Adaptabilities of Water Production Function Models for Rice in Cold and Black Soil Region of China

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Abstract: Crop water production function models (WPFMs) are a required method to study the relationships between yield and water consumption under regulated deficit irrigation (RDI). In this study, a pot experiment was established to study the effect of water deficit during both individual growth stages and across two consecutive growth stages of rice on yield, water consumption, and water use efficiency (WUE) in 2017 and 2018. Light, medium, and severe water deficits were set as 80~90%, 70~80%, and 60~70% of fully saturated soil moisture content, respectively. The accuracies of five WPFMs were tested based on the experimental results. The results showed that yields and WUE of a light water deficit were higher than those of medium and severe water deficits at each growth stage. The yields and WUE of light drought stress treatments in the flowering and milky stages were higher than the fully saturated soil moisture control by 4~7.4% and 5.3~20.6%, respectively. Water consumption decreased with increasing water deficit across two consecutive growth stages. The Minhas model had the highest simulation accuracy of the five WPFMs, with relatively lower AE, RMSE, Cv, CRM, and higher R2, which were 0.0002, 0.0634, 6.9965, 0.0002, and 0.9951 in 2017 and 0.0110, 0.0760, 8.9882, 0.0131, and 0.9923 in 2018, respectively. The sensitivity indices for the Minhas model more accurately reflected the sensitivity of rice yield to water deficit at different growth stages in 2017 and 2018, compared with the Jensen model, Stewart model, Blank model, and Singh model. Rice yield was most sensitive to water deficit at the jointing and booting stage. The results indicate that the Minhas model is the most suitable WPFM for guiding rice irrigation practices in cold black soil regions of China.

Keywords: rice; regulated deficit irrigation (RDI); water production function model (WPFM); water sensitivity index; yield; water use efficiency

1. Introduction

Rice (Oryza sativa L.) is a staple food for more than half of the world’s population, with a total of 1.76 billion tons consumed in the last two decades [1]. However, as the world’s population increases, rice consumption will continue to increase and is expected to reach 9 billion tons worldwide by 2050 [2]. Seventy percent of the world’s freshwater resources are used in agriculture, with rice consuming more than half of the water used in agriculture and the water consumption of rice is still increasing [3]. Balancing the relationship between
rice yield and its water consumption and further improving water use efficiency (WUE) has become vital to ensure food security.

In recent decades, disastrous droughts have occurred frequently due to temperature increases. It is estimated that the frequency of droughts could increase 1.7–4.1 times when the temperature increases within the range of 1–4 °C [4,5]. Drought stress leads to rice yield reduction, with an average decrease of 64% [6]. However, drought stress can occur at the different growth stages of rice and thereby various effects on yield reduction, the yield reduction rate may even reach 100% [7]. The traditional irrigation model lacks flexibility in the face of drought conditions, making it difficult to ensure stable yields [8,9]. Moreover, the excessive use of agricultural water by farmers for ensuring rice yields leads to the aggravation of the water shortage situation. Sometimes, excessive use of agricultural water does not contribute to increased yield but does reduce the WUE and take agricultural irrigation water away from other crops, especially in semi-arid areas [10,11].

Regulated deficit irrigation (RDI) has been used to study the impact of crop water deficit in different growth stages on yield [12]. The use of RDI was pioneered in the mid-1970s by the Tatura Centre of the Australian Institute of Sustainable Irrigated Agriculture. The initial focus of RDI was on fruit tree cultivation, only later was it applied to food crops [13]. As the water consumption of rice during its growth period is greater than that of upland crops, RDI has been widely used in rice planting to improve WUE. Li et al.’s experiment showed that, when the lower limit of irrigation in humid regions was controlled between 60% and 80% of saturated water content, the rice yield was 2–8% higher than that of flooding irrigation; however, the plant height was lower than that with flooding irrigation [14]. Liang et al. found by conducting RDI experiments on rice in water-scarce mountainous areas that maintaining the lower limit of rice irrigation at 70% of field capacity saved nearly 50% of irrigation water compared with flooding irrigation [15]. Wang found that a lower limit of 90% saturated water content in growing rice in RDI mode effectively reduced 10–32% of irrigation water in the flowering and milky stages, and increased yield by 0.4% compared with conventional irrigation [16]. Kang et al. found that controlling soil water content to half of the field capacity during the early growth stage of the crop had the least effect on plant yield. [17]. The relationship between crop yield and RDI is affected by many factors, including climate conditions, soil conditions, irrigation techniques, and methods. The practice of RDI needs to conform to the specific characteristics of the study area. In addition, the effect of water deficit on crop yield depends on when the water deficit occurred in the growth cycle, and its duration and degree. A quantitative study on adaptive crop growth stage, allowable duration, and water deficit degree suitable for RDI will be helpful to guide agricultural irrigation practice [18].

The crop water production function model (WPFM) is a required method to study RDI and has been used to quantitatively analyze the relationship between crop yield and water input or crop water consumption during its growth period [19]. As long ago as 1913, Briggs and Shantz first studied crop WPFPs [20]. Today, two main types of WPFPs are used in rice cultivation, multiplicative models, consisting of the Jensen model and Minhas model, and additive models, consisting of the Blank model, Stewart model, and Singh model [21]. Cheng et al. found that the Jensen model was applicable to the RDI of rice in the Songnen Plain of China, with a correlation coefficient exceeding 0.99 [22]. The modeling efficiency of the Minhas model was found to be 0.96 for different growth stages of tomatoes for RDI and was the most applicable to clay-loam soil in Turkey [23]. In a typical semi-arid region, there were no significant errors between the simulated and measured values of the Stewart model for potato cultivation under drought stress [24]. The appropriate WPFM varies according to the physiological characteristics and growing environment of the crops [25].

Black soil regions have the most fertile soil in the world and are mainly to be found in the Northeast Plain of China, the Mississippi River Basin of the USA, and the Great Plain of Ukraine. The Northeast Plain covers a total area of about 1.03 million hectares and has now become one of the world’s major commercial grain production bases [26]. The soils in black soil areas are high in organic matter, and their physical and chemical properties...
are suitable for rice cultivation [27]. However, drought stress has led to higher water use for rice irrigation, with water use increasing by 50–60% annually [28]. In recent years, the groundwater table in the Northeast Plain of China has been constantly falling with the rapid spread of rice cultivation areas. Over the past 60 years, the unscientific use of irrigation water has led to a decline of about 5.5 m in the groundwater table [29]. Therefore, the purpose of this study is: (1) To clarify the effect of RDI on rice yield, water consumption, and WUE; and (2) To reveal the applicability of different WPFMs to rice irrigation practice in cold black soil regions of China.

2. Materials and Methods

2.1. Study Area

The experiment was carried out at the National Key Irrigation Experimental Station (127°40′45″ E, 46°57′28″ N, altitude 140 m) in Qing’an County, Heilongjiang Province, China, from 18 May to 1 September 2017, and 20 May to 3 September 2018 (Table 1). The study area has a cold continental seasonal climate. The annual average temperature is 2–3 °C and the frost-free period is 128 days. The effective accumulated temperature ≥ 10 °C is 2500–2800 °C, the annual average precipitation is 500–600 mm, the annual average water surface evaporation is 700–800 mm, and the solar radiation is 4000–4300 MJ/(m²·a). The soil used in this experiment is classified as Mollisols with a saturated volumetric water content of 53.25% [30]. The content of soil organic matter was 23.81 g/kg, the pH was 6.45, the total nitrogen was 15.06 g/kg, the total phosphorus was 15.23 g/kg, the total potassium was 20.11 g/kg, alkali hydrolyzable nitrogen was 198.29 mg/kg, available phosphorus was 36.22 mg/kg, and available potassium was 112.06 mg/kg. The daily maximum and minimum air temperatures during the cultivation of the rice crop are shown in Figure 1. The average air temperatures during each growth stage of the rice crop in 2017 and 2018 are shown in Table 2. The average air temperature during the cultivation of the rice crop for 2018 was 0.3 °C higher than that for 2017.

Table 1. Duration of different rice growth stages in 2017 and 2018.

| Years | Re-greening | Tillering | Jointing and Booting | Flowering | Milky | Ripening |
|-------|-------------|-----------|----------------------|-----------|-------|----------|
| 2017  | 18 May–1 June (14 d) | 2 June–5 July (34 d) | 6 July–19 July (14 d) | 20 July–2 August (13 d) | 4 August–14 August (11 d) | 15 August–1 September (18 d) |
| 2018  | 20 May–4 June (15 d) | 5 June–9 July (35 d) | 10 July–22 July (13 d) | 23 July–5 August (13 d) | 6 August–15 August (10 d) | 16 August–3 September (19 d) |

Note: “d” is the abbreviation of “day”.

Figure 1. The daily maximum and minimum air temperature during the cultivation of the rice crop in (a) 2017 and (b) 2018. “Max Temp” is the maximum air temperature. “Min Temp” is the minimum air temperature.
Table 2. Air temperature during each growth stage of rice in 2017 and 2018.

| Years | Parameters | Rice Growth Stages | Weighted Average |
|-------|------------|--------------------|------------------|
|       |            | Re-Greening | Tillering | Jointing and Booting | Flowering | Milky | Ripening |
| 2017  | Average Daily Max Temp (°C) | 20.2 | 27.9 | 29.3 | 26.6 | 27.6 | 24.3 | 24.6 |
|       | Average Daily Min Temp (°C) | 9.5 | 17.4 | 19.8 | 17.7 | 20.1 | 13.5 | 14 |
|       | Average Daily Mean Temp (°C) | 14.8 | 22.6 | 24.5 | 21.8 | 23.3 | 18.6 | 19.3 |
| 2018  | Average Daily Max Temp (°C) | 25.7 | 25.1 | 28.4 | 28.3 | 26.9 | 24.6 | 24.5 |
|       | Average Daily Min Temp (°C) | 13.2 | 16.2 | 21.4 | 19.8 | 17.9 | 16.3 | 14.7 |
|       | Average Daily Mean Temp (°C) | 19.5 | 20.2 | 24.7 | 23.9 | 22.3 | 20 | 19.6 |

Note: “Max Temp” is the maximum air temperature. “Min Temp” is the minimum air temperature. “Mean Temp” is the mean air temperature.

2.2. Experimental Design

The pot experiment method was used in the study. Plastic buckets with an upper diameter of 32 cm, a lower diameter of 28 cm, and a height of 40 cm were used. After the soil was dried and screened, each pot was filled with 30 kg of dry soil (the initial moisture content of the air-dried soil was 14.53%). The tested rice variety was “longqingdao 3” (Oryza sativa L.). Two hills of rice seedlings (5 plants per hill) were transplanted into each pot. All pots were placed randomly in a mobile rain shelter equipped by the experimental station.

All treatments were arranged according to different drought levels in different growth stages of rice. According to the climatic conditions of the experimental site, the water layer must be preserved in the rice field during the re-green stage to prevent leaves from drying up due to water loss, and also to prevent seedlings from freezing damage at low temperatures. Drainage in the ripening stage was conducted to promote rice maturity. Therefore, RDI was not carried out in the re-green and ripening stages based on the requirements for high yield. For the other four growth stages (the tillering, jointing and booting, flowering, and milky stages), four irrigation levels were arranged, respectively, according to the percentage of soil moisture content in the soil, with saturated moisture content as the control index, light water deficit (L, soil moisture content controlled at 80~90% of soil saturated moisture content, hereafter referred to as light drought stress), medium water deficit (M, soil moisture content controlled at 70~80%, hereafter referred to as medium drought stress) and severe water deficit (H, the soil moisture content is controlled at 60~70% of the soil saturated moisture content, hereafter referred to as severe drought stress). To better meet the possible drought conditions encountered in production practice and comprehensively study the impact of water deficit conditions on rice, this experiment arranged the treatment of drought stress in both individual growth stages and two consecutive growth stages. There were 22 treatments in total, and each treatment was repeated three times. Among the treatments, CK was the control treatment, consisting of maintaining a 10~30 cm water layer throughout all growth stages (Table 3).

Nitrogen fertilizer (110 kg ha⁻¹) was applied separately according to the ratio of the basal fertilizer: tiller fertilizer: flower-promoting fertilizer: and flower-preserving fertilizer, which is 4.5:2:1.5:2. Phosphorus fertilizer (P₂O₅ 45 kg ha⁻¹) was applied once as the basal fertilizer, and potassium fertilizer (K₂O 80 kg ha⁻¹) was applied twice according to the ratio of basal fertilizer and 8.5 leaf age (young panicle differentiation stage), which was 1:1. The fertilization of each treatment was the same.
Table 3. Irrigation methods in different growth stages of all treatments in 2017 and 2018.

| Treatments | Rice Growth Stages |
|------------|--------------------|
| Re-greening | Tillering | Jointing and Booting | Flowering | Milky | Ripening |
| L1         | 10–30 mm | 80–90%θs | 10–30 mm | 10–30 mm | 10–30 mm | Natural drying |
| M1         | 10–30 mm | 70–80%θs | 10–30 mm | 10–30 mm | 10–30 mm | Natural drying |
| H1         | 10–30 mm | 60–70%θs | 10–30 mm | 10–30 mm | 10–30 mm | Natural drying |
| L2         | 10–30 mm | 10–30 mm | 80–90%θs | 10–30 mm | 10–30 mm | Natural drying |
| M2         | 10–30 mm | 10–30 mm | 70–80%θs | 10–30 mm | 10–30 mm | Natural drying |
| H2         | 10–30 mm | 10–30 mm | 60–70%θs | 10–30 mm | 10–30 mm | Natural drying |
| L3         | 10–30 mm | 10–30 mm | 10–30 mm | 80–90%θs | 10–30 mm | Natural drying |
| M3         | 10–30 mm | 10–30 mm | 70–80%θs | 10–30 mm | 10–30 mm | Natural drying |
| H3         | 10–30 mm | 10–30 mm | 60–70%θs | 10–30 mm | 10–30 mm | Natural drying |
| L4         | 10–30 mm | 10–30 mm | 10–30 mm | 80–90%θs | 10–30 mm | Natural drying |
| M4         | 10–30 mm | 10–30 mm | 10–30 mm | 70–80%θs | 10–30 mm | Natural drying |
| H4         | 10–30 mm | 10–30 mm | 10–30 mm | 60–70%θs | 10–30 mm | Natural drying |
| L1L2       | 10–30 mm | 80–90%θs | 10–30 mm | 80–90%θs | 10–30 mm | Natural drying |
| M1M2       | 10–30 mm | 70–80%θs | 10–30 mm | 70–80%θs | 10–30 mm | Natural drying |
| H1H2       | 10–30 mm | 60–70%θs | 10–30 mm | 60–70%θs | 10–30 mm | Natural drying |
| L2L3       | 10–30 mm | 10–30 mm | 80–90%θs | 10–30 mm | 80–90%θs | Natural drying |
| M2M3       | 10–30 mm | 10–30 mm | 80–90%θs | 10–30 mm | 80–90%θs | Natural drying |
| H2H3       | 10–30 mm | 10–30 mm | 60–70%θs | 10–30 mm | 60–70%θs | Natural drying |
| L3L4       | 10–30 mm | 10–30 mm | 10–30 mm | 80–90%θs | 70–80%θs | Natural drying |
| M3M4       | 10–30 mm | 10–30 mm | 10–30 mm | 70–80%θs | 70–80%θs | Natural drying |
| H3H4       | 10–30 mm | 10–30 mm | 10–30 mm | 60–70%θs | 60–70%θs | Natural drying |
| CK         | 10–30 mm | 10–30 mm | 10–30 mm | 10–30 mm | 10–30 mm | Natural drying |

Note: “10–30 mm” indicates that the field surface maintains a 10–30 mm water layer. “θs” represents the saturated moisture content. “80–90%θs” indicates the soil moisture content maintained at 80–90% of soil saturated moisture content, which represents light water deficit. “70–80%θs” indicates the soil moisture content maintained at 70–80% of soil saturated moisture content, which represents medium water deficit. “60–70%θs” indicates the soil moisture content maintained at 60–70% of soil saturated moisture content, which represents severe water deficit.

2.3. Data Collection

We recorded the amount of each irrigation from the re-green stage to the ripening stage. As the pot experiment was free from field seepage and precipitation, water consumption was the sum of the amount of each irrigation and the changes in soil water storage. Daily water consumption was recorded by weighing every 2 days. The change in soil moisture was detected by the weighing method, and the sensitivity of the electronic scale was 0.1 g.

\[
ET_{aj,j+2} = w_j - w_{j+2} + m
\]

where \(ET_{aj,j+2}\) is the amount of water consumed by the crop during the period (kg/pot); \(w_j\) is the weight of each pot on day \(i\) (kg/pot); \(w_{j+2}\) is the weight of each pot on day \(j+2\) (kg/pot); and \(m\) is the amount of irrigation during the period (kg/pot).

After harvesting, we measured the yield of each pot. Finally, the yield and WUE of each treatment were calculated.

\[
WUE = \frac{Y}{\sum_{i=1}^{n} (ET_i)}
\]

where WUE is water use efficiency (g/kg); \(Y\) is yield (g/pot); \(ET_i\) is water consumption per reproductive period (kg/pot); \(n\) is the total number of crop cultivation stages (consisting of the re-greening, tillering, jointing and booting, flowering, milky, and ripening stages), \(n = 6\); and \(i\) is the number of the growth stage.

2.4. Water Production Function Models

In this study, five WPFMs were used [22], including both multiplicative and additive models. The multiplicative models were the Jensen model and the Minhas model:
Jensen model:

\[ \frac{Y_a}{Y_m} = \prod_{i=1}^{n} \left( \frac{ET_a}{ET_m} \right)^{\lambda_i} \]  \hspace{1cm} (3)

Minhas model:

\[ \frac{Y_a}{Y_m} = \prod_{i=1}^{n} \left[ 1 - \left( 1 - \frac{ET_a}{ET_m} \right)^2 \right]^{\lambda_i} \]  \hspace{1cm} (4)

The additive models consisted of the Blank model, the Stewart model, and the Singh model:

Blank model:

\[ \frac{Y_a}{Y_m} = \sum_{i=1}^{n} A_i \left( \frac{ET_a}{ET_m} \right) \]  \hspace{1cm} (5)

Stewart model:

\[ \frac{Y_a}{Y_m} = 1 - \sum_{i=1}^{n} B_i \left( 1 - \frac{ET_a}{ET_m} \right) \]  \hspace{1cm} (6)

Singh model:

\[ \frac{Y_a}{Y_m} = \sum_{i=1}^{n} C_i \left[ 1 - \left( 1 - \frac{ET_a}{ET_m} \right)^2 \right] \]  \hspace{1cm} (7)

where, \( Y_a \) is the actual crop yield corresponding to the actual evapotranspiration (kg/pot); \( Y_m \) is the potential crop yield corresponding to the potential evapotranspiration, that is, the crop yield under full irrigation (kg/pot); \( ET_a \) is the actual evapotranspiration (kg/pot); \( ET_m \) is the potential evapotranspiration (kg/pot). The values of \( Y_m \) and \( ET_m \) are the actual yield and water consumption of CK, respectively; \( \lambda_i, A_i, B_i, \) and \( C_i \) are the water sensitivity indices of the \( i \)-th growth stage. Higher values of \( \lambda_i \) and \( B_i \) reflect that the rice yield is more sensitive to drought stress, while higher values of \( A_i \) and \( C_i \) represent that yield is less sensitive to drought stress; \( n \) is the number of crop growth stages (consisting of the tillering stage, jointing and booting stage, flowering stage, and milky stage), \( n = 4 \).

2.5. Simulation Accuracy Indices

To test the simulation effect of the five WPFMs, the following methods were used for accurate detection [19]. The growth stages involved in the simulation accuracy analysis are the tillering stage, jointing and booting stage, flowering stage, and milky stage. The average error (\( AE \)) is used to determine the magnitude of the difference between the simulated and measured yields. The root means square error (\( RMSE \)), whose value range is \( 0 \sim +\infty \), 0, represents the highest simulation accuracy. The coefficient of variation (\( C_v \)) is used to determine the variability of data. The coefficient of residual mass (\( CRM \)) can be positive or negative. A positive value indicates that the simulation value is high, while a negative value indicates that the simulation value is low, and 0 indicates that the simulation accuracy is the best. The range of the ratio of the sum of squares of regression to the sum of squares of total deviations (\( R^2 \)) is \( 0 \sim 1 \). The closer it is to 1, the better the simulation is.

\[ AE = \frac{1}{n} \sum_{i=1}^{n} (P_i - O_i) \]  \hspace{1cm} (8)

\[ RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (P_i - O_i)^2} \]  \hspace{1cm} (9)

\[ C_v = \frac{RMSE}{O} \times 100 \]  \hspace{1cm} (10)

\[ CRM = \frac{\sum_{i=1}^{n} P_i - \sum_{i=1}^{n} O_i}{\sum_{i=1}^{n} O_i} \]  \hspace{1cm} (11)
where, \( P_i \) is the model simulation value (kg/pot); \( O_i \) is the experimental observation value (kg/pot); \( O \) is the observation average value (kg/pot); and \( n \) is the number of crop growth stages, \( n = 4 \).

2.6. Statistical Analysis

The ANOVA analyses of rice yield, water consumption, and WUE were processed using SPSS17.0 (SPSS Inc., Chicago, IL, USA). The sensitivity indices of the WPFMs were calculated by the least square method using Minitap19 (Minitab Inc., State College, PA, USA). The simulation accuracy of the WPFMs was analyzed in Excel.

3. Results

3.1. Yield

The rice yield obtained in 2018 was mostly higher than that obtained with the same treatment in 2017 (Figure 2). Yield decreased gradually with increasing drought stress in individual growth stages and across two consecutive growth stages. In 2017, the yields of L3 and L4 were significantly higher than CK by 5.5% and 6.5% \((p \leq 0.05)\), respectively, while in 2018, the yields of L3 and L4 were significantly higher than CK by 4% and 7.4% \((p \leq 0.05)\), respectively. Moreover, the yield of L3L4 was 3% higher than CK in 2017, indicating that light drought stress at the flowering and milky stages had a positive effect on yield increase.

3.2. Water Consumption and WUE

The average water consumption of all treatments was 6.3% higher in 2018 than in 2017. In both 2017 and 2018, rice water consumption decreased with the increasing drought stress across two consecutive growth stages. In 2017, the water consumption of rice decreased the most with the increase in drought stress at the tillering stage, while water consumption increased when suffering medium or severe drought stress in the jointing and booting, flowering, and milky stages, compared with light drought stress. In 2018, rice water consumption decreased with the increase in drought stress at the tillering, jointing and booting, and milky stages. Moreover, the effect of medium or severe drought stress on rice water consumption at the jointing and booting, and flowering stages manifested a higher water consumption in the next stage than in light drought stress (Figure 3).
In both 2017 and 2018, the WUE of all treatments decreased with increasing drought stress, except for the tillering stage in 2017. In 2017, the WUE of L3 and L4 were higher than CK by 16.1% and 20.6%, respectively. And in 2018, the WUE of L3 and L4 were significantly higher than CK by 5.3% and 12.4%, respectively. (Figure 4).

Figure 3. Cont.
Figure 3. The water consumption during each growth stage (a) in 2017, (b) in 2018, and (c) total water consumption for the whole growth period in 2017 and 2018. Different lowercase letters represent significant levels of each column at $p \leq 0.05$ in 2017 or 2018. L: light water deficit, M: medium water deficit, H: severe water deficit. The number “1”, “2”, “3” and “4” represent the tillering, jointing and booting, flowering, and milk ripening stages, respectively.

Figure 4. WUE of different treatments in 2017 and 2018. Different lowercase letters represent significant levels of each column at $p \leq 0.05$. L: light water deficit, M: medium water deficit, H: severe water deficit. The number “1”, “2”, “3” and “4” represent the tillering, jointing and booting, flowering, and milk ripening stages, respectively.

3.3. The Sensitivity Indices

In 2017, the Jensen model, Minhas model, and Stewart model had the highest sensitivity index at the jointing and booting stage, which represented that drought stress at this stage led to the largest decrease in rice yield. However, the Singh model had a negative
value at the flowering stage. When the sensitivity index had a negative value, the ratio of actual crop yield to potential crop yield was likely to be negative when substituted into the formula. In 2018, the sensitivity indices of the jointing and booting stage and flowering stage of the Jensen model and the Stewart model were higher than for the tillering and milky stages. The Minhas model showed that the tillering stage of rice was more sensitive to drought stress than other stages in 2018 (Table 4).

Table 4. Sensitivity index of each model in 2017 and 2018.

| Year | Models | Parameters | Rice Growth Stages | Tillering | Jointing and Booting | Flowering | Milky |
|------|--------|------------|-------------------|-----------|----------------------|-----------|-------|
| 2017 | Jensen | \( \lambda_i \) | 0.104830 | 0.246291 | 0.468936 | 0.106340 |        |
|      | Minhas | \( \lambda_i \) | 0.104100 | 2.484440 | 1.188240 | 0.381090 |        |
|      | Blank  | \( A_i \)  | 0.006489 | 0.668534 | 0.075467 | 0.295784 |        |
|      | Stewart| \( B_i \)  | 0.097711 | 0.521946 | 0.046370 | 0.159350 |        |
|      | Singh  | \( C_i \)  | 0.118730 | 1.385370 | -0.600190 | 0.027590 |        |
| 2018 | Jensen | \( \lambda_i \) | 0.519549 | 0.655407 | 0.579629 | 0.330349 |        |
|      | Minhas | \( \lambda_i \) | 3.141450 | 2.353970 | 0.586240 | 0.048590 |        |
|      | Blank  | \( A_i \)  | 0.211679 | 0.342835 | 0.220606 | 0.113858 |        |
|      | Stewart| \( B_i \)  | 0.626302 | 0.724038 | 0.719480 | 0.290445 |        |
|      | Singh  | \( C_i \)  | 0.742707 | 0.077861 | 0.324258 | -0.297443 |        |

Note: “\( \lambda_i \), \( A_i \), \( B_i \), \( C_i \)” are the water sensitivity indices of the \( i \)-th growth stage. Higher values of \( \lambda_i \) and \( B_i \) reflect that rice yield is more sensitive to water deficit, while higher values of \( A_i \) and \( C_i \) represent that the yield is less sensitive to water deficit.

3.4. Simulation Accuracy

In 2017, the Minhas model had the smallest absolute values of \( AE \), \( RMSE \), \( C_v \), and \( CRM \) of the five WPFMs, which were 0.0002, 0.0634, 6.9965, and 0.0002, respectively. The Minhas model also had the highest \( R^2 \), at 0.9951. The Blank model had the same absolute values of \( AE \) and \( CRM \) as the Minhas model. In 2018, the Jensen model had the smallest values of \( RMSE \) and \( C_v \) of the five WPFMs, which were 0.0616 and 7.2774, respectively. The \( R^2 \) of the Jensen model was also the highest, at 0.9952. However, the Blank model had the smallest values of \( AE \) and \( CRM \) of the five WPFMs, which were 0.0025 and 0.0029, respectively. Moreover, the values of \( AE \), \( RMSE \), \( C_v \), and \( CRM \) of the Minhas model were between those of the Jensen model and the Blank model. Overall, the simulation accuracy of the Minhas model was better than that of the other models (Table 5).

Table 5. Simulation accuracy analysis of the five WPFMs in 2017 and 2018.

| Year | Index | Jensen | Minhas | Blank | Stewart | Singh |
|------|-------|--------|--------|-------|---------|-------|
| 2017 | \( AE \) | -0.0247 | 0.0002 | -0.0002 | -0.0024 | 0.0004 |
|      | \( RMSE \) | 0.0802 | 0.0634 | 0.0727 | 0.0732 | 0.0721 |
|      | \( C_v \) (%) | 8.8461 | 6.9965 | 8.0219 | 8.0719 | 7.9549 |
|      | \( CRM \) | -0.0273 | 0.0002 | -0.0002 | -0.0027 | 0.0005 |
|      | \( R^2 \) | 0.9938 | 0.9951 | 0.9936 | 0.9936 | 0.9937 |
|      | \( AE \) | 0.0143 | 0.0110 | 0.0025 | 0.0032 | 0.0013 |
|      | \( RMSE \) | 0.0616 | 0.0760 | 0.0781 | 0.0800 | 0.0987 |
| 2018 | \( C_v \) (%) | 7.2774 | 8.9882 | 9.2375 | 9.4603 | 11.6630 |
|      | \( CRM \) | 0.0169 | 0.0131 | 0.0029 | 0.0037 | 0.0016 |
|      | \( R^2 \) | 0.9952 | 0.9923 | 0.9916 | 0.9931 | 0.9866 |

Note: “\( AE \)” represents average error, which is used to determine the magnitude of the difference between the simulated and measured yields; “\( RMSE \)” represents root means square error, whose value range is 0~\( \infty \). 0, and represents the highest simulation accuracy; “\( C_v \)” represents the coefficient of variation, which is used to determine the variability of data; “\( CRM \)” represents the coefficient of residual mass, whose value can be positive or negative. A positive value indicates that the simulation value is high, a negative value indicates that the simulation value is low, and 0 indicates that the simulation accuracy is the highest; “\( R^2 \)” represents the ratio of the sum of squares of regression to the sum of squares of total deviations, whose range is 0~1. The closer it is to 1, the better the simulation is.
4. Discussion

4.1. Effect of Different Deficit Regulation Irrigation Treatments on Rice Yield, Water Consumption, and Water Use Efficiency

In this study, the yields of light drought stress treatments in individual growth stages were higher than yields of medium and severe drought treatments in both 2017 and 2018. This may be due to the poor drought tolerance of rice [31,32]. At the tillering stage, drought stress suppressed the leaf area index, stomatal opening, and leaf transpiration rate of rice, which may decrease effective tillers of rice and further negatively impact yield [33]. At the jointing and booting stage, drought stress inhibited plant growth and the dry matter accumulation in stems, and reduced the grain number of secondary branches of rice, further decreasing the grain filling efficiency [34]. However, light drought stress at the flowering stage and milky stages increased soil pores, thus enhancing rice root activity, which was conducive to an increase in yield [35,36]. Moreover, the sucrose synthase enzymes in the grains increased under aerobic conditions, which enhanced the growth and productivity of rice [37]. The above reasons may explain why yields significantly decreased when drought stress occurred in the tillering and jointing and booting stages, while the yields of L3 and L4 were significantly higher than CK.

Previous studies showed that higher air temperature led to a significant increase in water consumption [38,39]. The average water consumption of the rice crop was higher in 2018 than in 2017, and the average air temperature during the rice growth period in 2018 was 0.3 °C higher than in 2017. Moreover, when the rice was subjected to medium and severe drought stress at the jointing and booting stage, or the flowering stage, water consumption increased in the next growth stage because medium or severe drought stress at the jointing and booting stage induced the formation of cortical aerenchyma in roots, and accelerated the radial transport of water through the root’s central cylinder after re-watering in the next growth stage, leading to increased water consumption [40].

In this study, except for L1, M1, H1, and CK, the WUE of each treatment decreased with increasing drought stress. However, Lu et al. found that an increase in drought stress did not necessarily reduce WUE, and may even increase it [22]. The reason may be that the differences in the compensatory growth ability of rice varieties in different regions led to the rice being able to grow rapidly with severe drought stress [41]. Some studies found that drought stress at the flowering and milky stages decreased WUE because drought stress decreased the filled grains rate per plant, which increased sensitivity to water [19,22,42]. However, in this study, the WUE of L3 and L4 were significantly higher than CK. This is due to the fact that light drought stress at the flowering and milky stages may accelerate the growth of large xylem diameters in deep roots and improve root traits, and the capacity for roots to acquire water, which led to overcompensation of yield [43,44].

4.2. Selection of Five WPFMs

Full irrigation and non-full irrigation treatments were significant for establishing the highest adaptability of WPFMs under different irrigation levels [45]. Therefore, the pot experiment setting different drought stress levels at different growth stages under mobile rain shelters was feasible for the establishment of WPFMs in cold black soil areas. Moreover, the selection of the model was considered based on the main factors that affected rice yield and the rice growing environment [46]. Therefore, setting the tillering, jointing and booting, flowering and milky stages of rice as the research objects was also feasible.

The multiplicative WPFM models were able to accurately reflect the relationships of mutual promotion and mutual limitation at each growth stage [47]. In 2017, the simulated accuracy of all indices of the Minhas model was higher than those of the Jensen model. In 2018, the simulation accuracy index of the Minhas model was second to that of the Jensen model, except for in the AE and CRM (Table 5). However, the additive models could not accurately explain the scenario of water deficit in individual growth stages [47]. In this study, the indices of simulation by the Singh model gave negative values and the simulation accuracy of the Stewart model was lower than that of the other models.
Based on the simulations using the Jensen model and the Minhas model, the more sensitive growth stages were the jointing and booting and the flowering stages in 2017, while the Minhas model indicated that the tillering and the jointing and booting stages were the more sensitive growth stages in 2018 (Table 4). Most studies have shown that the sensitivity indices of the jointing and booting stage and the flowering stage were higher than those of the tillering and milky stages [19, 22]. This is probably because the average air temperature at the tillering stage was lower in 2018 than in 2017 (Table 1), which inhibited rice tillering and decreased yield due to the interaction between low air temperature stress and drought stress [48]. For rice planting in cold black soil regions, the Minhas model more accurately reflected the impact of air temperature stress and drought stress on rice yield, while the Jensen model generally reflected the relationship between rice water consumption and yield.

5. Conclusions

Rice yield and WUE under light drought stress at the flowering stage and the milky stage increased by 4~7.4% and 5.3~20.6% compared with saturated water conditions, respectively. The water consumption of rice in different years varied with the air temperature. Medium or severe drought stress at the jointing and booting and flowering stages leads to higher water consumption in the next stage compared with light drought stress treatments. Drought in two consecutive growth stages decreased rice yield, water consumption, and WUE. The Minhas model had the highest simulation accuracy, and accurately reflected the sensitivity of rice yield to different drought stress levels in each growth stage in cold black soil regions of China. The sensitivity indices of the Minhas model indicated that rice yield was most sensitive to water deficit at the jointing and booting stage.

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