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THE RELIABILITY TEST OF USING THE MODERATE SATELLITE IMAGES FOR METALS CONTAMINATED CORN PLANTS DETECTION IN THE NILE DELTA, EGYPT

Mayie M. AMER[1], Atef M. ELSBAAY[2]

[1]Tanta University, Faculty of Agriculture, Agricultural Engineering Department, Egypt. Phone: 00201202266172, E-mail: mai.amer@agr.tanta.edu.eg
[2]Kafrelsheikh University, Faculty of Agriculture, Agricultural Engineering Department, Egypt. Phone: 002 01007503876, E-mail: atef.ahmed@agr.kfs.edu.eg

Corresponding author: mai.amer@agr.tanta.edu.eg, mayieamer@yahoo.com

Abstract

For the synoptic assessment of corn plants content of Ca, and K accurate monitoring of land surface dynamics using remote sensing is needed. We looked at a full resolution dataset from the Medium Resolution satellite Imaging (Sentinel-2) as an open source as an alternative to the costly high resolution the more widely used high-resolution satellite Imaging (Worldview2) data for vegetation monitoring. We compared Sentinel-2 image and Worldview 2 data acquired in 2018 with in situ measured hyperspectral data and metal concentrations in plant samples collected from fields in the study area for this purpose. The current research was conducted on the experimental site during the 2018 corn cropping season (Zea Mayz). Results indicated that: The Difference Vegetation Index (DVI), the Enhanced Vegetation Index (EVI), the Green Normalized Difference Vegetation Index (GNDVI), and the Leaf Area Index (LAI) were the more sensitive indicators to Ca and K above ground corn plants content. These VIs had R^2 values more than 0.5 with the in-situ measurements for the both images. DVI, EVI, and GNDVI performed well in estimating plant dry matter Ca and K content with $R^2 > 0.5$, with a high significant level P-value < 0.001and LAI had a statistically significant impact with a P-value < 0.5 for WV2 image. The Sentinel-2 VIs performed well in estimating plant dry matter Ca and K content with R^2 values > 0.5, with a high significant level P-value 0.001. LAI had a statistically significant impact with a P-value < 0.5 with Ca concentration and P-value < 0.01 with K concentration. This study suggests that the moderate resolution satellite images can be used for corn plants Ca and K content.

Key words*: *Change detection, Remote sensing, plant stress, image processing

INTRODUCTION

Plant stress can be tracked in the field using in-field spectroscopy, which is both time and cost efficient [19]. Remote sensing change detection (CD) is commonly defined as a process to identify differences in geographical surface phenomena over time [8, 2]. Techniques of remote sensing (RS) have been shown to be a promising approach for crop development Observing [20], nutrition diagnosis, Identifying the geographical area, detecting and quantifying the types of changes, and finally determining the accuracy effects are all part of the general aim of change detection in remote sensing [11].

This field has attracted a lot of effort in research due to its applications in various areas as Land-use and land-cover (LULC). Vegetation change, Crop monitoring, Environmental change and crop stress detection [5].

Change detection (CD) on earth's surface is an active research topic since it can help in monitoring and optimal planning of Earth's resources and also help to arrest undesired changes. Any change detection system should be able to (a) define the change area and change rate; (b) distribution of change areas; (c) change trajectories; and (d) the accuracy assessment of the change detection methods [9].

[10, 8] classified CD techniques into (1) comparative analyses based on post-classified data and (2) simultaneous analyses of multitemporal images.

The conventional methods of soil contamination assessment in large areas involve field data collection, chemical analyses in a laboratory as well as geostatistical interpolation, which are expensive and time-consuming. For instance according to [14].

Satellite image processing plays a vital role for research and developments in Astronomy, Remote Sensing, GIS, Agriculture Monitoring, Disaster Management, change detection and many other fields of study. Satellite images are recorded in digital forms and then processed by the computers to extract information. Variations in the scene characteristics are represented as variations in brightness on images. In Remote Sensing, change detection means assessing or measuring the change on the Earth's surface by jointly processing multi-temporal images of the same geographical area acquired at different times.

[16] assessed a Medium Resolution Imaging Spectrometer (MERIS) full resolution dataset for vegetation monitoring as an alternative to the more commonly used Moderate-Resolution Imaging Spectroradiometer (MODIS) data. Data from low and medium spatial resolution (SR) satellites are frequently used for land monitoring. These data are freely accessed on the web and provide for observing nearly the entire Earth’s surface in a 24-hour period. The major satellite systems providing such types of data are the Moderate Resolution Imaging Spectroradiometer (MODIS)

This work indicates that optical sensors such as European constellations, such as the Sentinels can be used for change detection of corn plants content of Ca and K instead of the paid worldview 2 satellite imagery.

MATERIALS AND METHODS

Study area and data

El- Mahalla Al-Kobra, El- Gharbia Governorate, Egypt (latitude 31o 06.620 N, longitude 31o 03.665 E) is the current study site in the Middle Nile Delta. A map of the research site is shown in Figure 1. Metals resulting from manufacturing activities have polluted certain areas of the studied location by storm water discharge points. The crops in these areas are irrigated by the main drain of El Gharbia. Factory contamination has contaminated the irrigation water from this drain (textile, oil and soap, printing and chemicals).

Fig. 1. Study location
Source: QGIS 2.18.3 software [July 2018] [3].

Satellite imagery

Two different satellite imagery were used in this study for corn plants Ca and K content detection. The first image acquired from WorldView 2 sensor as a high spatial resolution image with 2m pixel spatial resolution. The second image was Sentinel 2 image. It has been developed and is being operated by the European Space Agency. The Sentinel-2 mission has 13 bands in the visible, near infrared, and short wave infrared part of the spectrum with three different spatial resolution 10, 20, and 60 m. The sensors specifications of the satellites summarised in Table 1.

Methods

The methodology considered of this paper is: (1) pre-processing of the original images. (2) processing and statistical analysis of the corresponding datasets, and (3) comparison of the results for the two images.

The data preparation involved the resampling of the S2 bands acquired at 20 m to obtain a layer stack of 10 spectral bands at 10 m. The resulting objects were labeled using the reference data and exploited for training and validation. For the object-based classification, we used various band-specific metrics (Mean, Standard deviation, Min, Median, Max, 25th and 75th Percentile) extracted from the image objects. For the pixel-based classification, we used the reflectance in the ten spectral bands for each pixel.

Reference data for the supervised classification were acquired in two ways:

- during a field survey for the cropland test site, and
- from inventory data and visual interpretation of high spatial resolution images for the test site.

Table 1. Sensor's specifications of WorldView 2 and Sentinel 2 Imagery

Sensor		
	WorldView-2 (WV2)	ESA's Sentinel 2 satellite
Acquisition date	July 2018	July 2018
Bands used	8	13
Spectral range (nm)	450-800	visible and near-infrared (VNIR) to the short-wave infrared (SWIR)
Spatial resolution (m)	2	10

Source: WorldView 2 and Sentinel 2 Imagery, July 2018 [18, 12].

A statistical analysis was run on the results. t-test, regression analysis and the significancy test were run to find the most sensitive vegetation indices. DVI, EVI, GNDVI, and LAI were the most sensitive VIs to Ca and K concentration accumulated in above ground plant dry matter. Table 2 shows the VIs were determined using ENVI 5.3 software from the WV2 and Sentinel 2 images captured on July 2018.

Table 2. The most sensitive VIs were determined using ENVI 5.3 software from the WV2 and Sentinel 2 images

Vegetation index	**Apriviation**	**Formula**	**Reference**
Difference Vegetation Index	DVI	$DVI = NIR - Red$	[15]
Enhanced Vegetation Index	(EVI)	$EVI = 2.5 * \frac{(NIR - Red)}{(NIR + 6 * Red - 7.5 * Blue + 1)}$	[7]
Green Normalized Difference Vegetation Index	(GNDVI)	$GNDVI = \frac{(NIR - Green)}{(NIR + Green)}$	[6]
Leaf Area Index	(LAI)	$LAI = (3.618 * EVI - 0.118)$	[1]

Source: https://www.l3harrisgeospatial.com/docs/vegetationindices.html, Accessed on July 2018 [17].

RESULTS AND DISCUSSIONS

The WV2 and Sentinel 2 images captured on July 2018 for the summer crop (corn) shown in Fig. (2a and b). The most sensitive VIs shown in Table 2 correlation coefficients with in situ hyperspectral vegetation indices were computed. The correlation coefficient, regression analysis, and the P-value for this VIs are shown in Table 3.

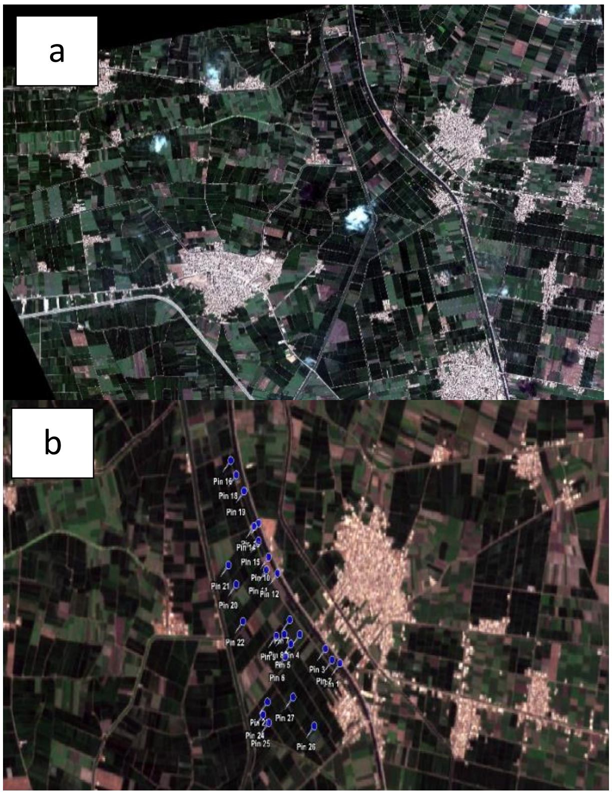


Fig. 2. (a) WorldView2 satellite image and (b) Sentinel 2 satellite image for the study location
Sources:
(a) European space agency, July2018 [4].
(b)https://www.sentinel-hub.com/, July2018 [13].

Table 3. Validation results of regression coefficient for estimating in-situ hyperspectral vegetation indices depends on hyperspectral vegetation indices calculated from the images

In-situ VIs	**WorldView 2**			**Sentinel 2**		
	r	**R^2**	**P-value**	**r**	**R^2**	**P-value**
DVI	0.765	0.585	0.000***	0.763	0.582	0.001**
(EVI)	0.743	0.553	0.005**	0.749	0.561	0.008**
(GNDVI)	0.823	0.675	0.329	0.876	0.767	0.2087
(LAI)	0.897	0.805	0.002**	0.820	0.673	0.000***

Source: WorldView2 data, July 2018 [18].

Using Worldview 2 image as a high spatial resolution satellite imagery for corn plants Calcium and Potassium content detection

Table 4 demonstrates the regression analysis and the fitting models of the relationship between corn plants dry matter Ca and K content and the published vegetation indices extracted from the WV 2 image. The majority of vegetation indices had negative relationships with the concentration of both elements. With R^2 values of 0.9013, 0.8019, 0.8997, and 0.783 respectively, DVI, EVI, and GNDVI performed well in estimating plant dry matter Ca and K content with high significant level P-value < 0.001. LAI had a significant effect with P-value <0.5 for both two elements. Figure 3 depict the relationships between Ca and K concentration in corn dry matter and the most highly correlated vegetation indices.

Table 4. Fitting model, R2, and P-value for the relationship between WorldView 2 VIs and calcium and potassium accumulation into the corn dry matter

VIs	WorldView 2 Image		
	Corn plants dry matter Calcium content		
	Fitting model	R^2	P - Value
DVI	Y = -0.8763X+ 2.4727	0.9013	< 0.001***
EVI	Y = -0.7661X + 2.626	0.8019	< 0.001***
GNDVI	Y= -1.9743X + 3.7517	0.8997	< 0.001***
LAI	Y= -0.2144X+ 2.6046	0.783	0.406 *
Corn plants dry matter potassium content			
DVI	Y= -0.701X + 1.9782	0.9013	< 0.001***
EVI	Y = -0.6129X+ 2.1008	0.8019	< 0.001***
GNDVI	Y = -1.5794X + 3.0013	0.8997	< 0.001***
LAI	Y = -0.1715X + 2.0837	0.783	0.1138*

Source: calculations from worldview2 satellite image , July 2018 [18].

Using Sentinel 2 image as a moderate spatial resolution satellite imagery for corn plants Calcium content detection

The regression analysis and fitting models of the relationship between corn plants dry matter Ca content and reported vegetation indices extracted from the Sentinel 2 image are shown in Table 5. The concentrations of the element had negative relationship with the majority of vegetation indices. DVI, EVI, GNDVI, and LAI performed well in estimating plant dry matter Ca content with R^2 values of 0.566, 0.5647, 0.3306, and 0.5647, respectively, with a high significant level P-value 0.001.

LAI had a statistically significant impact with a P-value of 0.5. The relationships between the concentrations of calcium and potassium in corn dry matter and the most closely associated vegetation indices are depicted in Fig. 4.

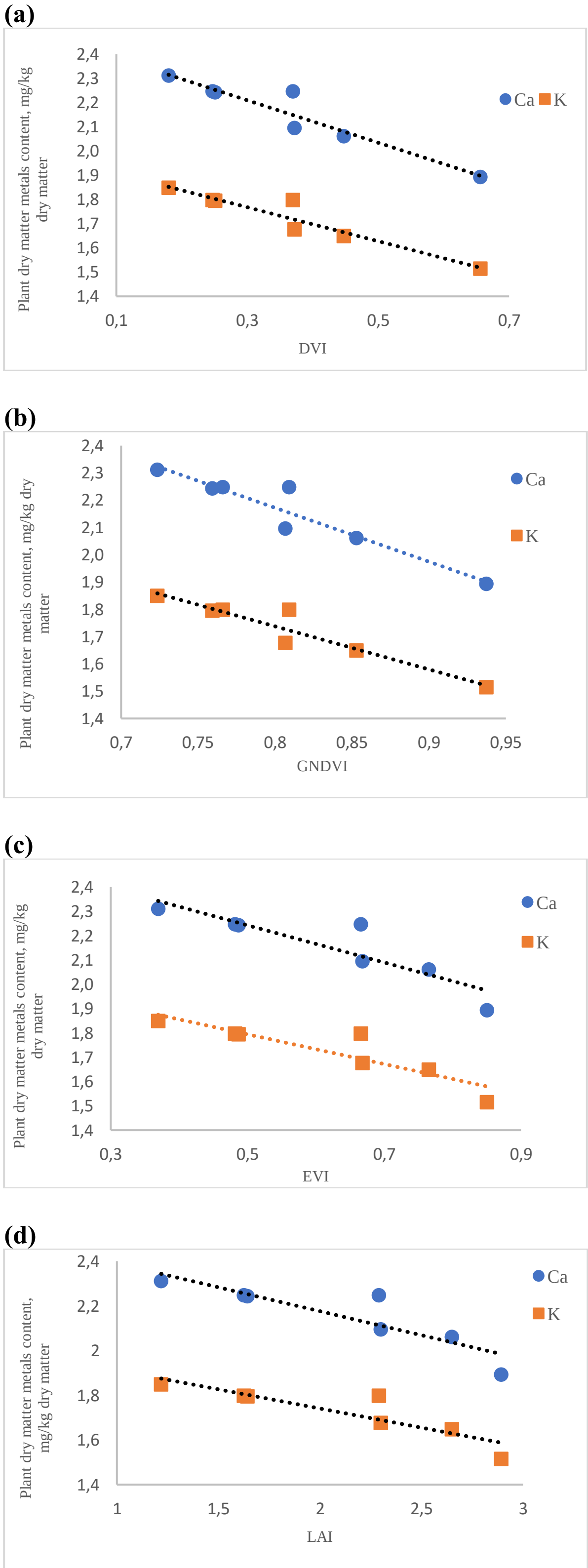
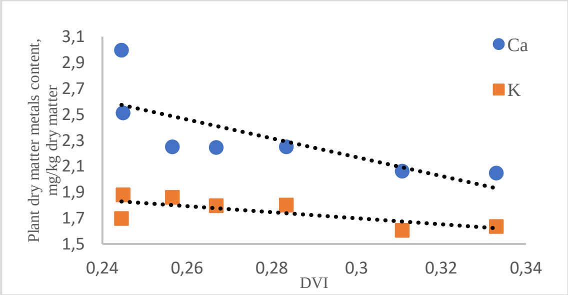
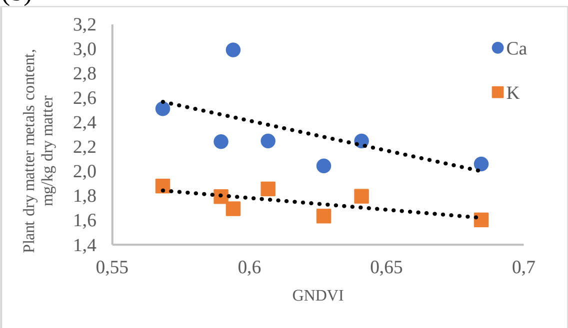


Fig. 3. Relationship between above ground plant dry matter Ca and K content and vegetation indices calculated from WorldView 2 satellite image
Source: calculations from worldview2 satellite image , July 2018 [18].

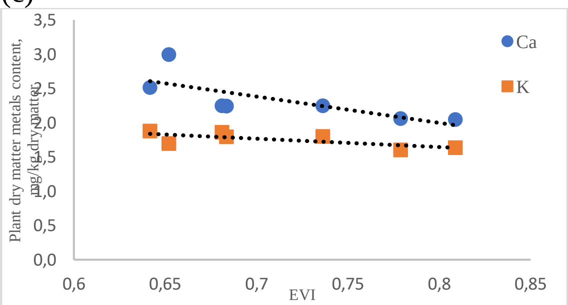
(a)



(b)



(c)



(d)

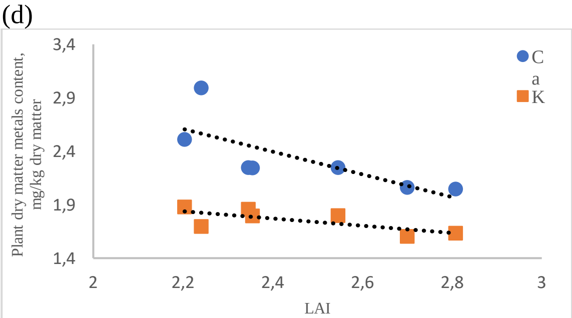


Fig. 4. Relationship between above ground plant dry matter Ca and K content and vegetation indices calculated from Sentinel 2 satellite image
Source: calculations from Sentinel 2 satellite image, July 2018 [12].

Using Sentinel 2 image as a moderate spatial resolution satellite imagery for corn plants Potassium content detection

Table 5 shows the regression analysis and fitting models for the relationship between dry matter K content of corn plants and recorded vegetation indices extracted from the Sentinel 2 image. The majority of vegetation indices showed a negative correlation with the element's concentrations. With R^2 values of 0.5343, 0.524, 0.4694, and 0.524 respectively, and a high significant level P-value < 0.001, DVI, EVI, GNDVI, and LAI performed well in estimating plant dry matter K material with a P-value < 0.01, LAI was statistically important. The associations between calcium and potassium concentrations in corn dry matter and the most closely related vegetation indices are shown in Fig. 4.

Table 5. Fitting model, R2, and P-value for the relationship between Sentinel 2 VIs and calcium and potassium accumulation into the corn dry matter

VIs	Sentinel 2 Image		
	Corn plants dry matter Calcium content		
	Fitting model	R^2	P - Value
DVI	Y= -7.2697X+ 4.3503	0.566	< 0.001***
EVI	Y= -3.8419X + 5.07	0.5647	< 0.001***
GNDVI	Y = -4.8848X + 5.3443	0.3306	< 0.001***
LAI	Y= -1.0619X + 4.9447	0.5647	0.28*
Corn plants dry matter potassium content			
DVI	Y = -2.3317X+ 2.3977	0.5343	< 0.001***
EVI	Y = -1.2217X + 2.621	0.524	< 0.001***
GNDVI	Y= -1.9214X + 2.935	0.4694	< 0.001***
LAI	Y = -0.3377X + 2.5812	0.524	0.001**

Source: calculations from worldview2 satellite image, July 2018 [18].

CONCLUSIONS

This study compared the using of multi-temporal Sentinel-2 images with the high resolution Worldview 2 image to detect Ca and K concentration on corn plants growing in a natural agriculture ecosystem irrigated with industrial waste water on the regional scale. (DVI), (EVI), (GNDVI), and (LAI) were selected as an effective indicator for Ca and K corn plants content based on data measured in the field and comparisons between ASD VIs , Sentinel-2 VIs, and WorldView 2 Vis, and these results also proved that the Sentinel-2 images are an effective remote data source for detecting plant stress.

The price volatility is reflected at all chin stages level and especially at the production stage and to a lesser degree at the marketing and processing levels.

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