

A Decision Support Framework for National Crop Production Planning

NIDA RASHEED^{ID}, (Graduate Student Member, IEEE), **SHOAB AHMED KHAN,**
ALI HASSAN, AND SARIA SAFDAR^{ID}

Department of Computer and Software Engineering, College of Electrical and Mechanical Engineering, National University of Sciences and Technology, Islamabad 44000, Pakistan

Corresponding author: Nida Rasheed (nida65@ce.ceme.edu.pk)

This work was supported by the National University of Sciences and Technology.

ABSTRACT This paper proposes a decision support framework for defining planning parameters for national crop production. The proposed framework addresses the gaps in policymaking, the role of all stakeholders, and uses historical data of crop production in different sectors of land in optimizing the profits that shall meet the defined constraints including national requirement, and export demand of different crops. There are many agro-economy-based countries where agriculture is the main contributor to their GDP, while there are others who always struggle to meet their national need while optimizing the agro-economy component of their earnings. Crops are not always produced with keeping the demand and production balance. Rather, the crops are mostly produced according to the farmer's ease and last year's prices for profit maximization leading to excessive production of one type of crop, lowering of profit margins, and shortage of some key crops for national need. This paper presents a decision aiding tool that can be used for farmer's awareness for crop production planning that meets the national and export needs while maximizing farmer's earnings. The model is tested on historical data of different segments of cultivated lands in Pakistan for validation, with the first experiment performed on single farmland with multi-fields while the second performed for multi-locations and multi-fields. The results are promising and provide estimates of net profit, expected production against the demand for each crop, and analysis that aids in crop planning, before and after the application of our model while meeting all necessary constraints.

INDEX TERMS Agriculture, decision making, decision support systems, intelligent systems, linear programming, optimization, planning, prediction methods, yield estimation.

I. INTRODUCTION

Agriculture is one of the key participants in the growth of an economy, especially for countries with rich soils full of nutrients and favorable weather [1], [2]. Nowadays, advanced technologies like automated machinery, precision agriculture, Machine Learning (ML) models for prediction of yield, IoT based smart farming, genetically altered seeds, and a lot more are employed to achieve sustainable agriculture and to boost the earnings by the agricultural setup [3]–[7]. Developing or underdeveloped countries lack the resources to adapt to these modern technologies and mostly rely on the farmers and ill-formed policies for agricultural production. This lack of framework and uniform policy becomes a reason for dis-balance between targets and production, creating a need to import [8]. The government, managers, and farmers

have a wide gap where bigger farms are tracked for yield and targets but farms which are smaller in size but serve as the major contributors to the targets set by the government are ignored. Farmers mostly plant what is easier to crop, or what provides the maximum profit to the farmer only. As an example, Pakistan has a big number of farms which are under 10 hectares than larger farms [9], led by the farmers with limited resources and knowledge with multi-dimensional challenges such as limited information about recent agricultural practices, poor financial condition, inadequate supply of resources by the government at a subsidized rate, lack of adequate storage in case of excess of crop and a lack of a uniform framework to connect with all farmers. Instead of earning through exportable items, the country suffers major losses to fulfill its own need. There is a dire need for such a framework that is cost-effective and produces results comparable to the global practices in terms of efficiency [10].

The associate editor coordinating the review of this manuscript and approving it for publication was Wei Liu.

A balance between national need and export demand of crops is a major challenge. Consideration of resources, finances, land suitability for profit maximization and stakeholders are the key factors whilst developing a model for real world. Pakistan as an example still has a huge gap between the need and demand despite working vigorously on agricultural reforms leading to a need to import major commodities like wheat, sugar, and cotton, etc [11]. A detailed analysis of the gap between the crop need and the production is presented in [12]. The production of every crop varies area-wise due to the deviation in climatic and non-climatic factors in different regions [13]. These factors are financially constrained and variance in the financial condition affects the overall productivity. Fig. 1 summarizes these factors. Usage of excessive pesticides and harmful chemicals to change the natural quality of soil and its components can damage the environment. An implementation of uniform policy also address the issue of sustainability by deciding ahead of time that which crop should be grown in which area. [14] explores the historical data of crop production in Pakistan, with the lack of a policy framework acting as a major contributor to the downfall of the agricultural system.

Following research questions are formed from the challenges stated above, which define our problem statement and motivation for this research:

- Are there any simple and user-friendly interfaces with models in the background in which the farmer can give inputs and that can get into the model to optimize profit and production of crops, along with national needs and export demands?
- Can a model be formulated which is scalable; that works equally good for a farmer/ farmland and then it can be expanded to a bigger region even to a province or a country? Is the tool addressing the challenges faced by all stakeholders?
- Can historical data be reliably used for the decision aiding system to suggest an area-specific crop production?
- Can remote sensing be used to gauge the quantity and quality of the crops? Can it be incorporated into the model?

A. RESEARCH CONTRIBUTIONS

We present a generic farmer-centric conceptual framework for crop allocation, usable at the farmer level and the same is scalable for implementation at the national level. This research uses the historical data for each field, with a focus on the costs for the non-climatic factors from Fig. 1. Our study has threefold research contributions:

- Usually there are no policy guidelines that keep the national need in perspective while suggesting the farmers to grow a particular crop, so this study addresses the gaps in policy-making, and a clear role of all stakeholders especially the individual farmer is described. The framework works in both top-down and bottom-up approaches starting from the division of larger areas at the national level to recording historical data for the smallest farms. The collection of data from every individual farmland directly or collected through managers assists in setting better targets for crop allocation at the national level. A user-friendly GUI is developed to assist the farmers, managers, and policymakers in the swift implementation of the desired output.
- The role of managers is explicitly explained. By pre-allocation of every single farm, the managerial implications of all kinds are well addressed by ensuring timely availability of the seeds, fertilizers, pesticides, nutrients, labor, water, storage, and machinery for the suggested crops. This pre-allocation also addresses the logistics concerns like management of transportation for delivery of crops to the mills and markets.
- A Linear Programming (LP) based optimization model is developed for the allocation of cropping area based on the constraints and binary decision variables. The aim is to optimize the profit of the crop export while ensuring that the crop meets the national requirement. Our developed model aids in the decision of plantation by analyzing the cost-benefit of each crop, especially export crops. This helps in deciding which crops to plant for maximum profit and which crops should be imported. This is elaborated with the help of detailed case studies with different scenarios.

The rest of the paper is organized into four sections. Section II contains the related work. Section III presents the study area selected for experimentation. Section IV briefs about the techniques adapted to conduct this study with the help of graphical workflow of the whole implementation. This section also presents the detail of individual components of the whole framework. Section V presents the experiments, results, analysis, limitations, and future work of our study.

II. LITERATURE REVIEW

In this section, we explore different techniques for optimized crop production, challenges of crop production in Pakistan, and methodologies for sustainable agriculture. We have already summarized the climatic and non-climatic factors

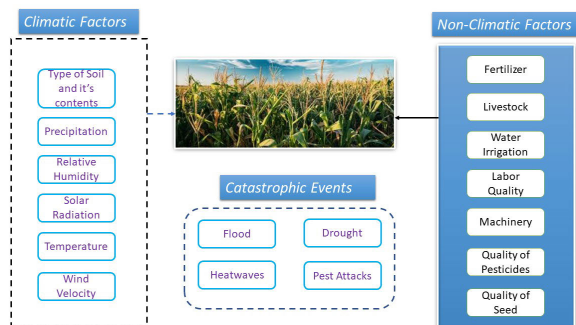


FIGURE 1. Factors affecting crop growth. This research is based on the non-climatic factors presented on the right side.

TABLE 1. Benchmark table to compare our study with the existing literature. The table highlights the contributions and limitations of each study with our research summarized at the end.

Sr. No.	Research and Year	Contributions of study with techniques	Limitation
1	S. Haider et al. (2019)	A forecasting model based on LSTM Neural Network is presented which uses historical yield data to predict wheat production for the next ten years in Pakistan.	This study is specific to wheat only. No framework is given for the general crop and the model is not implementable for real data. It works as a guideline for forecasting.
2	U. Ketsripongsa et al. (2018)	An improved Differential Evolution Algorithm-based optimization model is presented for profit maximization in Thailand. The model is mainly constrained by the expenses on transportation and logistics.	The roles of stakeholders are not considered with the overall problem. The model works well on large data but has computational complexity involved. It does not work efficiently for smaller scales. It provides an approximation of the crop allocation problem and can not be used by the farmer himself. The research is focused on the mathematical model only and is not focused on the development of a Decision support system for the national level.
3	F. Aslam et al. (2019)	A forecasting model for wheat production based on historical data and statistical indices.	It is a forecasting model for wheat only which is practically not implementable at the farmer or government level and provides a set of guidelines only.
4	Beal Cohen et al (2020)	An LP model is presented for Florida to address the effect of labor on crop production. The simulation is conducted for tomato and strawberry farms.	The model is based on assumptions and lacks the economic framework for real farms management. Historical data is not incorporated in the simulation of the model. The model is not implementable for real farms.
5	N. Rasheed et al (2021)	A complete generic framework is presented that works at the farm level and the same is scalable to the national level. The model includes guidelines for division of AOI and policy, role of each stakeholder, user-friendly GUI to be used at farmer level, and an Integer Linear Programming (ILP) based crop optimization model which considers national need and export demands as the main constraints. The model is developed for real data and aids in the decision of area-wise crop plantation, profit maximization through export crop plantation, and which crops to import without affecting the cost incurred. The scalability of the framework is what distinguishes it from the existing models since the model is usable at the farmer level and without any alterations in the methodology at the back-end, the same is scalable to a larger area such as a province or a country.	

affecting crop from [13] in Fig. 1. The production of crops varies area wise and one crop which yields a good amount at a certain location cannot be assured to have the same at another location. Some lands are good for crops with an increased export demand so planning the assignment ahead of time and assigning only export crops to such lands ensures profit maximization. Type of soil, temperature, relative humidity, precipitation, solar radiation, wind velocity, and the presence of nitrogen and other essential elements in the soil are the climatic factors that determine the growth of a certain crop [15]. Factors like the application of fertilizers, livestock, water irrigation, labor quality, use of advanced agriculture techniques, quality of seed, and rotation planning of crops are the external factors that can be controlled and affect the growth of the crop. Floods, droughts, pest attacks, and heat waves are natural disasters that can suddenly influence the yield and production of a crop. A detailed timeline of crop models is presented in [16]. This study summarizes the crop model evolution starting from foundation models of the 1950s to models driven by food security programs of today. The authors have suggested six different scales starting from field to farm level, going through agro-ecological and regional zones, and eventually national and global scales. The authors conclude that capitalization of crisis, using technological advances, open data access, trans-disciplinary and modular approaches, and user and data-driven models are the keys to effective agriculture practices. This section is further divided into subsections to highlight each part individually.

A. CROP PLANNING MODELS

This part is focused on different crop allocation and prediction models found in the literature. In [17], an Annual Crop Planning (ACP) is presented to address the increasing costs of agricultural production and irrigation. The study focuses on the development of an optimization model and implementing it using meta-heuristic algorithms. In [18], the authors have used Deep Neural Network (DNN) to predict yield for hybrid maize data using past 9 years data provided by [19]. The results suggest that out of all the input parameters, weather prediction plays the most important part. A global expansion model is presented in [20] to attain high yield farming. This research focuses on global spatial optimization of cropland to reduce the area by careful allocation of 16 major crops globally. This change affects the global fertilizer input, irrigation water requirements, and greenhouse gas emissions. In [21] a crop optimization model is presented to maximize the profits by optimizing transportation expenses. An improved differential evaluation algorithm is presented which finds the best optimal solution for the developed mathematical model. A survey is conducted in [22] on machine learning models for yield forecasting and compares all the models using various error measures. In [23], fuzzy multi-objective programming is applied for crop planning optimization in Iran. Simulated Annealing (SA) and Particle Swarm Optimization (PSO) are employed in [24] to address a multi-crop allocation optimization problem. In [25], a crop allocation model is presented to deal with the problem of labor shortage which in turn impacts crop production.

A Linear Programming (LP) based optimization model is presented in [26] to address the problem of land allocation for 10 crops. The research is conducted for the saline zone of Akola district in India. The model considers previous yields, labor wages, cost of machinery used, cost of fertilizers and seeds, and the sale price of crops. The model is solved using simplex algorithm [27] and Push-and-Pull algorithm [28]. In [29], a linear programming-based optimization model for the best cropping pattern is presented for a selected location in Indonesia. The optimized cropping pattern is suggested based on the irrigation and the land constraints. In another study, [30], a linear programming-based optimization model is presented for the Mekabo scheme in Ethiopia and a sensitivity analysis is performed to assess the impact of the proposed method. In [31], a Spatio-temporal crop allocation decision-aiding tool is implemented using a Weighted CSP solver and an ILP solver with farmer's choices as constraints.

B. CHALLENGES IN PAKISTAN

This section highlights the research specific to the study area. A foundation for a huge gap in the non-uniform production of crops across provinces in Pakistan is built through [11]. This data-set shows the variability in production and need from each province individually, along with the resources allocated nationwide. In [14], the authors forecasted the yield and per capita food availability in Pakistan through the ARIMA model for the next 21 years using the historical data of crop production in Pakistan. The authors have pointed out the lack of policy framework as a major hurdle in achieving maximized crop production. In [32], time-series data (1950-2015) of crops of Pakistan is analyzed and its relationship with agricultural GDP is investigated. The crops included are wheat, maize, cotton, sugarcane, and cotton. The results are obtained by using the Augmented Dickey-Fuller test, Johansen's co-integration test, and the ordinary least square method. In [33] an LSTM-NN based model is presented for forecasting wheat production in Pakistan. The research suggests that with the current scenario in Pakistan, the production to consumption ratio will decrease despite an increase in wheat production, and it is recommended to implement crop models at the national level. In [34], the authors have used data from 1948 to 2018 to forecast wheat yield in Pakistan. The research is implemented using Artificial Neural Network (ANN). In [35], the research explores the impact of climatic change on crop production in Pakistan and deduces that in the future, the focus should be made on crops that are drought-resistant and are not affected much by the drastic temperature changes. The research employs Feasible Generalized Least Square (FGLS) and Heteroskedasticity, and Auto-correlation (HAC) consistent standard error techniques on time series data from 1989 to 2015.

C. SUSTAINABLE AGRICULTURE

This section is focused on the importance of sustainable agriculture. Green agriculture is an evolving research area.

There is still a lot to research when we talk about sustainable agriculture where we have minimum carbon emissions, usage of organic fertilizers and pesticides, increased soil fertility and reduced soil erosion, increased water efficiency, and minimum waste products. A detailed review of frameworks and stakeholders for sustainable agriculture is presented in [36]. [37] explores the use of smart technology for green agriculture practices. In [38], policy analysis is done for sustainable agriculture. [39], [40] and [41] presents mathematical models for green and non-green products comparisons. The first presents a price competition of green and non-green products. The other two are based purely on the demand and supply of each. The developed models in all three studies for-profit function maximization against demand can be used for a comparison study between green and non-green agriculture practices. Similarly, [42] explores the effect of subsidy rates and policy framework for green products aided with the development of a mathematical model which can again be implemented for sustainable agriculture. In [43], a bi-level optimization model is presented for the agro-industry of cocoa with reference to the demand and supply of the product.

To summarize overall literature, the research through [17]–[31] presents crop allocation models and frameworks, crop prediction models and optimization models. These studies address the mathematical modeling part of our research. [11], [14], [32]–[35] provides a baseline for the challenges in Pakistan and hence provides the motivation for this study in accordance with Pakistan. The literature discussed in [36]–[43] provides a guideline for sustainable agriculture and through this research, we explore the quality impact of advanced crop allocation on the overall environment. A benchmark table is presented in Table. 1 in which we present contributions of main studies that we followed [21], [25], [33], [34], the limitation of each study and eventually summarize our research. The compared research provides gaps in the development of the crop allocation model, and in research specific to the study area which helps in the identification of the problem statement. The elements missing from the compared models are the practicality of the proposed models, too much dependency on the mathematical model only, role assignment for each stakeholder, and the relationship between import and export crops. These models are specific to areas and crops as well. Our research is focused on the development of a farmer-centric model, scale-able to the national level without any changes. The simplicity of the user interface with an abstract mathematical model derives the factor of ease of use at any stage without having any prior knowledge of the system beneath. The use of binary decision variables for crop allocation makes it a perfect choice for even distribution of crops within all selected areas. Our system also provides a firm guideline for the division of AOI, the role of every stakeholder, and how data travels within different stages of the model. The developed mathematical model provides the results very quickly and precisely. Further, our model also takes into account the impact of export crops on profitability and takes historical data of every field individually

TABLE 2. Export data of selected crops of Pakistan from year 2013-2018. The crops quantity is in '000' tons while the export value is in Million Rs.

Year		2013-14	2014-15	2015-16	2016-17	2017-2018
Wheat	Quantity	20.037	10.441	1.145	3.676	1189.604
	Export Value	732	311	35	101	27109
Rice	Quantity	3743.427	3786.111	4262.216	3518.819	4106.01
	Export Value	222885	206254	194227	168247	224907
Sugar	Quantity	647.333	708.968	293.541	307.862	1469.802
	Export Value	29638	32686	13818	16890	56379
Raw Cotton	Quantity	114.79	95.017	49.55	24.976	35.347
	Export Value	21353	14937	7948	4484	6183
Potato	Quantity	254.818	347.421	402.435	417.434	570.262
	Export Value	7985.194	10295.66	8419.735	8607.383	11807.35
Onion	Quantity	75.494	196.046	103.756	75.697	132.78
	Export Value	2011.315	3707.939	2524.938	1326.649	4185.684
Tomato	Quantity	11.962	7.694	25.547	5.674	16.858
	Export Value	472.295	303.305	1021.092	226.987	675.627

into consideration. Scarce resources play a big motivation for the development of our low-cost crop management solution. Our model is designed in such a way that it can be aligned with the existing frameworks and bypasses the need for the incorporation of expensive technologies.

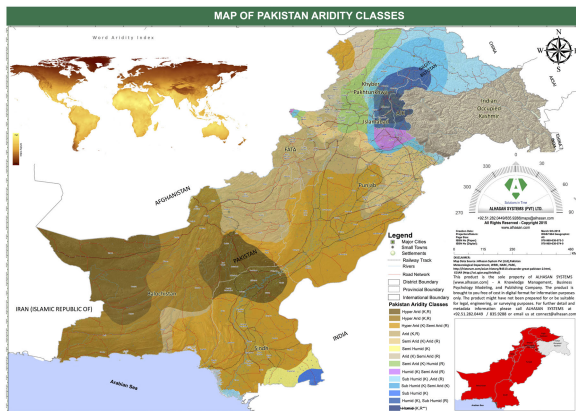


FIGURE 2. Aridity classes of Pakistan [48].

III. STUDY AREA

We have presented our case studies for Pakistan which is a country with a great potential for agricultural development, given the fertility of the land. The crops produced in Pakistan are of very good quality and a good share in GDP is earned by exporting high-quality crops. The targets for the national level are assigned by the Federal Committee on Agriculture (FCA) in Pakistan. For 2020-21 Rabi crops, targets of 26.78MT, 0.56MT, 4.87MT, 2.22MT, and 0.625 MT are set for wheat, gram, potato, onion, and tomato respectively. For 2020-21 Kharif crops, targets of 69.8015MT, 10.8MT, 7.99 MT, 5.012MT, 6.059MT, and 2.48MT are set for sugarcane, cotton, rice, maize, mash, and chilies respectively. These targets are further divided within the provinces. Despite having set targets, the country is failing to meet them due to changing weather conditions, increasing population, lack of a uniform policy at the national level, and the lack of education at the farmer level about what to plant. As an example, over the last

few years, farmers in Sindh are planting hybrid rice instead of cotton due to the low expenditure incurred on rice and high yield [47]. Further, there is a surge in the plantation of sugarcane after rice. This is affecting the production of cotton and unless a proper policy is imposed, more and more important crops would be required to import.

The contribution of agriculture to GDP will grow by addressing the gaps in policy making. Pakistan has the majority of arid climatic zones, followed by semi-arid and then humid climatic zones. Fig. 2 shows the aridity classes of Pakistan [48]. Fig. 3 shows data of major crops in Pakistan from 2013-2018 [9], [11]. The graphs show the area in '000' hectares under major crops, the produce of the crops in '000' tons, the yield in kg/hectare, and the comparison of the yield of each crop in the four provinces of Pakistan. In Fig. 3(b), the production of cotton is shown in '000' bales of 375 lbs for each. Table. 2 shows the export data of a few crops of Pakistan from 2013-2018 [11]. This data is shown for the same years as the graphs shown in Fig. 3. Crop calendars for each province or area are also useful for crop suggestions in the selected area. The crop calendar of crops in Pakistan can be found at [49].

For our first simulation explained later in Section. V, we have selected single farmland with 8 fields in the Bahawalpur district. Located in the south of Punjab, this district has a major desert with increasing vegetation index in the past few years [50]. It is an arid region [51] with an average annual temperature of 25.7 degrees and an annual rainfall of 143mm. In Fig. 4, the left side shows Bahawalpur district protruded out of the map [53] and the image on the right side shows the monthly average rainfall in Bahawalpur for the years 2014-2019 [52]. The main produce of this region is cotton, wheat, sugarcane, sunflower seeds, dates, mangoes, citrus, and mustard out of which dates, citrus, and mangoes are exported out of the country.

IV. SYSTEM DESIGN

A graphical representation of our whole system is presented in Fig. 5. Our system initiates with the division of AOI into meaningful zones, based on the same climate. This division

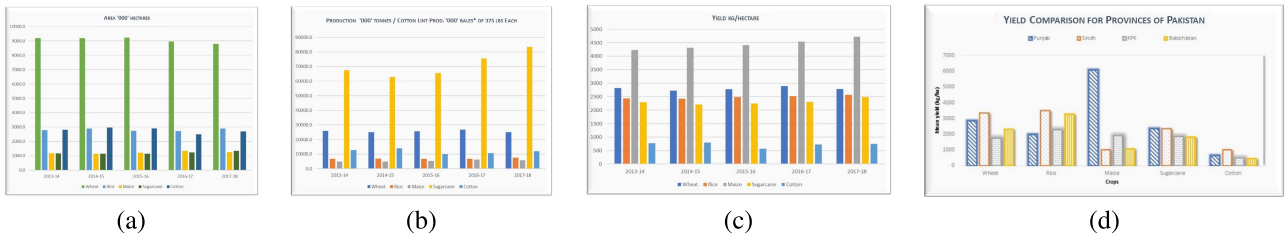


FIGURE 3. Historical data for major crops in Pakistan is shown for 2013-2018 (a) The area (000 hectares) under major crops, (b) Historical production (000 tonnes), (c) Historical yield (kg/ha) of the major crops, and (d) shows the comparison of yield of each crop in four provinces of Pakistan.

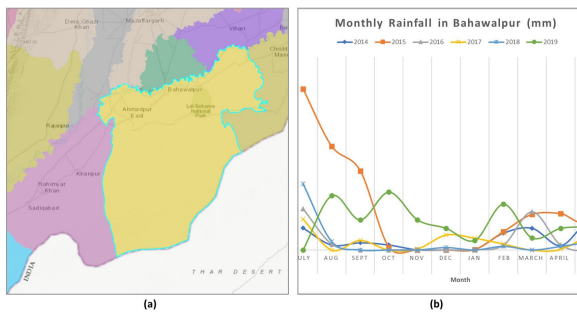


FIGURE 4. (a) Bahawalpur District, Punjab [53] and (b) Monthly rainfall data in (mm) of Bahawalpur for the years 2014-2019.

is based on the administrative structure followed by the country. Each zone is assigned to managers. The hierarchy of managers is again followed in the structure. Each manager is assigned multiple spatially distributed farmlands and for each field within each farmland, the manager records historical data into the system. Fig. 6 shows the GUI for the data entry section. Here we refer to farmland as a collection of fields belonging to a single farmer. In the case of an individual farmer managing his farm, this data is entered by the farmer himself which is stored in the central database that contains the historical data associated with each field, detailed in Fig. 5 as well as in Section IV-B. This database goes all the way up, from the farm level to the government level and helps in setting better targets for national and export crop production.

The crop allocation module is initiated through the user interface shown in Fig. 7. This module uses the area information to load the historical data and all the relevant constraints into the optimization module. The optimization module uses the historical data of each field from the whole AOI, and the crop calendars for each division, in suggesting crops for the selected area. The first aim of this model is to produce maximum crops locally for the national need so that there is a minimum need to import essential crops. The next target is to produce those crops which generate the maximum profit and help strengthen the economy, i.e. exportable crops. Every crop is categorized as national need, needed for both local consumption and export, and importable. The crops that are labeled as “Importable” are excluded from the optimization model. The import needs for the crops that fail to meet the national target are calculated after the production of the crop.

Certain assumptions are presented for our framework. We are assuming that whoever uses the system, has access to historical data for the analysis since we are using publicly available data for the verification of our model. We are not taking the crop rotation policy into account since this research is focused on the profit maximization part only. The rest of this section is focused on the details of the whole system.

A. STAKEHOLDERS

The three main stakeholders considered in our model are the farmers, the managers, and the government. Our model aids these stakeholders in optimizing crop allocation and works in a top-down approach. The top-most stakeholder is the government who is required to decide in advance about the needs of the population as well as the profit maximization for the betterment of the economy. Finding the right balance between the national needs and the export demand is the key. Our tool considers the historical data associated with each crop at the individual farm level, historical national needs, and export demands, and historical prices to set the current targets. The collected data goes all the way to the central database and is utilized in having an actual picture of resources available for setting the targets. The analysis presented by the tool also helps in deciding that out of all the crops, which crops require the same labor and other resources but does not maximize profit. If these crops can be imported at the same rate as of local production, then the crops which generate the maximum revenue can be planted without compromising the national need.

Associated with this are the whole supply chain and logistics process which kicks a process for the area managers and logistics managers to ensure the timely availability of seeds, fertilizers, pesticides, water resources, and other needs for that particular crop suggested in the selected areas. The whole logistics that relate to the complete life cycle of the particular crop from start till end benefits from this timely suggestion. A further aspect of logistics like collecting the crop and sending it to the user can also be added to the optimization model. As an example, the transportation cost to the sugar mills for the sugarcane or the transportation cost to the textile industry for the cotton can be added to the model to suggest the areas for plantations where there is minimum transportation cost. Additionally, the consumption of that

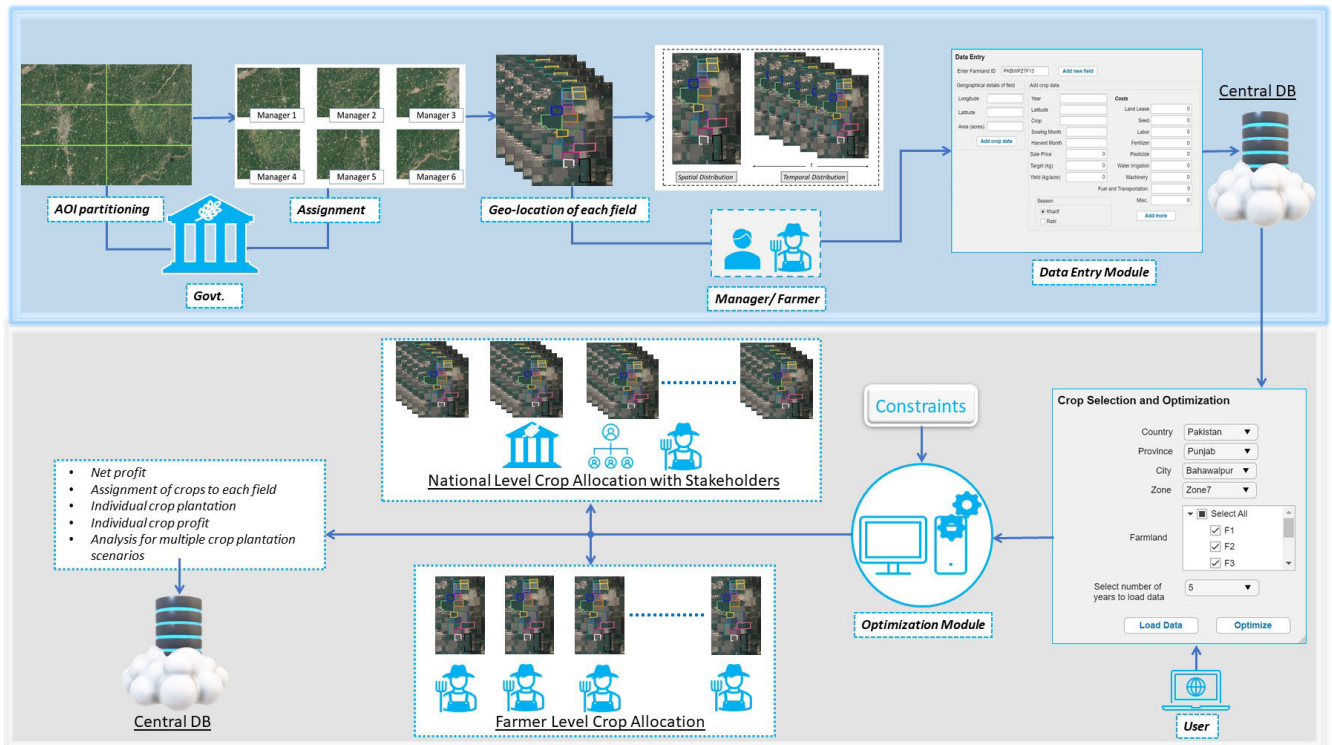


FIGURE 5. A complete workflow of our framework. The top unit shows the selection and division of AOI, assignment of the managers to each zone, assignment of the individual farmlands to each manager, geo-identification of each field within the farmland, and the historical crop data entry into the central DB for each field. The bottom unit is related to data retrieval, which shows the crop selection and optimization interface, optimization module, crop allocation for the individual farmlands after optimization, crop allocation after optimization for the selected AOI with all stakeholders and, outputs of the optimization module recorded into the central database.

particular crop in a certain area also has a direct relation with the transportation constraint so that we select areas where consumption of that crop is very high and the areas selected for the production of that particular crop have the minimum transportation cost. This logistics constraint will be presented in our future model. For now, we are assuming a collective cost model which includes the cost of the overall life-cycle of crop production. The third stakeholder is the individual farmer. The tool aids the farmers to plant only what is needed and which crop will bring the maximum profit. This will save the farmer from the overproduction of one type of crop and wastage of another, and in deciding that which crops can be planted in the given budget.

B. USER INTERFACES

The first User Interface (UI) shown in Fig. 6 is for the data entry. This interface is used to collect the data from the farmers or the managers. For a first-time entry, the historical data for each field is recorded for 't' years. The data needs to be entered for each field of the individual farmland. An individual ID is assigned to each farmland based on country, province, city, and assigned zone, and every field is entered against the master ID. Every farmland is geographically identified and the details of each field are entered. For a single Farmland ID, latitude, longitude, and area (acre) are recorded for every field. In our current interface, the Lat long are

The screenshot shows a web-based data entry form. At the top, there's a field for 'Enter Farmland ID' with the value 'PKBWPZ7F13' and an 'Add new field' button. Below this, the form is divided into two main sections: 'Geographical details of field' and 'Add crop data'. The 'Geographical details' section includes input fields for Longitude, Latitude, and Area (acres), with an 'Add crop data' button. The 'Add crop data' section includes fields for Year, Latitude, Crop, Sowing Month, Harvest Month, Sale Price, Target (kg), Yield (kg/acre), and Season (radio buttons for Kharif and Rabi). To the right of this section is a 'Costs' table with fields for Land Lease, Seed, Labor, Fertilizer, Pesticide, Water Irrigation, Machinery, Fuel and Transportation, and Misc., each with a numerical input field and a zero value. An 'Add more' button is located at the bottom right of the costs section.

FIGURE 6. GUI for data entry. The data is entered against a pre-allocated farmland ID. Geo-location of each field is recorded and the historical data is entered for every crop grown on that field for the said years.

entered manually using google earth [44]. For every field, historical data i.e. year, season, crop planted, sowing and harvesting months, cost of the land lease, cost of the seed, cost of the labor (all stages included), cost of the fertilizers and pesticides, cost of the water irrigation, cost of the machinery, cost of the fuel and transportation and miscellaneous costs, sale price, targets, and yield (kg/acre) are recorded.

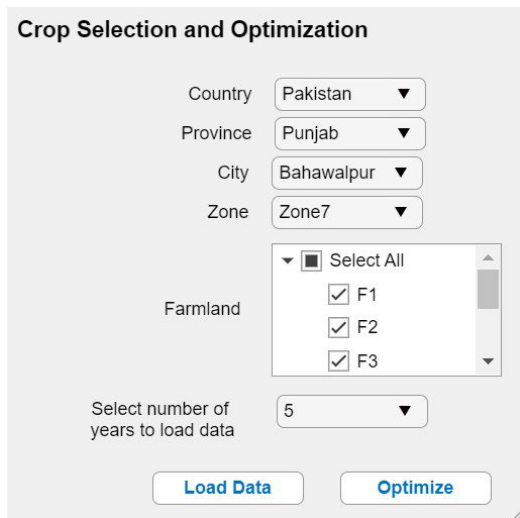


FIGURE 7. GUI for the crop selection and optimization module. The module takes the country, province, city, zone, farmland and number of years as input and return the historical data against the selections. The same data is used in the optimization module along-with the constraints.

For simplicity, we use an aggregate of all the costs in our current model.

Fig. 7 shows the UI for crop selection and optimization. A user will have to select the country, province, city/village, individual managerial zone, farmland, and the number of years for the historical data. The user can stop at any level of selection and all the data sets for the lower levels will be displayed. Once the user selects the desired areas, the crops for optimization, and the historical data is loaded from the database into the optimization module. For each field, an average of the yield and cost from the last ‘t’ years is used. The crop targets for the selected zones are loaded from the database coming from the top which uses the same historical data and assigns the targets for the lower level. In our model, we limit the farmer to plant only one crop on a single field. Total area of the selected fields is counted towards “Total area available for plantation”, total crops selected is ‘n’ and total fields selected is ‘j’. This data is fed into the optimization module which allocates each crop to the field with the most optimal yield, keeping a balance between the demand, profit maximization, and other constraints. Details on the optimization model are presented in the next section.

C. OPTIMIZATION MODEL

This section presents the main optimization model of the system based on zero-one Integer Linear Programming. This model aims to maximize the profit while addressing the constraints set on the model.

1) INDICES

There are three major indices used in this model.

- i* is the crop index where $i = 1, 2, \dots, n$
- j* is the field index where $j = 1, 2, \dots, m$

s is the season index where $s = 1$ for kharif and $s = 2$ for rabi

For a feasible solution to be obtained, *n* should always be less than or equal to *m*.

2) PARAMETERS AND UNITS

This section presents the parameters of the model. The units for all the parameters are given in Table 3.

- Y_{ijs} = Average Yield of crop *i* at field *j* in season *s*
- A_j = Area of the field *j*
- C_{ijs} = Cost of planting the crop *i* at field *j* in season *s*
- Sp_{ijs} = Sale price of the crop *i* at field *j* in season *s*
- P_{ijs} = Profit gained for the crop *i* at field *j* in season *s*
- Nn_{is} = National production target of the crop *i*
- Q_{is} = Minimum quantity of exportable the crop *i*
- In_i = Import need of the crop *i*
- Ex_{is} = Min Export demand of the crop *i* in season *s*
- Cp_{is} = Total crop *i* produced in season *s*
- A_s = Total land available in season *s*

TABLE 3. Units for Parameters.

Parameter	Unit
$C_{ijs}, Sp_{ijs}, P_{ijs}$	Rs.
Y_{ijs}	kg/acre
$Nn_i, In_i, Cp_{is}, Ex_i, Q_{is}$	kg
A_s	acre

3) DERIVED PARAMETERS

- The target for a crop that is to be produced for both local consumption and export is calculated using the national requirement and the export demand for that particular season.

$$Q_i = Nn_i + Ex_i \tag{1}$$

- Cost C_{is} is a derived parameter. The cost incurred on every crop is different for every field due to varying environmental factors discussed in Section I and the location of the land with respect to the water reservoir. This cost is calculated by combining all the following costs:

- 1) C_l : Cost of land lease
- 2) C_s : Cost of seed
- 3) C_{lab} : Cost of labor (all stages of crop)
- 4) C_{fert} : Cost of fertilizers and pesticides
- 5) C_w : Cost of water irrigation
- 6) C_m : Cost of machinery
- 7) C_f : Cost of fuel and transportation

This cost further differs for different seasons for the same crop due to the changes in environmental factors as well. As an example, the cost of wheat planted in winter is different from the cost of wheat planted in spring.

- Import is not part of our optimization model. The need for import is calculated once the crops are produced which is a part of the analysis phase. The case studies which will be presented later will further clarify this part.

Further, if the produced crop is less than the national target, the need for import is calculated as:

$$In_{is} = Nn_{is} - Cp_{is} \quad (2)$$

4) DECISION VARIABLES

$$x_{ijs} = \begin{cases} 1, & \text{if crop } i \text{ is assigned to field } j \text{ in season } s \\ 0, & \text{otherwise} \end{cases}$$

5) CONSTRAINTS

(a) The area assigned to each crop should be less than the total area available for that season

$$\sum_{i=1}^n \sum_{j=1}^m A_j x_{ijs} \leq A_s, \quad \forall s = 0, 1 \quad (3)$$

(b) The amount of crop i produced in all m fields for the season s should be greater than or equal to the national need of a crop

$$\sum_{i=1}^n \sum_{j=1}^m Y_{ijs} A_j x_{ijs} \geq Nn_i, \quad \forall s = 0, 1 \quad (4)$$

(c) For an exportable crop, the amount of crop i produced in all m fields for the season s should be greater than or equal to the minimum quantity required for an exportable crop.

$$\sum_{i=1}^n \sum_{j=1}^m Y_{ijs} A_j x_{ijs} \geq Q_{is}, \quad \forall s = 0, 1 \quad (5)$$

(d) This constraint limits a field to have more than one crop planted at a time. Only one crop i can be assigned to each field j in season s

$$\sum_{i=1}^n x_{ijs} \leq 1, \forall j, \quad \forall s = 0, 1 \quad (6)$$

6) OBJECTIVE FUNCTION

The output of the system is the area to be planted for each of the selected crops. The output is derived by the binary decision variable where each field can only be assigned to one crop, but one crop can be assigned to multiple fields to meet the constraints. The crops to be planted can be derived from the input to optimization module and the allocation is done such that the profit is maximized for all the crops planted. The objective function is derived from the yield, sale price, cost, and area for each field. The binary decision variable ensures the allocation of a single crop to each field. The objective function is presented in (7).

$$\max Z = \sum_{i=1}^n \sum_{j=1}^m \sum_{s=1}^2 [(Sp_{ijs} Y_{ijs} A_j) - (C_{ij} A_j)] x_{ijs} \quad (7)$$

V. EXPERIMENTS, RESULTS AND ANALYSIS

This section presents the experiments performed, the results, followed by the detailed analysis for the selected experiments and overall system. The section concludes with the limitation of our study and future work. Two case studies are presented for the selected area of study. The first one is an example of single farmland from Bahawalpur with ‘8’ fields and ‘3’ crops. The second case study is a complex one that involves four different farmlands in different climatic zones with each having multiple fields. We have implemented our model in MATLAB R2020b. The first experiment is described in detail to develop a thorough understanding of the whole allocation process. The second study is complex and is aided with the graphical representation.

A. SINGLE FARMLAND SCENARIO

This experiment is presented for the single farmland of Bahawalpur, previously explained in Section III. To make the problem easy to apprehend, this experiment is presented for Kharif season only where $s = 1$. Based on the historical data with maximum yield; rice, cotton, and maize are the crops selected for the simulation of the optimization model. Rice is sown from June till July and harvested from September to November. Cotton is sown from May to June and harvested from September to November. Maize is sown from June till July and harvested in October to mid-December. 8 fields belong to a single farmer in a 56.3-acre area all of which are available for cropping in Kharif season. Fig. 8 shows the historical data for the selected crops in the mentioned fields from 2015-2019. Table. 4 shows area (acre) of each field, and the yield (kg/acre), cost(Rs./kg), sale price (Rs./kg) and the minimum demand (kg) required for each crop at each field. The historical data helps to set the cost incurred on each crop at each field. The requirements are set according to the capacity of the land and crops with maximum profit. An increase in sale price of an exportable crop will not affect the efficiency of the model as the model can accommodate any change in price and the selected crop will be assigned to the fields where maximum revenue can be generated.

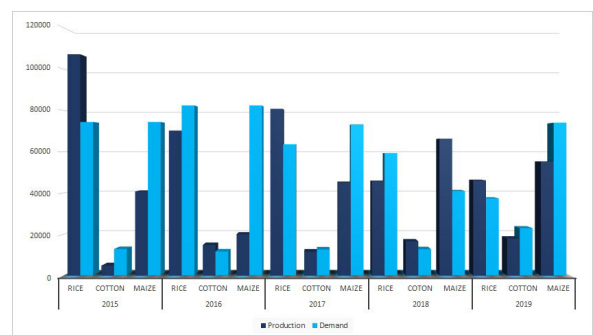


FIGURE 8. Yearly production and demand data in ‘kg’ for the selected crops before optimization.

From Table. 4, maize is a crop that is needed at both national level and for export, while the demand for other crops

TABLE 4. Yield, Cost and Profit for the crops selected for the optimization model. The costs are calculated with the rent of the land included.

Crop (<i>i</i>)		Fields with average yield in kg/acre and cost in Rs./kg								Price(Rs./kg)	Demand (kg)
		B1 (6.5 acre)	B2 (5 acre)	B3 (8.4 acre)	B4 (7.3 acre)	B5 (10.2 acre)	B6 (3.9 acre)	B7 (9 acre)	B8 (6 acre)		
Rice	Yield	1984	3493	2287	3270	1725	3100	2500	3900	50.76	46500 (NN_i)
	Cost	25.05	27	19.25	29.5	23	26	20	30		
Cotton	Yield	645	1006	481	441	782	849	912	563	96.08	20500 (NN_i)
	Cost	84.175	81	87.5	76.5	85	82	86	77		
Maize	Yield	6231	991	1878	1055	5487	2876	3476	5879	29.8	94000 (Ex_i)
	Cost	23.325	20.21	15.316	25.6	24.2	21.3	19	22		

is only at the national level. The model is initialized with the selection of a number of crops and fields. For this experiment, we have $n = 3, m = 8$ and $A_s = 56.3$. The user inputs the national need (Nn_i) / export need (Ex_i) of the crop. The first constraint of the algorithm is to ensure that whatever is produced, should be equal to or greater than the required amount of the need for that crop. It means that for each crop i , the sum of the yields on all fields assigned should be equal to or greater than the need for that crop. For rice crop, $i=1$, the constraint translates to:

$$12896x_{111} + 17465x_{121} + 19210.8x_{131} + 23871x_{141} + 17595x_{151} + 12090x_{161} + 22500x_{171} + 23400x_{181} \geq 46500$$

For cotton crop, $i=2$, the constraint translates to:

$$4192.5x_{211} + 5030x_{221} + 4040.4x_{231} + 3219.3x_{241} + 7976.4x_{251} + 3311.1x_{261} + 8208x_{271} + 3378x_{281} \geq 20500$$

For maize crop, $i=3$, the constraint translates to:

$$40501.5x_{311} + 4955x_{321} + 15775.2x_{331} + 7701.5x_{341} + 55967.4x_{351} + 11216.4x_{361} + 31284x_{371} + 35274x_{381} \geq 96000$$

The second constraint ensures that only one crop x_i can be planted in one field j at a time. For our selection, this constraint is translated as:

$$\begin{aligned} x_{111} + x_{211} + x_{311} &= 1 \\ x_{121} + x_{221} + x_{321} &= 1 \\ x_{131} + x_{231} + x_{331} &= 1 \\ x_{141} + x_{241} + x_{341} &= 1 \\ x_{151} + x_{251} + x_{351} &= 1 \\ x_{161} + x_{261} + x_{361} &= 1 \\ x_{171} + x_{271} + x_{371} &= 1 \\ x_{181} + x_{281} + x_{381} &= 1 \end{aligned}$$

The third and last constraint ensures that the area assigned to all crops should be less than or equal to the total area available A_s . The total cropping area available here is 56.3 acres, so this constraint is translated to:

$$A_1 + A_2 + A_3 + A_4 + A_5 + A_6 + A_7 + A_8 \leq 56.3$$

This model aims to maximize profit while meeting the minimum requirements for the demand. The objective function for this specific example is:

$$\begin{aligned} \max Z &= 331556.16x_{111} + 49911.7125x_{211} \\ &+ 262247.2125x_{311} + 414968.4x_{121} + 75852.4x_{221} \\ &+ 47518.45x_{321} + 605332.308x_{131} + 34666.632x_{231} \\ &+ 228487.9968x_{331} + 507497.46x_{141} + 63033.894x_{241} \\ &+ 32346.3x_{341} + 488437.2x_{151} + 88378.512x_{251} \\ &+ 313417.44x_{351} + 299348.4x_{161} + 46620.288x_{261} \\ &+ 95339.4x_{361} + 692100x_{171} + 82736.64x_{271} \\ &+ 337867.2x_{371} + 485784x_{181} \\ &+ 64452.24x_{281} + 275137.2x_{381} \end{aligned}$$

With this scenario, fields 4 and 8 are assigned to rice, field 2, 3, 6 and 7 are assigned to cotton, and fields 1 and 5 are assigned to maize. A net profit of Rs. 2.11375 Million is obtained from this allocation. For the presented scenario, the output of rice is 47271kg, cotton is 20590kg and maize is 96469kg. All these values correspond to the demand of each crop. The area assigned to each crop; rice, cotton, and maize is 13.3 acres, 26.3 acres, and 16.7 acres respectively. Fig.9 presents the demand and the expected output for each crop.

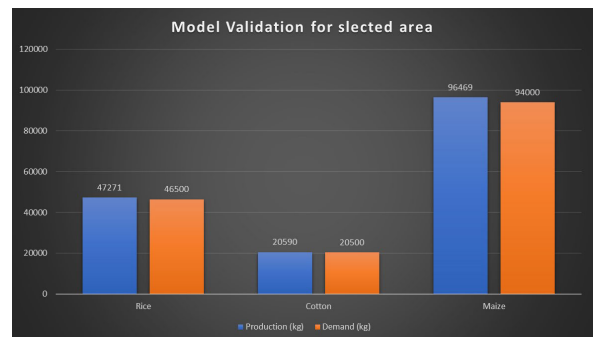


FIGURE 9. Comparison of expected production and demand in 'kg' for the selected crops after optimization which shows a very small gap between the two.

B. MULTI-LOCATION SCENARIO

This study is for four distinct climatic locations in Pakistan. We have used the data for the four provinces of Pakistan from [11] which is a comprehensive historical data-set

TABLE 5. Crop demand for five different scenarios.

Crop (i)	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
Wheat	24000	13000	14000	14000	9000
Maize	92000	52000	63000	33000	13000
Gram	69000	52000	42000	37000	27000
Masoor	2500	9500	25000	25000	25000
Potato	4000	11000	12000	12000	22000
Onion	5500	10000	11000	15000	15000
Tomato	3100	13000	11100	17000	17000

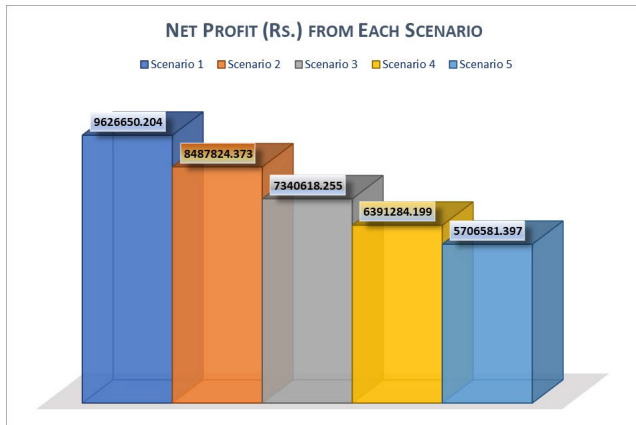


FIGURE 10. Expected net profit in 'Rs.' for each scenario after optimization.

providing details about the production of crops, livestock, machinery, water usage, import and export, prices of domestic and export crops, and area estimations for each province. This data-set is a perfect example of the national scale implementation of our designed framework. An average of each related data set is used for this example for Rabi crops. Our example is confined to a total area of 415.93 acres out of which zone 1 has a total area of 81.9 acres with 8 fields, zone 2 has 72 acres with 11 fields, zone 3 has 101.2 acres with 5 fields and zone 4 has 160.83 acres with 14 fields. The study is conducted for '7' different crops and a total of '38' fields, making $n = 7$ and $m = 38$. The crops selected for the allocation are wheat, maize(spring), gram, masoor, potato, onion, tomato.

We simulated our model with 5 different scenarios, each having a different demand set for each crop as shown in Table. 5. The demand for export crops is higher as compared to the local crop since it is usually needed for both local consumption and export, driven by the 1. In this particular case, gram and maize are labeled as export crops which are assigned to fields with a history of good crop production for these export crops. Fig. 10 shows net expected profit for each scenario whereas Fig. 11 shows a visual comparison of the demand of each crop and the recommended production based on cost-benefit and need analysis through the optimization model. Table. 6 shows the expected production in 'kgs' and the profit in 'Rs.' generated from each crop individually for each scenario.

C. ANALYSIS

The two different scenarios presented are carefully selected to show the diversity of our designed model. The first experiment emphasizes our claim that this model can be used for a single farmer with improved yield prediction. At the farmer level, this prediction is very helpful since with smaller farmland, finances are meager and any wastage or overproduction costs the farmer a lot. The comparison of Fig.8 with Fig.9 shows an improved yield prediction using our model. The original method of plantation adopted by the farmer is focused on one crop planted in the previous year, which can be seen from Fig. 8. Our model is designed to see what difference it would've made with the usage of historical data and constraints. We have applied this model to improve the output, to overcome the shortcomings, and to avoid wastage of any crop in particular. This test case validates the model with every crop meeting the demand. The output from Fig.9 shows that our model has a very little gap between the demand and expected output.

The second experiment shows the diversity of our model and supports our claim to cater to larger data. This experiment is based on five different scenarios with varying demands and four different climatic regions for crop production. The results not only show expected production for the selected crops but also helps in analyzing that restricting crop production to the best areas only will lead to an overall boost in the economy. The importance of policy implementation, pre-planning, and producing the best from every assigned region is very well explained through this experiment. Fig. 10, 11 and Table. 6 shows the profits earned from each scenario, comparison of demand and production after optimization, and individual crop's expected production with profit respectively.

Our model not only suggests future crop allocation at the most appropriate location, but it also helps in analyzing which two crops require the same resources, time, cost, and effort but produce different profits. This helps in deciding which crop should be imported instead of wasting efforts on the plantation and exportable crops with maximum profit benefit should be planted. The incorporation of roles of all stakeholders; the farmer, the managers, and the government helps in validating the practical implementation of the study. In all cases, this model is valid for any number of crops at the national level. The model works on meeting the constraints step-by-step and provides an optimal yield prediction with very little gap between the demand and production.

D. LIMITATIONS AND FUTURE WORK

The limitation of the work is the fine resolution at which you can get the data of the yield and the crop types. For smaller resolution, which means every farmer, more accurate data may be required but at the national level, even coarse resolution of the available data or information gives quite a good estimate for decision aiding which is shown in our second experiment. In our future work, the fine resolution of data will be addressed by incorporating the flow of the data

TABLE 6. Expected production (kg's) and profit (Rs.) in each scenario after the application of the optimization model.

Crop (i)	Scenario 1		Scenario 2		Scenario 3		Scenario 4		Scenario 5	
	Expected Production (kg)	Profit (Rs.)	Expected Production (kg)	Profit (Rs.)	Expected Production (kg)	Profit (Rs.)	Expected Production (kg)	Profit (Rs.)	Expected Production (kg)	Profit (Rs.)
Wheat	25039.741	234018.4175	13094.505	114053.1386	21833.847	251962.594	15348.848	143525.913	11979.007	117753.6388
Maize (spring)	92373.968	1363960.016	92373.968	1363960.016	69322.394	1066377.17	53688.125	825453.081	24180	353028
Gram	69111.508	7741271.861	55866.603	6269791.803	44534.739	4953500.36	38073.224	4237766.43	34537.302	3862859.927
Masoor	3359.86	59435.9234	9719.5	206279.297	25163.086	490107.635	25203.111	483577.659	25203.111	483577.6591
Potato	4487.72	83383.5796	11046.512	221471.2622	12222.023	247252.492	12036.235	235345.155	22027.931	423746.2128
Onion	5694.016	126479.7321	10435.049	228871.5306	11030.893	254281.816	15139.734	350513.901	15139.734	350513.9014
Tomato	3133.5529	18100.67525	13010.0729	83397.3259	11150.6259	77136.189	17085.7669	115102.059	17085.7669	115102.0585

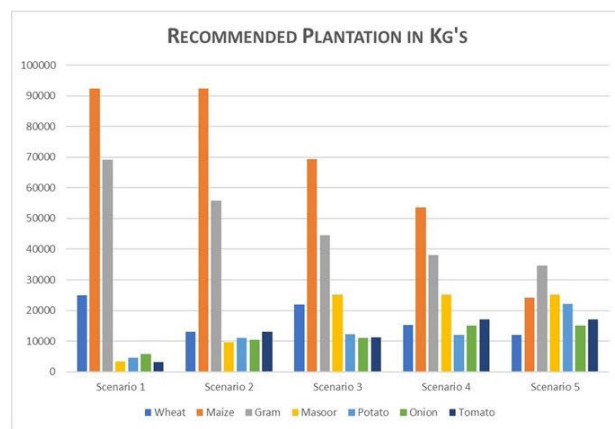
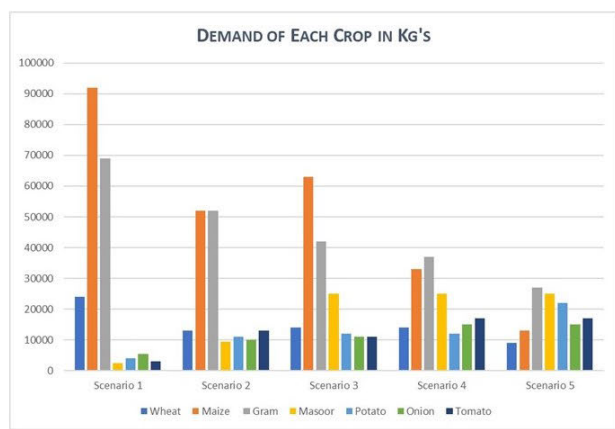


FIGURE 11. Demand in 'kg's' for each crop in 5 different scenarios vs. the recommended production in 'kg's' after optimization.

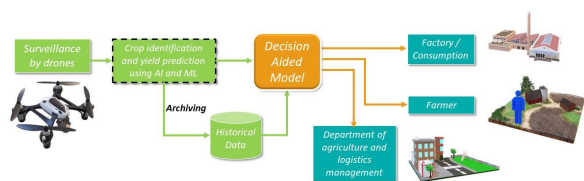


FIGURE 12. Complete model of the system including published work, present work from this paper and future work (shown as dotted module).

from multiple channels instead of only one channel. Fig. 12 shows the complete model of the system. This model shows our complete system in parts. One part of the system that we have published is converting an aerial video into high-quality mosaics [4]. The second module presented in this paper is the development of the decision aiding tool for the stakeholders involved. The third part, shown as a dotted section in the model, will be the Artificial Intelligence (AI) and Machine Learning (ML) based tool for building the knowledge base for the future that can be used to estimate the yield and can be fed into the archive to get more accurate data for future decision making and prediction.

VI. CONCLUSION

This study presents a novel framework for crop planning using Spatio-temporal data for the fields in the selected region. The framework addresses the gaps in policy making,

the managerial implications of the crop allocation problem, and uses historical data of each field for the past years for each season, the national need and the export demand of each crop, along all the necessary constraints for the crop production. This study focuses on proposing a solution for the countries which struggle to keep the balance between production and demand of the crops because the crops are mainly planted by the farmer's intent only. The model is developed to address the issue of crop planning at the national level and works towards the maximization of the profits while matching the necessary constraints. Two case studies are presented as part of the experimental validation where one case study is for single farmland with multiple fields and the other is a complex one with different farmlands in distinct climatic zones, each having multiple fields. Both experiments validate our claim of applicability at the farmer level as well as at the national level. A comparison is provided which shows that our model aids in planning ahead of crop plantation to achieve a low demand to production gap, in analyzing that which crops need to be imported by analyzing costs and future allocation, and in managing the overproduction and wastage of different crops. The decision aiding tool helps the various stakeholders related to crop allocation, plantation, and management and if the implementation is done according to the planned model, it precisely gives us yields of different crops to meet the national need and the

export demand of the country. Although our model addresses the real-time problem that Pakistan is facing, its design excludes environmental factors that affect the crop production. The inclusion of these factors in future research will enhance the model's productivity which is a part of our future work.

REFERENCES

- [1] D. Bertoni, D. Cavicchioli, F. Donzelli, G. Ferrazzi, D. Frisio, R. Pretolani, E. Ricci, and V. Ventura, "Recent contributions of agricultural economics research in the field of sustainable development," *Agriculture*, vol. 8, no. 12, p. 200, Dec. 2018, doi: [10.3390/agriculture8120200](https://doi.org/10.3390/agriculture8120200).
- [2] A. Anik, S. Rahman, and J. Sarker, "Agricultural productivity growth and the role of capital in south Asia (1980–2013)," *Sustainability*, vol. 9, no. 3, p. 470, Mar. 2017, doi: [10.3390/su9030470](https://doi.org/10.3390/su9030470).
- [3] J. Kim, S. Kim, C. Ju, and H. I. Son, "Unmanned aerial vehicles in agriculture: A review of perspective of platform, control, and applications," *IEEE Access*, vol. 7, pp. 105100–105115, 2019, doi: [10.1109/ACCESS.2019.2932119](https://doi.org/10.1109/ACCESS.2019.2932119).
- [4] N. Rasheed, W. S. Qureshi, S. A. Khan, M. A. Naqvi, and E. Alanazi, "AirMatch: An automated mosaicing system with video preprocessing engine for multiple aerial feeds," *IEICE Trans. Inf. Syst.*, vol. E104.D, no. 4, pp. 490–499, Apr. 2021, doi: [10.1587/transinf.2020EDK0003](https://doi.org/10.1587/transinf.2020EDK0003).
- [5] M. S. Farooq, S. Riaz, A. Abid, K. Abid, and M. A. Naeem, "A survey on the role of IoT in agriculture for the implementation of smart farming," *IEEE Access*, vol. 7, pp. 156237–156271, 2019, doi: [10.1109/ACCESS.2019.2949703](https://doi.org/10.1109/ACCESS.2019.2949703).
- [6] S. Fountas, B. Espejo-Garcia, A. Kasimati, N. Mylonas, and N. Darra, "The future of digital agriculture: Technologies and opportunities," *IT Prof.*, vol. 22, no. 1, pp. 24–28, Jan. 2020, doi: [10.1109/MITP.2019.2963412](https://doi.org/10.1109/MITP.2019.2963412).
- [7] M. Ayaz, M. Ammad-Uddin, Z. Sharif, A. Mansour, and E. M. Aggoune, "Internet-of-Things (IoT)-based smart agriculture: Toward making the fields talk," *IEEE Access*, vol. 7, pp. 129551–129583, 2019, doi: [10.1109/ACCESS.2019.2932609](https://doi.org/10.1109/ACCESS.2019.2932609).
- [8] K. Pawlak and M. Kołodziejczak, "The role of agriculture in ensuring food security in developing countries: Considerations in the context of the problem of sustainable food production," *Sustainability*, vol. 12, no. 13, p. 5488, Jul. 2020, doi: [10.3390/su12135488](https://doi.org/10.3390/su12135488).
- [9] (Jul. 2019). *Agricultural Statistics of Pakistan 2017-18*. Economic Wing, Ministry of National Food Security and Research, Government of Pakistan. Accessed: Jan. 2, 2020. [Online]. Available: <http://www.mnfsr.gov.pk/frmDetails.aspx>
- [10] S. Saravia-Matus, T. S. Amjath-Babu, S. Aravindakshan, S. Sieber, J. A. Saravia, and S. G. Y. Paloma, "Can enhancing efficiency promote the economic viability of smallholder farmers? A case of Sierra Leone," *Sustainability*, vol. 13, no. 8, p. 4235, Apr. 2021, doi: [10.3390/su13084235](https://doi.org/10.3390/su13084235).
- [11] *Historical Data of External Trade*. Agriculture Marketing Information Service (AMIS). Accessed: Jan. 7, 2020. [Online]. Available: <http://www.amis.pk/FBS/PBS.aspx>
- [12] (2020). *Crop Yield Gap Analysis Pakistan 2020*. Planning and Research Department Zarai Taraqati Bank Limited. [Online]. Available: <https://www.ztbl.com.pk/wp-content/uploads/Documents/Publications/Research-Studies/CropYieldGapAnalysis.pdf>
- [13] N. T. Liliane and M. S. Charles, "Factors affecting yield of crops," in *Agronomy—Climate Change and Food Security*. Rijeka, Croatia: IntechOpen, 2020, doi: [10.5772/intechopen.90672](https://doi.org/10.5772/intechopen.90672).
- [14] D. Ahmad, M. I. Chani, and A. A. Humayon, "Major crops forecasting area, production and yield evidence from agriculture sector of Pakistan," *Sarhad J. Agricult.*, vol. 33, no. 3, pp. 385–396, Aug. 2017, doi: [10.17582/journal.sja/2017/33.3.385.396](https://doi.org/10.17582/journal.sja/2017/33.3.385.396).
- [15] X. L. Xu, H. H. Chen, and Y. Li, "Exploring the influencing factors of continuous crop residue supply: From the perspective of a sustainable and bioenergy-oriented crop cultivation," *Energy, Sustainability Soc.*, vol. 10, no. 1, p. 35, Dec. 2020, doi: [10.1186/s13705-020-00267-0](https://doi.org/10.1186/s13705-020-00267-0).
- [16] J. W. Jones, J. M. Antle, B. Basso, K. J. Boote, R. T. Conant, I. Foster, H. C. J. Godfray, M. Herrero, R. E. Howitt, S. Janssen, B. A. Keating, R. Munoz-Carpena, C. H. Porter, C. Rosenzweig, and T. R. Wheeler, "Brief history of agricultural systems modeling," *Agricult. Syst.*, vol. 155, pp. 240–254, Jul. 2017, doi: [10.1016/j.agsy.2016.05.014](https://doi.org/10.1016/j.agsy.2016.05.014).
- [17] S. Chetty and A. O. Adewumi, "Comparison study of swarm intelligence techniques for the annual crop planning problem," *IEEE Trans. Evol. Comput.*, vol. 18, no. 2, pp. 258–268, Apr. 2014, doi: [10.1109/TEVC.2013.2256427](https://doi.org/10.1109/TEVC.2013.2256427).
- [18] S. Khaki and L. Wang, "Crop yield prediction using deep neural networks," *Frontiers Plant Sci.*, vol. 10, p. 621, May 2019, doi: [10.3389/fpls.2019.00621](https://doi.org/10.3389/fpls.2019.00621).
- [19] (2018). *Syngenta Crop Challenge in Analytics*. [Online]. Available: <https://www.ideaconnection.com/syngenta-crop-challenge/challenge.php/>
- [20] C. Folberth, N. Khabarov, J. Balkovič, R. Skalský, P. Visconti, P. Ciaia, I. A. Janssens, J. Peñuelas, and M. Obersteiner, "The global cropland-sparing potential of high-yield farming," *Nature Sustainability*, vol. 3, no. 4, pp. 281–289, Apr. 2020, doi: [10.1038/s41893-020-0505-x](https://doi.org/10.1038/s41893-020-0505-x).
- [21] U. Ketsripongs, R. Pitakaso, K. Sethanan, and T. Srivrapongse, "An improved differential evolution algorithm for crop planning in the northeastern region of Thailand," *Math. Comput. Appl.*, vol. 23, no. 3, p. 40, Aug. 2018, doi: [10.3390/mca23030040](https://doi.org/10.3390/mca23030040).
- [22] D. Elavarasan, D. R. Vincent, V. Sharma, A. Y. Zomaya, and K. Srinivasan, "Forecasting yield by integrating agrarian factors and machine learning models: A survey," *Comput. Electron. Agricult.*, vol. 155, pp. 257–282, Dec. 2018, doi: [10.1016/j.compag.2018.10.024](https://doi.org/10.1016/j.compag.2018.10.024).
- [23] A. Amini, "Application of fuzzy multi-objective programming in optimization of crop production planning," *Asian J. Agricult. Res.*, vol. 9, no. 5, pp. 208–222, Aug. 2015, doi: [10.3923/ajar.2015.208.222](https://doi.org/10.3923/ajar.2015.208.222).
- [24] B. Bou-Fakhreddine, S. Abou-Chakra, I. Mougharbel, A. Faye, and Y. Pollet, "Optimal multi-crop planning implemented under deficit irrigation," in *Proc. 18th Medit. Electrotech. Conf. (MELECON)*, Lemesos, Cyprus, Apr. 2016, pp. 1–6, doi: [10.1109/MELCON.2016.7495480](https://doi.org/10.1109/MELCON.2016.7495480).
- [25] A. A. B. Cohen, J. Judge, R. Muneeppeerakul, A. Rangarajan, and Z. Guan, "A model of crop diversification under labor shocks," *PLoS ONE*, vol. 15, no. 3, Mar. 2020, Art. no. e0229774, doi: [10.1371/journal.pone.0229774](https://doi.org/10.1371/journal.pone.0229774).
- [26] M. O. Wankhade and H. S. Lunge, "Allocation of agricultural land to the major crops of saline track by linear programming approach: A case study," *Int. J. Sci. Technol. Res.*, vol. 1, no. 9, pp. 21–25, 2012.
- [27] H. Karloff, "The simplex algorithm," in *Linear Programming*. Boston, MA, USA: Birkhäuser, 2009, pp. 23–47.
- [28] H. Arsham, G. Cimperman, N. Damij, T. Damij, and J. Grad, "A computer implementation of the push-and-pull algorithm and its computational comparison with LP simplex method," *Appl. Math. Comput.*, vol. 170, no. 1, pp. 36–63, Nov. 2005, doi: [10.1016/j.amc.2004.10.078](https://doi.org/10.1016/j.amc.2004.10.078).
- [29] P. T. Juwono, L. M. Limantara, and F. Rosiadi, "Optimization of irrigation cropping pattern by using linear programming: Case study on irrigation area of Parsanga, Madura Island, Indonesia," *J. Water Land Develop.*, vol. 39, no. 1, pp. 51–60, Dec. 2018, doi: [10.2478/jwld-2018-0058](https://doi.org/10.2478/jwld-2018-0058).
- [30] J. Jebelli, B. Paterson, and A. Abdelwahab, "A linear programming model to optimize cropping pattern in small-scale irrigation schemes: An application to Mekabo Scheme in Tigray, Ethiopia," *Int. J. Environ. Agricult. Res.*, vol. 2, no. 8, pp. 24–34, Aug. 2016.
- [31] M. Akplogan, S. de Givry, J.-P. Métivier, G. Quesnel, A. Joannon, and F. Garcia, "Solving the crop allocation problem using hard and soft constraints," *RAIRO-Oper. Res.*, vol. 47, no. 2, pp. 151–172, Apr. 2013, doi: [10.1051/ro/2013032](https://doi.org/10.1051/ro/2013032).
- [32] A. Rehman, L. Jingdong, B. Shahzad, A. A. Chandio, I. Hussain, G. Nabi, and M. S. Iqbal, "Economic perspectives of major field crops of Pakistan: An empirical study," *Pacific Sci. Rev. B, Humanities Social Sci.*, vol. 1, no. 3, pp. 145–158, Nov. 2015, doi: [10.1016/j.psrb.2016.09.002](https://doi.org/10.1016/j.psrb.2016.09.002).
- [33] S. Haider, S. Naqvi, T. Akram, G. Umar, A. Shahzad, M. Sial, S. Khaliq, and M. Kamran, "LSTM neural network based forecasting model for wheat production in Pakistan," *Agronomy*, vol. 9, no. 2, p. 72, Feb. 2019, doi: [10.3390/agronomy9020072](https://doi.org/10.3390/agronomy9020072).
- [34] F. Aslam, A. Salman, and I. Jan, "Predicting wheat production in Pakistan by using an artificial neural network approach," *Sarhad J. Agricult.*, vol. 35, no. 4, pp. 1054–1062, 2019, doi: [10.17582/journal.sja/2019/35.4.1054.1062](https://doi.org/10.17582/journal.sja/2019/35.4.1054.1062).
- [35] S. Ali, Y. Liu, M. Ishaq, T. Shah, A. Ilyas, and I. Din, "Climate change and its impact on the yield of major food crops: Evidence from Pakistan," *Foods*, vol. 6, no. 6, p. 39, May 2017, doi: [10.3390/foods6060039](https://doi.org/10.3390/foods6060039).
- [36] M. Lampridi, C. Sørensen, and D. Bochtis, "Agricultural sustainability: A review of concepts and methods," *Sustainability*, vol. 11, no. 18, p. 5120, Sep. 2019, doi: [10.3390/su11185120](https://doi.org/10.3390/su11185120).
- [37] S. Santiteerakul, A. Sopadang, K. Yaibuathet Tippayawong, and K. Tamvimol, "The role of smart technology in sustainable agriculture: A case study of wangree plant factory," *Sustainability*, vol. 12, no. 11, p. 4640, Jun. 2020, doi: [10.3390/su12114640](https://doi.org/10.3390/su12114640).

[38] B. Balázs, E. Kelemen, T. Centofanti, M. W. Vasconcelos, and P. P. M. Iannetta, "Integrated policy analysis to identify transformation paths to more sustainable legume-based food and feed value-chains in Europe," *Agroecol. Sustain. Food Syst.*, vol. 45, no. 6, pp. 931–953, Jul. 2021, doi: [10.1080/21683565.2021.1884165](https://doi.org/10.1080/21683565.2021.1884165).

[39] S. S. Sana, "Price competition between green and non green products under corporate social responsible firm," *J. Retailing Consum. Services*, vol. 55, Jul. 2020, Art. no. 102118, doi: [10.1016/j.jretconser.2020.102118](https://doi.org/10.1016/j.jretconser.2020.102118).

[40] S. S. Sana, "A structural mathematical model on two echelon supply chain system," *Ann. Oper. Res.*, pp. 1–29, Jan. 2021, doi: [10.1007/s10479-020-03895-z](https://doi.org/10.1007/s10479-020-03895-z).

[41] M. Bhattacharyya and S. S. Sana, "A mathematical model on eco-friendly manufacturing system under probabilistic demand," *RAIRO-Oper. Res.*, vol. 53, no. 5, pp. 1899–1913, Nov. 2019, doi: [10.1051/ro/2018120](https://doi.org/10.1051/ro/2018120).

[42] S. Saha, I. Nielsen, and S. S. Sana, "Effect of optimal subsidy rate and strategic behaviour of supply chain members under competition on green product retailing," *Math. Problems Eng.*, vol. 2021, pp. 1–23, Feb. 2021, doi: [10.1155/2021/66661103](https://doi.org/10.1155/2021/66661103).

[43] S. S. Sana, G. Herrera-Vidal, and J. Acevedo-Chedid, "Collaborative model on the agro-industrial supply chain of cocoa," *Cybern. Syst.*, vol. 48, no. 4, pp. 325–347, May 2017, doi: [10.1080/01969722.2017.1285160](https://doi.org/10.1080/01969722.2017.1285160).

[44] Google Earth. Accessed: Feb. 13, 2021. [Online]. Available: <https://earth.google.com/web/>

[45] Pakistan Agricultural Research Council Official Website. Accessed: Jul. 18, 2021. [Online]. Available: <http://www.parc.gov.pk/index.php/en/43-maps>

[46] Accessed: Jul. 18, 2021. [Online]. Available: <https://pakistan.gov.pk/>

[47] M. H. Khan. (Accessed: Sep. 5, 2020). *At Cotton's Expense*. DAWN.COM. Sep. 1, 2020. [Online]. Available: <https://www.dawn.com/news/1577229>

[48] Alhasan Systems Private Limited, "Crisis response bulletin," *Alhasan Syst.*, vol. 1, no. 8, p. 26, Mar. 2015.

[49] (Accessed: Mar. 3, 2020). *Crop Calender of Pakistan*. National Agromet Centre. [Online]. Available: <http://namc.pmd.gov.pk/crop-calender.php>

[50] Bahawalpur City Profile. The Urban Unit. Accessed: Feb. 13, 2021. [Online]. Available: <http://uu.urbanunit.gov.pk/Documents/Publications/0/109.pdf>

[51] K. Ahmed, S. Shahid, X. Wang, N. Nawaz, and N. Khan, "Spatiotemporal changes in aridity of Pakistan during 1901–2016," *Hydrol. Earth Syst. Sci.*, vol. 23, no. 7, pp. 3081–3096, Jul. 2019, doi: [10.5194/hess-23-3081-2019](https://doi.org/10.5194/hess-23-3081-2019).

[52] (Accessed: Jun. 3, 2020). *Crop Situation and Forecast*. [Online]. Available: <http://www.suparco.gov.pk/pages/pak-scms.asp>

[53] Saifullah, "Pakistan district boundaries," ArcGIS, Aug. 2018. Accessed: Dec. 17, 2020. [Online]. Available: <https://www.arcgis.com/home/item.html?id=b1bb833190524843b1d0d89bf7a3ab69>



SHOAB AHMED KHAN received the Ph.D. degree in electrical and computer engineering from Georgia Institute of Technology, Atlanta, GA, USA, in 1995. He has over 22 years of industrial experience at companies in USA and Pakistan. He is currently a Professor of computer and software engineering with the College of Electrical and Mechanical Engineering, National University of Sciences and Technology. He is an inventor of five awarded U.S. patents. He has more than 260 international publications. He has published a book on digital design by John Wiley & Sons. He is being followed by national and international universities. He has founded the Center for Advanced Studies in Engineering (CASE) and the Center for Advanced Research in Engineering (CARE). The CASE is a prime engineering institution that runs one of the largest post graduate engineering programs in the country and has already graduated 50 Ph.D. and over 1800 M.S. students in different disciplines in engineering, whereas, under the leadership of the CARE, has risen to be one of the most profound high technology engineering organizations in Pakistan developing critical technologies worth millions of dollars for organizations in Pakistan. The CARE has made history by winning 13 PASHA ICT awards and 11 Asia-Pacific ICT Alliance Silver and Gold Merit Awards while competing with the best products from advanced countries, like Australia, Singapore, Hong Kong, and Malaysia. He served as a member for the Board of Governance of many entities in the Ministry of IT and Commerce, the National Computing Council, and the National Curriculum Review Committee. He has received Tamgh-e-Imtiaz (Civil), the National Education Award (2001), and the NCR National Excellence Award in Engineering Education. He has served as the Chair for Pakistan Association of Software Houses.



ALI HASSAN received the B.E. and M.S. degrees in computer engineering from the College of Electrical and Mechanical Engineering (CEME), NUST, Islamabad, Pakistan, in 2004 and 2007, respectively, and the Ph.D. degree in electrical engineering from the University of Southampton, U.K., in 2012. He is currently the Head of the Department of Computer and Software Engineering, College of Electrical and Mechanical Engineering, NUST. His research interests include machine learning and speech processing.



NIDA RASHEED (Graduate Student Member, IEEE) received the B.S. degree in computer engineering from the University of Engineering and Technology, Taxila, in 2009, and the M.S. degree in computer engineering from the College of Electrical and Mechanical Engineering, National University of Sciences and Technology, in 2013, where she is currently pursuing the Ph.D. degree. She has more than 11 years of experience in teaching and research at COMSATS University Islamabad, where she is currently the Head of the Department of Computer Science, CUI Virtual Campus. Her research interests include video and image processing, machine learning, and aerial surveillance systems.



SARIA SAFDAR received the M.S. degree in computer software engineering from the National University of Science and Technology (NUST), Islamabad, Pakistan, in 2012, where she is currently pursuing the Ph.D. degree. She is currently a Lecturer with Fatima Jinnah Women University (FJWU), Rawalpindi, Pakistan. Her research interests include health informatics, computer networks, data mining, and machine learning algorithms.

•••