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Research Article

Predicting Barley Harvest Time in Dryland Conditions Using Satellite Images

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Abstract: Barley has an important role in livestock feed. Therefore, an accurate estimation of harvesting time is necessary to minimize the loss in barley farming. The aim of this study is to determine barley harvest time using satellite images accurately. Field data were sampled from the farms in the Dezaj region of the west of Iran. In addition, satellite remote sensing technique was applied during barley growing season in 2019 using Landsat 8 images. The vegetation indexes were-used as input in the prediction model in this study. The results showed that satellite imaging has enough potential to predict the harvesting time of barley accurately. R-squared and RMSE values of the best-structured stepwise regression model in this study were 0.791 as well, and 1.34 respectively. This method can be beneficially employed by farm managers to have an accurate estimation of the most appropriate harvesting time and be able to manage the process, which is an important challenge for them.

Uydu Görüntülerini Kullanarak Kurak Arazi Koşullarında Arpa Hasat Zamanını Tahmin Etme

Makale Bilgileri

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Anahtar Kelimeler
Arpa yetiştiriciliği,
Hasat zamanı,
Uydu görüntüleri.

Öz: Arpanın hayvancılık yeminde önemli bir yeri vardır. Bu nedenle, arpa yetiştiriciliğinde kaybı en aza indirmek için hasat zamanının doğru tahmin edilmesi gerekmektedir. Bu çalışmanın amacı, uydu görüntüleri kullanılarak arpa hasat zamanını doğru bir şekilde belirlemektir. İran'ın batısında Dezaj bölgesindeki çiftliklerden tarla verileri örneklenmiştir. Ayrıca 2019 yılında arpa yetiştirme sezonunda Landsat 8 görüntüleri kullanılarak uydudan uzaktan algılama tekniği uygulanmıştır. Bitki örtüsü indeksleri bu çalışmada tahmin modelinde girdi olarak kullanılmıştır. Sonuçlar, uydu görüntülemenin arpanın hasat zamanını doğru bir şekilde tahmin etmek için yeterli potansiyele sahip olduğunu gösterdi. Bu çalışmada da en iyi yapılandırılmış aşamalı regresyon modelinin R kare ve RMSE değerleri sırasıyla 0.791 ve 1.34 idi. Bu yöntem, çiftlik yöneticileri tarafından en uygun hasat zamanının doğru bir şekilde tahmin edilmesi ve onlar için önemli bir zorluk olan süreci yönetebilmek için faydalı bir şekilde kullanılabilir.

1. Introduction

Crop production is a vital element for securing the survival of the human. Cereals have the most important role in the human food supply. Among the cereals, barley is cultivated in most parts of the world. Furthermore, it is more tolerant of environmental stresses such as drought, salinity than the cereal family, and today this product constitutes a significant percentage of feeding livestock. Currently, barley plants in about 50 million hectares of the world's arable land. On the other hand, the highest area under barley cultivation in the world include European Union, Russia, Australia, Turkey, Ukraine, Canada, Kazakhstan, Iran and Morocco, respectively (FAO, 2017). This makes barley, one of the most important agricultural productions. Sustainable production of barley requires understanding the growth stages of barley (such as maturity and harvest time) and providing suitable machinery (cultivators, planters and harvesters) at these times (Anonymous, 2014). Therefore, there are some researches to estimate the growth stages of barley (Yin and Van Laar, 2005). The barley maturity stage is one of the most significant stages of barley growth. In general, barley maturity can be divided into two categories: morphological and technological maturity. At the technological maturity stage, the product is suitable for harvesting. The technological maturity stage is actually the harvest time and the quality and yield of barley is the maximum amount at this stage. Also, the growth stages of wheat and barley are similar together. Evers et al. (2010), used a model of wheat stages development combining aboveground, within the plant structure, assimilate distribution, plant structure, photosynthesis, and organ-level microclimate, organ growth and development. They used an experimental sigmoid relationship between leaf length and leaf mass for plant organ development calculation. The results showed that more efforts were necessary to modelling mechanistically other significant physiological processes such as nitrogen distribution and uptake, and leaf and tiller senescence. Other researchers (Gao et al., 2020, Canata et al., 2021, Mobe et al., 2021,) used some parameters such as weather temperature, soil moisture, etc. to predict barley growth stages. The disadvantage of these models is the unavailability of the above parameters for all farms. Therefore, it is needed to have an alternative or complementary method for these models. Harvest time (technological maturity) is an important factor in farm management. For example, harvest time has effects on the performance of the plants' rotation because delay in harvesting time could reduce the yield of the second crop in the plants' rotation. Sun et al. (2007) studied the effect of harvesting time in the rotation of winter wheat - maize. Results showed that each day of delay in barley harvesting (the first cultivated crop in the rotation) led to 0.6 % maize yield decrease (second cultivated crop). Remote sensing is fairly a new technique, which could help researchers to get more information about plants, periodically. Remote sensing, which concentrates on the images examination of the earth's surface, has quickly evolved since the discovery of the infrared spectrum in the early 1800s (Campbell, 2002). The application of remotely sensed images leads to collect of reliable and timely data from crop performance (Lyle et al., 2013, Taghizadeh et al., 2019). Most vegetation indexes (VIs) incorporate reflectance in a few wavebands, which could be collected mainly by satellite broadband sensors. VIs have been used to determine the plant stage of development (Huete, 2012). Within the final decade, remote sensing has been very effective in farm administration decisions such as cultivation, fertilization and yield determination (Bao et al., 2008). Jongschaap and Schouten (2005) showed that using remote sensing, the wheat area could be appraised with more than 80% accuracy. They also reported good fitting; i.e. model based estimations of regional wheat production were in accord with agricultural statistics. Ren et al (2008) predicted wheat yield using MODIS-NDVI (Normalized Difference Vegetation Index) data in Shandong, China. They reported that the relative errors of the predicted yield were in the range of 4.62 -5.40 % and RMSE was 214.16 kg/ha. Song et al. (2016) evaluated the performance of the time series of Landsat 8 images to barley yield prediction. They used NDVI. Their results showed that there was good fitting (R2 =0.87) between this vegetation index and the yield of barley. Although satellite images were used in some agricultural applications, no research has yet been conducted on harvesting time prediction using Landsat 8. Therefore, the main aim of this research was to evaluate the proficiency of Landsat 8 satellite images to determine barley harvest time. Furthermore, developing a regression model for estimating barley harvest time is another purpose of this study.

2. Material and Methods

2.1. Field description

The collecting Method in this study was done in the Dezaj region (35°09′N, 47°91′E) in the west of Iran in 2019 (Figure 1). This region has a cold mountainous climate with an average annual rainfall of 444 mm and annual temperature changes from -38 to +35 ^{0}C. The predominant product of this region is barley (Bahman cultivar). The growing season of wheat in this region is from mid-October to mid-July next year.

2.2. Field data

During field surveys before harvest season, 30 barley farms were selected from the study area for each year. The locations of farms were recorded using GPS (Garmin 62s). The required descriptive information of farms and the crop density of each farm were also recorded. The yield samplings were done (from the middle of June until harvesting day) using a 1m × 1m quadrate in the randomly selected points in each farm. The yield samplings were carried out by five random throws of the quadrate and choosing three crops in each throw. At each sampling, fifteen crops were sampled for each farm. As the plant densities were consistent in one farm, fifteen crops were sufficient for sampling. By measuring the grain mean weight of sampled crops in each farm and knowing crop density, the yield for each farm was calculated until harvest day. Yield samplings were performed with two days intervals and the yield of other days were obtained by interpolating. For each farm, the day with maximum yield was the best harvesting time.

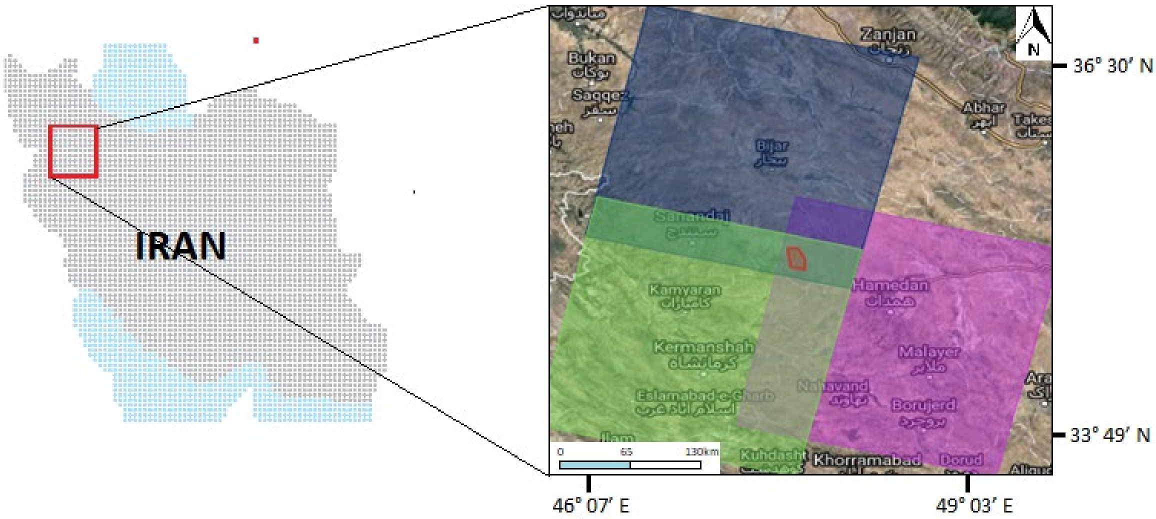

Figure 1. The study area is satellite imagery of Land.

2.3. Landsat 8 Images and spectral vegetation Indexes

Landsat 8 includes two sensors and eleven bands summarized in table 1 (Irons et al., 2012). Landsat gives the spatial determination and ceaseless record required to capture time histories and it is very useful for agricultural applications. In this study, the Landsat images of the study area were acquired according to the barley growing calendar. Seven cloud free images of the barley growing period were selected. Table 2 shows all images of the study area, from the tillering to ripening (maturity) of barley. FLAASH module/ ENVI was used for atmospheric correction. Also, the geometric correction was done for images. Then corrected images were used for the calculation of the VIs. These indices have made a simple and suitable approach for obtaining information from remote sensing data. In this study, we used four VIs as following:

1. Normalized Difference Vegetation Index (NDVI): NDVI is the most widely used index for remote sensing of vegetation in the past two decades. This index has been used in many applications, including the estimation of crop yields and above-ground dry biomass (Rouse et al., 1974; Tucker et al., 1986; Ren et al., 2008). NDVI is calculated by the following equation:

$$\mathrm{NDVI} = \frac{(\mathrm{NIR} - \mathrm{RED})}{(\mathrm{NIR} + \mathrm{RED})} \tag{1}$$

Where NIR and RED are spectral reflectances of Near Infrared and red bands.

Table 1. Description of Landsat 8 bands

Band Specifications	Wavelength (µm)
Band 1 — aerosol (30 m)	0.43–0.45
Band 2 — blue (30 m)	0.45–0.51
Band 3 — green (30 m)	0.53–0.59
Band 4 — red (30 m)	0.64–0.67
Band 5 — near infrared (30 m)	0.85–0.88
Band 6 — shortwave infrared (30 m)	1.57–1.65
Band 7 — shortwave infrared (30 m)	2.11–2.29
Band 8 — panchromatic (15 m)	0.50–0.68
Band 9 — cirrus (30 m)	1.36–1.38
Band 10 — thermal Infrared (100 m)	10.60–11.19
Band 11 — thermal Infrared (100 m)	11.50–12.51

2. Soil Adjusted Vegetation Index (SAVI): SAVI attempts to reduce the influence of the soil by assuming that most soil spectra follow the same soil line (Huete, 1998). The formula of SAVI is demonstrated in equation 2.

$$\mathrm{SAVI} = \frac{(1 + \mathrm{L})\ (\mathrm{NIR} - \mathrm{RED})}{(\mathrm{NIR} + \mathrm{RED} + \mathrm{L})} \tag{2}$$

Where the constant L = 0.5 has been adjusted to account for first-order soil background variation.

3. Enhanced Vegetation Index (EVI): EVI is developed as a standard satellite vegetation product for the Terra and Aqua Moderate Resolution Imaging Spectroradiometers (MODIS). EVI provides improved sensitivity in high biomass regions while minimizing soil and atmosphere influences (Huete et al., 1997). The formula of EVI is demonstrated in equation (3).

$$\mathrm{EVI} = \frac{2.5\ (\mathrm{NIR} - \mathrm{RED})}{(\mathrm{NIR} + 6 * \mathrm{RED} - 7.5 * \mathrm{Blue} + 1)} \tag{3}$$

Where Blue is the spectral reflectance of the blue band.

4. Normalized Difference Water Index (NDWI): NDWI is sensitive to changes in the liquid water content of vegetation canopies. NDWI is less sensitive to atmospheric effects than NDVI, (Gao, 1996). The formula of NDWI is demonstrated in equation 4.

$$\mathrm{NDWI} = \frac{(\mathrm{NIR} - \mathrm{SWIR})}{(\mathrm{NIR} + \mathrm{SWIR})} \tag{4}$$

Where SWIR is spectral reflectance of short wave infrared band.

The above mentioned spectral indices were calculated for farm pixels for all images from tillering to ripening stages.

2.4. Development of regression models for barley harvest date estimating

The stepwise regression method was used to determine affected growth stages using SPSS 16 software. Seven stepwise regression models of harvest date vs. vegetation indices were developed to find the relation between them for each barley growth stage. The models' inputs were spectral indices and the best harvest date was the output of models. Field observation data were divided into two categories: 70% of data were used for model development and 30 % were used for validation of models.

3. Results and Discussion

3.1. Developing regression models at different growth stages of barley

As be seen in Table 3, the stages after flowering have the stronger ability to predict the harvesting date of barley. Moreover, table 3 shows the image coincide provided the best regression model with the dough stage (R^2 = 0.791; RMSE= 1.34). The spectral indices were used in this model were NDVI and NDWI. NDVI is one of the most extremely used indices. The range of NDVI values is between [-1, +1]. Based on phenology studies18 of the United States Geological Survey (USGS), the NDVI values are categorized as follows; the regions of sand or snow usually have very low NDVI values (e.g. 0.1 or less). Sparse vegetation as grasslands or senescing crops has moderate NDVI values (i.e. nearly 0.2 to 0.5). Dense vegetation such as tropical forests13 or crops at their peak growth stage may result in high NDVI values (about 0. 4 to 0.8). In this research, the NDVI is the only index, which has been entered in all models. Song et al. (2016), demonstrated that Landsat NDVI data could be used to predict the wheat yield. In their research, the booting stage of wheat was the best stage for yield prediction. Also, the results of Ren et al. (2008) research which used NDVI to estimate wheat regional yield showed that the best predicted yield data of winter wheat could be achieved nearly 40 days before harvest time (about booting stage). However, to predict barley harvest time in the Dezaj region, we found that about 15- 20 days ahead of harvest time (dough development stage) is the best time. The results of this research and mentioned researches showed that NDVI could be a good index for agricultural applications such as harvest time prediction and yield estimation. In previous studies, the NDVI index has been used to estimate the area of agricultural crops, plant yield and growth monitoring and determine the phenological stages of crops, which the results have been in accordance with our study (Shi et al., 2013; Zhang et al., 2013).

Table 1. The developed models at barley different growing stages

No	The growth stage	Developed model	R^2	RMSE
1	Tillering	Y=-2.30 NDWI+3.90 EVI+5.66 NDVI+176.22	0.135	3.51
2	Stem elongation	Y=5.11 NDWI+1.28 SAVI+8.33 NDVI+172.87	0.388	3.03
3	Booting	Y=85.2 NDWI+7.21 EVI2+3.78NDVI+175.33	0.376	3.01
4	Awn emergence	Y=4.54 NDWI+5.83 EVI+8.66 NDVI+174.55	0.441	2.91
5	Flowering	Y=65.55 NDWI+18.66 NDVI+173.29	0.599	2.18
6	Dough development	Y=83.26 NDWI+86.2 NDVI+168.53	1.34	0.791
7	Ripening	Y=148.32 NDVI+158.62	1.95	0.571

The results showed that NDWI could predict mature dates with an accuracy of 0.65. 3.2. Evaluation of the developed regression model for harvest time predicting In order to assess the predictive performance of the developed models, we used three models, which had the better estimations (the models of flowering, dough development and ripening stages). In this step, we used the 30% remained data for evaluation. Additionally, it can be concluded that the best time for barley harvest time prediction is after the best time for yield estimation. Furthermore, NDWI is an index, which is sensitive to changes in the liquid water content of vegetation canopies. That interacted with the incoming solar radiation (Gao, 1996). NDWI is less sensitive to atmospheric effects than NDVI. In addition, in various stages of barley growth, the amount of liquid water content changes. Therefore, there is a relationship between harvest day of barley and NDWI, and the most relationship was found at the dough development stage. Also, Studies have reported that NDWI is a good index for estimating the mature date of cereals (Meng et al., 2011; Meng et al., 2015; Mulianga et al., 2015).

Figures 2, 3 and 4 illustrate the performance of these models, in a scatter plot between predicted and observed harvest days. The R^2 and RMSE values of the developed model based on the dough development stage were achieved 0.812 and 1.40, respectively. In addition, as it can be seen in Figure 2, the image coincides with the dough development stage had the best predictive performance. The performance of developed models at flowering (R2 = 0.557 and RMSE =2.51) and ripening (R2 = 0. 487 and RMSE = 2.84) stages were less than dough development stage. Therefore, it can be concluded that the suitable period for anticipated harvest time using satellite images for achieving the highest yield is the barley dough development stage.

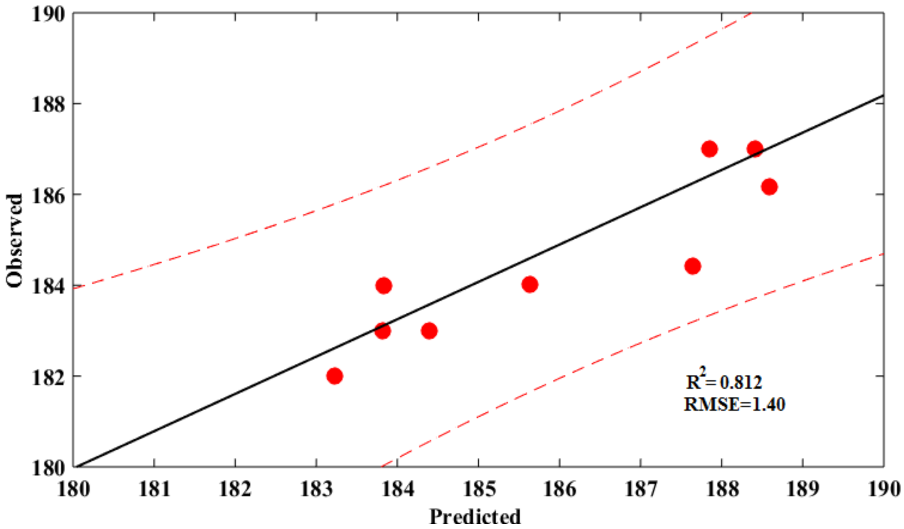

Figure 2. Scatter plot of predicted and observed harvest time for dough development stage (the boarder lines indicate confidence level of 0.01).

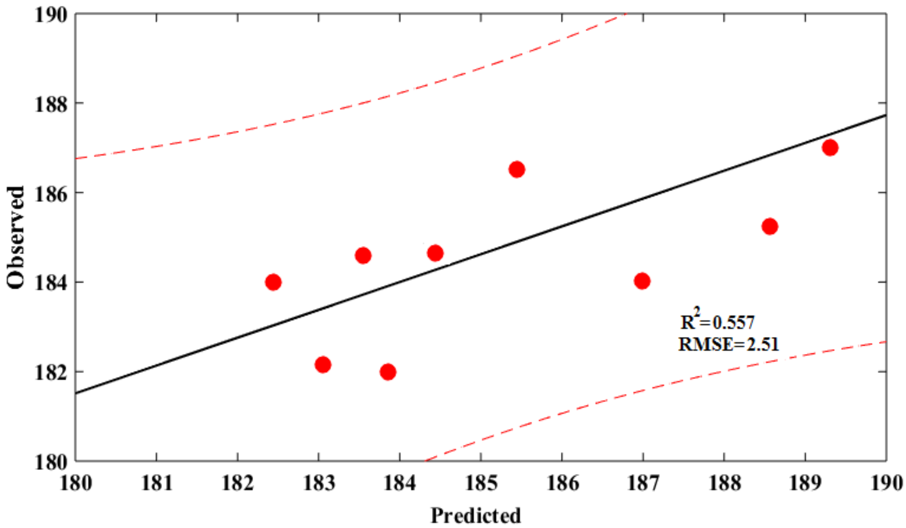

Figure 3. Scatter plot of predicted and observed harvest time for flowering stage (the boarder lines indicate confidence level of 0.01).

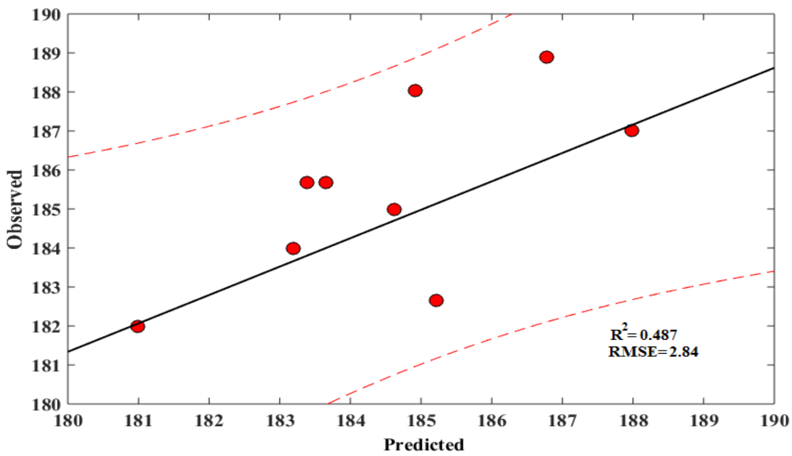

Figure 4. Scatter plot of predicted and observed harvest time for ripening stage (the border lines indicate confidence level of 0.01).

4. Conclusion

The objective of this study was to predict barley harvest time to reduce14 the yield gap (the difference between yield potential and the actual yield) using satellite images in the Dezaj region. The analyses of attained results showed Landsat satellite imagery is able to produce valuable information using spectral indexes. Regional estimation of harvest time has different important aspects including farm management, commercial politics and so on. Moreover, the knowledge of harvest time could help to crop harvest without decreasing yield. The advantage of remote sensing technologies and spectral indexes is their ability to continuous visit crops. However, many environmental factors such as the amount of clouds and atmospheric conditions could affect the estimations. It should be noted that NDVI and NDWI are important indexes in crop and vegetation studies. The best model to predict barley harvest time was extracted from indexes related to the barley dough development stage (R2 = 0.791; RMSE = 1.34). Therefore, Landsat 8 images could be used for harvest time prediction. This paper only demonstrates a primary research of crop harvesting time prediction using satellite imagery. To advance development the utilize of satellite remote sensing to accuracy harvest, the following researches are proposed: -The relationships between vegetation indexes and harvest time were influenced by satellite image procurement date, so the harvest time predicting models might be diverse when images on distinctive dates are utilized. Therefore, a general model could be developed using several years' data, which can actualize harvest time forecast with satellite images at diverse dates. integrating of crop models and satellite remote sensing based models could improve the predicting capability of these models. Therefore, a combination of these two categories of models is suggested for future researches.

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