Boffin Access

Open Access Journal | Volume: 1.2

Journal of Water Technology and Treatment Methods

ISSN 2517-7427

Selecting Sprinklers in a Self-Propelled Center-Pivot Irrigation System Based on Calculated Performance Indicators Using Data Mining Algorithms

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Abstract

Water uniformity is affected by sprinklers in a self-propelled center-pivot irrigation system. Thus sprinklers acceptability is very important in water management of such systems. In this paper the objective was focused on the applications of data mining algorithms for selecting a sprinkler based on calculated performance indicators like coefficient of uniformity, distribution uniformity in the low quarter of center pivot irrigation system, application efficiency, application efficiency in the low quarter, gross depth of water applied and the average of weighted depth in low quarter of caught water applied from a center pivot irrigation system. The tested sprinkler types were NelsonD3000 Sprayhead-3TN, Nelson R3000 Rotator-3TN, Nelson S3000 Spinner-3TN, Senninger i-Wob and Senninger LDN. Various data mining classification techniques such as J48, Random tree and Naïve Bayes were utilized. The classification was done by using Weka open source tool. The results were analyzed using training and testing data sets. Random tree gives the highest correctly classified percentage of 100%. Meanwhile, J48 and Naive Bayes give correctly classified percentage of 80% and 60%, respectively for testing data set. This study concludes that the irrigation data mining classification technique become highly active research to select sprayers in a center pivot irrigation system.

Keywords

Center Pivot Irrigation System, Modeling, Coefficient of Uniformity, Algorithms

Introduction

The application of classification in agriculture sector is increasing day by day to improve and increase the production of crops [1]. The classification purposes can be conducted for soil fertility, for crop with season, for soil nutrients for soil data to predict fertility rate, for rice grains, for Mushroom classification and for categorize the quality of cotton seeds [2-8]. Therefore, selecting a classification method that gives acceptable accuracy is very important. Alternatively, selecting an irrigation system can contribute in increasing agricultural production.

The center pivot irrigation system has some advantages including high potential for uniform and efficient water application; high degree of automation; and ability to apply water and nutrients over a wide range of soil, crop and topographic conditions [9]. It comprises a sprinkler pipeline of relatively large diameter, composed of high tensile galvanized light steel or aluminum pipes supported above ground by towers move on wheels, long spans, steel trusses and/or cables. One end of the line is connected to a pivot mechanism at the center of the command area; the entire line rotates about the pivot [10]. The sprayers, computerized sized and spaced for high uniformity of application, are mounted on the pipeline at spacing of 1.5 to 3.0 m, and 6 m approximately according to the type and coverage of the sprayer emitters, and operate when the system is in motion. Pressure/flow regulators are used in most cases. The discharge rate of the sprayers along the pipeline is not the same along the line, but varies from lower values near the center to higher ones towards the outer end by the use of small and large nozzles along the line accordingly and sometimes variable spacing.

Center pivot sprinklers can be classified generally into two broad types –impact sprinklers and spray heads. The operating pressure of most impact sprinklers is in the range of 170 to 280 kPa, but the operating pressure is higher for larger sized nozzles. Impact sprinklers have an advantage because they typically have a large radius of “throw”, thereby having a larger wetted area and smaller instantaneous application rate that can nearly match the soil infiltration rate with fewer runoff and erosion difficulties. Spray heads are a much more diverse classification. They can range from simple nozzles and deflector plates to more sophisticated designs involving moving plates that slowly rotate or types with spinning plates to designs that use an oscillating plate with various droplet discharge

Article Information

DOI: 10.31021/jwt.20181109
Article Type: Research Article
Journal Type: Open Access
Volume: 1 **Issue:** 2
Manuscript ID: JWT-1-109
Publisher: Boffin Access Limited

Received Date: December 13, 2017
Accepted Date: March 10, 2018
Published Date: March 16, 2018

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Citation: Dosary NMA, Ghobari HMA, Aboukarima AWMA, Marazky MSEM. Selecting Sprinklers in a Self-Propelled Center-Pivot Irrigation System Based on Calculated Performance Indicators Using Data Mining Algorithms. J Water Technol Treat Methods. 2018 Mar;1(2):109

angles and trajectories [11]. The most common sprayers in use the last few years are the Senninger's wobblers and the Nelson's rotators [10,12] indicated that Senninger had higher values of coefficient of uniformity of 80–85% than the Nelson of 75–80%.

The application uniformity of water depends on many factors and the main sprinkler factors affecting uniformity are the sprinkler spacing and the sprinkler type, classified pivot coefficient uniformity values as excellent: > 90%, good: 85 to 90%, fair: 80 to 85%, and poor: < 80%. To achieve this, the uniformity coefficient with which the irrigation systems apply water will have to be high [11,13]. The uniformity coefficient of a sprinkler irrigation system directly affects the system's application efficiency and crop yield [14]. Poor distribution uniformity reduces yields due to water stress. It also increases financial and environmental costs [15].

Data analytics plays a vital role for proper irrigation management. In particular, it focuses on selecting the precise variables that have impact on the performance of an irrigation system. Various techniques of data analysis including machine learning methods and other analysis methods have been used for data analysis [13,16-18]. However, the purpose of data analytical tool is used to obtain some significant message obtained from the model that may be effectively applied by the irrigation engineer for evaluation of irrigation system performance.

Data mining is defined as mining the knowledge from large amount of data. The knowledge refers to the useful information prediction from the database using with various data mining techniques. Data mining techniques are having an ability to find the relationship and pattern from existing database [19]. Moreover, data mining involves the use of sophisticated data analysis tools to discover previously unknown, valid patterns and relationships in large data set [20]. Classification and prediction techniques are among the popular tasks in data mining. Unsupervised (clustering) and supervised (classifications) are two different types of learning methods in the data mining [21]. There are many techniques used for classification especially in data mining [22].

Application of data-mining to water management is at a developmental stage and very few research works have been carried out on this domain [23]. Data mining discovers new and practically meaningful information from large datasets. Data mining techniques are having an ability to find the relationship and pattern from existing database [19]. Unlike any typical statistical methods, data mining techniques explores interesting and useful information without having any preset hypotheses.

[24] compared the effectiveness of six different data mining methods namely decision tree, artificial neural networks, systematically developed forest for multiple trees, support vector machine, logistic regression and the traditional evapo transpiration methods and evaluate the performance of these models to predict irrigation water demand using pre-processed dataset. The result indicated systematically developed forest produces the best prediction with 97.5% accuracy followed by decision tree with 96% and artificial neural networks with 95% respectively by closely matching the predictions for water demand with actual water usage. [25] suggested that Naive Bayes and J48 Classification Algorithm could be used for performance analysis of data classification. [26] applied data mining technique that can be able to know soil type and characteristics suitable for the crop cultivation from soil properties. The major concept is to predict the water percentage for irrigation in the soil for agricultural productivities by using data mining methods. To improve water management practices and maximize water productivity, application of data driven models using data mining methods have become very essential [27]. By browsing in literature, these methods have not been used for selection of sprinklers of self-propelled center-pivot irrigation systems.

In recent years, the rapid manufacture of sprayers' technology has made it possible for irrigation engineers to select the precise sprayer with available tool in their hands. With available performance criteria data about sprayers, researchers will be able to classify different sprayers according to different actual performance indicators to discover the relationship between sprayers and performance indicators to identify the best one. Thus, the aim of this study is to collect and pre-process the data set and to apply and compare the effectiveness of accuracies of different data mining algorithms for sprayers' selection based on their performance criteria.

Materials and Methods

Sprayers' data description

The performance data of fifty four low-pressure center pivot sprinkler irrigation systems operating on fields located at four different regions of Saudi Arabia, namely: Riyadh and Qassim, Jouf regions were collected. The regions are classified as hot and dry with desert climate, and the average annual rainfall and evaporation were about 50 mm and 4500 mm respectively [28]. Five sprayer types namely: (NelsonD3000 Sprayhead-3TN, Nelson R3000 Rotator-3TN, Nelson S3000 Spinner-3TN, Senninger i-Wob and Senninger LDN were installed in those systems. The details of experiments to obtain performance criteria of the investigated center pivot sprinkler irrigation systems such as Coefficient Of Uniformity (CU), distribution uniformity in the low quarter of center pivot irrigation system (DU), application efficiency (Ea), Application Efficiency in the Low Quarter (PELQ), gross depth of water applied (Dg) and the average of weighted depth in low quarter of caught water applied from a center pivot irrigation system (Dw) are seen in [29]. Statistical criteria for characteristics of the utilized irrigation systems are shown in Table 1. Meanwhile, Table 2 illustrates statistical criteria for the calculated performance indicator.

Classification technique

Classification is a data mining function that assigns items in a collection to target categories or classes. In data mining, classification is one of the most important tasks. It maps the data in to predefined targets. It is a supervised learning as targets are predefined. The aim of the classification is to build a classifier based on some cases with some attributes to describe the objects or one attribute to describe the group of the objects. Then, the classifier is used to predict the group attributes of new cases from the domain based on the values of other attributes [30]. In the model build (training) process, a

Items	Units	Min	Max	SD	Mean	Skewness	kurtosis
Sprayers spacing	(m)	1.49	2.90	0.36	2.04	0.79	0.61
Pressure	(Psi)	10.00	41.63	5.96	13.68	2.95	10.56
Tower height	(m)	39.50	55.00	4.15	49.90	-1.03	0.63
Discharge rate	(lit/s)	22.35	144.72	27.70	73.29	0.54	-0.14
Discharge losses	(lit/s)	3.03	28.01	5.68	13.94	0.76	0.26
Travel speed	(m/min)	0.83	2.80	0.54	1.66	0.42	-0.91
Wind speed	(km/h)	3.71	28.80	5.12	12.94	0.86	1.13
System age	(---)	1.00	25.00	5.35	14.94	-0.34	-0.58
Relative humidity	(%)	28.40	82.70	11.48	56.54	0.00	0.26
Air temperature	(°C)	15.00	32.00	3.46	26.05	-0.75	0.95

Table 1: Statistical criteria* for characteristics of the utilized irrigation systems

Items	Units	Min	Max	SD	Mean	Skewness	Kurtosis
CU	(%)	61.34	89.46	5.96	80.89	-1.09	1.29
DU	(%)	31.45	81.81	8.97	70.79	-1.86	5.82
Ea	(%)	67.39	89.04	4.29	80.72	-0.73	1.69
PELQ	(%)	24.75	76.49	8.59	58.09	-1.15	3.41
Dg	(mm)	2.76	15.36	2.32	7.59	0.29	1.83
Dw	(mm)	4.75	22.16	3.13	11.03	0.77	2.81
No. of systems	54	54	54	54	54	54	54

Table 2: Statistical criteria for the calculated performance indicator of the utilized systems

classification algorithm finds relationships between the values of the predictors and the values of the target. Different classification algorithms use different techniques for finding relationships. These relationships are summarized in a model, which can then be applied to a different data set in which the class assignments are unknown. Classification models are tested by comparing the predicted values to known target values in a set of test data. The data for a classification purpose is typically divided into two data sets: one for building the model; the other for testing the model

Procedures

Dataset having 7 attributes as coefficient of uniformity, distribution uniformity in the low quarter of center pivot irrigation system, application efficiency, application efficiency in the low quarter,gross depth of water applied and the average of weighted depth in low quarter of caught water applied from a center pivot irrigation system and sprinkler type. The data set consists of total 54 instances. Sprinkler type is class label which categorized as NelsonD3000 Sprayhead-3TN, Nelson R3000 Rotator-3TN, Nelson S3000 Spinner-3TN, Senninger i-Wob and Senninger LDN.

Weka 3-6-13 (Waikato Environment for Knowledge Analysis) open source data mining tool is used for experiment. The easiest way to use Weka is through a graphical user interface called Explorer. This gives access to all of its facilities using menu selection and form filling. Moreover, Weka workbench is known as easy-to-use and robust software for data mining [31]. All algorithms take their input in the form of a single relational table in the ARFF format.

The sprinkler type dataset is allowed to open in Weka as shown in Figure 1. After opening sprinkler type dataset in Weka, apply classification technique by using Classify tab and then choose J48 algorithm, Random treeand Naïve Bayes. Evaluation of algorithms was done with its default parameters defined in Weka application. For the purpose of training and testing, dataset is split into 44 instances for training and 10 instances for testing.

Random tree

Random tree (decision) algorithm of classification is used to generate rules for sprayer's classification. Decision trees are a simple, but powerful form of multiple variable analyses. The tree consists of internal nodes where a logical decision has to be made, and connecting branches that are chosen according to the result of this decision. The nodes and branches that are followed constitute a sequential path through a decision tree that reaches a leaf node (final decision) in the end [26].

Naïve Bayes

A Naive Bayes classifier is one of the classifiers in a family of simple probabilistic classification techniques in machine learning. It is based on the Bayes theorem with independence features. Each class labels are estimated through probability of given instance. It needs only small amount of training data to predict class label necessary for classification [32,33].

J48 (C4.5)

Based on Weka J48 is class for generating a pruned or unpruned C4.5 decision tree. The J48 is one of the classification-decision tree

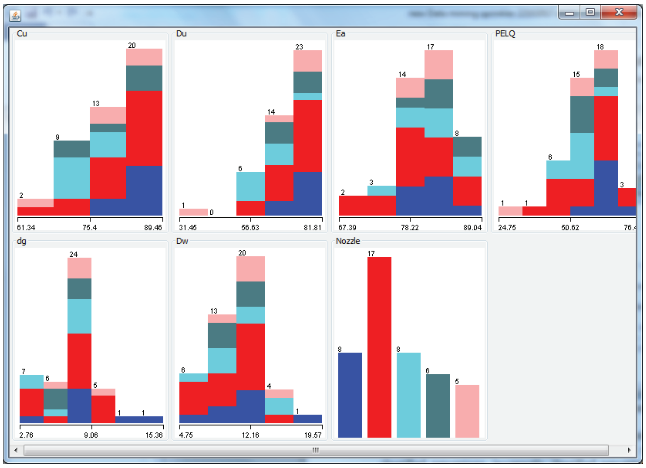

Figure 1: Sprinkler type dataset open in Weka.

algorithm and it slightly modified from C4.5 in Weka. It can select the test as best information gain. This algorithm was proposed by [34]. C4.5 is also referred to as a statistical classifier. J48 predicts dependent variable from available data. It builds tree based on attributes values of training data. This classifies data with the help of feature of data instances that said to have information gain. The importance of error tolerance is developed using pruning concept [35,36].

Performance evaluation

For evaluating the performance of the prediction tool, independent data test was carried out. In independent data test, training dataset and testing data set is considered to be independent of one another and hence the name. The tool was further evaluated by different performance on each data set by correctly classified percentage, incorrectly classified percentage and Kappa statistic. Moreover, accuracy by class was provided by different criteria namely Tp rate (True positive: Positive cases that were identified correctly), FP rate (False positive: Negative cases that were incorrectly identified as positive**)**, Precision (Precision = TP / (TP+FP**))**, Recall, F-Measure and ROC Area. The proportion of actual positives is called Recall and it measures the correctly identified data. The F-measure metric combines precision and recall by calculating their harmonic mean. Recall and precision metrics indicates that error of classifying negative instances as positive and classifying positive instances as negative respectively [37].

Results and Analysis

Analyzing data of the performance criteria

Coefficient of uniformity (CU) as shown in Table (2) was ranged between 61.34-89.46% with mean of 80.89% and according to, the performance of the utilized systems was classified to be fair and the lower value may be due to low maintenance of the systems [38]. Distribution uniformity in the low quarter of center pivot irrigation system (DU) as shown in Table 2 was ranged between 31.45-81.81% with mean of 70.79%. Application Efficiency (Ea) as shown in Table 2 was ranged between 67.39-89.04% with mean of 80.72%. Application efficiency in the low quarter (PELQ) as shown in Table 2 was ranged between 24.75-76.49% with mean of 58.09%. Gross depth of water applied (Dg) as shown in Table 2 was ranged between 2.76-15.36 mm with mean of 7.59 mm. Average of weighted depth in low quarter of caught water applied from a center pivot irrigation system (Dw) as shown in Table 2 was ranged between 4.75-22.16mm with mean of 11.03 mm.

Skewness is defined as a measure of the lack of symmetry in a distribution. A distribution is symmetric or normal if it looks the same to the left and right of the center point, yielding a zero value for perfect symmetry. A positively skewed distribution tails off to the high end of the scale while a negative skew tails off the low end of the scale [39]. For this study, CU, DU, Ea and PELQ was found to display negative skewed distribution with values of -1.09, -1.86, and -1.15, respectively (Table 2). Meanwhile, Dg and Dwwas found to display positive skewed distribution with values of 0.29, and 0.77, respectively, however, a low absolute skewness is desirable [39]. The Kurtosis is defined as a measure of the variance from the peak values in the distribution, relative to its width. The kurtosis statistic will be zero for a normal distribution, positive for peaked distributions and negative for flat distributions [39]. For this study, Kurtosis demonstrated positive value of 1.29, 5.82, 1.69, 3.41, 1.83 and 2.81 for CU, DU, Ea, PELQ, Dg and Dw, respectively (Table 2). The high value of Kurtosis value (5.82 and 3.41) may be attributed to erroneous or irrelevant observations in the DU and PELQ data.

J48 classifier performance analysis

In this study the following information was obtained from Weka: Scheme: weka. Classifiers. trees. J48 -C 0.25 -M 2 where -*C* specifies confidence Factor -- The confidence factor used for pruning (smaller values incur more pruning), -M specifies the minNumObj -- The minimum number of instances per leaf.

In training phase, J48 pruned tree as displayed in Weka result panel is shown in Figure 2. Confusion Matrix Table 3 is formed based on the correctly and incorrectly classified instances. J48 correctly classified 34 instances and incorrectly classified 10 instances Table 4. Here, Kappa statistics become nearest 0.6866 Table 5 for training data set. However, Kappa has a range between -1 and 1, where -1 is total misclassification and 1 is 100% accurate classification [41]. J48 performance analysis using testing data set is evaluated and from 10 data instances, J48 correctly classified 8 instances and incorrectly classified 2 instances (Table 4). The True Positive rate (TP), False Positive rate (FP), precision, F-Measure, ROC area and recall are also described in Table 6 for training and testing data.

Naive Bayes performance analysis

In this study the following information was obtained from Weka: Scheme: weka. classifiers. bayes. Naïve Bayes. Naïve Bayes performance analysis (training data set) Confusion Matrix Table 7, from 44 data instances; Naïve Bayes correctly classified 18 instances and incorrectly classified 26 instances. Here, Kappa Statistics become nearest 0.2643 for training data set (Table 5). In Table 8, Naïve Bayes performance analysis (testing data set) is shown, from 10 data instances, Naïve Bayes correctly classified 6 instances and incorrectly classified 4 instances. The True Positive rate (TP), False Positive Rate (FP), precision, F-Measure, ROC area and recall are also described in Table 6 for training and testing data. Naïve Bayes takes less time to build model (0.01 sec) as shown in Table 5 compared to other classifiers. However, in the study of, Naïve Bayes took less time to build model (0.03 s) compared to J48 and Random forest classifiers (0.06 s) [5].

```
J48 pruned tree
------------------

Cu <= 79.62
|  Ea <= 78.54
|  |  Dw <= 7.57: NelsonRotator (4.0)
|  |  Dw > 7.57: Nelsonhead (4.0/1.0)
|  Ea > 78.54
|  |  Ea <= 81.08: SenningerLDN (2.0)
|  |  Ea > 81.08
|  |  |  Ea <= 85.95: Nelsonhead (4.0)
|  |  |  Ea > 85.95: SenningeWob (3.0/1.0)
Cu > 79.62
|  Cu <= 84.33
|  |  PELQ <= 57.27: NelsonRotator (4.0/1.0
|  |  PELQ > 57.27
|  |  |  Du <= 76
|  |  |  |  Du <= 71.28: NelsonSpinner (2.0)
|  |  |  |  Du > 71.28: SenningeWob (3.0)
|  |  |  Du > 76: SenningerLDN (3.0/1.0)
|  Cu > 84.33: NelsonRotator (15.0/6.0)

Number of        10

Size of the      19
```

Figure 2: J48 pruned tree as displayed in Weka result panel

Class	Nelson S3000 Spinner-3TN	Nelson R3000 Rotator-3TN	NelsonD3000 Sprayhead-3TN	Senninger i-Wob	Senninger LDN
Nelson S3000 Spinner-3TN	2	5	0	0	1
Nelson R3000 Rotator-3TN	0	16	1	0	0
NelsonD3000 Sprayhead-3TN	0	0	7	1	0
Senninger i-Wob	0	1	0	5	0
Senninger LDN	0	1	0	0	4

Table 3: Confusion matrix for sprayer's classification results using J48classifier using training data

Class	Nelson S3000 Spinner-3TN	Nelson R3000 Rotator-3TN	NelsonD3000 Sprayhead-3TN	Senninger i-Wob	Senninger LDN
Nelson S3000 Spinner-3TN	0	0	0	0	1
Nelson R3000 Rotator-3TN	0	4	1	0	0
NelsonD3000 Sprayhead-3TN	0	0	1	0	0
Senninger i-Wob	0	0	0	3	0
Senninger LDN	0	0	0	0	0

Table 4: Confusion matrix for sprayer's classification results using J48classifier using testing data

Statistical criteria	Classifier		
	J48	Naïve Bayes	Random tree
Correctly classified percentage	77.27	40.91	100
Incorrectly classified percentage	22.73	59.09	0
Kappa statistic	0.6866	0.2643	1
Total number ofinstances	44	44	44
Time taken to build model (sec)	0.02	0.01	0.02

Table 5: The statistical analysis of training data set for specified classifier and the time taken to build model.

Class	J48											
	Training data set						Testing data set					
	Tp rate	FP rate	Precision	Recall	F-Measure	ROC Area	Tp rate	FP rate	Precision	Recall	F-Measure	ROC Area
Nelson S3000 Spinner-3TN	0.25	0	1	0.25	0.4	0.875	0	0	0	0	0	0.944
Nelson R3000 Rotator-3TN	0.941	0.259	0.696	0.941	0.8	0.9	0.8	0	1	0.8	0.889	0.98
NelsonD3000 Sprayhead-3TN	0.875	0.028	0.875	0.875	0.875	0.988	1	0.111	0.5	1	0.667	0.944
Senninger i-Wob	0.833	0.026	0.833	0.833	0.833	0.985	1	0	1	1	1	1
Senninger LDN	0.8	0.026	0.8	0.8	0.8	0.954	0	0.1	0	0	0	?
Weighted Average	0.773	0.112	0.814	0.773	0.745	0.929	0.8	0.011	0.85	0.8	0.811	0.979
	Naive Bayes											
Nelson S3000 Spinner-3TN	0.75	0.333	0.333	0.75	0.462	0.764	1	0.111	0.5	1	0.667	0.889
Nelson R3000 Rotator-3TN	0.176	0.111	0.5	0.176	0.261	0.617	0.4	0	1	0.4	0.571	0.96
NelsonD3000 Sprayhead-3TN	0.5	0.111	0.5	0.5	0.5	0.899	1	0.222	0.333	1	0.5	1
Senninger i-Wob	0.667	0.184	0.364	0.667	0.471	0.868	0.667	0.143	0.667	0.667	0.667	0.905
Senninger LDN	0.2	0	1	0.2	0.333	0.856	0	0	0	0	0	?
Weighted Average	0.409	0.149	0.508	0.409	0.378	0.756	0.6	0.076	0.783	0.6	0.602	0.94
	Random tree											
Nelson S3000 Spinner-3TN	1	0	1	1	1	1	1	0	1	1	1	1
Nelson R3000 Rotator-3TN	1	0	1	1	1	1	1	0	1	1	1	1
NelsonD3000 Sprayhead-3TN	1	0	1	1	1	1	1	0	1	1	1	1
Senninger i-Wob	1	0	1	1	1	1	1	0	1	1	1	1
Senninger LDN	1	0	1	1	1	1	0	0	0	0	0	0
Weighted Average	1	0	1	1	1	1	1	0	1	1	1	1

Table 6: Detailed accuracy by class for J48, Naïve Bayes and Random tree in training and testing data.

Class	Nelson S3000 Spinner-3TN	Nelson R3000 Rotator-3TN	NelsonD3000 Sprayhead-3TN	Senninger i-Wob	Senninger LDN
Nelson S3000 Spinner-3TN	6	1	0	1	0
Nelson R3000 Rotator-3TN	9	3	3	2	0
NelsonD3000 Sprayhead-3TN	0	1	4	3	0
Senninger i-Wob	1	0	1	4	0
Senninger LDN	2	1	0	1	1

Table 7: Confusion matrix for sprayer's classification results using Naïve Bayes classifier using training data set

Class	Nelson S3000 Spinner-3TN	Nelson R3000 Rotator-3TN	NelsonD3000 Sprayhead-3TN	Senninger i-Wob	Senninger LDN
Nelson S3000 Spinner-3TN	1	0	0	0	0
Nelson R3000 Rotator-3TN	1	2	1	1	0
NelsonD3000 Sprayhead-3TN	0	0	1	0	0
Senninger i-Wob	0	0	1	2	0
Senninger LDN	0	0	0	0	0

Table 8: Confusion matrix for sprayer's classification results using Naïve Bayes classifier using testing data set

Random tree performance analysis

In this study the following information was obtained from Weka confidence weka. classifiers. trees. Random Tree -K 0 -M 1.0 -S 1: where –K specifies K value, -M specifies minNum -- The minimum total weight of the instances in a leaf and S specifies seed -- The random number seed used for selecting attributes. In training phase, Random tree as displayed in Weka result panel is shown in Figure 3. Confusion Matrix of Random tree performance analysis (training data set) is shown in Table 9, from 44 data instances; correctly classified 44 instances and incorrectly classified 0 instances. Here, Kappa Statistics become 1 for training data set Table 5.

In Table (10), Random tree performance analysis (testing data set) Confusion Matrix is shown, from 10 data instances, Random tree correctly classified 10 instances and incorrectly classified

0 instances. The True Positive rate (TP), False Positive rate (FP), precision, F-Measure, ROC area and recall are also described in Table 6 for training and testing data.

For example (Table 9), Nelson S3000 Spinner-3TN sprayer class (class 1), a total of 8 were assigned in the data set, 8 of these were classified correctly by Random tree– an accuracy of 100%. This provides evidence of the consistency in the classifier results using performance criteria.

Figure 4 shows that correctly classified instances and incorrectly classified instances for all classifiers using testing data set. Meanwhile, Figure 5 shows Kappa statistic for all classifiers in testing phase. As comparing these three algorithms, Random tree resulted in high accuracy (100%) and Kappa statistic =1.

As shown in Figure 4 and Figure 5, the overall accuracies for investigated algorithms were different with high enough for Random tree with various criteria (correctly classified and Kappa statistic). The lowest accuracy was for Naïve Bayes; which is based on Bayes conditional probability rule, may be attributed the default settings in Weka as the performance of each classifier over the training data set, considering Weka's default parameters. However, the default values of the classifiers are often adopted by non-expert users, and provide a logical starting point for expert researchers [40]. Based on the training data set it is concluded that weighted average of True Positive Rate of Random tree classifier is 1. In the case J48 and Naïve Bayes Weighted Average TP Rate is 0.773 and 0.409 (Table 6) it indicates the low level. So, automatically Random tree classifier classified the data set in higher sense. In the study of, they reported that Random tree and J48 algorithms using Weka tool gave correctly classified percentage of 100% and 85% for their data, respectively [41].

Conclusion

Data mining is new research area in irrigation. As irrigation management is a process that required increasing yield. One of the tasks of irrigation management is water uniformity in the field. This could be accomplished by sprinklers acceptability in a self-propelled center-pivot irrigation system. In this paper, the comparative analysis of three algorithms like Naïve Bayes, Random tree and J48 is projected. Study shows that among the classifier Random tree

Class	Nelson S3000 Spinner-3TN	Nelson R3000 Rotator-3TN	NelsonD3000 Sprayhead-3TN	Senninger i-Wob	Senninger LDN
Nelson S3000 Spinner-3TN	8	0	0	0	0
Nelson R3000 Rotator-3TN	0	17	0	0	0
NelsonD3000 Sprayhead-3TN	0	0	8	0	0
Senninger i-Wob	0	0	0	6	0
Senninger LDN	0	0	0		5

Table 9: Confusion matrix for sprayer's classification results using Random tree classifier using testing data set

```
RandomTree
==========

Du < 76.52
|   PELQ < 54.4
|   |   Ea < 78.63
|   |   |   Dw < 7.67 : NelsonRotator (4/0)
|   |   |   Dw >= 7.67
|   |   |   |   Ea < 74.73 : NelsonRotator (1/0)
|   |   |   |   Ea >= 74.73 : Nelsonhead (2/0)
|   |   Ea >= 78.63
|   |   |   Du < 42.78 : SenningerLDN (1/0)
|   |   |   Du >= 42.78 : Nelsonhead (3/0)
|   PELQ >= 54.4
|   |   Cu < 79.9
|   |   |   Du < 66 : SenningeWob (2/0)
|   |   |   Du >= 66
|   |   |   |   PELQ < 55.73 : SenningerLDN (1/0)
|   |   |   |   PELQ >= 55.73 : Nelsonhead (3/0)
|   |   Cu >= 79.9
|   |   |   Du < 74.12
|   |   |   |   Ea < 81.33
|   |   |   |   |   Cu < 81.06 : NelsonRotator (1/0)
|   |   |   |   |   Cu >= 81.06 : SenningeWob (3/0)
|   |   |   |   Ea >= 81.33
|   |   |   |   |   Cu < 80.64 : NelsonRotator (1/0)
|   |   |   |   |   Cu >= 80.64 : NelsonSpinner (2/0)
|   |   |   Du >= 74.12
|   |   |   |   Du < 75.79
|   |   |   |   |   Cu < 86.03 : NelsonRotator (3/0)
|   |   |   |   |   Cu >= 86.03 : SenningerLDN (1/0)
|   |   |   |   Du >= 75.79
|   |   |   |   |   Ea < 79.76 : SenningerLDN (1/0)
|   |   |   |   |   Ea >= 79.76 : SenningeWob (1/0)
Du >= 76.52
|   Cu < 82.91 : SenningerLDN (1/0)
|   Cu >= 82.91
|   |   dg < 7.17 : NelsonSpinner (2/0)
|   |   dg >= 7.17
|   |   |   dg < 10.21
|   |   |   |   Cu < 84.36 : NelsonSpinner (1/0)
|   |   |   |   Cu >= 84.36
|   |   |   |   |   PELQ < 65.7 : NelsonRotator (5/0)
|   |   |   |   |   PELQ >= 65.7
|   |   |   |   |   |   Cu < 85.4 : NelsonRotator (1/0)
|   |   |   |   |   |   Cu >= 85.4
|   |   |   |   |   |   |   PELQ < 67.77 : NelsonSpinner (1/0)
|   |   |   |   |   |   |   PELQ >= 67.77 : NelsonRotator (1/0)
|   |   |   dg >= 10.21 : NelsonSpinner (2/0)

Size of the tree : 47
```

Figure 3: Classifier model Random tree

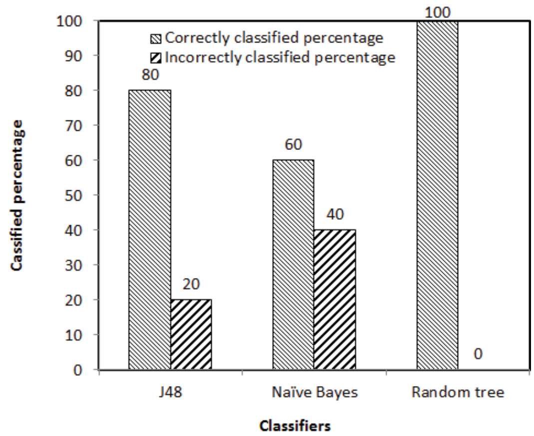

Figure 4: Correctly classified percentage and incorrectly classified percentage for all classifiers

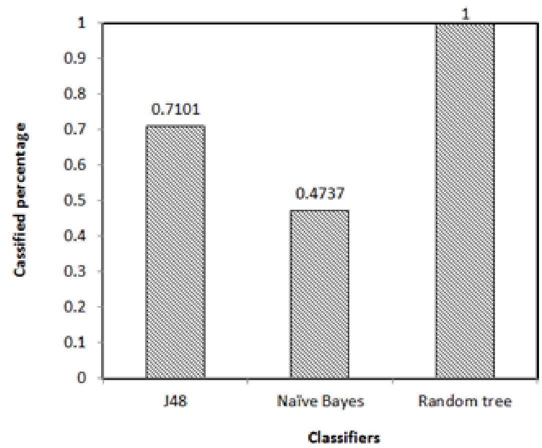

Figure 5: Kappa statistic for all classifiers in testing phase

classifier perform better to select sprinklers. Random tree can be recommended to select sprinklers of a self-propelled center-pivot irrigation based on a function of coefficient of uniformity, uniformity of low quarter, application efficiency application efficiency in the low quarter, gross depth of water applied and the average of weighted depth in low quarter of caught water applied from a center pivot irrigation system. This will help to decision maker to recommend sprinklers accordingly.

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