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An Automatic Irrigation System Based on Hourly Cumulative Evapotranspiration for Reducing Agricultural Water Usage

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Abstract: This study investigates the development and application of an automatic irrigation system based on hourly cumulative evapotranspiration (ET) to optimize cabbage growth while reducing agricultural water usage. Traditional irrigation methods often result in inefficient water use due to reliance on human judgment or fixed schedules. To address this issue, the proposed system utilizes environmental data collected from a field sensor (FS), the Korea meteorological administration (KMA), and a virtual sensor based on a machine learning model (ML) to calculate the hourly ET and automate irrigation. The ET was calculated using the FAO 56 Penman–Monteith (P-M) ET_o. Experiments were conducted to compare the effectiveness of different irrigation levels, ranging from 40, 60, 80, and 100% crop evapotranspiration (ET_c), on plant growth and the irrigation water productivity (WP_I). During the 46-day experimental period, cabbage growth and WP_I were higher in the FS and KMA 60% ET_c levels compared to other irrigation levels, with water usage of 8.90 and 9.07 L/plant, respectively. In the ML treatment, cabbage growth and WP_I were higher in the 80% ET_c level compared to other irrigation levels, with water usage of 8.93 L/plant. These results demonstrated that irrigation amounts of approximately 9 L/plant provided the optimal balance between plant growth and water conservation over 46 days. This system presents a promising solution for improving crop yield while conserving water resources in agricultural environments.

Keywords: precision agriculture; machine learning; environmental data; sustainable agriculture; irrigation water use efficiency

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1. Introduction

Water is an essential element used in various fields, including domestic use, agricultural use, industrial use, environmental maintenance and restoration, recreation, and tourism [1–4]. Although water covers 71% of the Earth's surface, the water resources available for human use are limited [5]. As of 2024, many countries are experiencing water shortages due to the increasing global population [6–8]. To resolve these issues, many countries are implementing Integrated Water Resources Management (IWRM) policies. IWRM is a method for effectively and sustainably managing water resources [9]. It coordinates the development and management of water, land, and related resources to maximize economic and social welfare without compromising the sustainability of vital ecosystems [10,11]. In the Republic of Korea, the IWRM policy is being applied in agriculture, aiming to minimize unnecessary agricultural water usage [12,13]. It is essential to collect sensor-based data on environmental factors and perform real-time crop monitoring to minimize unnecessary agricultural water use [14,15]. Additionally, a comprehensive irrigation strategy for managing agricultural water is necessary.

As climate change becomes more extreme, the amount of water required by crops is changing [16–18]. Traditional irrigation methods relied on experience. Farmers manually irrigated the fields or used agricultural machinery such as sprinklers and irrigation systems. For instance, cabbage cultivation can utilize methods such as sprinkler and drip irrigation [19]. Applying the proper amount of water at the appropriate time is essential for maximizing yield and improving water efficiency [20]. However, these irrigation methods, which rely on human experience, often lead to unnecessary agricultural water use and are not effective in water management.

Therefore, a precision agriculture-based irrigation system is necessary to reduce agricultural water use. Precision agriculture is a farming approach that utilizes advanced technology to increase agricultural productivity and maximize resource use efficiency [21,22]. It is essential to collect data through real-time monitoring of environmental factors and crops to maximize resource use efficiency, ensuring resources are supplied when needed for crop cultivation. In precision agriculture, environmental data that can be collected include temperature, relative humidity, atmospheric pressure, precipitation and rainfall, wind speed, solar radiation, soil moisture content, and temperature [23,24]. Efficient agricultural water management methods in precision agriculture based on environmental data include soil moisture sensor-based water management and evapotranspiration (ET)-based water management [25,26].

Soil moisture sensor-based water management involves determining soil moisture content in real-time and supplying the appropriate amount of water when needed [27]. This method allows for the direct assessment of TAW (Total Available Water) and RAW (Readily Available Water) ranges, thereby reducing unnecessary agricultural water use and supplying crops with the exact amount of water they need, resulting in efficient use of water resources [28,29]. However, the installation and cost of sensors are high, and the measurement results can vary depending on the accuracy and reliability of the sensors. Maintenance is required to prevent sensor failures or malfunctions, and, since sensors only reflect the soil conditions of specific areas where they are installed, it can be difficult to achieve consistent management over large areas. Additionally, due to the need for reinstallation of sensors each season, soil moisture sensors are often used for research purposes rather than practical field agriculture.

ET-based agricultural water management estimates ET using meteorological data and the physiological characteristics of crops to manage water resources [30,31]. a representative method is using the P-M equation to estimate the grass reference evapotranspiration (ET_o). The environmental data required for estimating ET_o include solar radiation, soil heat flux density, temperature, wind speed, and both saturated and actual vapor pressure [32–34]. By calculating ET_o from these environmental data and multiplying by the crop coefficient (K_c) for each growth stage, the crop evapotranspiration (ET_c) can be estimated, and the required amount of water can be supplied [35–37]. The ET-based water management method is not limited to specific areas and allows for broader water management using meteorological data. However, the collected meteorological data may be inaccurate, or the calculated ET may differ from actual values due to changing environmental conditions. Additionally, the greater the distance between the meteorological sensors and the actual field, the more the calculated ET values may vary.

A broad water management approach is needed to conserve agricultural water in field agriculture. Therefore, water management based on the ET is deemed more efficient than water management based on soil moisture. To overcome the limitations of water management based on ET, machine learning was used to reduce the differences between the meteorological administration data and actual field data. Additionally, to minimize the impact of real-time environmental changes on the calculated ET values, an irrigation strategy is proposed that calculates and accumulates the hourly ET_o, resulting in a cumulative ET irrigation approach. The irrigation method based on cumulative evapotranspiration can reduce errors caused by real-time environmental changes more effectively than the irrigation method based on the daily evapotranspiration, enabling timely and accurate water estimation for irrigation. Based on the field sensor, meteorological administration sensor, and virtual sensor utilizing machine learning, environmental data would be used to calculate the hourly ET_o and determine the required water volume in this study. Therefore, the purpose of this study is to calculate the cumulative $ET_{o,}$ using weather data based on field sensor values, Korea Meteorological Administration data values, and virtual sensor values from ML, and to cultivate cabbage with irrigation strategies according to 40, 60, 80, and 100% ET_c under each condition to find the optimal irrigation algorithm.

2. Materials and Methods

2.1. Plant Materials and Experimental Site

This experiment was conducted in a site (36°22′02″ N 127°21′12″ E, elevation = 47 m) located at Chungnam National University (99 Daehak-ro, Yuseong-gu, Daejeon 34134, Republic of Korea). According to the Korea Meteorological Administration (https://data.kma.go.kr/, accessed on 22 January 2025), the average temperature in the experimental region from April to June was 18.9 °C, with a minimum temperature of 13.4 °C and a maximum temperature of 24.9 °C. The total precipitation during this period was 268.21 mm. These meteorological parameters reflect the standard conditions of an average year. The plant material used was cabbage (*Brassica oleracea* 'Daebakna', Asia Seed Korea Co., Ltd., Seoul, Republic of Korea). On 11 March 2024, seeds were sown in rock wool substrate (2.5 × 2.5 × 4 cm, Grodan, Roermond, The Netherlands) in a 128-cell seedling tray at a plant factory. After 2 days of dark treatment, the seedlings were grown under conditions of light intensity 150 ± 10 μmol m^{-2} s^{-1}, photoperiod 16/8 h (light/dark), temperature 25 ± 2 °C, and relative humidity 70–75%. After the true leaves had developed, the plants were supplied with Yamazaki nutrient solution composed of N 8 me L^{-1}, P 1.5 me L^{-1}, K 4.5 me L^{-1}, Ca 2 me L^{-1}, Mg 1 me L^{-1}, and S 3 me L^{-1}, with a pH of 6.5 ± 0.3 and an EC of 0.8 dS m^{-1}.

On 18 April, four weeks after sowing, the cabbages were transplanted to a field. The field was mulched with black plastic, and the cabbages were planted at a spacing of 30 cm. Before transplanting, considering the characteristics of the field soil, a basal application of 6.1 kg ha^{-1} of 21N-17P-17K compound fertilizer, 3.4 kg ha^{-1} of phosphate, and 0.8 kg ha^{-1} of potassium was applied (Table 1). After transplanting, the cabbages were cultivated for a total of 72 days until they were harvested on 28 June. Until 12 May, the cabbages were irrigated with equal amounts of water using drip pipes (UniRamTM AS, 13.7 mm diameter, 0.3 m emitter spacing, 1 L h^{-1} at 0.5–4 kPa, Netafim Korea Co., Ltd., Seongnam, Gyeonggi-do, Republic of Korea). From 13 May to 27 June, an automatic irrigation system was applied, and water was supplied based on the cumulative evapotranspiration measured for the duration of 46 days.

Table 1. The field soil properties at 0–20 cm depth at the experimental site in 2024.

Year	Bulk Density ($g\ cm^{-3}$)	pH (H_2O)	AP ($mg\ kg^{-1}$)	K ($cmol\ kg^{-1}$)	Ca ($cmol\ kg^{-1}$)	Mg ($cmol\ kg^{-1}$)	EC ($dS\ m^{-1}$)
2024	2.57	6.7	126	0.2	3.6	0.9	0.2

Note: AP, available phosphate content.

2.2. Calculation of the Hourly Reference Evapotranspiration

The hourly reference evapotranspiration was calculated based on the P-M ET_o as shown in Equation (1):

$$ET_o = \frac{0.408\Delta(R_n - G) + \gamma\frac{37}{T_{hr}+273}u_2\left(e^0(T_{hr}) - e_a\right)}{\Delta + \gamma(1 + 0.34u_2)}, \quad (1)$$

where ET_o is the grass reference evapotranspiration [mm hour^{-1}], R_n is net radiation at the grass surface [MJ m^{-2} h^{-1}], G is soil heat flux density [MJ m^{-2} h^{-1}], T_{hr} is mean hourly air temperature [°C], Δ is saturation slope vapor pressure curve at T_{hr} [kPa °C^{-1}], γ is psychrometric constant [kPa °C^{-1}], e^0 (T_{hr}) is saturation vapor pressure at air temperature T_{hr} [kPa], e_a is average hourly actual vapor pressure [kPa], and u_2 is average hourly wind speed [m s^{-1}].

Wind speed, solar radiation, relative humidity, and temperature were collected using the field sensor (FS), the Korea Meteorological Administration (KMA), and the virtual sensor based on machine learning (ML) to estimate evapotranspiration. In the FS treatments, meteorological factors were measured every three minutes using weather sensors installed at the Chungnam National University field. The hourly grass reference evapotranspiration (ET_o) was then calculated by averaging the meteorological data collected over each hour. In the KMA treatments, the hourly reference evapotranspiration was calculated using meteorological data measured every hour by the KMA, located 1091 m from the experimental field. In the ML treatments, an XGBoost (Extreme Gradient Boosting) model was trained using sensor data and the KMA data from January 2023 to April 2024 (Figure 1). The trained machine learning model estimated the meteorological data for the experimental site when input with data from the KMA. The performance of the virtual sensor based on the XGBoost model is shown (Table 2). The meteorological data for the experimental site were output hourly, and the ET_o was calculated based on this data.

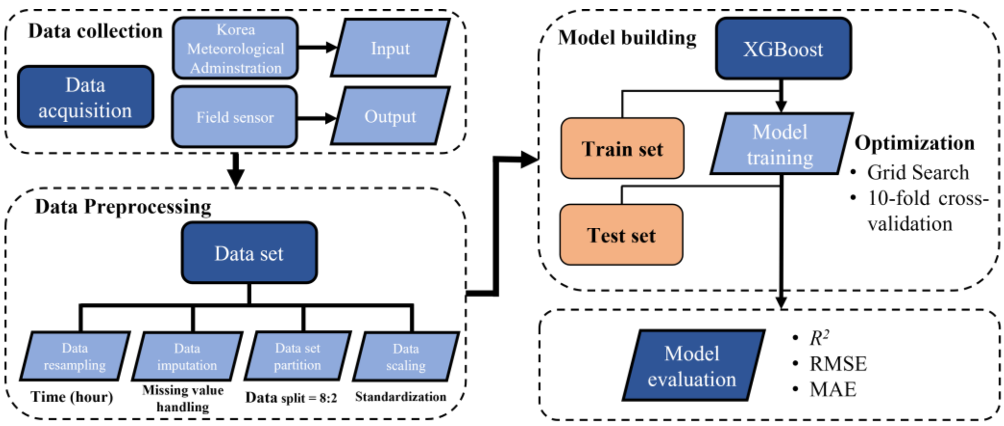

Figure 1. Flowchart representing the process of training a virtual sensor based on machine learning (XGBoost Model).

Table 2. Performance evaluation of XGBoost model for each meteorological factor.

Model Evaluation	Solar Radiation (W/m^2)	Temperature (°C)	Relative Humidity (%)	Wind Speed (m/s)
R^2	0.848	0.982	0.930	0.730
RMSE	101.036	1.340	5.892	0.384
MAE	56.453	0.845	3.924	0.264

Note: R^2, coefficient of determination; RMSE, root mean squared error; MAE, mean absolute error.

2.3. Experimental Design Using Automatic Irrigation System

An automatic irrigation system was developed and used to supply water based on the ET_o. Each treatment calculated the ET_o based on meteorological data determined by the FS, the KMA, and the ML. The ET_o was accumulated each hour, and, when the cumulative ET_o reached 1 mm hour^{-1}, water was supplied using solenoid valves (HPW2110A (10A), Autosigma Hyosin Co., Ltd., Bucheon-si, Republic of Korea) and pumps (PW-200SMA, 19 L·min^{-1}, Wilo Pumps Co., Ltd., Busan, Republic of Korea). The irrigation amounts were 40, 60, 80, and 100% of the crop evapotranspiration (ET_c), supplied via drip pipes (Table 3). According to data from Nongsaro (http://www.nongsaro.go.kr), managed by the Rural Development Administration of Korea, the crop coefficients during the mid-growth (17 days) and late-growth (29 days) stages are set to 1.11 and 1.13, respectively. The ET_c was calculated as shown in Equation (2):

$$ET_c = 0.8 \times K_c \times ET_o, \tag{2}$$

where ET_c is the crop evapotranspiration [mm hour^{-1}], K_c is the crop coefficient, ET_o is the grass reference evapotranspiration [mm hour^{-1}], and 0.8 is the mulching coefficient.

Table 3. Water use per irrigation according to irrigation levels.

Irrigation Levels	Mulching Coefficient	Plant Density (cm)	Water Use per Irrigation (mL/plant)	
			$K_{c\mathrm{mid}}$ (1.11)	$K_{c\mathrm{end}}$ (1.13)
40% ET_c	0.8	0.30.3	32	32.4
60% ET_c			48	48.6
80% ET_c			64	64.8
100% ET_c			80	81

Note: K_c, crop coefficient; $K_{c\mathrm{mid}}$ was applied for 17 days, and $K_{c\mathrm{end}}$ was applied for 29 days.

From 13 May to 27 June, water management was conducted using an automatic irrigation system. When the cumulative ET_o reached 1 mm, the FS, the KMA, and the ML treatments were each supplied with water at 20, 30, and 40 min past the hour, respectively.

2.4. Measurements of Plant Growth Parameters

On 28 June, five cabbages from each treatment were harvested, and plant growth was measured. Each treatment consisted of a single plot with 40 plants, from which five plants were randomly analyzed from each plot (n = 5). The parameters measured included the number of leaves, leaf area, head diameter, shoot fresh weight, head fresh weight, root fresh weight, shoot dry weight, head dry weight, and root dry weight. The dry weight was determined by placing the samples in sample analysis bags and drying them in an oven (HB-501M, Hanbaek Scientific Technology Co., Ltd., Bucheon-si, Republic of Korea) set at 70 °C for 4 days. Additionally, a small portion of the samples collected for component analysis was dried in a freeze-dryer (TFD5503, Ilshin BioBase Co., Ltd., Dongducheon-si, Republic of Korea) for 4 days. The weights were measured using an electronic balance (SPX2202KR, Ohaus Co., Ltd., Parsippany, NJ, USA) and summed to obtain the final dry weight. The leaf area was measured using a leaf area meter (LI-3100, LI-COR Co., Ltd., Lincoln, NE, USA).

2.5. Water Usage and Irrigation Water Productivity

To evaluate water usage after applying the automatic irrigation system, a water meter ([MW] 15 mm, Dae Han Meter Tech Co., Ltd., Gimpo-si, Republic of Korea) was installed (Figure 2). Water usage was measured from 13 May to 27 June. The water usage per plant for each treatment was determined, and the water use per irrigation was calculated using Equations (3) and (4). Additionally, irrigation water productivity (WP_I) was measured using Equation (4), with reference to [38].

$$Water\ use\ per\ irrigation\ (mL) = \frac{Total\ irrigation\ water\ use\ (L)}{Total\ number\ of\ irrigations}, \quad (3)$$

$$Irrigation\ water\ productivity\ (WP_I) = \frac{Marketable\ head\ weight\ (kg)}{Irrigation\ water\ use\ (m^3)}, \quad (4)$$

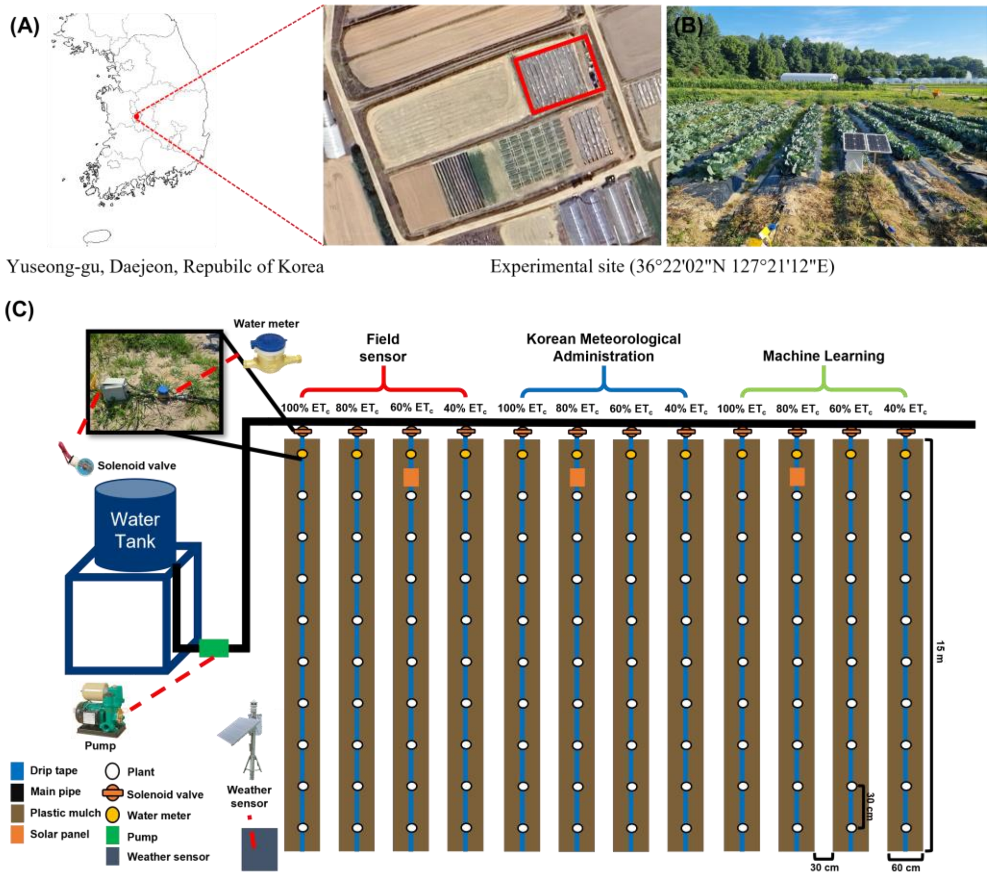

Figure 2. Location and layout of cabbage irrigation experiment. (**A**) Location of experimental site for field cabbage irrigation experiment. (**B**) 72 days after transplanting. (**C**) Schematic diagram of the experimental field setup for cultivating cabbages.

2.6. Statistical Analysis

The statistical analysis was conducted with one-way ANOVA using the SPSS program (version 26, SPSS Inc., Chicago, IL, USA). To determine significant differences between means of irrigation levels, Tukey's honestly significant difference test was applied at a significance level of $p \leq 0.05$. Graphs were generated in Sigmaplot (version 15.0, Systat Software Inc., Chicago, IL, USA). a hierarchical clustering heatmap was created based on normalized average data from various parameters. Principal component analysis

(PCA) followed the modified method by [39] and was performed using XLSTAT software (version 26.4.1, Addinsoft, Paris, France).

3. Results

3.1. Cumulative Evapotranspiration and the Number of Irrigations

From 13 May to 27 June, the mean temperature, the mean relative humidity, the mean solar radiation, and the mean wind speed were measured over a 46-day period using the FS, the KMA, and the ML (Figure 3). The mean temperature measured by the FS, the KMA, and ML ranged from 13.9 to 27.3 °C, 13.5 to 27.5 °C, and 13.9 to 26.5 °C, respectively. Using the KMA, the total precipitation over the 46-day period was measured at 64 mm (Figure 3A). The mean relative humidity measured by the FS, the KMA, and ML ranged from 57.34 to 94.53%, 42.27 to 86.65%, and 59.61 to 95.88%, respectively (Figure 3B). The mean solar radiation measured by the FS, the KMA, and ML ranged from 38.32 to 424.78 W/m^2, 43.00 to 554.81 W/m^2, and 65.30 to 323.78 W/m^2, respectively (Figure 3C). The mean wind speed measured by the FS, the KMA, and ML ranged from 0.55 to 1.95 m s^{-1}, 0.92 to 2.60 m s^{-1}, and 0.60 to 1.34 m s^{-1}, respectively (Figure 3D).

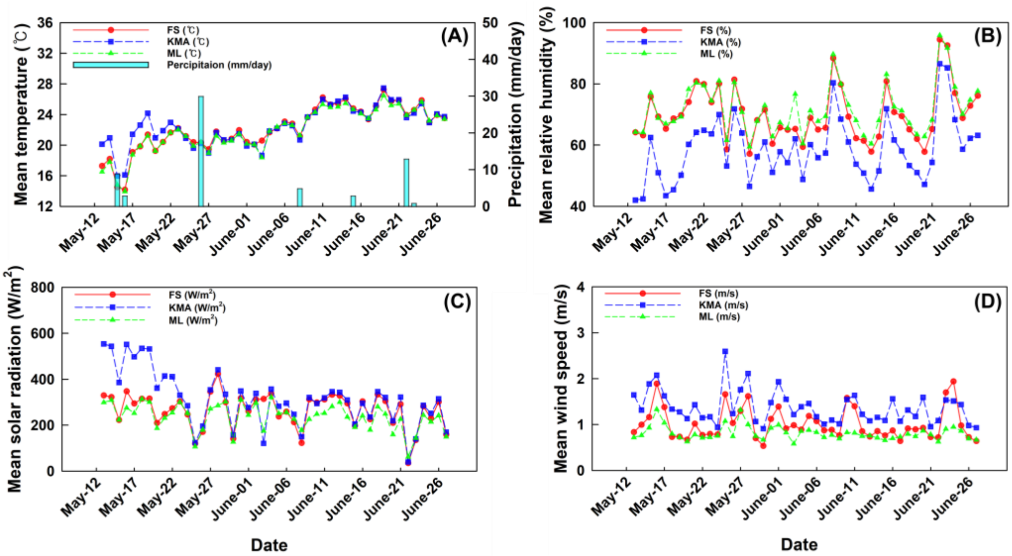

Figure 3. Precipitation and daily temperature from 13 May to 27 June. (**A**) Mean temperature and precipitation, (**B**) mean relative humidity, (**C**) mean solar radiation, and (**D**) mean wind speed were measured by the FS (field sensor), the KMA (Korea Meteorological Administration), and the ML (machine learning). Precipitation was measured by the KMA.

The cumulative evapotranspiration was measured at 5.51, 4.03, and 3.62 mm/day from 24 May to 26 May and at 6.06, 4.68, and 7.44 mm/day from 16 June to 18 June, respectively (Figure 4). The peaks in soil moisture content indicate the operation of the automatic irrigation system and confirm that irrigation was conducted appropriately based on cumulative evapotranspiration (Figure 4). During the experiment period, the hourly evapotranspiration was calculated using meteorological data collected from the FS, the KMA, and the ML. Over the 46-day period from 13 May to 27 June, the total cumulative evapotranspiration was measured at 209.50, 225.41, and 183.42 mm for the FS, the KMA, and the ML, respectively (Figure 5). The solenoid valve of the automatic irrigation system operated 172, 183, and 141 times in the FS, the KMA, and the ML treatments, with operation rates measured at 82.3%, 81.3%, and 77.0%, respectively (Figure 5).

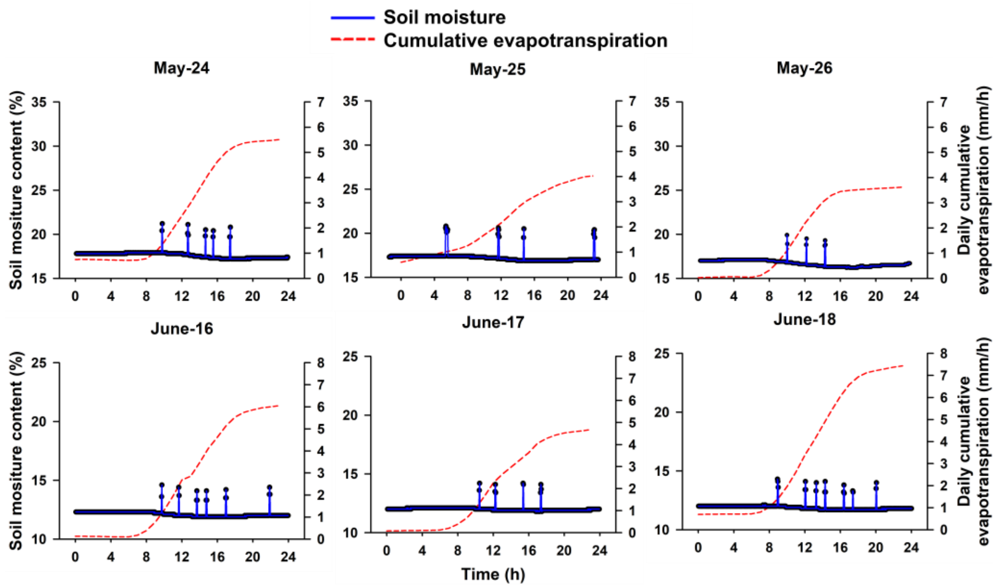

Figure 4. Soil moisture content and daily cumulative evapotranspiration from 24 to 26 May and from 16 to 18 June. Soil moisture content was measured using a soil moisture sensor in 100% ET_c measured by the KMA (Korea Meteorological Administration), and cumulative evapotranspiration was measured based on the KMA.

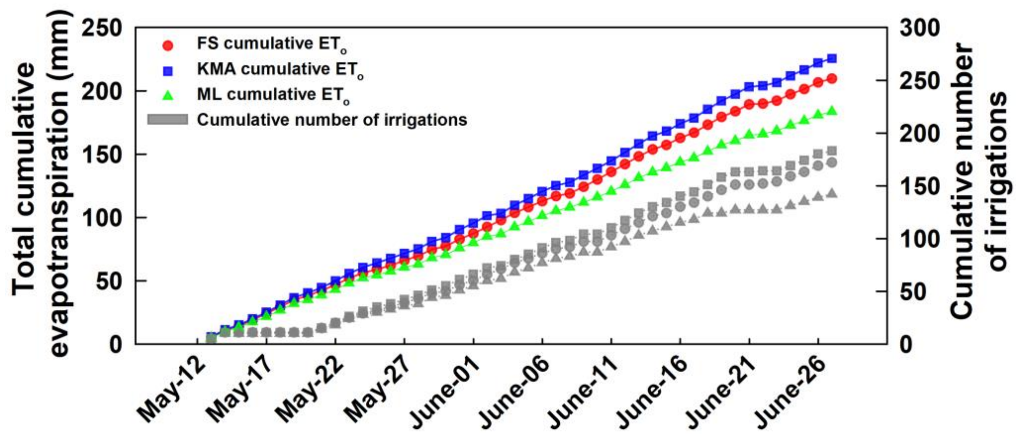

Figure 5. Total cumulative evapotranspiration and number of irrigations of the FS (field sensor), the KMA (Korea Meteorological Administration), and the ML (machine learning) over 46 days (13 May–27 June).

3.2. Growth Parameters of Cabbage

The cabbage was cultivated using an automatic irrigation system for 46 days, from 13 May to 27 June, and the growth parameters such as NL (leaf number), LA (leaf area), SPAD, Fv/Fm, SFW (shoot fresh weight), SDW (shoot dry weight), RFW (root fresh weight), and RDW (root dry weight) were investigated (Table 4). The image presents cabbages harvested on 28 June (Figure 6). In the FS treatment, there were no significant differences in LA, SPAD, Fv/Fm, and RFW between irrigation levels based on ET_c. The LA measured 7303, 11,808, 8501, and 8647 cm^2 for the 40, 60, 80, and 100% ET_c levels, respectively, showing reductions of 38.2, 28, and 26.8% for the 40, 80, and 100% ET_c levels compared to the 60% ET_c level. The SFW was 2393 and 3935 g for the 40 and 60% ET_c levels, respectively, which shows a 64.4% increase in the 60% ET_c treatment compared to the 40% ET_c level. The SDW measured 250.7, 356.4, 246.8, and 243.7 g for the 40, 60, 80, and 100% ET_c levels, respectively, showing reductions of 29.6, 30.7, and 31.6 in the 40, 80, and 100% ET_c

levels compared to the 60% ET_c level. The RDW measured 34.6 and 20.6 g for the 60 and 100% ET_c levels, respectively, showing a 67.5% increase in the 60% ET_c level compared to the 100% ET_c level.

Table 4. The growth parameters of cabbage under different evapotranspiration (ET) conditions, measured by the FS (field sensor), the KMA (Korea Meteorological Administration), and the ML (machine learning), were analyzed under various irrigation levels (40, 60, 80, and 100% of ET_c) from 13 May to 27 June.

Treatment		No. of Leaves	Leaf Area (cm^2)	SPAD	Fv/Fm	SFW (g)	RFW (g)	SDW (g)	RDW (g)
Evapotranspiration	Irrigation Levels								
FS	40% ET_c	20.0 ± 0.63	7303 ± 690.98 b	76.16 ± 3.80	0.75 ± 0.02	2393 ± 170.15 b	115.14 ± 14.98	250.67 ± 21.24 b	27.26 ± 2.12 ab
	60% ET_c	19.4 ± 0.40	11808 ± 963.27 a	76.10 ± 0.53	0.80 ± 0.01	3935 ± 500.63 a	133.06 ± 13.28	356.40 ± 34.55 a	34.57 ± 2.58 a
	80% ET_c	19.2 ± 0.97	8501 ± 516.66 b	73.88 ± 1.50	0.77 ± 0.02	3079 ± 291.71 ab	98.01 ± 10.70	246.83 ± 25.66 b	26.32 ± 4.35 ab
	100% ET_c	18.8 ± 0.49	8647 ± 389.59 b	76.48 ± 2.83	0.80 ± 0.02	2937 ± 156.76 ab	87.77 ± 5.59	243.67 ± 13.92 b	20.64 ± 1.18 b
Significance		NS	**	NS	NS	*	NS	*	*
KMA	40% ET_c	20.4 ± 0.24 ab	9273 ± 1525.18 ab	75.14 ± 2.68	0.75 ± 0.02	2844 ± 538.44 ab	133.68 ±29.76	279.21 ± 47.49 ab	34.23 ± 7.45 a
	60% ET_c	19.0 ± 1.30 b	13,368 ± 563.70 a	78.98 ± 2.49	0.75 ± 0.01	4041 ± 24.31 a	150.19 ± 6.04	345.28 ± 16.20 a	34.31 ± 1.43 a
	80% ET_c	23.8 ± 1.11 a	9603 ± 1757.29 ab	75.90 ± 2.45	0.78 ± 0.01	2588 ± 331.46 b	86.98 ± 8.77	204.32 ± 31.89 b	16.58 ± 2.18 b
	100% ET_c	20.0 ± 0.89 ab	7843 ± 248.45 b	72.10 ± 2.12	0.80 ± 0.01	2535 ± 159.21 b	92.62 ± 4.58	213.97 ± 11.82 b	20.86 ± 0.86 ab
Significance		*	*	NS	NS	*	*	*	*
ML	40% ET_c	25.6 ± 1.63 a	5916 ± 252.88 b	68.26 ± 2.12 b	0.83 ± 0.00	1541 ± 136.11 b	85.06 ± 12.19 b	149.99 ± 8.62 b	17.22 ± 1.73 b
	60% ET_c	17.8 ± 0.58 b	9107 ± 380.63 a	73.98 ± 1.43 ab	0.80 ± 0.01	2998 ± 166.14 a	120.40 ± 7.20 a	298.77 ± 16.81 a	31.99 ± 2.59 a
	80% ET_c	19.4 ± 1.03 b	8533 ± 498.90 a	72.84 ± 1.65 ab	0.82 ± 0.01	3207 ± 231.67 a	109.53 ± 7.99 ab	279.76 ± 18.44 a	24.98 ± 1.63 a
	100% ET_c	18.8 ± 0.8 b	7701 ± 353.19 a	75.48 ± 1.67 a	0.80 ± 0.02	2717 ± 131.61 a	118.92 ± 3.46 a	277.09 ± 12.70 a	28.53 ± 1.47 a
Significance		***	***	NS	NS	***	*	***	***

Note: SFW, shoot fresh weight; RFW, root fresh weight; SDW, shoot dry weight; RDW, root dry weight; NS, not significant ($p > 0.05$); significance at * $p \leq 0.05$, ** $p \leq 0.01$, *** $p \leq 0.001$. Values are the mean ± SE (standard error) of five samples ($n = 5$). Different letters indicate a significant difference between various irrigation levels via Tukey's HSD test at $p \leq 0.05$.

In the KMA treatment, there were no significant differences in SPAD, Fv/Fm, and RFW between irrigation levels based on ET_c (Table 4). The NL was measured as 19.0 and 23.8 for the 60 and 80% ET_c levels, respectively, showing a 25.3% increase in the 80% ET_c level compared to the 60% ET_c level. The LA was 13,368 and 7843 cm^2 for the 60 and 100% ET_c levels, respectively, showing a 70.4% increase in the 60% ET_c level compared to the 100% ET_c level. The SFW was 4041, 2588, and 2535 g for the 60, 80, and 100% ET_c levels, respectively, showing decreases of 36.0 and 37.3% in the 80 and 100% ET_c levels compared to the 60% ET_c level. The SDW was 345.3, 204.3, and 214.0 g for the 60, 80, and 100% ET_c levels, respectively, representing decreases of 40.8 and 38.0% in the 80 and 100% ET_c levels compared to the 60% ET_c level. The RDW was 34.2, 34.3, and 16.6 g for the 40, 60, and 80% ET_c levels, respectively, indicating increases of 106.4 and 106.9% in the 40 and 60% ET_c levels compared to the 80% ET_c level.

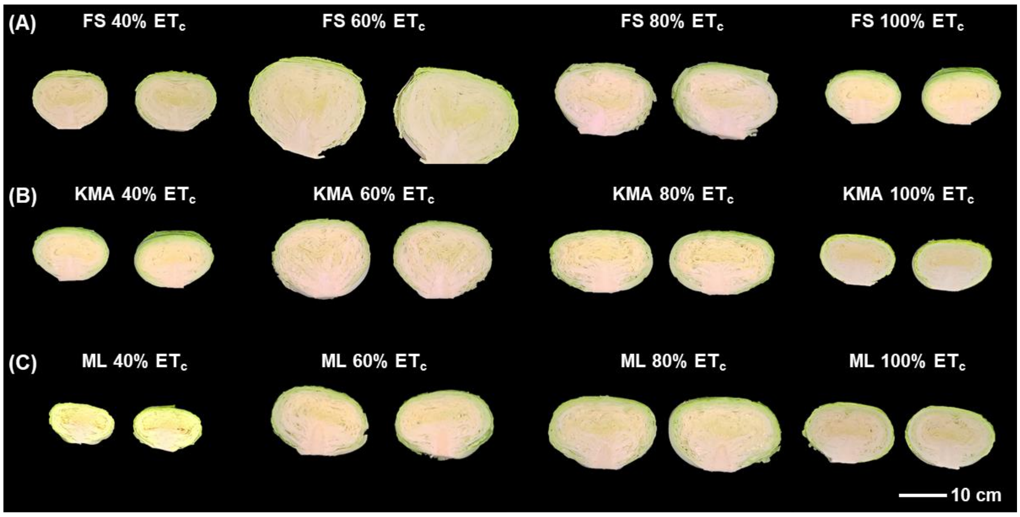

Figure 6. Comparison of cabbage growth under different evapotranspiration (ET) conditions measured by (**A**) the FS (field sensor), (**B**) the KMA (Korea Meteorological Administration), and (**C**) the ML (machine learning) over various irrigation levels (40, 60, 80, and 100% ET_c). The cabbages were grown in an experimental field for a total of 72 days from 18 April to 27 June. The scale bar represents 10 cm.

In the ML treatment, there were no significant differences in SPAD and Fv/Fm between irrigation levels based on ET_c (Table 4). The NL was 25.6, 17.8, 19.4, and 18.8 for the 40, 60, 80, and 100% ET_c levels, respectively, showing reductions of 30.5, 24.2, and 26.6% for the 60, 80, and 100% ET_c levels compared to the 40% ET_c level. The LA measured 5916, 9107, 8533, and 7701 cm^2 for the 40, 60, 80, and 100% ET_c levels, respectively, representing increases of 53.9, 44.2, and 30.2% for the 60, 80, and 100% ET_c levels compared to the 40% ET_c level. The SFW was 1541, 2998, 3207, and 2717 g for the 40, 60, 80, and 100% ET_c levels, respectively, indicating increases of 94.5, 108.1, and 76.3% for the 60, 80, and 100% ET_c levels compared to the 40% ET_c level. The RFW measured 85.1, 120.4, and 118.9 g for the 40, 60, and 100% ET_c levels, respectively, showing increases of 41.5 and 39.8% in the 60 and 100% ET_c levels compared to the 40% ET_c level. The SDW was 150.0, 298.8, 279.8, and 277.1 g for the 40, 60, 80, and 100% ET_c levels, respectively, indicating increases of 99.2, 86.5, and 84.7% for the 60, 80, and 100% ET_c levels compared to the 40% ET_c level. The RDW measured 17.2, 32.0, 25.0, and 28.5 g for the 40, 60, 80, and 100% ET_c levels, respectively, representing increases of 85.8, 45.0, and 65.7% for the 60, 80, and 100% ET_c levels compared to the 40% ET_c level.

3.3. Cabbage Head Parameters

The diameter, HFW (head fresh weight), HDW (head dry weight), and yield of the cabbages were examined across five replicates (Table 5). In the FS treatment, the diameter was 15.08 and 17.66 cm for the 40 and 60% ET_c levels, respectively, representing an 11.8% increase in the 60% ET_c level compared to the 40% ET_c level. The HFW was 1195 and 1956 g for the 40 and 60% ET_c levels, respectively, indicating increases of 63.7% for the 60% ET_c levels compared to the 40% ET_c level. There were no significant differences in the HDW between irrigation levels based on ET_c.

In the KMA treatment, the diameter was 16.08 and 19.81 cm for the 40 and 60% ET_c levels, respectively, representing a 23.2% increase in the 60% ET_c level compared to the 40% ET_c level (Table 5). There were no significant differences in the HFW and yield between irrigation levels based on ET_c. The HDW was 133.5, 66.5, and 80.1 g for the 60, 80, and 100% ET_c levels, respectively, showing decreases of 50.1 and 40.0% in the 80 and 100% ET_c levels compared to the 60% ET_c levels.

Table 5. The cabbage head parameters and yield under different evapotranspiration (ET) conditions measured by the FS (field sensor), the KMA (Korea Meteorological Administration), and the ML (machine learning), were analyzed under various irrigation levels (40, 60, 80, and 100% of ET_c) from 13 May to 27 June.

Treatment		Head Diameter (cm)	HFW (g)	HDW (g)	Yield (t ha^{-1})
Evapotranspiration	**Irrigation Levels**				
FS	40% ET_c	15.08 ± 0.41 b	1195 ± 97.93 b	84.83 ± 9.34	44.22 ± 3.62 b
	60% ET_c	17.66 ± 0.60 a	1956 ± 238.91 a	117.58 ± 12.64	72.37 ± 8.84 a
	80% ET_c	17.56 ± 0.68 ab	1665 ± 191.70 ab	97.11 ± 11.68	61.60 ± 7.09 ab
	100% ET_c	17.54 ± 0.78 ab	1618 ± 123.35 ab	93.52 ± 7.34	59.87 ± 4.56 ab
Significance		NS	*	NS	*
KMA	40% ET_c	16.08 ± 0.86 b	1369 ± 259.87	96.56 ± 14.34 ab	50.65 ± 9.62
	60% ET_c	19.81 ± 0.84 a	1999 ± 115.78	133.45 ± 7.02 a	73.96 ± 4.28
	80% ET_c	16.98 ± 1.23 ab	1270 ± 195.43	66.53 ± 11.61 b	46.99 ± 7.23
	100% ET_c	16.41 ± 0.56 ab	1325 ± 132.13	80.12 ± 6.83 b	49.03 ± 4.89
Significance		*	NS	**	NS
ML	40% ET_c	13.19 ± 0.9 b	605 ± 238.35 b	41.09 ± 4.84 b	22.39 ± 3.94 b
	60% ET_c	18.34 ± 0.38 a	1564 ± 142.58 a	123.55 ± 9.30 a	57.87 ± 2.36 a
	80% ET_c	19.59 ± 0.59 a	1809 ± 345.42 a	125.93 ± 11.43 a	66.93 ± 5.72 a
	100% ET_c	18.93 ± 0.44 a	1517 ± 211.85 a	111.42 ± 9.87 a	56.13 ± 3.51 a
Significance		***	***	***	***

Note: HFW, head fresh weight; HDW, head dry weight; Yield was converted to fresh weight per hectare. NS, not significant ($p > 0.05$); significance at * $p \leq 0.05$, ** $p \leq 0.01$, *** $p \leq 0.001$. Values are the mean ± SE (standard error) of five samples (n = 5). Different letters indicate a significant difference between various irrigation levels via Tukey's HSD test at $p \leq 0.05$.

In the ML treatment, the diameter was 13.19, 18.34, 19.59, and 18.93 cm for the 40, 60, 80, and 100% ET_c levels, respectively, showing an increase of 39.0, 48.5, and 43.5% for the 60, 80, and 100% ET_c levels compared to the 40% ET_c level (Table 5). The HFW was 605, 1564, 1809, and 1517 g for the 40, 60, 80, and 100% ET_c levels, respectively. This represents increases of 158.5, 199.0, and 150.7% in the 60, 80, and 100% ET_c levels compared to the 40% ET_c level. The HDW measured 41.1, 123.6, 125.9, and 111.4 g for the 40, 60, 80, and 100% ET_c levels, respectively, showing increases of 200.7, 206.5, and 171.2% for the 60, 80, and 100% ET_c levels compared to the 40% ET_c level.

3.4. Water Usage During the Experimental Period

The water usage by the automatic irrigation system was measured over a 46-day period from 13 May to 27 June. In the FS treatment, total water usage per plant for the 40, 60, 80, and 100% ET_c levels was 6.30, 8.90, 11.22, and 11.55 L, respectively (Figure 7A). The water usage per irrigation for the 40, 60, 80, and 100% ET_c levels was 36.65, 51.73, 65.24, and 67.13 mL, respectively (Figure 7B). In the KMA treatment, total water usage per plant for the 40, 60, 80, and 100% ET_c levels was 6.71, 9.07, 12.95, and 15.28 L, respectively (Figure 7A). The water usage per irrigation for the 40, 60, 80, and 100% ET_c levels was 36.66, 49.54, 70.74 and 83.48 mL, respectively (Figure 7B). In the ML treatment, total water usage per plant for the 40, 60, 80, and 100% ET_c levels was 4.86, 7.09, 8.93, and 11.31 L, respectively (Figure 7A). The water usage per irrigation for the 40, 60, 80, and 100% ET_c levels was 34.47, 50.29, 63.34 and 80.21 mL, respectively (Figure 7B).

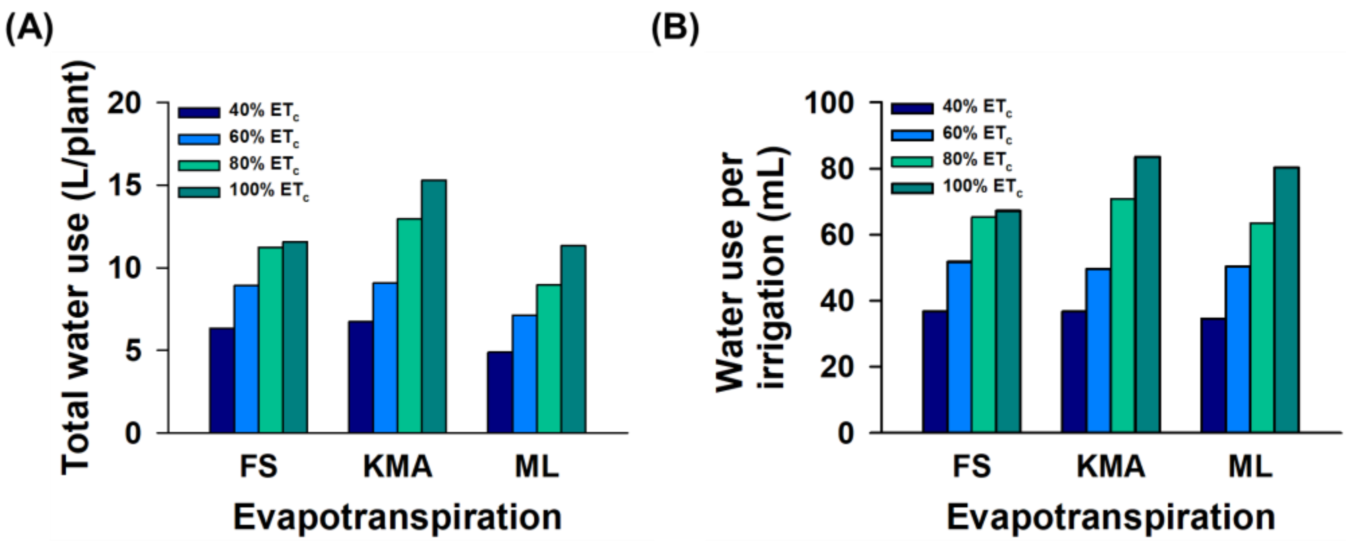

Figure 7. Total water use of the automatic irrigation system for cultivating cabbage from 13 May to 27 June. Evapotranspiration (ET) conditions measured by the FS (field sensor), the KMA (Korea Meteorological Administration), and the ML (machine learning). (**A**) Total water use per plant. (**B**) Water use per irrigation.

3.5. Irrigation Water Productivity of Cabbage and Yields

The irrigation water productivity (WP_I) of cabbage was analyzed over a 46-day period from 13 May to 27 June (Figure 8). In the FS treatment, the WP_I for the 40, 60, 80, and 100% ET_c levels were measured at 189.58, 219.83, 148.38, and 140.14 kg m^{-3}, respectively. Compared to the 100% ET_c level, the 60% ET_c level increased by 56.9%. The coefficient of determination for the FS treatment was 0.67 (Figure 8A). In the KMA treatment, the WP_I for the 40, 60, 80, and 100% ET_c levels were measured at 204.05, 220.49, 98.10, and 86.73 kg m^{-3}, respectively. Compared to the 60% ET_c level, the WP_I decreased by 55.5 and 60.7% in the 80 and 100% ET_c levels, respectively. The coefficient of determination for the KMA treatment was 0.79 (Figure 8B). In the ML treatment, the WP_I for the 40, 60, 80, and 100% ET_c levels were measured at 124.48, 220.56, 202.54, and 134.14 kg m^{-3}, respectively. Compared to the 60% ET_c level, the WP_I decreased by 43.6 and 39.2% in the 40 and 100% ET_c levels, respectively. The coefficient of determination for the ML treatment was 0.97 (Figure 8C).

Water supplied by irrigation and cabbage yields were compared in all treatments (Figure 8D and Table 5). In the FS treatment, when irrigation was supplied at 223.10, 329.30, 415.14, and 427.35 m^3, the yields were 44.22, 72.37, 61.60, and 59.87 t ha^{-1} (converted to fresh weight per hectare units), respectively. In the KMA treatment, irrigation amounts of 248.72, 335.59, 479.15, and 565.36 m^3 resulted in yields of 50.66, 73.96, 46.99, and 49.03 t ha^{-1}, respectively. In the ML treatment, irrigation at 179.82, 262.33, 330.41, and 418.74 m^3 led to yields of 22.39, 57.87, 66.94, and 56.13 t ha^{-1}, respectively. The results of the regression analysis showed a coefficient of determination of 0.71. The maximum expected yield, using an automatic irrigation system, was 65.83 t ha^{-1} with 385.8 m3 of water, corresponding to 10.43 L/plant and a head weight of 1.78 kg.

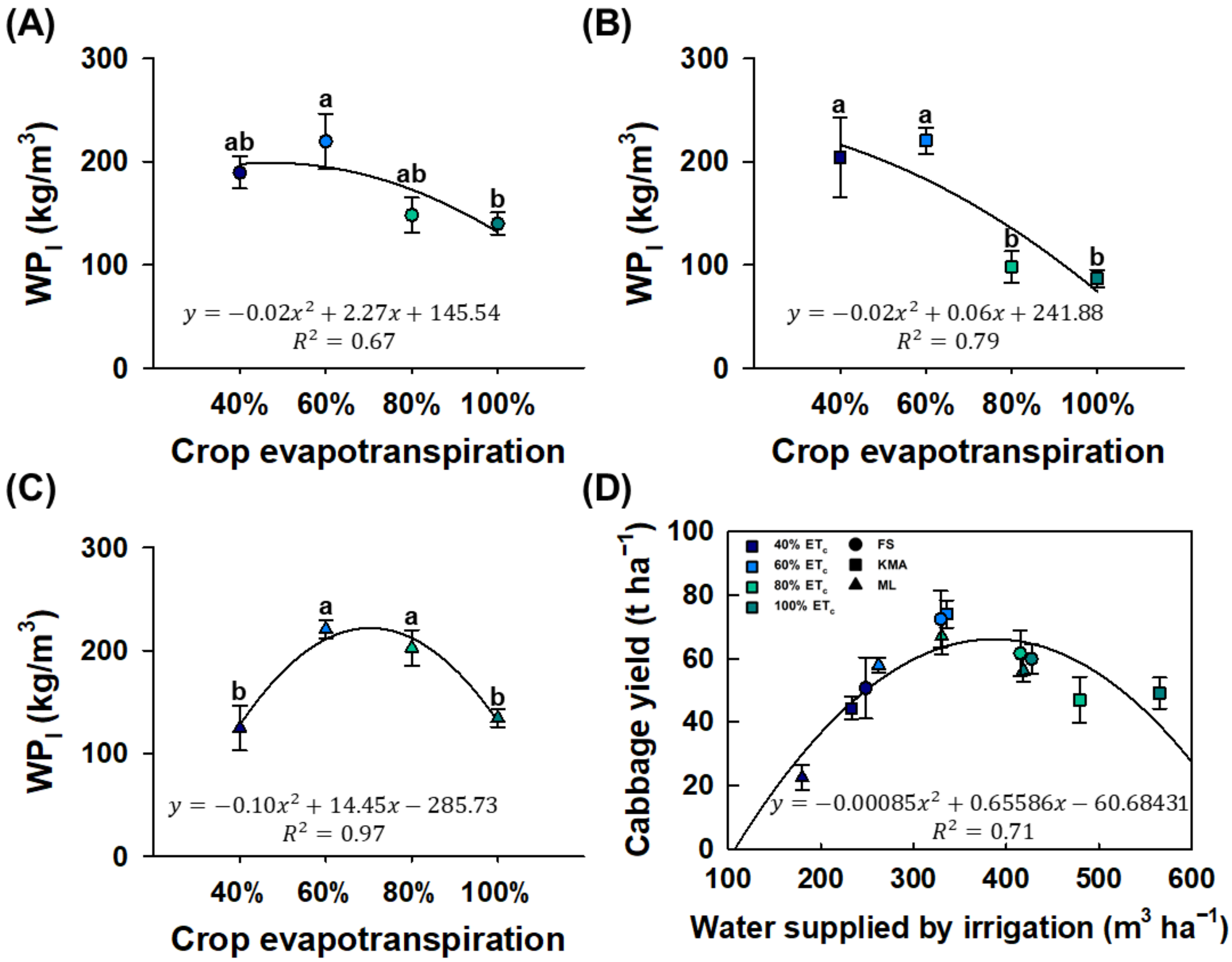

Figure 8. Irrigation water productivity (WP$_I$) and cabbage yield of the automatic water supply system for cultivating cabbage from 13 May to 27 June. Evapotranspiration (ET) conditions measured by (**A**) the FS (field sensor), (**B**) the KMA (Korea Meteorological Administration), and (**C**) the ML (machine learning) over various irrigation levels (40, 60, 80, and 100% ET$_c$). (**D**) Cabbage yield versus water supplied by irrigation (converted to hectare units). Data are represented as the mean ± SE (standard error) of five samples (n = 5). Different letters indicate a significant difference between treatments based on ET$_c$ irrigation levels (Tukey's HSD test at $p \leq 0.05$).

3.6. Hierarchical Clustering Heatmap and Principal Component Analysis

A heatmap was generated using color gradients to visualize the performance of different parameters across each treatment. Normalized average data of different variables were used for the heatmap (n = 5). The parameters were clustered into two groups using hierarchical clustering (Figure 9A). The 'Cluster A' included SFW, SDW, HFW, diameter, LA, RFW, RDW, HDW, SPAD, and WP$_I$. The 'Cluster B' consisted of NL and Fv/Fm. All raw data were analyzed using PCA. The results of the PCA showed that PC1 accounted for 61.05% of the total variance and PC2 accounted for 9.26%, with the two components explaining 70.31% of the total variance (Figure 9B). PC1 was determined by growth parameters such as SFW, SDW, HFW, diameter, LA, RFW, RDW, HDW, WP$_I$, and NL, while PC2 was determined by SPAD and Fv/Fm. The parameters in 'Cluster A' had a positive correlation with each other.

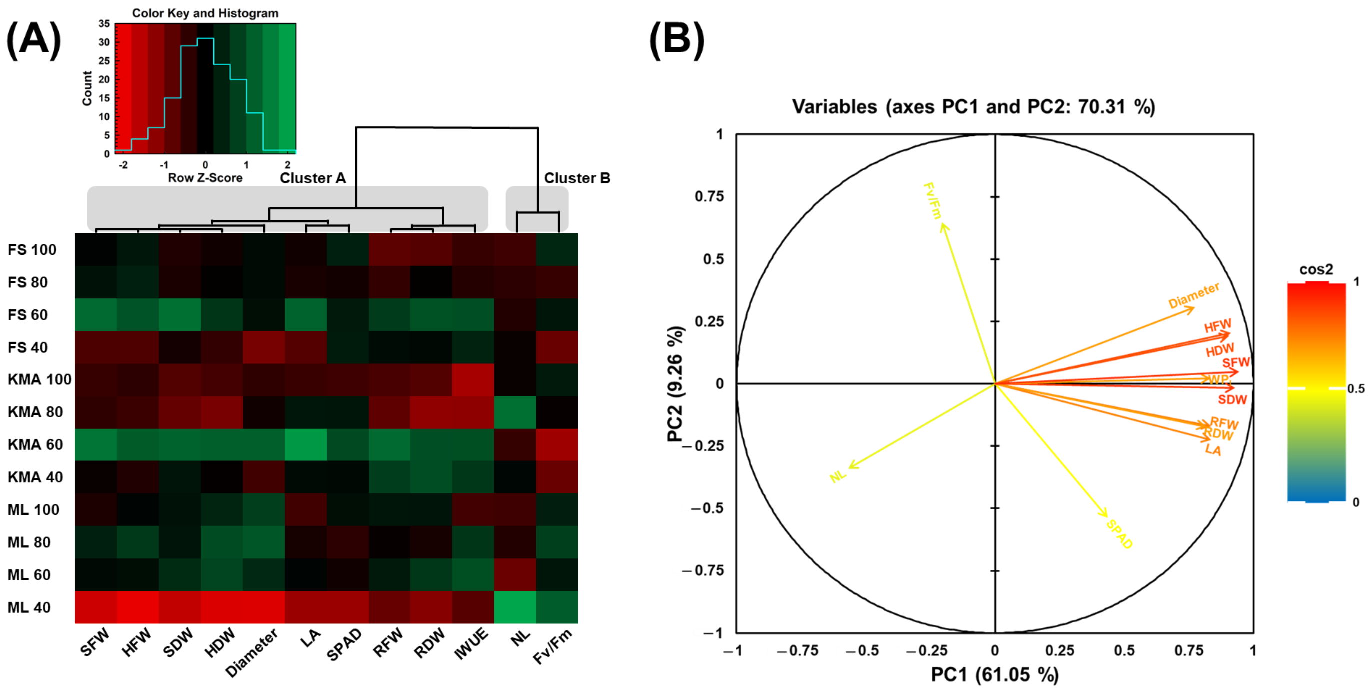

Figure 9. (**A**) Hierarchical clustering heatmap representing different variables under the treatments (FS, field sensor; KMA, Korea Meteorological Administration; ML, machine learning) based on ET_c irrigation levels. Normalized average data of different variables were used to the heatmap (n = 5). The variables were grouped into two clusters (Cluster a and Cluster B). (**B**) PCA (principal component analysis) represents the relationship among various irrigation levels and variables. The variables included HFW (head fresh weight), SFW (shoot fresh weight), HDW (head dry weight), LA (leaf area), SDW (shoot dry weight), WP_I (irrigation water productivity), RDW (root dry weight), RFW (root fresh weight), diameter, NL (number of leaves), SPAD, and Fv/Fm.

4. Discussion

The automatic irrigation system operated based on cumulative evapotranspiration, and the cumulative evapotranspiration was measured as highest for the KMA, followed by the FS, and then the ML treatments. Accordingly, water usage for each irrigation level followed the same results: the KMA, the FS, and the ML treatments (Figure 7A). In the FS treatment, the water usage of the 100% ET_c level was similar to that of the 80% ET_c level due to a malfunction in the solenoid valve operation time (Figure 7). Consequently, the FS treatment had the lowest coefficient of determination for WP_I among all treatments (Figure 8). In contrast, the ML treatment exhibited accurate water use per plant and the highest coefficient of determination for WP_I across all treatments (Figures 7B and 8). Therefore, it is concluded that the ML treatment provided the most accurate irrigation management when the automatic irrigation system was in operation.

In our study, the FS and the KMA 60% ET_c levels exhibited higher WP_I, along with increased RDW, SFW, SDW, HFW, and HDW (Figure 8 and Table 4). In 2016, the cabbage yield for 0.4, 0.6, 0.8, 1.0, and 1.2 ET_c levels were 27.90, 34.68, 42.64, 43.88, and 38.81 t ha^{-1}, respectively. As the irrigation amount increased, cabbage yield also increased; however, the yield decreased at the 1.2 ET_c level, and WP_I sharply declined from the 0.8 ET_c level [40]. Similarly, in a three-year study conducted between 2009 and 2012, the average cabbage yield for 0.8, 0.9, 1.0, and 1.1 ET_c levels was 23.2, 29.7, 31.7, and 26.4 t ha^{-1}, respectively. While the yield increased with irrigation up to the 1.0 ET_c level, they declined in the 1.1 ET_c level [19]. Notably, the highest water use efficiency was observed in the 0.9 ET_c level, and water use efficiency declined as irrigation levels increased thereafter. a similar finding was reported by [41], where the average cabbage head weight in 1997 was 1.1, 1.8, 2.3, 2.6, and

2.7 kg in the 20, 40, 60, 80, and 100% pan evaporation levels, respectively, with the 60% pan evaporation level showing the highest water use efficiency. These results suggest that irrigation levels have a significant effect on cabbage growth and yield, and it is important to determine the optimal water use efficiency.

Plant roots absorb various mineral ions from the soil through both the apoplast and symplast pathways [42,43]. Both pathways are involved in the transport of water and mineral ions, and sufficient water supply to the rhizosphere is essential for the absorption of mineral ions by the roots [44,45]. The absorbed ions are transported to the shoot via the xylem, where they are utilized for cell differentiation, elongation, and turgor [46–48]. Therefore, root growth is closely related to shoot growth, and many plant studies have confirmed the strong correlation between root and shoot growth [49–51]. Hierarchical clustering and PCA analysis showed that WP_I, root parameters, and shoot parameters clustered together, indicating a positive correlation between root and shoot parameters (Figure 9). Consequently, the 60% ET_c level could positively influence WP_I and RDW, which in turn could also have a positive effect on shoot growth parameters belonging to the same cluster.

On the other hand, in the KMA treatment, SFW and HDW decreased in the 80 and 100% ET_c levels compared to the 60% ET_c level (Tables 4 and 5). Overly wet conditions in the rhizosphere can reduce root respiration and inhibit root growth [52,53]. Reduced root growth can lead to decreased shoot growth and yield, as there is a positive correlation between root and shoot growth (Figure 9). The 80 and 100% ET_c levels not only resulted in unnecessary water usage but also had a negative impact on shoot growth (Figure 8 and Table 4). Therefore, the automatic irrigation system based on hourly cumulative evapotranspiration, supplying 12.95 and 15.28 L over 46 days, could potentially reduce cabbage yield.

In the ML treatments, cabbage under the 40% ET_c level showed a decrease in LA, head diameter, HFW, HDW, SFW, SDW, RDW, and yield compared to the 60, 80, and 100% ET_c levels, although LA was higher (Tables 4 and 5). Similarly, in the FS treatment, SFW, head diameter, HFW, and yield were reduced at the 40% ET_c level. In 2012, 50% ET_c treatment after 133 days of transplanting resulted in an 8.4, 25.3, and 17.8% reduction in head width, fresh weight, and yield, respectively, compared to the 100% ET_c treatment [54]. In 2020, the 0.6 ET_o level showed a 3.6, 13.9, and 9.1% reduction in head diameter, fresh weight, and yield, respectively, compared to the 1.0 ET_o level [55]. These findings suggest that lower irrigation levels based on ET_c can negatively impact cabbage growth and yields.

Water moves from the soil to the roots, from roots to stems and leaves, and eventually evaporates into the air through transpiration [56,57]. Water moves from areas of higher to lower water potential [58]. Lower irrigation amounts can reduce soil water potential more than larger amounts of irrigation [59,60]. As a result, when soil and root water potential differences decrease, it becomes more difficult for water to move from the soil to the plant roots. Since soil mineral ions are absorbed with water by plant roots, lower irrigation amounts can make it difficult for plants to absorb the materials necessary for growth. Therefore, low irrigation amounts can lead to reduced plant growth. Using the automatic irrigation system based on hourly cumulative evapotranspiration, supplying less than 6.30 L of water over 46 days, can lower soil water potential compared to other treatments, making it difficult for roots to absorb water and thereby reducing cabbage head fresh weight and yields (Table 5).

5. Conclusions

The automatic irrigation system based on hourly cumulative evapotranspiration positively impacted cabbage growth by supplying water in a timely and appropriate amount. Hierarchical clustering and principal component analysis (PCA) showed that root growth parameters and shoot parameters were grouped together, indicating a positive correlation between them. An irrigation amount of 4.86 L/plant (ML 40% ET_c) over 46 days reduced root growth, which in turn led to a decline in shoot growth. On the other hand, 12.95 L/plant (KMA 100% ET_c) caused over-watering in the root zone, thereby reducing shoot growth and leading to unnecessary agricultural water usage. Irrigation levels based on evapotranspiration measured by the FS, the KMA, and the ML at 60, 60, and 80% ET_c levels excluding natural rainfall, respectively, showed optimal results for cabbage growth and WP_I. Water usage in the FS 60% ET_c level was 8.90 L/plant, while, in the KMA 60% ET_c level, it was 9.07 L/plant, and, in the ML 80% ET_c level, it was 8.93 L/plant. Based on these findings, the optimal irrigation amount for cabbage cultivation is approximately 9.0 L/plant over 46 days, considering both yield and WP_I. The automatic irrigation system based on hourly cumulative evapotranspiration can efficiently increase cabbage yields while reducing unnecessary agricultural water usage. These findings can be applied to other crops, highlighting the broader potential of this irrigation system for optimizing water use.

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