RESEARCH ARTICLE

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Precipitation forecast with logistics regression methods for harvest optimization

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Abstract
This paper proposes a model that forecasts the weather and then, based on that forecast, uses an income-oriented linear programming method to optimize the harvesting process. Data representing a total yearly output capacity of 472,878 tons from 214 different field locations were used to test the model for sugar beet production. Prior to optimization, long-term one-year weather rainfall forecasting was done using 10 years of actual weather data for the field locations. Weather precipitation was forecasted using logistic regression with an accuracy of 84.16%. The outcome of the weather precipitation prediction model was a parameter in the optimization model. The weather forecast for precipitation led to the 120-day harvest planning being optimized. Comparative analysis was done on the outcomes of the developed model and the current scenario. Comparing the current situation to the proposed one, revenue would have increased by 16.7%. Given that it incorporates weather forecasts into the harvest optimization process, the methodology presented in this paper is more practical than other harvest optimization models.
Keywords: Precipitation forecast, Machine learning, Logistic regression, Harvest efficiency, Optimization

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INTRODUCTION

Throughout human history, agricultural pursuits have been of utmost significance. Farmers are now looking for different alternatives to boost their earnings due to the rise in global competition in agricultural activities conducted at the micro and macro levels. Some of these alternatives include switching from low-yielding seeds to high-yielding yet unsustainable seeds, as well as using excessive irrigation, fertilizers, and pesticides. The environmental sustainability of agricultural production is jeopardized by these possibilities, which also drive up the costs of production for farmers daily.

Aside from the current challenges in agricultural activity production, extraordinary occurrences like pandemics and recent wars have disrupted the global supply chain network and made already challenging agricultural activity production processes much more challenging. Cost items including seeds, fertilizers, gasoline, electricity, and equipment have gone up, and agricultural activities that try to produce with poor profit margins have come to a halt as a result of the disruption of the global supply chain and the onset of economic bottlenecks.

Farmers that attempt to carry on their agricultural operations using conventional methods either search for other solutions for the production processes or discontinue their production activities when their profit margins decline, which is a bad situation. States have created incentive programs to encourage the continuation of manufacturing of essential production products because of this (Şaşmaz and Özel, 2019).

For cost items incurred during production activities, there are alternate chances for improvement and cost savings. Sectoral clustering and collective purchasing can create economies of scale and lower the cost of a unit of production, even though it may not be possible to cut cost items in the import-based procurement for manufacturing at the first stage (TÜSSİDE, 2019). Operational plans created using scientific methods may even be more successful in lowering production costs. the selection of ideal planting sites, the identification of ideal products based on soil and climate analysis, the use of experimental design methods to increase productivity during the production period (Ranka and Sharma, 2012), the selection of irrigation and fertilization techniques that will increase productivity (Hill and Keller, 1980), the real-time continuous monitoring of irrigation needs by controlling humidity with Internet of Things (IoT) sensors for optimal irrigation (Mat et al., 2016), and harvest planning.

Recent or continuing rain increases harvesting costs while the commodity is being harvested. The duration of harvesting time per unit increases when these expenditures are considered because of the muck that is present during and after rainfall. Additionally, the mud creates a lot of sludge in the harvested product, increasing the operating costs of washing and cleaning the products before final consumption while reducing the useable unit product load on the transport vehicles.

This study looks at how sugar beet products are harvested and transported to a processing plant with an annual output of 472,878 tons. The alternate optimum harvesting plan based on weather forecasting and the current harvest plan were compared and contrasted. Ten years' worth of daily weather data were gathered for the study from the Turkish State Meteorological Service. The maximum, lowest, and average temperatures as well as the amount of precipitation per square meter are all included in this weather information. Regression models based on data mining were employed to attempt to forecast precipitation in the relevant area. Python language coding was used to create a solution for the prediction approach. Categorical categorization was employed to identify whether the weather would be rainy. An yearly harvest plan was created following the completion of the long-term weather forecast. The OpenSolver plugin was used to resolve the integer linear programming model created for the harvest plan.

Section 1 is informed in general terms about the study. The Section 2 literature review is also included. This section examines studies on the topic and the article's addition to the body of knowledge. Section 3 provides a definition of the issue and an explanation of its scope. The procedures and model are the same as those in Chapter 4. Real data were used in the study connected to part 5, and the findings were shared with section 6. There was a broad assessment given in the final section.

For the business sectors of manufacturing, agriculture, and tourism to employ resources effectively, weather forecasting is crucial. When businesses have access to weather information in advance, they can make plans more successfully. Numerous research studies have been conducted to forecast meteorological events as a result. A linear link between weather-dependent data and weather conditions has been proposed in recent studies on weather forecasting. Because weather patterns are erratic and nonlinear, artificial neural networks have been employed as an alternative. One study used artificial neural networks to try and estimate the maximum temperature from the minimum and highest temperature data (Abhishek et al., 2012). Another study used machine learning techniques to create minimum and maximum temperature projections for the past two days. This was done since traditional weather forecast models are unreliable in the presence of disruptions (Holmstrom et al., 2016). Other studies used temperature, humidity, dew point, pressure, wind, and rain data to create weather forecast models using deep learning techniques and iterative neural networks (RNN) (Salman et al., 2015), LSTM (Long Short Term Memory) methods (Fente and Singh, 2018), and temperature prediction models using the LSTM method (Karevan and Suykens, 2018).

Forecasting precipitation is a challenging task for weather forecasting techniques. Pressure, temperature, wind speed, and wind direction are only a few of the many factors that affect the amount and spatial distribution of precipitation. Due to the complexity of the atmospheric processes that cause precipitation and a lack of data, forecasting precipitation is frequently impossible (Luk et al., 2001). Alternative approaches to precipitation forecasting are now available because to advancements in artificial intelligence applications. It has been demonstrated that artificial neural networks, which execute a non-linear mapping between input and output, can predict precipitation with reasonable accuracy. The month-based ANN model created for precipitation forecasting has been found to be accurate in determining the risk level of heavy precipitation events (Sulaiman and Wahab, 2017). Artificial neural networks have been used to create new methods that enhance the performance of precipitation forecasting. The relative humidity, air pressure, wet bulb temperature, and cloudiness data from 75 measurement locations over a 4-year period were used in one novel model to produce relevant findings (Hung et al., 2009).

When the parameters of the data set (minimum and maximum temperature, average temperature, average humidity, atmospheric pressure, precipitation amount, sunshine duration, maximum and average wind speed) are enlarged in precipitation forecasting systems, the forecasts' accuracy rises. While the accuracy rate of processes covering short time periods can be up to 72% with a fuzzy inference system model (Safar et al., 2019), the accuracy rate of precipitation forecasts can be up to 86% with machine learning techniques (Anwar et al., 2020). Utilizing extensive weather data six hours in advance, substantial precipitation forecasts can be made, and effective outcomes can be attained using genetic algorithms (Lee et al., 2014). Similarly, using machine learning techniques, it is feasible to forecast harmful severe rains four days in advance (Choi et al., 2018).

For a variety of industries, including business, tourism, and agriculture, weather and precipitation forecasting is crucial. When precipitation affects the harvest plan, operating costs are higher than anticipated, the harvest plan is delayed, and ongoing activities are disrupted. Planning for harvest is crucial for determining capacity for product transportation and storage activities (Khalilzadeh and Wang, 2021). Real-time techniques have been established about when and how much product will be harvested, stored, and processed in order to preserve the post-harvest product quality for perishable food goods (Lin et al., 2018).

Statistical models have been created to help analyze the impact of changes in characteristics like temperature, fog, humidity, and precipitation on sugarcane production when the research evaluating the weather and crop harvest together in the literature are examined (Priya and Suresh, 2009). Similar to this, a harvest prediction model based on weather characteristics was created in another study. This prediction model utilized the multiple regression model (MLR). A region that produces rice was used to test the appropriate model. The created estimate model can account for the yield variation at a rate of 89% (Dhekale et al., 2014). The estimated harvest date, which is determined by the weather, is determined by the product's level of maturity and productivity. Some products need to be harvested quickly in order to preserve their economic value. So that the product can be collected at a time when it is commercially viable, models that forecast harvest dates based on weather conditions have been established in this scenario. The created model was used to harvest plums with a 30-day maturation period (DeBuse et al., 2010). The operational procedures used for harvesting are also impacted by the weather. Through interviews with wheat harvest specialists, the effects of the harvesting process on operational and logistic services were investigated (Medvediev et al., 2017). There are no studies that optimize the harvesting process using a cost-oriented strategy depending on whether it is raining or not, according to the literature review. This study tries to close this gap in the body of knowledge.

Problem Definition

When harvest time comes, the grown agricultural goods must be rapidly collected, processed, or consumed while being mindful of the perishability of the product. This makes it vital to arrange the labor, equipment, and tools, as well as the logistics activities, before the commodity is harvested. Planning is also necessary for the facility's capacity use if the items are to be transported there for processing or storage. These strategies must serve as the foundation for resource planning. Failure at any point in the supply chain between the harvest and the production facility results in idle planned resources and raises wastage rates as the product's delivery time is prolonged. For this reason, when resource planning has a small margin of error, economic damages to the businesses will be kept to a minimal.

Natural occurrences like rain can make it challenging to employ resources, even while resources like the labor, equipment, vehicles, capacity, and logistics can be controlled in the issues experienced in planning based on resource assignments. Because personnel, equipment and trucks cannot operate in the muddy fields where the harvest will take place during rainfall, this results in a waste of resources.

While resource allocation plans are being formed, natural occurrences like rain cannot be controlled; nevertheless, if such weather conditions are expected and resource distribution plans are made based on these forecasts, the danger of resources becoming idle can be avoided. In order to manage resource distribution more effectively,

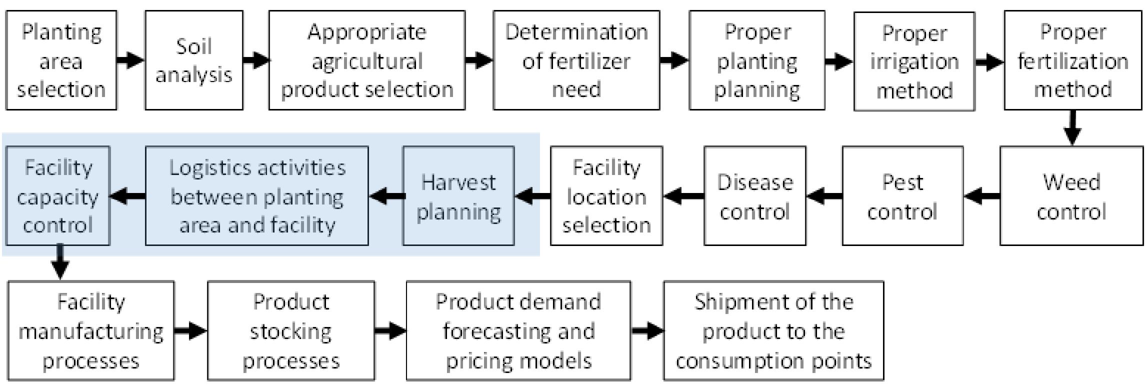

Figure 1. Life cycle of agricultural goods and research area

this study tries to forecast rain.

The problem for which a solution proposal is developed covers the stages of "harvest removal planning," "logistic activities between the planting area and the facility," and "plant capacity control" taking into account the general life cycle of agricultural products from the planting decision to the consumption point. The broad life cycle of agricultural products and the place of the research scope within this life cycle are schematized in the picture below.

Through reductions in cost factors for agricultural activities, this study will support the sustainability of agricultural activities.

METHOD

In order to solve the issue, two approaches were utilized sequentially. The first method involved examining the weather information at the harvesting locations and using a logistic regression algorithm to forecast precipitation. An integer linear programming model was used to optimize the harvest after weather predictions. The methodology listed below provides a general method for solving problems. machine learning process. Machine learning algorithms work iteratively until the right model is produced after preparing the data for the learning process. The program is run after the proper model has been chosen. The learning process will be improved by having more data. The general machine learning process is depicted in the following diagram.

Categorical data are used in logistic regression algorithms to produce better results. As a result, the weather forecast that will be fed into the model will categorize predictions as either raining or not. machine learning algorithms are classified under 4 groups. Classification, Regression, Clusrting and Deep Learning. Logistic regression is included in the Regression group within these groups (Wang et al., 2020).

The linear relationship between the dependent and independent variables is investigated by linear regression models. With linear regression, variables can be projected (Maulud and Abdulazeez, 2020). When using categorical or continuous data, logistic regression is employed (LaValley, 2008). When handling problems involving categorical classification, the logistic regression method yields trustworthy findings. The data are classed as 1-0

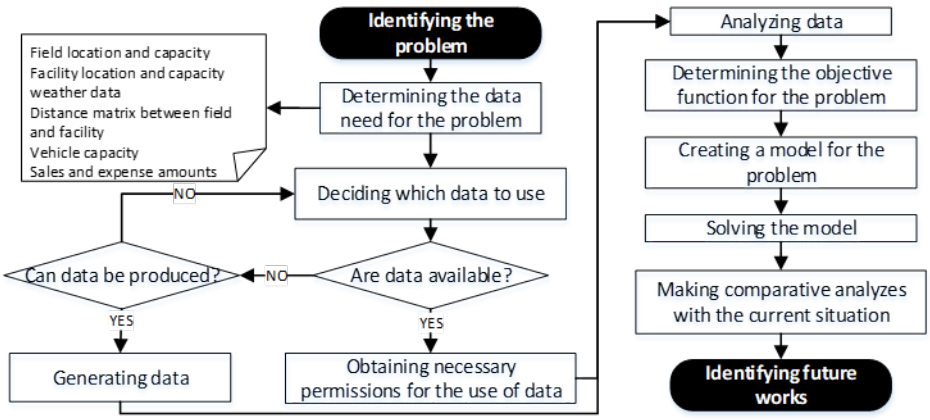

Figure 2. General study methodology

Logistic regression method

Artificial intelligence has a component called machine learning that focuses on learning by mimicking human intellect. Algorithms are used to examine data, and learning that is based on these analyses goes on and gets better (Helm et al., 2020). With data comes the in logistic regression, and the s-shaped logistic function curve is utilized since it better fits the data (Gianey and Choudhary, 2017).

Determine which category the people belong to using logistic regression (Çokluk, 2010). When some of the case studies created with the logistic regression model

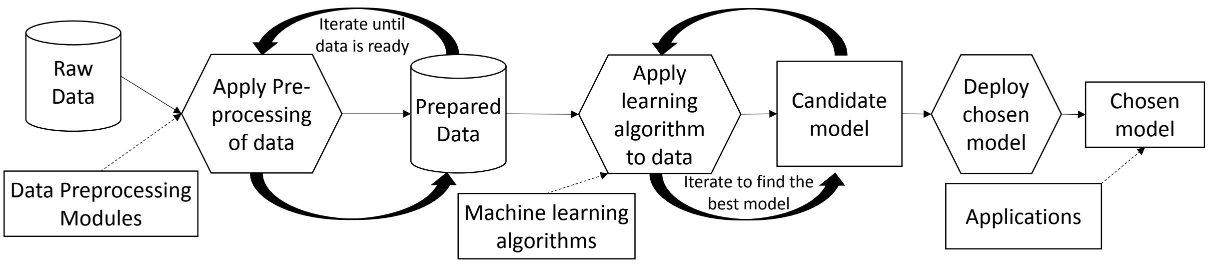

Figure 3. Machine learning process (Chappell, 2015)

are examined, it can be used to classify financial success of enterprises (Kaygın et al., 2016), to evaluate the risk status of bank credit customers (Budak and Erpolat, 2012), to examine the effects of factors that create customer satisfaction on customer adherence (Mutlubaş and Soybalı, 2017), and to model weather conditions like fog (Aktaş and Erkuş, 2009). Compared to linear models, logistic regression models are distinct. The graphic below shows the graph and formula variations between logistic and linear regression.

- The soil at the field point will continue to be wet for three days after the precipitation.
- The car is a unique creation.
- When the relevant field is unable to fill the vehicle tonnage, it is unable to purchase goods from another field to meet the available capacity.
- The amount of daily trips may require vehicle exits from one or more fields.
- The product's unit kilogram value is five times its dry air operating cost.

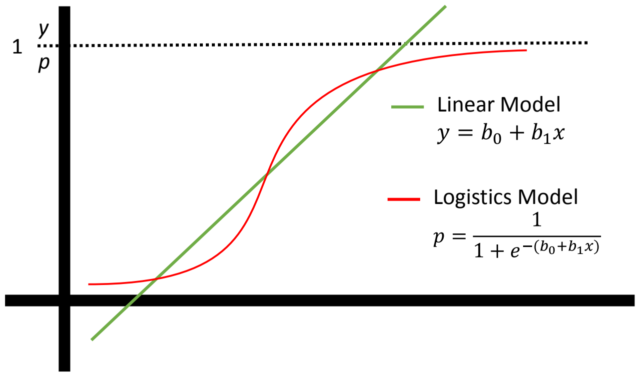

Figure 4. Linear regression and logistics regression (Gianey and Choudhary, 2017)

Weather precipitation forecasting was accomplished using Python and the Scikit-Learn library's logistic regression techniques, one of the libraries frequently utilized in machine learning challenges. Whether there will be rain or not, regardless of how much rain falls per square meter, it is rated as 1-0 in the weather forecast. With the logistic regression method, the first nine years of the pertinent data set will serve as training data and the last year will serve as test data, and daily estimates of whether it will rain or not encompass a one-year period.

Harvest optimization model

After using the logistic regression technique to predict the weather, an integer linear programming model was created to optimize the harvesting process. The system's overall revenue will be maximized by the developed model.

Model Assumptions

To address the issue, several assumptions have been made. Following the model solution, comparative analyses were assessed within the parameters of these hypotheses.

- The product is shipped from a special facility with a finite capacity.
- In the fields, only one kind of product is produced.
- Field locations and plant locations are already known.
- The actual road distances are the ones between the field and the plant.
- The product's economic value fluctuates with time.
- Operating costs for harvesting in dry soil and wet soil are split in half.

Model Sets

The harvests from the fields shall be brought to a single facility within the parameters of the issue.

$i \in I$ To be harvested fields

$i \in I$ Points of facilities (There is one facility within the scope of this problem)

$k \in K$ Weather condition

$t \in T$ Day

Parameters [unit]

$UC_{i,j,t}$ The cost of transportation on day t from fields i to facility j

$P_{i,t}$ $\in N$ Time dependent amount of income of the crops in the fields i

TKi Production capacity of the field i

FKj Production capacity of the facility j

NF: Number of active facilities (There is 1 facility for this problem)

Variables

$X_{i,j,t}$ $\in N$ Amount transported daily on day t from field i to facility j

$W_{i,t}$ $\in B$ Harvesting of crops from field on day {0,1}

K_{it} $\in N$ Weather-dependent unit operation cost coefficient from field on day t (obtained by logistic regression)

Y_j $\in B$ Facility is active or passive

MODEL

$$\max z = \sum_{i \in I} \sum_{j \in J} \sum_{t \in T} (P_{i,t} - K_{it} UC_{i,j,t}) X_{i,j,t} \qquad (1)$$

Constraints

$$\sum_{i \in I}(X_{i,j,t} - TK_i Y_{i,t}) = 0 \quad \forall i \in I, t \in T \qquad (2)$$

$$\sum_{i \in I} X_{i,j,t} \leq FK_j \quad \forall j \in J, t \in T \qquad (3)$$

$$\sum_{j \in J} Y_j = NF \qquad (4)$$

214 fields in various locations and with varying output capacity are used to grow sugar beets. Figure 6 shows the distribution of the fields' production capacities, and Figure 7 shows the distribution on a map.

The product is harvested over a 120-day period, and lorries with a 25-ton capacity maximum are used to transport it to the plant. In order to determine how

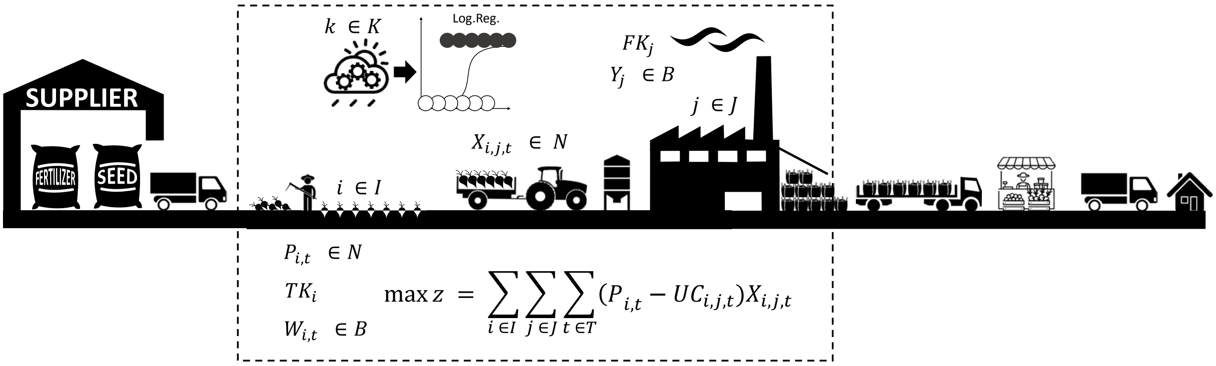

Figure 5. Model scope

(1) Displays the mathematical model's objective function. It seeks to optimize revenue from the arrival of weather-dependent, variable-cost goods at the facility.

(2) Illustrates the restriction that sends the goods to the plant on the day of field harvest.

(3) Illustrates the constraint that the facility's capacity is not exceeded by the products arriving at the facility.

(4) Displays the restriction with the number of open facilities. One facility is present in this instance.

The OpenSolver optimization plugin is used to resolve the weather-dependent harvest optimization model. The ba of the issue is depicted in the figure below.

Case study

The approach created within the parameters of the issue was used as an actual case in a facility with a total yearly capacity of 472,878 tons for processing sugar beet.

many cars would travel from each field to the facility, the field tonnage was divided into 25 and the total number of visits to the fields was spread evenly across the 120-day harvesting plan. These calculations show that there would be 19,007 truck trips overall. Figure 8 shows the distribution of the fields' distances from the facility, which will be taken into account when calculating the expenses associated with logistics.

In terms of the problem, there is only one facility. The total revenue from the products entering the facility is the goal of the integer linear programming model created to solve the challenge. In order to create a solution suggestion for the issue, 10 years' worth of meteorological data from 214 field points were gathered and examined from the Turkish State Meteorological Service. Measurement stations near field locations were found and included in the estimation after 31.9 million lines of data from all

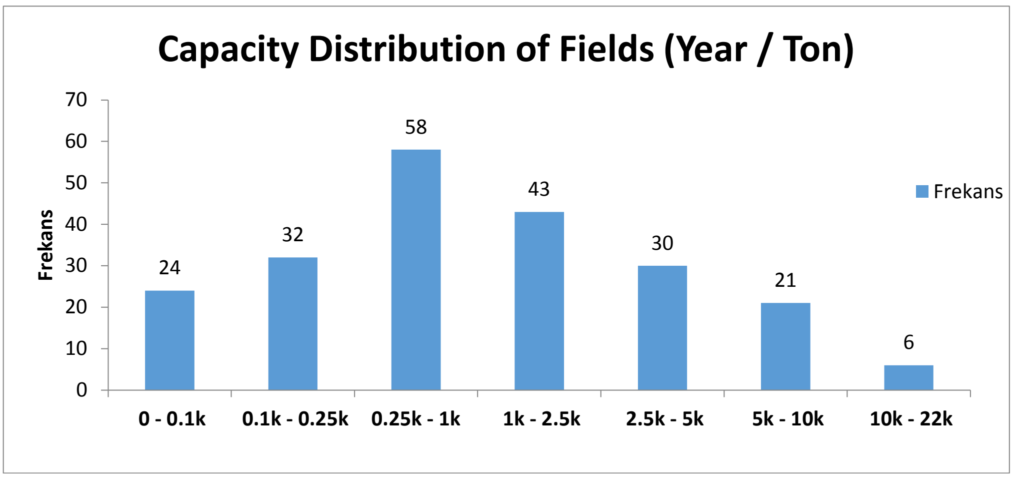

Figure 6. Capacity distribution of fields

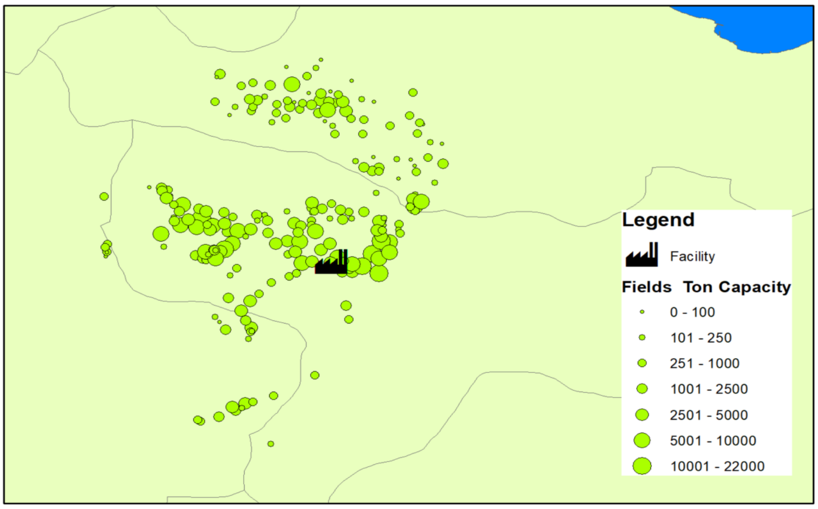

Figure 7. Facility and fields locations

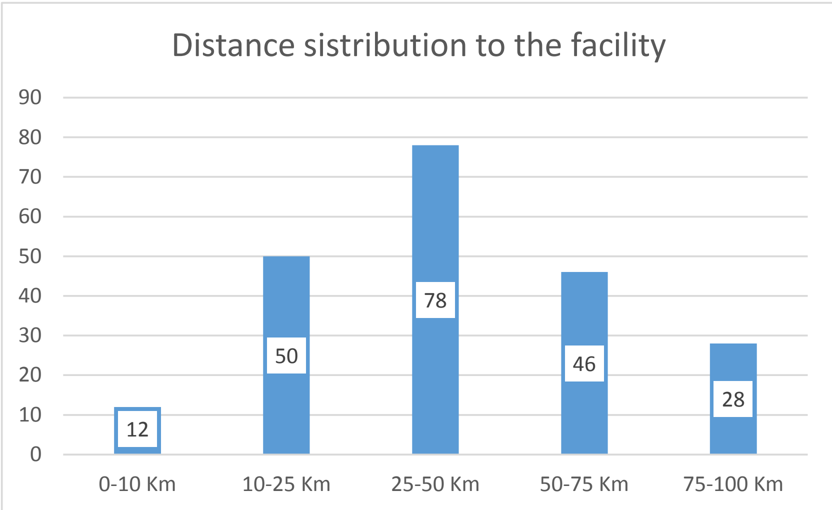

Figure 8. Distance distribution of the facility

around Turkey were evaluated. The maximum, lowest, average temperature, and precipitation are broken down into 4 columns in the pertinent field locations. The daily 365 days x 10 years for each field location are detailed in the 10-year data.

The literature review demonstrates how challenging it is to handle complicated, multidimensional problems like weather forecasting technologies. Data from lowest and maximum temperatures, average temperatures, average humidity, atmospheric pressure, amount of precipitation, length of sunshine, and maximum and average wind speeds are used to forecast weather and precipitation when previous studies are taken into consideration. The study's use of weather data might have less scope than earlier research. The estimating model, however, includes a 1-year time frame, in contrast to prior studies. Additionally, because the study's primary objective is income maximization, its scope includes an examination of the benefits of harvest planning through weather forecasting.

RESULTS

In the annual precipitation forecast within the scope of the study, the 120-day period covering September-December dates was determined as the harvest time. When the 10-year weather data of the harvest period is examined, it is seen that the number of rainy days in the harvest period tends to decrease and the average temperature values tend to increase.

In the weather predictions made using the logistic regression method, it was seen that precipitation was favorably associated to the minimum temperature and date and negatively related to the maximum temperature. Whether the length is long or short, the accuracy rate in prediction models varies. Although short-term forecast models have a high accuracy rate, long-term projections may have a lower accuracy rate. In this work, logistic regression was used to forecast long-term precipitation. It was attempted to estimate the precipitation of the weather in 2020 by using the meteorological data from the field locations as training data for the years 2010

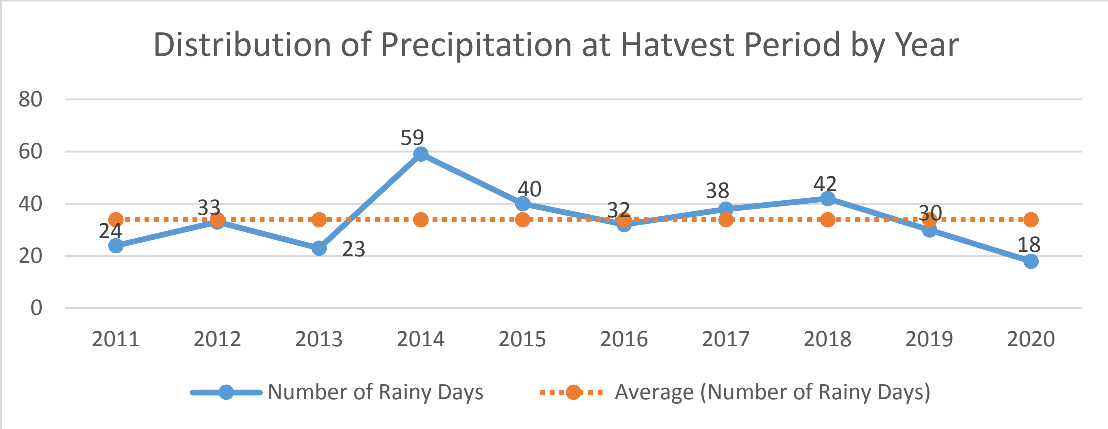

Figure 9. Distribution of precipitation at harvest time by years

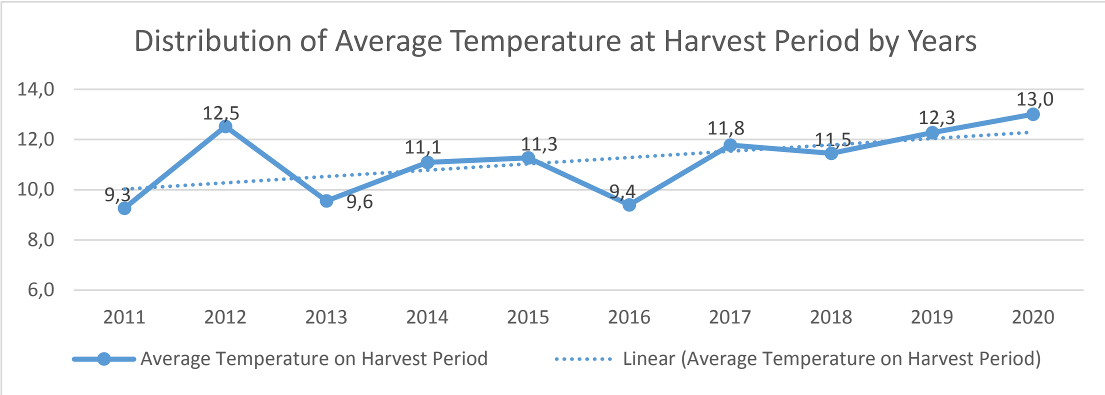

Figure 10. Distribution of average temperature at harvest by years

through 2019. The acquired results were compared to the data from 2020. The estimation using the logistic regression model had an accuracy rate of 84.16%. The outcomes support effective resource allocation in the current harvest plan, which is created well in advance of the harvest.

The economic return of the product's maturity due to sugar polarization depends on time at 4 distinct levels in the problem of harvesting after the weather forecast, whether it is raining or not at 2 different levels, and the weather itself at 1 level. The optimal choice was determined using opensolver using 214 fields, 120 harvesting days, and 205.440 account combinations. 159 vehicles per day were transported to the factory during the 119 days of harvesting, with 86 vehicles being transported on the final day. The calculated average tonnage load for each vehicle was 24.88 tons.

Depending on whether it is raining or not, the expenses in the example studied within the parameters of the problem differ. Rainy days result in higher operational costs because regular harvest planning is weather-independent. In the integer linear programming model solution implemented via OpenSolver utilizing the weather forecast data generated by logistic regression, it is evident that the operational profit of the business will increase by 16.7% compared to the usual harvesting plan. (Present harvest plan revenue is 16.566.398, alternative harvest plan revenue dependent on weather forecast is 19.329.205). Making short-term weather forecasts when necessary can help an organization boost its operational profit when harvest season, which is prepared in accordance with the long-term strategy, starts.

CONCLUSION

Results from supplementing the planning process for the sugar beet harvest with weather forecasting techniques were compared to those from the existing harvest plan in this study. Within the parameters of the study, 10 years of weather data from the field sites where the harvest will be made were examined, and a logistic regression model was used to anticipate precipitation. A harvest schedule for the crop was created using integer linear programming and included the results of the precipitation forecast as a parameter. When compared to the present harvest plan, it was determined that the alternative harvest plan may potentially boost operating profit by 16.7%.

If the forecast model is created in two stages in a way that they complement one another in the long and near term, further research may try to go into greater depth about the weather data sets and look at the overall possible benefit. Alternative model approaches that could improve the planning of tools, machines, and labor in harvesting operations may be possible when weather forecasting systems for harvest planning are established.

The examination of the weather data shows that there is a risk for the productions to be achieved in the upcoming years because to the rise in yearly average temperature values and the decline in precipitation data. Future research can create models that take into account weather trends to get outcomes that are more accurate.

Over 6.5 million tons of sugar beets are produced in Turkey overall. Averaging 2200 vehicles per day are required during the 120-day harvest period. A short-term vehicle demand constraint in the logistics industry may result from poor supply chain management choices for these products. For this reason, it's critical to effectively and efficiently arrange the logistical procedures for sugar beet.

This investigation was conducted in order to produce sugar beets. Fresh perishable products such as fresh olives, strawberries, mushrooms, tomatoes, lettuce, etc. degrades more quickly than sugar beet. Because of this, it is essential to design the harvest strategy for these products in a way that minimizes waste. In the future, fertilization activities of the products and plans that will spread the ripening process of the product throughout time based on the demand by estimating the demand in harvest planning for perishable agricultural products may be new research areas.

COMPLIANCE WITH ETHICAL STANDARDS

Conflict of interest

The authors declared that for this research article, they have no actual, potential or perceived conflict of interest.

Author contribution

The contribution of the authors to the present study is equal. All the authors read and approved the final manuscript. All the authors verify that the Text, Figures, and Tables are original and that they have not been published before.

Ethical approval

Ethics committee approval is not required.

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Data availability

Not applicable.

Consent for publication

Not applicable.

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