STUDY ON PREDICTION MODEL OF CROP EVAPOTRANSPIRATION BASED ON WEATHER FORECAST

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ABSTRACT

The prediction of crop evapotranspiration (ET_c) is critical for making reasonable irrigation plan and improving water use efficiency, and the meteorological factors have a great effect with the ET_c. To construct the prediction model of ET_c in the whole growth period of winter wheat, the meteorological observation data of 2000-2015 and the historical weather forecast data of 2014-2015 were collected in Daxing District, Beijing, China. The modified Penman Monteith (PMT), Hargreaves (HAG) and McCloud (Mc) models were adopted to predict reference crop evapotranspiration (ET_0), and then the ET_c prediction models were established based on the crop coefficient method (FAO-56). In addition, the prediction of ET_c was verified by the observed from Eddy Covariance. Results showed that, PMT, HAG, and Mc models had high prediction accuracy for ET_0,among which Mc model had the highest accuracy, with the R^2 of more than 0.76, the absolute error and RMSE were less than 1.3mm/d, and the prediction accuracy (error < 1mm/d)was more than 74%. Among the ET_c prediction models verified by Eddy Covariance, Mc prediction model also had high accuracy, the consistency index were more than 0.78, MAE were less than 0.146mm/d, and the prediction accuracy (<2mm) were more than 80.59%, which could meet the estimation accuracy of ET_c in the study area.

Keywords: Reference crop evapotranspiration (ET_0), evapotranspiration (ET_c), crop coefficient method, prediction model

1. INTRODUCTION

The key of water-saving irrigation is to carry out real-time irrigation prediction and the prediction of daily crop evapotranspiration (ET_c) is the basis of real-time irrigation prediction, which accurate prediction has important guiding significance for irrigation planning and regional water resource allocation.

Crop coefficient method has been widely used and proved to have certain accuracy. ET_0 is calculated by using PM model recommended by FAO, although it has sufficient theoretical basis and high calculation accuracy (Zhao et al., 2010), the method requires more meteorological elements. In addition to temperature, most of the current meteorological forecast information is relatively fuzzy qualitative information (Liu et al., 1997). There are multiple meteorological factor data in the application of PM model. For some undeveloped areas, the data are not easy to obtain all, which brings certain inconvenience to the application of PM model（Aboitiz et al., 1986). Therefore, how to use the temperature models to calculate ET_0 are explored, including the Hargreaves

(HAG) model, the temperature based P-M revision (PMT) model and the McCloud (Mc) model. These models only need the daily average maximum temperature and minimum temperature to calculate the ET_0 (Park et al., 2017; Xu and Chen., 2005).

The relevant research showed that the calculation results of ET_0 under different time scales by PMT and HAG were close to those by PM, and the trend of change was consistent. However when ET_0 was small, the calculation value of PM was underestimated (overestimated) while that of Mc was quite different from that of PM. Luo and Cui(2005) put forward the Fourier series prediction model . Li and Chen(2005) and others applied the multiple linear regression method to establish the prediction model , Li (1994) put forward the correction method day by day, Cai and others used the artificial network or its optimization model (Cai and Liu., 2005; Duan and Qiu., 2006; Gu and Wang., 1997; Liu, 2007; Kumar et al., 2002; Slayisa et al., 2003). These researches provide method for ET_0 estimation and theoretical basis for timely irrigation prediction, but most of them were single method with a large amount of meteorological data. There were few comparative studies on multiple estimation methods based on measurable factors of weather prediction, which brought difficulties to accurate dynamic irrigation prediction in areas with little or no meteorological data. At present, ET_0 method based on weather forecast has been widely used. In addition, many researchers have used temperature to calculate K_c, but the combination of the ET_0 and K_c to predict ET_c was rare. The existing calculation model needs more data to predict ET_c, and it is difficult to obtain more comprehensive quantitative through weather forecast information.

In this paper, the winter wheat (2014, 2015) in Daxing experimental station of National water saving irrigation engineering technology research center of China Institute Water Resources and Hydropower Research were taken as the research object. A simple, accurate calculation model of ET_0 based on temperature effect was tried to be selected, and then the crop coefficient method was used to calculate the $ET_c$of winter wheat. The data measured by Eddy Covariance was used for ground verification to evaluate the reliability and applicability of the calculation results, to provide relatively reliable data support for agricultural water management in irrigation area.

2. MATERIALS AND METHODS

2.1 Study area

Daxing District, Beijing (39°26′-39°51′N, 116°13′-116°43′E) is located in the impact plain of Yongding River in the north of North China Plain. With a total area of 1031km^2, belonging to the temperate semi humid monsoon climate with an average annual temperature of 12.1 ℃. The average annual rainfall for many years is 540mm, and there is more rainfall from June and September, accounting for more than 80% of the total rainfall in the whole year. The rainfall in flood season is mostly concentrated in July and August, accounting for about 60% of the total rainfall in the whole year. The minimum evaporation is 980mm, the maximum evaporation is 1100mm, and the multi-year evaporation is 1021mm. The maximum evaporation is in spring and the minimum in winter. Daxing District is rich in light and heat conditions. The coverage rate of underlying farmland is 86%, and the main crops planted on the underlying are winter wheat. The whole growth period of winter wheat is about 260 days. In normal years, winter wheat needs supplementary irrigation to ensure the water demand of crops. According to the comparative analysis of the climate and underlying surface conditions of the test station and Daxing area, the test station has good typicality (Han et al., 2019).

2.2 Data acquisition

In this experiment, the ET_c of Winter Wheat in Daxing District of Beijing in 2014 and 2015 were measured by Eddy Covariance. The winter wheat was sown on October 1 and harvested on June 30 of the next year. Data of vorticity correlator and high-precision meteorological station were selected for corresponding period. The historical meteorological data of the station (http://cdc.cma.gov.cn) from 2000 to 2015 were collected in the China Meteorological Science sharing service network, and the daily 1d weather forecast (http://www.tianqi.com) data of 2014-2015 were collected in the weather network.

2.3 Methods

2.3.1 Prediction model of crop coefficient based on temperature

The model used the temperature and the structure of the model. Considering the influence of three base point temperature on crop growth, the calculation formula of daily crop coefficient was proposed.

The temperature effect model reflected the response of crop growth and development to different temperatures. The model was as follows:

$$\mathrm{T}F_i = e^{-\left(\frac{T_i - T_0}{\beta}\right)^2} \quad (1)$$

Where, TF_i was the response to temperature on day i, T_i was the average temperature on day i, taking the average value of the highest temperature and the lowest temperature on that day; T_0 was the optimum temperature for physiological and ecological processes such as crop growth and photosynthesis, and β was the parameter to be estimated.

Using the above model structure, the daily crop coefficient can be obtained by multiplying the daily temperature response by the crop coefficient at the optimum temperature:

$$Kc_i = K_0 e^{-\left(\frac{T_i - T_0}{\beta}\right)^2} \tag{2}$$

2.3.2 Prediction method of ET_0

The principle of PM model was to assume the hypothetical reference crop water demand with 0.12m crop height and fixed surface resistance and reflectance, which was equivalent to the water demand of open green land with uniform height, vigorous growth and complete coverage of the ground without water shortage. The calculation formula was (Liu et al., 1997):

$$ET_{(0,PM)} = \frac{0.408\times\Delta(Rn-G)+\gamma\times\frac{900}{T_{mean}+273})\times u_2\times(e_s-e_a)}{\Delta+\gamma\times(1+0.34\times u_2)} \tag{3}$$

Where, $ET_{(0,PM)}$ was the possible evaporation. Δ is the slope of the saturated water pressure curve; Rn was the surface net radiation. G was the soil heat flux, γ was the dry and wet meter constant. T_{mean} was the daily average temperature. u_2 was the wind speed at 2m height. e_s was the saturated water pressure. e_a was the actual water pressure, matching with the ET_0 value.

When the meteorological data are not complete and only the daily average maximum and minimum temperatures were available, other items in the PM model could be estimated by using temperature. This method was called PMT. The wind speed was replaced by multi-year average wind speed. In the process of calculating net radiation, formula (4) was used to calculate solar or short wave radiationR_s:

$$R_s = K_{Rs}\sqrt{(T_{max} - T_{\min})}R_a \tag{4}$$

In the formula (4), K_{Rs} was the adjustment coefficient, 0.17 was taken according to the literature inland; $T_{max}$and T_{min} were the highest and lowest temperature (°C).

$$ET_{(0,HS)} = 0.408K(T_{max} - T_{min})^n(T_{mean} + T_{off})R_a \tag{5}$$

In the formula(5), $ET_{(0,HS)}$ was the reference crop water demand, mm/d; K was the conversion coefficient, the recommended value was 0.0023; T_{max}, T_{min}were the highest and lowest temperature,℃; n was the index coefficient, the recommended value was 0.5; T_{mean} was the average temperature,℃; T_{off} was the temperature offset, the recommended value was 17.8; R_a was the top radiation of the atmosphere, MJ/(m^2.d). (Hargreaves and Allen, 2003; Irmak, 2005)

In this study, the daily maximum temperature, minimum temperature and solar radiation at the top of the atmosphere of Beijing Meteorological Station from 1961 to 2012 were taken as independent variables, and the daily ET_0 calculated by PM was taken as dependent variable. The original parameters K =0.0023 , n=0.5, T_{off}=17.8 of HAG formula were taken as initial values, and non-linear regression analysis was carried out on the HAG. After several iterations, new parameter fitting values were obtained (Xu et al., 2010). The calibrated parameters were K=0.001138, n=0.4925, T_{off}=43.33.

McClound was originally used to estimate ET_0 of grass (McCloud., 1995), which was based on daily average temperature and regards ET_0 as an exponential function of temperature:

$$ET_{(0,Mc)} = KW^{1.8T} \tag{6}$$

The original parameters of McClound K=1.24, W=1.030 as the initial value. Through the meteorological data of Daxing District, Beijing from 1961 to 2011, the parameters of Mc were calibrated, and the nonlinear regression analysis was carried out. After several iterations, the new parameter fitting values were obtained. The parameters after calibration were K=1.243, W=1.022, respectively.

2.4 Evaluation

The evaluation indexes include mean absolute error (MAE), root mean square error (RMSE), regression coefficient (b), determination coefficient (R^2) and consistency index(d_{IA}), which are used to evaluate the calculation accuracy of the above different calculation models of ET_0, ET_c. In addition, the prediction accuracy was used for evaluation, and it was defined that the accuracy of the corresponding prediction was the percentage of the number of samples whose prediction or decision error is within $\pm 1\mathrm{mm}\cdot\mathrm{d}^{-1}$or $\pm 2\mathrm{mm}\cdot\mathrm{d}^{-1}$ in the total number of samples. The calculation formula of other statistical indicators was as follows (Wang et al., 2010; Cui et al., 2018; Zhang et al., 2016; Zhou et al., 2016) :

$$\mathrm{MAE} = \sum_{i=1}^{n} |x_i - y_i| / n \tag{7}$$

$$\mathrm{RMSE} = \sqrt{\sum_{i=1}^{n} \frac{(x_i - y_i)^2}{n}} \tag{8}$$

$$\mathrm{b} = \frac{\sum_{i=1}^{n} y_i \cdot x_i}{\sum_{i=1}^{n} {y_i}^2} \tag{9}$$

$$R^2 = \frac{\sum_{i=1}^{n}(x_i-\bar{x})^2(y_i-\bar{y})^2}{\sum_{i=1}^{n}(x_i-\bar{x})^2 \sum_{i=1}^{n}(y_i-\bar{y})^2} \tag{10}$$

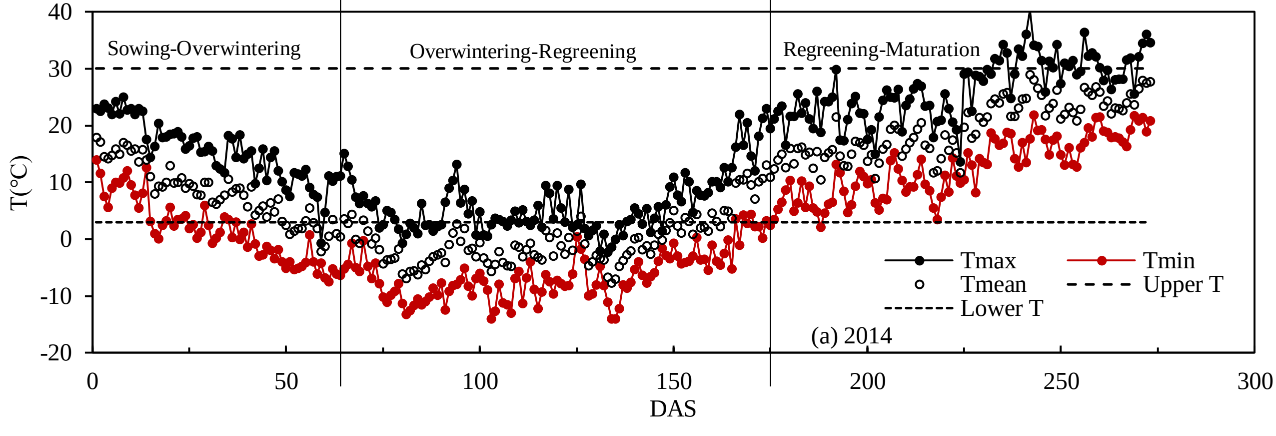
$$d_{IA} = 1 - \frac{\sum_{i=1}^{n}(y_i - x_i)^2}{\sum_{i=1}^{n}(|x_i - \bar{y}| + |y_i - \bar{y}|)^2} \tag{11}$$

In the formula, x_i was the predicted value of ET_0 or ET_c; y_i was the calculated value of $\mathrm{ET}_{(0,PM)}$ or the measured value of eddy correlator ET_c; i was the predicted sample series, $\mathrm{i} = 1,2, \ \ldots, \mathrm{n}$; x, y were the mean value of the forecast value and the calculated value sequence; n is the sample number of the forecast value. The consistency index d_{IA} could measure whether the external prediction ability of a single model reaches the accuracy required by statistics. The closer the value was to 1, the more consistent the predicted value with the measured value. It was generally considered that the model has actual prediction value only when $d_{IA} > 0.6$.

3. RESULTS AND ANALYSIS

3.1 Analysis of temperature change in research area

Based on the literature (Xiao et al.,2010 ; Qi et al., 2007; Cao et al., 1985), the lower and upper temperature limits of wheat in the whole growth period of Daxing region were selected at 3℃ and 30℃.The temperature change process of winter wheat in the whole growth period from 2014 to 2015 was shown in Figure. 1 (a),(b), The average temperature of winter wheat could reflect the slow growth of crops in the early stage, and the invalid temperature of winter wheat from green to maturity was less. In 2014 and 2015, the highest temperature in the whole growth period of winter wheat were 40.3°C, 34.6 °C, respectively, and the lowest temperature were - 14.1℃, - 11.8 ℃, respectively, the highest average temperature were 29.0°C, 27.6°C, respectively, and the lowest average temperature were - 14.5 ℃, - 5.8 ℃, respectively. Before sowing and overwintering, the temperature decreased with the increase of sowing day; before overwintering and reviving, the temperature first increased and then decreased with the increase of sowing day, and the minimum value appeared on 135d, 133d and 135d after sowing; during reviving and maturing, the temperature increased with the increase of sowing day. Before sowing and overwintering, the three temperatures (maximum temperature, minimum temperature and average temperature) were more in the upper and lower temperature limits (3°C~30°C), but less in the upper and lower temperature limits(3℃~30℃) before overwintering and seeding, and all the temperatures were basically in the upper and lower temperature limits in the maturity period. Therefore, when ET_0 and Kc are used to predict the growth period of winter wheat, there are some differences in the prediction accuracy (Wang et al., 2019).



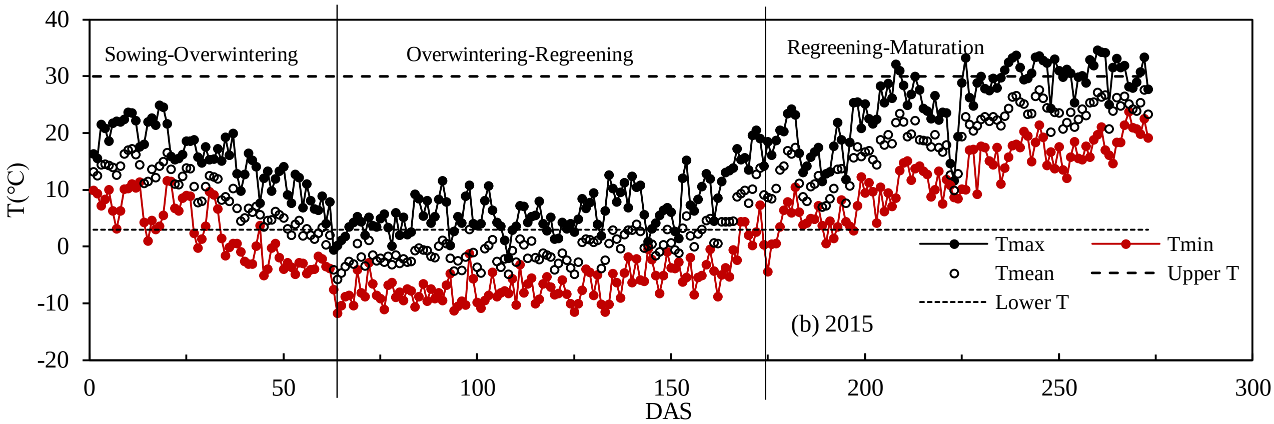


Figure1.Temperature change of winter wheat in the whole growth period in Daxing District

3.2 Crop coefficient calculation based on temperature information

The least square estimation model (2) was used, the parameters K_0 , T_0 , and β were 1.15, 21.34 and 7.76 respectively, and the goodness of fit was 0.7. Taking the result as the initial value, the sequential quadratic programming method was used to search the optimal solution of each parameter.

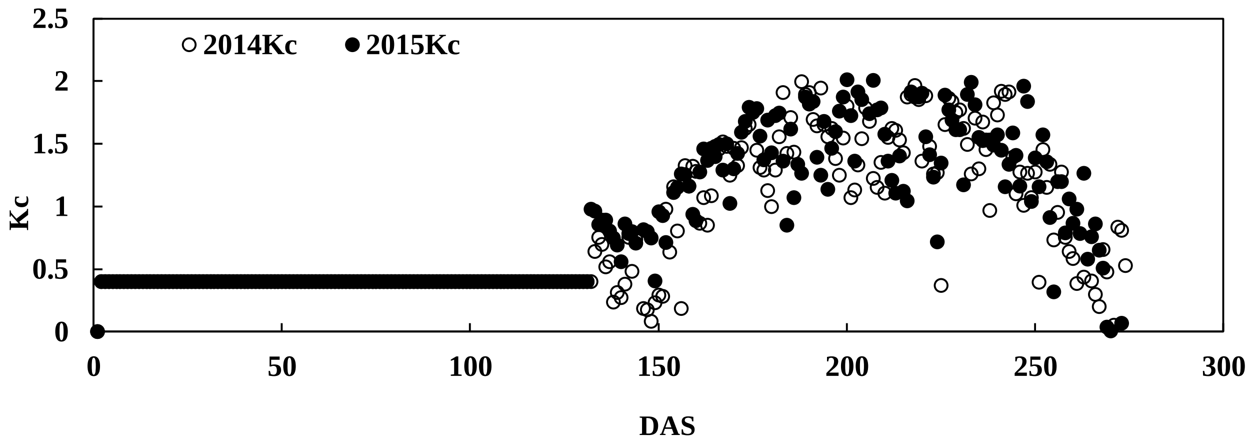


Figure 2. Crop coefficient of winter wheat in the whole growth period from 2014 to 2015 in Daxing District

The crop coefficient of winter wheat from 2014 to 2015 were estimated by using formula (2) in Daxing District. According to some measured data, the crop coefficient can be treated as 0.4 during the freezing period, before and just after the freezing period; the crop coefficient can be obtained by difference. Moreover, during the above period, the crop coefficient has been in a small value, which will not cause a large absolute error.

It can be seen from Figure 2 that the trend of K_c was the initial stage of jointing decreased and then increased in the early stage of jointing (150d after sowing) in the early stage of growth. There was no vegetation coverage in the field, which wheat need less water, and K_c will reach the maximum value. After jointing, water requirement increased and K_c increased. At heading stage and filling state, water requirement was the highest, K_c reached the peak, water requirement decreased and K_c decreased in wheat mature stage. The optimum temperature changed from 24 to 30, showing an upward trend. Compared with the recommended value of FAO, except for the simulation value before overwintering and returning to green was small, the simulation value at maturity was large, and the change trend of the two values were basically the same.

3.3 Prediction model of ET_0 based on temperature information

Previous studies had shown that the calculated value of PM model was generally underestimated in the period of low temperature. While the calculated value of PM model was generally overestimated in the case of high temperature, with a few exceptions due to the interference of other temperature factors, such as wind speed, relative humidity, and sunshine hours (Tao et al., 2014). As shown in Figure 3, the calculated values of the three model showed similar, PMT model and modified Mc model were more consistent with the calculated value change of PM model, and the modified HAG model was more different from the calculated value change of PM model (Yu et al., 2017). Before 150 days after sowing, the calculation results of ET_c and PM model obtained by the three methods were close to each other.

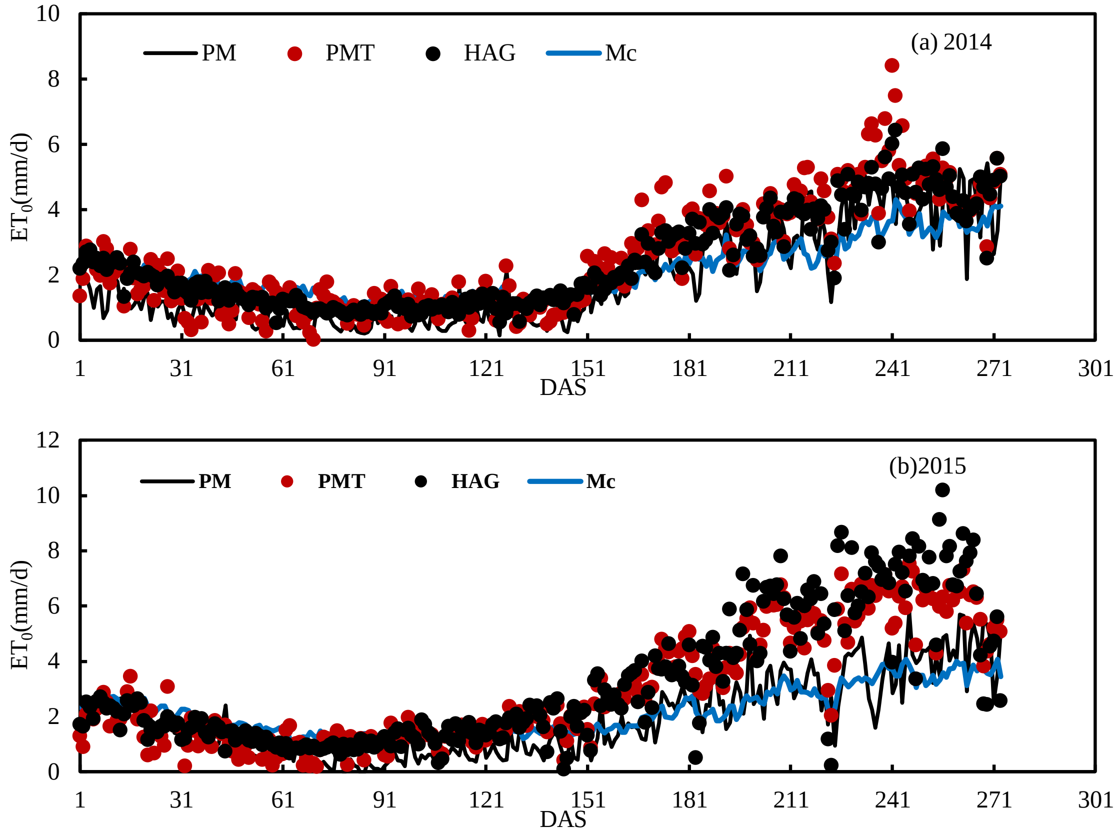


Figure 3. The models of PM, PMT, HAG and Mc

Table 1. Prediction of $\boldsymbol{ET_0}$ accuracy evaluation of winter wheat

Year	Model	Mean (mm/d)	a	b	r^2	MAE (mm/d)	RMSE (mm/d)	d_{IA}	Accuracy (error<1mm/d)	Accuracy (error<1mm/d)
2014	PM	1.89								
	PMT	2.51	0.78	-0.08	0.80	0.097	1.602	0.69	76.2	94.1
	HAG	2.68	0.60	-0.14	0.79	0.108	1.79	0.63	66.7	88.6
	Mc	2.30	1.02	-0.47	0.76	0.083	1.374	0.77	79.5	97.4
2015	PM	1.94								
	PMT	2.95	0.60	0.18	0.72	0.111	1.839	0.66	70.7	83.2
	HAG	3.15	0.47	0.45	0.61	0.124	2.047	0.59	71.1	74
	Mc	2.15	1.54	-1.38	0.8	0.071	1.176	0.91	74.4	99.6

It can be seen from Table 1 and Figure 3 that, PMT (2.509mm/2.949mm), HAG (2.680mm/3.152mm), Mc (2.30mm/2.15mm) and PM (1.89mm/1.94mm) were close to each other in the growth period of winter wheat from 2014 to 2015. And the regression relationship between PMT, MC and PM were closer, and the corresponding determination coefficient R^2 were 0.80, 0.72, 0.76, 0.8, respectively, and the regression coefficient were 0.78, 0.60, 1.02, 1.54. The MAE (0.108/0.124mm/d) and RMSE (1.79/2.047mm/d) of HAG model were the largest. The consistency index d_{IA}(0.63 / 0.59) and accuracy rate (accuracy rate of error < 1mm/d were 66.7% ,71.1%, accuracy rate of error < 2mm/d were 88.6%, 74%) were the smallest. The model of Mc was the best, then the PMT model, which the MAE and RMSE were larger than Mc. The d_{IA} and accuracy error of PMT were smaller than Mc.

In summary, Mc model was slightly better than PMT model as a whole, probably because PMT model considered the influence of wind speed instead of relative humidity, and the precision of wind speed and relative humidity affected PMT. However, they were very close, after calculation, the consistency index d_{IA} between the results of Mc and PMT were close to 1. Considering the simplicity and practicability of calculation, Mc can meet the accuracy requirements and simplify the calculation procedure (Reynolds et al., 2014).

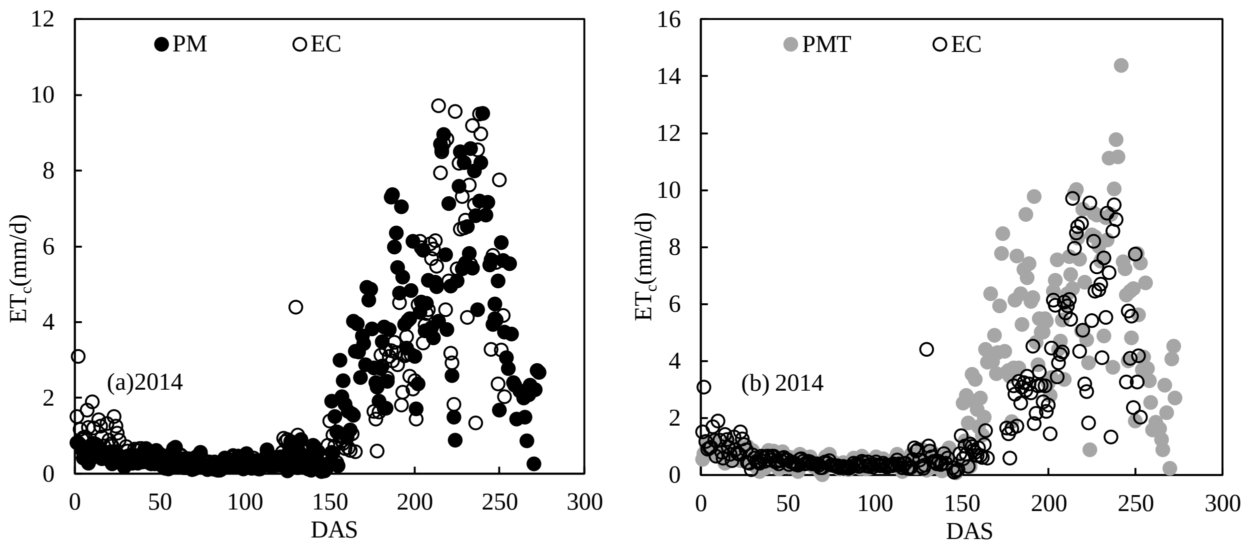
3.4 Prediction model of ET_c

According to the prediction model of ET_0 and K_c in Part 3.3 and 3.2, based on the single crop coefficient method, the winter wheat ET_c were predicted, and the predicted value was verified by the measured data of Eddy Covariance.

It was shown in Figure 4 (a) (b) that, compared with the measured value of the Eddy Covariance, the predicted value of PM / PMT / HAG / Mc model in the early growth period were consistent with the measured value. In the middle growth period, the predicted value were higher than the measured (more rainfall after 150 days of sowing), and the predicted value in the later growth period was lower than the measured value. The predicted value and the measured value were significantly correlated, among which the predicted value of Mc model in the whole growth period were the best. The predicted value of Mc and measured value determined coefficient were 0.62, 0.81, RMSE were 2.36 mm/d, 2.42mm/d (Table 2), PM/PMT/HAG determined coefficient were 0.63/0.75, 0.62/0.80, 0.61/0.82, RMSE were 2.36/2.27mm/d, 2.75/3.40mm/d, 2.94/3.68 mm/d, respectively. According to the regression equation, during the whole growth period, the predicted value was larger than the measured value. In 2015, the predicted value of PM model was slightly smaller than the measured value. The abnormality of this rule should be the reason why PM model considers too many meteorological factors. Compared with the measured value, the d_{IA} of PM/PMT/HAG/Mc were 0.81/0.92,0.75/0.90,0.73/0.88, 0.78/0.90.The prediction accuracy (error<2mm) were 78.39%/ 84.25%、73.26%/ 77.66%, 71.06%/ 69.60%, 80.59% / 80.95%, respectively. The prediction accuracy of Mc model was relatively high, which might be due to the fact that Mc model considers less meteorological parameters and reduced the uncertainty of some parameters.

Table 2. Prediction of $\boldsymbol{ET_c}$ accuracy evaluation of winter wheat

Year	**Model**	**Mean (mm/d)**	**a**	**b**	**r^2**	**MAE (mm/d)**	**RMSE (mm/d)**	d_{IA}	**Accuracy (error<1mm/d)**	**Accuracy (error<2mm/d)**
	EC	1.96								
	PM	2.87	0.78	0.44	0.63	0.14	2.36	0.81	67.40	78.39
2014	PMT	3.80	0.62	0.36	0.62	0.17	2.75	0.75	62.64	73.26
	HAG	3.03	0.57	0.41	0.61	0.18	2.94	0.73	61.17	70.70
	Mc	1.86	0.87	0.15	0.61	0.14	2.26	0.78	68.86	80.59
	EC	2.05								
	PM	3.35	1.07	0.04	0.75	0.16	2.63	0.92	69.60	84.25
2015	PMT	3.61	0.68	-0.07	0.80	0.21	3.40	0.90	60.07	77.66
	HAG	2.02	0.62	-0.02	0.83	0.22	3.68	0.88	55.31	69.60
	Mc	2.22	1.41	-0.64	0.81	0.15	2.42	0.90	63.37	80.95



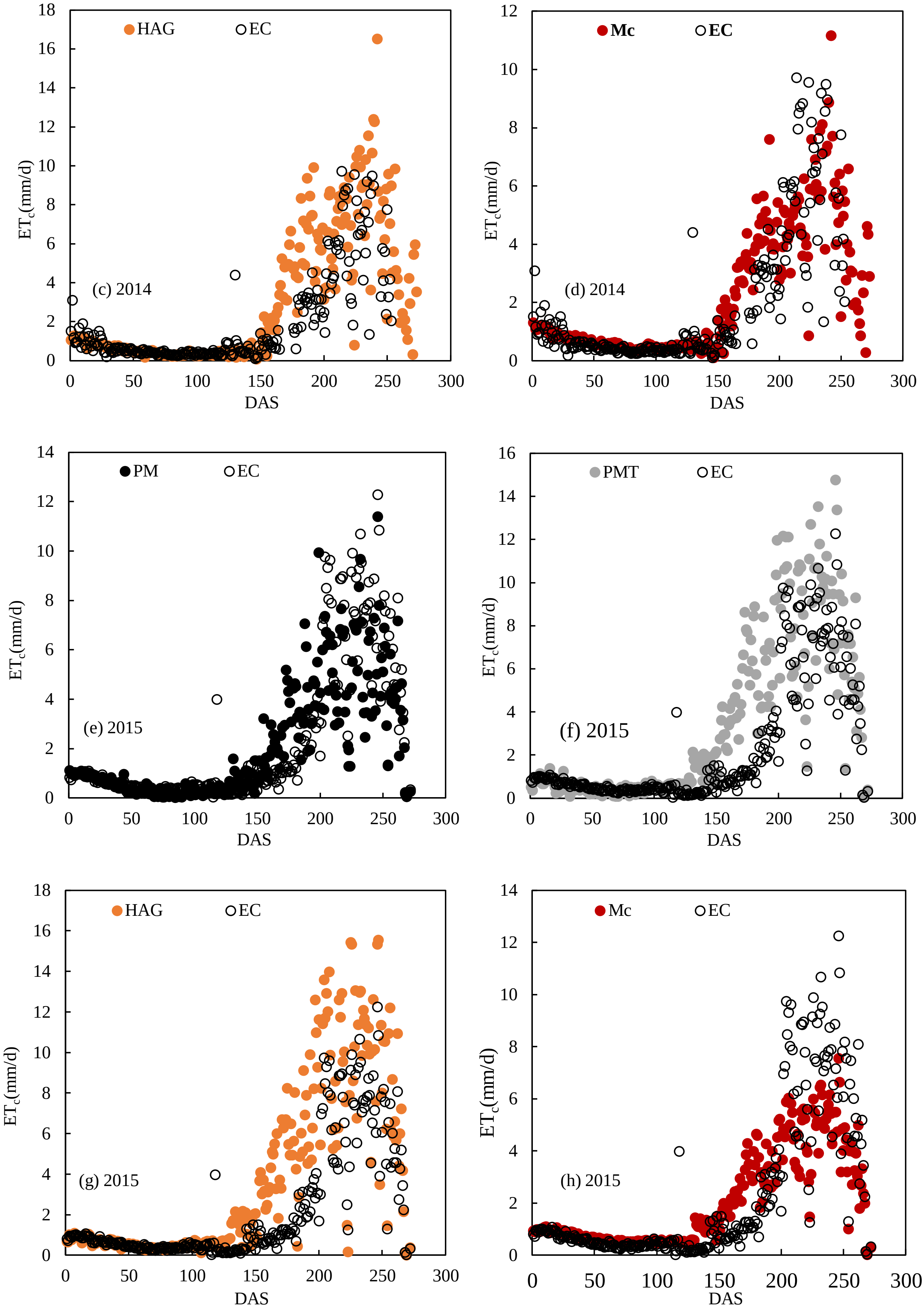


Figure 4. Comparison between the predicted value of ET_c and the measured value of Eddy Covariance in Daxing District

4. CONCLUSION

Taking winter wheat as an example, this paper verified the prediction model of ET_0, then the prediction model of winter wheat ET_c combining with crop coefficient model were established, and the prediction ET_c was verified by Eddy Covariance. The conclusions were as follows:

(1) Compared with the calculation results of FAO56-PM model, the accuracy of three prediction models (PMT, HAG, Mc) were different, which the Mc prediction method was the most advantageous, and the consistency index between the calculation results of Mc and PM method was close to 1. The 1d accuracy (error < 2mm) in the study area were 97.4%, 84.5% (year of 2014 and 2015).

(2) There were also differences in the accuracy of the four winter wheat ET_c prediction models based on the crop coefficient calculation method. According to the results of Eddy Covariance verification, Mc prediction method was the best, and the consistency index were 0.776 and 0.887(2014 and 2015), which were close to 1. The accuracy of 1d prediction were 80.59% and 94.14%. This method has a wider application prospect in the prediction of ET_c.

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