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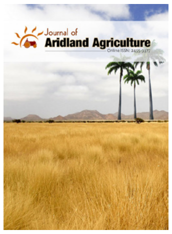
Research Article



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Cereal yield forecasting in semi-arid region of Algeria using MODIS-NDVI

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ABSTRACT

The prediction of cereals yields today is very important for global food security and helps decision-makers in the import-export operations of countries, especially with the rise world population. The advent of remote sensing technologies in precision farming systems has made cereal yield predictions possible, providing valuable insights into the temporal and spatial variations in cereal conditions across both large and small-scale crop lands. Among the various vegetation indices used to analyze these conditions, the normalized difference of vegetation index (NDVI) has emerged as a key indicator. The main objective of this study is to evaluate the possibility of using MODIS-NDVI data to forecast the yield of cereal crops (wheat and barley) in semi-arid region of Algeria (Setif). Additionally, identify the optimal timing for reliable and accurate crop yield forecasts. The remote sensing data utilized in this study covered the growing seasons from February to June, from 2002 to 2022. The results indicated a strong correlation between cereal grain yield and NDVI from late February to mid-March, with R^2 values ranging from 0.55 to 0.82 for the two cereal species. The RMSE of the NDVI based prediction model ranged from 0.01 t ha^{-1} to 0.276 t ha^{-1}. The approximate average increase in the grain yield of barley and wheat lies between 0.659 to 0.746 t ha^{-1} with an increase of 0.1 in NDVI value. These results demonstrate the effectiveness of using MODIS-NDVI data for cereal yield forecasting in semi-arid region of Algeria, offering valuable predictions two to three months before the harvest.

KEYWORDS: Predicting, Yield, Remote sensing, NDVI

INTRODUCTION

Wheat, along with rice and maize, is one of the main three world food crops (Cai *et al.*, 2019). Soft wheat is one of the most important food crops that feed 40% of the world population (Liu *et al.*, 2020). Without forgetting, barley grain which ranks fourth in terms of quantity produced and area cultivated in the world after wheat, rice and corn (Geng *et al.*, 2022). In Algeria cereals play a significant role in the dietary habits of the population, encompassing production and processing activities such as semolina production and bakery in the food industry (Ammar, 2014). According to the Algérie Eco (2022), the area occupied by cereals is 3.5 million ha which is very small compared to the total area of Algeria (238 million ha). The national agricultural production is heavily influenced by its climatic conditions, which are primarily characterized by annual fluctuations in precipitation, water scarcity, and high temperatures during crop growth periods, these factors have a negative impact on production (Mekhlouf *et al.*, 2012). In 2022, Algeria imported 10.6 million tons of cereals. The majority of these imports were soft wheat, accounting for almost 6.1 million tons, followed by maize with 2.6 million tons (a decrease from 4.8 million tons in the previous campaign), durum wheat with nearly 1.4 million tons, and 571,000 tons of barley (Algérie Eco, 2022). For this reason, accuracy and timeliness of regional crop yield estimation is crucial for ensuring national and international food security (Becker-Reshef *et al.*, 2020), it is also beneficial for policymakers in making informed decisions regarding import and export policies and determining acceptable support prices for the market (Dorosh & Salamn, 2006). In particular, weather variability and biological stresses (including pathogens and arthropods) have an increasing impact on food security (Al-Ani *et al.*, 2011; Khalaf *et al.*, 2019, 2023; Adhab & Alkuwaiti, 2022), the importance of accurate and timely regional crop yield estimation has become even more significant (FAO, 2018). Although traditional field surveys and crop statistics are useful for accurately estimating crop yield, they prove to be insufficient when predicting crop yield for large regions due to constraints such as budget, time, and shortage of skilled manpower (Fang *et al.*, 2008). Using Artificial Intelligence (AI) and computerization have contributed to the field of biotechnology and agriculture and supported the sustainability endeavor (Anaz *et al.*, 2023). Advancements in satellite sensor technology have led to the development of remote sensing, which is a science and technique focused on acquiring information about on-land objects from satellite imagery without the need for direct contact (Sabins, 1987). Today, remote sensing is widely used for monitoring and predicting crop yields across region of varying sizes due to its large coverage area, non-invasive nature, and ability to provide rapid and long-term time series data. This makes it an important tool for policymakers and stakeholders in ensuring food security and developing effective agricultural policies (Zhang *et al.*, 2020). The application of vegetation indices (VIs) derived from satellite images is considered the most promising and convenient method for forecasting crop yield using remote sensing data, they are effective indicators of vegetation status and have a positive correlation with crop yield. Among the various VIs, the Normalized Difference Vegetation Index (NDVI) is frequently used for studying vegetation dynamics because of its high correlation with photosynthetic capacity, leaf area index, biomass, and net primary productivity (Li *et al.*, 2014). The NDVI is also a popular choice for crop yield prediction due to its accessibility and ease of use (Phiri *et al.*, 2020). The Normalized Difference Vegetation Index (NDVI), which was first introduced by Rouse *et al.* (1974), defined as the ratio between the difference in near-infrared and red spectra reflections from the Earth's surface and their sum. The NDVI scale ranges from -1 to 1, with higher positive values indicating greater vegetation coverage and activity (Fang *et al.*, 2004). Negative NDVI values indicate the presence of clouds, snow, water, or a bright, non-vegetated surface (Yin & Williams, 1997). In recent years, the focus of remote sensing-based yield forecasting research has shifted towards the use of National Aeronautics and Space Administration's (NASA) Moderate Resolution Imaging Spectroradiometer (MODIS) and other sensors with different spatial resolutions. The MODIS data has a spatial resolution of 250 m, 500 and 1000 m (Atzberger *et al.*, 2016). Remote sensing studies used the empirical regression models linking historical crop yield as dependent variable and administrative units-averages of seasonal satellite data for cultivated region as independent variable (Becker-Reshef *et al.*, 2010). Numerous research studies have proved the effectiveness of remote sensing in predicting crop yields, such as, Mulianga *et al.* (2013) used the MODIS-NDVI data in the study on the sugarcane yield estimation on large territories. Kouadio *et al.* (2014) applied MODIS-NDVI and EVI data to forecast spring wheat yield at the ecodistrict scale. Huang *et al.* (2013) used time series data of NDVI values in their regression model to predict rice yield. Nagy *et al.* (2018) developed regression models using 15 different peak-season MODIS-derived NDVI time series to predict wheat and maize yields. The reported yield values were regressed against the NDVI data, and they found that MODIS-NDVI data could effectively predict crop yield for the Tisza river catchment area 6-8 weeks before harvest. Similarly, Lykhovyd (2020) and Vozhehova *et al.* (2020) applied NDVI-based regression models for forecasting yield of spring row crops at the field scale. The combination of crop models and remote sensing data has increasingly been used to forecast crop yield.

This study fills a significant research gap by introducing a new methodology for accurately forecasting cereals grain yield in Algeria's semi-arid region using MODIS-NDVI remote sensing data. The study's objectives are two-fold. To begin, it intends to assess the feasibility of using MODIS-NDVI data at various dates between 2002 and 2022 to forecast cereal yields before harvest, specifically wheat and barley, in semi-arid region of Algeria. Second, it seeks to determine the best time of year for accurate prediction of cereal grain yield at a regional level in Algeria, given that previous studies have produced inconsistent results regarding the best time for prediction in this specific semi-arid area.

MATERIALS AND METHODS

Study Area

The research was conducted at the Technical Institute of Large Crops (ITGC) in Setif, Algeria. The experimental site is located at latitude 36°10'17' North, longitude 5°21'55' East, and an altitude of 1080 m (Google Earth Pro, 2023). The experimental site is located in the central zone of the high plains, which is favorable for cereal cultivation (Figure 1). The climate site was characterized by hot and dry summers and cold and humid winters (Chennafi *et al.*, 2006). The annual precipitation reaches 458 mm (Rouabhi, 2017), which mainly occurs between January to April and an average annual temperature of 13.5 °C (Climate Data, 2022). The experimental site is characterized by flat, relatively infertile land and a high risk of late frost and drought towards the end of the crop cycle. The physic-chemical analysis shows that the soil has a silty-clayey texture and an average organic matter content of 2.13%. The Bulk density of is 1.51 g/cm^3, with a field capacity of 23% and a wilting point of 10%.

Data Collection

Crop yield data

The crop grain yield data (t ha^{-1}) of wheat and barley were collected from the Technical Institute of Large Crops (ITGC) of Setif, which cover a period of twenty years (2002-2022).

MODIS-NDVI data

The time series of average NDVI for the study area were obtained from the Global Agricultural Monitoring (GLAM) system (https://glam1.gsfc.nasa.gov/), hosted by the USDA and NASA. The data was downloaded on January 12th, 2021 (GIMMS, 2021). The GLAM system was developed as part of the Global Agricultural Monitoring project. This initiative has the objective of regularly assessing worldwide forecasts of agricultural production and conditions affecting global food security in an unbiased and timely manner. The GLAM system provides 8-day composited NDVI data sets that are derived from MODIS sensors onboard the Terra satellite platform. These data sets have a spatial resolution of 250 or 500 m and are based on the MOD09 product (MODIS collection 6). Our study focused on the growing season in Algeria, which spans from February end to June 1st, and covers data collected from 2002 to 2022. To obtain the NDVI values, we used the GFSAD30 2015 Crops crop mask developed by the NASA Global Food Security-Support Analysis Data project, which has a spatial resolution of 30 m (https://croplands.org) (USGS, 2021). To ensure high-quality data, the collected information underwent radiation, atmospheric, and geometric corrections. These measures were taken to make the data more accurate and reliable for use in studying regional vegetation.

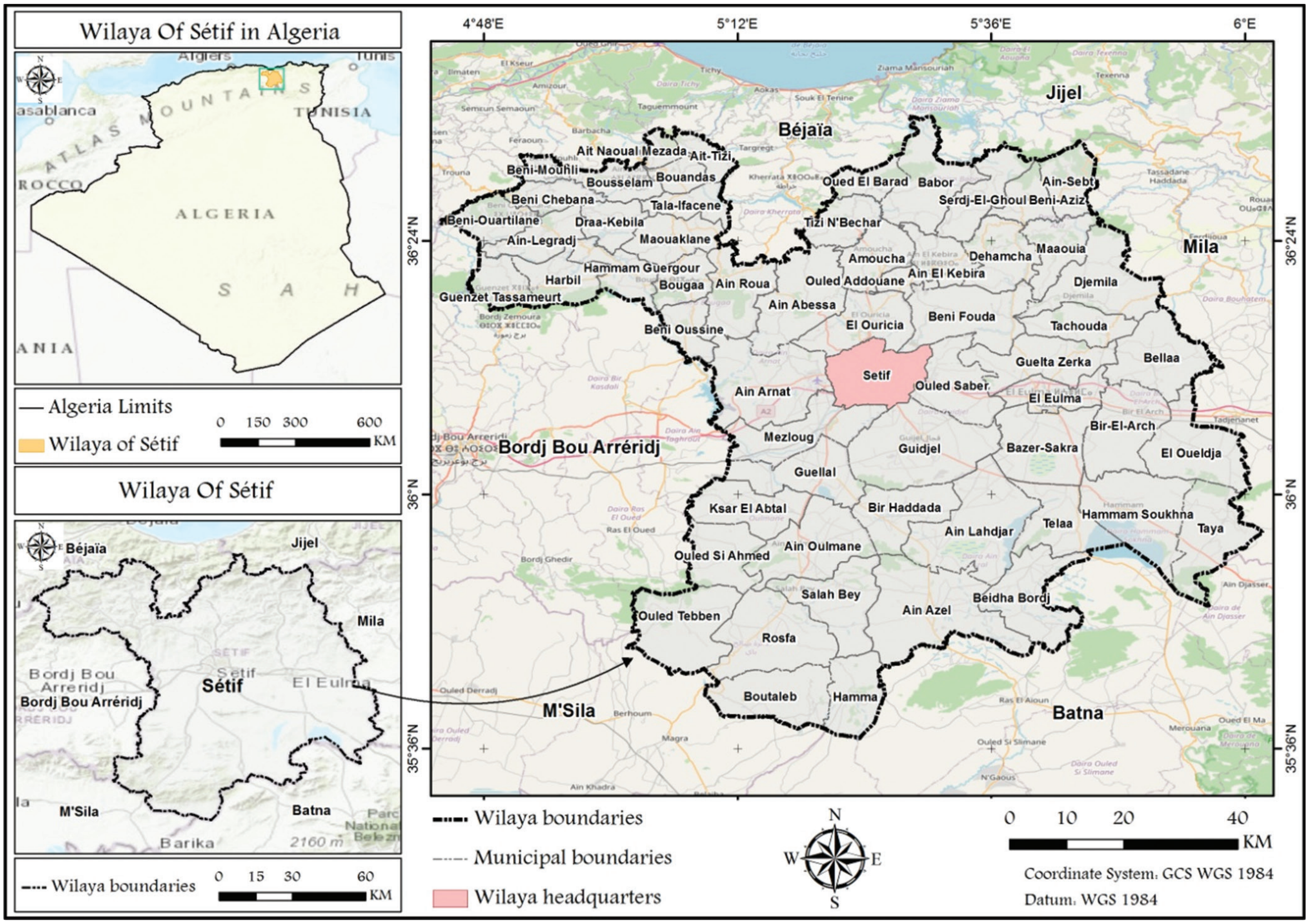

Figure 1: Geographical location of the experimental site

Statistical Analysis

In this study we employed a separate correlation and linear regression analyses for each crop. The independent variable was the NDVI values, while the dependent variable was the yield data of two cereal crops. Regression analysis aims to identify trends in the relationship and describe the relationship mode with a particular function, thereby quantifying causal relationships. The regression coefficient measures the average change in the explanatory variable per unit change in the response variable. Meanwhile, the linear correlation coefficient, determines the percentage of variance in the response variable that is explained by the factor variable, thereby indicating its reliability. We can represent this relationship using the following equation:

$$Y = \beta 0 + \beta 1X \quad (1)$$

Where β1 represents the regression coefficient. Parameter β0 can usually only be interpreted mathematically if the variable X is set to 0, then β0 is the estimate given 0 in X.

To assess the performance of the developed models, widely employed statistical metrics were used in this study. The coefficient of determination (R2) was used to measure the degree of linear relationship between observed and forecasted cereal yield. The mean squared error (MSE) was used to measure the average of the squares of the errors. Meanwhile, the Root Mean Square Error (RMSE) measured the discrepancy of the forecasted yield around observations. All statistical analyses were carried out using SPSS (version 19). The R2, RMSE, MSE was calculated using equations (2), (3) and (4).

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(yi - y^{1}\right)^2}{\sum_{i=1}^{n}\left(yi - \bar{y}\right)^2} \quad (2)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left(yi - \grave{yi}\right)^2}{n}} \quad (3)$$

$$MSE = \frac{\sum\left(yi - \widehat{yi}\right)^2}{n} \quad (4)$$

RESULTS

Temporal Variability of Cereal Grain Yield

The average grain yields of two cereals varied over the study period (2002-2022) are presented in Figure 2. Wheat had the highest averaged grain yield in 2018 with 3.07 t ha^{-1} while barley had the highest averaged grain yield in 2019 with 2.2 t ha^{-1}. Conversely, the lowest grain yield for wheat was observed in 2015 with 1 t ha^{-1}, for barley it was in 2002 with 0.7 t ha^{-1}. Differences in the mean grain yield of two cereals in arid and semi-arid regions of Algeria across years were primarily due to weather conditions, such as Variability of rainfall, very low temperatures during winter or droughts during spring and early summer.

NDVI Temporal Variability from 2002 to 2022

Figure 3 illustrate the temporal patterns of vegetation index throughout the growth period of barley and wheat crops respectively. The NDVI values were lowest during the transplanting phase and gradually increased as the vegetative parts grew. They reached their peak during the late vegetative

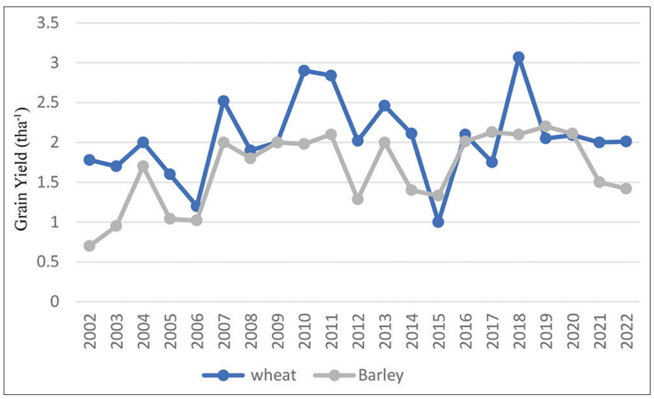

Figure 2: Temporal variability of cereals grain yield (wheat and barley) from 2002 to 2022

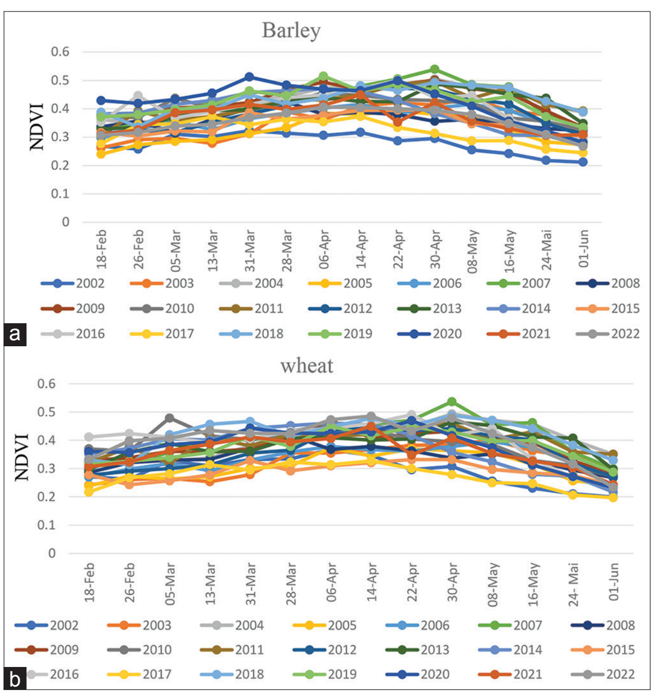

Figure 3: NDVI temporal variability for a) barley and b) wheat from 2002 to 2022

phase and remained high until the flowering phase, which occurred between March and April.

During the post-flowering phase, (i.e., the ripening phase), the vegetation index values started to decrease and reached their minimum at the fully ripened harvesting phase in June. The NDVI values ranged from 0.212 to 0.539 for all study years for barley, and from 0.197 to 0.537 for wheat. The NDVI values varied from one year to another, depending on factors such as rainfall, temperature during the seasons and sowing dates.

Relationship between NDVI at Different Dates and Cereals-grain Yield

The NDVI is an effective tool for measuring the impact of various environmental factors and their interactions with crops. It provides valuable information on the combined effects of weather conditions, crop varieties, soil types, cultivation methods, and other factors. The results of our study demonstrate a strong linear relationship between MODIS-NDVI and grain yield for the two winter cereals (wheat and barley) at the regional level. The correlation coefficients are presented graphically in Figure 4.

The highest correlation between NDVI and cereals grain yield occurs between 26 February and 13 March (R^2 ranged from 0.71 to 0.8 for barley, R^2 ranged from 0.55 to 0.82 for wheat). The peaks of correlation correspond to the NDVI peaks during the growing season. We can observed that at later dates (growing season progresses), the relationships and the prediction accuracy were weaker, which may have been caused by NDVI saturation in the later growth stages of cereals. Based on these results, the best time to predict cereals grain yield accurately using MODIS-NDVI in semi-arid region of Algeria is the beginning of spring, specifically 13 March (120th after sowing). We can observe that at later dates, the relationships and the prediction accuracy were weaker, which may have been caused by NDVI saturation in the later growth stages of cereals.

A linear regression analysis was conducted to examine the relationship between NDVI and cereals grain yield (wheat and barley). The means NDVI values from 18 February to

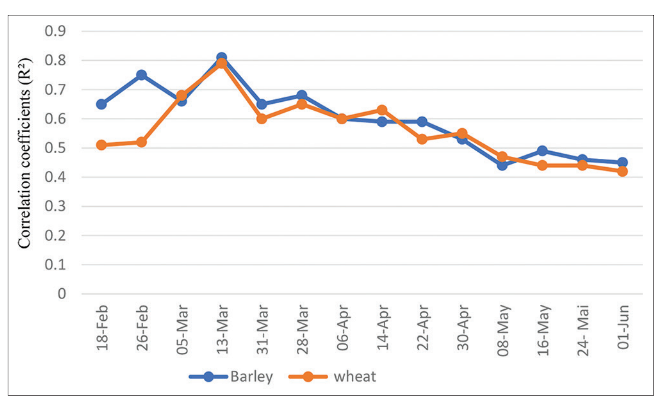

Figure 4: Correlation coefficients between grain-yield and NDVI for the two cereals (barley, and wheat) from February 18th to June 1st, covering the period from 2002 to 2022

01 June (2002-2022) were used as independent variables, while the dependent variable was grain yield for wheat and barley. The results are graphically presented in Figure 5, indicating a strong relationship between NDVI in early spring (13 March) and grain yield for two cereals. The regression coefficients for wheat and barley were 6.598 and 7.461 respectively which implies that an increase of 0.1 in NDVI is associated with an average increase of 0.659 t ha^{-1} and 0.746 t ha^{-1} in grain yield for wheat and barley respectively. The strength of the relationship is supported by strong Pearson's correlation coefficients (R) of 0.82 and 0.80 for wheat and barley, respectively.

Model Performance Verification

The accuracy of the models was assessed by comparing the predicted yields with the actual yields obtained in the study area. Four measures of forecast accuracy were used: root mean square errors (RMSE), mean square error (MSE), correlation coefficients (R) and the coefficient of determination (R^2) for each cereals crop (wheat and barley). The results showed a strong correlation between the measured and predicted yield, with correlation coefficients of 0.80, 0.901 for wheat and barley, respectively. And low RMSE values ranged from 0.01 to 0.276 t ha^{-1}, the MSE values ranged from 0.061 to 0.076, the results are presented in the Table 1, these results indicating that the predicted values are close to the actual observed values, which confirm that the yield was predicted with great accuracy, three months before harvest which implies the proper functioning of the created model (Figures 6 & 7).

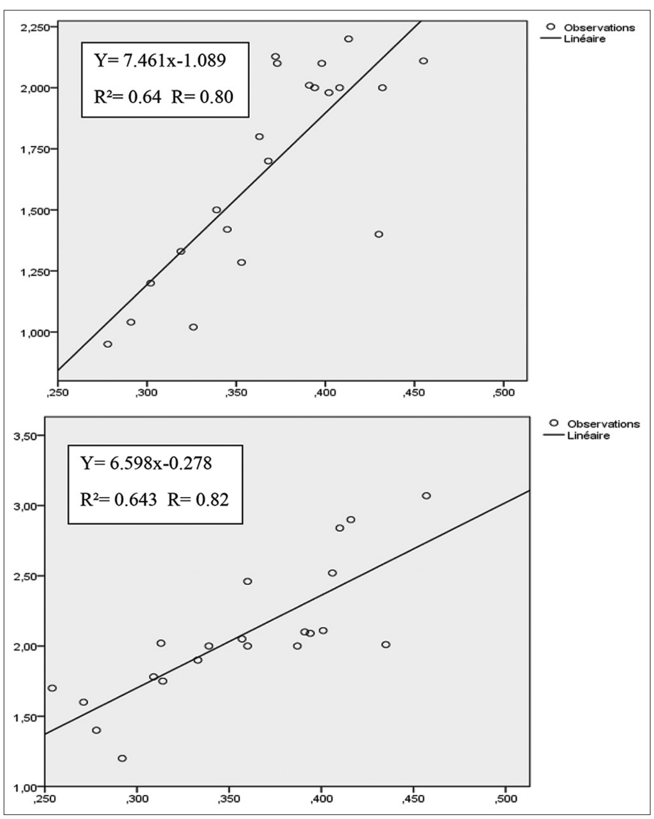

Figure 5: Linear regression model and correlation of barley (above), wheat (At the bottom), yield with the MODIS- NDVI for March 13th

DISCUSSION

Forecasting crop yields is a critical and complex task in modern agriculture due to various challenges. These challenges include the impacts of global climate change, such as extreme weather events like droughts, floods, and other natural disasters, as well as the increasing global population and demand for food. Accurately predicting crop yields is crucial for effective agricultural planning, maintaining food safety and availability. Satellite remote sensing is widely used for forecasting cereal yield production, given its ability to be utilized at a global level. According to our results, we have demonstrate that the early spring stage of development is critical for achieving high grain yield for the three dominant cereals (durum wheat, soft wheat, and barley) in Algeria's most valuable semi-arid areas. Mkhabela *et al.* (2010) found that MODIS-NDVI could effectively predict crop yields across the Canadian Prairies with a lead time of one to two months before harvest. The results indicated that a power function best described the relationship between MODIS-NDVI and grain yield for all the crops and agro-climatic zones studied, with coefficient of determination (R^2) ranging from 0.48 to 0.90 for barley and 0.47 to 0.80 for wheat. Interestingly, the strength of the relationship was similar or even stronger when compared to the findings of our study, with R^2= 0.64 for barley, and R^2= 0.643 for wheat. In a study on predicting the grain yields of wheat Adeniyi *et al.* (2020), proves that the use of Normalized Difference of Vegetation Index (NDVI) derived from Landsat 8 time series data, from 2013 to 2019 growing seasons, are effective in predicting winter wheat yield in Jász-Nagykun-Szolnok county (Northern Great Plain region of central Hungary). The highest determination coefficient (R^2=of 0.569) was found on the 160th day, which is lower than the value obtained in the current study (R^2 = 0.643). The study reported an average increase of 0.1 t/ha in grain yield of wheat with an increase of 0.1 in NDVI value, which is lower than the result obtained in the current study. Panek and Gozdowski (2021), employed a linear regression analysis to investigate the correlation between normalized difference vegetation index (NDVI) obtained from MODIS satellite data, and grain yield of wheat and barley in 20 European countries between 2010 and 2018. They found a strong relationship between NDVI and cereals grain yield in early spring for several countries, including Croatia, Czechia, Germany, Hungary, Latvia, Lithuania, Poland and Slovakia, which is similar to the results of our study. The strength of the relationship was also similar to our study, with an R^2 of 0.610 for wheat and 0.614 for barley. The results of the regression showed that a 0.1 unit increase in NDVI is related to a 1.35-1.65 t ha^{-1} increase in grain yield of cereals. Wang *et al.* (2019), employed an enhanced Carnegie-Ames-Stanford approach (CASA) model, combined with time-series satellite remote sensing images obtained from MODIS, to estimate the

Table 1: Model performance results expressed as the correlation coefficients (R), coefficients of determination (R^2), root mean square errors (RMSE), and mean squared errors (MSE)

Crop	R^2	R	RMSE	MSE	Equation
Barley	0.811	0.901	0.01	0.061	Y=1.187x-0.266
wheat	0.640	0.8	0.276	0.076	Y=1.02x-0.003

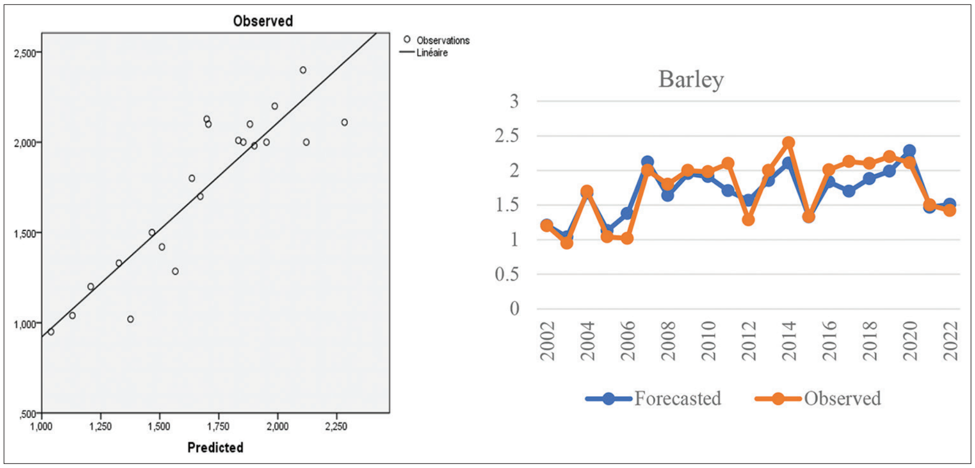

Figure 6: The scatter plot between observed and predicted values according to the created model for barley

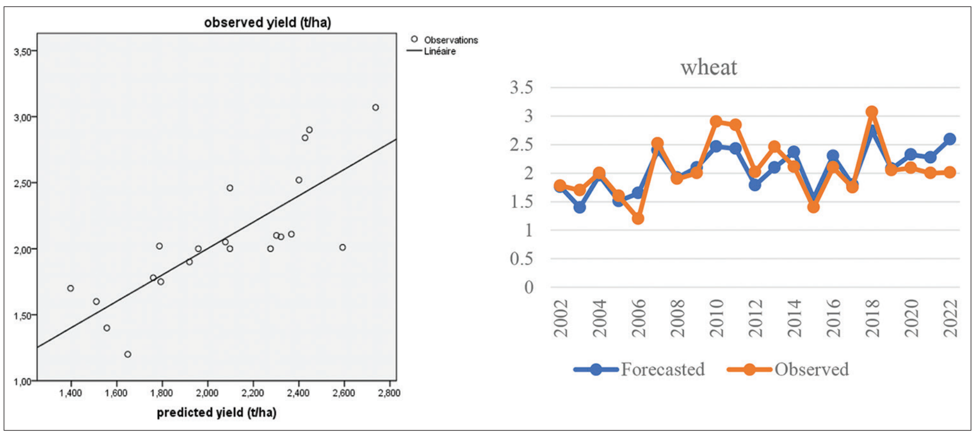

Figure 7: The scatter plot between observed and predicted values according to the created model for wheat

yield of winter wheat in selected regions of China. The study reported a determination coefficient of R2 = 0.56 between the estimated and measured winter wheat yield, which is lower than that found in our study (R^2= 0.640), a root mean square error (RMSE) of 1.22 t ha^{-1}, which is higher than that found in our work (RMSE= 0.276 t ha^{-1}). Nagy *et al.* (2021), found a high regression coefficients between the vegetation indices and the wheat yield (R^2= 0.757, RMSE= 0.357 tha^{-1}). The best time for wheat yield prediction with Landsat 8-NDVI was found to be the beginning of full biomass period from the 138th to 167th day after sowing (18 May to 16 June), which it is the same period that we found in our study. Gop and Savenkov (2016), found that The correlation was significant between the yield of spring wheat and the NDVI (R^2= 0.859). The study demonstrated that the NDVI was shown to be responsible for 85% of the variation in the yield of spring wheat. The approximate average increase in the grain yields of spring wheat was about 6.7 t ha-1, with an increase of 0.1 in NDVI value. Tuğaç *et al.* (2022) found that the highest correlation between NDVI and yield was during the flowering period (R^2= 0.63). They also found that the best prediction performance was achieved with the MLP model for MODIS, with a root mean square error (RMSE) ranging from 0.23-0.65 t ha^{-1}. According to Mashaba *et al.* (2017), the relationship between NDVI and wheat yield was significant with an R^2 value of 0.73 and RMSE of 0.41 t ha^{-1}. In Latvia, Vannoppen *et al.* (2020) found that the linear regression model fit had a good estimate of the model parameter, with an adjusted R^2 of 0.71. Pismennaya *et al.* (2021), investigated the correlation between MODIS-NDVI and winter wheat yield in the arid zone of the Central Pre-Caucasus region, using data from 2017-2020. Their findings revealed a very strong positive correlation (R^2= 0.78) between winter wheat yield and NDVI. Moreover, they reported an average increase of 0.20 t ha^{-1} in wheat grain yield for every 0.1 increase in NDVI value. In central Europe, Panek and Gozdowski (2020), found a strong relationship between cereal-grain yield and MODIS-NDVI in spring (April), three to four months before the harvest. The increase in the NDVI in early spring by 0.1 unit increases the grain yield of cereals by about 1.1 to 2.6 t ha^{-1}.

This fluctuation in results between different studies is due to That NDVI measures the potential yield and does not account for any subsequent crop developments that occur after the forecast date. Factors such as drought, diseases, or pest outbreaks occurring after the forecast date may lead to overestimations of crop yield. Additionally, satellite images are susceptible to various atmospheric effects, including clouds and volcanic eruptions, which can compromise data quality and subsequently affect the developed crop-yield models. Further research is necessary to validate the equations under different weather scenarios and to enhance the relationship's strength by incorporating auxiliary data

CONCLUSION

This study has successfully demonstrated the effective utilization of MODIS-NDVI for predicting cereal crop yield (wheat and barley) in the semi-arid regions of Algeria, providing reliable forecasts two to three months before harvest. A robust correlation between cereals-grain yield and NDVI was observed during early spring (specifically on March 13th). From the forecasting model that was developed based on twenty training years a 0.1 unit increase in mean NDVI during April corresponded to a cereals-grain yield increase ranging from 0.659 to 0.746 t ha^{-1}. The root mean square error (RMSE) for the two crop cereals ranged from 0.01 t ha^{-1} to 0.276 t ha^{-1}. These findings highlight the utility of MODIS satellite data in enhancing the accuracy of regional-level cereal-grain yield prediction in Algeria, particularly during the early spring period. This enables improved planning of trade and food policies, which heavily rely on cereals-grain production.

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