Role of agricultural engineering in environmental and sustainable development for the valley and delta areas: 1811 - 1822

USING IN SITU HYPERSPECTRAL MEASUREMENTS AND HIGH RESOLUTION SATELLITE IMAGERY TO DETECT STRESS IN WHEAT IN EGYPT

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ABSTRACT

Mapping and detecting stress at both local and regional scales are very important in site specific management. Launching the first generation of high spatial and spectral resolution remote sensing satellite at the beginning of the 21st century provides the opportunity to have better understanding of crop stress and the extent of stress in a specific environment. This work was carried out to assess the ability of hyperspectral and high spatial resolution remote sensing imagery to detect stress in wheat in the Nile Delta of Egypt. A field work visit was undertaken during winter season of 2007 in March (5-30: wheat) to collect ground reference data including soil samples, vegetation samples, water samples, chlorophyll estimates, reflectance measurements and GPS coordinates. The work visit was timed to coincide with the acquisition of QuickBird satellite imagery (7 April, 2007). The results further showed that the QuickBird image successfully detected stress within field and local scales, and therefore can be a robust tool in identifying issues of crop management at a local scale. a strong linear relation between RVI derived from in situ and RVI derived from satellite data (R = 0.75; p = 0.000). The results further showed that MLC is an effective classification algorithm for differentiating different crops within the study area.

INTRODUCTION

Maximising crop production at a minimum cost is very important for farmers. Mapping and predicting yield at an early growth stage is therefore essential for farmers to take decisions to improve their agricultural practices. Monitoring plant status by means of remotely sensed data will enable farmers to maintain optimal levels of soil moisture and nutrients and avoid overuse of different chemicals, which potentially contaminate soil and water.

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A further advantage is the possibility to quantify the amount of grain needed to satisfy population demand. It is therefore evident that using satellite imagery could be a robust tool in site specific management in the Nile Valley and Delta of Egypt. The improvements and advances in satellite sensor technology providing higher resolution (e.g. QuickBird and Ikonos sensors) can perhaps provide a useful tool in site specific management. These two satellite sensors have significantly narrowed the gap in spatial resolution between satellite and airborn imagery (Yang *et al*., 2006). The advantage of these satellites is the revisit period (1-3 days), which was difficult to be accomplished with many other satellite systems (Moran, 2000). Some researchers used QuickBird satellite images for detecting biochemical and biophysical properties in crops (Wu *et al*., 2007a; Wu *et al*., 2007b). Yang *et al*. (2006a and 2006b**)** investigated the potential of QuickBird satellite images to predict and map cotton and grain sorghum yield patterns; they established strong correlations between vegetation indices derived from QuickBird images and both crop yields. Recently, hyperspectral satellite images such as Hyperion have been used in monitoring vegetation; this satellite has more than 200 spectral bands, which enable the construction of effective continuous spectra for every pixel in the scene. This will enable researchers to develop new vegetation indices for detecting stress in crops and facilitate the process of distinguishing different sources of stress in crops such as moisture induced stress from salinity induced stress. Bannari *et al*. (2008) developed several spectral indices to quantify chlorophyll concentration of wheat crops at both the canopy and the leaf scales using remotely sensed data. These chlorophyll indices were derived from Hyperion imagery and the results demonstrated that NDPI is the best index for estimating wheat chlorophyll concentration. The overall aim of our research was to assess the efficiency of *in situ* hyperspectral measurements and high resolution satellite remote sensing imagery to detect stress in wheat in the Nile Delta of Egypt. The specific objectives of this study were to:

(1) evaluate whether *in situ* hyperspectral measurements can detect stress in wheat (2) Assess the efficiency of classification algorithms to map different crop types and (3) Having mapped individual crop types

through remote sensing, predict wheat biophysical and biochemical properties via remotely sensed data.

MATERIAL AND METHODS

Study area

The study area is located in south-west Alexandria, Egypt (latitude of 30° 55` 50`` and longitude of 29° 53` 35.6``). To have a range of stress levels in fields, three study sites were chosen; Naser, Kahr and Bangar. The soil at these sites is a sandy loam with low concentration of nitrogen, as these sites have been reclaimed recently from the eastern desert. The majority of the fields within the study area use flood irrigation with a few farms irrigated by sprinkler or trickle irrigation, especially at the Bangar site. The weather in this area is characterised by hot summers and mild winters.

In situ hyperspectral measurements and sampling strategy

An *in situ* hyperspectral survey was undertaken in the study area during the winter growing season of 2007 (8-30 March) concurrent with the acquisition of satellite imagery. The hyperspectral survey was conducted in random fields depending on the size of the field and the status of these fields in terms of stress. An ASD FieldSpec hand-held spectroradiometer was used to measure reflectance from plant canopies. The reflectance measurements were restricted between 10 am and 3 pm to minimise the influence of changes in solar zenith angle. During the *in situ* hyperspectral survey, the sensor was kept at a constant distance from the soil surface using an iron stand of 2 m height. Vegetation samples were collected immediately after measuring reflectance from plant canopies to quantify biomass, plant height and Leaf Area Index (LAI). Soil and water samples at each site were also collected for chemical analysis.

Chlorophyll determination

For the measurement of chlorophyll concentrations during field work in Egypt, a hand-held SPAD 502 meter (Minolta, Osaka, Japan) was used due to difficulties accessing laboratory equipment. Twenty apical leaves were sampled and put in a plastic bag then kept cool in an ice box and then the chlorophyll concentration was measured in the laboratory.

Spectral data analysis

Following the measurements of reflectance by ASD FieldSpec Pro spectroradiometer, the data was downloaded to a PC and pre-processed with an ASD software. The *in situ* hyperspectral and laboratory darkroom spectral data were interpolated to a final spectral resolution of 0.5 nm then truncated between 300 and 1000 nm. Finally the reflectance was smoothed to further reduce the noise at the start and the end of the magnetic spectrum by passing a 5 nm running mean filter over the whole spectrum.

Remote sensing data acquisition and analysis

The 7th April QuickBird multispectral image was acquired covering wheat crops of the 2006-07 growing season. QuickBird satellite is a high spatial resolution satellite comprises four multi spectral bands (blue, green, red and near-infrared) of 2.4 m spatial resolution. The QuickBird image of wheat fields was acquired at 09:06 h GMT on 7th April 2007 for the study area. The image was geo-corrected using image to image technique by infoterra (the image supplier). The image was atmospherically corrected using the dark pixel method (Tyler *et al.*, 2006). The image was also classified using both unsupervised classification (k-means) and supervised classification (MLC) to identify different crops in each image.

Calculating spectral vegetation indices

To achieve the objectives of this research twelve commonly used broad band vegetation indices (Table 1) were derived from both *in situ* hyperspectral and satellite imagery to assess the ability of remotely sensed data to detect stress in wheat.

Table 1 formulae of different vegetation indices and references collected from the literature

Notation	Formulae	Reference
NDVI	(NIR-Red)/(NIR+Red)	Rouse *et al*., 1974
RVI	NIR/Red	Pearson &Miller, 1972
SAVI	[(NIR-Red)/(NIR+Red+L)]*(1+L)	Huete, 1988
$GNDVI_{br}$	(NIR-green)/ (NIR+green)	Yang *et al*., 2006a
DVI	NIR-Red	Tucker, 1979
SR	NIR/Red	Aparicio *et al*., 2002
SLAVI	NIR/(Red+NIR)	Lymburner *et al*., 2000
OSAVI	[(NIR-Red)/(NIR+Red+L)]*(1+L), L = 0.16	Rondeaux *et al*., 1996
VI1	NIR/(green-1)	Vina, 2003
RDVI	$\sqrt{NDVI \times DVI}$	Reujean & Breon, 1995
SI	Red/NIR	Jiang *et al*., 2003
IPVI	NIR/(NIR+Red)	Crippen, 1990

NDVI, Normalized Difference Vegetation Index; RVI, Ratio Vegetation Index; SAVI, Soil Adjusted Vegetation Index; GNDVI, Green Normalized Difference Vegetation Index; DVI, Difference Vegetation Index; SR, Simple Ratio; SLAVI, Specific Leaf Area Vegetation Index; OSAVI, Optimized Soil Adjusted Vegetation Index; VI1, Vegetation Index One; RDVI, Renormalized Difference Vegetation Index; SI, Stress Index; IPVI, Infra-Red Percentage Vegetation Index

Statistical analysis

Data were checked for normality using Anderson-Darling method with 95% significance level. The Pearson Product Moment correlation coefficient was used to test the association between different vegetation indices and crop properties and to identify optimum vegetation indices. Simple linear and multiple regression analyses were used to derive regression equations to the retrieval of grain yield under moisture and salinity stressors.

RESULTS AND DISCUSSIONS

Identifying different crops in the study area

K-means unsupervised and Maximum Likelihood (MLC) supervised algorithms were used to identify different crops within the study area. Both algorithms were performed on QuickBird image using ENVI v4.4. Figure 1 shows different classes of crops using MLC and it is noticeable that the spectral signature from wheat fields is different from clover, bare soil and water. To evaluate the classification methods, a confusion matrix was derived for both k-means and MLC of the QuickBird image. In supervised algorithm, a validation dataset, which was independent from the training dataset, was created manually. The validation dataset composed at least 1000 pixels for each class.The classification produced two distinct crops (wheat and clover) and two more classes (water surfaces and bare soil). The results of the confusion matrix showed that the overall accuracy of the k-means classification was slightly high of 77.4 % even with poor classification for specific targets. The classification accuracy varied for identifying different classes ranging from 42.24% (for bare soil) to 97.60% (for wheat crops). The classification accuracy for clover and water are 94.36 and 72.45% respectively (Table 2). The slightly low classification accuracy for water may be a result of the spectral confusion between water and shadows.

The low classification accuracy for identifying bare soil may be a result of spectral confusion between dry soils and wet soils. However, the k-means produced high classification accuracy it might produce too many misclassified pixels. For example the > 0.95 accuracy for identifying wheat crops may lead to high percentage of misclassified pixels.

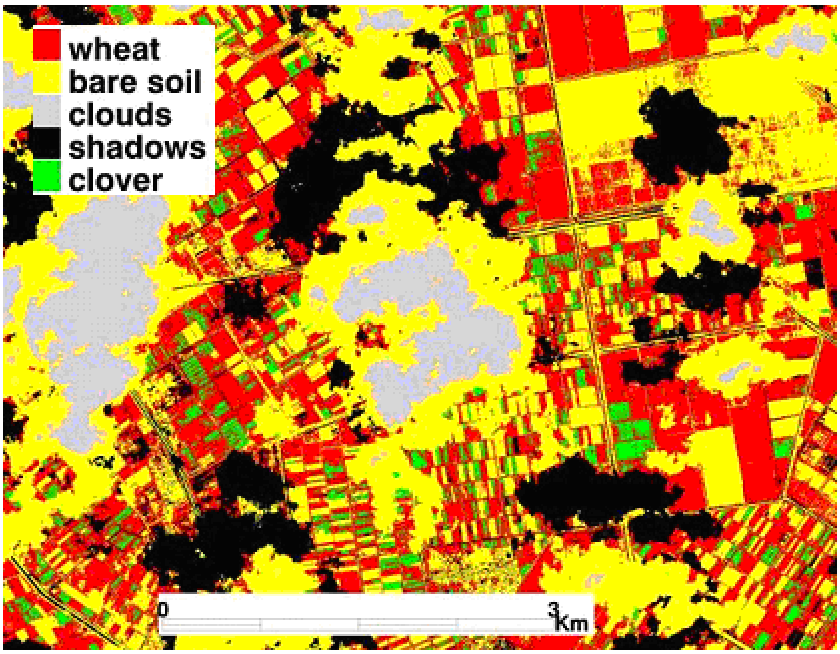

Figure 1 MLC of QuickBird image acquired on 7th April 2007 for different crops in south-west Alexandria, Egypt.

The confusion matrix derived for MLC (Table 3) showed that the overall classification accuracy is high (91.77%) associated with high kappa coefficient (0.89). The classification accuracy for different classes is also high, ranging from 85.95% (for classifying clover) to 97.79% (for classifying water).

Detecting stress in wheat

Different broad band vegetation indices derived from both in situ hyperspectral and satellite imagery data established strong relationships with different biochemical and biophysical properties including chlorophyll concentration, biomass and LAI (Table 4).

Table 2 Confusion matrix results for k-means algorithm of wheat and other crops in south-west Alexandria, Egypt.

Class	**Ground truth (Percent)**					**User's Accuracy**
	Wheat	**water**	**Bare soil**	**Clover**	**total**	
Unclassified	0.00	0.00	0.00	0.00	0.00	(%)
Wheat	97.60	25.82	12.65	4.17	35.09	69.90
Water	2.02	72.45	45.1	0.28	29.43	61.74
Bare soil	0.38	0.29	42.24	0.93	10.42	96.06
Clover	0.00	1.45	0.00	94.63	25.06	98.55
total	100.00	100.00	100.00	100.00	100.00	
Producer's Accuracy (%)	97.60	72.45	42.24	94.63		
Kappa Coefficient	**0.698**					
Overall Accuracy	**0.774**					

Table 3 Confusion matrix results for MLC algorithm of wheat and other crops in south-west Alexandria, Egypt.

Class	**Ground truth (Percent)**					**User's Accuracy**
	Wheat	**Clover**	**Bare soil**	**Water**	**Total**	
Unclassified	0	0	0	0	0.00	(%)
Wheat	90.42	1.28	2.04	0.00	22.75	96.29
Clover	4.26	85.95	3.99	0.09	22.63	90.67
Bare soil	5.32	11.10	92.46	2.12	28.92	84.51
Water	0.00	1.67	1.51	97.79	25.70	96.9
Total	100	100	100	100	100.00	
Producer's Accuracy (%)	90.42	85.95	92.46	97.79		
Kappa Coefficient	**0.890**					
Overall Accuracy (%)	**91.77**					

The results at the three sites demonstrated that vegetation indices successfully showed the potential of predicting biophysical and biochemical properties of wheat. OSAVI derived from *in situ* data produced the strongest correlation with the measured chlorophyll whilst RVI and SR derived from satellite imagery produced the strongest correlation with the measured chlorophyll (r = 0.667). RDVI produced the strongest correlation with biomass and LAI (r = 0.92). the results therefore revealed that QuickBird satellite imagery successfully mapped the spatial variability of aboveground biomass, chlorophyll, LAI and plant height which are closely linked to crop grain yield. These results are in agreement with those obtained by Yang *et al*., 2006b. Grain yield can therefore be predicted using this type of satellite imagery. Successful mapping of agricultural grain crops at early stages will provide a useful tool to detect areas suffering from stress and therefore enable remediation to be implemented to increase yield. Avoiding and managing crop stress in the Nile Valley and Delta may increase crop productivity, which is crucial to a country like Egypt to sustain the rapid population growth. The combined dataset collected from different sites was also used to assess the relationship between different vegetation indices derived from in situ hyperspectral data and those derived from satellite data. Figure 2 shows that there is a strong linear relation between RVI derived from in situ and RVI derived from satellite data (R = 0.75; p = 0.000). The results further showed a decrease in the relationship between the calculated indices from both platforms, which may be attributed to (1) the time difference between collecting *in situ* data and satellite image acquisition (2) the *in situ* hyperspectral survey was restricted between 11 am and 3 pm whilst satellite image acquired mid morning and therefore different solar angles and (3) *in situ* data collected at nadir position whilst satellite data acquired at off nadir. The results further demonstrated that QuickBird has low spectral capabilities and subsequently it is not dependable to be used for distinguishing moisture and salinity stress. in this context hyperspectral infrared imager (HyspIRI; 2013-2016) would be effective satellite imagery in detecting stress and distinguishing source of stress at a regional scale since it provides images at 400-2500 nm with 45 m spatial resolution. Using this imager with the new advances in detectors, optics and electronics could acquire images with 210 spectral bands and thus calculating both broad band and hyperspectral vegetation indices.

Table 4. Coefficient of correlation between different broad band vegetation indices derived from both in situ hyperspectral and QuickBird satellite data and wheat properties collected in March 2007in south-west Alexandria, Egypt

Index	Chlorophyll		Biomass		Height		LAI	
	In situ	**Satellite**	***In situ***	**Satellite**	***In situ***	**Satellite**	***In situ***	**Satellite**
NDVI	0.76	0.627	0.82	0.905	0.85	0.885	0.72	0.894
RVI	0.78	**0.669**	0.82	0.839	0.85	0.811	0.74	0.884
SAVI	0.79	0.627	0.78	0.905	0.69	0.885	0.51	0.894
$GNDVI_{br}$	0.79	0.627	0.82	0.884	**0.87**	0.836	**0.76**	0.884
DVI	0.73	0.498	0.63	0.919	0.53	0.856	0.38	0.916
SR	0.78	**0.669**	0.82	0.839	0.85	0.811	0.74	0.884
SLAVI	0.76	0.627	0.82	0.904	0.85	0.885	0.72	0.894
OSAVI	**0.80**	0.627	**0.83**	0.904	0.78	0.885	0.61	0.894
VI1	-0.30	0.666	-0.11	0.829	0.02	0.797	0.12	0.878
RDVI	0.77	0.544	0.82	**0.927**	0.85	0.873	0.74	**0.919**
SI	-0.75	-0.619	-0.82	-0.908	-0.84	**-0.889**	-0.72	-0.88
IPVI	0.76	0.627	0.82	0.905	0.85	0.885	0.72	0.894

SUMARY AND CONCLUSION

The results of this research showed that using high spatial resolution satellite remote sensing such as QuickBird can give a better understanding about stress at a local scale. Due to limited spectral resolution of QuickBird satellite images, it is difficult to distinguish different sources of stress. However, this may be resolved in the nearest future with the launch of new satellite systems (HyspIRI, 2013-2016) with high spectral resolution and low revisit cycles. The results also established the possibility for mapping different crops within the study area. Moreover, The results demonstrated the high efficiency of both in situ hyperspectral and high spatial resolution remote sensing imagery to predict wheat properties such as LAI, biomass, plant height and chlorophyll concentration.

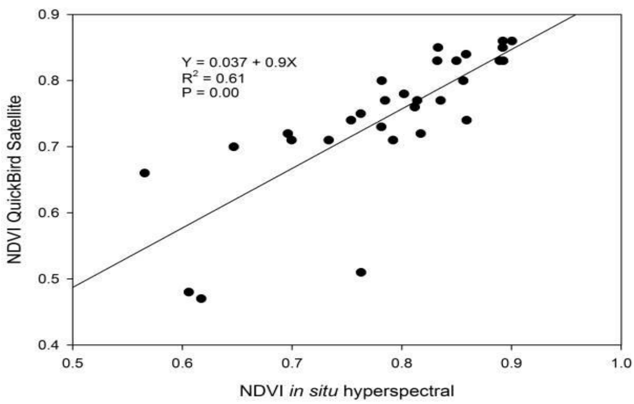

Figure 2 the relationship between NDVI derived from in situ hyperspectral survey and NDVI derived from QuickBird image collected from wheat fields in south-west Alexandria, Egypt.

Using this technique in the Nile Valley and Delta will maximise the efficiency of water use and decrease input costs (pesticides, fungicides, fertilizers, seeds and irrigation). Remote sensing can therefore be used as a useful, quick and cost-effective tool in precision farming and regional analysis giving timely information about crops in specific areas.

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الملخص العربى

استخدام قياسات الانعكاس وصور الاقمار الصناعية عالية الدقة الايضاحية فى التنبؤ بالاجهاد على محصول القمح بمصر

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أجريت هذه الدراسة على محصول القمح صنف سخا ٨ خلال الموسم الشتوى ٢٠٠٦/ ٢٠٠٧ بالصوب الزجاجية بمزرعة جامعة سترلينج بالمملكة المتحدة بهدف دراسة امكانية استخدام بيانات الاستشعار عن بعد سواء الارضية منها أو صور الاقمار الصناعية للتنبؤ بالاجهاد على محصول القمح ولقد تمت الدراسة على مرحلتين: الاولى دراسة العلاقة بين الخواص الطبيعية والكميائية لمحصول القمح والمؤمشرات الخضرية المحسوبة من بيانات الانعكاس والمرحلة الثانية تعميم النتائج المتحصل عليها من تجارب الصوب على نطاق كبير باستخدام صور الاقمار الصناعية عالية الدقة الايضاحية. ولقد تم عمل زيارات حقلية لمنطقة الدراسة بمصر خلال شهرى مارس وابريل ٢٠٠٧ لتجميع بيانات الاستشعار عن بعد على المستوى الارضى وعينات تربة وعينات من مياه الرى من مناطق الدراسة بالاضافة الى عينات النبات لتقدير خواص النبات المختلفة واظهرت الدراسة النتائج التالية:

صور الاقمار الصناعية عالية الدقة الايضاحية يمكن استخدامها بنجاح للتنبؤ بالاجهاد على النبات يعتبر الامثل فى التنبؤ بكل من الكتلة الخضرية ودليل مساحة سطح الاوراقRDVI بمعامل ارتباط ٠,٩٢ ، ٠,٩٣ على الترتيب يعتبر الامثل فى التنبؤ بتركيز الكلوروفيل حيث كان معامل الارتباط بينهما ٠,٦٧ RVI

أظهرت النتائج أيضا علاقة ارتباط قوية بين الدلائل الخضرية المحسوبة من قياسات الانعكاس فى الحقل وتلك المحسوبة من صورة القمر الصناعى حيث كانت قيمة معامل الارتباط ٠,٧٥ للدليل RVI

ومن خلال نتائج هذا البحث نجد أن استخدام صور الاقمار الصناعية عالية الدقة الايضاحية سيساعد فى استخدام الموارد المتاحة بكفاءة عالية وبالتالى معظمة انتاجية المحصول وذلك بالتنبؤ بالاجهاد على النبات عند مراحل نمو مبكرة واتخاذ القرار المناسب لتجنبه.

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