Development of short-term evapotranspiration forecasting model using time series method for supporting the precision agriculture management in tropics

A P Nugroho1*, D E Rahayu1, L Sutiarso1, Murtiningrum1, M A F Fallah2 and T Okayasu3

1 Smart Agricultural Research, Department of Agricultural and Biosystems Engineering, Faculty of Agricultural Technology, Universitas Gadjah Mada. Jln. Flora No. 1 Bulaksumur, Yogyakarta 55281, Indonesia
2 Department of Agroindustrial Technology, Faculty of Agricultural Technology, Universitas Gadjah Mada. Jln. Flora No. 1 Bulaksumur, Yogyakarta 55281, Indonesia
3 Department of Agro-Environmental Sciences, Faculty of Agriculture, Kyushu University, 744 Motooka, Nishi-ku, Fukuoka 810-0395, Japan

Corresponding author: andrew@ugm.ac.id

Abstract. To support daily farm management through the environmental challenges, it is necessary to have short-term evapotranspiration forecasting to predict an n-hour step. Evapotranspiration (ET) is the sum of evaporation and transpiration from the soil surface and plant tissue that can be used to assess the water loss behaviour in open-field cultivation. The objective of this study was to develop a short-term evapotranspiration forecasting model using the time series method. The model is based on the Seasonal Autoregressive Integrated Moving Average (SARIMA). The environmental data of air temperature, relative humidity, and solar radiation were observed at Rejeki Tani Yogyakarta from January to August 2014. The ET was estimated using the FAO56 Penman-Monteith. A suitable parameter of non-seasonal autoregressive order \((p)\), the degree of differencing \((d)\), moving average order \((q)\), and their seasonal parameter \((P, D, Q)\) were investigated to predict 12-hour ahead of ET. As the result, the suitable parameter was \(SARIMA(2,1,2)(1,1,1)\). From the six months model validation with the different monsoons, the MAE and RMSE ranged from 0.035636 to 0.063419, and 0.045893 to 0.079961 respectively. The R2 was between 0.8045 and 0.85902. The developed forecasting model can be used to predict the hourly evapotranspiration with acceptable error and accuracy.

1. Introduction
Open field tropical horticulture production is highly affected by the uncontrollable environment. Indonesian agriculture is strongly affected by ENSO (El Nino Southern Oscillation) which intensifies the extreme meteorological conditions. Impacts of climate change have been intensifying with an increasing number of extreme weather patterns occurrences, climate anomalies, and interannual variations in precipitation [1]. Accordingly, the agricultural production system should consider global climate change as well as maintaining productivity. Consequently, the farmers manage their farming
activity to adapt to the environment, such as appropriate planting schedule, plant maintenance, and daily management.

Precision agriculture (PA) provides a set of technologies that combines sensors, information systems, enhanced machinery, and informed management to optimize production by accounting for variability and uncertainties within agricultural systems [2]. The precision farming approach was introduced by the utilization of an on-site environmental monitoring system to support the decision-making process for daily operations. In general, the on-site measurement can be handled by the utilization of environmental monitoring node to record the local microclimates parameter as well as assess the local condition. In our previous work, a remote environmental monitoring framework had been developed to perform online monitoring and control for tropical horticulture under the unstable network condition in the rural area [1,3–5]. However, a rapid environmental assessment of local conditions needs to be addressed for supporting the tactical day-to-day operation precisely.

To extend the functionality of the remote environmental monitoring system, it is necessary to have a special parameter that can be used to assess the parameters based on measured environmental data. Evapotranspiration (ET) is the sum of evaporation and transpiration from the soil surface and plant tissue [6,7] that can be used to assess the water loss behavior in open-field cultivation. Dealing with daily tactical operations in farm management, it is necessary to have short-term evapotranspiration forecasting features to predict an n-hour step.

The objective of this study was to develop a short-term evapotranspiration forecasting model using the time series method. The Seasonal Autoregressive Integrated Moving Average (SARIMA) was applied to forecast the evapotranspiration in Rejeki Tani Home Farming at Kaliurang, Yogyakarta, Indonesia.

2. Materials and methods

2.1. Cloud-based environmental field monitoring system

Figure 1 shows the conceptual diagram of the cloud-based environmental field monitoring system adopting the remote monitoring and control framework developed from the previous study [3,4]. The system is consisting of the monitoring node as local management and the cloud server as global management. The Arduino Ethernet board (www.arduino.cc) was used as the main computer in the local node, equipped with a real-time clock (SparkFun DS3234 RTC, USA). The environmental sensors were digital air temperature and humidity Sensirion (SHT71) and solar radiation sensor BH1603FVC (ROHM Co., Ltd, Japan). To provide the Internet connection, a GSM router (HUAWEI B970b, Huawei Technologies Co., Ltd., China) equipped with a SIM card from Telkomsel (internet provider company) was employed. The cloud server provided real-time processing and data visualization, presentation, and analysis. The utilization of cloud-technology allows multi-platform access through web applications by the client. Also, it supports the data exchange features to another web server via the API (Application Programming Interface).

2.2. Study site and data collection

The environmental field monitoring systems have been deployed in the horticultural field at Rejeki Tani Home Farming, located in Sardonoharjo, Ngaglik, Sleman, Yogyakarta (~7.703757, 110.41543). The farm is a private home farming with a 1509 m² area for horticultural cultivation. The commodities are mostly fruits and vegetables, such as Mustard greens (Brassica rapa parachinensis), Pakcoy (Brassica chinensis), Bitter gourd (Momordica charantia), and Cabbage (Brassica oleracea). The system had been used to record the environmental data (air temperature, relative humidity, and solar radiation) from December 2013 to August 2014.
2.3. Evapotranspiration estimation
Evapotranspiration (ET) is the sum of evaporation and transpiration from the soil surface and plant tissue respectively [6,7]. Reference evapotranspiration (ETo) is the ET from the reference surface that has been used here to estimate water loss from an open-field cultivation surface. The ETo value can be estimated from the collected environmental data, measured by the attached sensor, using the mathematical Penman-Monteith (PM) model. This model is widely used by the agronomist, irrigation engineers, and other scientists on-field practices and researchers [8]. The hourly step PM model to estimate the ETo (mm h$^{-1}$) as explained in the Food and Agricultural Organization’s Irrigation and Drainage No.56 (FAO56-PM) is presented as follows:

$$ET_o = \frac{0.408 \Delta \left( R_o - G \right) + \gamma \left( \frac{37}{T_o + 273} \right) U_2 VPD}{\Delta + \gamma (1 + 0.34 U_2)}$$

where $T_o$ is hourly mean air temperature ($^\circ$C), $\Delta$ is the slope of saturation vapor pressure curve at $T_o$ (kPa $^\circ$C$^{-1}$), $R_o$ is net radiation at the surface (MJ m$^{-2}$ h$^{-1}$), $G$ is the soil heat flux density (MJ m$^{-2}$ h$^{-1}$), $U_2$ is average hourly wind speed at 2 m height (m s$^{-1}$), $VPD$ is the vapor pressure deficit (kPa), $\gamma$ is the psychrometric constant (kPa $^\circ$C$^{-1}$). For the daytime period, ($R_o > 0$), $G = 0.1* R_o$, while for the night time period, ($R_o < 0$), $G = 0.5* R_o$.

2.4. Short-term evapotranspiration forecasting model
The short-term evapotranspiration forecasting model was based on seasonal Autoregressive Integrated Moving Average (SARIMA). The seasonal ARIMA [10-12] with $S$ observation per-period in season can be denoted as SARIMA(p, d, q)(P, D, Q)$S$ and formulated as follows

$$\Phi_p B^S \phi(B) (1 - B^S)^D (1 - B)^d y_t = \Theta(B^S) \theta(B) \varepsilon_t,$$

and it can be expanded as

$$\left(1 - \Phi_1 B^S - \Phi_2 B^{2S} - ... - \Phi_p B^{pS}\right) \left(1 - \varphi_1 B - \varphi_2 B^2 - ... - \varphi_p B^p\right) (1 - B^S)^D (1 - B)^d y_t = \left(1 - \Theta_1 B^S - \Theta_2 B^{2S} - \Theta_q B^{qS}\right) (1 - \theta_1 B - \theta_2 B^2 - ... - \theta_q B^q) \varepsilon_t.$$
where $\phi$ and $\psi$ are Autoregressive (AR) parameter of seasonal and non-seasonal components, respectively. $\theta$ and $\psi$ are Moving Average (MA) of seasonal and non-seasonal components, respectively. $\beta$ is backward operator, $B(yt) = yt - 1$. $(1 - \beta^S)^d$ is Dth seasonal difference of season S. $(1 - B)^d$ is the dth non-seasonal difference. $\epsilon$ is random variable. $P$ and $p$ are AR orders. $Q$ and $q$ are MA orders. $D$ and $d$ are differencing terms. The systematic scheme of ET can be seen in Figure 2.

![Figure 2](image)

**Figure 2.** Flowchart of the evapotranspiration forecasting system

### 3. Results and discussion

Figure 3 shows the measured environmental data on December 27, 2013, to January 4, 2014, for air temperature (a), relative humidity (b), solar radiation (c), and estimated evapotranspiration using the FAO-56 Penman-Monteith in Eq. (1). The ET data then used as the input for the forecasting model. Dataset between December to January had been used for the forecasting model development, and the rest was used as model validation (February to August). From the data visualization in Figure 3(c), the evapotranspiration data has seasonal elements or repeated over a period of time.

![Figure 3](image)

**Figure 3.** Environmental data of temperature (a), humidity (b), solar radiation (c), and reference evapotranspiration (d)
3.1. Model parameter estimation

Figure 4 displays the Box-Cox test result of the evapotranspiration for checking the stationarity in variation. As the result, the p-value was 0.19, which means that the data was not stationary (stationary in variation when p = 1). Accordingly, the transformation was required to obtain stationarity. For checking the stationarity on average, Autocorrelation Function (ACF), Partial Autocorrelation Function (PACF), and Augmented Dickey-Fuller (ADF) unit root analysis were applied. As the result, with one-time differencing for seasonal and non-seasonal, the data could be stationary on average, as checked by statistical test ADF.

Accordingly, the initial model parameter could be determined as a boundary limitation in the finding for the optimum parameter. The seasonal (s) is 24, according to the repetition over a period of time. For the non-seasonal part, the differencing was conducted one time, which means that d = 1. From the PACF plot, we could obtain the cutoff after lag 2 and 4, so the p could be set to 4 (p = 4). For the seasonal part, the differencing also one time (D = 1). From the ACF plot, the cutoff was occurred after lag 24, thus Q = 1. The cutoff from ACF was obtained after lag 24, so the P = 1. Therefore, the initial model parameter for SARIMA for evapotranspiration forecasting was SARIMA (4,1,1)(1,1,1)24.

3.2. Diagnostic checking

According to the boundary limit, a potential optimum parameter could be obtained by overfitting the result with the initial model. From the 72 sets of models, 27 models were significant. Selected model sets then tested for the diagnostic test by checking using the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and log-likelihood also testing the normality test, autocorrelation, and heteroskedasticity test. As a result of the diagnostic test, the model parameter which meets the criteria was SARIMA (2, 1, 2)(1, 1, 1)24.

3.3. Evapotranspiration forecasting

Figure 5 shows the result of the short-term evapotranspiration forecast for 12-hour ahead starting from 06:00 in the morning using the SARIMA (2, 1, 2)(1, 1, 1)24. Time series of actual and predicted can be seen in (a), and the scatter plot in (b). The determination coefficient (R2) was 0.75774 from January 5 to 7, 2014. For the experimental data, the coefficient of determination is acceptable (>0.6) to forecast the evapotranspiration, the model can be used to represent the n-hour step ahead of evapotranspiration.
3.4. Model validation and evaluation

Table 1 shows the model validation for six months' observation (February to July). The value of Mean Average Error (MAE), Root Mean Square Error (RMSE), and coefficient of determination (R²) were used to verify the accuracy of the model for a different month and monsoon (dry and wet season). The MAE ranged from 0.035636 to 0.063419, and the RMSE was between 0.045893 and 0.079961. The value of R² was between 0.8045 and 0.85902. According to the value of MAE and RMSE, the error was still below 0.1, and the determination coefficient also close to 1, which means that the forecasting model can be used to predict the hourly evapotranspiration.

| Month | Average of MAE | Average of RMSE | Average of R² |
|-------|---------------|----------------|--------------|
| February | 0.050731 | 0.067895 | 0.827200 |
| March | 0.063419 | 0.079961 | 0.804500 |
| April | 0.058893 | 0.075361 | 0.859020 |
| May | 0.035636 | 0.045893 | 0.850678 |
| June | 0.040361 | 0.048669 | 0.851230 |
| July | 0.040531 | 0.050681 | 0.812725 |

4. Conclusion and future works

The proposed short-term evapotranspiration forecasting model based on Seasonal Autoregressive Integrated Moving Average (SARIMA) was developed. The best suitable model parameter for hourly evapotranspiration forecast was SARIMA (2, 1, 2)(1, 1, 1)24. From the six months model validation, the MAE ranged from 0.035636 to 0.063419, and the RMSE was between 0.045893 and 0.079961. The value of R² was between 0.8045 and 0.85902. Therefore, the developed forecasting model can be used to predict the hourly evapotranspiration with acceptable error and accuracy.

Acknowledgement

This study was supported by 2017 Research Grant of Directorate of Research and Community Service, Universitas Gadjah Mada No. 2378/UN1/P.III/DIT-LIT/LT/2017 from the Ministry of Research and Higher Education. We thank all member of Smart Agriculture Research UGM, and Department of Agro-environmental Sciences, Kyushu University, Japan, for the research facilities during the preliminary experiment. We thank also Mr. Mino Purwodiharjo and Ms. Sribudi Astuti from Rejeki Tani, Yogyakarta, Indonesia for the help on the implementation of the system.

References

[1] Nugroho A P, Sutiarso L and Okayasu T 2019 IOP Conference Series: Earth and Environmental Science vol 355 (Indonesia: IOP Publishing)
[2] Gebbers R and Adamchuk V I 2010 *Science* **327** 828–31

[3] Nugroho A P, Okayasu T, Hoshi T, Inoue E, Hirai Y, Mitsuoka M and Sutiarso L 2016 *Comput. Electron. Agric.* **124** 325–39

[4] Nugroho A P, Okayasu T, Inoue E, Hirai Y and Mitsuoka M 2013 *IFAC Proceedings Volumes* **46** 181–6

[5] Nugroho A P, Okayasu T, Horimoto M, Arita D, Hoshi T, Kurosaki H, Yasuba K, Inoue E, Hirai Y, Mitsuoka M and Sutiarso L 2016 *Agric. Inf. Res.* **25** 86–95

[6] Allen R G, Jensen M E, Wright J L and Burman R D 1989 *Agron. J.* **81** 650–62

[7] Allen R G 1996 *J. Irrig. Drain. Eng.* **122** 97–106

[8] Alexandris S and Kerkides P 2003 *Agric. Water Manage.* **60** 157–80

[9] Ziegel E R, Box G, Jenkins G and Reinsel G 1995 *Technometrics* **37** 238

[10] Box G E P, Jenkins G M and Reinsel G C 2013 *Time Series Analysis: Forecasting and Control*: 4th ed. (New Jersey: John Wiley & Sons, Inc)

[11] Wang J, Du Y H and Zhang X T 2008 *Theory and Application with Seasonal Time Series

[12] Tsay R S 2002 *Analysis of Financial Time Series* (New Jersey: John Wiley & Sons, Inc)