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Original Research

The Feasibility of Using Vegetation Indices and Soil Texture to Predict Rice Yield

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Abstract

Identifying plant-environment interactions along with remote sensing provides grounds for designing management methods as well as predicting rice yield in different conditions; accordingly, it is very helpful to use vegetation indices for identifying the vegetation and greenness of farms. The regression between the local and high-yield varieties of rice in 2012 and the NDVI, SAVI, LAI, DVI, and RVI indices derived from Landsat 7 in northern Iran indicate the superiority of the NDVI index in the flowering stage of rice. Results show that the coefficient of determination of the fitted model for local and high-yielding varieties is 0.71 and 0.70, respectively, which indicates the good consistency of the results with the regional data. We evaluated the models for the local and high-yielding varieties in crop year 2013 with RMSE of 406 and 272 kg ha^{-1} and NRMSE of 12% and 6%, respectively. Moreover, the simulation results show that the yield of the models is well fitted with the observed values; besides, there is high correlation ($R>0.80$) between the real and predicted yield values. As shown by the investigation of the region's soil texture, the fine-texture paddy fields have better yield.

Keywords: crop yield, remote sensing, rice, vegetation indices

Introduction

Crop monitoring is of great importance in the economic development of any country due to the production of crops and predicting annual yield having direct effects on the national and international economies and playing an important role in food management [1]. Therefore, it is essential to perform the early estimation of crops and provide the resulting information for planners of the agricultural sector [2].

Today the assessment of different production options, extrapolation, and generalization of the results to other regions with different climates and conditions can be accomplished through simulating the production process [3]. Soil is considered as the base of production security; thus, in order to achieve more effective crop management programs, yield-limiting soil features should be taken into account [4]. Soil properties vary over time and space. The soil spatial variations are naturally caused by soil-forming factors [5] and are

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affected by two factors, namely intrinsic (soil-forming factors such as parent material) and external (agricultural management practices such as fertility and irrigation) properties [6]. The relationship between crop yield and soil is very complicated and depends on the interactions between the physical and chemical properties of soil as well as natural external factors; thus, soil texture can have a variant relationship with crop yield [7-8].

By providing the spatial information of large areas, remote sensing has provided users with the opportunity to predict crop yield before harvesting [9-10]. Plant production is directly dependent on the interactions between solar energy and plant surface [11]; thus, remote sensing techniques can help determine plant production by measuring this energy [10, 12]. One of the most efficient methods for monitoring agricultural products is to use spectral indices [13-14]. Most of the indices, which are used to estimate the yield, use the red band and near-infrared (NIR) within their structure [10, 15], and the modeling process is performed based on the vegetation indices (VI) derived from remote sensing data [16-17]. Numerous studies have investigated how to use this technology [9-11, 13, 14, 18].

Rice is among the most important agricultural crops and is the main food source for more than half of the world's population [10]. Furthermore, in Iran the coastal areas of the Caspian Sea account for more than 70% of paddy fields [19]. Various studies have indicated that rice farming is common in a wide range of climatic and hydrological features. The soil substrate of rice farming can tolerate the texture range of clay to sand, pH of 3-10, organic matter of 1-50%, salinity of 0-1%, as well as low- (under-nutrient) and high-nutrient (over-nutrient) conditions [20].

Identifying plant-environment interactions along with remote sensing technology facilitates designing management methods as well as predicting rice yield in different conditions. Sanchez [21] showed that the amount of crop could be tripled by appropriate soil management; moreover, the study conducted by Juhos et al. [7] indicated that the effects of soil properties depended on grain yield, weather, and topography.

Following the studies conducted on vegetation indices and considering the region's soil potentials for rice production would help estimate the pre-harvesting yield. Similar studies have been conducted to estimate wheat yield using spectral indices, which have led to favorable results [17, 22]. The study conducted by Wei-guo et al. [11] in China to estimate rice yield using HJ-1A satellite imaging indicated the closeness of the real and estimated values of the model so that the model could predict the yield up to 85%.

Moreover, by establishing a direct relationship between the vegetation indices derived from the SPOT satellite imagery and rice yield in a small research farm, Aboelghar et al. [23] could predict the yield one month before harvesting ($R^2 = 0.86$). Nuarsa et al. [12] employed NDVI index resulted from Landsat ETM+ satellite imagery to present an exponential model for estimating the rice yield ($R^2 = 0.852$). Assessment of the model indicated a strong relationship between the observations and estimated data.

In another study, Noureldin et al. [16] used the normalized difference vegetation index (NDVI) combined with the leaf area index (LAI) to estimate the rice yield, the result validation of which indicated the high precision of the model that could be implemented in similar environmental conditions and the same rice farming methods. Moreover, in Vietnam, Son et al. [10] used the rice yield during 2002-2011 and the NDVI and EVI indices derived from the MODIS satellite for extracting the model, the results of which approved the relationship between the assessed indices and rice yield.

In another study, Siyal et al. [9] attempted to estimate the rice yield in 2013 using the NDVI and RVI indices derived from 8-year Landsat ETM+ satellite imagery. Their proposed regression model was applied between the values of the harvested crop and the NDVI and RVI indices at the peak of greenness period with the determination coefficients (R^2) of 0.94 and 0.875, respectively, in order to estimate the yield. The strong relationship between the produced and predicted rice crop confirmed the model's capability to estimate the yield.

In wide ranges of spatial variations and diversity, the factors affecting the yield, including soil type and crop management, can result in errors of estimating the yield because it is impossible to control all the environmental conditions. The use of satellite imagery and ground-based observational data is an appropriate integration for yield assessment. Investigating the NDVI, SAVI, LAI, DVI, and RVI indices and calculating them at the given dates provide the possibility of choosing an appropriate index for the studied region and the ground for monitoring the plant's growth as well as yield accuracy of the indices with regard to the measured plant's growth phase and identifying the soil properties in the region.

Materials and Methods

Region and Field Data

Shaft County in southwest Guilan Province is located between 36°56'-37°18'N latitude and 49°10'-49°31'E longitude in northern Iran. The area of the studied region embraces nearly 14000 ha of the total area of the city undergoing rice farming. The region is temperate and humid and the paddy fields are located in plains and foothills (Fig. 1).

The rice varieties in the farms of this region are categorized into two major groups, including local varieties, namely Hashemi and Ali Kazemi, and high-yielding (modified) varieties, namely Khazar and Gohar. In fact, the local varieties account for two-third of the paddy fields. In the present research, the ratio of the varieties was maintained besides the proper distribution

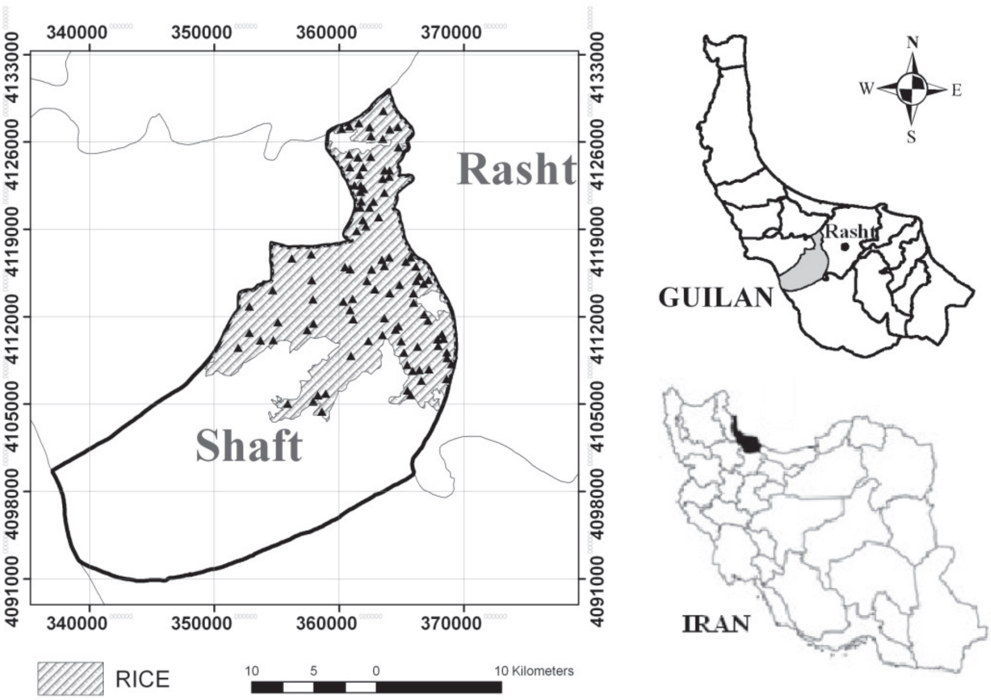

Fig. 1. Geographic location of study area in the city of Shaft, Guilan, Iran.

of the farms across the region. Thus, data of the farms, including type of variety, yield value, area of rice paddies, and onset dates of planting and harvesting, were received during two years (2012 and 2013). Then the results were compared with the available maps of land use and differentiation of the agricultural products. The data of the first and second years were used for deriving the equations and evaluating the best extracted equations, respectively.

Duration of rice farming period in the region for different varieties was 120-150 days, and the paddy fields should be flooded within 90 days from the beginning of cultivation. In the north of Iran, this period coincided with the beginning of April up to August [24]. Table 1 represents the raining status and temperature in the rice-farming period; furthermore, Fuman Water Channel was used for irrigation.

Sampling the surface soil of the paddy fields was performed from the depth of 0-30 cm at 100 points of the region. The samples were tested after being dried in the open space and being passed through a 2 mm sieve. The soil texture was hydrometric the soil particle-size distribution was determined for each sample using the hydrometer method from which the soil textural classes were obtained [8]. Organic material was using wet oxidation [5]. Electrical conductivity (EC) and pH were measured in saturated extract using a conductimeter and electrode methods, respectively [4].

Satellite Data

Among the environmental satellites, Landsat with multi-spectral scanners and the capability of providing satellite imagery with spatial resolution of less than 30 m is widely used for the biophysical parameters of vegetation [12]. In addition, the images of this sensor are appropriate for investigating the vegetation status [9] and monitoring plant growth [14] due to the 16-day visit period.

In order to determine the appropriate time for receiving the satellite imagery with regard to the agricultural calendar of rice planting and harvesting as well as the information available in the Department of Agriculture, flowering time and the maturity stage

Table 1. Monthly temperature and rain in tested years.

Year	Parameter	April	May	June	July	August
2012	Temp (ºC)	17.3	22.6	24.6	25.2	26.6
	Rain (mm)	67.8	30.2	116.2	76.8	89.4
2013	Temp (ºC)	15.7	21.8	25.7	26.7	25.4
	Rain (mm)	58.1	25.7	8.3	58.2	49.8

were specified in the second halves of June and July, respectively. The multi-spectral digital data of ETM+ sensor of Landsat 7 were used from route 166 and row 34 in accordance with World Reference System (WRS) on 15 June and 17 July 2012 and 18 June 2013.

Due to system failure, the ETM+ data contained bands without information, since 2003 onwards and a part of the studied region were located in this area. In order to fill the bands, gap-fill tool was added to ENVI v.4.7 software and the images were corrected. Furthermore, the radiometric and geometric corrections were made based on the specified points using Google Earth images in this software. The reflectance values in the third and fourth bands were obtained as red equal to 650 nm and NIR equal to 860 nm [13], respectively, for the above-mentioned images. Finally, the NDVI, SAVI, LAI, DVI, and RVI indices were calculated using the equations that will be introduced in the following section based on the proposed coefficients:

$$\mathrm{NDVI}^{1} = \frac{\rho_{nir}-\rho_{red}}{\rho_{nir}+\rho_{red}} \quad (1)$$

$$\mathrm{SAVI}^{2} = \frac{\rho_{nir}-\rho_{red}(1+L)}{(\rho_{nir}+\rho_{red}+L)} \quad (2)$$

$$\mathrm{LAI}^{3} = -\frac{Ln(\frac{C_1-SAVI}{C_2})}{C_3} \quad (3)$$

$$\mathrm{DVI}^{4} = \rho_{nir} - \rho_{red} \quad (4)$$

$$\mathrm{RVI}^{5} = \frac{\rho_{red}}{\rho_{nir}} \quad (5)$$

P_{nir} and P_{red} values in order of reflectivity were in the red and NIR bands [9, 25]. The value of coefficient L was calculated equal to 0.1 with regard to the regional studies; moreover, C1, C2, and C3 constant coefficients, the values of which depend on the type of product, were considered equal to 0.69, 0.59, and 0.91, respectively, for the rice plant [26].

Statistical Indices

The information obtained from the paddy fields in 2012 was divided into two parts. The first part containing 75 positions was used to extract the regression equations of the local and high-yielding varieties and the second part including 25 data was used for validating the equations. Accuracy of the images in predicting the yield was evaluated using the statistics of the root mean square error (RMSE), normalized RMSE (NRMSE), mean bias error (MBE), and coefficient of determination (R^2). Also, the data of 75 farms in 2013 were used for re-evaluating the best equations derived from the first-year data:

$$\mathrm{RMSE} = \left[\frac{\sum_{i=1}^{n}(P_i-O_i)^2}{n}\right]^{1/2} \quad (6)$$

$$\mathrm{NRMSE} = \frac{\mathrm{RMSE}}{\bar{O}} \times 100 \quad (7)$$

$$\mathrm{MBE} = \frac{\sum_{i=1}^{n}(P_i-O_i)}{n} \quad (8)$$

…where P_i, O_i, $\bar{O}$, and n indicate the estimated or replicated values, observational (measured) values, average of the observational (measured) values, and number of samples (observed, calculated or estimated varieties), respectively. The above-mentioned indices have been widely used in various studies, including Son et al. [10] and Siyal et al. [9], for valuation of the models; accordingly, the straight-line equation is drawn for the two models that have allocated the highest regression coefficients.

Moreover, diversity of the soil properties in farms is interpreted using the classical statistical methods [5] and data distribution is demonstrated by mean, minimum, maximum, standard deviation (SD), and coefficient of variations (%CV). In order to compare the distribution in one or two separate populations, the coefficient of variations is used. The coefficient of variations indicates the data dispersion around the mean; thus, the higher the value of this index, the higher the dispersion of data relative to the mean. Variables with CV of less than 15% have low variations, while those with CV of 15-35% have moderate variations and those with the CV of above 35% have high variations.

Results and Discussion

Relationships between Indices and Crop Yield

Vegetation indices were calculated for local and high-yielding varieties in the region in both flowering and maturity periods based on the ground reflection of the images. In order to find the correlation between the dependent (crop yield or y-axis) and independent variables (vegetation indices or x-axis) as well as the

[1] Normalized Difference Vegetation Index [27]

[2] Soil Adjusted Vegetation Index [28]

[3] Leaf Area Index [29]

[4] Difference Vegetation Index [30]

[5] Ratio Vegetation Index [31]

Table 2. Relationship between yields of rice varieties and indices in 2012.

Variety	INDEX	Stage crop	MODEL	R^2	RMSE (Kg ha^{-1})	NRMSE (%)
Local	**NDVI**	**Flowering**	**Y= 4389.5x+1042.7**	**0.71**	**310**	**10**
		Maturity	Y= 4594.2x+792.5	0.61	495	15
	SAVI	Flowering	Y= 6640.3x+27.003	0.65	440	14
		Maturity	Y= 6023.7x+372.91	0.44	431	14
	LAI	Flowering	Y= 944.54x+2111.8	0.60	447	14
		Maturity	Y= 899.35x+2219.2	0.40	446	14
	DVI	Flowering	Y= 22.397x+2172.7	0.65	428	13
		Maturity	Y= 26.96x+2005.4	0.52	448	14
	RVI	Flowering	Y= 420.5x+2001.3	0.65	408	13
		Maturity	Y= 472.44x+1694.8	0.57	423	13
High-yielding	NDVI	Flowering	Y= 3574.1x+2576.9	0.70	**321**	**7**
		Maturity	Y= 4103.6x+2361.5	0.57	459	10
	SAVI	Flowering	Y= 5234.8x+1820.7	0.61	506	11
		Maturity	Y= 5256.9x+1754.4	0.56	547	12
	LAI	Flowering	Y= 799.74x+3396.4	0.62	511	11
		Maturity	Y= 757.23x+3401.4	0.60	554	12
	DVI	Flowering	Y= 14.908x+3618.2	0.65	375	8
		Maturity	Y= 15.953x+3514.9	0.58	455	10
	RVI	Flowering	Y= 278.39x+ 3459.3	0.65	422	9
		Maturity	Y= 334.33x+3258.8	0.48	442	9

model fit, the linear regression model was used. The ANOVA results showed that the relationship between vegetation indices and rice yield was significant (Sig<0.05). Statistical criteria of the equations between the yield of rice varieties and vegetation indices derived from the images are shown in Table 2.

As seen in Table 2, the highest value of the coefficient of determination (R^2) of the equations derived for local varieties was related to the flowering period and NDVI index. Other indices have lower coefficient of determination and lacked favorable precision for estimating the yield. Measurement error for the NDVI index in flowering period was 10%, which was equivalent to 310 kg ha^{-1} (Fig. 2).

Investigating the regression relationships between the plant parameters and yield for high-yield varieties (Table 2) indicated that the NDVI index equation extracted from the flowering period images with the determination coefficient of 0.70 had maximum coordination with the production yield of the varieties. Validation of the model indicated the measurement error of 7% equivalent to 321 kg ha^{-1}, which was more accurate than other equations.

As inferred from the observation of the table, the highest coefficient of determination between the production yield and indices existed in the flowering period. Besides, among the studied indices, the NDVI index was the most favorable criterion for estimating the local and high-yield varieties' yield in the region. Furthermore, the diagram of the models proposed for estimating the yield of the studied varieties using NDVI index was shown; however, due to the decreased correlation of the other indices, their diagrams were not drawn, but the coefficient of determination and error of equations are presented in Table 2.

Based on the obtained results, it can be found that by approaching the end of the growth season, the relationship of the indices extracted from the satellite images with the plant variables is reduced so that the indices obtained from the maturity period images do not have favorable efficiency for yield estimation. The difference in reflectance rate distinguishes the objects from each other and the presence of water, and moisture affects the reflectance rate of the electromagnetic spectrum; thus, at the final stage of rice growth (on almost the 100th day), after completion of the clustering levels and, finally, formation of the seeds leading to the heaviness of the clusters, the plant is laid down and the seeds lose water. Since the studied vegetation indices result from the reflection of the red and NIR bands and

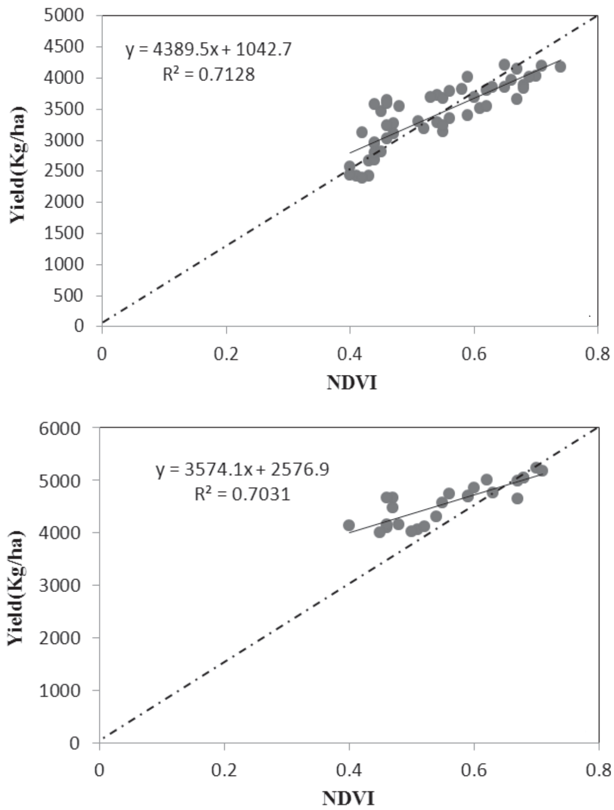

Fig. 2. Relationship between NDVI and productive performance in 2012: a) local rice and b) high-yield rice.

the maximum chlorophyll absorption occurs in these two bands [13, 32], the relationship of this index with the growth of plants and vegetation can be justified. Nuarsa et al. [12], Son et al. [10], and Siyal et al. [9] have also reported high precision of the NDVI index for yield estimation.

As previously stated, the images were taken at the peak of the plant's growth; as a result, since the soil surface was covered, the SAVI index that was developed to reduce the background soil reflectance from the plant reflectance could not provide precision better than that of the NDVI index. Moreover, the equations derived from LAI had less precision than other equations, which seems to be due to the linear relationship. Many attempts have been made to increase the coefficient of determination of the relationship between LAI and rice yield so that even Noureldin et al. [16], by designing a bivariate (bi-variable) regression model (NDVI and LAI indices), tried to increase the precision of the proposed linear model, which led to acceptable results. Another important point is to use the coefficients presented in the references for calculating the LAI index in the present research, which might increase the error rate. Apropos of the DVI and RVI indices, some studies have been conducted to help estimate the yield along with other common indices [9, 11, 16, 23], leading to good results; thus, in the present research, they were next to the NDVI index in terms of precision.

Assessing Proposed Equation

Table 3 shows the results of the proposed equation's efficiency for 75 data taken from the farms in 2013. In estimating the yield of the local varieties by the model, a slight difference could be seen between the model's average yield and the observed values, and it can be said that the model's estimation accuracy in the average yield range was high and the obtained results were similar to the reality, but for the above average yield range, the yield value was underestimated; on the other hand, for the below average range, the model yield was overestimated so that the model tended toward the average. As for the high-yielding varieties, as shown in Table 3, the model provided values above the real values for estimating the average and minimum yield, just like the local varieties. In other words, the yield range of the estimated data was lower than the observational data. In other words, the MBE index showed that the model overestimated the yield value in this region [9].

In evaluating the yield estimation accuracy of the images of the flowering period for the proposed model of the local varieties, the RMSE and NRMSE values were 406 kg ha^{-1} and 12%, respectively, and the accuracy rate was slightly reduced compared to the validation period. As for the proposed model for the high-yielding varieties of the region, the measurement error was 6% equivalent to 272 kg ha^{-1}. The NRMSE value for both categories was in the favorable range [10] and did not exceed 12%.

The simulation results indicated that the models' yields were well fitted with the observed values and the high correlation could be seen (R>0.80) between the real and predicted values. Nuarsa et al. [12] also reported the high correlation of the predicted values

Table 3. Results of the model in the city in 2013.

Variety	Variable plant	Model	Mean (Kg/ha)	Min (Kg/ha)	Max (Kg/ha)	Range (Kg/ha)	R^2	RMSE (Kg/ha)	NRMSE (%)	MBE
Local	Observed	-	3502	2190	4380	2190	-	-	-	-
	Estimated	Y = 4389.5NDVI+1042.7	3594	2842	4159	1317	0.70	406	12	92
High-yielding	Observed	-	4649	4022	5280	1258	-	-	-	-
	Estimated	Y = 3574.1NDVI+2576.9	4800	4435	5150	715	0.66	272	6	151

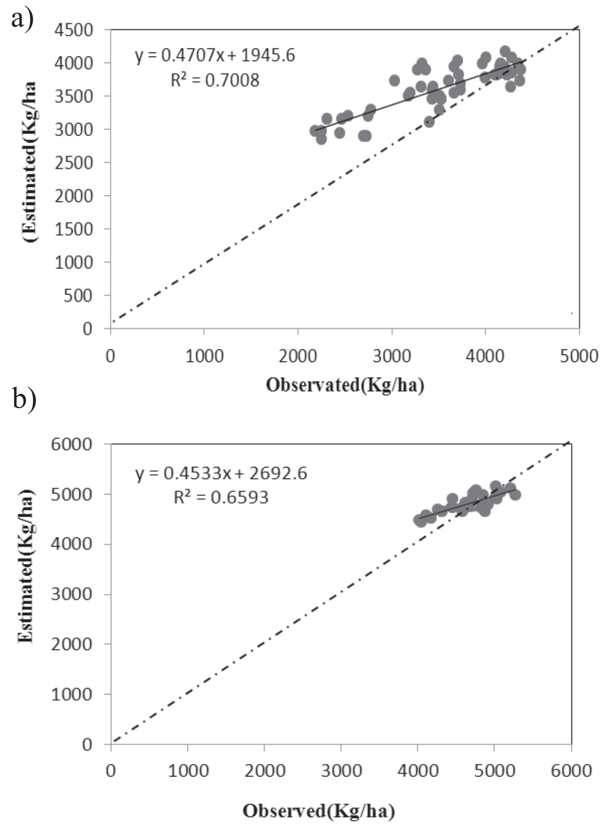

Fig. 3. Comparison of observed yield with estimated yield: a) local rice and b) high-yield rice.

using remote sensing for rice plants. The coefficient of determination of 0.70 and 0.66 (Fig. 3) between the real and estimated yields could be due to the changed crop conditions and crop management, pests and plant diseases, local weather conditions, and many other environmental variables; for example, heavy rainfall at an inappropriate time not only reduces the crop, but also disrupts the yield prediction process by creating a cloudy atmosphere in the images of the region. However, the data of consecutive years can be used on larger scales in order to improve accuracy.

Finally, after analyzing the results, it should be noted that due to the importance of regional yield estimation, the ETM+ sensor is capable of producing the favorable data with desirable efficiency and the images taken by this sensor would provide a real representation of the crop status as Nuarsa et al. [12], Matinfar [17], Mosleh et al. [2], and Siyal et al. [9] have also considered the use of these images to be useful in their studies.

Relationship between Soil Properties and Yield

Soil texture is the percentage ratio of soil components, including sand, silt, and clay, which determines the soil texture class in a texture triangle [8]. Among the physical properties, soil texture has significant effects on important features such as growth of the plant and development of underground organs. Furthermore, soil texture is one of the indices influenced by many physical and behavioral features of the soil, including water retention ability, nutrient-preserving capacity, and susceptibility to erosion [8, 33].

It is of great importance to understand the distribution of soil properties on the farm scale for improving the agricultural management practices and assessing the agricultural effects on the environment [5]. Based on the results of the soil tests, the soil texture of the region includes clay, clay loam, loam, sandy loam, and silt loam classes. The statistical data of the soil properties of the paddy fields, classified in two groups of local and high-yielding varieties, are briefly shown in Table 4.

Table 4. Soil texture properties for local and high-yield rice.

Variety	Soil properties	Min (%)	Max (%)	Mean (%)	SD (%)	CV (%)
Local	Sand	16	61.60	38.94	9.28	23.83
	Silt	28	61.60	42.70	10.20	23.89
	Clay	3.60	48	18.35	11.33	61.74
	O.C	0.55	3.55	2.04	0.67	32.84
	pH	4.55	7.31	6.16	0.67	10.88
	EC	0.22	2.03	0.65	0.31	47.70
High-yield	Sand	22.40	66.40	44	9.74	22.14
	Silt	28.40	62.80	42.85	8.47	19.77
	Clay	4.40	41.60	13.15	9.50	72.24
	O.C	0.39	3.86	2.04	0.70	34.31
	pH	5.14	7.50	6.42	0.53	8.25
	EC	0.29	1.84	0.71	0.36	50.70

Reviewing the data showed that the variables of clay and electrical conductivity (EC) have high coefficients of variation, implying high variations of the parameters in the region. The clay changes were influenced by the inherent processes of soil, including parent material, pH, climate, and topography. In addition to the inherent processes, the salinity variations were influenced by management (waterlogging, land drainage conditions, fertilizer consumption rate, depth and number of plowings, and burning rice crop residuals). According to the zoning map of the paddy fields, it was observed that the high-yielding farms were mainly located in the suburbs close to the water channels so that this phenomenon could be attributed to the effects of the urban activities on agriculture.

In the statistical investigations on the soil information and crop yield, no direct relationship was observed between the two variables, but it seems that in the fine-texture paddy fields, a higher yield was achieved. This phenomenon could be due to the increased CEC as well as the increased specific surface area of the particles; therefore, it is necessary to conduct further studies on the soil science and crop yield reports.

Comparing Real and Potential Yields

The potential crop growth in a region is determined by genotype and climate, while the real yield results from the interactions of the local growth constraints and the growth reduction factors [34]. The crop yield is influenced by various factors: 1) availability of nutrients in the soil; 2) inputs that are under control of the farmer, including varieties, crop rotation, and weed control; 3) soil properties; and 4) climatic factors that cannot be fully controlled by the farmer [35].

As Wit and Diepen [36] have stated, relying on the spatial distribution of the growth model in the vast regions, the application of the crop yield prediction programs commonly lacks the sufficient certainty in the spatial distribution of soil properties, soil initial conditions, crop parameters, and weather forecasts. Furthermore, continuous cultivation over the years influences the availability of water and nutrients and, consequently, reduces the crop yield by increasing the specific gravity and reducing the fine and coarse pores of the aggregates [37].

Since the soil science information of different regions is not comprehensively available in Iran, it would probably be simpler and more feasible to use the satellite data obtained from different months. Moreover, by separating rice varieties of the paddies in the region into two groups of local and high-yielding varieties, it has been attempted to minimize the difference between the model and the real data. Another important point is that model calibration was carried out using the point data, and model evaluation was performed on a large scale. In research projects, the plant's yield is closer to the potential yield, while on a large scale, the difference of crop management, spatial variations, and parameters affecting the yield, and the type of soil lead to errors in yield estimation [19].

Conclusions

The present research aimed to predict rice yield. It can be said that choosing an appropriate modeling method does not necessarily mean using complex methods with numerous input factors; but the use of empirical correlations and regression between the plant parameters or soil science with crop yield is preferable to the complex methods due to the convenience of implementation and generalization to other regions. Nevertheless, such simplicity of models should not be defined as their low accuracy. Farm management requires identifying soil texture in order to achieve the optimal consumption of inputs. Besides, due to the importance of rice farming, the local capacities for developing the cultivation of this plant should be identified and the environmental potentials should be used maximally. Results of the present study provide the possibility for planners to easily predict rice yield for the two groups of local and high-yielding varieties with acceptable accuracy by providing images in subsequent years and extracting superior index (NDVI) in the flowering phase. Also, it is an effective step in approaching the real yield to the favorable yield level.

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Conflict of Interest

The authors declare no conflict of interest.

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