrose levels from leaf reflectance data acquired on the field.

In a research conducted by Zhao et al. (2012), the spectral response of in situ measurements on 87 different sugarcane genotypes was used to estimate the chemical composition of the leaves (chlorophyll, N, and C), and cane yield. The results obtained from measured and estimated values of chlorophyll, N, and C had ratios of 0.543 and 0.824 ($p<0.0001$) for all variables. Notwithstanding, parameters related to productivity (sucrose, recoverable sugar, tons of sucrose per hectare) showed no significant correlation ($p<0.01$).

Although there is a high demand for simple methods of sucrose prediction and sucrose prediction by remote sensing technology has been studied extensively for several decades, there is hardly feasible prediction method developed for monitoring sugarcane sucrose content. The reason is that Sucrose accumulation is a very complex process. The sucrose accumulation process has little correlation with classical vegetation index such as NDVI. The accumulation amount cannot be introduced easily by what we can grasp from remote sensing data. For different growth steps, the factors of sucrose accumulation are totally different and cannot be easily introduced by literature. However, there are also indications that remote sensing can be a simple way to evaluate sucrose in the plant, considering indirect measurements through hyper spectral sensors.

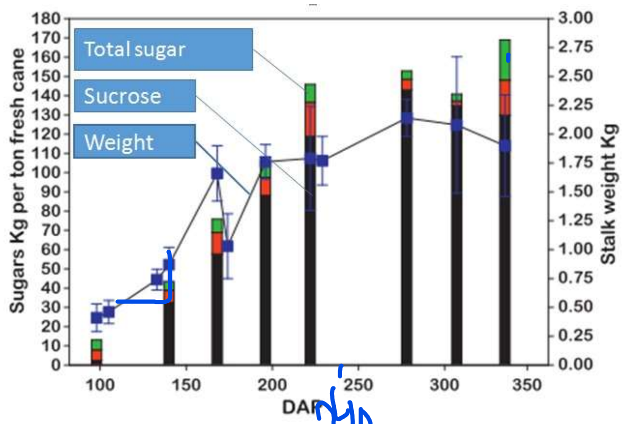


Figure 4: Sucrose change for sugarcane growth

In this research, we tried to utilize the complex statistical model and the characteristic of indirect parameters to simulate the accumulation of sucrose to achieve our research objective of sugarcane sucrose prediction.

3. PROPOSED METHOD

3.1 Ground data acquisition and analysis

The experiment has been conducted in two sugarcane sites in Sao Paulo State, Brazil during the collaborative research with Campinas University. Campinas University have been involved in the data acquisition by very hard work. The climate is tropical to subtropical, and mean annual rainfall and temperature are 1560mm and 22.9 degree, respectively. The two sites had been under continuous sugarcane cultivation for decades of years. As these two sites have different in temperature, rainfall and humidity, it is helpful for us to analysis the growth variety of sugarcane in different environment. Figure.5 shows the two sites where we get sugarcane ground data.

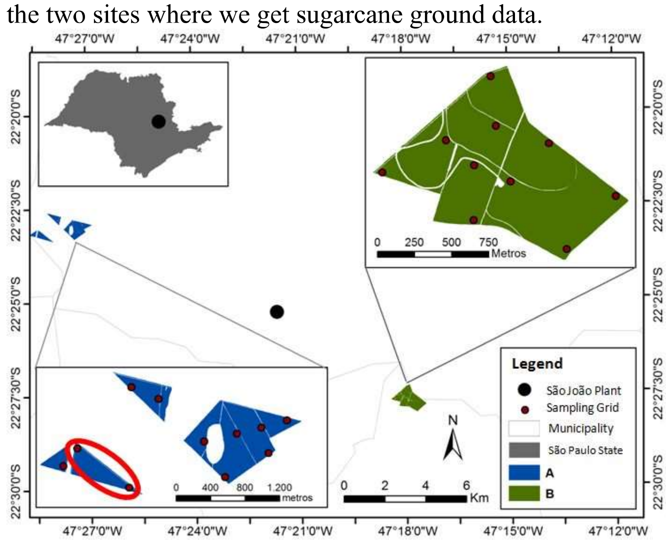


Figure 5: Two Sugarcane Sites

Ground data including crop and soil data were acquired with sampling at grids points. Grid points were located on the field using a handheld DGPS. Crop and soil sampling took place in four periods which showed in Figure.6. These four periods is all in the elongation and ripening steps of sugarcane growth. As the sucrose accumulation is very significant in the elongation and ripening steps, we try to analysis the change pattern of sugarcane biometry characteristics to build the reasonable model for sugarcane sucrose prediction. Figure.6 shows ground data catalogues.

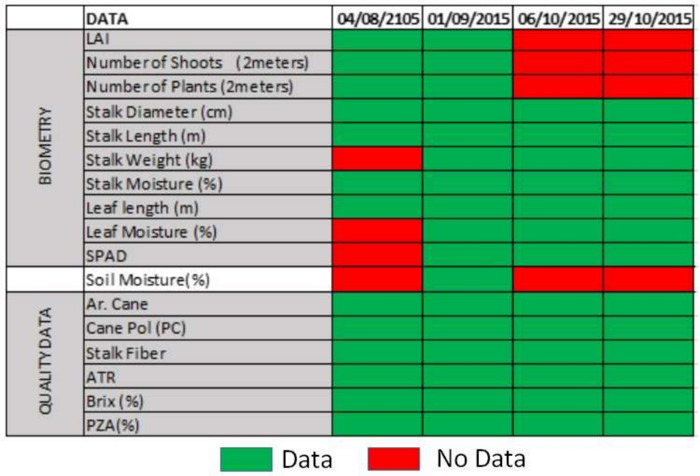


Figure 6: data acquisition

Since data acquisition process is very difficult and costly for the sugarcane yield, we failed to have some data which is red in Figure.6.

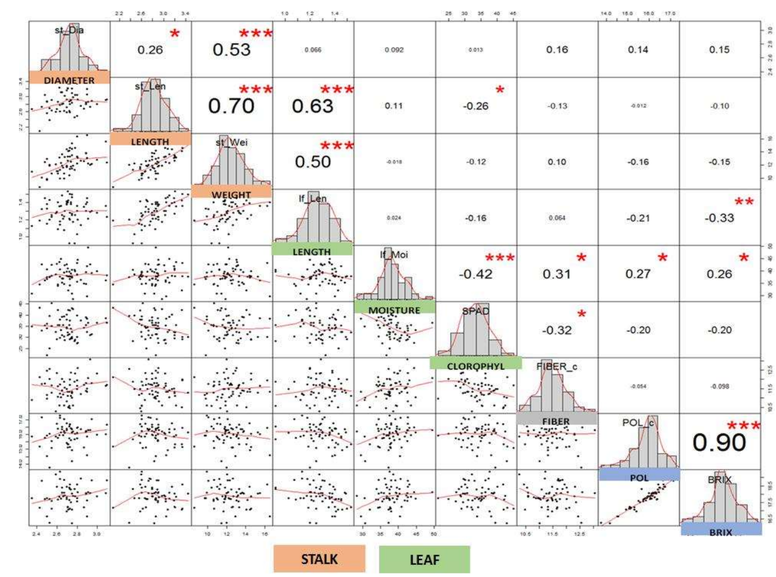


Figure 7: Correlation map for ground data

Using the ground data, statistical analysis was implemented and Figure.7 have shown the result. Most of the correlation of data pairs is analyzed and the result shows that there is a certain correlation in moisture and POL (BRIX), as well as in chlorophyll and POL (BRIX). The result also shows that POL and BRIX have a high correlation, which is because POL and BRIX are just different index for same sucrose content.

Figure.8 shows the characteristics and distribution of sucrose change for four periods. The result shows that the peak of sucrose accumulation comes in the first October which is about in the middle of ripining steps. This characteristics should be campared with biomass change pattern for the deep understanding of sucrose accumulation.

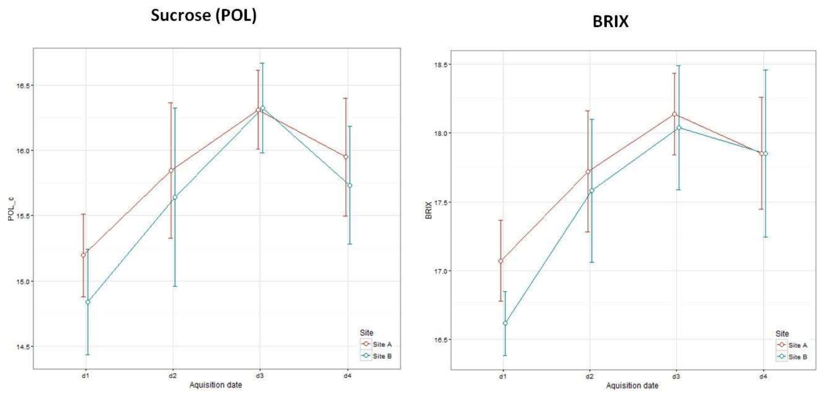


Figure 8: Sucrose content distribution

3.2 Satellite data acquisition and post-processing

Crop biomass change can be monitored by satellite imagery. In this research, two kinds of satellite images are utilized for analysis. Table shows the basic information of RapidEye and LandSat8 sensor satellite images.

Table 1: Spec of satellite imagery

Sensor	LandSat8	Rapid Eye
Resolution	30m	6.5m
Band	Band 1~7 (Table.)	Band 1~5 (Table.)
Price	Free	\0.7m/image
Period	2014/9~2015/10 (14images)	2015/8/8,8/29,10/7 (3images)

Table 2: Bands information of LandSat8

Spectral Band	Wavelength	Resolution
Band1- Coastal	433-453nm	30m
Band2-Blue	450-515nm	30m
Band3-Green	525-600nm	30m
Band4-Red	630-680nm	30m
Band5-Near Infrared	845-885nm	30m
Band6-Short Wavelength Infrared	1560-1660nm	30m
Band7-Short Wavelength Infrared	2100-2300nm	30m

Table 3: Bands information of RapidEye

Spectral Band	Wavelength	Resolution
Band1- Blue	440-510nm	6.5m
Band2-Green	520-590nm	6.5m
Band3-Red	630-680nm	6.5m
Band4-Red Edge	690-730nm	6.5m
Band5-Near Infrared	760-850nm	6.5m

Post-processing of satellite imagery including brightness correction (Figure.9) and atmosphere correction are necessary and NDVI change curve from 200 DAP (day after planting) to 360 DAP is mapped by vegetation index extracted from time series LandSat8 images.

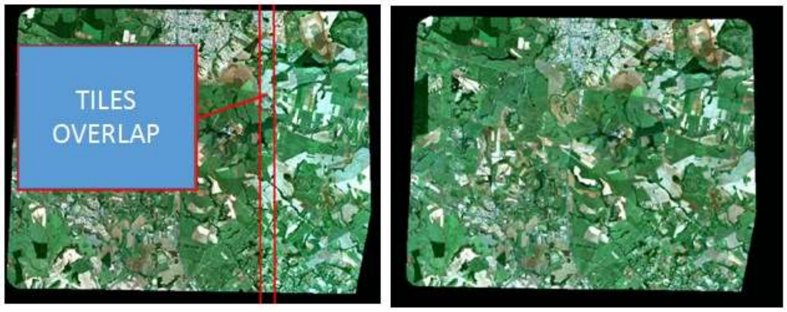


Figure 9: Post-processing of satellite imagery (brightness correction)

3.3 Modeling for sugarcane sucrose monitoring

To model sugarcane sucrose accumulation, the relation of biomass change and sucrose accumulation is considered significant. For biomass growth, we can identify that the NDVI variation have a conspicuous peak which almost correspond to the time when the sugarcane body growth is about to end. Before the peak, body grows rapidly and NDVI information indicated it clearly, while after the peak, crop activity become lower and transfers to the sucrose. As biomass growth peak shows the potential of sucrose accumulation, we consider that peak biomass growth is a significant parameter.

Comparing to sucrose accumulation curve (Figure.4), it shows that the peak of biomass growth steps is different from that of sucrose accumulation steps. It is obviously that there is a delay for sucrose accumulation happening comparing to the biomass growth.

Main sucrose accumulation for the cycle is considered elongation period and ripening period. To indicate the growth situation of potential, we consider that photosynthesis (Chlorophyll) amount is a significant parameter. As NDVI has high correlation with the crop photosynthesis amount, we introduce parameters to demonstrate the photosynthesis amount. The calculation of parameters is showed in Equation.2. NDVI (peak of biomass growth) and NDVI (peak of sucrose growth) are extracted from RapidEye images, while NDVI (elogation and ripening period) is calculated by time-series LandSat images from 28th JUL to 26th OCT. Figure.10 illustrates our method to model sugarcane sucrose accumulation. Parameters we introduced as our index illustrate the potential sucrose content of sugarcane and the photosynthesis amount accumulation.

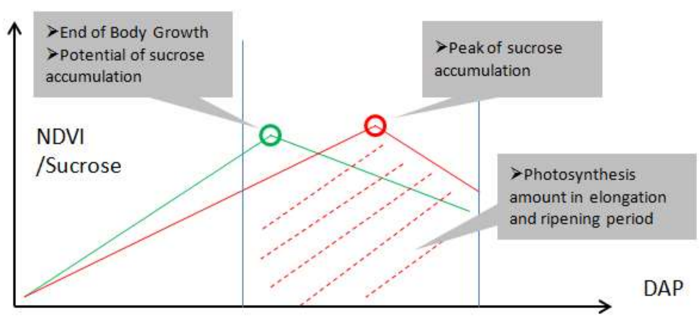


Figure 10: Yield prediction modeling based on growth mechanism

In this study, each index is calculated by the average NDVI value of each farming field which can effectively remove the noise, reduce deviation on the yield prediction. However, there are needs on the prediction on each pixel and sampling point. In this case, cloud processing, noise rejection is necessary and the stability of index also need to be evaluated, which will serve as the next topic of our research on crop modeling.

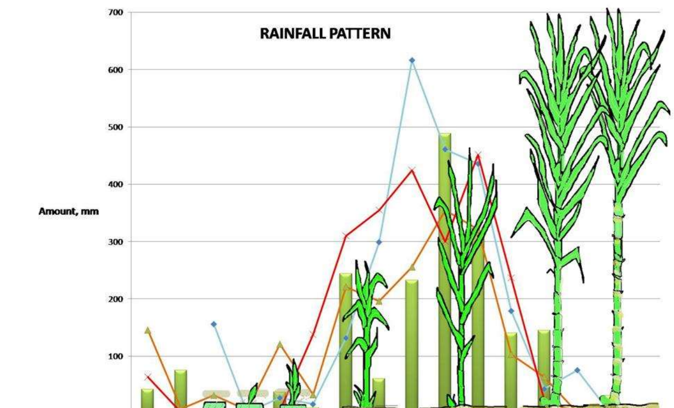
$$NDVI_{(PeakOfBiomassGrowth)}$$
$$NDVI_{(PeakOfSucroseGrowth)} \qquad (2)$$
$$\sum NDVI_{(ElongationAndRipeningPeriod)}$$

4. EVALUATION

4.1 Regression analysis for sucrose prediction

To make the model more robust, weather condition for sugarcane is also considered. Rainfall and humidity plays an essential role in sugarcane sucrose accumulation. Higher rainfall with wetter humidity in body growth steps leads to the better growth as well as better potential for sucrose accumulation. Then, dryer humidity in ripening steps leads to higher sucrose accumulation. Figure.11 shows the best rainfall pattern for sugarcane growth steps. To takes advantages of these features of sugarcane growth, soil moisture is considered significant for sucrose prediction. NDWI (Normalized Different Water Index Equation.3), an index to illustrate moisture is considered important parameter for our model. NDWI for peak time of biomass growth is present in our model.

$$NDWI = \frac{NIR - Green}{NIR + Green} \tag{3}$$



	NOV	DEC	JAN	FEB	MAR	APR	MAY	JUNE	JULY	AUG	SEP	OCT	NOV	DEC	JAN	FEB
MS. 07-08 (722,335.17 TC)	42.4	75.3	1.0	0.0	37.6	10.0	243.7	60.6	232.2	488.0	323.4	140.6	145.2	7.4	31.4	5.6
MS. 06-07 (549, 949.61 TC)			155.6	1.8	27.0	16.0	131.4	298.6	615.7	460.5	435.2	178.6	42.4	75.3	1.0	0.0
MS. 08-09 (606, 887.40 TC)	145.2	7.4	31.4	5.6	120.6	32.6	220.8	195.8	255.2	354.3	320.7	102.8	63.8	1.4	0.00	0.00
MS. 09-10 (557,728.15)	63.8	1.4	0.00	0.00	4.40	138.00	310.00	354.90	424.39	299.9	451.4	236.4	24.6	0	0	0

Figure 11: Rainfall pattern in sugarcane growth

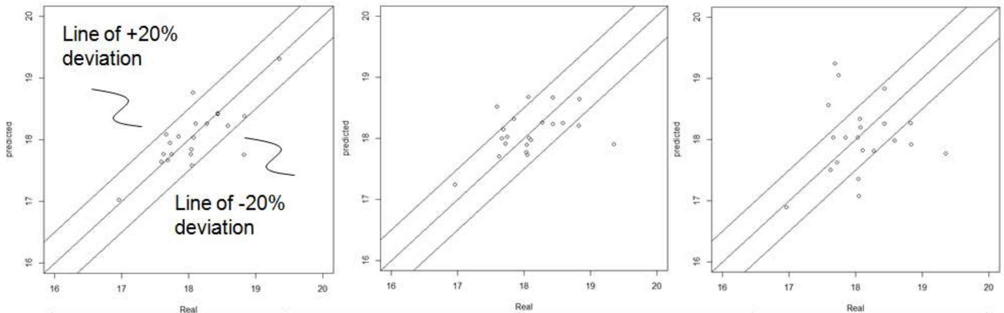
For the evaluation method, we applied Mixed Model which is a statistical model containing both fixed effects and random effects. The real sucrose data is taken as the dependent variable and our proposed index are taken as the independent variables. The prediction accuracy is calculated by percentage of the field whose deviation of predicted sucrose content is less than 20% of the deviation of maximum and minimum sucrose content. In our research, we take POL as the sucrose content. To set the random effect in mix model, we divide the 21 sampling points to two groups using two different sites which have different environment for sugarcane growth.

$$Yield = r_1\alpha + r_2\beta + r_3q + r_4p + r_0 + U_0 + \varepsilon \tag{4}$$

where r1,r2,r3,r4...represent the gradient and r0 represents the intercept. U0 represents the random affect which is site number in our research. In equation.4 α,β,q represent the index we modeled in equation.2 and p represents NDWI in the period of peak sucrose accumulation.

4.2 4.2 Prediction results

Regressive analysis using mixed model is applied for the sucrose prediction. Figure.12 shows the result of the sugarcane sucrose prediction accuracy using proposed index. The prediction accuracy using modeling including NDWI is 90.4% with a mean absolute error (MAE) of 0.24% and standard deviation (SD) 0.27%. The prediction accuracy using modeling including only NDVI is 81.0% with MAE of 0.33% and SD 0.33%. The prediction accuracy is higher than the conventional method and has lower error distribution and model with NDWI makes prediction more accurate.



Method	MODEL(NDWI)	MODEL	USDA
Accuracy	90.4%	81.0%	57.3%
MAE	0.24	0.33	0.76
SD	0.27	0.33	0.76

Figure 12: Prediction Result

5. CONCLUSION

Accurate and timely monitoring is significant for monitoring sugarcane growth, in particularly for large-scale farming. As an effort to strengthen the capability of crop monitoring in the solution, we developed a model to predict sugarcane's sucrose content using time-series satellite imagery. We have achieved the goals listed as follow:

- We analyzed the sugarcane growth characteristics and paid attention to the difference of peak time of biomass and sucrose growth. Using the delay mechanism of sucrose growth, we modeled the sucrose accumulation process.
- Take advantage of NDVI of two peak times and crop photosynthesis amount in elongation and ripening period, we developed three index of sucrose. NDWI is also used in our model. The preliminary experiments show that our method can predict sugarcane sucrose with 90.4% accuracy.
- Using both high and low resolution images the present method is able to take advantage of each kind of images, as well as keep the reduce data cost in a reasonable level without a big loss of accuracy, therefore it has great potential for construction of operational and dynamical monitoring solution.

As future works, it will be an important subject to make the prediction more robust and accurate. Taking into account the main goals of the sugarcane industry, which is based on sugar production, it is very important to have both the harvest occurring at the peak of sugar concentration to maximize productivity and optimize the logistic process. We are planning to evaluate the method using more data, as well as to practical utilize the prediction result for optimization of sugar content harvest and logistic process.

6. REFERENCE

[1].Matsuoka, S., Stolf, R., 2012. SUGARCANE TILLERING AND RATOONING: Key factors for profitable cropping, in: Sugarcane: Production, Cultivation and Uses. pp. 137–157.
[2].D.C. Fontana, et al., "Assessing the relationship between shire winter crop yield and multi-temporal MODIS NDVI and EVI images" The national biennial conference of the spatial Sciences Institute, September, 2005. Melbourne: Spatial Science Institute.
[3].Paul C.D, et al., "operational prediction of crop yields using MODIS data" 2007 international Archives of Photogrammetric, Remote Sensing and Spatial Information Sciences Special Publications
[4].Yoriko Kazama, et al, "Development of Soybean Yield Prediction System by SSD-Hierarchical Bayesian Model"
[5]. Yu Zhao, et al, "Crop growth dynamics model using time-series satellite imagery
[6]. HongWei Zhang, HuaiLiang Chen, "The model of wheat forcast based on MODIS-NDVI- A case study of XINXIANG " ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences, Volume I-7, 2012 XXII ISPRS Congress, 25 August – 01 September 2012, Melbourne, Australia.

[7]. Ping Zhang, Bruce Anderson," MONITORING CROP YIELD IN USA USING A SATELLITE-BASED CLIMATEVARIABILITY
IMPACT INDEX"
[8]. Paul J. Pinter, Jr., Jerry L. Hatfield, James S. Schepers, Edward M. Barnes, M. Susan Moran,Craig S.T. Daughtry, and Dan R. Upchurch. "Remote Sensing for Crop Management"
[9].Tewari, J.; Irudayaraj, J., 2003. Rapid Estimation of pol content in sugarcane juice using FTIR-ATR spectroscopy. Sugar Technology, 5(3), 143–148.
[10].Valderrama, P.; Braga, J.; Poppi, R., 2007. Validation of multivariate calibration models in the determination of sugar cane quality parameters by near infrared spectroscopy. Journal of the Brazilian Chemical Society, 18(2), 259–266.
[11].Melquiades, F. L., Bortoleto, G. G., Marchiori, L. F. S.; Bueno, M. I. M. S., 2012. "Direct determination of sugar cane quality parameters by X-ray spectrometry and multivariate analysis." Journal of agricultural and food chemistry, 60(43), p. 10755–61.
[12].Watt, D.; Mccormick, A.; Cramer, M. Source and Sink Physiology, 2014. In: P. H. Moore; F. C. Botha. (Eds.); Sugarcane: Physiology, 1st ed., p.483–520, 2014. John Wiley & Sons, Inc.
[13].Matsuoka, S., Stolf, R., 2012. SUGARCANE TILLERING AND RATOONING : Key factors for profitable cropping, in: Sugarcane: Production, Cultivation and Uses. pp. 137–157. [7]. HongWei Zhang, HuaiLiang Chen, "The model of wheat forcast based on MODIS-NDVI- A case study of XINXIANG " ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences, Volume I-7, 2012 XXII ISPRS Congress, 25 August – 01 September 2012, Melbourne, Australia.