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Cultivation-time recommender system based on climatic conditions for newly reclaimed lands in Egypt

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Abstract

This research proposes cultivation-time recommender system for predicting the best sowing dates for winter cereal crops in the newly reclaimed lands in Farafra Oasis, The Egyptian Western Desert. The main goal of the proposed system is to support the best utilization of farm resources. In this research, predicting the best sowing dates for the aimed crops is based on weather conditions prediction along with calculating the seasonal accumulative growing degree days (GDD) fulfillment duration for each crop. Various Machine Learning (ML) regression algorithms have been used for predicting the daily minimum and maximum air temperature based on historical weather conditions data for twenty-five growing seasons (1990/91 to 2014/15). Experimental results showed that using the M5P and IBk ML regression algorithms have outperformed the other implemented regression algorithms for predicting the daily minimum and maximum air temperature based on historical weather conditions data. That has been measured based on the calculated mean absolute error (MAE). Also, obtained experimental results obviously indicated that the best cultivation-time prediction by the proposed recommender system has been achieved by the M5P algorithm, based on the seasonal accumulative GDD fulfillment duration, for the coming five growing seasons (2016/17 to 2019/20).

Peer-review under responsibility of KES International

Keywords: climate conditions, recommender system, regression, growing degree days (GDD), Farafra oasis, Western Desert, Egypt

1. Introduction

Food security has become a pressing challenge due to rapid population growth, climate change, and water shortages, especially in developing countries [1,2].

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Despite the fact that wheat production in Egypt for the current season of 2015/16 is estimated to 9 million tonnes, it remains the world's largest wheat importer with wheat imports estimated at 11 million tonnes [1,3,4,5]. Moreover, growth ratio of Egyptian imports of other cereal crops, such as barley, for the same season reached around 96.08% compared to the previous season [3,6]. It is noteworthy that climate change is a major reason that causes large variations in crop yields from decade to decade. Also, as plant development is tightly aligned with weather conditions, especially temperature, uncertainty in weather creates a risky environment for agricultural production.

Therefore, the cultivation area of winter cereal crops increased in the newly reclaimed lands under various irrigation systems. Both crops are suitable to be widely grown in the rain-fed areas of the north coastal region. In addition, the newly reclaimed lands with saline soils in Egypt, such as the newly reclaimed lands in the western desert, are appropriate to grow both crops [7].

Commonly, people often count on a calendar to predict plant development for making management decisions. However, as plant development depends on temperature that can vary greatly from year to year, it's hard to depend on the calendar days that can be undeniably misleading for predicting plant growth, especially for early stages of crop growth [8]. Therefore, weather forecasting is very important to determine the suitable cultivation dates of various crops for agricultural development in the newly reclaimed lands, especially the Egyptian western desert.

This paper proposes a cultivation-time recommender system for predicting the best sowing dates and cultivation times for cereal crops in the newly reclaimed lands. A case study considered two strategic cereal crops in Egypt, namely winter wheat and barley, has been presented. The scope and focus cultivation location of this research is the newly reclaimed lands in Farafra Oasis, The Egyptian western desert. The main goal of the proposed system is to enable the best utilization of farm resources and to support the farmers as well as governmental authorities and decision makers via predicting the best sowing date for a certain cereal crop during a given (future) cultivation season.

The proposed recommender system consists of two main phases; namely *weather prediction* and *Growing Degree Days (GDD) based sowing date prediction*. In this paper, various Machine Learning (ML) regression algorithms have been used for predicting the daily minimum and maximum air temperature based on historical weather conditions data. The predicted daily minimum and maximum air temperature have been used to calculate the seasonal accumulative GDD fulfillment duration, and to accordingly predict the best sowing dates for the aimed crops.

The rest of this paper is organized as follows. Section 2 presents a brief review of related recent research work. Section 3 describes the different phases of the proposed recommender system along with briefing the details of the used prediction methods. Section 4 introduces the tested weather conditions data and the case study location in addition to depicting and discussing the obtained experimental results. Finally, section 5 presents conclusions and discusses future work.

2. Related work

Numerous studies have been conducted on cultivation in the Nile delta, however, few researches have addressed cultivation in the desert region, especially oasis. Moreover, very limited research studies have proposed computational intelligence based recommender systems for predicting the best planting dates, especially for the newly cultivated lands, based on the required temperature for crops growth stages. For example, in [1], authors proposed a recommender system, based on the rough mereology theory, for predicting best cultivation dates for wheat in Egyptian Sinai Peninsula according to the required mean temperature for germination stage.

However, several research works addressed the usage of crop growth models and weather conditions prediction software for studying the impact of related phenomena. For example, authors, in [9], studied the SIRIUS crop growth model program under Egyptian climatic conditions in order to investigate the effects of increasing temperature and Co^2 on wheat production and help the decision maker to set mitigation plans for facing climate changes. While, in [10], authors used the ArcGIS 10.1 software to create classified maps for presenting GDD at ten governorates in the Egyptian Nile Delta considering three selected base temperatures. Prediction equations were implemented to predict annual accumulative GDD for crop management decisions. In [11], CERES-Wheat simulation model in the DSSAT package has been used for describing daily phenological development and growth, in response to environmental factors (soils, weather and management), at three agroclimatic locations in in Nile Valley and Delta, in Egypt. Authors in [12] used CropSyst crop growth simulation model to quantify a range for calibration parameters for four wheat cultivars grown in nine growing seasons at four governorates, in Nile Valley and Delta, in Egypt. Also, authors in [13] used CropSyst crop growth simulation model to study the effect of climate change on wheat grown under sprinkler irrigation.

In this research, a novel prediction model for the best cultivation time of cereal crops, which tightly relates crop life cycle to the accumulation of given quantities of heat, calculated as thermal time or GDD, has been proposed. It utilized various ML regression algorithms for predicting the daily minimum and maximum air temperature based on historical weather conditions data.

3. The proposed GDD based cultivation-time recommender system

In this research, the proposed cultivation-time recommender system consists of two main phases; namely *weather prediction* and *Growing Degree Days (GDD) based sowing date prediction*. Fig. 1 shows the phases and corresponding stages of the proposed recommender system.

3.1. Weather prediction

In this phase, various regression ML algorithms; namely, M5Rules [15], M5P [16], Multi-layer Perceptron (MLP) regressor [17], and IBk [18], have been tested for weather forecasting via predicting the daily minimum and maximum air temperature based on historical weather conditions data.

3.1.1. M5Rules algorithm

In M5Rules algorithm, a decision list for regression problems is generated using divide-and-conquer (separate-and-conquer) rule learning. The key idea of this approach is to replace the purity heuristic of the decision tree algorithm

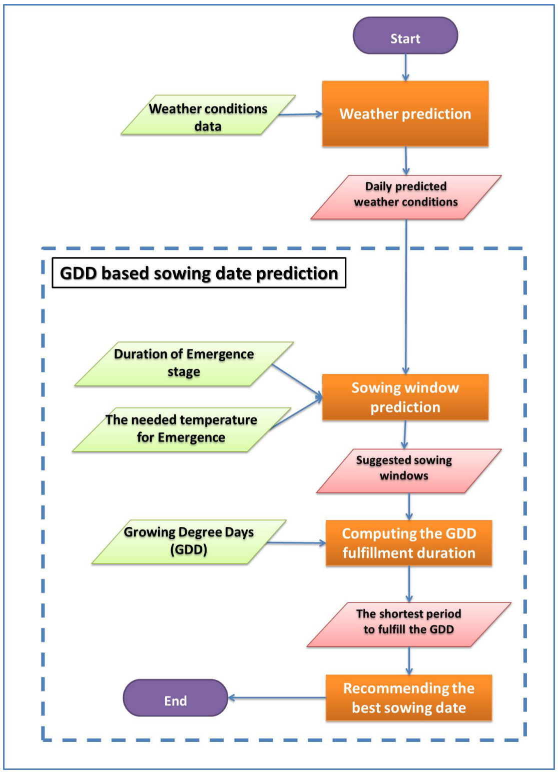


Fig. 1. General structure of the proposed GDD based cultivation-time recommender system

with a heuristic that measures the reduction in variance. So, in each iteration of progress, a model tree is built using the M5 model tree and the *best* leaf is made into a rule. Basically, these model trees are decision trees with linear models at the leaves [15]. Technically, M5Rules algorithm is straightforward method for generating a rules-set from the M5 model tree inducer [15]. Steps of the M5Rules algorithm is shown in Algorithm 1.

Algorithm 1 M5Rules algorithm

1: Apply M5 model tree to the full training dataset and a pruned tree is learned.
2: Select the best leaf and made it into a rule (According to some heuristic) and the tree is discarded.
3: Remove all instances, covered by the rule, from the dataset.
4: Apply the process recursively to the remaining instances.
5: Terminate when all instances are covered by one or more rules (The rules are generated based on an unsmooth linear models).

3.1.2. M5P algorithm

The M5P is the most widely used algorithm based on decision tree for data prediction [16]. It is a multivariate tree linear model algorithm, which is utilized for noise removal and also used for huge database. M5P algorithm is advantageous as compared to other algorithms as it is used for both categorical and continuous variables and for missing values. At each leaf of the tree, a linear regression model predicts the class value of instances that reach the leaf. It combines a predictable decision tree and the possibility of linear regression functions at the nodes [16]. Steps of the M5P model tree learner algorithm is shown in Algorithm 2.

Algorithm 2 M5P algorithm

1: **Construction** Construct a tree via splitting the data to minimize intra-subset variation in the class values of instances down each branch.
2: **Pruning** For each node, a linear model is computed, then the tree is pruned back from the leaves, as long as the expected estimated error decreases.
3: **Smoothing** To compensate for sharp discontinuities that occur between linear models at the leaves of the pruned tree, a smoothing procedure is used.

3.1.3. MLP regressor

The most widely used model in time series prediction is the MLP network for regression. It is a front-forward neural network model. It can be used from one hidden layer to multiple layers. Each hidden layer is fully connected to the succeeding layer [17].

The MLP maps sets of input data onto a set of appropriate outputs using historical data, so that the model can be used to produce the output when the desired output is not identified. The MLP regressor is implemented by equation (1).

$$Y_j = f(\sum_i w_{ij} X_{ij}) \tag{1}$$

Where Y_j is node j output, w_{ij} is the connection weight between node j and node i in the lower layer, and X_i is the input signal from the node i in the lower layer. The function $f()$ is the transfer function. It trains a multilayer perceptron with one hidden layer.

3.1.4. IBk: k-nearest neighbor learner algorithm

The IBk is a k-nearest neighbor (k-NN) classifier, which is an instance based learning (IBL) method that implements the k-NN algorithm [18,19]. The IBk classifier is used for regression and classification problems. Instead of building a model, IBk algorithm provides the closest k entries of the training dataset that have the highest similarity to the test sample using a similarity metric; such as Euclidean distance. Then, a majority vote is performed among the selected k entries to determine the property value of the test sample [18,19]. Steps of the k-NN algorithm is shown in Algorithm 3.

Algorithm 3 k-nearest neighbor (k-NN) algorithm

1: Determine a positive integer *k* (the number of nearest neighbors), along with a new sample.
2: Compute the similarity measure between the training entries and the testing sample.
3: Sort all training entries according to the similarity values.
4: Use a majority vote for the class labels of *k* nearest neighbors, and assign it as a prediction value of the testing sample.

3.2. GDD based sowing date prediction

During this phase, the predicted daily maximum (Tmax) and minimum (Tmin) air temperature data, resulted from the first weather prediction phase, has been used to calculate the seasonal accumulative growing degree days (GDD) for the aimed crops, as shown in equation (2) [8]. The GDD is a heat driven development model, based on actual temperatures, is used as an alternative to provide the potential plant stage, represents a simple and accurate way to predict when a certain plant stage will occur [8].

$$GDD = \sum_{n} [(Tmax + Tmin)/2] - Tb \tag{2}$$

Where n represents the number of days in each growth stage throughout the growing season, $Tmax$ and $Tmin$ are the maximum and minimum daily temperature, and Tb is the crop base temperature (the temperature below which plant development stops). The resulting *thermal time* could more consistently predict when a certain plant growth stage will occur. Accordingly, the seasonal accumulative GDD of the aimed crop is resulted when the calculated thermal times (GDD values) of the plant growth stages are summed together.

Moreover, for concluding the best sowing date recommendations of the aimed crops, other parameters for each specific crop, such as: *the number of days for plant initiation growth stage till emergence completion*, *the needed temperature range for emergence completion* [20], and *the total GDD range* [8], are required to be identified. It's noteworthy to mention that, according to the Food and Agriculture Organization (FAO) [5], sowing winter wheat and barley starts in November to early December. Whereas, for both crops, harvesting starts from mid-April. Also, for winter wheat and barley, the number of days for plant initiation growth stage till emergence completion is around two weeks (15 days), the needed temperature range for emergence completion is generally within the range of [5° to 25°] [20], and the total GDD range of winter wheat and barley are [1538-1665] and [1269-1522] [8], respectively.

4. Experimental results and discussion

Experiments implemented in this research have been conducted using the WEKA open source software [21] in addition to additional calculations programming performed in the Java environment. As previously stated, four ML algorithms have been tested in this research for daily temperature prediction of the coming five growing seasons (2016/17 to 2019/20) based on the climatic parameters; namely daily maximum and minimum temperatures, for twenty-five growing seasons (1990/91 to 2014/15) at the Farafra Oasis, New Valley Governorate, Western Desert, Egypt (near latitude 27.06 ° North and longitude 27.97 ° East) [22].

The meteorological data that has been used for validating the proposed cultivation-time recommender system was obtained from the NASA project for Prediction of Worldwide Energy Resource (POWER) as Climatology Resource for Agroclimatology [23].

Moreover, four years; namely 2000, 2004, 2008 and 2012, have been used for testing and validating the performance of each implemented algorithm via calculating the *Mean Absolute Error (MAE)* measure, as shown in equation (3). The MAE measure is defined as the average of the difference between the predicted and the actual values.

$$MAE = \frac{|a_1 - c_1| + |a_2 - c_2| + \cdots + |a_n - c_n|}{n} = \frac{\sum_{i=1}^{n} |a_i - c_i|}{n} \tag{3}$$

Where a is the actual value, c is the calculated (predicted) value, and n is the total number of values.

Table 1 shows the performance MAE measure of the M5Rule, M5P, MLP regressor, and IBk algorithms for the daily temperature prediction.

Table 1. Mean Absolute Error (MAE) of the implemented ML regression algorithms

Year	M5Rules		M5p		MLP regressor		IBK	
	MAE (Tmax)	MAE (Tmin)	MAE (Tmax)	MAE (Tmin)	MAE (Tmax)	MAE (Tmin)	MAE (Tmax)	MAE (Tmin)
2000	2.269	1.714	2.281	1.713	1.835	1.832	2.785	2.149
2004	2.57	1.767	2.57	1.767	2.575	2.136	3.607	2.254
2008	2.735	1.694	2.735	1.694	3.57	1.882	3.701	2.253
2012	2.242	1.531	2.242	1.531	3.427	1.723	2.694	2.291

For each of the testing years, used for validating the proposed weather conditions prediction system, the following observations have been concluded.

Firstly, in some cases, it has been observed that there is an inverse relationship between the calculated MAE for the whole year and the trend of predicted maximum daily temperature. For example, when high maximum daily temperature values have been predicted, whereas the average MAE value calculated for the whole year has been observed to be within a limited range of values. That leads to the observation of the occurrence of unusual temperatures in some days of that year.

Also, that explains the performance of the MLP and the M5Rules algorithms. So, when applying the MLP regressor algorithm, the highest MAE was for the daily maximum temperature prediction of the validation year 2012 ranges as [1.4336 to 4.5049]. Similarly, when applying the M5Rules algorithm, the highest MAE for the daily maximum temperature prediction has been also obtained for the year 2012 as [1.4849 to 3.7468].

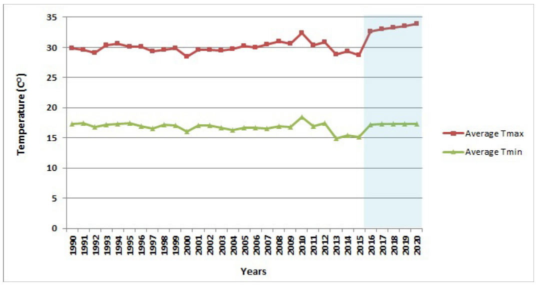
On the other hand, in other cases, it has been observed that there is a direct relationship between the calculated MAE for the whole year and the trend of predicted maximum daily temperature. So, this reflects the case that when applying the IBk and M5P algorithms, the highest MAE for the daily maximum temperature prediction has been obtained for the year 2008 as [2.7457 to 7.8] and [1.6019 to 6.3295], respectively.

These observations fairly explains the curves depicted in Fig. 2 (a), (b), (c), and (d), which show the trend of the average daily minimum temperature (Tmin) and maximum temperature (Tmax) values of the years (1990 to 2020) obtained by the M5Rules, M5P, MLP regressor, and IBk prediction algorithms, respectively. The shaded area in the figures highlighting the predicted average daily Tmin and Tmax values of the coming five years (2016 to 2020).

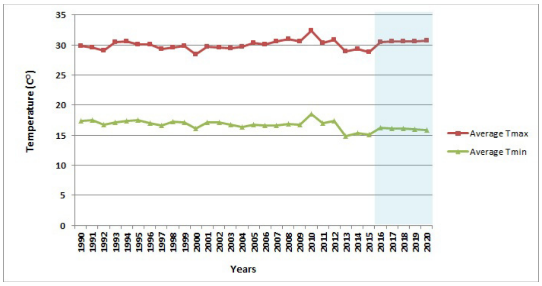
Also, considering the tested weather conditions dataset, results showed that the M5P and the IBk regression algorithms have achieved the best sowing date prediction, based on the predicted average daily Tmin and Tmax values of the coming five years (2016 to 2020). Moreover, the same prediction algorithms, using the maximum and minimum temperature of four validation years (2000, 2004, 2008, 2012), have achieved MAE ranges as [2.242 to 2.735] and [2.694 to 3.607], respectively, for the Tmax and ranges as [1.531 to 1.767] and [2.149 to 2.254], respectively, for the Tmin.

Table 2, 3, 4, and 5 show the recommended sowing times for the aimed crops during the coming five growing seasons (2016/17 to 2019/20), using the M5Rules, M5P, MLP regressor, and IBk prediction algorithms, respectively.

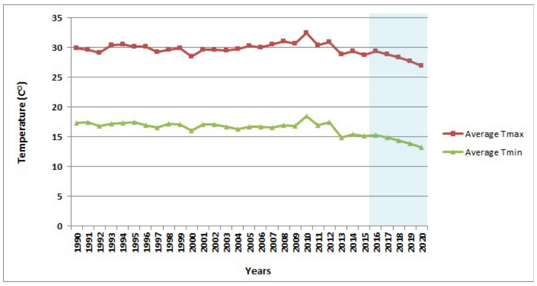
Generally, obtained experimental results obviously indicated that the best recommendation for the cultivation-time by the proposed recommender system has been achieved by the M5P algorithm, based on the seasonal accumulative growing degree days (GDD) fulfillment duration, for the coming five growing seasons (2016/17 to 2019/20).



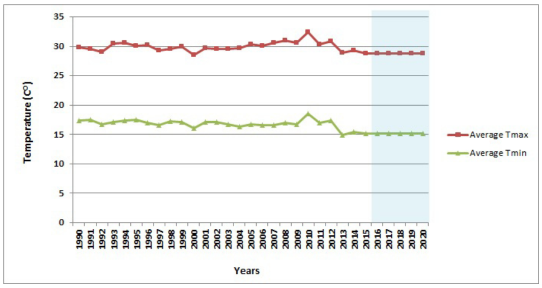
(a) M5Rules algorithm



(b) M5P algorithm



(c) MLP regression algorithm



(d) IBk algorithm

Fig. 2. Trend of the average daily minimum temperature (Tmin) and maximum temperature (Tmax) values of the years (1990 to 2020)

Table 2. The recommended sowing times for the aimed crops during the coming five growing seasons (2016/17 to 2019/20) using the M5Rules algorithm

Growth season	Sowing date	Achieved GDD	Number of Days
2015 - 2016	11/1/2015	1254.3034	86
	11/8/2015	1262.1795	89
	11/15/2015	1255.7404	90
2016 -2017	11/12/2016	1257.48515	83
2017 -2018	11/1/2017	1251.30	91
	11/8/2017	1252.75	93
	11/15/2017	1252.750	97
2018 -2019	11/1/2018	1251.30	91
	11/8/2018	1252.750	93
	11/15/2018	1252.750	97
2019 - 2020	11/1/2019	1251.30	91
	11/8/2019	1252.750	93
	11/15/2019	1252.750	97

5. Conclusions and future work

This research proposes a recommender system for support the best utilization of farm resources in the newly reclaimed lands in Farafra Oasis, The Egyptian Western Desert. The proposed cultivation-time recommender system predicts the best winter cereal crops sowing dates based on calculating the seasonal accumulative growing degree days (GDD) fulfillment duration for each crop. Experimental results showed that using the M5p and IBk ML regression algorithms have outperformed using the M5Rules and MLP resgressor algorithms for predicting the daily minimum

Table 3. The recommended sowing times for the aimed crops during the coming five growing seasons (2016/17 to 2019/20) using the M5P algorithm

Growth season	Sowing date	Achieved GDD	Number of Days
2015 - 2016	1/1/2015	1253.7279	86
	11/8/2015	1259.7504	89
	11/15/2015	1254.2792	90
2016 - 2017	11/1/2016	1259.8866	76
	11/8/2016	1252.7897	80
	11/15/2016	1254.6721	83
2017 - 2018	11/2/2017	1260.64695	77
	11/9/2017	1256.7152	81
	11/16/2017	1262.52295	84
2018 - 2019	11/2/2018	1258.06845	77
	11/9/2018	1253.95875	81
	11/16/2018	1259.7698	84
2019 - 2020	11/2/2019	1255.3167	77
	11/9/2019	1251.062049	81
	11/16/2019	1256.914449	84

Table 4. The recommended sowing times for the aimed crops during the coming five growing seasons (2016/17 to 2019/20) using the MLP algorithm

Growth season	Sowing date	Achieved GDD	Number of Days
2015 - 2016	11/1/2015	1262.01	88
	11/8/2015	1263.15	91
	11/15/2015	1263.28	93
2016 - 2017	11/1/2016	1250.282	86
	11/8/2016	1258.639	90
	11/15/2016	1257.897	92
2017 - 2018	11/1/2017	1261.6418	90
	11/8/2017	1262.8226	93
	11/15/2017	1263.1058	95
2018 - 2019	11/1/2018	1256.2259	93
	11/8/2018	1261.5044	96
	11/15/2018	1250.29445	97
2019 - 2020	11/1/2019	1260.33325	97
	11/8/2019	1255.64515	99
	11/15/2019	1258.1188	101

and maximum air temperature based on historical weather conditions data for twenty-five growing seasons (1990/91 to 2014/15).

Also, considering the tested weather conditions dataset, results showed that the best sowing date prediction, based on the predicted average daily Tmin and Tmax values of the coming five years (2016 to 2020), have been achieved by the M5P and the IBk regression algorithms. Moreover, using the maximum and minimum temperature of four validation years (2000, 2004, 2008, 2012), the M5P and the IBk prediction algorithms have achieved MAE ranges as [2.242 to 2.735] and [2.694 to 3.607], respectively, for the Tmax and ranges as [1.531 to 1.767] and [2.149 to 2.254], respectively, for the Tmin.

Generally, obtained experimental results indicated that the best cultivation-time prediction by the proposed recommender system has been achieved by the M5P algorithm, based on the obtained MAE ranges for the Tmax and

Table 5. The recommended sowing times for the aimed crops during the coming five growing seasons (2016/17 to 2019/20) using the IBk algorithm

Growth season	Sowing date	Achieved GDD	Number of Days
2015 - 2016	11/1/2015	1251.3	91
	11/8/2015	1252.750	93
	11/15/2015	1252.750	97
2016 - 2017	11/1/2016	1251.3	91
	11/8/2016	1252.75	93
	11/15/2016	1252.75	97
2017 -2018	11/1/2017	1251.30	91
	11/8/2017	1252.751	93
	11/15/2017	1252.750	97
2018 - 2019	11/1/2018	1251.30	91
	11/8/2018	1252.750	93
	11/15/2018	1252.750	97
2019 - 2020	11/1/2019	1251.30	91
	11/8/2019	1252.750	93
	11/15/2019	1252.750	97

the Tmin as well as the seasonal accumulative growing degree days (GDD) fulfillment duration, for the coming five growing seasons (2016/17 to 2019/20).

For future work, it is planned to improve the overall performance of the system in this paper via considering additional regression algorithms. Furthermore, in order to increase the use of the proposed GDD based cultivation-time recommender system, more experiments will be employed considering extended study areas in further newly reclaimed lands in Egypt.

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