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The Effect of Water and Vegetation Vigor on Citrus Production in Egypt Using Remotely Sensed Data and Techniques

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Authors' contributions

This work was carried out in collaboration between all authors. Authors MAES and MHE designed the study, wrote the protocol and wrote the first draft of the manuscript. Authors AMA and ASD managed the literature, analyses of the study, performed the data analysis and statistical analysis. Authors MHE and GAB managed the experimental process. All authors read and approved the final manuscript.

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ABSTRACT

The vigor of vegetation and water availability are major components in agricultural production which are affecting on crop yield quantity and quality. Crop water stress occurs continuously over the total growing period or during any one of the individual growth periods of the crop. This study aims at quantifying the Vegetation and water stress effect on Valencia orange yield through remotely sensed data and techniques to predict the yield. Landsat OLI satellite imageries provide Red (*R*) and Near-Infra-Red (*NIR*) measurements which used to calculate the Normalized Difference Vegetation Index (*NDVI*). Land Surface Temperature (LST) was calculated from the thermal spectral region (band 10) and integrated with air temperature measurements to estimate Crop Water Stress Index (CWSI). Three Valencia orange farms were studied and 27 samples were

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collected (9 samples/farm). Two cultivation seasons data sets were investigated (2013/2014 and 2014/2015). Many regression models were produced. NDVI and CWSI were modeled with yield through a regression model analysis. The first season multi-regression model was the best model where R^2 was high as 0.852 and regression validation was very good. The predicted yield map showed the spatial distribution of Valencia orange yield in the field, which ranged from 6.9 (ton/fed) to 29.2 (ton/fed).

Keywords: Crop Water Stress Index (CWSI); valencia orange; yield prediction map and Landsat OLI.

1. INTRODUCTION

Citrus is the major fruit crop cultivated in Egypt. Valencia orange is a late harvesting horticulture crop so, it has a great potentiality for export to European and Arab markets. The total area of Valencia orange in Egypt is about 50000 fed (fed. = 4200 m^2) and the most of them located in newly reclaimed areas. The tree vigorous large and prolific very wide of climatic adaptation of any orange variety of commercial it is suitable for the heat deficient mild sub-tropical a humid semi-tropical and tropical [1].

The Valencia orange is a well-colored cortex at maturity, a summer ripening fruit, seeds few or none, and much juice. Management of citrus orchards depends on personal experiences that differ from one farm to another within small areas. Mismanagement of orchards leads to yield reduction and loss of income. Some growers are now shifting from one crop to another due to difficulties they have experienced with kind of management.

Yield prediction is predicting crop yield two months before the harvest in the optimal case. [2] investigated a case study in Florida using Landsat ETM+ imageries to delineate citrus groves for economic assessment. Their results showed a significant correlation between citrus production and income with remotely sensed imagery-derived citrus area coverage.

Vegetation indices have used to monitor terrestrial landscapes by satellite sensors since the beginning of the 1970s. It had succeeded in assessing vegetation conditions, foliage, cover, phenology, and processes related to the fraction of photosynthetically active radiation absorbed by a canopy [3-4].

In Egypt, various studies on vegetation indices and water stress using remote sensing techniques were executed [5-9].

[10] found that the sensitivity of *NDVI* to chlorophyll concentration varied depending on the visible region which has significant affects the correlation between the *NDVI* and canopy properties. The values of NDVI less than 0.1 correspond to non-vegetation coverage. Moderate values represent shrub and grassland (0.2 to 0.3) while high values indicate temperate and tropical rainforests (0.6 to 0.8).

Crop water stress is detected remotely through the measurement of a crop's surface temperature. The correlation between canopy temperature and water stress is based on the assumption that as a crop transpires, the evaporated water cools the leaves. When the crop becomes water stressed, transpiration will decrease, and thus, the leaf temperature will increase. The leaf or canopy temperature is used as an indicator of plant water stress [11-13]. The crop water stress is an indicator for crop irrigation needs.

The main objective of this study is developing the yield prediction models for citrus through proper management of citrus orchards under different conditions, including irrigation, fertilization, and collect data regarding prevailing varieties, phenological stages, and duration, agricultural practices, farm conditions, yield potential of the crop yield forecasting model. These models require few input factors to be applied few months before harvesting. The study also will lead to correlate remotely sensed data represented as vegetation indices and plant biophysical parameters that could be retrieved from remotely sensed data.

2. MATERIALS AND METHODS

2.1 Study Area Location

The study is located in the eastern part of the Nile Delta as shown in (Fig. 1). Drip irrigation is the common irrigation system in the region. The climate in the study area is Dry Arid according to the Köppen Climate Classification System, where precipitation is less than 50% of potential evapotranspiration.

2.2 Satellite Data

Landsat8 imageries (Table 1), with a path (176) and row (039), around 10 a.m. local time, on 3rd of Aug. 2013 and 6th of Aug. 2014 were used in the current study to extract *LST* and *NDVI*.

The ENVI software package was used to process satellite data. Atmospheric and radiometric corrections were applied.

SPSS software was used for statistical analysis. The package is particularly useful for studying psychology, sociology, psychiatry, and other behavioral sciences [14].

Table 1. The specifications of Landsat8

Band	µm	Resolution
1	0.433–0.453	30 m
2	0.450–0.515	30 m
3	0.525–0.600	30 m
4	0.630–0.680	30 m
5	0.845–0.885	30 m
6	1.560–1.660	30 m
7	2.100–2.300	30 m
8	0.500–0.680	15 m
9	1.360–1.390	30 m
10	10.6-11.2	100 m
11	11.5-12.5	100 m

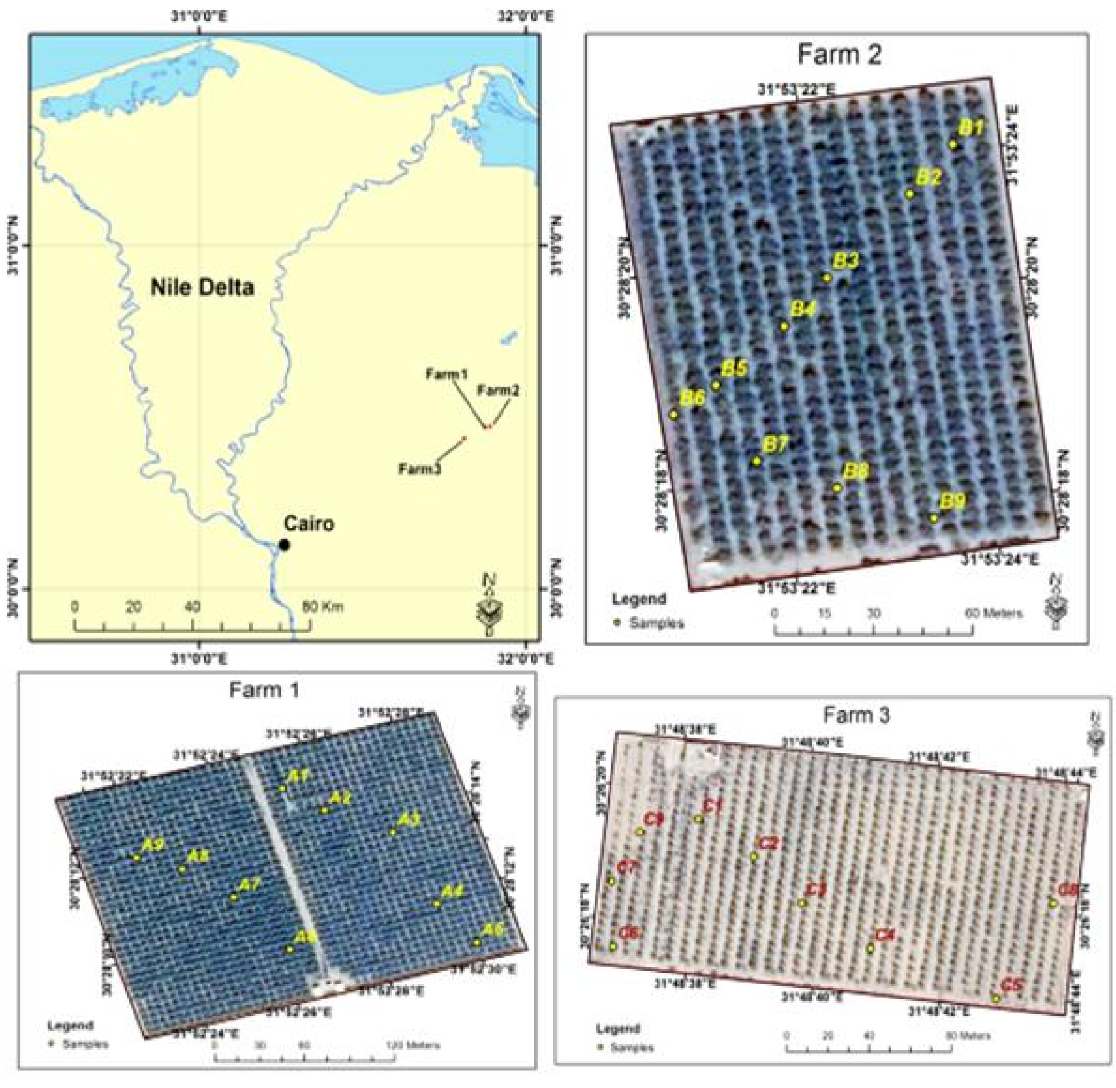

Fig. 1. Study area location

2.3 NDVI, LST and CWSI Estimation

NDVI is computed as the ratio of the measured intensities in the *R* and *NIR* spectral bands which measured through many satellites. The resulting index value is sensitive to the presence of vegetation cover. It could be used to indicate the vegetation type, amount, and condition. Landsat8 bands 4 and 5 can be used to calculate *NDVI* with the following formula:

$$NDVI = (\text{Band 5} - \text{Band 4}) / (\text{Band 5} + \text{Band 4}) \tag{1}$$

LST was calculated from the top of atmosphere radiant temperature (*To*) and estimated surface emissivity (*Eo*) as:

$$LST = To/Eo \tag{2}$$

The recorded digital numbers (*DN*) for Band 10 is converted to radiance units (*Rad*) using the calibration coefficients as follow:-

$$Rad = 0.0003342 * DN + 0.10000 \tag{3}$$

The developed empirical equation was used to estimate surface emissivity (*Eo*) based on *NDVI* according to [15] method.

$$Eo = 0.9932 + 0.0194 \ln NDVI \tag{4}$$

The calibration constants *K1*=774.89 and *K2*=1321.08 were used to calculate radiant temperature (*To*) from band 10 radiance (*Rad10*). The constants *K1* and *K2* were obtained from NASA website (http://landsat.usgs.gov/Landsat8_Using_Product.php).

$$To = K2/ \ln((K1/Rad10) + 1) \tag{5}$$

The resulting temperature unit is Kelvin. It could be converted to Celsius degree by dividing the result by 273. The atmospheric effects and surface thermal emissivity have to be considered in order to obtain the accurate estimation [16].

CWSI approach was processed and developed by [11,17]. They proposed the empirical and theoretical methods to estimate *CWSI* as follows:-

$$CWSI = \frac{\Delta T - \Delta Tm}{\Delta Tx - \Delta Tm} \tag{6}$$

Where: ΔT is the difference between measured surface and air temperature, ΔTm is the difference between minimum surface and air temperature, ΔTx is the difference between maximum surface and air temperature. *CWSI* is a dimensionless ratio. The values of *CWSI* are ranged between zero and one where zero indicates no stress and value of one indicates maximum stress.

3. RESULTS

Two season's data were used to predict the yield. 27 points of each season were collected for the model building. The model validation was applied to other fields in the same region. The detailed explanation of the modeling process for each season is explained in the following sub-sections:-

3.1 Yield Prediction Models

Many regression models were produced in this study. These models depend on a single factor or many factors. In the next section, the regression models will be described.

3.1.1 First season models

The yield of Valencia orange is affected directly by NDVI and CWSI. The relation between Yield and NDVI was positive and good where R^2 was high as 0.704. On the other hand, the relation between yield and CWSI was negative and better than NDVI with yield where R^2 was 0.85. NDVI-Yield and CWSI-Yield regression models were described in the Table 2. Figs. 2A and 2B shows the relation between NDVI and yield (Ton/fed) and CWSI and yield (Ton/fed) respectively.

Table 2. Simple regression models for Valencia orange yield prediction in the season 2013/2014

Input factor	Intercept (a)	Slope coeff. (b)	Generated model	R^2
NDVI	-24.252	60.084	Y=-24.252 +60.084*NDVI	0.704
CWSI	40.432	– 60.980	Y=40.432 – 60.980*CWSI	0.852

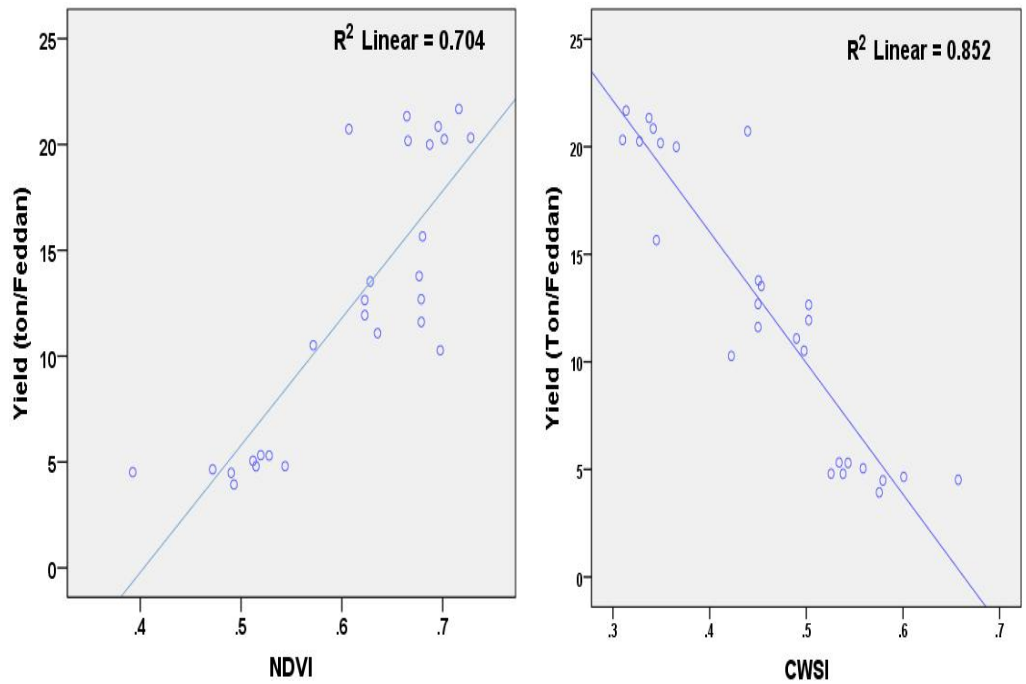

Fig. 2A **Fig. 2B**

Fig. 2A. Shows the correlation coefficient between NDVI and yield, 2B. Shows the correlation coefficient between CWSI and yield through the season 2013/2014

3.1.2 Second season models

In the second season, the relation between Yield and NDVI was positive and good where R^2 was high as 0.703. On the other hand, the relation between yield and CWSI was negative and slightly higher than NDVI with yield where R^2 was 0.743. NDVI-Yield and CWSI-Yield regression models were described in the Table 3. Figs. 3A and 3B shows the relation between NDVI and yield (Ton/fed) and CWSI and yield (Ton/fed) respectively.

3.1.3 Multi-regression models

Multi-regression models depend on many variables. NDVI and CWSI were used together to produce multi-regression models through the seasons 2013/2014 and 2014/2015 to predict Valencia orange yield (Table 4). The correlation coefficient was changed from the first season to the second one where R^2 was 0.852 and 0.751 respectively.

3.2 Models Validation

Regression validation is a method of deciding if the results quantifying the relationships between variables obtained from regression analysis are acceptable as a description of the data or not. If the R^2 is close to one, it does not mean that the model fits the data well. A high R^2 can occur in the presence of miss-specification of the functional form of a relationship or in the presence of a true relationship. To get good regression validation the results must be arranged close to the line.

Table 3. Simple regression models for Valencia orange yield prediction in the season 2014/2015

Input factor	Intercept (a)	Slope coeff. (b)	Generated model	R^2
NDVI	-22.406	55.861	Y=-22.406+55.861*NDVI	0.703
CWSI	42.938	-53.762	Y=42.938– -53.762*CWSI	0.743

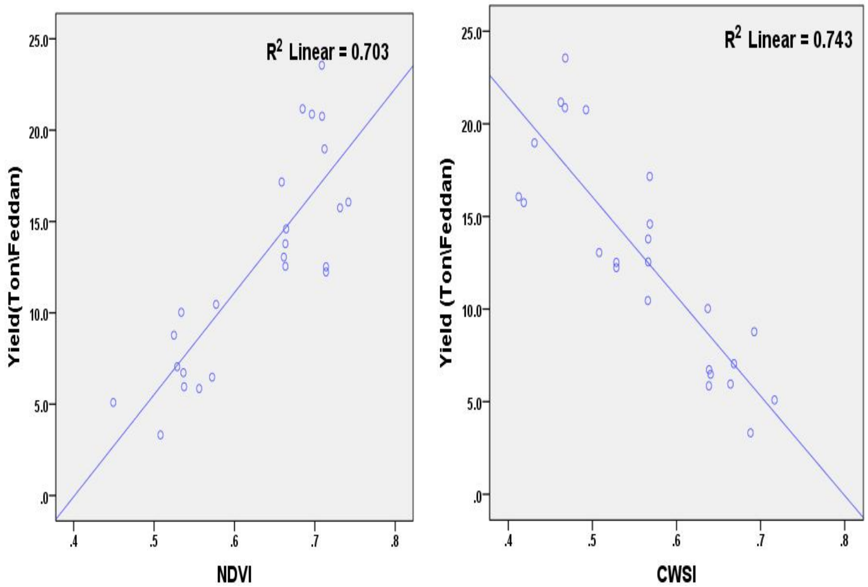

Fig. 3A **Fig. 3B**

Fig. 3A. Shows the relation between NDVI and yield, and 3B. Shows the correlation between CWSI and yield through the season (2014/2015)

Table 4. Multi regression models for Valencia orange yield prediction

Input factor	Intercept (a)	Slope coef. (b)	Slope coef. (b)	Generated model	R^2
2013/2014	44.81	-64.70	-4.38	44.81-64.70*CWSI-4.38*NDVI	0.852
2014/2015	23.51	-38.58	17.34	23.51-38.58*CWSI+17.34*NDVI	0.751

3.2.1 First season validation

In the first season, the regression validation was done according to the correlation coefficient between actual and predicted yield according to NDVI model and the correlation was very good where R^2 was high as 0.972 and the data distribution was close to the line Fig. 4A. On the other hand, the regression validation was done according to the correlation coefficient between actual and predicted yield according to CWSI model and the correlation was very good where R^2 was high as 0.912 and the data distribution was close to the line (Fig. 4B).

3.2.2 Second season validation

In the second season, the regression validation was done according to the correlation coefficient between actual and predicted yield according to NDVI model and the correlation was good where R^2 was high as 0.762 and the data distribution was close to the line Fig. 5A. On the other hand, the regression validation was done according to the correlation coefficient between actual and predicted yield according to CWSI model and the correlation was very good where R^2 was high as 0.912 and the data distribution was close to the line Fig. 5B.

3.2.3 Multi-regression model validation

The multi-regression model validation was done between actual and predicted yield through NDVI and CWSI. The correlation in the first and second seasons was very good where R^2 were high as 0.91 and 0.917 respectively (Figs. 6A and 6B).

3.3 Yield Prediction Map

Yield prediction map produced according to the first season multi-regression model which is the best model produced and validated in this study. It depends on two factors; NDVI and CWSI. A 0 value of the CWSI indicates no water stress, and a value of 1 represents maximum water stress.

The yield prediction map shows the variation of Valencia orange yield in a farm with an area about 580 feds. It ranged from 6.9 (ton/fed) to 29.2 (ton/fed). Fig. 7 represents the variation of NDVI, CWSI and predicted the yield of Valencia orange.

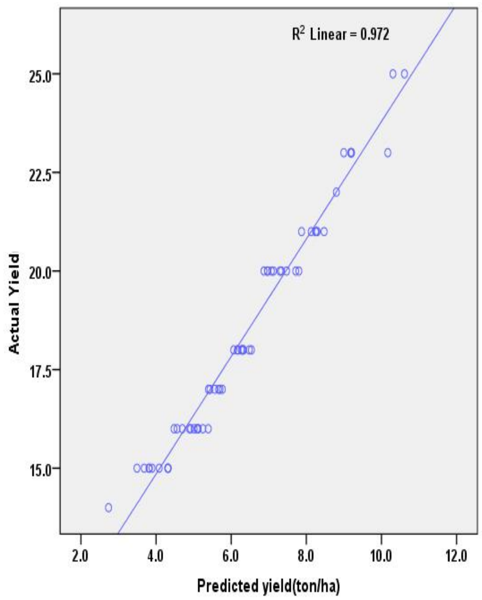

Fig. 4A

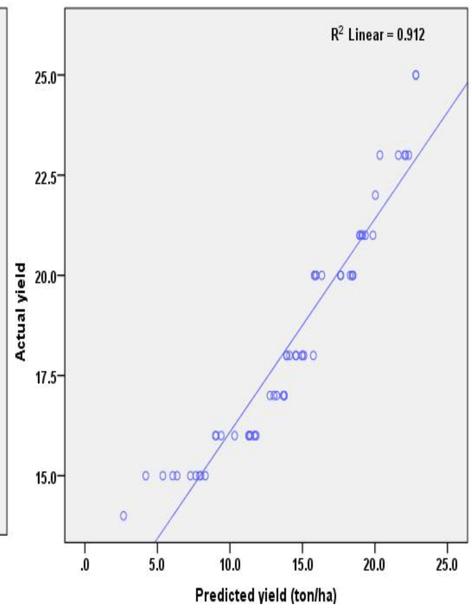

Fig. 4B

Fig. 4A. Shows the model validation between actual and predicted yield according to NDVI 2013/2014 model (R^2= 0.972) and 4B. Shows the model validation between actual and predicted yield according to CWSI 2013/2014 model (R^2= 0.912)

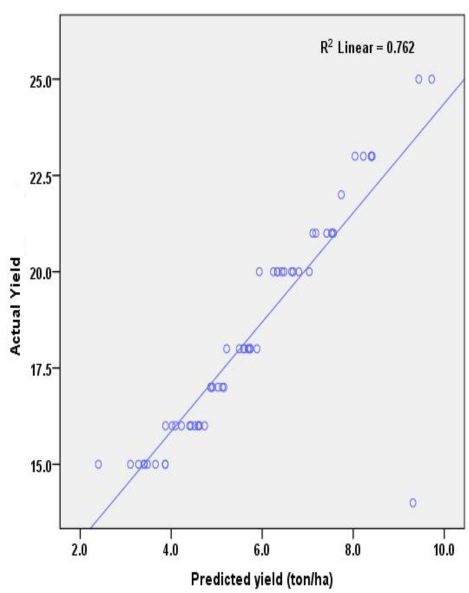

Fig. 5A

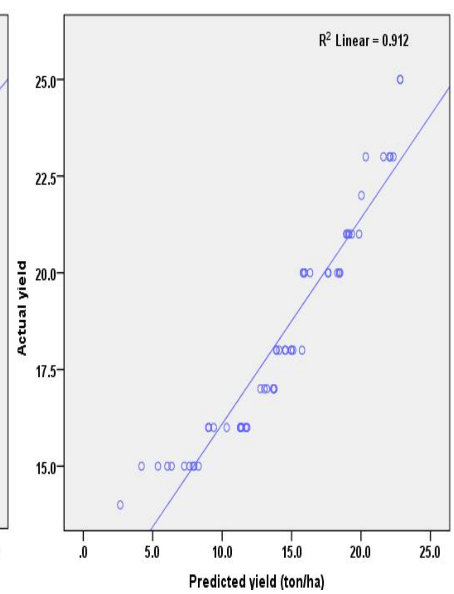

Fig. 5B

Fig. 5A. Shows model validation using correlation coefficient between actual and predicted yield according to NDVI 2014/2015 model (R^2= 0.762) and 5B. Represents the model validation correlation coefficient between actual and predicted yield according to CWSI 2014/2015 model (R^2= 0.912)

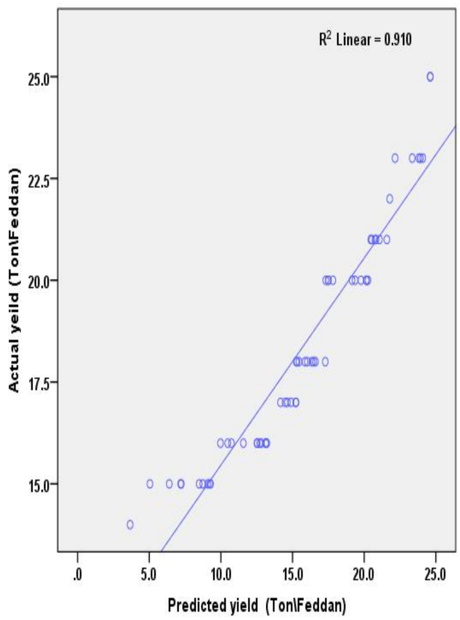

Fig. 6A

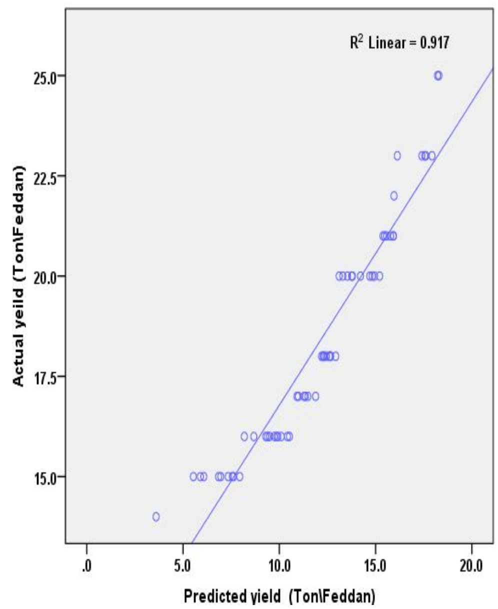

Fig. 6B

Fig. 6A. Describes the model validation between actual and predicted yield according to multi regression model (2013/2014) with R^2= 0.910, and 6B. Describes the model validation between actual and predicted yield according to multi regression model (2014/2015) with R^2= 0.917

4. DISCUSSION

Yield prediction is a very priority in limited agricultural resource countries. At the same time, is very difficult because of uncertainty and numerous uncontrolled factors nearby the crop which affects directly on the yield. In this study, the NDVI was represented as a crop's nutrient and canopy vigor status while CWSI was represented as a crop's micro-climate and irrigation status.

Many researchers have investigated the effect of canopy vigor on yield. Citrus canopies, numbers of new leaves, and floral buds have been studied by [18]. [19] suggested a correlation between canopy features and the yield of citrus trees. The results illustrated the good performance of the proposed model in exploring the potential of predicting citrus yield from airborne hyperspectral imagery. [20] did a relation between canopy reflectance and citrus yield and the higher correlation (R^2) was high as 0.81.

CWSI is a valuable method to assess the water status, as well as to quantify the spatial variability of citrus orchards water stress using a high-resolution airborne thermal data [21].

We used 27 samples collected from 3 farms to build the models and 35 samples collected from other farms around the study area to validate the data. The best validation result was for NDVI model in the first season, but the correlation of the NDVI in the first and in the second seasons was the worst (Table 5).

Table 5. The correlation coefficients of Valencia orange yield prediction models and validation

Parameter	R^2 for the first season		R^2 for the second season	
	Model	Validation	Model	Validation
NDVI	0.704	0.972	0.703	0.762
CWSI	0.852	0.912	0.743	0.912
NDVI-CWSI	0.852	0.910	0.751	0.917

The yield prediction map represents the yield distribution in the farm

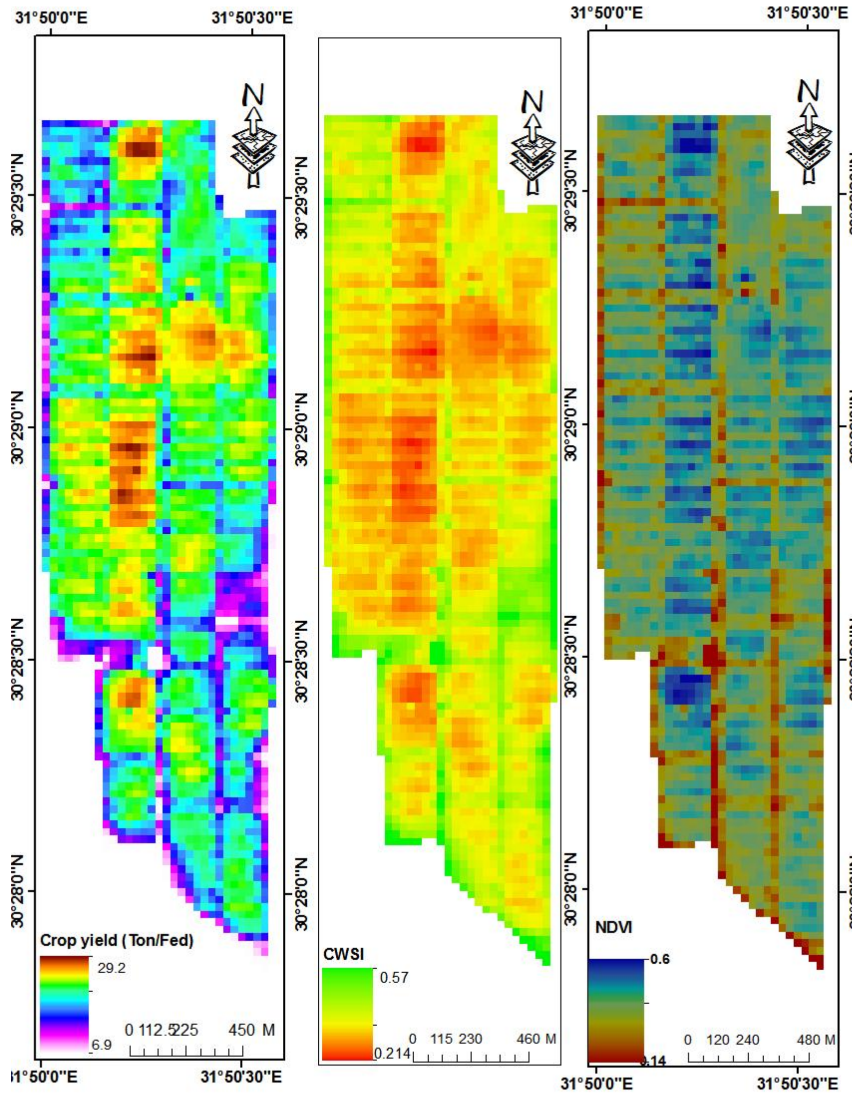

Fig. 7. Shows the maps of NDVI, CWSI and predicted the yield of Valencia orange

On the other hand, the validation results were more than 90% in other models, so the choosing of the best model was among them. The correlations of the CWSI model and NDVI-CWSI model in the first season were good in both model and validation stages, but the CWSI model depends on one parameter and more sensitive than the NDVI-CWSI model, so we selected the NDVI-CWSI model to produce the prediction yield map.

The low yield areas, maybe happened because of the shortage of water or/and nutrients. Numbers of Valencia trees in the cultivated area will affect also. On the opposite, the high yield areas, conflict the optimal of Valencia orange density, nutrients, and irrigation.

5. CONCLUSION

The planning of crop management will be easier with approaches which use remotely sensed derived parameters. Many models used to predict the yield. These models vary in complexity but the accuracy of yield prediction is proportional to the degree of calibration and validation of the used model. Low ground data availability is a serious problem in Egypt and developing countries, but the free satellite data may be used as an alternative method if it is used after calibration and evaluation especially in the agricultural field [22]. It could be a useful and low-cost method for crop stress detection and enhance regional yield prediction. Regression models are a good way to predict the yield if the data were well represented. It is necessary to produce crop distribution map to produce a large scale yield map prediction.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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