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Assessing the Impact of Reference Evapotranspiration Models on Decision Support Systems for Irrigation

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Abstract: Reference evapotranspiration (ET_0) is a major estimator for crop water requirements predicted by decision support systems for irrigation. However, the impact of different ET_0 s on the predicted amount of water supply and counts of irrigation events has not been evaluated. Simulations of the Geisenheim Irrigation Scheduling (GS) for vegetable crops with two different ET_0 s, P2- ET_0 and FAO56- ET_0 , were evaluated to assess exemplarily the impact of ET_0 s. The sensitivity of both ET_0 s to local climate conditions was characterized through a random forest analysis, and a linear regression model was used to adjust the original GS by adapting K_c -values to the exchange ET_0 . For assessing the outcomes of GS irrigation decision, simulations of 173 individual cropping cycles including six vegetable crops over eight years were conducted. After adjusting P2- ET_0 K_c -values to FAO56- ET_0 K_c -values, there was no impact of the ET_0 -model on the practical irrigation scheduling with GS. Finally, we discuss that any ET_0 -model, if adjusted accordingly, might have little impact on similar irrigation systems and provide a method to exchange ET_0 s.

Keywords: irrigation scheduling; random forest; crop water balance; K_c -values; vegetable crops

1. Introduction

Water resources are limited; however, the worldwide water demand is increasing with a growing population and industry [1]. The naturally-available water supply is decreasing as a result of changes in precipitation and water ecosystems caused by climate change [2]. In contrast, horticultural crops have a high demand for water. Thus, crop growth and quality can only be secured by providing sufficient irrigation, especially for leafy vegetables. In this context, horticulture is forced to justify irrigation decisions, as well as optimize water use efficiency. A significant key to meet these challenges is an efficient and comprehensible irrigation scheduling system. For open field irrigation, there are several procedures available for estimating crop water requirements [3]. Irrigation scheduling based on estimating crop water requirements with reference evapotranspiration (ET_0) and crop coefficients (K_c -values), also called “crop water balance (CWB)”, is internationally well-established [4,5]. The CWB approach has been found to be simple, convenient, and reproducible for many crops in different climate conditions ([6] and the references therein). The reference evapotranspiration (ET_0) represents the potential evapotranspiration of a model surface or crop. For crop-specific evapotranspiration, ET_0 is adapted by K_c -values. K_c -values are scaling factors generated by adjusting the measured actual crop evapotranspiration (ET_c) to a ET_0 (Equation (1)).

$$K_c = \frac{ET_c}{ET_0} \quad (1)$$

Since K_c -values are a relative measure of the crop’s evapotranspiration, each ET_0 and each CWB model need specifically parametrized and evaluated K_c -values. Therefore, high quality and

validly-calculated ET_0 , as well as carefully-parametrized K_c -values, are crucial for the CWB [5]. There are three types of ET_0 models: first, models depending exclusively on ambient temperature (e.g., [7]), second, radiation and temperature-based models [8], and third, combination models additionally containing aerodynamic properties (e.g., [9]). The ET_0 models differ in their calculation procedures by the effort involved in the calculation, local adjustment, and the quantity and quality of data acquisition for precise ET_0 estimates. The FAO56 Penman–Monteith- ET_0 , which is a combination model (FAO56- ET_0 ; [5]), is currently the commonly-used and most positively-evaluated ET_0 [10–12]. It is used in the “ K_c - ET_0 approach” to calculate and schedule crop irrigation [4,5]. Besides the FAO24 K_c - ET_0 approach, there are further CWB procedures or software-based irrigation recommendation systems, as reviewed by Cahn and Johnson [3] (Section 4.1). Some of them represent more advanced decision support systems for irrigation scheduling [13–22]. Their underlying concept of ET_c estimation is similar to the above-mentioned approach. One of these is the Geisenheim Irrigation Scheduling (GS), which is locally developed and applied under German climate conditions [23]. The GS approach is similar to the FAO56 single K_c procedure (see the Materials and Methods). GS has been developed over the past 30 years, and there are K_c -values evaluated for about 27 vegetable crops [24]. For calculating GS, as well as the evaluation of the corresponding K_c -values, the Penman- ET_0 [9] has been used, which was adapted and adjusted for the research site (further called P2- ET_0). An external service provider supplied this P2- ET_0 . This is not unusual, since some ET_0 s, as the FAO56- ET_0 , are data demanding, and for some regions, the availability of all required model parameters is limited. Therefore, there are efforts to utilize statistically-adjusted and less data-demanding ET_0 models (e.g., [10,25–31]). Consequently, the P2- ET_0 data, like any other statistically- or methodically-adjusted ET_0 , is proprietary and exclusively available for the research site. To overcome this lack of universal applicability and, in our case, to eliminate the dependency on an external service provider, it can be necessary to exchange the ET_0 used to calculate CWB.

However, the effect of this ET_0 exchange on the recommendations of a decision support system for vegetable irrigation is not yet known: Federer et al. [32] found ET_0 s to differ in their accuracy, affected by different climates and regions, with no consistent trend. Therefore, in general, there should be differences between P2- ET_0 and FAO56- ET_0 . Further, there have been attempts to optimize the ET_0 used in dynamic crop models, e.g., in a maize model, the effects of different ET_0 s were assessed, finding no statistical difference in the modeling-based conclusion [33]. Hence, the ET_0 exchange might not affect the basic functionality of GS, also considering it is a much simpler model. However, this kind of models covers only one specific crop. Furthermore, they evaluate the effect of ET_0 on the performance of crop growth systems rather than the quality of irrigation decisions. Xu and Chen [34] found small deviations in water balances depending on different ET_0 s in a model for groundwater recharge. This suggests that different ET_0 s might produce small deviations in crop water balances, as well. Even though, the impact of different ET_0 s on decision support systems for vegetable irrigation has not been evaluated so far. To fill this gap, we assess exemplarily the impact of P2- ET_0 and FAO56- ET_0 on GS irrigation recommendations.

To exchange the ET_0 model in an irrigation decision support system, several requirements have to be met. These requirements are described for GS in the following points: (I) The ET_0 model has to provide a reliable estimation of ET_0 without the need for adjustments to local conditions and a robust, well-documented calculation procedure with broad application and implementation. (II) The ET_0 model requires a similar sensitivity to the input data such as temperature, air humidity, global radiation, and wind speed as P2- ET_0 . (III) The exchange of the ET_0 model has to be enabled via an adjustment of the K_c -values to sustain GS for practical application. (IV) The exchanged ET_0 model should produce similar irrigation patterns and volumes as the original ET_0 model. We assumed that GS could be driven with FAO56- ET_0 by using statistically-adjusted K_c -values, which were evaluated with P2- ET_0 , without significant changes in the resulting irrigation patterns and volumes. This study focused on performing sensitivity analysis for ET_0 values and the statistical adjustment of K_c -values for FAO56- ET_0 with an added validation with computer simulations. We hypothesize that CWB procedures, in general, do not

solely depend on the ET_0 and can be driven with different ET_0 s, producing the same outcomes when adjusted correctly. This paper will describe a method that may enable the adjustment of irrigation decision support systems with similar constraints in ET_0 data availability.

2. Materials and Methods

2.1. Geisenheim Irrigation Scheduling

Geisenheim Irrigation Scheduling [23,24] is a decision support system for sprinkle irrigation management of vegetable crops. GS was developed in Geisenheim (Germany, Hesse, lat 49.98 long 7.96, soil: sandy loam, mean precipitation 549 mm/a) over the past 30 years. It is parametrized for 27 vegetable crops. These parametrizations are based on marketable yield. The underlying principle of GS is a crop water balance. Parameters of GS have been evaluated in an open-air gravimetric container system (similar to lysimeters), as well as in multi-annual open field experiments. The actual crop transpiration and soil evaporation (ET_c) is balanced with the incoming precipitation and irrigation over the cultivation time on daily steps (see Equation (3)). For calculating ET_c , GS uses an ET_0 adjusted by K_c -values, representing the crop's evapotranspiration (see Equation (2)). The K_c -values are gradually adjusted over the cultivation period in stages, depending on the phenological development of the crop, which is measured in BBCH ("Biologische Bundesanstalt, Bundessortenamt und Chemische Industrie") code states [35]. The calculation of the GS procedure can be described as follows: first, crop K_c -values and rooting depths with their corresponding developmental stages are selected from the GS data tables [24]. Second, the irrigation thresholds for every developmental stage are calculated. The thresholds represent the soil water content available for evapotranspiration (mm) and are determined by the available field capacity of the soil (AFC) concerning the maximum rooting depth and the rooted zone of the crop at the corresponding developmental stage. For each crop's developmental stage, there is an individual number of soil layers defined. Thus, the first threshold equals the soil water content in the first rooted soil layer held between 60% to 90% AFC; the next threshold consists of 60% to 100% AFC of the first layer plus 60% to 90% AFC of the second layer. The AFC in the first layer is held to 90% to prevent nutrient leaching due to precipitation. This procedure applies to all following layers and developmental stages, accordingly. Third, a starting point for the soil water content for the field is set. This point is defined at 90% AFC. Either the corresponding soil water content can be measured gravimetrically or it can be induced by extensive irrigation or precipitation, filling the soil pores with water. This results in the soil reaching field capacity approximately two days after. At the beginning of cultivation, the calculation of the CWB starts with the daily crop water balance. Therefore, daily ET_c is calculated from ET_0 and the current K_c -values (Equation (2)), which is balanced with the precipitation and irrigation of the day. This daily water balance is then summed up over the cultivation period as the total water balance (see Equation (3)). If this total water balance equals or exceeds a deficit equivalent to the respective irrigation threshold, this amount of water is recommended for irrigation (see Equation (4)). In case total water balance exceeds 100% AFC due to an irrigation or rainfall event, this water drains into deeper soil layers, and the total water balance is set to zero. If this excess is caused by heavy rainfall, causing a total saturation of the coarse soil pores, the calculation is interrupted for two days to allow the coarse soil pores to drain again to field capacity. Over the whole cultivation period, phenological development of the crop is observed regularly, so, by reaching the defined BBCH code states, K_c -values and irrigation thresholds for the daily calculation step are adjusted to the next stage.

$$ET_c = K_c \cdot ET_0 \quad (2)$$

$$\text{water balance}_{GS} = \sum_{Start}^{End} \text{irrigation} + \text{rainfall} - ET_c \quad (3)$$

$$\text{if } \text{water balance}_{GS} \geq \text{water threshold} \Rightarrow \text{irrigation} \quad (4)$$

2.2. Data

Weather data from the years 2000–2009, as well as the P2- ET_0 were recorded daily, nearby the experimental site in Geisenheim and provided by the German weather forecast (DWD) (<http://www.dwd.de>). FAO56- ET_0 was calculated from these weather data. The corresponding units and abbreviations of the data are displayed in Table 1.

The calculation of FAO56- ET_0 was based on the standard procedure as described by Allen et al. [5] for daily steps. This includes the use of maximum and minimum air temperatures and the zeroing of soil heat flux ($G = 0$; see Equation (5)). Contrary to the recommended procedure, actual vapor pressure (e_a) is calculated by Equation (6). This is because the minimum and maximum air humidity were not logged and thus were not available for the recommended calculation procedure. For GS simulations, a total of 173 individual recorded cultivation datasets from years 2000–2008 were used. They include K_c -values and BBCH state dates for six cultivars: cauliflower (*Brassica oleracea* var. *botrytis* L.), broccoli (*Brassica oleracea* var. *italica* Plenck), bush bean (*Phaseolus vulgaris*), carrot (*Daucus carota* subsp. *sativus*), leek (*Allium porrum*), and onion (*Allium cepa*).

Table 1. Overview of the daily weather data with units and abbreviations.

Value	Abbreviation	Unit
Penman-P2- ET_0	P2- ET_0	mm · d ⁻¹
FAO56 Penman–Monteith- ET_0	FAO56- ET_0	mm · d ⁻¹
Temperature mean (24 h)	Temperature	°C
Temperature mean (max/min)	Tmm	°C
Temperature maxima	Tmax	°C
Temperature minima	Tmin	°C
Relative air humidity mean (24 h)	AirHumidity	%
Global radiation	Radiation	MJ · m ⁻² · d ⁻¹
Wind speed at 2 m height mean (24 h)	Windspeed2m	m · s ⁻¹

$$FAO56-ET_0 = \frac{0.408\Delta(R_n - G) + \gamma \frac{900}{T+273} u_2 (e_s - e_a)}{\Delta + \gamma(1 + 0.34u_2)}, \quad (5)$$

where

FAO56- ET_0 is reference evapotranspiration (mm · d⁻¹),

R_n net radiation at the crop surface (MJ · m⁻² · d⁻¹),

G soil heat flux density (MJ · m⁻² · d⁻¹),

T mean daily air temperature at 2 m height (°C),

u_2 wind speed at 2 m height (m · s⁻¹),

e_s mean saturation vapor pressure (kPa),

e_a actual vapor pressure (kPa),

$e_s - e_a$ saturation vapor pressure deficit (kPa),

Δ slope vapor pressure curve (kPa · °C⁻¹), and

γ psychrometric constant (kPa · °C⁻¹), and:

$$e_a = \frac{RH_{mean}}{100} e_s, \quad (6)$$

where

e_a is actual vapor pressure (kPa),

e_s mean saturation vapor pressure (kPa), and

RH_{mean} mean relative air humidity (%).

2.3. Sensitivity Analysis with Random Forest

The differences of $P2-ET_0$ and $FAO56-ET_0$ were statistically assessed by an analysis of sensitivity to the environmental conditions in Geisenheim (weather data 2000–2009) using a random forest model [36,37]. In contrast to classical sensitivity analysis methods, which often observe local and one-dimensional parameter sensitivity, random forest allows for global multidimensional estimates of parameter sensitivity [38]. The random forest algorithm builds randomly-generated “regression decision trees”. For each tree, the algorithm samples a random subsample of the input and training data, which is known as “bagging”. This machine learning model was built for $P2-ET_0$ and $FAO56-ET_0$ depending on the weather data, which also included the measuring date as a predictor. The random forest regression trees were built by using three of eight variables (Table 1, plus date as a variable) in each tree, in a total of 500 trees for each ET_0 . To determine the count of variables in each tree, the square root of total variables was rounded to the next full number [37]. The sensitivity was assessed by the inherent variable importance of the random forest models. It was measured as a relative increase in mean squared error (%IncMSE), as recommended by Breiman [37]. This value describes the increase in predicting performance loss of the random forest model if the factor in question is excluded from the model. The variable importance is statistically independent of the parametrization data, because it is generated from bagged data and, is thus, a very reliable value [36]. The relative rank of %IncMSE compared the sensitivity of the random forest ET_0 models to the input variables, since the absolute value has no meaning for a comparison of random forest models. The random forest function used to predict either $FAO56-ET_0$ or $P2-ET_0$ out of the most important variable (factor) of the models was plotted to compare them visually.

2.4. Regression Model

To utilize $P2-ET_0-K_c$ -values ($P2-K_c$) in the calculation of GS with $FAO56-ET_0$ as $FAO56-K_c$, a linear regression model without intercept was parametrized. This simplified model approach enables the easy mathematical transposition from ET_0 to K_c -values as follows: The abundance of an intercept allows for a static adjustment of K_c -values, without the need for daily recalculations depending on ET_0 . Consequently, $P2-ET_0$ was predicted from $FAO56-ET_0$ (Equation (7)), so that $P2-K_c$ could be transposed to $FAO56-K_c$ (Equation (8)). For parametrization of the regression model, we used the dataset from 2009 and excluded it from simulation data to maintain statistical independence to prevent overfitting. The performance of the regression model was assessed via residual standard deviation, relative residual standard deviation, and analytical plots of the residuals versus predicted values.

$$P2-ET_0 = x \cdot FAO56-ET_0 \quad (7)$$

(7) in (2):

$$ET_c = (P2-K_c \cdot x) \cdot FAO56-ET_0 \quad (8)$$

2.5. Simulations

Computer simulations of GS were evaluated to assess the predicting performance of the $FAO56-K_c$ model. The impact of a replaced ET_0 and statistically-adjusted K_c -values in contrast to the original GS was measured by comparing simulations of irrigation events. Weather data from 2000–2008 and cultivation data for the six crops (see Section 2.2) were input into an R-script (see Section 2.6), which implemented both ET_0 s in GS (GS_{P2} , GS_{FAO56}).

The $FAO56-K_c$ in GS_{FAO56} were statistically adjusted through the parametrized regression model (see Section 2.4). Since precipitation adds a random error to the irrigation calculations, precipitation data were excluded for these simulations. Hence, no calculation pauses due to an excessive water supply for the soil were included in the simulations. The model output was summarized as differences in the total amount of water given (IWD), the total count of irrigation events ($IC_{GS_{P2}}$, $IC_{GS_{FAO56}}$), and differences in the total count of irrigation events (ICD) for each of the six crops.

2.6. Computer Software

All statistical analyses and simulations were calculated using the R-programming language [39]. For the random forest model generation, the package randomForest was used [40]. Graphs were produced with the R-Package ggplot2 [41] with the color palette developed by Brewer [42]. The document was built with \LaTeX and the dynamic document generation package knitr [43–45].

3. Results and Discussion

3.1. Regression

To adjust $P2-K_c$ statistically for the use with $FAO56-ET_0$ in GS, we conducted a regression analysis between $P2-ET_0$ and $FAO56-ET_0$ with a simple linear regression model without intercept. $P2-ET_0$ was predicted by $1.33 \cdot FAO56-ET_0$ with a residual standard deviation of 0.37 mm (Figure 1). This corresponds to a relative error of 0.13%. The regression model (Figure 1) fit well to the data. The analytical plot of the residuals versus predicted revealed a very slightly skewed relationship at low and high ET_0 values (blue line, Figure 2). The residuals of this model subsided at low and high values. Additionally, the residual mean (red dotted line) did not match the zero (black dotted line) exactly (Figure 2). These observations indicate a slight underestimation of the regression model and might question the linearity of the model. There might be better-fitting statistical models to estimate the relationship between $P2-ET_0$ and $FAO56-ET_0$. However, our model is the only approach that allows for a one factorial adjustment of the K_c -values without the influence of the ET_0 . Consequently, $FAO56-K_c$ were calculated by $1.33 \cdot K_{c,P2}$ (Equations (7) and (8)). A final evaluation of this regression model requires the combination with the irrigation model, which is described in Section 3.3.

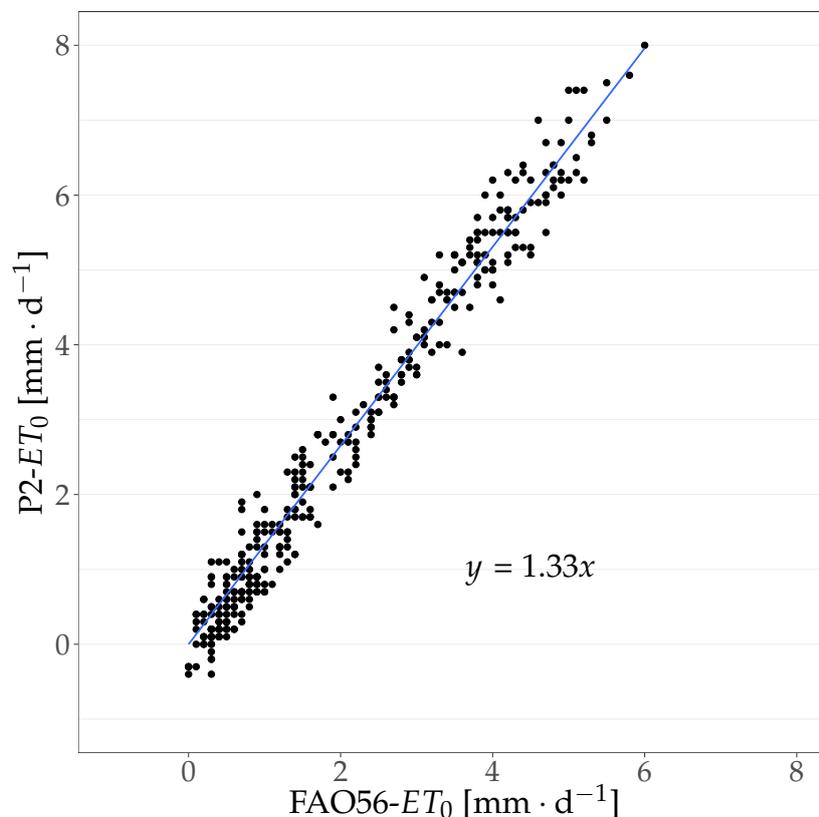


Figure 1. Simple linear regression model (blue line) for $P2-ET_0 \sim FAO56-ET_0$ ($\text{mm} \cdot \text{d}^{-1}$). Data for the year 2009, Geisenheim, Germany.

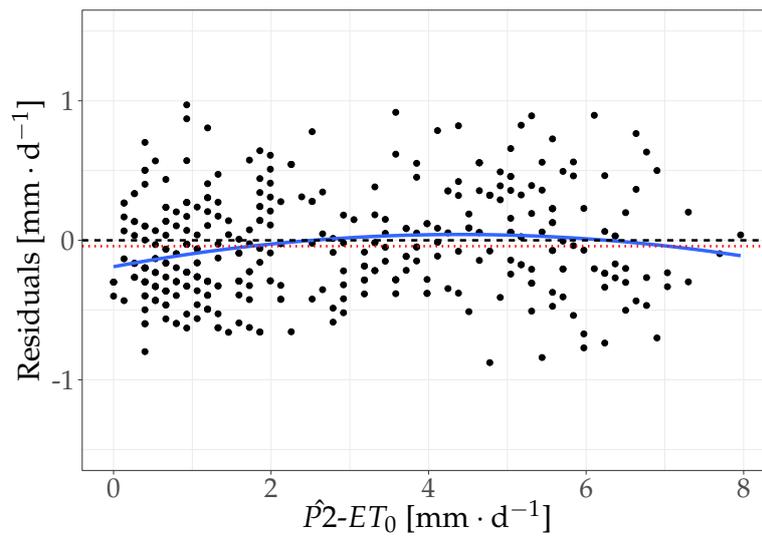


Figure 2. Residuals ($\text{mm} \cdot \text{d}^{-1}$) versus predicted ($\text{mm} \cdot \text{d}^{-1}$) plot of the regression model $\text{P2-ET}_0 \sim \text{ET}_0$: $\text{P2-ET}_0 - \hat{\text{P2-ET}}_0$ versus $\hat{\text{P2-ET}}_0$. With the null line (black), residual mean (red line), and polynomial trend line of residuals (blue line, $y = 1.07 \cdot x^2 - 0.82 \cdot x - 0.04$, $\alpha = 0.01$, $\text{adj.}R^2 = 0.03$).

3.2. Sensitivity of Random Forest

The factor importance of the FAO56-ET_0 and P2-ET_0 random forest models is shown in Figure 3. In both cases, the most important factor was global irradiation, followed by air temperature and relative air humidity. The overall order of the variables differed only slightly. Consequently, it was likely that there were no significant differences in the fluctuations of P2-ET_0 and FAO56-ET_0 at the research site. This conclusion is supported by the partial dependence plot for the most important variable, global radiation (Figure 4). Both ET_0 models followed the global radiation similarly. For instance, irregular patterns such as the sudden rise of the curves between $12 \text{ MJ} \cdot \text{m}^{-2} \cdot \text{d}^{-1}$ to $15 \text{ MJ} \cdot \text{m}^{-2} \cdot \text{d}^{-1}$ were present in both models. These findings suggest that a simple linear scaling factor, as achieved with the regression model, may be capable of adjusting both ET_0 s on an equal value. Moreover, a similar order of sensitivity rankings in the main vegetation period was also found for FAO56-ET_0 , e.g., by Gong et al. [46], DeJonge et al. [47]. Due to this, the method for P2-ET_0 to FAO56-ET_0 adjustments appears applicable in other regions, as well.

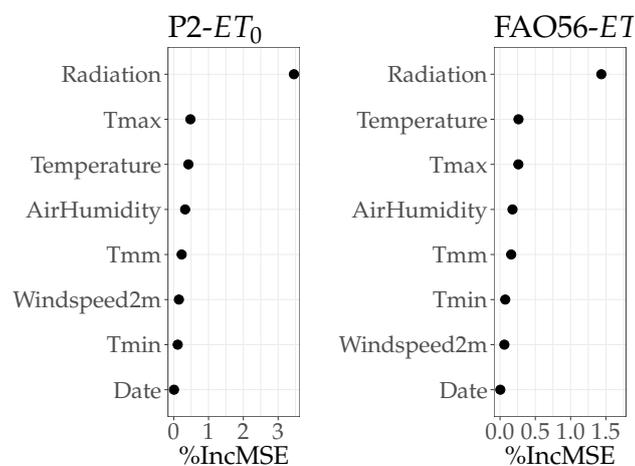


Figure 3. Ranks of variable importance (%IncMSE), for the Random Forest Models P2-ET_0 and FAO56-ET_0 , using weather data of the years 2000–2009 (Explanation of parameters in Table 1).

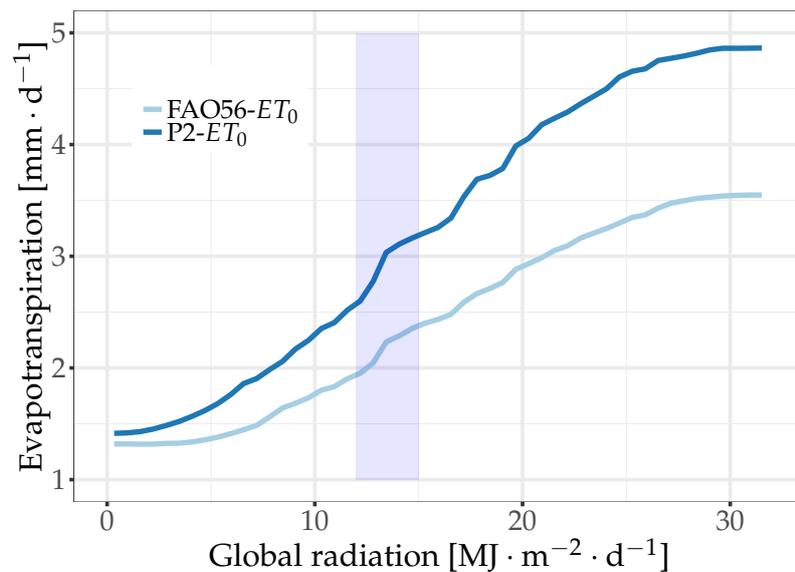


Figure 4. ET_0 ($\text{mm} \cdot \text{d}^{-1}$) predicted by global radiation ($\text{MJ} \cdot \text{m}^{-2} \cdot \text{d}^{-1}$), based on functions of random forest models for P2- ET_0 and FAO56- ET_0 . The shaded box marks a similar the sudden rise of both ET_0 s in response to the global radiation.

3.3. Simulations of GS

The comparison outcomes for GS_{P2} and GS_{FAO56} are shown in Table 2. Aggregated results are presented for the six vegetable crops. There are averaged and relative differences of totaled irrigation water (IWD) and counted irrigation events (ICD). The mean IWD varied between 1.18% for broccoli and 6.76% leek. This means that irrigation with the original P2- ET_0 -driven GS produced higher amounts of irrigation water than the FAO56- ET_0 adjusted GS. The highest standard deviation was observed in bush beans (12.57%) with a mean IWD of 5.45%. This may be due to the high variability in cultivation periods, which is also represented by the standard deviation of IC FAO56- ET_0 and IC P2- ET_0 (Table 2). The boxplot (Figure 5) pictures the distribution patterns of the IWD. A widespread distribution of IWD was observed in bush bean. ICD ranged between 0.25 and 0.76 counts (Table 2). Thus, on average, there was a 0.45 irrigation events difference between the simulated GS irrigation scheduling systems. The simulations of broccoli, carrot, cauliflower, leek, and onion seemed to generate negligible differences in irrigation water when compared to common water distribution patterns produced by sprinkler irrigation. For instance, the variation of the applied amount of water from common sprinkler irrigation techniques in comparison to the water available to the crop was reported between 55% to 85% [48]. Zhang et al. [49] described an average sprinkler system uniformity (defined as the distinct distribution uniformity of water applied in the whole irrigation system on the field). They found a sprinkler system uniformity of 79% on average over several sprinkler types and terrain topographies. The ICD of the simulations strengthen the implication that there are negligible differences between GS_{P2} and GS_{FAO56} for practical irrigation purposes. The ICD did not exceed one irrigation on average (Table 2).

The distribution of ICD is given in Figure 6. In 59% of the cases, there were no differences between GS_{FAO56} and GS_{P2} at all. Over all crops, the ICD showed that GS_{FAO56} irrigated slightly less often than GS_{P2} . One less irrigation event was simulated in 36% of all irrigation events. Two fewer irrigation events were simulated in only 5% of the cases ($n = 173$). Nonetheless, crops, which were the most likely to have simulated two fewer irrigation events, leek and onion, produced a mean IWD of just 6.76% and 1.87%. This low level of different water supply was also covered by the technical constraints of common irrigation techniques mentioned above. Overall, the simulation results met our expectations concerning the exchange of the ET_0 with adjusted K_c -values for GS. The exchange resulted in similar irrigation patterns and water volumes for our simulation study.

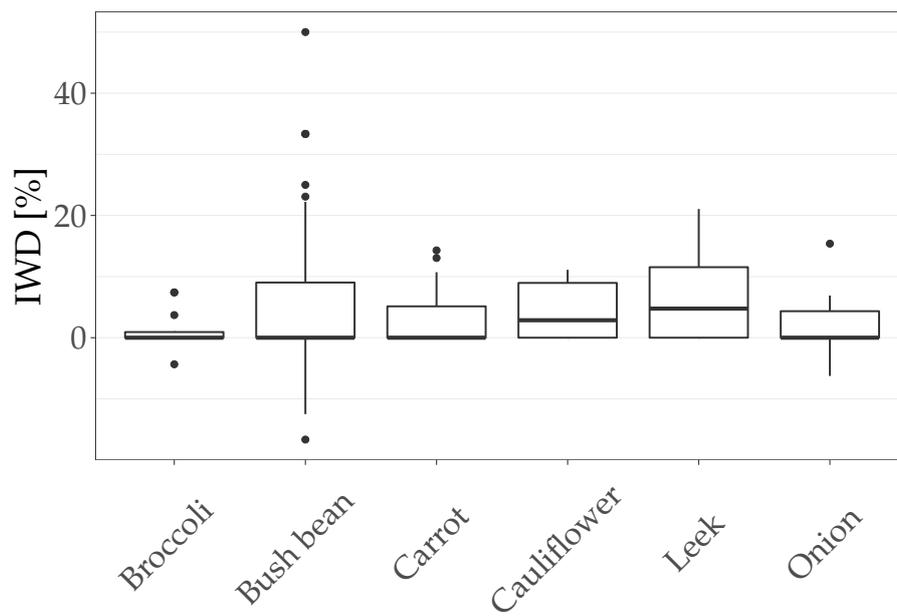


Figure 5. Boxplot of relative irrigation water differences (IWD %), $GS_{P2} - GS_{FAO56}$, by GS simulations for the six vegetable crops. Black line = median, Boxes = second and third quantile, points = outliers.

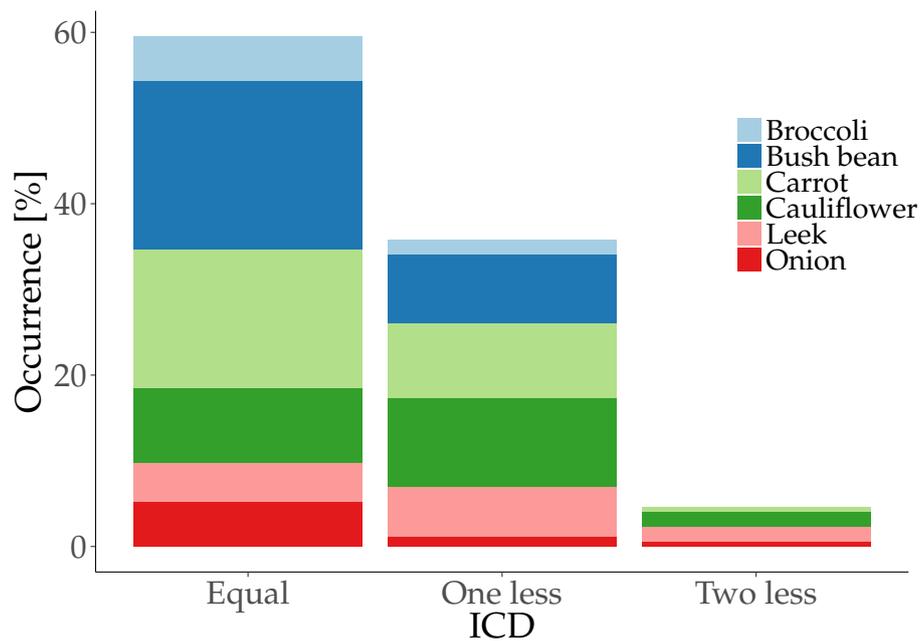


Figure 6. Occurrence (%) of irrigation count differences, ICD, of GS_{P2} relative to GS_{FAO56} ($GS_{P2} - GS_{FAO56}$) as simulated using the six vegetable crops.

Table 2. Simulation results comparing GS_{P2} and GS_{FAO56} ($GS_{P2} - GS_{FAO56}$) with mean irrigation water differences (%) (IWD), mean irrigation counts for both models (IC GS_{P2} , IC GS_{FAO56}), and mean irrigation count differences (ICD) and their corresponding standard deviation.

Crop	IWD	±	IC GS_{P2}	±	IC GS_{FAO56}	±	ICD	±
Broccoli	1.18	3.38	11.50	2.32	11.75	2.70	0.25	0.45
Bush bean	5.45	12.57	7.46	1.80	7.75	1.86	0.29	0.46
Carrot	2.84	4.19	15.98	3.83	16.36	4.01	0.39	0.54
Cauliflower	4.03	4.32	16.78	1.82	17.44	2.10	0.67	0.63
Leek	6.76	7.14	17.00	5.36	17.76	5.54	0.76	0.70
Onion	1.87	5.88	17.25	4.58	17.58	4.74	0.33	0.65

3.3.1. The Precision of the CWB and ET_0 Model

The limits and validity range of both the CWB procedure and the ET_0 model are crucial for a better comprehension of the limits and validity range of our study. Individual, local parametrizations of $FAO56-ET_0$ can also cause daily, site-specific errors ranging from -4% to 15% [12]. These errors may be related to the non-linear residual deviations due to the exclusion of the intercept in the model (Figure 2). However, also Xu and Chen [34] found a maximum error of 10% for CWB models, when used to calculate groundwater recharge, that have not been calibrated for their research site. Apart from the variability, the mean IWD was positive over all crops. This may be due to the differing assumptions of the Penman reference evapotranspiration and the $FAO56-ET_0$. Penman is known to overestimate ET_0 , because of the hypothesized free evaporating water surface [5]. This is accounted for in the $FAO56-ET_0$ using crop surface resistances. Therefore, the observed decrease in amounts of irrigation water and count of irrigation events might also be an improvement over the original GS. The irrigation decision may be more resource efficient, by recommending fewer irrigation events due to a more accurate representation of ET_c . Furthermore, similar comparison between a Penman-1963- ET_0 and the FAO-modified Penman- ET_0 equation produced a difference of 23% in annual ET_0 [50]. However, the observed difference of 33% (factor 1.33) in our study in comparison to the difference of 23% [50] may be caused by different climate conditions and the modifications in the $P2-ET_0$.

3.3.2. Numerical and Statistical Issues

The statistical and numerical features of the model were essential constraints when rating the outcome of this study. In the first instance, as for any other model, parametrization an experimental validation was necessary for other locations. Further, the regression factor of 1.33 to adjust $P2-K_c$ to ET_0 may be titled as “yet another trimming screw”. However, this factor influences the resulting irrigation decisions in GS simulations. When compared with terms like the albedo coefficient used in the Penman–Monteith- ET_0 or the whole net radiation model in different ET_0 s, the observed effect of these factors might be similar to the K_c -values’ adjustment at the end. As a generalization, the regression model used was a one-factor representation of the differences between $FAO56-ET_0$ and $P2-ET_0$. Simplified and less data-demanding models to predict ET_0 are frequently reported in the literature [10,25–31]. In these studies, the authors successfully adjusted statistical ET_0 models for their region with $FAO56-ET_0$ as a reference, also neglecting the physically-based assumptions made in the $FAO56-ET_0$.

Further, it is in the nature of statistical model parametrizations to fit for the parametrization site. This is even true with bad parametrization for a single submodel in a complex model. However, with each additional parameter, an additional source of error arises. The more different the location from the parametrization site, the more significant is the error, due to overfitted parameters. Thus, the single parameter K_c -value model may work as well as, or outperform, complex models at other non-parametrization sites.

Another cause of differences in the simulations might be the binary nature of the irrigation trigger, amplifying the contrast between the models. However, no examinations were carried out to determine whether an irrigation event occurred one or two days after the end of the irrigation model period. Since precipitation was excluded for simulations, it is likely that the influence of natural precipitation patterns may decrease or also level the observed differences.

3.3.3. Practical Considerations

Based on the study, GS seemed to be useful for practical application with statistically-valid adjusted K_c -values and FAO56- ET_0 . As it is a decision support system for irrigation scheduling, one fewer recommended irrigation has little practical meaning. In contrast to the considerable impact that natural precipitation, as well as a false prediction of this precipitation may have on cultivation and irrigation practice, the influence of the model recommended irrigation water may vanish. Moreover, two fewer simulated irrigation events may result in very different patterns if natural rainfall comes into consideration. Furthermore, irrigation decisions are, in practice, considered based on many other technical constraints, e.g., availability of irrigation systems and pest control. Those constraints might find consideration in complex future irrigation decision support systems.

As emphasized before, we used a simple method to estimate and adjust the differences necessary to facilitate the future use of GS. There is a need for simple methods for decision support systems because GS has to serve as a practical model for an economic decision. An overly complicated system might lead to failure, because of the need for dedicated labor to evaluate the model and adjust it for the needs of the farm, also reducing the economic value of the complex. Additionally, the transferability of GS might be facilitated by this simple method, as we eliminated the dependency on an external service provider for calculating GS. Moreover, the FAO56- ET_0 adjusted K_c -values may be more easily modified for other climates by the method of Allen et al. [5], enabling the use of GS in other regions.

4. Conclusions

In the Geisenheim Irrigation Scheduling, the reference evapotranspiration $P2-ET_0$ can be replaced by the scientifically known ET_0 to form FAO56- ET_0 . Both ET_0 s have a similar sensitivity to the weather conditions on the parametrization and evaluation site of GS in Geisenheim. With this prerequisite fulfilled, it was possible to parametrize a simple linear regression model to transpose K_c -values from $P2-ET_0$ to the use with FAO56- ET_0 . Therefore, the practical application of GS is possible with FAO56- ET_0 and adjusted K_c -values. GS produces similar irrigation recommendations with the ET_0 changed to FAO56- ET_0 with adjusted K_c -values as with $P2-ET_0$ and the original K_c -values. Furthermore, there is a potential for optimized irrigation recommendations with the more physically-adequate FAO56- ET_0 .

This study enabled us to eliminate the dependency on external weather service and to provide the Geisenheim Irrigation Scheduling with a commonly-available ET_0 for a universal application. In the process of the evaluation of the ET_0 exchange in GS, we used random forest as the statistical procedure to assess the local sensitivities of the two ET_0 s. It proved to be a valuable tool and may be of good use in similar “black box” applications. We replicated irrigation events with computer simulations from GS with FAO56- ET_0 and yielded nearly the same outcome concerning common irrigation practices. The ET_0 model itself has no impact on the practical irrigation scheduling recommendations of GS. Thus, the validity of a similar irrigation decision support system based on CWB might be independent of the incorporated ET_0 , as well, if adjusted accordingly. Overall, we provide a proven method to adjust CWB procedures to an exchanged ET_0 .

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Abbreviations

The following abbreviations are used in this manuscript:

AFC	Available field capacity of the soil
BBCH	Crop phenology index
CWB	Crop water balance
GS	Geisenheim Irrigation Scheduling
ET_0	Reference evapotranspiration
ET_c	Actual crop evapotranspiration
FAO56	Reference evapotranspiration based on the FAO56 paper
GS_{FAO56}	GS simulation model with FAO56
GS_{P2}	GS simulation model with P2
ICD	Differences in total counts of irrigation events
IWD	Differences in total amounts of irrigation water
P2	Adjusted Penman reference evapotranspiration
%IncMSE	Relative increase in mean squared error

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