

# Parallel crop planning based on price forecast

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## Funding information

National Natural Science Foundation of China, Grant/Award Number: 62076239; Chinese Academy of Science (CAS)—Thailand National Science and Technology Development Agency (NSTDA) Joint Research Program, Grant/Award Number: GJHZ2076

## Abstract

Agrifood system actors operate within diverse socio-cultural, economic, and biophysical settings. For growers, crop planning, usually a yearly business plan, is a key decision to make on when, what, and how many to plant. It is a challenging task as it deals with multiple constraints in volatile economic and/or climate environment. Most crop planning models have difficulty in adapting to changing situation. In this study, a parallel system of crop planning composed of the artificial system, computational experiment, and parallel execution is proposed. The farmers are described as agents, and the decision is made based on the heuristic searching of optimal plan; the adaption of plan is triggered autonomously given strong environment changes. Focus is given to economic environment, which is indicated as product price. In a case study, the economic environment of the artificial system is built based on the monthly and weekly price information for 13 products during 7 years. The computational experiment provides the initial cropping plan and harvest time, with social and ecological constraints. Result shows that the cropping plan can further adapt to price variation. This flexible cropping plan system can strengthen the capability of cooperatives serving small-scale farmers.

## KEYWORDS

agent-based modeling, crop planning, parallel agricultural management, price prediction

## 1 | INTRODUCTION

Many actors (growers, distributors, consumers, etc.) in agrifood systems make decisions independently in pursuit of their own objectives and naturally most objectives end up in conflict with each other.<sup>1</sup> Agrifood system actors operate within diverse sociocultural, economic, and biophysical settings. In China and many Asian countries, small-scale farms are dominating, and it is expected to last for a long time.<sup>2</sup> Although it is recognized that small-scale farms are more ecologically sustainable than large-scale industrialized farms,<sup>3</sup> due to information inconsistency and geographical distance, it is often reported that agricultural products are too cheap to harvest at the supply side, which harms the income of farmers and causes waste. Farmers often decide when and what to plant according to the near temporal and spatial information, a similar behavior to how a driver chooses its way at road. Low economic benefits lead to a lot of idle farmland,<sup>4</sup> which produces many potential risks.

Crop planning is the decision on when, what, and how many to plant.<sup>5</sup> It is supposed to be a key service to small-scale farmers by agricultural cooperative, which is expected to strengthen small-scale farmers by providing technical support and information service.<sup>6</sup> Being a joint organization of individual farmer, a cooperative can provide considerable products to deal with big market need, which seems to be a solution to overcome the information inconsistency. The modern agricultural cooperatives is expected to become knowledge developers and disseminators, for the benefit of members and their communities.<sup>7</sup> However, the operators of cooperatives are often unable to provide desired services due to the lack of knowledge or capacity.

In previous crop planning, ecological, social and economic constraints have been considered.<sup>8</sup> Among them, product price is a key factor for evaluating the profit.<sup>9</sup> However, due to its complexity, the uncertainty in price was simply modeled as stochastic variable without temporal information.<sup>10</sup> Although solutions can be provided for a given situation, many crop planning models have difficulty to adapt to evolving environment.<sup>11</sup> The age of big-data brings new chances as the daily price information is open and accessible in web. The prediction of price for the following days, weeks, or months becomes possible,<sup>12</sup> which allows the corresponding adjustment of crop planning to adapt to evolving conditions.

In this study, a parallel system of crop planning is proposed based on the theory of artificial system, computational experiment, and parallel execution. The farmers are described as agents, the decision is made based on the heuristic searching of optimal plan, and the adaption of plan is triggered autonomously given strong environment changes. The aim is to maximize the total income of cooperative with multiple constraints. Focus is given to economic environment, which is indicated as product price. Both monthly and weekly prices are used for deciding the initial plan and harvest time. The cropping plan is adapted according to price variation through the interaction between the actual and digital systems.

The novelties of this paper lie on (1) a parallel management framework is proposed for flexible crop planning with closed loop between theoretical plan and actual situation; (2) the artificial system composed of farmers, crops, and economic environment based on price of weekly and monthly scales is described, which can serve the decision on cropping plan and harvest time.

This paper is organized as follows.

The literature review of related works is presented in Section 2. The materials and methods are presented in Section 3, describing the three components of the parallel system of crop planning, which are artificial system (A), computational experiment (C), and parallel execution (P). An illustrative example is developed and analyzed to validate the algorithm in Sections 4 and 5. Sections 6 and 7 are dedicated to Discussion and Conclusions, respectively.

## 2 | RELATED WORKS

### 2.1 | Crop planning

Crop planning is an extensively studied topic that can be dated back to 1893.<sup>13</sup> An excellent review has been made by Glen<sup>14</sup> concluding the state-of-the-art of models in the year 1987. In 2012, another extensive review was made on this domain that discussing the several aspects of crop planning.<sup>8</sup> It points out that the crop planning at date is mainly based on the static concept, and the uncertainty of information is generally defined as random factors or probability of occurrence, so it is impossible to dynamically adjust the cropping plan in the process of planting.

According to the emphases of the optimization objectives and constraints, the crop planning problems can be roughly distinguished to two issues: the issue focusing on ecological sustainability and the issue focusing on social and economic attributes.

Regarding to the issue of ecological sustainability, the maximum of land-use efficiency is usually used as the optimization objective. The constraints involving crop rotation include spatial and temporal ones,<sup>15</sup> including (1) the crops of the same botanic family cannot be planted in adjacent plots, (2) each plot cannot grow crops of the same botanic family in sequence, (3) to improve soil fertility, green manure crops should be planted in each rotation cycle, (4) the fallow period should be designed in each rotation cycle, so that the free growth of weeds can restore the animals and structure of the soil. Moreover, crops can be allocated according to the characteristics of different land, so as to reduce soil erosion and improve soil fertility.<sup>16</sup> To achieve these goals, the “unacceptable planting sequence” can be added as constraints.<sup>17</sup>

Regarding to the economic and social attributes, the optimization objective is generally to maximize the total profit. Filippi et al.<sup>18</sup> used Conditional Value-at-Risk as the objective function to model the crop planning problem by considering the effect of price fluctuation on farmers' profit, which was in line with farmers' expectation of reducing risks. Regarding to the economic constraints, the most common one is the satisfaction of cooperative demands.<sup>19</sup> Pakawanich et al.<sup>20</sup> considered the balance of income among farmers in a cooperative. Najafabadi et al. arrange the cropping plan according to the actual soil conditions of each plot to reduce the resource consumption and scheduling costs.<sup>21</sup>

Since the definition of planting planning problem, the linear programming model has been introduced,<sup>22</sup> and the method based on operational research has become the main solution.<sup>14</sup> Usually the 0–1 linear programming model is chosen as the model of agricultural planning.<sup>19</sup> Sometimes, the integer linear programming model is applied to represent the multiple harvest characteristics of crops.<sup>23</sup> Regarding to problem-solving methods, the column generation method is commonly used: after the original problem is decomposed by Dantzig Wolfe, the branch-and-price-and-cut approach with different rules is used to solve the problem.<sup>19,23</sup>

In the existing economic models, the modeling of general price is of relatively coarse scale, taking one year or one month as a cycle. Often a fixed-price information is used.<sup>18,24,25</sup> However, dynamic price information based on price prediction is rarely used.

### 2.2 | Parallel management

The agricultural system is a complex system, which is hard to model. Although a mathematical model can perfectly define a crop modeling problem, the gap between theory and practice

hinders the application of crop planning into practice. This is actually a typical challenge for many sophisticated mathematical models.

Parallel method is proposed to solve the Uncertainty, Diversity, and Complexity (UDC) problem of a system. It has been used in the description and management of different complex systems, such as a transportation system,<sup>26</sup> large factories,<sup>27</sup> power grid,<sup>28</sup> and social public opinion.<sup>29</sup> Parallel management provides a framework of managing complex system with Artificial system, Computational experiment, and Parallel execution.<sup>30</sup> The knowledge and data from the real world help build the artificial system, while the almost costless computational experiment in cyber world gives decision support to the actual system. One can continuously adjust the artificial system through the feedback of the real system.<sup>31</sup> For the application of parallel management method in agricultural, the crop models with the physical information can be integrated.<sup>32</sup> An analogy in industry is digital twins. A parallel system can not only describe and simulate the actual physical system like digital twins, but also guide the adaptive optimization of the actual system through the virtual and real interaction with parallel execution.<sup>33</sup>

In reality, farmers need to constantly adjust their planting plans to achieve sustainable agricultural development according to changes in climate, market, and policies and regulations.<sup>8</sup> For example, if the price of a crop is expected to augment, a new planting schedule for future needs to be made for the cooperative. If the price of crops in the following weeks will change, suggestion on the harvest time should be given accordingly. Thus, the frame of parallel management is applied to fit the volatile situation.

### 2.2.1 | Building the artificial system with agent-based modeling

A key method for building the artificial system for a parallel system is agent-based modeling. An agent is defined as a human or a robot of physical and information world with four characteristics of autonomy, sociality, responsiveness, and initiative.<sup>34</sup> The interactions between agents and environment can affect the performance of the system by defining the state and behavior of agents in the system. The idea of agent-based modeling has been widely used in economics,<sup>35</sup> traffic,<sup>36</sup> smart grid,<sup>37</sup> and social evolution.<sup>38</sup> Li et al.<sup>25</sup> applied agent-based method to the crop planning problem.

The key to solve the agent-based model lies in the construction of an agent decision-making system, that is, how to choose the next action according to the current environmental information. This idea can play a very important role in dealing with the interaction between multiple agents in the system.

### 2.2.2 | Price forecast model, the economic environment in an artificial system

As mentioned, product price is the indicator of economic environment affecting the decision of growers. The prices of agricultural products are affected by many factors, which are highly complex and nonlinear.<sup>39</sup> Many methods have been used for the short-term price forecast of agricultural products, including “cobweb theory” by combining the demand and supply of agricultural products with economic principles,<sup>40</sup> autoregressive integrated moving average (ARIMA) model,<sup>41</sup> vector autoregression model,<sup>42</sup> support vector machine (SVM) method,<sup>43</sup> neural network prediction algorithm,<sup>44</sup> recurrent neural network,<sup>12</sup> and so forth. Like the stock

or climate, long-term prediction of price is no more precise. This led to the idea of using price data of different temporal scales.

### 3 | MATERIALS AND METHODS

The overall framework is as in Figure 1.<sup>45</sup> This figure shows the parallel management framework in agricultural crop planning. An agent-based artificial system is to be built in cyberworld which describes the real system, composed of farmers, crops, and their environment; the price forecast model is to give the economic environment to compute the total profit. Computational experiment is to find the best planning process (optimization) with given situation (price, demand, type of crop, number of farmers, area of field, etc.). The computed plan gives the prescription to the real system; in case that the real system deviates from the expected one, new solution is to be given based on the current situation, which is parallel execution, forming closed loop between the real and artificial systems. The description module is built and adjusted according to the crop data and price data collected from the real system. After the prediction and prescription module, it outputs the instruction on crop planning and recollects the data from the real system to repeat the above processes. This loop continues until the end of cropping period. The components are described below.

#### 3.1 | Artificial system with agent-based modeling

##### 3.1.1 | Problem formalization

Both farmer and crop are modeled as agents. Each individual farmer in a cooperative is defined as an agent. The total number of farmers in the cooperative is  $L$ . The status of a farmer is defined in Equation (1).

$$farmer_k = \{id_k, area_k, schedule_k\}, \quad k = 1, \dots, L. \quad (1)$$

Among them,  $id_k$  is the identification (ID) of a farmer,  $area_k$  is the total planting area of farmer  $k$ ,  $schedule_k$  is a set of crop sequences of farmer  $k$  in the production cycle. For example,  $schedule_k = \{cabbage, tomato, turnip\}$  means that the planting order of farmer  $k$  is cabbage, tomato, and turnip.

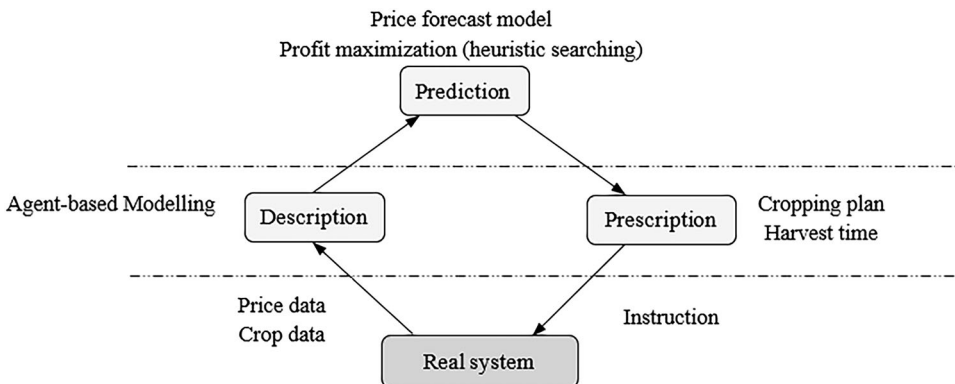


FIGURE 1 Framework of a parallel system for cropping plan

The total number of produced crops is supposed to be  $I$ , with each type being distinguished with an index  $i$ . The attributes of vegetables involved in crop planning are defined in Equation (2), where  $name_i$  is the name of crop  $i$ ,  $family_i$  represents the botanical family of crop  $i$ . The total number of botanic families is  $NF$ .  $pt_i$  is the length of planting duration of crop  $i$ ,  $ht_i$  is the length of a harvest period of crop  $i$ ,  $c_i$  is the cost per hectare of planting crop  $i$ ,  $y_i$  is the yield per hectare of crop  $i$ ,  $D_i$  is the total demand of crop  $i$ ,  $price_{ij}$  is the price of crop  $i$  at time  $j$ , and  $Dn_i$  is the demand that has not been completed under the current crop plan of all farmers.

$$crop_i = \{name_i, family_i, pt_i, ht_i, c_i, y_i, D_i, price_{ij}, Dn_i\}, \quad i = 1, \dots, I, \quad j = 1, \dots, J. \quad (2)$$

The predicted monthly price,  $price_{ij}$ , is used to guide the overall scheduling plan. The main parameters in the model are shown in Table 1.

### 3.1.2 | Price forecast model

Prices of different scales have different characteristics. The monthly average price reflects the overall trend of price in a year, while the weekly average price gives a more detailed indication of changes in a short period. The accuracy of weekly or monthly price forecasts over a long period is poor.<sup>12</sup> Fortunately, 3 or 4 months is enough to cover the growth period of most crops. Therefore, monthly price prediction can be used for crop planning. For the initial plan, the monthly average price of crops in the past few years is selected to express the change of price data within 1 year, which can well reflect the trend of price, eliminating the influence of random disturbance. The price information at a finer temporal scale, weekly price, is used for short-term crop harvest decision.

The time series decomposition tool Seasonal and Trend decomposition using Loess (STL) was used to analyze the information in the weekly average price (Supporting Information).<sup>46</sup>

The STL decomposition on the weekly price data shows that they are nonstationary time series with strong random volatility, thus the ARIMA model is not suitable. Hence, the Gradient Boosting Decision Tree (GBDT) algorithm<sup>47</sup> is applied to forecast the weekly price.

The weekly average price of the first 20 weeks is used to predict the price of the next week. The weekly price data from July 9, 2014 to October 9, 2019 and from October 10, 2019 to April 29, 2020 are used as the training set and testing set, respectively. Storable and nonstorable products are distinguished for price prediction.

## 3.2 | Computational experiment for crop planning

### 3.2.1 | Objective and constraints

For farmers, a 0–1 linear crop planning model is established. The objective of crop planning is the maximum of the total profit, as below.

$$\max P = \max \sum_{k=1}^L \sum_{i=1}^I \sum_{j=1}^J \pi_{ij} a_k x_{ijk}. \quad (3)$$

TABLE 1 Attributes in descriptive models

Notions	Descriptions	Unit
$L$	Total number of farmers	–
$J$	Total length of crop planning cycle	Month
$P$	Total profit of all farmers	CNY
$a_k$	The area of land owned by farmer $k$	Hectare
$I$	Total number of crops	–
$NF$	Total number of botanic families in crops	–
$F(p)$	A set of crops in the botanic family $p$	–
$\pi_{ij}$	The profit of crop $i$ planted in month $j$	CNY/hectare
$pt_i$	The total planting period of crop $i$	Month
$ht_i$	The harvest period of crop $i$	Month
$c_i$	Cost per hectare of planting crop $i$	CNY/hectare
$y_i$	Yield per hectare of crop $i$	kg/hectare
$price_{ij}$	The monthly price of crop $i$ at time $j$	CNY
$D_i$	Total demand of crop $i$	kg

Equation (3) shows that the goal of the crop planning model is to maximize the total income of the cooperative as a whole, where  $\pi_{ij}$  is the profit of crop  $i$  planted in month  $j$ ,  $a_k$  is the area of land owned by farmer  $k$ ,  $x_{ijk}$  is the decision variable: if farmer  $k$  plants crop  $i$  at time  $j$ , it is 1, otherwise it is 0.

For single harvest crops,  $\pi_{ij}$  is calculated as shown in Equation (4), where  $c_i$  is the cost per hectare of planting crop  $i$ .

$$\pi_{ij} = price_{i(j+pt_i)} y_i - c_i. \quad (4)$$

For multiple harvest crops, the calculation of  $\pi_{ij}$  is shown in Equation (5), where  $ht_i$  is the harvest period of crop  $i$ ,  $y_i(t)$  is the distribution of crop yield during harvest period. In this paper, it is simply assumed that the yield of multiple harvest crops is uniformly distributed in the harvest period, although with crop models, the yield can be estimated according to climate data.<sup>32</sup>

$$\pi_{ij} = \sum_{t=j}^{ht_i} price_{it} y_i(t) - c_i. \quad (5)$$

The constraints of the model can be defined as follows:

$$\sum_{i=1}^I x_{ijk} = 1, \quad k = 1, \dots, L, \quad j = 1, \dots, J, \quad (6)$$

$$\sum_{i \in F(p)} \sum_{r=0}^{pt_i} x_{i(j-r)k} \leq 1, \quad p = 1, \dots, NF, \quad j = 1, \dots, J, \quad k = 1, \dots, L, \quad (7)$$

$$\sum_{i=1}^I \sum_{j=1}^J pt_i x_{ijk} \leq J, \quad k = 1, \dots, L, \quad (8)$$

$$\sum_{k=1}^L \sum_{j=1}^J y_i a_k x_{ijk} \geq D_i, \quad i = 1, \dots, I. \quad (9)$$

Constraint (6) ensures that each farmer can only plant one crop at a specific time.

Constraint (7) requires that the crops of the same botanic family cannot be planted sequentially.

Constraint (8) limits the total time of the crop planning of each farmer, where  $pt_i$  is the total planting period of crop  $i$ ,  $J$  is the total length of crop planning cycle. Thus, the total crop planning time of farmer  $k$  does not exceed the scheduling period  $J$ .

Constraint (9) ensures that the yield of crop  $i$  produced by all farmers under the current crop plan can exceed the crop  $i$  orders accepted by cooperatives, where  $y_i$  is the yield per hectare of crop  $i$ ,  $a_k$  is the area of land owned by farmer  $k$ , and  $D_i$  is the total demand of crop  $i$ .

### 3.2.2 | Profit maximization

Heuristic searching of a feasible solution is applied. Searching is done by adding or deleting schedule sequences. In doing so, the agents judge the status of themselves and the system: **average\_check** is used to check whether the profit per hectare exceeds the overall profit per hectare; **pt\_check** is to check whether the total planting time exceeds the limit of crop planning period; **demand\_check** is to check whether the demand of all crops has been met.

The calculation of average profit of the farmer  $k$  with  $schedule_k$  is shown in Equation (10), where  $average_k$  is the average profit of the farmer  $k$  with  $schedule_k$ ,  $pt_i$  is the length of planting time of crop  $i$ .

$$average_k = \sum_{i=1}^{schedule_k} \pi_{it}, \quad \text{where } t = \sum_{m=1}^{i-1} pt_m. \quad (10)$$

When the farmer agents add crops to their own crop sequence, they can select according to the net profit per month of crops **profit\_based** or the uncompleted demand of crops **demand\_based**. To model the complexity of the system, Boltzmann Softmax distribution of profit or demand is used when the agent chooses their crops.<sup>24</sup> This method increases the randomness of agents' choice and makes the model more comprehensive to the actual situation. The Boltzmann Softmax distribution based on profit and uncompleted demand is shown in Equations (11) and (12), where  $P_{profit}(i, j)$  is the probability distribution of agent selecting crop  $i$  based on profit at time  $j$ ,  $P_{demand}(i)$  is the probability distribution of agent selecting crop  $i$  based on uncompleted demand.

$$P_{profit}(i, j) = ((\pi_{ij} y_i - c_i) / pt_i) / \sum_{i=1}^I ((\pi_{ij} y_i - c_i) / pt_i), \quad (11)$$



$$P_{demand}(i) = Dn_i / \sum_{i=1}^I Dn_i. \quad (12)$$

When the agents delete crops from their own scheduling sequence, deletion strategies are generated, respectively. If **average\_check** finds that its own profit is lower than the average value, it will delete the crop with the smallest net income per month and its follow-up in the crop plan, which is **average\_based**. If **pt\_check** finds that the total planting time exceeds the crop planning period, the crop with the longest growth period and its follow-up are deleted, which is called **pt\_based**.

The algorithm can be described as below.

- (a) *Initialization*: The crop sequence of all agents was randomly initialized to meet the constraints (6)–(8).
- (b) Agents first do **average\_check**. If their profit exceeds the average profit of all the agents, they do not update their own schedule. Otherwise, they do **average\_based**.
- (c) Agents do **demand\_check**, if there are still some crops not meeting the demand, they do **demand\_based** to select crops; if not, they do **profit\_based** to select.
- (d) Agents do **pt\_check**. If it is far less than the crop planning period, do the selection above; if it exceeds the scheduling cycle, do **pt\_based**; if the total planting time of the agent  $k$  is very close to the crop planning period  $J$ , as shown in Equation (13), the update will end.

$$0 \leq J - \sum_{i \in \text{schedule}_k} pt_i \leq 1. \quad (13)$$

- (e) In each iteration of the system, all agents update their crop schedule in order according to steps (b)–(d).

The workflow is shown in Figure 2.

When solving the crop planning problem based on agent-based method, the convergence of the algorithm depends on whether and when the scheduling system enters into the end-less loop.

### 3.3 | Parallel running

Under the framework of parallel management, when the external conditions change during planting, the crop schedule should be adjusted according to the actual situation. Two different scales of adjustment strategies are designed in this study.

#### 3.3.1 | Decision on replanning

If the crop schedule needs to be adjusted during planting, the crops that agent has planted before the current month are fixed already in its crop schedule. The coming action is re-optimized starting from the current situation. For the actions of the agent, the **average\_based**

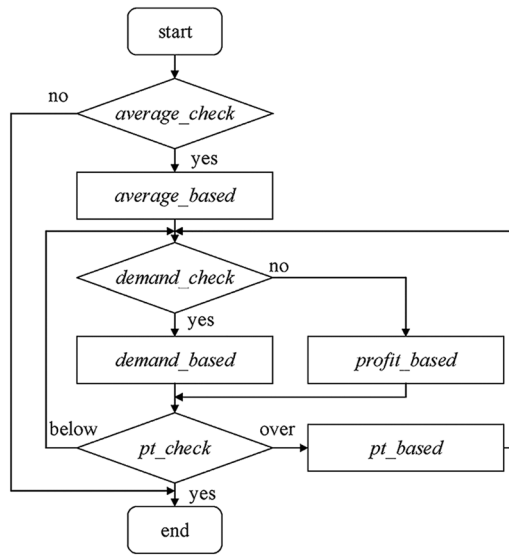


FIGURE 2 Heuristic searching of farmer's crop schedule

is changed to delete the crop with the smallest net income per month and its follow-up in the changeable crops, the **pt\_based** is changed to delete the crop with the longest growth period and its follow-up in the changeable crops. Then, the agent updates its own scheduling plan in the iterative process according to Figure 2.

There are many scenarios of crop planning adjustment, such as adjusting crop demand, adding or deleting crop types, and some crop prices fluctuate strongly. Accordingly, the corresponding parameters in the algorithm will update and make effect. For example, the abnormal price fluctuation will influence the price in the next few months and trigger the following plan adjustment: if the price of crop  $i$  in the month  $m$  fluctuates, the monthly price of the next year  $price'_{ij}$  will change according to Equation (14). Let  $\gamma$  represent the level of the abnormal fluctuation, it is calculated according to Equation (15), where  $realPrice_{im}$  is the abnormal price of crop  $i$  in month  $m$ . Under more general case, the price forecast model should be updated automatically according to monitored data.

$$price'_{ij} = (1 + \gamma)price_{ij}, \quad (14)$$

$$\gamma = (realPrice_{im} - price_{im})/price_{im}. \quad (15)$$

### 3.3.2 | Decision on final harvest date

The above adjustment of the crop schedule is based on the monthly average price, and the temporal scale is a month. With the weekly average price, one can help make a finer scale of adjustment. On the basis of the predicted weekly average price from the GBDT algorithm, the exact harvest week during that month can be decided, so that farmers can harvest crops in the week with the highest forecast price.

## 4 | CASE STUDY

We worked on an agricultural cooperative with 30 farmers ( $L = 30$ ). The planting area (in hectare) of farmers in the cooperative is from the literature.<sup>25</sup>

$$a = [1.07, 0.87, 0.73, 1.07, 0.6, 1.2, 0.93, 1, 1.13, 0.53, 0.6, 1, 0.53, 1, 0.8, 0.93, 0.8, 0.53, 0.8, 0.8, 0.53, 0.53, 1.2, 1, 0.73, 0.8, 0.6, 0.8, 0.73, 0.73].$$

The types of vegetables are selected from 13 common crops in Beijing agricultural products market, and the specific information of crops is shown in Table 2. Among them, harvest period is mainly used to distinguish single harvest and multiple harvest crops, where “–” represents single harvest and other numbers represent corresponding harvest period (between the first and last harvest time); the demand can be adjusted according to actual orders of the cooperative, but the overall demand cannot exceed the production capacity of cooperative.

The price data are from “China National Agricultural Product Price Database.” We chose 13 common crops: pakchoi, broccoli, cabbage, turnip, lettuce, Chinese watermelon, cucumber, green bean, tomato, green pepper, potato, eggplant, and celery. The daily price records of crops in Beijing Xinfadi Agro Wholesale Market (the biggest market in Beijing) from January 1, 2014 to October 31, 2020 are obtained from the website.

For each crop product, a total of 82 monthly average price data and 357 weekly average price data are obtained.

## 5 | RESULTS

### 5.1 | Price data analysis and prediction

Product price of long-term and short-term storage is distinguished, the latter is further distinguished for fruit and leafy product (Supporting Information, Figures 1–3). Figure 3 shows the average monthly and weekly price for potato (long-term storage), cucumber (short-term storage and fruit vegetable), and pakchoi (short-term storage and leaf vegetable), respectively. Both show similar trends, but the weekly price shows more detail.

For the short-term storage products like turnip, potato, and Chinese watermelon, the average price remains relatively stable within 1 year, with a soft peak around April. For short-term storage fruit vegetables like cucumber, tomato, green bean, green pepper, and eggplant, the monthly average price of these crops fluctuates greatly within 1 year, reaching the peak around Spring Festival (usually around February) and the bottom around May (starting of open-field products). For short-term leaf vegetables, such as pakchoi and lettuce, the monthly average prices are similar to those of fruit vegetables. However, the peak is around August and the bottom is around April.

The GBDT method is used for weekly price with and without considering the seasonal components, both of them are tested five times, respectively. The mean value of the mean absolute errors (MAEs) on the testing set for each crop is shown in Table 3, with (MAE\_1) or without (MAE\_2) considering the seasonal components.

The MAEs of tomato, green bean, and green pepper with a strong periodicity of prices have large differences. Thus, the prediction accuracy can be improved by stripping off the seasonal

TABLE 2 Parameter values involved in the agent-based model

Crop name	Botanic family	Planting time (month)	Cost (CNY ha <sup>-1</sup> )	Yield (kg ha <sup>-1</sup> )	Harvest period (month)	Demand (kg)
Pakchoi	<i>Brassicaceae</i>	1	27,000	21,000	–	100,000
Broccoli	<i>Brassicaceae</i>	4	54,000	36,000	–	100,000
Cabbage	<i>Brassicaceae</i>	5	30,000	45,000	–	100,000
Turnip	<i>Brassicaceae</i>	4	21,000	49,500	–	100,000
Lettuce	<i>Compositae</i>	2	37,500	30,000	–	100,000
Chinese watermelon	<i>Cucurbitaceae</i>	3	60,000	63,000	1	150,000
Cucumber	<i>Cucurbitaceae</i>	4	73,500	45,000	2	100,000
Green bean	<i>Leguminosae</i>	4	75,000	25,500	2	100,000
Tomato	<i>Solanaceae</i>	5	82,500	48,000	2	100,000
Green pepper	<i>Solanaceae</i>	4	50,000	27,000	1	100,000
Potato	<i>Solanaceae</i>	4	30,000	30,000	–	100,000
Eggplant	<i>Solanaceae</i>	5	71,000	52,500	3	100,000
Celery	<i>Umbelliferae</i>	4	27,000	31,500	–	100,000

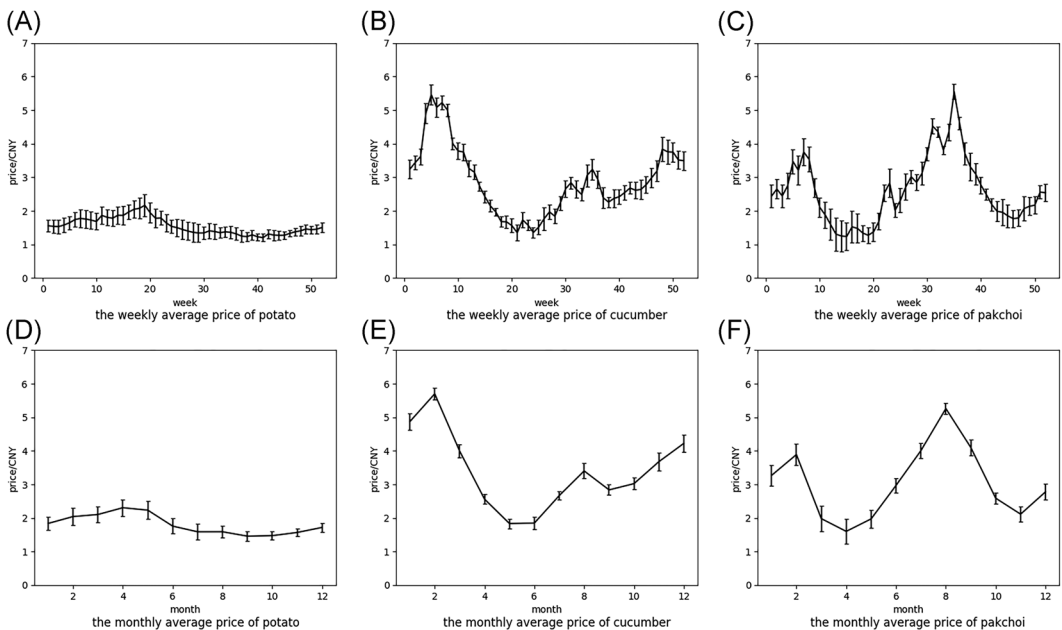


FIGURE 3 The weekly and monthly average price for potato, cucumber, and pakchoi

TABLE 3 Comparison of MAEs of various crops using the GBDT method

Crop	Cucumber	Tomato	Pakchoi	Broccoli	Cabbage	Turnip	Lettuce
MAE_1	0.65	1.00	0.57	0.25	0.16	0.13	0.35
MAE_2	0.53	0.64	0.43	0.42	0.20	0.13	0.47
Crop	Chinese watermelon	Green bean	Green pepper	Potato	Eggplant	Celery	
MAE_1	0.12	1.05	0.86	0.27	0.39	0.24	
MAE_2	0.19	0.77	0.47	0.38	0.50	0.22	

Abbreviations: GBDT, Gradient Boosting Decision Tree; MAE, mean absolute error.

components when the seasonal components are high. For other crops the MAE\_1 and MAE\_2 are similar. Therefore, the predicted weekly average price is given using the GBDT with a smaller MAE on the testing set. The real and the predicted values with smaller MAEs for each crop are shown in Figure 4.

5.2 | Results of computational experiment

The iterations with the maximum total profit are shown in Figure 5. At the beginning, the total profit of farmers rapidly increased and gradually reached the convergence, or fell into a dead loop. Thus, the heuristic algorithm with 200 iterations is repeated 50 times to prevent the iteration process falling into the endless loop. The stable values of different iterative processes differ among the final convergences, since the algorithm may converge to a local optimal value of the scheduling problem.

The crop schedule will be given when the total profit reached the maximum value (Figure 5). The maximum value of the total profit is expected to be 7.5 million CNY, and the crop schedule under this profit is shown in Figure 6. It can be seen that with heuristic searching, the cropping plan can be produced automatically, otherwise, which is a very time-consuming procedure.

5.3 | Repanning on price fluctuation

Experiment is designed to show the autonomous adaption of the crop schedule. Assume that the monthly average price of green bean increases from 7.2 to 12.5 CNY/kg at the third month. According to the presented process, the crop schedule adjustment is carried out to get a new crop schedule shown in Figure 7, where the gray part means the already fixed schedule, while the blank part is recalculated plan. Due to the rising price of green bean, the planning frequency of green bean in the new crop schedule increases significantly.

The profit before and after crop schedule adjustment is shown in Figure 8. The profits of the two crop schedules are identical in the first 3 months, and begin to differ in the fourth month. Although the profit before adjustment maybe higher during middle months, the total profits of the original and adjusted crop schedule are 7.9 and 8.8 million CNY, respectively, showing that the algorithm can improve farmers' income based on price changes.

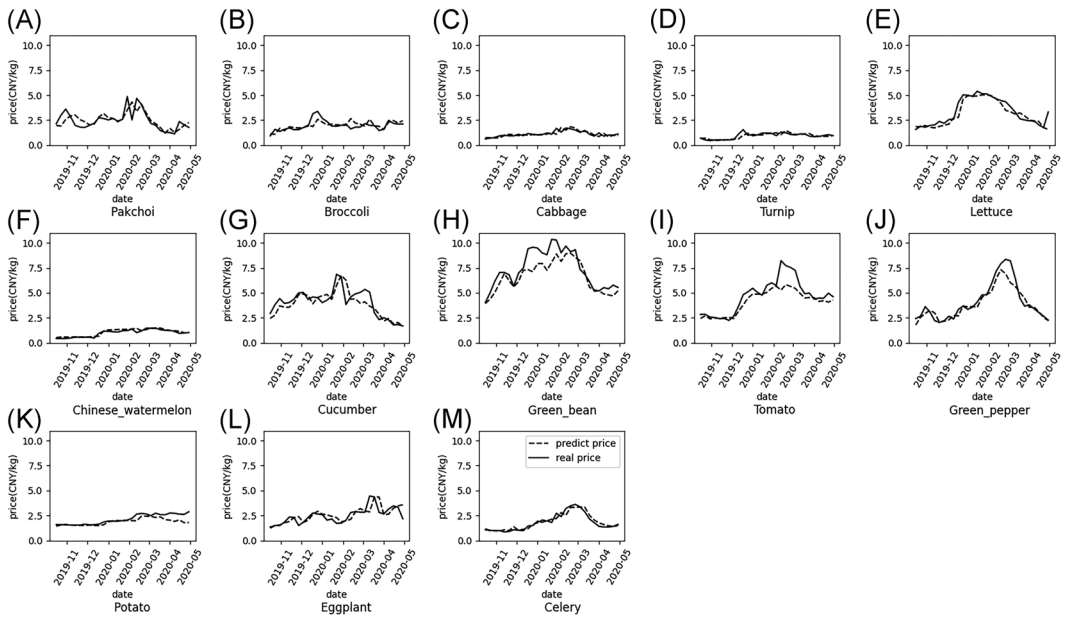


FIGURE 4 The real and the predicted weekly prices for each crop

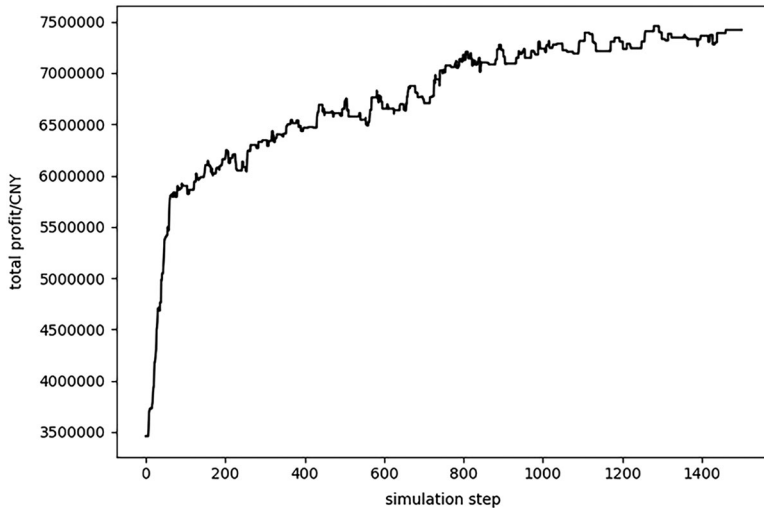


FIGURE 5 Iterative process maximizing the total profits

## 5.4 | Decision on harvest time

While the cropping plan is computed based on monthly price, at harvest time, the weekly price is referred. The harvest time adjustment is about the decision on crop schedule according to the weekly price. In computing the final profit, initially, for single harvest crops, the weekly price of the last week of the growth period is chosen, and for multiple harvest crops, the weekly price corresponding to the harvest period is used. The total profit before the harvest time adjustment is 8.8 million CNY. Given that there is some flexibility for harvest time. That is, crop can be

number	area/ha	1	2	3	4	5	6	7	8	9	10	11	12
1	1.07	lettuce		pakchoi		cucumber			pakchoi		cucumber		
2	0.87	lettuce			green bean				cabbage				
3	0.73	pakchoi	Chinese watermelon		pakchoi	lettuce			pakchoi		cucumber		
4	1.07		green pepper			turnip					cucumber		
5	0.6	pakchoi	Chinese watermelon			broccoli					cucumber		
6	1.2	pakchoi	lettuce			potato			pakchoi		cucumber		
7	0.93	pakchoi	lettuce			potato			pakchoi		cucumber		
8	1		Chinese watermelon			green pepper			pakchoi		cucumber		
9	1.13	lettuce		pakchoi		celery			pakchoi		cucumber		
10	0.53	pakchoi	Chinese watermelon		pakchoi			cucumber			lettuce		
11	0.6	pakchoi		green bean		lettuce		pakchoi			cucumber		
12	1	lettuce			celery			lettuce			turnip		
13	0.53	pakchoi	lettuce		Chinese watermelon			pakchoi	lettuce		pakchoi	lettuce	
14	1		Chinese watermelon		broccoli				lettuce		pakchoi	lettuce	
15	0.8	pakchoi	lettuce			celery			pakchoi		cucumber		
16	0.93		lettuce	pakchoi	lettuce		pakchoi	lettuce			cucumber		
17	0.8		lettuce			tomato			pakchoi		green bean		
18	0.53		Chinese watermelon		lettuce		pakchoi	lettuce		pakchoi	lettuce		
19	0.8		Chinese watermelon			celery			pakchoi		green bean		
20	0.8		Chinese watermelon			cabbage					green pepper		
21	0.53	pakchoi	lettuce			potato			pakchoi		green bean		
22	0.53		lettuce	pakchoi	lettuce		pakchoi	lettuce		pakchoi	Chinese watermelon		
23	1.2		Chinese watermelon			broccoli					eggplant		
24	1		Chinese watermelon		pakchoi	lettuce		pakchoi	lettuce		pakchoi	lettuce	
25	0.73			eggplant				lettuce	pakchoi		cucumber		
26	0.8		lettuce	pakchoi	lettuce		pakchoi		cucumber			lettuce	
27	0.6		lettuce			tomato			pakchoi		green bean		
28	0.8		lettuce			tomato			pakchoi		potato		
29	0.73		Chinese watermelon			green pepper			pakchoi		cucumber		
30	0.73	pakchoi	lettuce			cabbage					green pepper		

FIGURE 6 Crop schedule for 30 farmers in 12 months, with the total profit in Figure 5

harvested earlier or later without harming its quality, if the week of highest weekly price for the single harvest crop is chosen based on price forecast, the total profit is 9.9 million CNY. The change of the total profit before and after the adjustment of harvest time in 2019 is shown in Figure 9.

## 6 | DISCUSSION

### 6.1 | Comparison on a descriptive model

In this study, the crop planning problem is solved based on parallel method. Compared with the traditional optimization algorithm, the advantage of this method includes skipping the process of analytical mathematical modeling, and being more flexible in adding constraints or changing the parameters, which makes it easy to adapt to the environmental changes. It can generate a suboptimal solution to meet the constraints, which is important for the the situation where the calculation accuracy is not necessarily highest. However, the agent-based algorithm cannot always find the optimal solution of the problem as it may fall into a local minimum, and there is also the problem of unstable calculation results. Therefore, the computational experiments need to be repeated many times to output the scheduling plan with the best total profit. Machine learning algorithm<sup>48,49</sup> can be combined to deal with more complex constraints, which will be the further work of this study.

number	area/ha	1	2	3	4	5	6	7	8	9	10	11	12
1	1.07	lettuce	pakchoi		celery				pakchoi		green bean		
2	0.87	lettuce		green bean				pakchoi		green bean			
3	0.73	pakchoi	Chinese watermelon		lettuce			pakchoi		green bean			
4	1.07		green pepper			pakchoi		lettuce	pakchoi		green bean		
5	0.6	pakchoi	Chinese watermelon					celery			green bean		
6	1.2	pakchoi	lettuce			turnip				potato			
7	0.93	pakchoi	lettuce			cucumber				broccoli			
8	1		Chinese watermelon		lettuce			turnip			lettuce		
9	1.13	lettuce		pakchoi		green pepper			pakchoi		green bean		
10	0.53	pakchoi	Chinese watermelon			green pepper					green bean		
11	0.6	pakchoi		green bean				lettuce	pakchoi		cucumber		
12	1		lettuce			celery			lettuce		green bean		
13	0.53	pakchoi		lettuce			potato		pakchoi		green bean		
14	1		Chinese watermelon				celery		pakchoi		green pepper		
15	0.8	pakchoi		lettuce				cabbage			green bean		
16	0.93		lettuce		pakchoi		lettuce		pakchoi		lettuce		green bean
17	0.8		lettuce				tomato			pakchoi	lettuce		pakchoi
18	0.53		Chinese watermelon			lettuce		pakchoi		lettuce		green bean	
19	0.8		Chinese watermelon			lettuce		pakchoi		lettuce		green bean	
20	0.8		Chinese watermelon				broccoli				cucumber		
21	0.53	pakchoi		lettuce			cabbage				green bean		
22	0.53		lettuce		pakchoi			celery		pakchoi		green bean	
23	1.2		Chinese watermelon				broccoli				eggplant		
24	1		Chinese watermelon					potato		pakchoi		green bean	
25	0.73			eggplant				lettuce		pakchoi		green bean	
26	0.8		lettuce		pakchoi			tomato				green bean	
27	0.6		lettuce				tomato			pakchoi		green bean	
28	0.8		lettuce				tomato			pakchoi		green bean	
29	0.73		Chinese watermelon				potato				cabbage		
30	0.73	pakchoi		lettuce				cabbage				green bean	

FIGURE 7 Crop schedule after adjustment in the third month

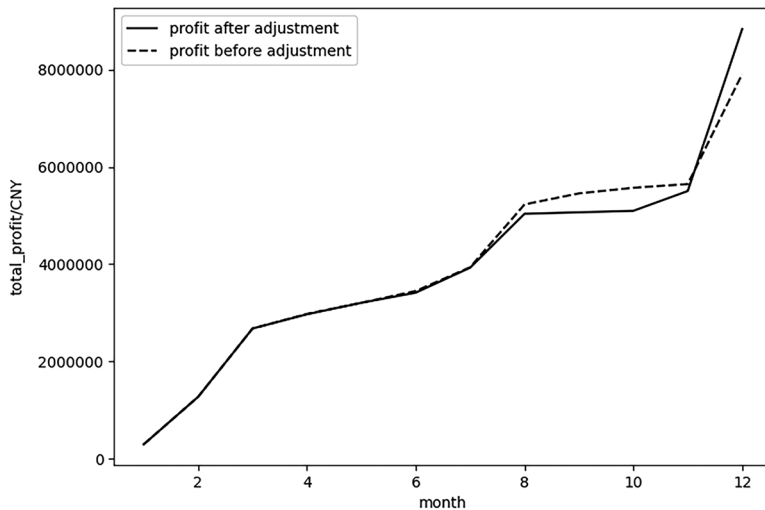
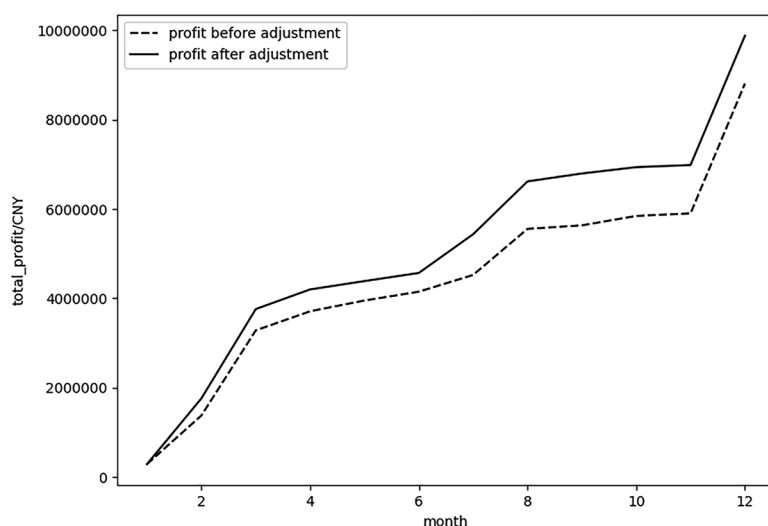


FIGURE 8 Total profit before and after the adjustment of crop schedule

The crop planning method for cooperatives combines the price analysis and forecast of different scales. The monthly average price data are used to solve the overall scheduling plan, and the weekly average price data are used to adjust the harvest time of crops to maximize the profit of the cooperative. In doing so, not only scheduling can be made with price expectation,





**FIGURE 9** Total profit before and after the adjustment of harvest time in 2019

but also the profit can be maximized with weekly and even daily (not introduced here) price forecast. Previous models did not deal with finer temporal scales and can serve only at the beginning of crop planning. The physical factors are not considered here, such as the local climate conditions. This could be solved by coupling a knowledge model of crop growth<sup>50</sup> containing the environment and suitable cultivar information. Given ecological, physical, and economic information, different weights can be allocated in building the constraints.<sup>51</sup>

## 6.2 | Product price: The key indicator of supply–demand balance

Price contains rich information related to crop production. For the nonstorable crops, the fruit vegetables such as cucumber, green bean, tomato, green pepper, and eggplant, the prices fluctuate significantly with strong periodicity. This may be partly because fruit vegetables are more dependent on the temperature and light. In winter, the planting cost is higher due to higher energy consumption and lower growth speed. Besides, random fluctuation components in the price are high for these crops due to the planting complexity and storage difficulty. Pakchoi and lettuce, as fast-growing leafy vegetables, also have obvious periodicity, possibly due to their short growth period. Usually, these kinds of crops will be planted in large quantities in the suitable growth period, which will make their prices drop obviously when they are harvested. Therefore, the seasonal components of the price of fast-growing leafy vegetables are closely related to the growth period of the crop. Of all the crops, the prices of Chinese watermelon, potato, and turnip are most stable. This is due to their storable characteristic. They can maintain a relatively stable price even in the harvest period. Interestingly, the overall vegetable prices did not fluctuate significantly in the early 2020, at the outbreak of COVID-19.

The idea of real-time adjusting crop schedule according to market price is similar to the industrial system. In industry, Manufacturing Execution System (MES) is responsible for implementing the production plan, collecting the data generated in the production process, and reporting it to the enterprise resource planning (ERP) layer. Then the ERP layer

formulates and adjusts the production plan according to the information of production and market demand.<sup>52</sup> However, there is a big difference between industry and agriculture, that is, the time of the feedback of information and the adjustment of production plan. The acquisition cycle of feedback information is too long to flexibly adjust the agricultural scheduling plan, not to mention that the crops cannot be changed since they have been planted on the fields. With the forecast of price data at different scales, the adjustment is more data based. When the price of a certain crop fluctuates, the agent-based algorithm can be rerun to adjust the global scheduling plan. Furthermore, the harvest time of crops can be adjusted according to the predicted weekly average price. This kind of detailed adjustment is not involved in the other related works.<sup>25</sup>

### 6.3 | Price is the environment or the result of agent behavior?

Through the observation of the actual price fluctuation, it is often found that after a large sharp rise, the price will drop seriously, even lower than the price of the same period in previous years. This maybe partial due to the blind “catch-up” psychology of growers. When the price is very high, many farmers begin to plant this crop. When a large number of crops come into the market, the price will drop seriously. Although the frequent implementation of scheduling adjustment can better complete the price fitting, they may cause further “catch-up” phenomenon and affect the total profit.<sup>25</sup> Such phenomenon can be modeled through game theory<sup>53</sup> where conflict may exist, and the price become an emergent property of the system. In that case, to predict the price only is not sufficient. Instead, the price pattern, such as low variation of price, can be set as target and guide the behavior of individual participants through reinforcement learning. The best prediction of the future is to create the future, especially for a human-involved system. The agent-based crop planning model, as presented in this study, will be useful in computing the reward in reinforcement learning for a target price pattern.<sup>54</sup>

### 6.4 | Conditions for a closed loop in parallel management

For parallel management, there must be a closed information loop, including planning, preparation, production, and evaluation. While the planning system provides the recommendation to farmers, the decision of farmers, the actual planting and harvest dates, planting area, and the final yield are preferably noted and give feedback for evaluation. Such information should be part of a product tracing system that can promote the reliability of the product; application of block train techniques<sup>55,56</sup> help further in building the transparency of field production. Otherwise, the field activity remains black-box as it is, which causes information inconsistency for markets and third-party service (e.g., insurance). Farmers may be not willing to record the planting information by hand. In such case, making the best use of mobile phones, which are very common in countryside, can provide information with little effort, such as the land use.<sup>57</sup> However, in practice, a challenge is that farmers may not accept the recommended planning because of the lack of trust. Delivering explainable recommendation instead of simply the result could increase the acceptance as proved in other domain.<sup>58</sup>

## 7 | CONCLUSION

The crop planning problem is solved under the framework of parallel management. The cropping plan is produced during planting based on two different temporal scales of price. The monthly average price is used to guide the formulation of the whole cropping plan; if the monthly average price fluctuates sharply, the agent-based algorithm can update the following plan. The predicted weekly average price is used to decide the harvest time of the crop, to ensure that the crops are harvested at the highest price. Better profit is achieved with such adaptive planning. This method can support agricultural cooperatives with decision making on crop planning, by making full use of the price information.

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## SUPPORTING INFORMATION

Additional supporting information may be found in the online version of the article at the publisher's website.

**How to cite this article:** Fan M, Kang M, Wang X, Hua J, He C, Wang F-Y. Parallel crop planning based on price forecast. *Int J Intell Syst.* 2021;1-22. doi:[10.1002/int.22739](https://doi.org/10.1002/int.22739)