Prediction of pesticide residues in agricultural products based on time series model in Chengdu, China

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Abstract. Pesticides are chemicals that can improve the efficiency of agricultural production, but also cause harm to human health and the environment. Besides effective supervision means, prevention work is also indispensable for pesticide residue safety in agricultural products. The Shuangliu and Pidu districts of Chengdu, capital city of Sichuan Province, China, were selected as the focus areas. Pesticide residue levels in leafy and starchy vegetables were measured for 15 months, analyzed with paired-sample t-tests to construct four ARIMA time series models. The results showed that pesticide residue levels of different types of agricultural products in the same area as well as those of the same agricultural products in different areas differed within the same time interval. Meanwhile, the pesticide residue levels of different agricultural products and areas showed distinct seasonal characteristics and variations. The ARIMA models were effective for short-term forecasting of agricultural pesticide residue levels. They could be used in related fields to predict crop pesticide residue levels pre-emptively based on actual usage patterns, crop type, season, and other parameters. The findings in this study may help government and traceability agencies releasing early warnings of potential agricultural product pesticide contamination. It may also help mitigate the risk of crop and environmental contamination as well as consumer health endangerment.

1. Introduction
Pesticides are chemicals [1] widely used in agriculture to protect crops from pests, fungi and other factors [2]. Although pesticides can improve agricultural production efficiency [3], [4], they pose health risks to humans [5]–[7] and the environment [8], [9]. According to the sampling inspection of 2018 disclosed by China State Administration for Market Regulation, microbial contamination, and excessive residues of agricultural chemicals as well as veterinary drugs were the major causes for food sample rejection in 2018. The proportion of rejected samples containing excess pesticide and veterinary drug residues ranged from 21% to 25% every quarter [10]. The widespread use of pesticides is responsible for the long-term presence of pesticide residues in soil, air [11], water ecosystems [12]; [9] and human bodies [5], [13]. Potential health problems brought by pesticide exposure include metabolic disorders, diabetes, cancer, organic failure, neuropathy and respiratory diseases [2], [7]. Since the problems caused by pesticide residues are serious worldwide, many countries have set up monitoring systems and legislated to control the use of pesticides.
The pesticide residue detection level in the agricultural product supply chain has gradually increased. However, consumer distrust and poor disclosure of pesticide residue data have prioritized the quality and safety of agricultural products, for which early detection and warning of pesticide residue levels are urgently needed. To analyze pesticide residue levels, most scholars conducted exposure risk assessments and plant uptake models based on mass balance. Wu et al. [14] measured pesticide residue levels in vegetables from Xinjiang during the period of 2010–2014. Pesticide contamination was found to be the most serious risk in January–March, thereafter the levels of contamination tend to decrease. Chen et al. (2011) used a gas chromatography-electron capture detector to determine the concentrations of 22 pesticide residues in fruits and vegetables collected in Xiamen, China from October 2006 to March 2009 [15]. Tesfamichael et al. [16] used 21 pesticides and 99 river basins as inputs for an orderly logistic regression model of the distribution, chemical and watershed properties, and use patterns of pesticides to forecast their residue levels and compartmentalization in riparian surface waters. Rein Legind & Trapp [17] compared different dynamic modelling methods of plant uptake and proposed a new model concept for plant uptake model. This model can identify relevant processes and timescales of processes in the soil-plant-air system. Weiwei used a time-sequence prediction method, i.e., Auto Regressive Integrated Moving Average (ARIMA) model, to monitor and predict organophosphorus pesticide residues in leafy vegetables [18]. Existing pesticide residue prediction methods have problems such as short prediction time and insufficient interpretation of seasonal fluctuations in crop pesticide residue levels.

The advent of Internet and big data has made it possible to analyze and predict pesticide residues in crops. Based on the theoretical and empirical data provided by traceability testing institutions, this study established an ARIMA model for predicting pesticide residue levels. The ARIMA model, proposed by Box and Jenkins in 1970, is a classical time series model consisting of observational data recorded in chronological order. Time series data in agriculture, business, economics, medicine, and other fields show patterns, trends, seasonal fluctuations, irregular cycles, and variability. Time series analysis infers dynamic data patterns, which can be used to predict future trends [19]. It has been widely used in various fields and has high accuracy and applicability. Previous scholars used it to monitor and predict organophosphorus pesticide residues in leafy vegetables, demonstrating that time series analysis could serve as an effective tool for comprehensive food contamination monitoring and prediction [18]. This study aims to overcome the limitations of monitoring and predicting pesticide residues through modelling. The results can be used by relevant government agencies to monitor and predict the pesticide residues in the future and to take further measures to reduce public health risks.

2. Material and methods

2.1. Coverage and condition of study area

Chengdu, capital city of Sichuan Province, China, is situated between 102°54′-104°53′E and 30°05′-31°26′N. It is located at the western edge of the Sichuan Basin and has a subtropical humid monsoon climate with four distinct seasons, each having equal periods of rain and heat. The terrain tilts from northwest to southeast. This dramatic vertical height differential creates a unique geomorphology consisting of 1/3 plain, 1/3 hills, and 1/3 mountains all within the city limits. Substantial regional differences in climate create thermal differentials in the vertical climate zone. Consequently, there are broad local variations in biological resources. They are entirely distributed and yet relatively concentrated throughout the region. These conditions are highly conducive to agricultural development.

Pidu and Shuangliu are situated in the northwest and southwest, to the main urban area of Chengdu respectively. Pidu is a typical agrarian area and is located at the Dujiang Dam irrigation site of the Chengdu Plain. The conditions for raising various crops there are favorable [20]. Shuangliu comprises plains, tableland, hills and landforms. Its rural topography is complex and consists of less plain area than Pidu [21]. In the evaluation of soil organic matter in Chengdu, the soil organic matter content in the Shuangliu District is better than that in the Pidu District [22]. Shuangliu and Pidu differ in terms of their geographical locations and environment characteristics. In this study, Pidu district and Shuangliu district
of Chengdu were selected as the study areas, as shown in Figure 1. Taken together, however, they reflect the trends in pesticide residue level of the crops raised in the surrounding areas of Chengdu.

![Map of Chengdu](image.png)

**Figure 1.** Map of Chengdu.

2.2. Sample selection
Analysis of food safety inspection sampling data for Sichuan Province in 2018 indicated that this region had the highest detection rates of unacceptable pesticide residue levels in vegetable crops. Earlier studies reported that the levels of pesticide residues in leafy vegetables were higher than those in other types of vegetable crops [14], [23], [24]. The growth cycle of leafy vegetables ranges from 30 to 50 days, while that of starchy vegetables is between 90 and 120 days. Pesticide residues decompose more rapidly in starchy than leafy vegetables. Leafy vegetables account for 22.4% of the total vegetable consumption in China [25]. However, potato, a starchy vegetable, had the highest sale in 2017 [26]. Thus, this study examined pesticide residue levels in both leafy and starchy vegetables.

In order to further explore the difference of pesticide residues between leaf vegetables and starchy vegetables, two representative vegetables were selected from each leafy and starchy vegetable. Lettuce and spinach were selected as the representative leafy vegetables in this study as their growth cycles are similar, that is they mature by 10-12 month and tolerate low temperatures. Potatoes and yams served as representative starchy vegetables in this study. Under the unique climate of the Chengdu Plain, potatoes were segregated into the winter variety planted in December and the autumn variety planted in August. Potato has ideal crop research value for being the most consumed starchy vegetable in China. Nevertheless, yam was also evaluated along with potato in this study for maturing generally in autumn and winter as well.

2.3. Data sources
The data used in this study was provided by SD Co., which is the largest traceability service in southwest China. This service uses Internet of Things intelligent detection equipment and provides food suppliers with safety assessment and high-throughput traceability systems for the entire food processing chain.
By now, SD Co. platform has been implemented in 19 cities throughout China. The detection equipment used by SD technology Co. is a rapid detection instrument for pesticide residues. The instrument contains cholinesterase and can quickly detect the residues of organophosphorus and carbamate pesticides. This rapid detector is a new food safety testing equipment developed by referring to the enzyme inhibition rate method in Chinese national standard (GB/t5009.199-2003) and agricultural standard method (NY/t448-2001) and combined with the rapid detection method. Under certain conditions, organophosphorus and carbamate pesticides inhibit the normal function of cholinesterase, and the inhibition rate is positively correlated with the concentration of pesticides. If the inhibition rate of the sample is $\geq 50\%$, it means that the agricultural residue of the sample exceeds the standard.

In this study, SD Co. furnished traceability testing data for the period from July 2017 to November 2018. The database included basic and testing information on agricultural products, buyer/seller trading information, agricultural product distribution data, etc. The data focused on the urban areas of Chengdu and its surrounding suburbs and the agricultural products tested there. The platform data of SD Co. was provided in the form of an open remote database. This study used the MySQL workbench database tool to import and export data remotely. The following information was extracted from the data table: test time, product type, commodity name, actual test value, test result, and regional name. Using the SQL language, select data in the two regions of Shuangliu and Pidu in the same period. The mean and standard deviation of pesticide residues in leafy vegetables and starchy vegetables were calculated on a weekly basis and use these data as the research basis.

2.4. ARIMA model
The model borrows the thinking model of OLAP multidimensional online analysis. The research model framework is shown in Figure 2. Based on time series, we added the agricultural product type dimension and the agricultural product area dimension which are closely related to agricultural product pesticide residues. Thus, a three-dimensional analysis model (time dimension, area dimension and agricultural product type dimension) is constructed. The model can be used to predict the pesticide residues of various agricultural products in different regions at a specific time.

ARIMA comprises several key modelling processes described below [27].

1. Stationarity test
   This assessment determines whether an original time series is stationary. The most commonly used methods are sequence and autocorrelation diagrams and unit root tests. After differential processing of non-stationary sequences, the stationarity of the differential sequences may also be tested using the aforementioned methods.

2. Model identification
   The ARIMA model is usually denoted as ARIMA (p,d,q) where “p” is the order of the autoregressive model, “d” is the degree of differentiation, and “q” is the order of the moving average model. Model identification is the process of determining these ARIMA parameters (p, d, q) based on data analyzes and graphs. The most commonly used ARIMA model identification method is to determine p and q based on the truncation and trailing characteristics of the autocorrelation (ACF) and partial autocorrelation functions (PACF) of the time series. The differentiation process determines the parameter d.

3. Model test
   To verify the usability of the ARIMA model, a white noise test must be run on the model residuals. In this way, it may be determined whether the residuals are completely random sequences. If the result is white noise (completely random sequence), then the residuals contain no useful information and the model passes.

4. Model prediction
   After the model has been constructed and has passed the test, it is used to predict data and these forecasts are compared with the actual values.
3. Results and discussion

3.1. Sample feature analysis

3.1.1. Descriptive statistical analysis. Sample data exported from the database of Chengdu SD Technology Co. Ltd. were used to compile the basic information shown in Table 1.

| Data group | Time span      | Total number of inspections | Pesticide residue level mean average | Average standard deviation |
|------------|----------------|-----------------------------|-------------------------------------|---------------------------|
| Leafy-SL   | 2017.29–2018.46| 13,881                      | 37.26                               | 29.91                     |
| Leafy-PD   | 2017.30–2018.47| 1,879                       | 18.99                               | 22.24                     |
| Starchy-SL | 2017.28–2018.47| 37,906                      | 34.85                               | 32.72                     |
| Starchy-PD | 2017.29–2018.46| 6,631                       | 15.07                               | 17.71                     |

Note: The date format shown here is yyyy.ww. So, for instance, 2017.29 indicates the 29th week of the year 2017. SL=Shuangliu; PD=Pidu.

The sample testing time span varied slightly because of differences in the regions and/or agricultural products. In general, more samples were obtained from Shuangliu than Pidu. The mean data indicated differences in pesticide residue level among regions and crops. These discrepancies require further verification. SD Co. revealed that the Starchy-Pidu data varied the least in terms of pesticide residue level whereas the Starchy-Shuangliu data showed the highest variability in pesticide residue level.
3.1.2. Analysis of crop species and regional differences in terms of pesticide residue level. To compare the characteristic regional and crop pesticide residue levels and identify differences among them, four sets of data were paired by a sample t-test. To maintain a consistent time span throughout, the data analysis was conducted from week 30 of 2017 to week 46 of 2018, a total of 58 weeks. The results are shown in Table 2.

Table 2. Paired sample test.

| Paired Differences | Mean | SD  | SE  | Mean Difference 95% CI | t    | df  | Sig.  |
|--------------------|------|-----|-----|------------------------|------|-----|-------|
| Pair 1 LeafyPD-StarchyPD | -4.06 | 13.96 | 1.67 | -0.73 (0.73, 7.39)    | 2.44 | 69.00 | 0.017 |
| Pair 2 LeafyPD-LeafySL | -17.63 | 16.17 | 1.95 | -21.51 (-21.51, -13.75) | -9.06 | 68.00 | 0.000 |
| Pair 3 StarchyP-StarchySL | -19.37 | 14.91 | 1.80 | -22.95 (-22.95, -15.79) | -10.79 | 68.00 | 0.000 |
| Pair 4 StarchySL-LeafySL | -2.60 | 17.80 | 2.14 | -6.88 (-6.88, 1.67)    | -1.22 | 68.00 | 0.229 |

Sig = 0.017 < 0.05 for Pair 1 means that there were significant differences between the leafy and starchy vegetables in Pidu in terms of their pesticide residue levels. Sig = 0.229 > 0.05 for Pair 4 means that there were no significant differences between the leafy and starchy vegetables in Shuangliu in terms of their pesticide residue levels. Analysis of Pairs 2 and 3 showed that Sig = 0.000. Thus, the pesticide residue levels in the leafy and starchy vegetables significantly differed in both Pidu and Shuangliu.

As a rule, the pesticide residues in the leafy vegetables were higher than those in the starchy vegetables. This conclusion corroborated those reported in previous studies. This is because leaf crops have a short growth cycle, a low pesticide degradation rate, and are more likely to attract pests[24], [28], while underground crops such as tubers, bulbs, corms, straight roots, and rhizomes degrade pesticides relatively quick[14]. Both datasets demonstrated that the pesticide residue levels in the vegetables of Shuangliu were significantly higher than those for the vegetables in Pidu.

3.1.3. Analysis of seasonal variations in crop pesticide residue level. It was necessary to plot various time series in order to observe the relative changes in pesticide residue level among the different regions and agricultural products. Stata software was used to plot summary and comparative time series and detect alterations in the pesticide residue levels of the various agricultural products in different regions. Figure 3 shows a summary time series.

(1) Analysis of time series characteristics of the pesticide residue levels in different agricultural products within the same region.

Figure 4 shows that in Shuangliu the relative changes in pesticide residue level in the leafy and starchy vegetables did not significantly differ after 2018. Both crop categories shared similar peak and trough pesticide residue level phases. At week 37 (September) of 2018, the pesticide residue levels had reached a maximum. The gap between the two pesticide residue levels was relatively large by week 33 (late August) of 2017. For Pidu variability in the pesticide residue level data for the leafy vegetables was significantly wider than that for the starchy vegetables. The latter did not present with any obvious seasonal trends in pesticide residue level.

(2) Analysis of time series characteristics of pesticide residue levels in the same agricultural product grown in different regions.

Figure 5 shows that the trends for the pesticide residue levels were roughly the same for the leafy vegetables in Shuangliu and Pidu. However, the actual pesticide residue levels were higher for the leafy crops in Shuangliu. The trends markedly differed at week 40 (October) of 2017 and week 17 (late April).
of 2018. Figure 6 indicates that the changes in pesticide residue level in the starchy vegetables were relatively stable but presented with frequent cyclical fluctuations. However, the pesticide residue levels in the starchy vegetables of Shuangliu were more variable than those of the same crop type in Pidu. In general, peak pesticide residue levels were most likely to occur in September–October.

**Figure 3.** Summary time series.

**Figure 4.** Comparison time series of different agricultural products within the same area.

**Figure 5.** Comparison time series of the same agricultural product in different regions.
The aforementioned timing chart comparisons disclosed that both the leafy and starchy vegetables presented with the highest pesticide residue levels at ~week 40 (September–October). However, they reached their maxima in Shuangliu at week 30 (July) and their minima in Pidu at weeks 13-17.

3.2. **ARIMA model establishment**

Construction of the ARIMA model involves several key validation steps including time series stability and model identification, order, residual, and prediction. The ARIMA model building process described below is used as an example the pesticide residue level data for the leafy vegetables in Pidu. All modelling results are presented in the final model summary.

3.2.1. **Analysis of seasonal variations in crop pesticide residue level.** The present study used the commonly applied Dickey-Fuller test to determine time series stability. Table 3 shows that the unit root test value \( Z(t) = 0.537 \) was significantly larger than the 5% critical level at the 0.05 significance level. Therefore, the null hypothesis was accepted, the sequence had a unit root, and the timing was non-stationary [29], [30].

| Dickey-Fuller test for unit root | Number of obs=69 |
|---------------------------------|------------------|
| Interpolated Dickey-Fuller      |                  |
| Test Statistic                  |                  |
| 1% Critical Value               |                  |
| 5% Critical Value               |                  |
| 10% Critical Value              |                  |
| \( Z(t) \)                      | -1.492           |
|                                 | -3.553           |
|                                 | -2.915           |
|                                 | -2.592           |

MacKinnon approximate p-value for \( Z(t) = 0.537 \)

As this time series was non-stationary, it was necessary to create a first-order difference in the pesticide residue time series for the leaf class and evaluate its stationarity [29]. The results of the first-order difference unit root test are shown in Table 4:

| Dickey-Fuller test for unit root | Number of obs=68 |
|---------------------------------|------------------|
| Interpolated Dickey-Fuller      |                  |
| Test Statistic                  |                  |
| 1% Critical Value               |                  |
| 5% Critical Value               |                  |
| 10% Critical Value              |                  |
| \( (t) \)                       | -6.279           |
|                                 | -3.555           |
|                                 | -2.916           |
|                                 | -2.593           |

MacKinnon approximate p-value for \( Z(t) = 0.000 \)

After the first-order difference was created, the unit root test result \( Z(t) = 0.00 \) was significantly < 0.05. Thus, the time series had no unit root and was stable. Therefore, after the first-order difference, it was confirmed that the Leafy-Pidu pesticide residue level time series was stationary.

3.2.2. **Model identification and ordering.** The ARIMA model was determined by the autocorrelation and partial autocorrelation coefficients. The time series was deemed stationary after passing the first-order difference. Thus, a coefficient of \( d = 1 \) was verified. A confidence interval map of the autocorrelation and partial autocorrelation coefficients was then plotted. The graph of the autocorrelation coefficient after the first-order difference of Figure 6 and the partial autocorrelation coefficient of Figure 7 clearly show that both parameters were tails. Therefore, it was preliminarily established that this model was an ARIMA (p, q) type.

After an autocorrelation coefficient lag of five units, the ACF stabilized and fell within the confidence interval (CI). Therefore, the initial \( q = 5 \). The partial autocorrelation coefficient was comparatively difficult to assess. Figure 7 indicates that the change in PACF was relatively stable after the lag period of five units. Thus, comparative verifications of \( p = 1, 2, 3, 4, \) and 5 could be made. Table 5 compares the stationary R squares, mean absolute errors, maximum absolute errors, and normalized Bayesian
Information Criterion (BIC). Reading from top to bottom, the models are ARIMA (1, 1, 5), ARIMA (2, 1, 5), ARIMA (3, 1, 5), ARIMA (4, 1, 5), and ARIMA (5, 1, 5).

Figure 6. First-order differential autocorrelation graph.

Figure 7. First-order differential partial autocorrelation graph.

Table 5. Normalized BIC function value comparison table.

| Model  | Model fitting statistic | Stationary R Square | R Square | MAPE  | MAE   | MaxAPE | MaxAE | Normalized BIC |
|--------|-------------------------|---------------------|----------|-------|-------|--------|-------|----------------|
| ARIMA (1, 1, 5)  | .441                    | .922                | 10.868 | 1.719 | 49.183 | 6.471  | 2.125 |
| ARIMA (2, 1, 5)  | .466                    | .926                | 10.386 | 1.699 | 38.112 | 5.758  | 2.158 |
| ARIMA (3, 1, 5)  | .467                    | .926                | 10.457 | 1.699 | 38.019 | 5.744  | 2.235 |
| ARIMA (4, 1, 5)  | .467                    | .926                | 10.471 | 1.699 | 37.928 | 5.731  | 2.314 |
| ARIMA (5, 1, 5)  | .454                    | .924                | 10.536 | 1.709 | 41.210 | 6.317  | 2.417 |
Table 5 reveals that the normalized BIC for the ARIMA (1,1,5) model is smaller than the other four. Therefore, the model is p=1, q=5.

3.2.3. Model test. Figure 8 shows that the autocorrelation coefficients for the ARIMA (1,1,5) model were all within the 0.05 CI, with their absolute values all smaller than 0.2. Thus, the sequence was completely random and residual and the model passed the difference test.

3.2.4. Model prediction. The ARIMA model is superior to the others in terms of short-term forecasts. Model data selection was based on simulation data between week 30 of 2017 and week 43 of 2018. The predictions were made for the interval from week 44 of 2018 to week 47 of 2018 (1 month). Figure 9 shows the simulated predictions made by the model.
Table 6 compares the actual and predicted values from week 44 of 2018 to week 47 of 2018 based on the ARIMA (1,1,5) model and the error analysis.

**Table 6. Leafy-Pidu data prediction error analysis table.**

| Date    | Actual | Forecast | Error | Error rate |
|---------|--------|----------|-------|------------|
| 2018w44 | 27.41  | 29.33    | -1.92 | 0.07       |
| 2018w45 | 27.66  | 29.05    | -1.38 | 0.05       |
| 2018w46 | 23.71  | 28.12    | -4.42 | 0.19       |
| 2018w47 | 23.80  | 27.76    | -3.96 | 0.17       |
| Average error rate | 0.12 |

Figure 9 and Table 6 show that this model had a relatively superior fitting effect. It was comparatively more accurate at predicting and trending the data. Its short-term prediction error rate was relatively low while its long-term prediction error rate was high. The aforementioned prediction results were consistent with the characteristics of the ARIMA model.

### 3.2.5. Other data modeling results

The other three models were constructed using the same techniques and steps as those for ARIMA (1,1,5). Following are the results obtained for the establishment of the other three ARIMA models.

1. **Leafy-Shuangliu pesticide residue level data model**

Pesticide residue level data for the leafy vegetables in Shuangliu were simulated from week 29 of 2017 to week 42 of 2018. Predictions were made from week 43 of 2018 to week 46 of 2018. Multiple data analyze and repeated attempts confirmed that the ARIMA (1,1,1) model best fit the data. Figure 10 shows the convergence of model predictions with actual values.

![Figure 10. Leafy-Shuangliu data model forecast map.](image)

Table 7 compares the actual and predicted values from week 43 of 2018 to week 46 of 2018 based on the ARIMA (1,1,1) model and the error analysis.
Table 7. Leafy-Shuangliu data prediction error analysis table.

| Date     | Actual | Forecast | Error | Error rate |
|----------|--------|----------|-------|------------|
| 2018w43  | 39.84  | 39.40    | 0.44  | 0.01       |
| 2018w44  | 40.03  | 39.23    | 0.80  | 0.02       |
| 2018w45  | 38.90  | 39.10    | -0.20 | 0.01       |
| 2018w46  | 39.57  | 38.99    | 0.58  | 0.01       |

Average error rate 0.01

(2) Starchy-Pidu pesticide residue data model

Pesticide residue level data for the starchy vegetables in Pidu were used to forecast the data from week 29 of 2017 to week 42 of 2018 and week 46 of 2018. The ARIMA (1,0,0) model was obtained by data analysis. Figure 11 shows the simulated predictions made by the model.

Figure 11. Starchy-Pidu data model forecast map.

Table 8 compares the actual and predicted values for the pesticide residue level data from week 43 of 2018 to week 46 of 2018 based on the ARIMA (1,0,0) model and the error analysis.

Table 8. Starchy-Pidu data prediction error analysis.

| Date     | Actual | Forecast | Error  | Error rate |
|----------|--------|----------|--------|------------|
| 2018w43  | 17.80  | 15.95    | 1.84   | 0.10       |
| 2018w44  | 13.73  | 15.78    | -2.05  | 0.15       |
| 2018w45  | 13.57  | 15.63    | -2.06  | 0.15       |
| 2018w46  | 16.37  | 15.49    | 0.88   | 0.05       |

Average error rate 0.11

(3) Starchy-Shuangliu pesticide residue data model
Pesticide residue level data for the starchy vegetables in Shuangliu were simulated from week 28 of 2017 to week 43 of 2018. Data were predicted from week 44 of 2018 to week 47 of 2018. The simulation data indicated that the ARIMA (1,1,0) model had a relatively higher degree of fit. Figure 12 shows the simulated predictions made by the model.

![Figure 12. Starchy-Shuangliu data model forecast map.](image)

Table 9 compares the actual and predicted values of the pesticide residue level data based on the ARIMA (1,1,0) model from week 44 of 2018 to week 47 of 2018 and the error analysis.

| Date    | Actual | Forecast | Error | Error rate |
|---------|--------|----------|-------|------------|
| 2018w44 | 41.48  | 42.01    | -0.53 | 0.01       |
| 2018w45 | 43.55  | 42.05    | 1.51  | 0.03       |
| 2018w46 | 44.24  | 42.09    | 2.15  | 0.05       |
| 2018w47 | 46.23  | 42.13    | 4.10  | 0.09       |
| Average error rate | 0.05 |

Establishment of the model for the four pesticide residue datasets indicated that overall fitting was effective and the predicted value approached the actual value.

(1) The ARIMA model is useful for short-term predictions of the pesticide residue levels in agricultural products and fits the data well. This model showed that time series contained most of the pertinent information on the pesticide residue levels of agricultural products. Therefore, these data may be predicted based on the time series model.

(2) The ARIMA model is best suited for short-term pesticide residue level predictions. However, it is prone to bias in long-term forecasting. Moreover, its forecasting efficacy is substantially reduced by highly volatile data.

(3) The ARIMA model only considers the time series of the pesticide residue level itself and does not predict or account for other factors that could affect the results.
4. Conclusions
In this study, seasonal variations in the pesticide residue levels in leafy and starchy vegetables were investigated from July 2017 to November 2018 in the Pidu and Shuangliu districts of Chengdu, Sichuan, China. The ARIMA model was used to predict short-term pesticide residue levels. Results of paired-sample t-tests revealed several facts. (1) The pesticide residue levels in different agricultural products from the same region varied after the same time interval. The pesticide residue levels in leafy vegetables were generally higher than those in starchy ones, which is in accordance with previous reports [23]. (2) The pesticide residue levels in the same types of agricultural products from different regions differed at the same time interval. The pesticide residue levels in the leafy and starchy vegetables of Shuangliu were significantly higher than those in the leafy and starchy vegetables of Pidu. Spatially, the relatively heavier pollution of heavy metals and higher potential eco-risk in suburban vegetable soils were found in Shuangliu and Pidu. The soil pollution in Shuangliu District is heavier than that in Pidu District, while both are below the Chinese agriculture quality standard (I) for soils [31]. This may explain why the level of pesticide residues in Shuangliu is generally higher than that of Pidu.

Comparative analysis of the time series diagram disclosed that the pesticide residue levels in leafy and starchy vegetables of Shuangliu and Pidu peaked between September and October. In contrast, the pesticide residues in all vegetables reached the lowest levels in Shuangliu during July and in Pidu during April. It is found that pesticide residues have obvious seasonal regularity [32], which is related to crop growth cycle and pest activity. According to the growth cycle of the sample vegetables, starchy vegetables in September and October are usually planted in July and August, when the temperature in Chengdu is the highest and pest activity usually peaks. Therefore, it is speculated that the use of pesticides will increase, leading to the peak of pesticide residues in starchy vegetables in September and October.

According to the data analysis and model predictions, the following suggestions may be provided to the government, traceability monitoring organizations and food purveyors:
(1) Peaks of pesticide residue levels in both leafy and starchy vegetables occur from September to October, during which the government should enhance its monitoring on pesticide residue and food purveyors should also focus more on the quality and safety of agricultural products.
(2) The ARIMA model may help traceability monitoring organizations to predict short-term pesticide residue levels. Forecasting efficacy is expected to increase with time intervals shortening between measurements.
(3) Traceability monitoring organizations should pay close attention to the differences among regions and agricultural products in terms of pesticide residue levels when making short-term predictions.

The findings of this study may help the government and third-party traceability agencies release early warnings of potential agricultural product pesticide contamination. When objective historical data are applied to agricultural product safety warnings, passive feedbacks can turn into active predictions. Based on the predicted results, pre-emptive countermeasures can be taken to ensure and maintain agricultural product safety and quality in order to protect public health, as well as effectively reduce hazards caused by pesticide residue in agricultural products.

The sample data in this study were missing from the agricultural product test data at some time points, so the time granularity could only be divided by weeks instead of being accurate to every day. Therefore, pesticide residue levels predicted by ARIMA models may be inaccurate in some cases. This study only predicted data for four phases. However, the actual time span was one month and the prediction efficacy of ARIMA became comparatively lower for periods longer than one month. In practice, the seasonal trends, and patterns of the pesticide residue levels in vegetables of Chengdu are not as evident as previously predicted, possibly influenced by the climate and soil conditions of Chengdu or insufficient granularity of the time series. Future research can expand the ARIMA model by combining regional climate (temperature, rainfall) and soil pollution.
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