Precision spray modeling using image processing and artificial neural network

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Abstract: This study employed artificial neural network method for predicting the sprayer drift under different conditions using image processing technique. A wind tunnel was used for providing air flow in different velocities. Water Sensitive Paper (WSP) was used to absorb spray droplets and an automatic algorithm processed the images of WSPs for measuring droplet properties including volume median diameter (Dv0.5) and Surface Coverage Percent (SCP). Four Levenberg-Marqurdt models were developed to correlate the sprayer drift (output parameter) to the input parameters (height, pressure, wind velocity and Dv0.5). The ANN models were capable of predicting the output variables in different conditions of spraying with a high performance. Both models predicted the output variables with R2 values higher than 0.96 indicating the accuracy of the selected networks. Therefore, the developed predictor models can be used in precision agriculture for decreasing spray costs and losses and also environmental contamination.

Keywords: sprayer, drift, image processing, artificial neural network.

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1 Introduction

One of the seminal agents of environment's pollution is pesticide drift during agricultural operations (Gil and Sinfort, 2005). The effective factors on spray drift are the technique of spray application, canopy properties, meteorological conditions, and physicochemical properties of the spray liquid (De Schampheleire et al., 2008). In recent years, many studies have been performed to reduce the spray drift and optimize the spray deposition (Jamar et al., 2010; Wolf and Gardisser, 2014).

Industry, technology, education, and research are being employed to address these concerns. Hence, several standards and protocols including laboratory tests, modeling, and under field condition tests are used to evaluate sprays (Fritzet al., 2012). Using the mentioned methods and protocols, researchers have studied spray flow (Deleleet al., 2005; Endalew et al., 2010; Endalew et al., 2010), dispersion of droplets (García-Santos et al., 2011; Han et al., 2014), roll and pitch angles (Khot et al., 2008), spray characteristics (Guler et al., 2006; Hewitt et al., 2009; Jamar et al. 2010), drift risk (Balsari et al., 2007; Qi et al., 2008), and canopy size (Escolà et al., 2013). However, spray drift profusely is influenced by some other factors such as equipment, application technique, spray properties, operator skills, and environmental conditions (Gilet al., 2014).

Therefore, the main reason of studies in this field is to determine the most important factors and appropriate measures for minimizing the drawbacks of spray applications (Baetenset al., 2009). Different analytical, numerical and predictive models have been used to understand and reduce the drift phenomenon within a

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virtual environment based on the real data of equipment, weather conditions and spray characteristics (Baetenset al., 2007; Bartzanas et al., 2013; Endalew et al., 2010; Kennedy et al., 2012; Lebeau et al., 2011). However, just in few studies Artificial Neural Networks (ANN) technique for predicting spray process characteristics has been developed. Pandaet al. (2001), studied the influence of process parameters, drying conditions, impact velocities and physical properties of sprayed solutions on the kinetics of granulation and on the morphology of the end product. They modeled the droplet deposition behavior on a single particle in fluidized bed spray granulation process using ANN led to useful results in understanding the growth kinetics in spray-coating process (Pandaet al., 2001). Krishnaswamy and Krishnan (2002), predicted the nozzle wear rates for four fan nozzles by using neural network technique and compared the results with the regression technique. In another study, a precision herbicide-spraying system was developed for real-time image collection and processing, weed identification, mapping of weed density, and sprayer control (Yanget al., 2003). Heinleinet al. (2007), fitted neural network models to the experimental data for mapping the structure of a liquid spray system along the spray cone. They reported that the general trends could not be well predicted by the ANN models and they concluded that it was due to unsteady spray conditions or incomplete atomization (Heinleinet al., 2007).

In the current study, spray drift was investigated using a wind tunnel. For this aim, the droplet diameter and drift were measured by image processing technique and predicted by artificial neural network. Also various conditions including different wind speed, spraying height and pressure were considered.

2 Materials and methods

The research was conducted at Mechanical Engineering of Biosystems Department, Ilam University, Ilam, Iran in October, 2014.

2.1 Experimental station and conditions

As the Figure 1 shows, a setup was used including wind tunnel, sprayer system and mobile parts. The setup was implemented on the ground. For stimulating the tractor movement, a DC electromotor was used to power the mobile parts. An air compressor provided various spray pressures. A plate was used to hold the nozzle and a rail was provided to support and facilitate its automatic motion. The spraying liquid, water, was supplied in a tank under the pressure of an air compressor.

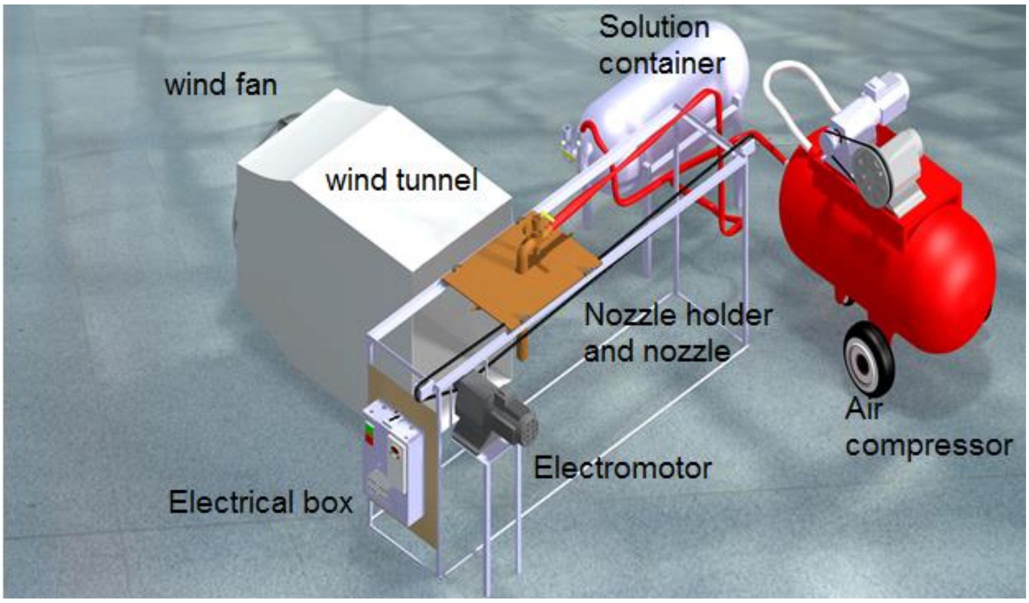


Figure 1 The equipment used for the experiments

A wind tunnel was set for providing air flow in velocities of 0, 4, 8 and 12 km/h. At the entrance of wind tunnel, an anemometer (AM-4206, Lutron, Taiwan) was used for monitoring the air velocity. The spray pressure was evaluated with a calibrated gauge that it was connected to a capillary before the nozzle. The experiments were performed for three different pressures of 3, 4, and 5 bar. Temperature and moisture were monitored using a digital thermometer (TM-917, Lutron, Taiwan) and a hygrometer (HT-3015, Lutron, Taiwan), respectively. Also the setup had an electrical box including start and stop keys and a contactor for switching the power.

For all of the experiments, an 11003 flat fan nozzle (TeeJet, US) was used. Parameters of nozzle operation were opted based on desired field application rates, plant and products limitations and management practices. Three spraying heights of 35, 50, and 65 cm were chosen as the distance between the nozzle's orifice and the ground.

In order to provide high quality data, water sensitive paper (WSP) was utilized for absorbing the spray droplets. WSPs were situated in the positions of 1, 2, 3, and 4 m far from the nozzle orifice (Figure 2). All of the experiments were replicated three times.

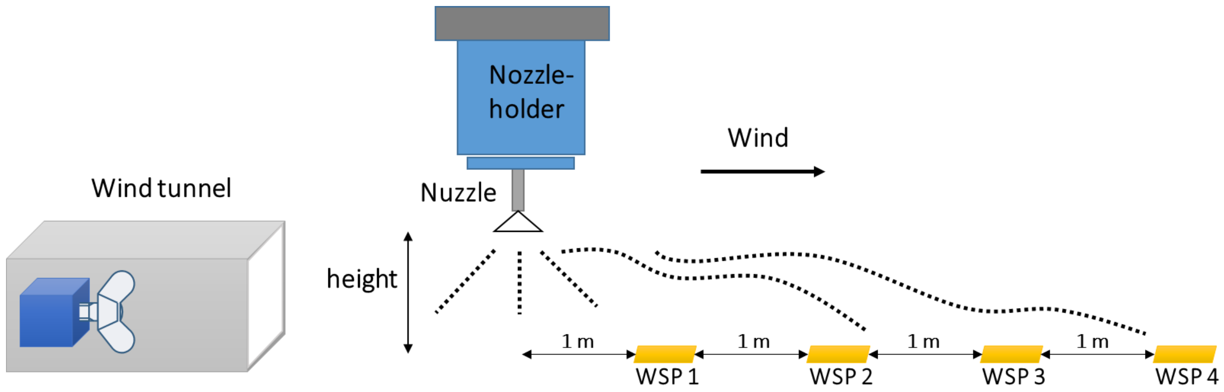


Figure 2Details of WSPs situated in four different positions for absorbing spray droplets

2.2Image Acquisition and Processing

Images of WSPs were scanned by a photographic scanner (CanoScanLiDe 110, Vietnam) to be processed. Figure 3a indicates the WSP after absorbing water. As the figure shows, the yellow paper has blue spots as droplets.

An automatic algorithm was developed in MATLAB 2010a software (The Mathworks Inc., USA) for images processing. In the first step, images were imported to the software and borders and interrupted edges were removed (Figure 3b). Then, the red channels of the images were obtained from RGB images (Figure 3c). After this, the images were converted to binary images (Figure 3d).

The number of spray droplets were figured out and the image of each droplet were separated in a special name. After calculating area and equivalent diameter of droplets, the surface coverage percent (SCP) was computed for each place, e.g. SCP1, SCP2, SCP3 and SCP4 respectively for 1, 2, 3 and 4 m horizontal distance from the nozzle.

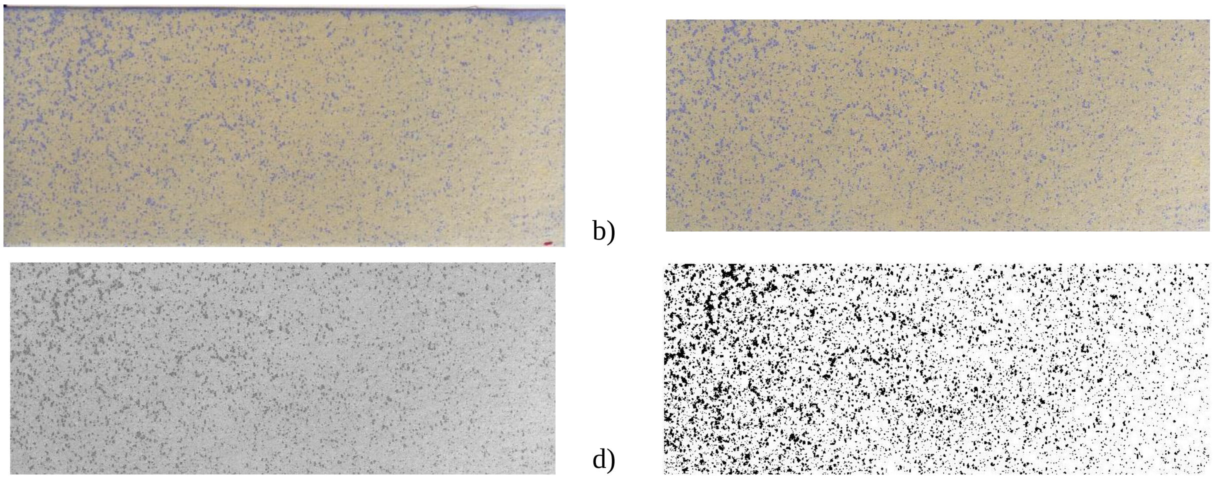


Figure 3 Image analysis, a) the original image b) trimmed image c) obtained red channel image and d) binary image

Then, the algorithm classified the droplets into five different groups depending on the diameter of the spots. After multiplying each diameter group in corresponding coefficients (Nuyttenset al., 2007), the Volume Median Diameter (VMD, $D_{v0.5}$), a diameter which smaller droplets from that constitute 50 % of the total droplet volumes, 10th and 90th percentile ($D_{v0.1}$ and $D_{v0.9}$) of volume diameter and Relative Span Factor (RSF) were calculated. For calculating these factors, first droplets scattered on WSPs are arranged in order of droplets sizes. Then, volumetric diameter and mean diameter of each group are determined. VMD is the diameter that divides all diameters into equal groups. Droplet size and spectrum have been documented as the most influential factor on drift (Wolf and Minihan, 2001). This variable is expressed in microns and usually drift potential is identified as the number of droplets smaller than a special amount in microns. This variable can be used to determine some valuable statistics including the percent coverage, the spray deposition rate, droplet size uniformity, drift profile, and swath pattern width (Wolfet al., 2000). In addition, RSF and drift was calculated as following (Nuyttenset al., 2007):

$$RSF = (D_{v0.9} - D_{v0.1})/ D_{v0.5} \quad (1)$$

$$Drift = SC_1+SC_2+SC_3+SC_4 \quad (2)$$

2.3 Data Analysis

To predict the drift and VMD data, artificial neural network (ANN) method was used. Thus, ANN technique was employed to describe the relationships among operating conditions of spraying pressure, wind velocity, nozzle height, and RSF to associate them with drift. The information about inputs and outputs of the models have been presented in Table 1.

Table 1 The inputs and target variables of neural networks

No.	Inputs	No. of neurons of input layer	Output
Net. 1	Pressure, Wind Velocity, Height	3	VMD
Net. 2	Height, Wind Velocity, RSF, VMD	11	Drift

The Levenberg-Marqurdt model was used for training the network and the transfer functions of ‘tansig’ and ‘purelin’ were chosen for hidden and output layers, respectively. All data sets were divided into three groups, randomly: 70% for training the networks, 15% for validation of the networks and the last 15% for testing the networks. For sophisticated and non-linear relationships appropriate number of hidden neurons is necessary to correctly approximate the desired input-output relationships (Safa and Samarasinghe, 2013). Therefore, many various types of network topologies were tested to achieve the best predicting networks. One hidden layer was considered and the number of its neurons was changed to find the best model. A range of 3-20 neurons were tested in the hidden layer. MATLAB 2010a (The Mathworks Inc. USA) was used for designing and running of all ANN models.

Many various neural networks were developed and the optimum values of network's performance were obtained by trial and error. In order to estimate the performance of trained networks, three factors including mean square error (MSE) of validation data, correlation (r) of test data, and coefficient of determination (R^2) for prediction of all data were used.

3 Results and discussion

Different types of neural networks topologies were developed to model the relationships between the input and output variables to produce models for predicting the volumetric median diameter and drift phenomenon. The performance of ANNs was evaluated using the mean square error (MSE) of validation data, correlation (r) of test data and R-square of prediction of all data. Tables 2 and Table 3 provide an overview of performance of the neural networks for the best cases of topology for predicting VMD and drift, respectively.

The best topology for predicting the VMD at each distance was 3-20-4 that 3 is the number of input data (pressure, wind velocity and height), 20 is the number of neurons in hidden layer and 4 stands for the number of output data (VMD at 1, 2, 3, and 4 m distance from nozzle). The mean square error (MSE, Figure4a) of whole validation set was 53.141.The correlation (r) for whole test set was obtained as 0.9958. The coefficient of determination (R^2) for predicting VMD in each WSP position, i.e. 1, 2, 3 and 4 m, was 99.99%, 99.07%, 96.36% and 96.55%, respectively (Figure5).

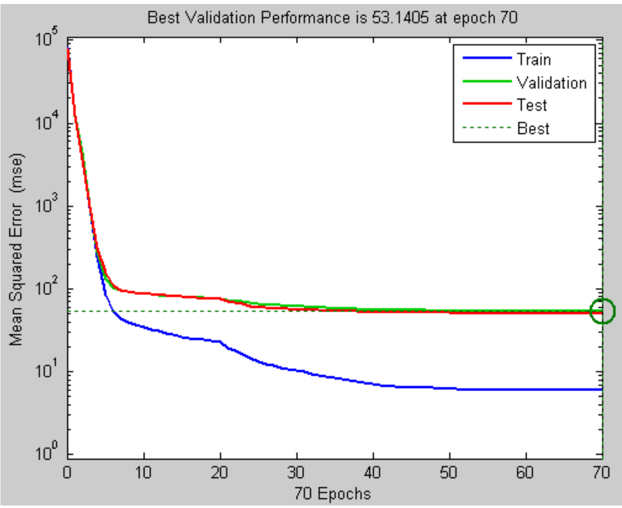
Table 2Performance of ANN model to predict VMD for different positions of WSPs

Topology	Mean square error (MSE) of validation set	Correlation (r) for test set	Coefficient of determination (R^2) for each WSP position			
			1 m	2 m	3 m	4 m
3-3-4	783.373	0.9344	98.5938	36.4524	19.0087	31.8315
3-4-4	508.723	0.9511	96.8247	73.3971	41.4875	48.7400
3-5-4	496.594	0.9559	97.2570	59.0028	69.8364	42.6915
3-6-4	498.378	0.9602	98.5644	69.7867	54.0582	41.6353
3-7-4	332.283	0.9664	99.0765	68.8292	78.9285	48.9701
3-8-4	394.421	0.9620	97.6985	66.6990	75.8429	57.8639
3-9-4	279.170	0.9752	98.8367	82.6077	81.2075	58.8401
3-10-4	201.502	0.9811	99.6010	86.2159	80.3423	72.1938
3-11-4	246.313	0.9769	98.7730	86.5984	82.1377	68.3326
3-12-4	179.143	0.9834	99.5984	85.8166	87.5802	79.3748
3-13-4	142.803	0.9976	99.7099	89.2078	92.6103	76.9835
3-14-4	94.958	0.9927	99.8756	94.0679	94.1962	92.0767
3-15-4	104.680	1.0	99.8598	88.6212	95.2870	89.2454
3-16-4	77.669	0.9933	99.9447	96.8720	94.5484	90.8686
3-17-4	67.961	0.9948	99.9828	98.9752	95.3588	92.7042
3-18-4	59.917	0.9951	99.9829	98.9433	96.0927	93.4531
3-19-4	53.701	0.9959	99.9912	99.0713	96.3628	96.4807
3-20-4	53.141	0.9958	99.9914	99.0748	96.3641	96.5476

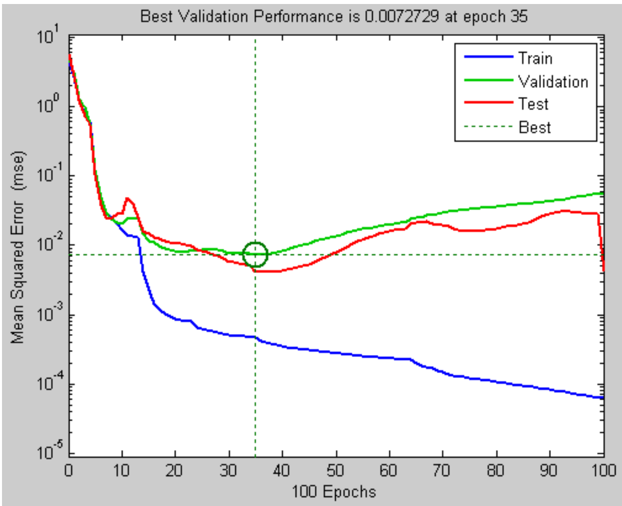
Table 3Performance of ANN models to predict drift

Topology	Mean square error (MSE) of validation set	Correlation (r) for test set	Coefficient of determination (R^2) for drift
11-3-1	0.0141	0.9918	98.9805
11-4-1	0.258	0.9932	98.6601
11-5-1	0.0101	0.9971	99.6048
11-6-1	0.0226	0.9980	99.4143
11-7-1	0.0349	0.9975	97.7931
11-8-1	0.0273	0.9960	99.1060
11-9-1	0.0073	0.9987	99.8126
11-10-1	0.0112	0.9862	99.1702
11-11-1	0.0448	0.9966	99.1022
11-12-1	0.0144	0.9897	99.2980
11-13-1	0.0217	0.9225	96.0021
11-14-1	0.0149	0.9934	99.4621
11-15-1	0.0146	0.9984	99.7124
11-16-1	0.0126	0.9983	99.7186
11-17-1	0.0265	0.9973	99.4392
11-18-1	0.0457	0.9950	98.3802
11-19-1	0.0201	0.9901	99.2532
11-20-1	0.1716	0.9830	96.2011

According to Table 3, the best topology for predicting the drift was gained with 11-9-1 structure. Eleven is the number of input data (height, wind velocity, RSF at each situation and VMD at each situation), 9 is the number of neurons in hidden layer and 1 is the number of output data (drift, D). In Figure 4b, the mean square error (MSE) of validation set was presented as 0.0073.The correlation (r) for test set of the model was 0.999. The coefficient of determination (R^2) was 99.81 % (Figure6).



(a)



(b)

Figure 4 The networks' mean square error through training, validation and testprocesses to predict a) VMD and b) drift

The training process and learning the relationships between the input and output data is very important for finding the best model (Safa and Samarasinghe, 2013). The less amount of network's error, the more accurate predictions will be. Figure 4 illustrates the values of training, validating, and testing errors for each neural network through learning processes. It shows that in each case the network's error had reducing trend and was minimized after several epochs for both training and validating data. It is clear from the figure that mean square error values were decreasing while the number of iterations was rising. In this case, the network's error is fed back to the neurons and used for adjusting the network weights.

The training of each network was performed for many various architectures and different number of iterations. In all networks, training, validation and test lines converged after some ten iterations and the training line could reach the best point after a number of iteration (Figure5). This is a valuable property for the models because these trainings provide very fast and light neural networks. Also, the figure shows that the learning processes get closer and closer to develop the desired accuracy. As well, it indicates that the neural networks successfully have been trained and the chosen topologies were capable to produce proper ANNs for well-predicting the output variables. This is an important step because training of the network in a proper way is vital to map input-output relations (Aghbashloet al., 2012).

Linear regression indicates the strength of the linear relationship between the independent and dependent variables. In this study, the predicted and real value of whole data (train, validation and test) for each neural network was plotted and studied (Figure5for VMD and Figure6for drift). As the figures show, all networks estimated the new data with proper R-squares. A general conclusion can be drawn from the results of two networks; ANN could model the spray drift and VMD accurately. Performance of both networks was acceptable whereas the results for predicting drift were gained a better accuracy. Both networks had one hidden layer with fewer than twenty neurons led to simple and fast networks avoiding over-fitting drawback.

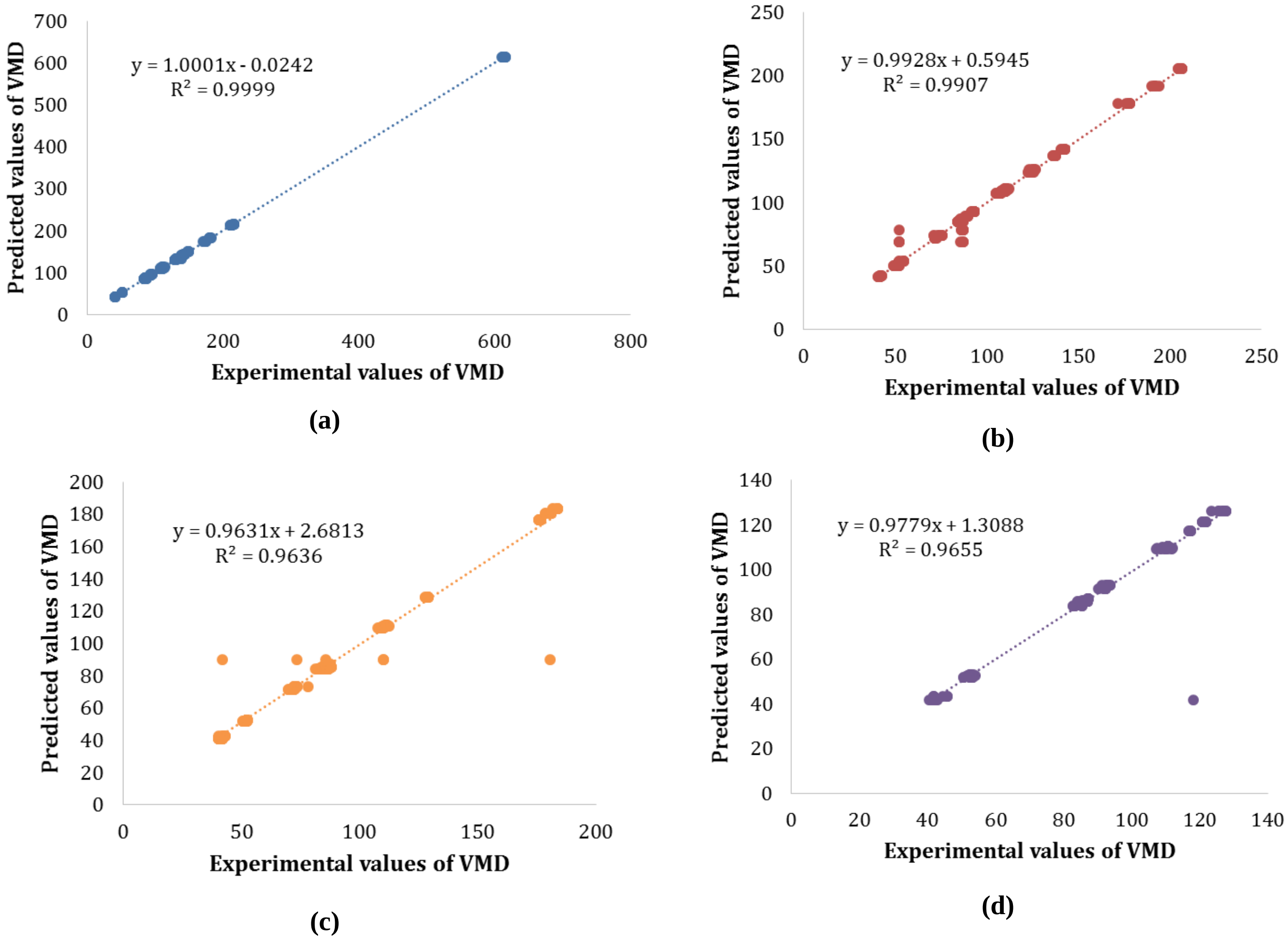


Figure 5 The correlation between observed and predicted VMD data for: a) 1 m distance, b) 2 m distance, c) 3 m distance and d) 4 m distance from nozzle

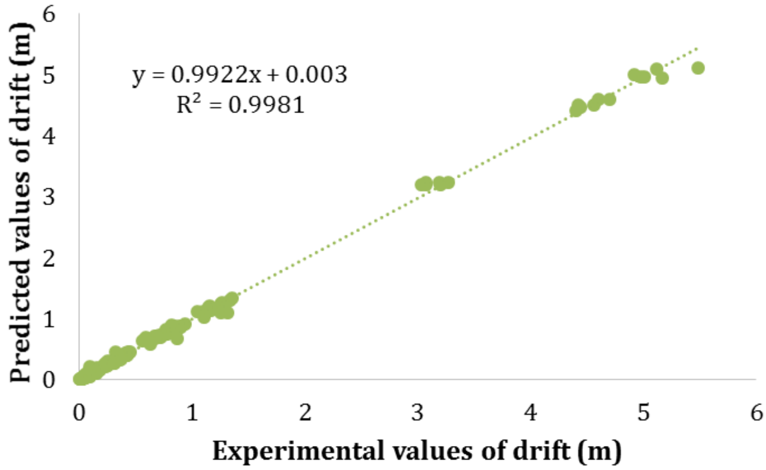


Figure 6 The correlation between observed and predicted values of spray drift

4 Conclusion

The results of this study indicate that spray drift can be monitored and predicted. Image processing technique and ANN modeling were applied successfully to understand and describe the relationships between the spraying properties and target variables. Two neural networks were developed to predict drift and VMD of spray droplets through five sets of data processing elements including pressure, wind velocity, height, RSF, and VMD. The data gathered by experimental tests, image analysis, and calculation of variables. Based on R-square and MSE of the networks, can produce satisfied correlation between observed and predicted data. Therefore, using image processing and ANN modeling provides a promising tool for estimating sprayer drift based on given series of input parameters.

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