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Normalized difference vegetation index relationships with rainfall patterns and yield in small plantings of rain-fed sugarcane

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Abstract

Cane growth in rain-fed sugarcane production, with an abrupt end to rainfall months before harvest, could differ from what is known in better-studied systems. Therefore, we evaluated the relationship between the normalized difference vegetation index (NDVI) from the Moderate Resolution Imaging Spectrometer (MODIS) obtained for 2,854 sugarcane farmers' fields and rainfall patterns in northeastern Thailand. Temporal changes of NDVI were related to rainfall patterns. The regional monthly average NDVI and the regional monthly average rainfall, calculated by averaging weather station data representing four individual provinces in the region were linearly related (r^2 = 0.867, p<0.001) during the rainy season. Similarly, the average monthly MODIS NDVI for farmers' fields situated within a five km radius of the weather stations representing sugarcane management zones, was significantly related to monthly rainfall for both individual weather stations and average weather station data. Neither average rainfall nor average MODIS NDVI was related to the average sugarcane yield of the farmers' fields situated within the five km radius of the nine weather stations. On a larger scale, MODIS NDVI had a positive correlation (r = 0.565) with yield when averaged across all nine management zones, but only for the rainy-season planting. Commercial pre-harvest yield prediction would likely need to be made between the end of the rainy season (mid-October) and mid-January. Our results showed that NDVI is a confounded measurement during this evaluation period which is associated with the differences in both plant biomass and cane maturity. Once the rainy season ends, NDVI declines while stalk weight increases. Therefore, NDVI-based yield predictions may be difficult even with higher quality imagery.

Keywords: planting types; planting seasons; rainfall; sugarcane; yield estimation.
Abbreviations: AVHRR = advanced very high resolution radiometer, DMSV = digital multi-spectral video system, ETM = enhanced thematic mapper, EVI = enhanced vegetation index, GIS = geographic information system, GPS = global positioning system, HDF = hierarchical data format, LAI = leaf area index, LP DAAC = land processes distributed active archive center, MODIS = moderate resolution imaging spectrometer, MRT = MODIS re-projection tool, NDVI = normalized difference vegetation index, NIR= near infrared, NOAA = national oceanic and atmospheric administration, r = correlation coefficient, r^2 = coefficient of determination, RVI = ratio vegetation index, red VIS = red visible

Introduction

Remote sensing technology is widely used in environmental and agricultural research. The normalized difference vegetation index (NDVI), one of the most well-known vegetation indices derived from optical remote sensing imageries, has been extensively used to estimate plant biomass (Prince, 1991), leaf area index (Asrar et al., 1984), patterns of productivity (Goward and Dye, 1987), growth status and spatial density distribution (Purevdorj et al., 1998), and plant phenology (Derrein et al., 1992). It was first formulated by Rouse et al. (1973) as the difference between near-infrared (NIR) and red visible (red VIS) reflectance values received by the sensors normalized over the sum of the two. The value increases with increasing vegetation cover because leaf chlorophyll and other pigments absorb a large proportion of the red VIS radiation and the internal mesophyll cells of healthy green leaves strongly reflect NIR radiation (Tucker, 1979). Chlorophyll reflectance is about 20% in the red spectrum and 60% in the NIR spectrum and the contrast between the responses of both bands allows the quantification of the energy absorbed by chlorophyll, thereby providing indicative levels of different vegetation surfaces (Tucker and Sellers, 1986). When an area is covered by the vegetation, its NDVI value is a positive number. There has been a global record of NDVI data since 1981 from the national oceanic and atmospheric administration (NOAA) advanced very high resolution radiometer (AVHRR) that has contributed to global climate, ecosystem and agricultural studies. A new generation of data from the moderate resolution imaging spectrometer (MODIS) on the Terra satellite has been inter-calibrated with AVHRR NDVI, and provides near daily coverage of the earth at 250 m pixel resolution (Glenn et al., 2008). Many studies have used NDVI to monitor the response of vegetation to climatic fluctuations. Several global and regional studies have previously investigated the relationship between NDVI and rainfall in different parts of the world. Generally, the results indicate a relationship between the two aforementioned variables (Kawabata, 2001; Onema and Taigbenu, 2009). Temporal variations of NDVI are closely related to precipitation and there is a strong linear (Malo and Nicholson, 1990) or log-linear (Davenport and Nicholson, 1993) relationship between NDVI and precipitation in cases where monthly or annual precipitation is within a certain range (500-1,000 mm/year). Wang et al. (2003) reported that the NDVI values were correlated with precipitation received during 2-4 preceding biweekly periods; and response time of NDVI to a major precipitation event was 2-4 weeks. The relationship between NDVI and rainfall regionally varies due to variation in properties such as vegetation type and soil background (du Plessis, 1999; Nicholson and Farrar, 1994). There is considerable interest in using remote assessments of rainfall as input into models to predict yield (Prasad et al., 2006; Balaghi et al., 2008) and pest incidence (Pinter et al., 2003). Remote estimations of sugarcane yield could also enhance mill management and harvest logistics (Abdel-rahman and Ahmed, 2008). More detailed analyses are needed for sugarcane planting areas where sugarcane production depends mostly on rainfall with minimal supplemental water sources. These rain-fed systems are very important in Southeast Asia, but differ from other better-studied sugarcane production systems in that rainfall abruptly ends months before harvest (Prasertsak, 2005). The objective of this research was to better understand the relationships among NDVI, rainfall and sugarcane production in Thailand's northeastern sugarcane growing area. We wanted to determine if the poor correlation between sugarcane yield and NDVI observed in preliminary evaluations was due to a failure to predict rainfall in regions with very small fields. We were especially interested in how NDVI, and stalk weight change once the rainy season ends, and how these changes might be related to final yield.

Results and discussion

NDVI and rainfall

The temporal NDVI values derived from averaging data from all sugarcane fields reasonably corresponded to the regional temporal rainfall pattern for both planting seasons (Fig 2). The rainy season in this region occurs from late April to late November while the highest rainfall is usually recorded in October. Thereafter, the dry season generally starts in November and ends in March (Sakuratani et al., 2002). The highest monthly rainfall that generally occurs in September is consistent with the maximum NDVI occurring in the same month. The correlation coefficient (r) between the monthly total rainfall and the average NDVIs for all the farmers' fields situated within five km radius of the nine weather stations for any individual month are low (data not shown). In contrast, the average NDVI from all the farmers' fields within the four provinces and the corresponding monthly regional rainfall (averaged for all four provinces) in the rainy season were linearly related (r^2 = 0.867, $p<0.001$) (Fig 3). The rainfall and NDVI patterns arising from the nine weather stations are generally similar (Fig 4). However, the r^2 values between the average NDVI for farmers' fields within five km radius of the weather stations and average monthly rainfall (for the rainy season) are generally lower for the individual weather stations (Fig 4) than the regional average data (Fig 3). The r^2 for the combined weather station data is 0.6255 while the relationships for individual weather stations vary from 0.3155 to 0.7185 (Fig 4).

Our finding using average NDVI is similar to that reported by Mingjun et al. (2007), who indicated that the correlation between monthly maximum NDVI and monthly precipitation from 1982 to 1999 was very strong in the central and eastern Tibetan plateaus. Nicholson and Farrar (1994), who examined the variability of the NDVI over Botswana during the period 1982-1987, also found a linear relationship between rainfall and NDVI as long as rainfall did not exceed approximately 500 mm/year or 50-100 mm/month and the correlation between NDVI and rainfall was highest for a multi-month average. Al-Bakri and Suleiman (2004) found that the correlation between rainfall and NDVI was improved when the rainfall data were averaged, summed and correlated with the average NDVI.

NDVI and sugarcane yield

The relationship between sugarcane yield and NDVI with sampling times (October 2008 to March 2009) differ. Fresh stalk weight increased but NDVI decreased over the sampling time (Fig 5). This could create difficulties for managers that hope to utilize NDVI as a prediction tool for yield. Commercial pre-harvest yield prediction would likely need to be made between the end of the rainy season (mid-October) and mid-January. Our results showed that NDVI is a confounded measurement during this evaluation period which is associated with the differences in both plant biomass and cane maturity. Once the rainy season ends, NDVI declines while stalk weight increases. Leaf senescence occurring during the ripening stage is directly caused by chlorophyll degradation. Therefore, the red spectral reflectance which is normally absorbed by chlorophyll is increased. On the contrary, the NIR spectral reflectance is decreased due to a change in leaf internal structure (Gate, 1970). When sugarcane attains the ripening stage, the color of its leaves turns yellow, thus NDVI declines. This results in lower NDVI. NDVI declination in other crops has also been reported when they reach the reproductive stage (Campbell, 1996). NDVI values appear to be related to rainfall, but rainfall patterns and amounts may not be a powerful predictor of yield or equally important for different types of sugarcane plantings. Neither rainfall nor the MODIS NDVI derived from individual fields was related to the sugarcane yield of the farmers' fields situated within five km radius of the nine weather stations for any of the planting types we evaluated. However, the maximum NDVI which occurred in September and sugarcane yield for all farmers' fields planted at the beginning of the rainy season (averaged across individual management zones) were positively correlated for individual and combined years (Table 1). Our finding was similar to that reported by the Agricultural Research Council (ARC, 2000a, b), which investigated the use of coarse-resolution satellite imagery from NOAA/ AVHRR and fine-resolution digital multi-spectral video system (DMSV) for sugarcane yield prediction in the Pongola mill supply area, South Africa. It was found that there was no significant correlation between either the estimated or recorded yield and median NDVI derived from DMSV. However, the NDVI derived from AVHRR showed a significant correlation with yield at the mill level but no correlation at the farm level. For the other planting types we evaluated, including ratoon cane, dry-season sugarcane and irrigated sugarcane of which planting period did not synchronize with the onset of the rainy season, the maximum NDVI was generally unrelated to final cane yield. This suggests that the seasonal maximum NDVI from the canopy of these sugarcane types was independent of previous or future stalk growth and final yield. Although the

Table 1. Relationship between averaged ranked September MODIS NDVI and combined ranked October (t_1) and ranked November (t_2) yields for the farmers' fields in two different years that are within each of the nine Mitr Phol management zones in northeastern Thailand. Yield-NDVI relationship is shown for planting types that were established at different times and ratoon fields that were established in previous seasons.

Statistical parameter	Dry-season sugarcane[1]	Irrigated sugarcane[2]	Rainy-season sugarcane[3]	Ratoon cane[4]
		2007-2008 Season		
Correlation coefficient	-0.607	ns	0.525	ns
p-value	0.013		0.025	
		2008-2009 Season		
Correlation coefficient	0.619	ns	0.619	0.483
p-value	0.011	-	0.011	0.042
		Combined seasons		
Correlation coefficient	ns	ns	0.565	ns
p-value	-	-	<0.001	-

1, 2 and 3 are the planting types for cane planted during Sep-Oct, Jan-Feb and Apr-May, respectively. 4 Ratoon cane indicates cane that has been previously harvested and regrown in the current season.

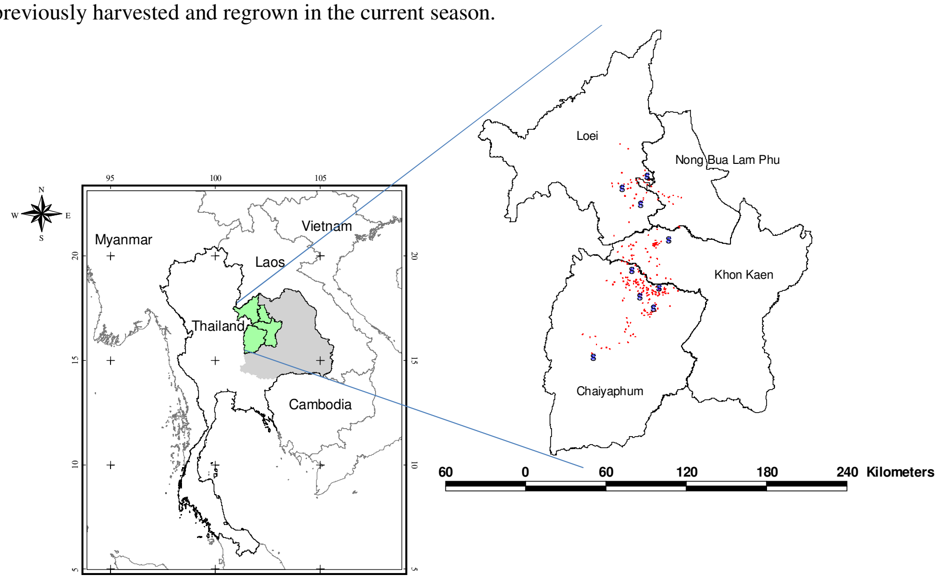

Fig 1. Study site for this research. The large blue points represent nine weather stations located in four provinces and the small red dots symbolize 2,854 farmers' fields.

relationship between NDVI and final cane yield was only found for sugarcane planted at the onset of the rainy season and this relationship was not exceptionally strong, better results might be obtained when higher-spatial-resolution images are used. As the spatial resolution of MODIS NDVI product (6.25 ha) was larger than the average field size, spectral data in one pixel did not entirely belong to sugarcane plants. Other vegetation could contribute to the NDVI value. This is the drawback of using coarse-resolution imagery. However, one advantage of using this MODIS product is that the image of the same location is captured on a daily basis. Besides, the obtained image covers a very wide area. Almeida et al. (2006), who found more success forecasting sugarcane yield in Brazil by using ASTER (resolution = 30 m) and Landsat enhanced thematic mapper (ETM) (resolution = 60 m) sensors of which spatial resolution are higher than MODIS (resolution = 250 m). However, since NDVI is likely associated with the differences in both plant biomass and cane maturity, remote assessments may be difficult even with higher quality imagery. Other variables such as topography, sugarcane variety, soil type and spectral resolution might affect the quality of the correlation and the forecast of sugarcane yield. Although NDVI is a standard index commonly used to monitor a change in vegetation, attempts have been made to find other indices that can better describe the variability of sugarcane yield. Simões et al. (2005) reported that the ratio vegetation index (RVI) and NDVI were two variables that could describe sugarcane productivity. Another indicator related to sugarcane yield is the leaf area index (LAI) (Simões et al., 2009). However, it was suggested that a relationship established between the LAI and NDVI in a particular year might not be applicable in other years, so attention must be paid when the NDVI-LAI relationships are applied (Wang et al., 2005). Enhanced vegetation index (EVI) is another available product from MODIS sensor. The EVI is more functional on near-infrared reflectance than on red absorption. Therefore, it does not saturate as rapidly as NDVI in dense vegetation, and it has

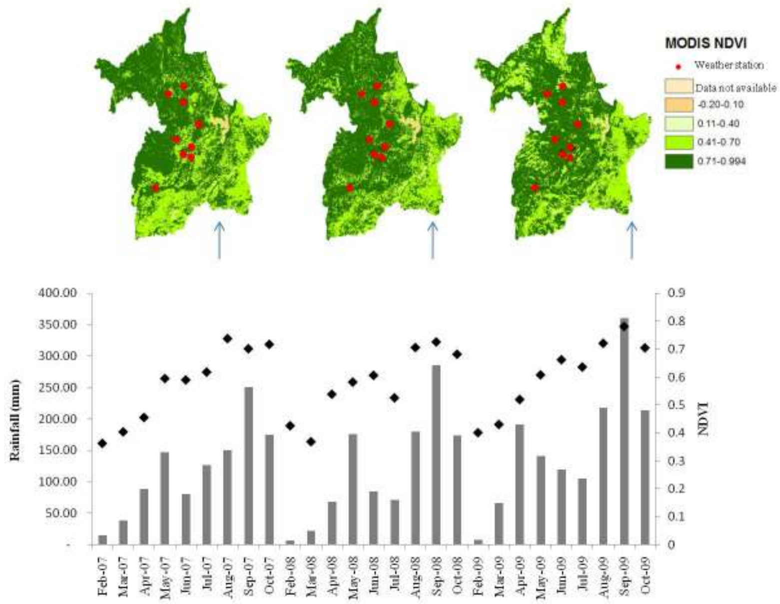

Fig 2. MODIS NDVI (◆) and monthly average rainfall (▮) from the nine weather stations. The NDVI maps are illustrated using the maximum NDVI in September 2007, September 2008 and September 2009.

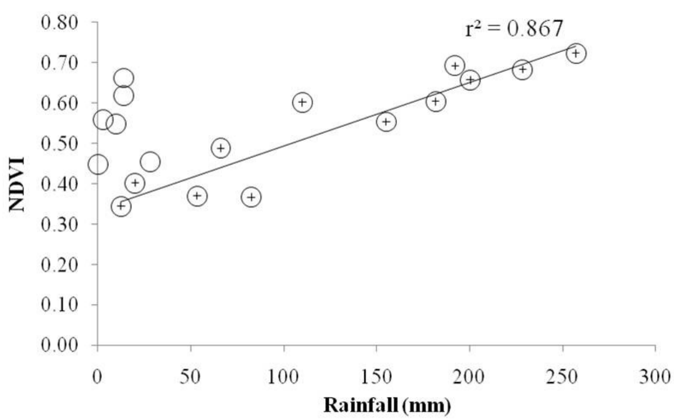

Fig 3. The relationship between seasonal average MODIS NDVI and average seasonal rainfall for all the farmers' fields in the study site. Rainfall is the average of rainfall for different time periods in four provinces. Data for all time periods (○) and only the rainy-season (March through October) (⊕) points are shown. The best-fit regression line is for the rainy-season points.

been shown to be highly correlated with photosynthesis and plant transpiration in a number of studies (Glenn et al., 2008). The success of using EVI to identify sugarcane planting areas has been reported (Xavier et al., 2006; Rudorff et al., 2009).

Materials and methods

Sugarcane field and rainfall data

The study area is located in 4 provinces in northeastern Thailand (Fig 1). The size of individual studied fields is quite small with an average area of 1.801 hectares. The boundary and position of all the farmers' fields were determined using a hand-held global positioning system (Garmin GPS 76, Kansas, USA) with an accuracy of < 15 m. The correctness of plot size, shape and position obtained from the GPS was confirmed by each sugarcane farm owner and slightly modified when appropriate to match imagery. The data were subsequently imported to the geographic information system (GIS) database developed by Mitr Phol Sugarcane Research Center. A total of 2,854 farmers' fields were used for estimating sugarcane yield in the 2007-2008 and 2008-2009 seasons. The estimated yield (ton/ha) was calculated from 3 sampling plots selected at random from each farmer's field. Six sugarcane stalks randomly chosen from each plot in early October and early December were cut, striped of leaves and subsequently weighed in the field. The rainfall data used in this study were collected from nine weather stations situated among the farmers' fields. Each weather station was centrally located in each of the nine management zones which supply harvested sugarcane to Mitr Phu Kieo Sugar Mill in Chaiyaphum province and Mitr Phu Viang Sugar Mill in Khon Kaen province. Another set of monthly average rainfall data for individual provinces was obtained from the Thailand's Ministry of Agriculture and Cooperatives (http://www.moac-info.net/). In order to monitor sugarcane

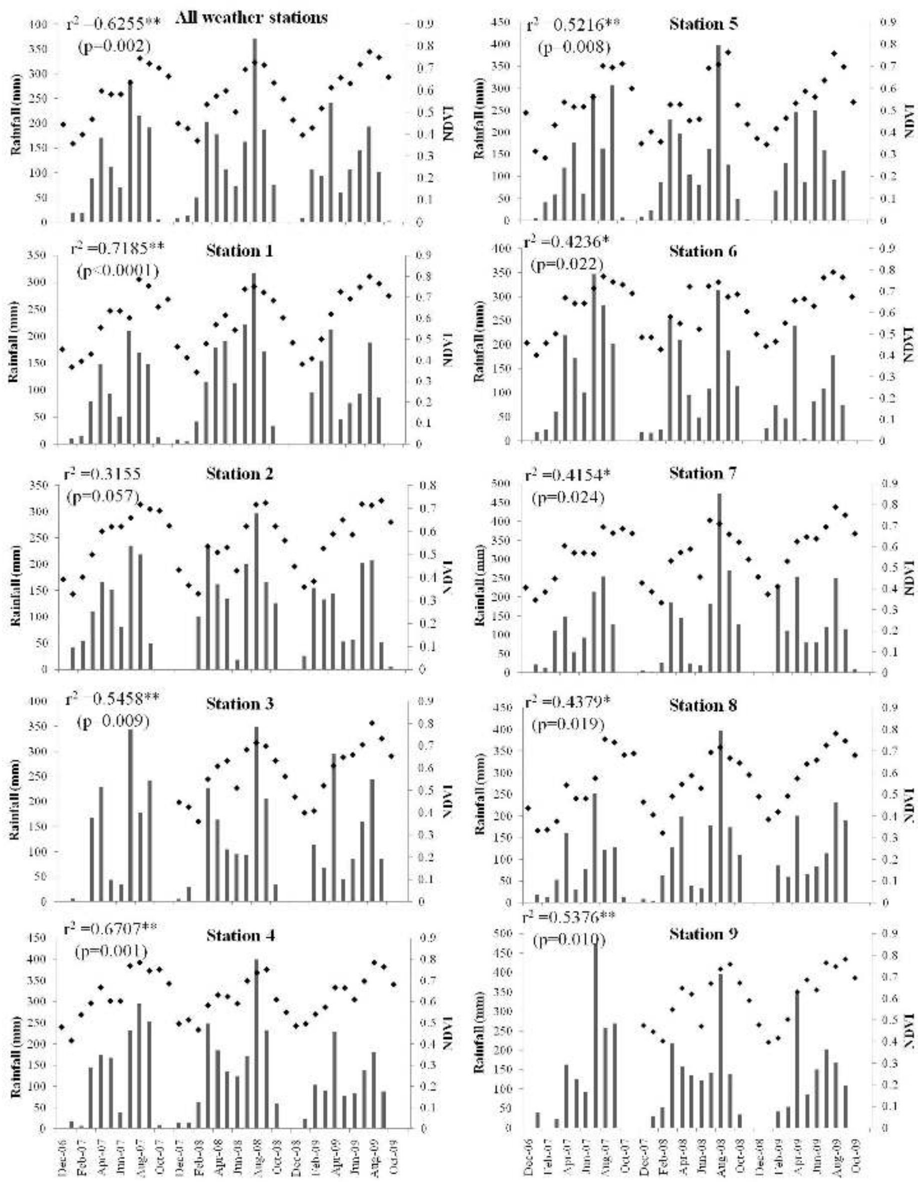

Fig 4. MODIS NDVI (◆) from all the farmers' fields that fall within five km radius of weather stations and monthly rainfall (■) from individual weather stations. There were no farmers' fields in stations 3 and 9 in the 2007-2008 planting season. The r^2 values shown for combined and individual weather stations describe the relationship between NDVI and rainfall for the rainy-season months (March through October).

growth status at additional sampling times during the last 6 months (October - March) before harvest in the 2008-2009 season, stalk weight was monthly determined from 43 selected farmers' fields located near the weather stations.

MODIS NDVI data

The MODIS NDVI data in this study were acquired via LP DAAC data pool from the data series MOD13Q1.5 (https://lpdaac.usgs.gov/lpdaac/get_data/data_pool). This global MODIS data are provided every 16 days at 250-meter spatial resolution as a 16-day composite gridded level-3 product in the sinusoidal projection. Red and NIR reflectances, centered at 645 and 858 nm, respectively are used to calculate the NDVI. A total of 34 hierarchical data format (HDF) files were downloaded. Only the NDVI dataset was used for this study. Since the original projection system of NDVI data and sugarcane field maps were different, the MODIS re-projection tool (MRT) was used to transform the sinusoidal projection system into geographic projection system (Geographic projection system, WGS 1984) and to limit extraction, only the NDVI data (https://lpdaac.usgs.gov/lpdaac/tools/modis_reprojection_tool) were employed.

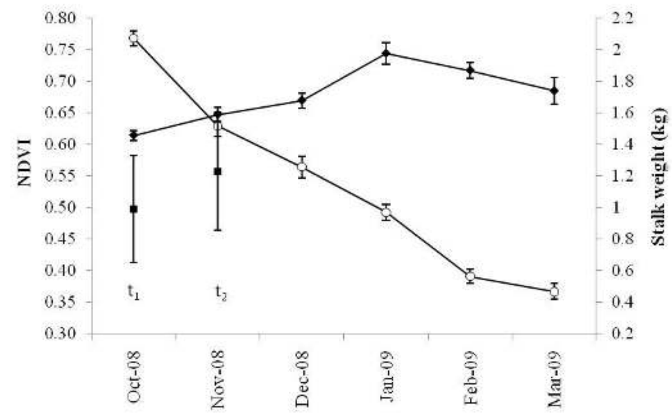

Fig 5. Changes in northeastern Thailand seasonal average MODIS NDVI ( ) and average stalk weight ( ) for research fields planted in January through February. The trends for NDVI are very similar to the average trends presented for over a thousand farmers' fields shown in Fig 2. Also shown are the average stalk weight for farmers' fields (■) in mid-October (t_1) and late November (t_2). The vertical bars represent standard errors of the means (n=18 and 1,513 for the research fields and farmers' fields, respectively).

The 16-day composite NDVI images for 2 planting seasons from January, 2007 to October, 2009 were used.

Data analysis

After the NDVI data and farmers' fields were assigned the same projection system, the average NDVI value within each farmer's field boundary was extracted using ArcGIS 9.2 software and the Hawths' tool analysis add-in. For small plantings, the pixel that included the largest portion of a given sugarcane field was used to obtain an NDVI value. All sugarcane fields within five km radius of the individual weather stations were selected. Although sufficient information on the relationships between rain gauge density and rainfall spatial variability is unavailable for Thailand, a five km rain gauge spacing has been proposed as a reasonable minimum in US studies (Workneh et al., 2004). Average monthly NDVI values, estimated yield and monthly rainfall were obtained for individual fields. Correlation analysis (Spearman's rank correlation coefficient, ρ or r_s) between the ranked NDVI and rainfall or yield was conducted using SPSS statistical software (version 17). Simple linear regression analysis was carried out to quantify the strength of the relationship between rainfall and yield with NDVI.

Conclusion

The results of the investigation on the relationship between MODIS NDVI and rainfall patterns for the sugarcane farmers' fields in northeastern Thailand can be concluded as follows: (1) The temporal change of NDVI was related to and in conformity with the rainfall pattern in northeastern Thailand. (2) Neither rainfall nor MODIS NDVI was related to the sugarcane yield of the farmers' fields situated within five km radius of the nine weather stations. (3) On a larger scale, MODIS NDVI was related to yield when both were averaged for individual management zones, but only for the rainy-season planting. (4) The MODIS NDVI is a confounded measurement during the evaluation period that would most likely be used to make pre-harvest yield predictions. Once the rainy season ends, NDVI declines while weight increases.

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