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Fertigation Management System Model Using Supervised Machine Learning and Time-Duration Method on Agricultural Industrial Land

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ABSTRACT
This paper contains an explanation of the fertigation management system model to deal with the water crisis and the efficient use of plant nutrients in the case of agricultural industrial land in Lembang, Indonesia. The method developed uses a time-duration method equipped with supervised machine learning. Machine throughout the year learns the schedule of agricultural expert operators in providing water and nutrition. At the same time, the machine records the microclimate of humidity, rain, and sunny around the agricultural land. The time-duration and microclimate relationships were plotted with a linear approach. Obtained three time-equation TON and three duration-equation DUR over 24 hours with an average of R^2 0.5654, around 04:58 with duration 2 hours and 23 minutes, around 09:44 with duration 2 hours 43 minutes, and around 14:44 with duration 5 hours 19 minutes.

Keywords: *Fertigation management system, supervised machine learning, time-duration method*

1. INTRODUCTION

The water availability crisis in agricultural industrial land has become an important issue in optimizing water use in addition to the efficient use of fertilizers. The Fertigation management system aims to obtain a more precise and efficient regulation of water and fertilizer use. This paper contains an explanation to develop a model of the fertigation management system in the case of agricultural industrial land in the Lembang area, Indonesia.

Several studies have been done in several ways. One of them is the proximal "on-farm" sensing technique applied to the field of tomato drip irrigation which includes Vegetation Index (VI), Water index (WI / NDVI) and Transformed Soil Adjusted Vegetation Index (TSAVI) (1). The study aimed to analyze the correlation between VI and tomato yield in assessing the spatial variability of tomato plants and identifying crop area homogeneity. The results showed that the tomato plane was almost uniform, both visually according to the spectroradiometer readings. TSAVI is the most effective index for detecting water conditions of planting media. This study strengthens the possibility of the detection of plant water pressure by a spectroradiometer. Another fertigation management system study uses the energy balance estimation method of crop evapotranspiration (ET), E*ddy covariance*, and *Bowen ratio* for irrigation scheduling in vegetable farms (2).

The use of fertigation coupled with micro-irrigation has continued to increase since it was first introduced to the horticultural cropping system. This combination provides a technical solution whereby nutrients and water can be supplied to plants promptly and as needed, thus enabling high efficiency of nutrient use (3). However, proper control of plant nutrients and water requirements is essential for proper plant nutrition and efficiency.

The recirculating aquaculture system (RAS) has a high nitrogen concentration which is a valuable asset as a fertilizer. The use of an automated system of 24 lysimeter-plots to determine the optimal irrigation rate for cucumber plants fertilized with RAS waste using three different nitrogen concentrations. The two outcome responses to the nitrogen fertigation model match the measured data, although the model yields different conclusions. However, in terms of optimal fertigation, it can be a useful tool for decision support. The observed data can be used to optimize irrigation for any nitrogen concentration, but the value is highly dependent on climate, plant type, and root zone characteristics, suggesting the need for more inclusive modelling (4).

The use of mobile applications in fertigation system settings is divided into two parts: (1) determining the amount of water lost by transpiration using sensors to estimate energy costs and determine irrigation needs, and (2) determining the fertilizer that needs to be applied per litter of water in the nutrient tank (2) kg / l) (5). The platform provides an ample supply of various fertilizers as well as electrical conductivity and pH, possible precipitation in the final solution, and drainage or soil analysis to help optimize nutrient strategies.

The use of technology on agricultural land in poor areas using networked wireless sensors to address the issue of water shortages has been developed in India concerning the environmental-related potential for improved agricultural strategies. The method of application used is an iterative participatory approach (6).

Drip irrigation and fertility optimization programs to maximize nutrient uptake by plants and minimize water and solute losses using the HYDRUS Model (2D / 3D) were used to simulate water and nitrogen transport in the soil (7). In the first stage, the amount of irrigation flow rate, duration of fertilizer injection, and injection initiation time are simultaneously optimized to minimize the leaching of nitrates in the fertility cycle. In the second stage, the amount of fertilizer injection at each fertility stage is optimized during the growing season using the optimal value from the previous step.

The study of the impact of the fertigation strategy on nitrate leaching and absorption into maize plants using numerical model calibration for drip irrigation in sandy loam soils using a calibrated model was used to simulate uptake of plant and crop nitrates (8). Fertility scenarios based on different fertility durations and different start times. Nitrogen uptake is compared to maize demand during the growth stage.

This paper will describe the design of the use of the time-duration method (8) using farming technology (5) based on humidity, rainy day, and Sunny of the plant environment (2) in a drip irrigation system (1) (3) (5) (8). The main difference proposed in this paper compared to the studies that have been discussed is the approach of using supervised machine learning methods with multiple linear regression based on the consideration of expert operators on the farm. The proposed method is expected to replace the use of expert operators in considering the water and fertilizer application process while maintaining the expected product standards.

2. METHODS

The method developed uses a time-duration method equipped with supervised machine learning using multiple linear regression. The time-duration defines when and how long fertilizer is given. Machine every day for a year will study this based on expert operators by taking into account the microclimate conditions around the land. In the next stage, the machine will perform multiple linear regression calculations connecting time-duration with microclimate conditions. This paper uses the year of 2019 data and applies it to the year of 2020 conditions. This method is applied to head lettuce farms to measure the success rate in replacing the work function of expert operators.

The Fertigation Management System is equipped with a microclimate sensor and a sensor that can detect the time and duration of watering. This monitoring is done online by a single board controller. The data obtained were used to calculate the time and duration for a suitable microclimate condition.

Daily microclimate data and watering time are stored in a single board controller database. The average change in the condition of the microclimate every day during one month is represented by the name of the month which reflects the overall weather conditions around agriculture land. The equation of this condition is stated in Equation (1), while the watering duration is related to the month using Equation (2).

$$TON\#n \sim ct_{1n}.h+ct_{2n}.r+ct_{3n}.s+it_n \quad (1)$$

$$DUR\#n \sim cd_{1n}.h+cd_{2n}.r+cd_{3n}.s+id_n \quad (2)$$

where:

TON = time of nutrition.
DUR = duration of nutrition.
h = humidity (%)
r = days of rain (%)
s = sunny (%)
ct = regression coefficient in the equation of time
cd = regression coefficient in the equation of duration.
it = intercept in the equation of time
id = intercept in the equation of duration

3. RESULTS

3.1. Time-Duration

When (TON) and how long (DUR) of fertilization performed by expert operators are recorded by the machine, then the average is calculated each month. The average calculation result data is shown in Table 1(3). The results of the calculation of the machine, each day within a period of 24 hours, obtained three times the application of nutrition, at 4:58 (average TON # 1) for 2 hours 23 minutes (average DUR # 1), at 9:44 (TON # 2) for 2 hours 43 minutes (average DUR # 2) and at 14:44 (average TON # 3) for 5 hours 19 minutes (average DUR # 3). Graphically the whole year is depicted in Figure 1.

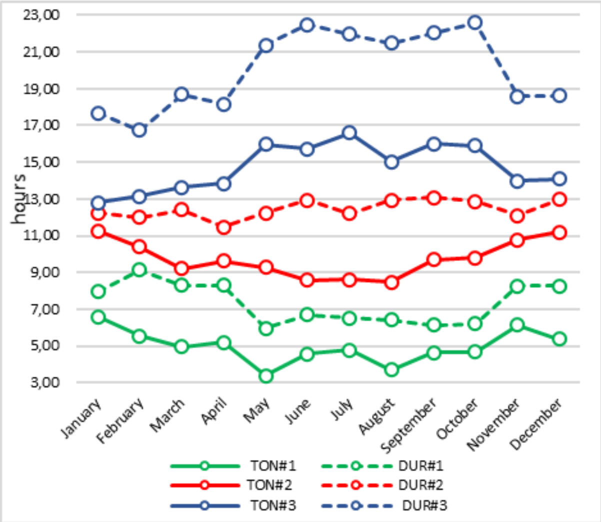

Figure 1 Time-duration of nutrient application

3.2. Microclimate Data

The microclimate conditions of the land are monitored every day through a sensor device. The machine records the data and calculates an average each month. Microclimate data of the year 2019 are presented in Table 1(4). There are six microclimate variables and three were selected as the most influential variables based on the strength of their correlation as shown in Table 2. The selected microclimate data are shown in Table 1(5). The selected variables are depicted in percent of the maximum value as shown in Figure 1. The microclimate variables selected were Humidity, Rainy Day, and Sunny.

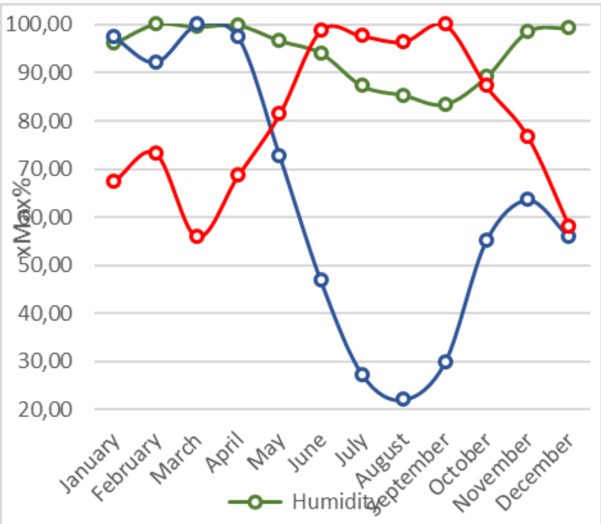

Figure 2 Microclimate Data in 2019

4. DISCUSSION

The application of multiple linear regression to time-duration (Figure 1) as a function of microclimate (Figure 2) will obtain a linear regression coefficient as shown in Table 3. So that Equation (1) and Equation (2) can be written as Equation (3) and Equation (4). If we plot it as a function of microclimate changes in each month, the results as shown in Figure 3 and from Table 3 an average R^2 of 0.5654 is obtained at around 04:58 with a duration of 2 hours and 23 minutes, around 09:44 with a duration of 2 hours 43 minutes, and around 14:44 with duration 5 hours 19 minutes.

$$TON\#1' = 0.0693h - 0.0002r - 0.0119s - 0.57922 \quad (3)$$
$$TON\#2' = -0.0541h - 0.0028r - 0.0570s + 20.0513$$
$$TON\#3' = -0.0560h + 0.0024r + 0.0680s + 14.4909$$
$$DUR\#1' = -0.0144h0.0104r - 0.0382s + 11.1978 \quad (4)$$
$$DUR\#2' = 0.0035h - 0.0057r + 0.0052s + 12.0133$$
$$DUR\#3' = 0.0068h - 0.0255r0.0648s + 15.6848$$

where:
TON = time of nutrition.
DUR = duration of nutrition.
h = humidity (%)
r = days of rain (%)
s = sunny (%)

To test the effectiveness of using the proposed method, a test application was carried out on head lettuce plantations. The results of the test data are shown in Table 4. The results obtained show that the product standard is still acceptable.

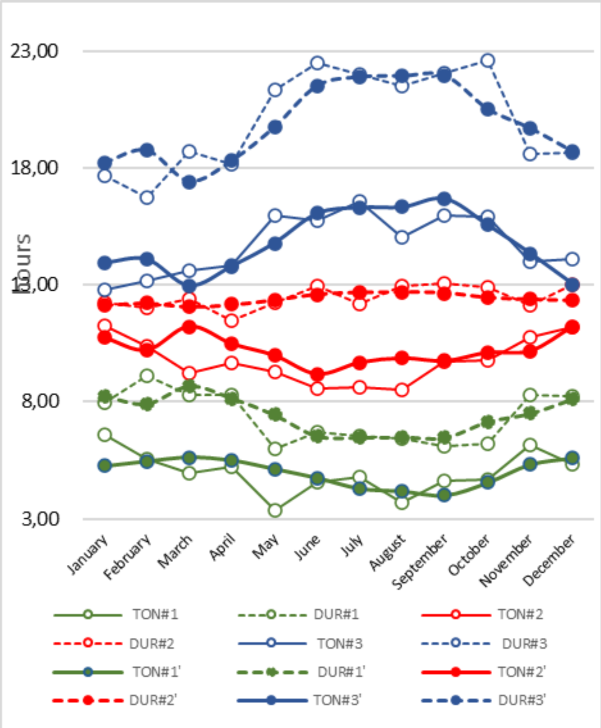

Figure 3 Application of multiple linear regression on time-duration as a function of Microclimate

5. CONCLUSION

The model of a fertigation management system using time parameters of fertilization times TON#1', TON#2', TON#3' built on Equation (3) and using parameters of fertilization durations DUR#1, DUR#2', DUR#3' built on Equation (4) fulfil the quality standards expected using control table based on Head Lettuce Farm results in Table 4.

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Table 1 Nutrition Time Schedule and Microclimate Data

ID (1)	MONTH (2)	REALTIME DATA of NUTRITION TIME SCHEDULE (3)						REALTIME DATA of MICROCLIMAT (4)						REALTIME DATA of MICROCLIMAT (xMax%) (5)		
		(in hours)						(mb)	(%)	(day)	(%)	(knot)	(°C)	(%)	(day)	(%)
		TON#1	DUR#1	TON#2	DUR#2	TON#3	DUR#3	Air Pressure	Humidity	Day of Rain	Sunny	Wind	Temp	Humidity	Day of Rain	Sunny
1	January	6,59	7,95	11,26	12,24	12,80	17,68	922,15	77,13	25,00	58,00	5,50	23,70	96,02	97,40	67,44
2	February	5,53	9,14	10,39	12,01	13,16	16,73	923,55	80,33	23,67	63,00	4,50	23,80	100,0	92,21	73,26
3	March	4,96	8,30	9,21	12,41	13,64	18,69	922,90	79,90	25,67	48,00	5,00	23,60	99,46	100,00	55,81
4	April	5,20	8,29	9,64	11,46	13,83	18,16	922,45	80,17	25,00	59,00	4,00	23,90	99,79	97,40	68,60
*5	May	3,37	5,98	9,26	12,26	15,96	21,36	923,15	77,60	18,67	70,00	4,50	23,90	96,60	72,73	81,40
*6	June	4,56	6,69	8,57	12,94	15,73	22,50	923,65	75,53	12,00	85,00	4,50	23,30	94,02	46,75	98,84
*7	July	4,79	6,52	8,61	12,19	16,59	21,98	923,45	70,07	7,00	84,00	4,50	22,70	87,22	27,27	97,67
*8	August	3,72	6,42	8,49	12,95	15,04	21,50	923,70	68,53	5,67	83,00	4,50	23,00	85,31	22,08	96,51
*9	September	4,63	6,13	9,70	13,09	15,99	22,03	924,35	67,03	7,67	86,00	4,50	23,80	83,44	29,87	100,00
*10	October	4,68	6,21	9,80	12,88	15,89	22,58	923,60	71,57	14,15	75,00	4,50	24,90	89,09	55,14	87,21
11	November	6,15	8,27	10,77	12,11	13,99	18,59	923,50	79,10	16,32	66,00	4,00	24,20	98,46	63,58	76,74
12	December	5,36	8,26	11,21	12,98	14,08	18,63	923,10	79,73	14,36	50,00	4,50	23,70	99,25	55,95	58,14

*Dry season

Table 2 Correlation of Microclimate variables

	Air Pressure	Humidity	Day of Rain	Sunny	Wind	Temp
Air Pressure	1					
Humidity	-0,6371	1				
Day of Rain	-0,7501	**0,8348**	1			
Sunny	0,7173	**-0,8343**	**-0,8086**	1		
Wind	-0,3956	-0,0153	0,2807	-0,2500	1	
Temp	-0,0382	0,2607	0,3748	-0,2851	-0,1655	1

Table 3 Coefficient of Regressions

	Coefficients of Regression				Regression Statistics				
Output	Humidity	Day of Rain	Sunny	Intercept	Multiple R	R Square	Adj. R Square	Stand. Error	Observations
TON#1	0,0693	-0,0002	-0,0119	-0,5792	0,6262	0,3921	0,1641	0,8600	12
DUR#1	-0,0144	0,0104	-0,0382	11,1978	0,8205	0,6732	0,5507	0,6494	12
TON#2	-0,0541	-0,0028	-0,0570	20,0513	0,6986	0,4881	0,2961	0,7280	12
DUR#2	0,0035	-0,0057	0,0052	12,0133	0,5407	0,2924	0,0271	0,3938	12
TON#3	-0,0560	0,0024	0,0680	14,4909	0,8861	0,7851	0,7045	0,8144	12
DUR#3	0,0068	-0,0255	0,0648	15,6848	0,8728	0,7617	0,6724	1,0805	12

Table 4 Algorithm Testing Results on Head Lettuce Farm

Standard Planting Period : 90 days
Standard Weights : 300-500 grams

	Planting Period	Weights
	Result	Result
Farm 1	64	410
Farm 2	61	380
Farm 3	63	390
Average	**63**	**393**

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